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Design of industrial equipment and systems under uncertainty and variable operating conditions

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Abstract

Variability and uncertainty often strongly affect the industrial environment. When this happens, it is impossible to neglect uncertainty, ensuring that this does not lead to incorrect decisions and wrong estimation of the inherent technical and economic risk. Although variability and uncertainty concepts have often been treated simultaneously with indistinct methods, they differ. Indeed, uncertainty may often describe something unknown, like unperfect knowledge of a correlation, whereas variability is the behaviour of random variables within time and space, like changes in market demand. However, when epistemic and aleatory uncertainty are considered, variability is also.

Industrial equipment, components, and systems often operate under conditions of deep uncertainty and variable operating conditions. However, they are usually designed based on nominal conditions, neglecting sources of uncertainty. Traditional design methods commonly assume constant process conditions and known values of the various design factors involved. However, this approach may fail to meet specifications when operational conditions change and can lead to inaccurate decisions and underestimation of inherent risk. Using safety factors or worst-case design can result in a conservative design, with components and equipment being oversized.

Several papers available in the literature and commercial software attempt to address these issues by designing the system for nominal conditions and performing a sensitivity analysis, changing one element at a time. However, this approach fails to provide a complete picture of uncertainty propagation effects. Some other works involve only a limited number of sources of uncertainty, which leads to the neglect of interactions between different sources of uncertainty. When easy-to-design elements with known nominal conditions are under analysis, another commonly used approach is to design the system assuming nominal conditions and evaluate it under off-design cases. However, this is an iterative process that is only feasible if the number of off-design cases is tiny, and this approach is practical only when random variables do not strongly influence the system under design. Moreover, industrial systems may experience changing scenarios and requirements during their life cycle and be affected by random events and internal parameter uncertainty. Thus, assessing the performance of each design in all possible scenarios is very complex.

On the other hand, some authors have proposed frameworks to deal with uncertainty propagation and estimate the uncertainty's effect on the output variables, even if they do not often include final design optimization or counteractions to mitigate the uncertainty effects. Additionally, pieces of commercial software have been introduced, either for general purpose or suited for specific applications. Some authors proposed advanced methods to deal with uncertainty. However, these methods are often suited for specific applications. This work will briefly discuss the advantages and limitations of these approaches and software.

In past years, the acronym VUCA has been introduced. The acronym VUCA stands for Volatility, Uncertainty, Complexity, and Ambiguity. Volatility describes rapid and unexpected challenges, uncertainty refers to the difficulty in predicting changes, complexity pertains to the number of key factors involved in decision-making, and ambiguity refers to a lack of certain information and the difficulty in obtaining it.

In this VUCA context, starting from a literature analysis of the existing methods and framework, this research aims to propose a general framework that extends the existing ones, including, incorporating, and systematising already available methods and approaches, dealing with two different macro-problems: incorporating uncertainty during the design phases and performing accurate risk assessments under uncertainty. Uncertainty can be aleatoric if it is characterized by random changes in variables and processes that are not theoretically reducible or epistemic if it arises from a lack of knowledge that is theoretically reducible. This thesis also introduces a novel classification of uncertainty based on the variables' behaviour. This new clustering technique aims to streamline selecting the proper methods to represent the uncertainty sources.

The framework comprises different blocks, and each block can be activated or switched off to achieve different objectives. Although the objectives can be divided into several groups, two main clusters of goals are system design optimization and system performance evaluation. Firstly, it is necessary to identify the most significant sources of uncertainty in the system under analysis and develop models to capture the variability of input factors. Next, it is crucial to model the industrial system using analytical methods, surrogate models or discrete event simulations. Subsequently, the variable or variables of interest should be carefully selected, and their values can be evaluated by propagating the uncertainty through the system model. Finally, optimisation methods can be employed to optimise the variables of interest by adjusting design parameters, or the values of the variables of interest can be manipulated to assess both technical and economic risks. This process may also involve planning and implementing corrective actions to mitigate the effects of uncertainty sources.

Two case studies have been conducted to demonstrate the capabilities of the proposed general framework. The chosen application examples are emblematic for different reasons, and the industrial systems involved have never been studied from the uncertainty perspective in the proposed way.

The first study involves the design optimisation of a shell and tube heat exchanger, along with a thorough analysis of the selection of the optimisation function. The optimisation function represents the variable of interest, and the discussion emphasises the importance of selecting the correct variable. Even if heat exchangers experiment changing conditions of the inlet fluids, to the best of our knowledge, shell and tube heat exchangers optimisation under uncertainty has not been previously proposed. Furthermore, the application of the framework allows us to compare the capabilities in dealing with the uncertainty of different existing design methods.

The second case study involves the economic assessment of a wind power system. Although the interest in renewable energies and in particular in offshore wind power systems, has grown in recent years, and this type of systems is strongly affected by the variability of the renewable resources availability, to the best of our knowledge, there were no contributions that consider simultaneously several sources of uncertainty in their economic evaluation. Only a few papers consider some sources of uncertainty, but their strengths and limitations will be discussed in the following pages of this work. In this study, the economic evaluation of several sources of uncertainty has been carried out, and countermeasures are proposed to cope with uncertainty and mitigate risks. The complexity increases compared to the first case study as the application moves from a single piece of equipment to a process plant.

Following the general framework approach in the application examples shows how this approach may lead to a more manageable selection of the proper methods to model, propagate, and assess the uncertainty effects while implementing optimization and counteraction for risk mitigation.

The results of the general framework's application to different case studies have shown the subsequent fact. The uncertainty should be considered to obtain a more effective design and assess the economic and technical risk adequately. Including several sources of uncertainty dramatically increases the dispersion of the industrial system’s output, showing the impact of uncertainty sources on the system's performance. A technically and economically viable design obtained under deterministic conditions may be ineffective when uncertainty is included.

In other words, this thesis proposes a general framework for designing and evaluating industrial systems under uncertainty using a full probabilistic evaluation method.

Future work will apply this methodology to manufacturing plants and include real-time data to adapt mitigation instruments to different cases by selecting the most appropriate ones.

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Introduction

Motivation

Industrial systems are subject to various sources of uncertainty, which can be better understood through different clustering techniques. Uncertainty can be divided into two groups: epistemic and aleatoric [1]. Epistemic uncertainty arises from imperfect knowledge of the relationships used to model the system and is often due to approximations and the imperfect capabilities of models to represent reality. Since epistemic uncertainty arises from a lack of knowledge, it is theoretically reducible by removing simplifications and assumptions of the models. Aleatoric uncertainty describes the inherent behaviour of variables and is not theoretically reducible, as it represents the randomness of events and system inputs. Another classification of uncertainty sources is the one that divides uncertainty sources into endogenous and exogenous [2]. Endogenous uncertainty arises within the system, such as failure events, while exogenous uncertainty comes from outside the system, such as demand variability. Proper classification of uncertainty sources is crucial in selecting the most appropriate method to model the variables that affect the performance of industrial systems. Since traditional classification methods often do not provide enough information to select the proper modelling method, this thesis proposes a new classification of sources of uncertainty.

Numerous sources of uncertainty and variability significantly impact the design and assessment of industrial equipment, components, and systems. While this is widely recognized, considering easy-to-design elements with known nominal, traditional design and evaluation methods often rely on nominal conditions, thereby overlooking the sources of uncertainty. Another commonly used approach is to design the system under nominal conditions and evaluate it under off-design cases. This is an iterative process that may work, but it is only practical if the number of off-design cases is minimal. Furthermore, industrial systems may encounter changing scenarios and requirements during their life cycle and are affected by random events, as well as the uncertainty of their internal parameters. It is very complex to assess the performance of each design in all these possible scenarios. In several papers, uncertainty is included by conducting a sensitivity analysis that involves changing one element at a time. However, this approach may fail to provide a complete understanding of the propagation effects of uncertainty. Other design methods incorporate only a few sources of uncertainty, neglecting interactions between different sources.

Despite the considerations mentioned above, the literature still lacks the ability to address these problems [3]. To the best of our knowledge, one of the most important works in this field was conducted by de Rocquigny et al. [4]. The authors proposed a framework for quantitative uncertainty management from a practical perspective without resorting to complex formulations that would inhibit their applicability in a real context. Additionally, one of the authors attempted to extend the framework to cope with risk assessment problems [5]. Some advanced works have been carried out in recent years focused on specific engineering fields. For example, Zimmermann et al. [6] studied the solution space on which a system is guaranteed to deliver the required performance by analysing the tolerance to parameter variations, and Zimmermann et. al [7] proposed a method to design under uncertainty in the automotive industry. As reviewed in the next sections, software tools to cope with uncertainty have also been proposed in other fields, either for general purpose or specific applications. However, none of them consider the effects of epistemic and aleatoric uncertainty of several sources simultaneously.

In the past years, the acronym VUCA (Volatility, Uncertainty, Complexity, Ambiguity) was introduced in literature. VUCA denotes an environment influenced by market volatility, weather fluctuations, customer behaviour, and other factors. It encompasses the uncertainty surrounding inputs, the complexity of multiple processes, variables, and parameters involved in designing and evaluating industrial systems, as well as the ambiguity inherent in representing reality through models. Nowadays, industrial designers and managers operate within a VUCA context, necessitating the proposal of new methods to navigate this dynamic environment. Introducing new methods and frameworks entails confronting various challenges, and the primary tasks can be summarized as follows.

- Identification and modelling of uncertainty sources. The most significant sources of uncertainty need to be identified and accurately represented. For instance, the uncertainty associated with wind speed can be modelled by employing Monte Carlo sampling from a predefined Weibull distribution. However, methods such as Markov Chain or stochastic processes may be more suitable to account for state-to-state variations.

- System modelling. The relationships employed to represent the system should be sufficiently solvable to minimise simulation time and detailed enough to mitigate the epistemic uncertainty stemming from their formulation. Additionally, certain systems may not lend themselves to analytical methods, necessitating the implementation of discrete event models. Validating such models can present a significant challenge.
- Selection and modelling of variables of interest. The process of selecting the variable of interest is not a straightforward task. The analyst must consider whether it should be a technical or economic parameter, adding complexity to the decision-making process. Moreover, a single variable may not capture a system's complete performance, leading to many variables of interest, often in trade-offs. Finally, the chosen variable or variables of interest must be effectively represented to aid decision-makers. This can involve presenting them as a single value, a probability distribution, a graph, or other appropriate formats.
- Selection of optimisation problems or risk mitigation tools. Following the assessment, the challenge lies in appropriately designing the optimisation problem, considering the necessary level of detail and computational cost. Alternatively, the challenge lies in determining the most appropriate risk mitigation tools to address the specific system being analysed.

Starting from existing frameworks available in the literature, this thesis aims to provide a comprehensive framework for designing and evaluating industrial systems under uncertainty. Numerous existing methods available in literature often overlook uncertainty, but given the significance that it can have in certain cases, this thesis aims to suggest the inclusion of uncertainty by proposing tools for its more agile management. The proposed framework tackles the aforementioned issues by propagating uncertainty within a model of the industrial system and assessing its impact on the variable of interest.

The specific objectives are:

1. Introduce a novel classification of uncertainty that facilitates the selection of appropriate modelling methods for representing variable and process uncertainty.

2. Develop a general framework for incorporating uncertainty into the design and evaluation phases, extending the existing ones, including and systematising already proposed approaches and methods.
3. Use the framework to investigate the need to incorporate uncertainty in the design and evaluation of industrial systems in order to avoid erroneous decisions.
4. Implement the framework for equipment design optimisation under uncertainty to assess its effectiveness in optimisation problems. The selected equipment is a shell and tube heat exchanger. This way, the existing research gap in the design under uncertainty of shell and tube heat exchangers is addressed.
5. Apply the framework to the performance evaluation under uncertainty of an industrial system. This application allows the author to evaluate the framework's ability to assess an industrial plant's technical and economic performance. The selected case study is the uncertain assessment of investment in wind power plants. This way, the existing research gap in the economic evaluation of renewable energy systems is addressed. This is a more complex case study, wherein the number of uncertainty sources is increased.

In summary, this thesis presents a comprehensive framework for designing and evaluating industrial systems under uncertainty, adopting a full probabilistic evaluation approach.

Research questions

Based on the problem outlined above, there are several research questions being investigated. Firstly, it is crucial to determine whether the additional modelling efforts required by the proposed general framework are justified in terms of improving the technical performance of a design or enabling a more accurate evaluation of economic investments. Specifically, the following research question is addressed:

- Is there an economic and technical benefit in considering uncertainty during the design and evaluation of equipment and industrial plants?

Next, the focus is on understanding which sources of uncertainty have a tangible impact on the performance of the system and the evaluation of economic performance. The following research question is addressed:

- To what extent does incorporating uncertainty related to correlations, component failures, disruptive events, and similar elements in a probabilistic evaluation method impact the performance of the system or the economic evaluation of the project?

Lastly, the objective is to determine whether employing a probabilistic evaluation method is essential to avoid making incorrect decisions resulting from oversimplified evaluation processes and erroneous assumptions. The following research question is addressed:

- In various case studies, if a project is deemed cost-effective when evaluated using a deterministic scenario, does it still maintain cost-effectiveness when assessed using fully probabilistic evaluation methods?

Outline of the Thesis

The outline can be divided into three parts.

1. This thesis focuses on the several aspects of designing and evaluating an industrial system under uncertainty. For that reason, the first part involves a literature review of the methods, approaches and works that address the different elements of the procedure. Three chapters are provided to describe these items.
    a. Chapter 1 analyses the literature on the uncertainty classification and the uncertainty modelling methods. Indeed, in the first part of the chapter, a brief description of the commonly adopted clustering methods of uncertainty sources is provided. In particular, epistemic and aleatory, appearance and effect, endogenous and exogenous, and controllable and uncontrollable clustering approaches are given. The second part of the chapter is focused on the uncertainty modelling methods. The following approaches are summarised: probability theory, Bayesian theory, Dempster-Shafer theory, possibility theory, interval analysis, stochastic processes, approaches for continuous variables, autoregressive models, scenario building and planning, and info-gap decision theory. Finally, some suggestions on the use of methods in practice are provided.
    b. Chapter 2 focuses on the system modelling and uncertainty propagation methods. There are mainly three different approaches for representing industrial systems: analytical, simulation, and surrogate models. Each approach has its limitations and advantages, and a discussion of them is used to highlight when one method is preferred over another. Therefore,

some widely adopted uncertainty propagation methods are introduced. They are crucial to link the input of the industrial system, also the uncertain ones, to the output. Deterministic, analytical, sampling-based and sensitivity analysis approaches are described in brief to underline that some methods cannot be used with some uncertainty modelling approaches or some system models because of the incompatibility of the algebras involved.

c. Chapter 3 discusses the problems of designing and evaluating under uncertainty. Some common issues are pointed out to share the similarities across different problems. Furthermore, some common methods to design under uncertainty are briefly exposed, i.e., robust design, reliability-based design, flexibility-based design, reconfigurability-based design, resilience-based design, and the real option theory. Some strategies for design optimisation and some design-based risk mitigation strategies are discussed. Subsequently, the risk assessment problem is introduced, and the literature-available uncertainty quantification frameworks, commercial software for uncertainty quantification, and risk mitigation strategies are analysed. Although some approaches to deal with uncertainty exist, the analysis of the literature allows the author to understand that a comprehensive general framework for optimising and evaluating under uncertainty is not already available. Moreover, the available approaches often focus on some specific sources of uncertainty, some specific methods for modelling the several items involved or suited for specific problems. This chapter poses the basis to fill the found literature gaps.

2. The second part of this thesis is composed of Chapter 4. This chapter proposes a general framework for designing and evaluating industrial systems under uncertainty. The framework comes from the systematisation of the reviewed literature. It aims to include as many as possible uncertainty and system modelling approaches, uncertainty propagation methods, risk assessment methods, optimisation methods, and risk mitigation strategies to extend its applicability fields. Additionally, the chapter proposes a new uncertainty classification method

based on the variables' behaviour over time, aiming to simplify the selection process of the methods to model and propagate the uncertainty. This new method comprises four clusters of uncertainty: Type I, II, III, and IV. Type I represents random variation over time, Type II refers to uncertainty around a constant value, Type III depicts random events, and Type IV represents random discontinuities. Since the framework's structure is modular, and different goals can be achieved, the single items composing the framework are described. At the end of the chapter, some considerations are provided.

3. The third part of the thesis is focused on the case studies. These case studies are used to demonstrate the capability of the proposed general framework and answer the above research questions. Additionally, the complexity of the modelled industrial system, in terms of parameters and variables involved, increases as it passes from the first to the second case study. Furthermore, since there is a substantial difference between the two considered industrial systems, the generality of the framework is shown. Two chapters involve the case studies' presentation and discussion.
    a. Chapter 5 focuses on shell and tube heat exchanger design optimisation. This case study analyses the framework behaviour when the optimisation goal is performed. The literature review highlights the absence of works focused on optimising heat exchangers under uncertainty, and this gap is addressed in this thesis. The chapter is divided into two parts. The first one discusses the importance of selecting the proper variables of interest to perform a useful risk assessment procedure. The role of the objective functions for optimisation purposes has been analysed. The results highlighted that economic functions are preferrable. The second part adapts the general framework to the shell and tube heat exchanger case and analyses the design procedure under uncertainty of this type of equipment. Both the epistemic uncertainty of involved design formulas and parameters and the aleatory uncertainty of fluids mass flow rates and temperature are included. Several approaches are analysed, and the relevance of considering the uncertainty and the variability of the operating conditions during the design phase is demonstrated. Indeed, the

traditional design approaches seemed incapable of coping with uncertainty. Additionally, the above research questions are addressed from the perspective of this industrial field.

b. Chapter 6 focuses on the evaluation of the technical and economic performance of offshore wind power plants. This case study analyses the framework behaviour when the evaluation goal is performed. Additionally, it assesses the relevance of scenario analysis during the economic evaluation under uncertainty. The literature review underlines the lack of contributions for this specific type of industrial system. Moreover, the uncertainty of the availability of renewable resources is crucial for determining the vital role of including uncertainty in the analysis of renewable energy systems. For that reason, in this chapter, the general framework is adapted to evaluate the performance of offshore wind power plants, considering several sources of uncertainty, including scenarios' variables. This way, the impact of wind farms is assessed. Both the modelling of the system and the market environment are performed. Furthermore, financial derivatives are included to mitigate the market risk of this industrial initiative. This case study demonstrates that uncertainty plays a crucial role in evaluating the considered industrial systems and helps address the above research questions from the perspective of this industrial field.

Eventually, the conclusion of this thesis is provided. This conclusion pertains to the main contribution of the proposed approach, the limitations of the conducted study, and the future development of the work. The future works section points out the research question that should be investigated.

Parts of this thesis have been developed starting from the ideas and with the support and advice of Professor Antonio Casimiro Caputo [8].

List of the papers

The studies conducted for this thesis produced six papers. Three of them have been published in peer-reviewed international journals, one has been published in the proceedings of a conference, and two of them are currently under review. The papers are listed below.

Caputo, A. C., Federici, A., Pelagagge, P. M., & Salini, P. (2022). On the design of shell-and-tube heat exchangers under uncertain operating conditions. Applied Thermal Engineering, 118541.

Caputo, A. C., Federici, A., Pelagagge, P. M., & Salini, P. (2022). On the selection of design methodology for shell-and-tube heat exchangers optimization problems. Thermal Science and Engineering Progress, 101384.

Caputo, A. C., Federici, A., Pelagagge, P. M., & Salini, P. (2023). Offshore wind power system economic evaluation framework under aleatory and epistemic uncertainty. Applied Energy, 350, 121585.

Caputo, A. C., Federici, A., Pelagagge, P. M., & Salini, P. (2023). Offshore wind power system economic evaluation under uncertainty: scenario analysis. Proceedings of the Summer School Francesco Turco, 06-08 September 2023, Genova, Italia.

Caputo, A. C., Federici, A., Pelagagge, P. M., & Salini, P. (2023). Scenario analysis of offshore wind power systems under uncertainty. Sustainability, 15(24), 16912.

Caputo, A. C., Federici, A., Pelagagge, P. M., & Salini, P. (2023). Offshore wind farm economic evaluation under uncertainty and market risk mitigation. Unpublished manuscript.

Chapter 1

Uncertainty classification and modelling

Uncertainty and variability are often used as synonymous. However, although variability and uncertainty concepts have often been treated simultaneously with indistinct methods, they differ. Indeed, uncertainty may often describe something unknown, like imperfect knowledge of a correlation or predictability about an outcome. On the contrary, variability is related to the differences, fluctuations and variations within a system or dataset and refers to the spread or diversity of possible outcomes. Indeed, the variability can represent the behaviour of random variables within time and space, like changes in market demand. However, when epistemic and aleatory uncertainty are considered, variability is also because aleatory uncertainty and variability are both about a variable's randomness. For these reasons, variability is considered and treated like aleatory uncertainty in this thesis.

This chapter will provide an overview of uncertainty classification and modelling. Understanding the type of uncertainty and adopting the proper classification approach is crucial to selecting the most appropriate model for the uncertainty sources representation. Three different classifications will be discussed. The most widely used is the division into epistemic and aleatoric. However, the analysis of the effects and probability and the grouping within endogenous and exogenous, with a focus on controllable and uncontrollable sources of uncertainty, will be analysed.

After the classification, a review of the methods and approaches that can be used to model the uncertainty sources will be provided, and the uncertainty effects on the evaluation and design of the system will be examined.

1.1 Uncertainty classification

Industrial systems are affected by several sources of uncertainty. The uncertainty can arise from numerous factors, such as material properties, manufacturing tolerances, applied loads, market conditions, technological advancements, customer requirements, correlation used to represent the system, failures events, availability of the resources, disruptive events, and so on [9, 10].

1.1.1 Epistemic and aleatory uncertainty

Uncertainty is often divided into aleatoric uncertainty and epistemic uncertainty [11].

- **Epistemic uncertainty**. It is the uncertainty theoretically reducible, arising from the lack of information and knowledge [12, 13]. For example, it can result from the small size of a sample used to estimate a probability distribution or from imperfect knowledge of the mathematical relationships employed to construct a model. Consequently, this uncertainty arises from the combination of uncertainties in the data and uncertainties in the model description. This uncertainty is the inadequate understanding of the underlying processes, incomplete knowledge of the phenomena, or imprecise evaluation of the related characteristics [14].
- **Aleatoric uncertainty**. Under this category, we have the non-theoretically reducible uncertainty, which is characteristic of phenomena and processes. For instance, it encompasses uncertainties such as the variability in product demand over time, the seasonal temperature trends, or the electricity consumption of a tool within a fixed time interval [15].

These two groups of uncertainty have a tendency to overlap and blend together, resulting in effects that a single model cannot adequately represent. Therefore, to address this issue, only when these two types of uncertainty overlap each other uncertainty analysis can be divided into two levels [4].

1. **I level**: aleatory uncertainty.
2. **II level**: epistemic uncertainty.

To provide further clarification, let us consider a hypothetical aleatoric variable, denoted as x, which is dependent on an array X consisting of all the input variables of a selected system model. The variable x is described by a probability density function (*pdf(x)*), which represents the aleatory uncertainty. The *pdf* is assumed to follow a normal distribution characterized by its mean and standard deviation. However, these two parameters are not known a priori and need to be estimated through the analysis conducted by an analyst. Therefore, even these two elements (mean and standard deviation) are subject to uncertainty, but of the II level (1.1).

$$pdf(x) = NORM(UNIF(a,b), NORM(c,d)) \quad (1.1)$$

Where *a* and *b* are the boundary of the uniform distribution respectively, representing the mean of *pdf(x)*, while c and d represent the mean and the standard deviation of the normal distribution, which describes the standard deviation of *pdf(x)*.

The aleatoric, or aleatory, uncertainty cannot be reduced in any case. Indeed, increasing the number of experiments does not shrink because it is attributed to the inherent randomness of real processes, parameters, and the physical world. The division of uncertainty into epistemic and aleatory resides mainly in the way that they can be treated. While the latter has often been modelled like the quantity's actual value is within an interval, the former has often been described using classical probabilistic frameworks [16].

1.1.2 Appearance and effect of the uncertainty

In the same way, it is possible to analyse the appearance and effect of the uncertainty. From this perspective, uncertainty is divided into stochastic uncertainty, incertitude, and ignorance [10]. Starting from the analysis of process property or the structure's function and state of the system, the first question to answer is whether the effects of this uncertainty are known or not. If they are quantifiable, a classical probabilistic framework is established, and if the probability density function is certain, we can talk of stochastic uncertainty, otherwise about incertitude (e.g., tolerances). When stochastic uncertainty is on the table, the analysts often resort to known probability distributions, whereas when incertitude is identified, they often resort to known intervals. Instead, when the effects of uncertainty are not known, one can talk about ignorance and assume a fixed value in some way.

Another adopted approach that follows the division by effect and quantification to uncertainty clustering is the grouping by considering the elements with which the uncertainty is associated. With this approach, the uncertainty is classified by data, component, and structure, and it is motivated by system design [10]. Data uncertainty can be, as previously said, modelled with a known distribution, unknown distribution, and ignored data uncertainty if it is stochastic, incertitude or ignorance, respectively. Model uncertainty can be represented by resorting to joint probability distributions, unknown distribution and interval analysis, or ignored model confidence and prediction interval if it is stochastic, incertitude or ignorance. Finally, if the uncertainty is related to the system's structure under analysis, only ignorance can be modelled using unexplored design space [10].

1.1.3 Endogenous and exogenous uncertainty

It can also be useful to understand from where the uncertainty comes. Two clusters can be identified [2, 17] (Figure 1.1).

- **Endogenous uncertainty**. This type of uncertainty pertains to the inherent variability within the product or system. While it is possible to reduce this uncertainty during the design phase, there is still a plausible possibility that not all relationships and relevant interactions have been accurately modelled.
- **Exogenous uncertainty**. This type of uncertainty originates from the external environment outside the plant or product. For example, an item may be designed for a specific application under predetermined conditions of use. However, it may end up being utilized in a different environment altogether, leading to different outcomes. Other sources of similar uncertainties include market uncertainties, demand uncertainties, and so on.

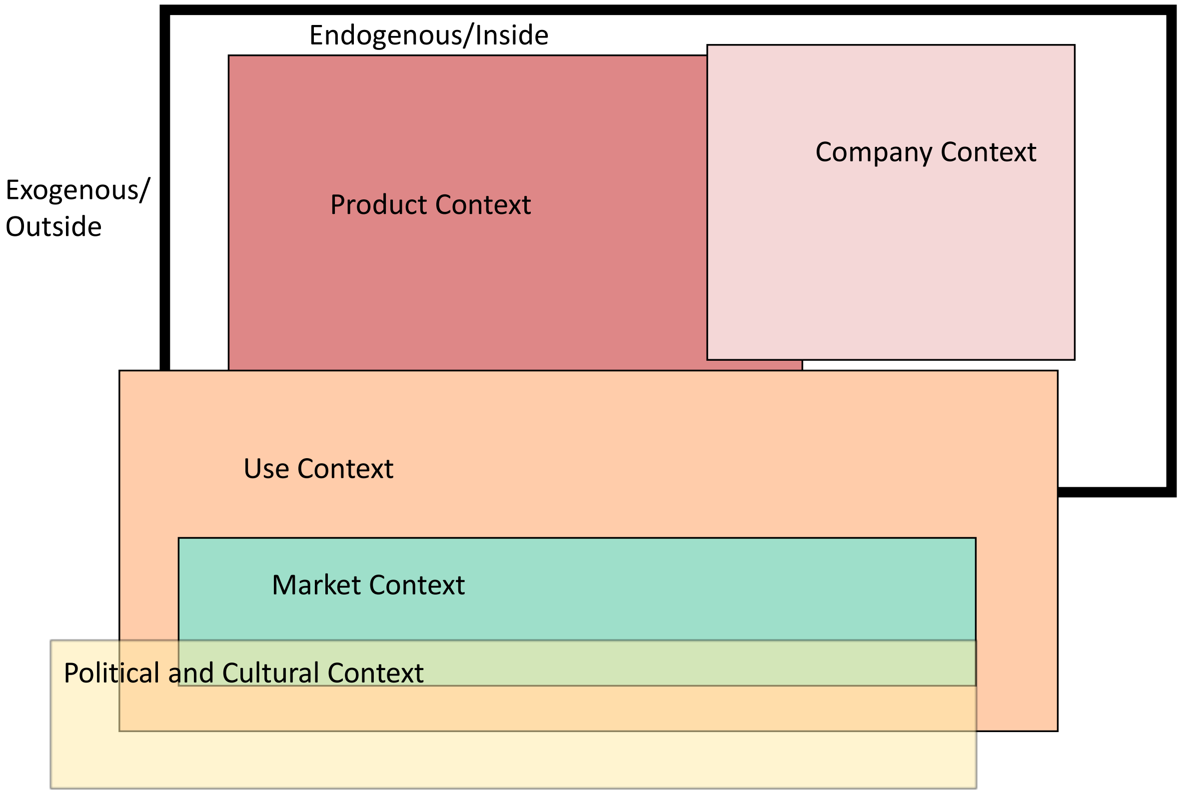

Figure 1.1 Endogenous and exogenous uncertainty

Endogenous uncertainty is often related to the product or corporate contexts. The development process of a product should always be considered a component of technical risk due to the novelty of the design or at least the design process itself in the firm context. Even if the potential sources of uncertainty are assessed at the beginning of the design process, they are usually solved during the design process. In any case, companies very often use the collected best practices they have already used for other products, but all products are different; thus, a solution that works for one element could not work for another. Moreover, the uncertain interactions between the components of a product can propagate failures, affecting the product's reliability over its life cycle. Instead, the corporate context refers to the plant and the firm's environment. The supply chain and firm’s assets issues can strongly influence the product's financial viability, and so can the company's economic sustainability.

Exogenous uncertainty is related to the use context, the markets, and the political and cultural context. The sources of uncertainty grouped in this cluster are not in the company's control. The use context is linked to the different ways and environments in which the product can be used. For instance, the same tool can be used on a mountain and at sea, so it may be able to operate in several conditions. Additionally, the uncertainty arises also from the end users, which are different. The market uncertainty is due to the enormous geographic areas in which the products are sold. These geographic areas have several differences and currencies with no constant exchange rates. Finally, the political and cultural context influences the market as well as the consumer or more. Changing regulatory policies, e.g., subsidies, taxation, or economic legislation, can determine the non-economic viability of a product in a country. Moreover, changes in the product design can be required. Additionally, introducing score indexes that classify an item's safety or healthiness can strongly reduce or increase its penetration in the local market.

1.1.4 Controllable and uncontrollable uncertainty

Since endogenous and exogenous uncertainty sources could overlap, losing their independence, the uncertainty can be classified according to [18]. As depicted in Figure 1.2, the engineering activity can directly influence some sources and none others.

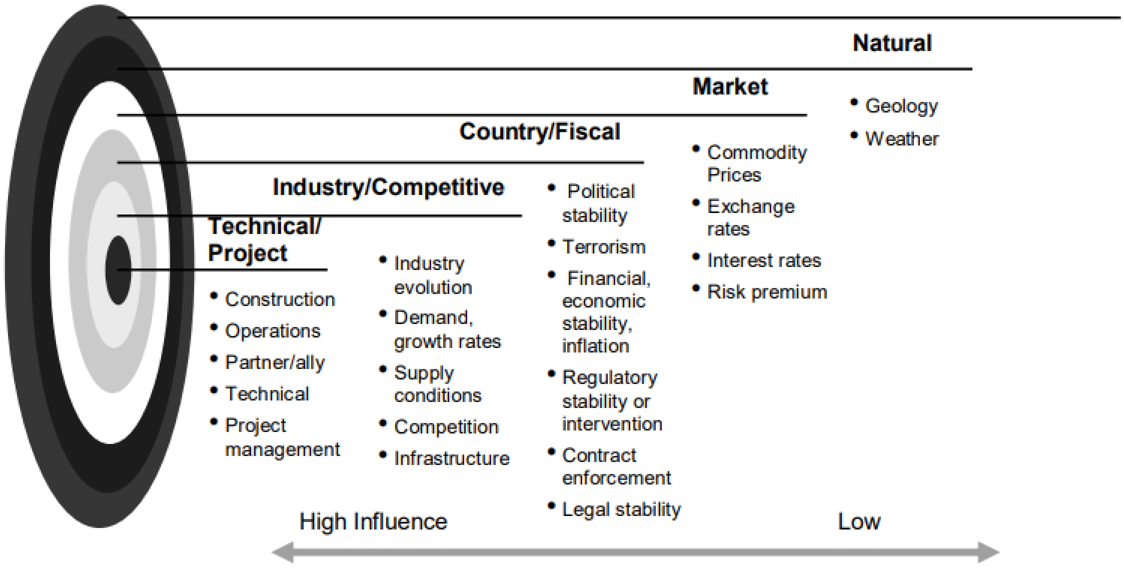

Figure 1.2 Layered uncertainty representation [2]

However, when the design process cannot influence them, counteract actions against the effects of uncertainty can be done.

Technical and project uncertainty corresponds to construction, operations, partner ally, technical, and project management risks. The industry and competition are related to the industry evolution, the demand, the supply conditions, and the infrastructure risk. The country and fiscal uncertainty introduce the risk of political stability, terrorism, financial and economic stability and inflation, regulatory stability or intervention, contract enforcement, and legal stability. The market uncertainty represents the commodity prices, exchange rates, interest rates, and risk premiums. Finally, natural uncertainty is related to disruptive events that can damage industrial systems.

The layers of uncertainty model present the capabilities of designers and management in mitigating risk or exploiting opportunities that uncertainty sources point out. The inner layers are highly influenceable, whereas the outer ones are uncontrollable. Indeed, a company can act directly on the products, equipment, and assets but cannot on the regulatory policy or natural events. Still, the management can consider insurance and financial products to mitigate the risk of the noncontrollable sources of uncertainty.

As a result of the aforementioned considerations, the sources of uncertainty can be classified as controllable or uncontrollable. When the sources of uncertainty are controllable, it is possible to design systems that perform optimally across various scenarios. One common approach to achieving this goal is to reduce tolerance intervals, thereby minimising the range of variability within which the system operates.

1.2 Uncertainty modelling

Numerous authors have proposed many methods to cope with the uncertainty modelling problem in the literature. In this section, with the aim to give a representative picture of the available techniques for modelling uncertainty, the main ones are described.

Several approaches are suitable depending on the type of uncertainty and the level of adherence to reality required. Generally, methods for uncertainty modelling can be divided into two groups: formal approaches and practical approaches.

Formal approaches, while capable of describing the behaviour of generic uncertain input variables, are challenging to use and implement and are mathematical or theoretical. On the one hand, they offer a comprehensive understanding of uncertainty; however, their high complexity in terms of theories and the time required for formulation and simulation significantly limit their adoption in productive firms. Moreover, in a probabilistic approach, uncertainty is characterized using probability distributions. However, in some instances, such as when limited data is available, it may be difficult to specify precise values for input distribution parameters, precise probability distributions, and dependencies between input parameters. In such situations, the probabilistic approach may not be effective, and alternative uncertainty handling theories have been developed to address these limitations. The formal approaches considered in this work are probability theory, Bayesian theory, Dempster-Shafer theory, possibility theory, interval analysis, and stochastic processes.

Practical approaches are heuristic or empirical and primarily rely on data available in databases and expert judgments. They are relatively easy to implement but can be far from reality in certain cases. The practical approaches included in this work are methods for continuous variables, autoregressive models, scenario building and planning, and info-gap decision theory [2]. Although autoregressive models are formal with respect to their statistical foundation, they are often considered practical because of their application in real-world scenarios for forecasting and understanding temporal data patterns.

In the following, these methods will be reviewed without providing a detailed description or step-by-step instructions for the sake of brevity.

1.2.1 Probability theory

From a traditional perspective, probability is the widely adopted tool to represent uncertainty in risk assessment and design under uncertainty [19]. This method's versatility resides in dealing with random aleatory uncertainty using experiments and subjective aleatory uncertainty by statistical analysis of surveys.

From a frequentist perspective, probability is defined as "*the fraction of times an event A occurs if the situation considered were repeated an infinite number of times. Taking a sample of repetitions of the situation, randomness causes the event A to occur a number of times and to not occur the rest of the times. Asymptotically, this process generates a fraction of successes, the "true" probability P(A). This uncertainty (i.e., variation) is sometimes referred to as aleatory uncertainty*" [19].

Traditional probability theory is focused on assessing the belief that an event will occur by analysing random phenomena, resorting to experiments founded on trials and analysis to estimate the probability of an event starting from a statistical analysis [15]. Considering a discrete case and assuming that Ω is a sample space of the events A_i, which are subsets of Ω, the probability P must satisfy three properties: Normality (1.2), Nonnegativity (1.3), Additivity (1.4), and Self-duality (1.5).

$$\mathrm{P}(\Omega) = 1 \tag{1.2}$$

$$\mathrm{P}(A) \geq 0 \tag{1.3}$$

$$\mathrm{P}\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} P(A_i) \tag{1.4}$$

$$\mathrm{P}(A) = 1 - \mathrm{P}(\bar{A}) \tag{1.5}$$

In other words, the probability of the sample space is almost surely. The probability of a single event ranges between 0 and 1. If the events of the sample space are mutually exclusive, so if an event of the sample space occurs none of the others can, the union of the probability of the occurrence of all the events is equal to the sum of the single probability of occurrence of the single events. Finally, the probability of an event occurring and the probability of the same event not occurring must sum to one.

In the continuous case, it is possible to define the Cumulative Distribution Function (F, 1.6) of the random variable Y such as:

$$F(y) = P\big((-\infty, y]\big) = P(Y \leq y) = \int_{-\infty}^{y} p_y(t)dt, \forall y \in \Omega \tag{1.6}$$

Figure 1.3 shows an example of a probability density function and its cumulative distribution.

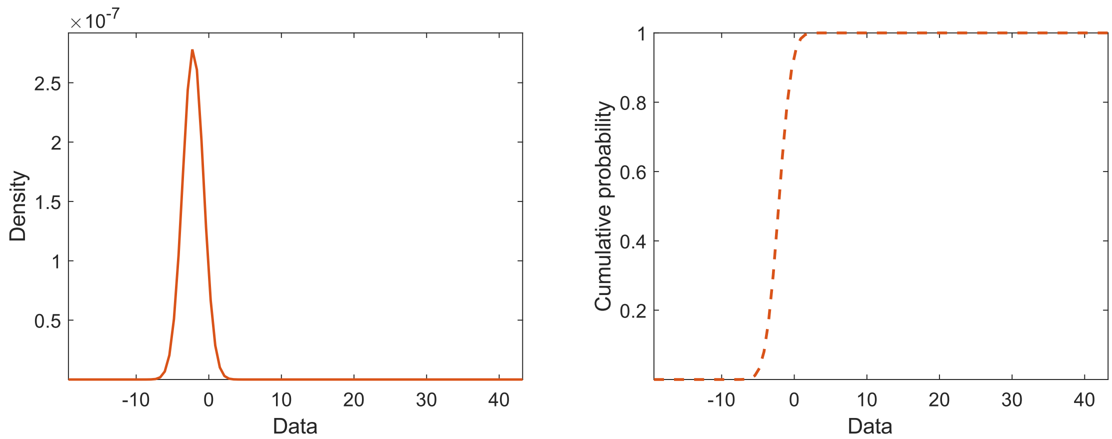

Figure 1.3 Probability density function and its cumulative distribution function

The versatility of this method allows us to represent both aleatory and epistemic uncertainty. The assessment of the probability of occurrence of an event usually requires random experiments to deal with the natural variability. As a matter of fact, repeated experiments permit the computation of the frequency of a specific event, reaching an estimation of the actual probability. The higher the number of repetitions, the more accurate the probability estimation.

Since it is not possible to perform an infinite number of experiments, the value of *P(A)* needs to be estimated by the relative frequency of occurrence of the event in the finite sample considered. The lack of knowledge about the actual probability is related to the epistemic uncertainty, as already specified in section 1.1.1.

These techniques can accurately model potential events and the mechanics of complex systems in a highly realistic manner. However, utilizing these techniques often incurs a high computational cost for the model. In probability theory, uncertain variables are described by known probability density functions or cumulative distribution functions.

In the end, a possible procedure to model uncertainty sources with probability theory follows the subsequent steps.

1. Identify uncertainty sources by determining the variables and factors that contribute to uncertainty.
2. Associate a random variable to each uncertainty source.
3. Define a probability distribution for each random variable by selecting the one that best represents the uncertainty characteristics. This step involves available data or assumptions based on the nature of the source to define the distribution's parameters.
4. Understand if there are relationships between different variables. Use correlations, conditional probabilities, and joint distributions if they have dependencies.

The accuracy of the representation is related to the quality of data and the goodness of selected distributions. Moreover, using probability theory some uncertainties might not be fully captured.

1.2.2 Bayesian theory

The Bayesian theory gives a subjective interpretation of the probability that arises from an epistemic expression of uncertainty based on the knowledge of the assigner. In this view, the probability of an event is "*the degree of belief of the assigner with regard to the occurrence of A. The probability can be assigned with reference to either betting or some standard event*" [19].

Bayesian theory, rooted in probability theory, expresses probability as a measure of belief in an event. The fundamental tool of this theory is Bayes' theorem (1.6), initially introduced by Bayes [20], which establishes a connection between multiple events through conditional probabilities to draw inferences. To derive these estimations, it is crucial to possess prior knowledge or conduct experiments. Indeed, Bayesian theory is particularly suitable in scenarios where direct information about an event is lacking. It enables the description of the probability of an event based on prior knowledge and offers a framework for updating the probability of that event when new or additional evidence becomes available.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{1.6}$$

Where *P(A|B)* is the probability of event *A* if *B* is true, *P(B|A)* is the probability of event *B* if *A* occurred, and *P(A)* and *P(B)* are the probability of *A* and *B* to occur without any conditions, respectively.

The relative frequency begot by randomness is considered as a chance to differentiate that from probability, which is linked to the epistemic uncertainty based on belief. Indeed, probability refers to the unknown value of a chance. This epistemic-based probability is often used to describe the uncertainty about the actual value of a relative frequency probability. In such a way, combining this approach with the frequentist approach, the epistemic and aleatory probability are simultaneously considered.

This theory involves reasoning rather than random sampling, and it can be used to generate a probabilistic graphical model called Bayesian network. Using a directed acyclic graph, this graphical model depicts a group of random variables and their dependencies. For instance, the interdependencies of four events named A_1, A_2, A_3, and A_4 can be represented as shown in Figure 1.4. In such a network, the events A_1 and A_2 are independent, while A_3 is related to A_1 and A_2, and A_4 is linked only to A_2.

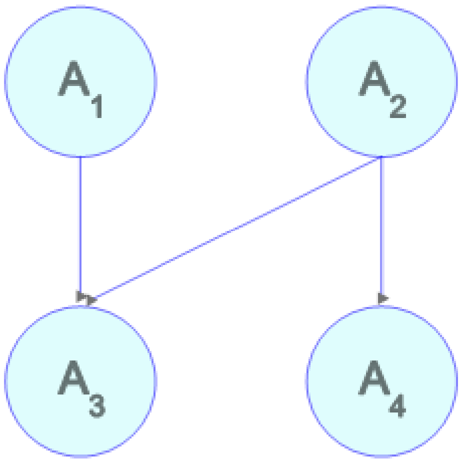

Figure 1.4 Bayesian network example

In the end, a possible procedure to model uncertainty sources with Bayesian theory follows the subsequent steps.

1. Identify uncertainty sources by determining the variables and factors that contribute to uncertainty.

2. Assign an uncertain variable to each source of uncertainty and use assumptions, historical data, and available knowledge to define prior probability distribution for each uncertain variable. Then, associate beliefs on the possible values of variables.
3. Collect evidence and observations about the uncertain variables.
4. Use Bayes' theorem to achieve posterior distribution using the evidence collected in step 3.
5. Iterate the process if new evidence arises and update the beliefs to refine the uncertainty model.

The model's goodness is related to priors, and their selection process is crucial and arduous, especially when poor data is available.

1.2.3 Dempster-Shafer theory

Dempster-Shafer theory (DST) considers different sources' evidence and combines them to achieve a degree of belief in an event occurrence by considering all the available evidence [15]. It is also known as evidence theory and encompasses the integration of diverse pieces of evidence from various sources to establish a degree of belief in an event. It is characterized by two fundamental concepts: belief and plausibility, which represent the lower and upper bounds, respectively, of a set of belief and plausibility distribution functions utilized to describe input uncertainty. In contrast to Bayesian theory, evidence theory does not necessitate the same assumptions or requirements [21, 22].

DST introduces a space of mass (m), another name for the degree of belief, which is represented by a belief function (1.7).

$$m: 2^X \rightarrow [0,1] \tag{1.7}$$

X is the set of all possible states, and 2^X is the set of all subsets of X, including the empty set. For a generic subset S that belongs to 2^X, the mass of S (1.8) comes from all the evidence that supports S.

$$\sum_{S \in 2^X} m(S) = 1 \tag{1.8}$$

The Belief function (1.9) is the sum of all the masses of *S*, i.e. the evidence that supports *S*. In this sense, this is the lower bound of the set.

$$belief(S) = \sum_{T|T\subseteq S} m(T) \tag{1.9}$$

On the other hand, the Plausibility function (1.10) is the sum of all the masses of sets that intersect *S*, so all the evidence that partly or fully supports *S*. In this sense, this is the upper bound of the set.

$$plausibility(S) = \sum_{T|T\cap S\neq\emptyset} m(T) \tag{1.10}$$

Additionally, the two measures, i.e. the plausibility and belief functions, are related to each other according to (1.11).

$$plausibility(S) = 1 - belief(\bar{S}) \tag{1.11}$$

As per the remark, the probability of a set $S \epsilon 2^X$ is in the range between the value of belief and plausibility.

Considering the mutually exclusive events A_1, A_2, and A_3 for which a collection of evidence was made from experts and one of these events must happen, Table 1.1 is an example of how data can be presented.

Table 1.1 Example of table that resumes data about a set of events according to Dempster-Schafer theory

Event	**Mass**	**Belief**	**Plausibility**	**Range**
$\emptyset$	0	0	0	[0,0]
A_1	x_1	x_1	x_2	$[x_1,x_2]$
A_2	y_1	y_1	y_2	$[y_1,y_2]$
A_3	z_1	z_1	z_2	$[z_1,z_2]$

This theory plays a crucial role in combining different information to estimate the probability of an event.

In the end, a possible procedure to model uncertainty sources with Dempster-Shafer theory follows the subsequent steps.

1. Identify the uncertainty sources and the related possible hypotheses and outcomes.
2. Assign the belief level in each hypothesis using expert judgments, data, or statistical analysis.
3. Use Dempster's rule to combine the belief levels and/or mass function, considering the dependence or independence of the hypotheses.
4. Use the mass functions obtained in step 3 to derive the belief and plausibility functions.

This theory provides a more flexible representation of uncertainty than probability theory but can be complex and computationally expensive when numerous hypotheses are involved.

1.2.4 Possibility theory

Fuzzy sets extend the concept of crisp sets expressing classes with no well-defined boundaries. Indeed, the transition between set members and non-members is gradual [15]. It can be defined as the degree of membership of every member in the universal set *X* with a value in the range [0,1].

Considering the fuzzy set A, its membership function (μ_A) is defined in (1.12). At the same time, in Figure 1.5, there is a graphical representation of a generic trapezoidal membership degree function of the think "*abc*" to the universal set *X*.

$$\mu_A: X \to [0,1] \tag{1.12}$$

Resorting to fuzzy logic, fuzzy sets are handy for reducing the differences between human thinking about a set of data and their representation for including them in the decision process.

Possibility theory is based on the notion of fuzzy sets. It is an alternative to probability theory and differs from the former by using a couple of set functions to describe a measure: the possibility and the necessity measures [23]. The probability is a measure of the frequency of event occurrence. On the other hand, the possibility is employed to quantify the significance or meaning of an event [24]. Probability distribution functions must sum up to 1, whereas for possibility distributions, the highest values are set to 1. Consequently, the

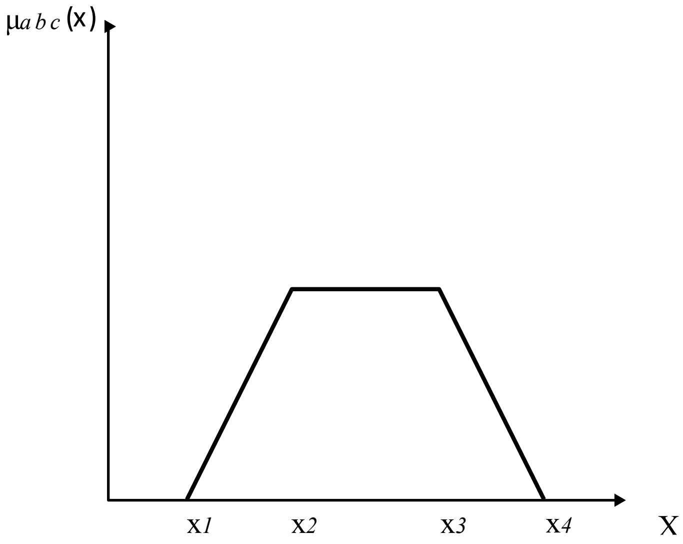

Figure 1.5 Example of trapezoidal fuzzy set

possibility can be considered as an upper bound on probability. The possibility distribution must satisfy three properties: normality (1.13), nonnegativity (1.14), and if the considered events A_i, which are a subset of the universe Ω are disjoint, the property of maximality (1.15).

$$possibility(\Omega) = 1 \tag{1.13}$$

$$possibility(\emptyset) = 0 \tag{1.14}$$

$$possibility\left(\bigcup_{i=1}^{\infty} A_i\right) = \max_{1<i<\infty} possibility(A_i) \tag{1.15}$$

In the end, a possible procedure to model uncertainty sources with possibility theory follows the subsequent steps.

1. Identify uncertainty sources by determining the variables and factors that contribute to uncertainty.
2. Associate a possibility distribution to each variable.
3. Define the possibility distribution for each variable to represent the possibility that the variable assumes a value of is within a range.
4. Define the membership functions that refers about the degree of membership of elements in the fuzzy set.
5. If multiple variables are involved combine the possibility measures.

6. Use inference mechanisms to reason under uncertainty and apply operations. If possible, quantify the possibility measures numerically. Otherwise use qualitative values.

1.2.5 Interval analysis

Prosaically, the main difference between this approach and the probability approach is that the interval analysis works with ranges that define the values the variable can assume instead of working with random and uncertain variables. In this way, it is possible to calculate straightforwardly the upper and lower bound of the range of a function.

An interval is defined as in 1.16.

$$[a, b] = \{x \in \mathbb{R} | a \leq x \leq b\} \tag{1.16}$$

It is widespread to use interval when it is needed to represent a quantity like a measure. For the sake of example, if the sensitivity of a measurement instrument is the nearest whole number. As a matter of fact, the interval that describes the quantity value will be $x \epsilon [a,b]$, where a is equal to $(x1-0.5)$ and b is equal to $(x1+0.5)$. In Figure 1.6, the example interval is shown. The light red area is outside the interval, while the light blue area is inside the interval.

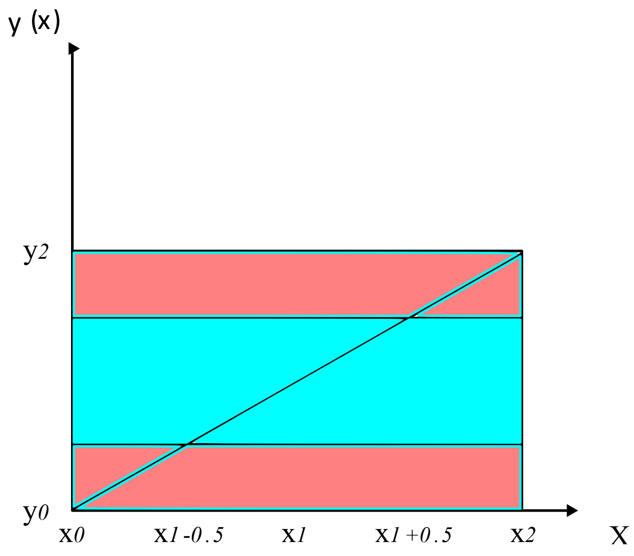

Figure 1.6 Example of an interval

Intervals can be added, subtracted, multiplied, and divided [25]. Furthermore, generic functions can be applied to intervals, but some limitations appear for the dependency problem, which may lead to overestimating the resulting intervals.

In the end, it is a branch of numerical analysis that enables us to calculate closed intervals for the precise values of integrals [26]. In interval analysis, the uncertain parameter is represented by a simple range, and a preference function is used to describe the desirability of utilizing different values within this range.

Eventually, a possible procedure to model uncertainty sources with interval analysis follows the subsequent steps.

1. Identify uncertainty sources by determining the variables and factors that contribute to uncertainty.
2. Associate an interval to each variable to represent the range in which it may lie by defining the lower and upper bound of the range.
3. Define and conduct arithmetic and logical operations on intervals, maintaining their uncertainty properties.
4. Use the intervals to assess potential outcomes, accounting for dependencies between variables.

Interval analysis is practical when dealing with uncertainty with bounded information and simplifies complex calculations, allowing the assessment of ranges of potential values for uncertain variables.

1.2.6 Stochastic processes

Stochastic processes are the probabilistic version of a dynamic system. As a matter of fact, without rigorous definitions, a stochastic process is a set of stochastic variables which represents the evolution of a random variable over time. In other words, they could be considered random variables which consider the time dimension. Each random variable of the stochastic process is associated with an element in the set called index set. The index set is the interpretation of time.

From a practical perspective, this family of processes gives a picture of the time evolution of a random variable, and by reiterating the same process several times, we will obtain different time evolution. In fact, considering a generic time instant *t*, we can observe a probability density function of the values that the variable can assume. A single outcome of a stochastic process is called sample function, thus a realization of the process. In other words, a sample function represents the process's trajectory or path. Additionally, the mathematical space of a stochastic process is called state space. The elements that reflect the several values that the process can take define this state space. Finally, the increment is the difference between two random variables that pertain to the same stochastic process.

Stochastic processes are divided into discrete time and continuous time stochastic processes. The former has an index set comprising a finite number of elements, whereas the latter is characterised by an index set defined in an interval of the real line. If the index set is composed of integers, the random process can be called a random sequence.

Stochastic processes encompass a considerable number of processes. Below is provided a non-exhaustive list of processes that belong to this family.

- Bernoulli process.
- Wiener process.
- Poisson process.
- Markov process and chains.

The Bernoulli process is one of the most straightforward stochastic processes [27]. It is a discrete-time process, and the random variables that describe this process are independent and identically distributed and can assume either the value of 0 or 1. Additionally, it is a memoryless process. Therefore, the past outcomes provide no information about the future outcomes. Actually, a generalization of the Bernoulli process, called the Bernoulli scheme, admits more than a binary configuration, and the outcomes can assume more than only two values.

The Wiener process is a continuous-time stochastic process, and the unconditional probability of the increments is normally distributed linked to the size of the increments [28]. There are several Weiner-related processes, such as the Levy processes, Markov process, and geometric Brownian motion.

The Poisson process is pervasive in modelling random events, like in queuing theory, when defined on the real line. It is a collection of wholly independent and random subregions [29].

The Markov process is a stochastic model that can be either discrete or continuous time. It has a memoryless property, so only the current state influences the following state [30]. The changes in the system's state are called transitions, and each transition has an associated transition probability. Nevertheless, some authors have partially modified the Markov chain to allow a few states behind the current state to influence the subsequent state [31].

In the end, a possible procedure to model uncertainty sources with stochastic processes follows the subsequent steps.

1. Identify uncertainty sources by determining the variables and factors that contribute to uncertainty.
2. Understand the stochastic process that suits the identified uncertainty sources and the possible states that it can assume.
3. Define the time and/or spatial domain over which the process evolves.
4. Identify the transition probabilities between the admittable states, and if possible, estimate parameters of the process using observed data.

Stochastic processes are helpful when uncertain variables evolve over time and/or space. However, the understating of the dynamics of the process may be a complex task, depending on the nature of the considered system.

1.2.7 Continuous variables

They can be employed to model continuous processes, such as time-dependent demand or price. The most commonly used methods are diffusion models and lattice models. Diffusion models assume that the variable's initial value is known, and from this initial value, there is a random diffusion process.

The most commonly used diffusion model is Geometric Brownian Motion (GBM) [2]. GBM is a continuous-time stochastic process in which the logarithm of the random variable follows a Wiener process. If there is a trend, it can be estimated from the past time history. The variability of the expectation (1.16) of the relative change in quantity over one time period is represented by the square of the standard deviation multiplied by the time period (1.17).

$$E[\Delta x/x] = \mu \Delta t \tag{1.16}$$

$$\text{var}[\Delta x/x] = \sigma\text{^}2\ \Delta t \tag{1.17}$$

E represents the expected value of the change Δx in the value of the variable x, while σ is the standard deviation, and Δt is the time period. Equation (1.18) describes the GBM and specifies that uncertainty grows linearly with the square root of the reference time period.

$$\frac{\Delta x}{x} = \mu \Delta t + \sigma \varepsilon \sqrt{\Delta t} \tag{1.18}$$

ε is a uniformly distributed random variable between 0 and 1.

While diffusion models can produce an infinite number of scenarios that require the use of statistical sampling methods, lattice models [2], considering a more significant time span for each prediction, can obtain a finite number of future stories. The initial state is known, and the number of dimensions of the model determines how to go on. For instance, in the binomial lattice, the uncertain variable can increase (u) or decrease (*d*) of a quantity with a probability of p and *(1-p)*, respectively. The subsequent equations (1.19, 1.20, and 1.21) clarify these notions.

$$u = e^{\sigma\sqrt{\Delta t}} \tag{1.19}$$

$$\mathrm{p} = \frac{e^{\sigma \Delta t} - d}{u - d} \tag{1.20}$$

$$d = \frac{1}{u} \tag{1.21}$$

The size of the movement depends on the volatility and length of the time period. Suppose one wants to determine the probability of occurrence of a specific scenario in the path of the lattice. In that case, he can use the 1.22, where *k* is the number of the time periods, and *n* is the time period of the scenario of interest.

$$P(i) = p^k (1 - p)^{n-k} \tag{1.22}$$

Figure 1.7 shows a generic binomial lattice model, the unit of measurement of the variable values and of the time interval there is not only for this generic schematization.

In the end, a possible procedure to model uncertainty sources with diffusion models follows the subsequent steps.

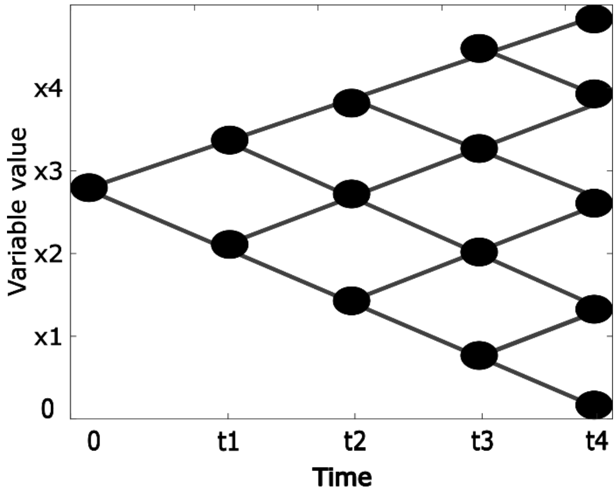

Figure 1.7 Schematization of the binomial lattice method

1. Identify uncertainty sources by determining the variables and factors that contribute to uncertainty.
2. Understand the diffusion model that suits the identified uncertainty sources, the states variables and define its parameters, like drift and volatility.
3. Define the initial conditions for the state variables, using available data or assuming them.
4. If the model includes stochastic differential equations, define them.

Diffusion processes are continuous-time models and the accuracy of selected parameters significantly impact their performance.

1.2.8 Autoregressive models

The autoregressive models are a representation of a specific type of stochastic process. Indeed, they represent the variations of a quantity over time. They can be written with stochastic difference equations or recurrence relations [32].

Autoregressive models are often combined with moving average models that are stationary. Furthermore, they can be merged with an integration component, giving the autoregressive integrated moving average models of time series (ARIMA), commonly used in economics.

The order of the polynomial that describes the model is one of the main characteristics to classify the model. An autoregressive model (AR) of order p is shown in equation 1.23. X_t is the value of the variable at time t, φ_i is the parameters of the model of the member i of the polynomial, and ϵ_t is the white noise at time t.

$$X_t = \sum_{i=1}^{p} \varphi_i X_{t-i} + \epsilon_t \tag{1.23}$$

The autocorrelation function of an autoregressive model is a sum of decaying exponential in which the roots of the polynomial contribute to the autocorrelation function.

After the regression and the estimation of the parameters for building the model, this approach is helpful in forecasting the values of quantity in the future. The combination of Monte Carlo methods and the autoregressive model is ubiquitous in a vast number of fields. For instance, a possible realization of the process is shown in Figure 1.8.

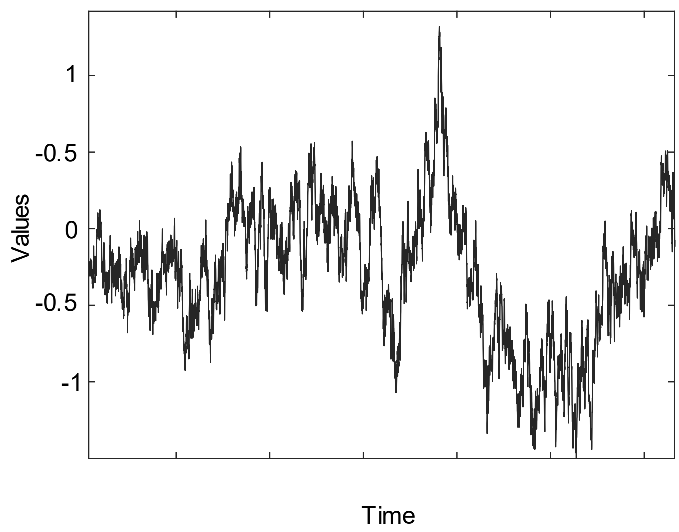

Figure 1.8 A possible realisation of a process simulated combining Monte Carlo sampling and ARIMA model

Eventually, a possible procedure to model uncertainty sources with autoregressive models follows the subsequent steps.

1. Identify uncertainty sources by determining the variables and factors that contribute to uncertainty.
2. Identify the time series representing the variables and understand their characteristics by analysing statistics, trends, seasonality, and stationarity.
3. Define the autoregressive order by analysing autocorrelation functions.

4. Define the autoregressive model using the selected order and estimate the model's coefficients.
5. Evaluate the performance of the model by analysing its residual errors.

This approach helps cope with time-dependent data. However, the selection of the order and the model diagnostic strongly influences its accuracy.

1.2.9 Scenario building and planning

During system design or evaluation, a typical case is the presence of scenario variables that can assume different values in the future. A set of scenarios can represent them to depict potential future outcomes. Scenario building and planning [33, 34] are challenging and often rely on expert judgments rather than the mathematical formulation of possible outcomes. Generally, the analysts resort to games, round tables, reports information, and key driving factors to depict future trends. A key driving factor is a variable that strongly influences the variables for which the scenarios are built, i.e. the variables which are affected by uncertainty. The scenarios include plausible situations that may happen in the future due to something that is happening nowadays, but also unexpected situations that could happen. Several qualitative techniques are aimed to help analysts in scenario generation, such as alternative e alternative futures analysis, cone of plausibility, morphological analysis, multiple scenarios generation, outside-in-thinking, simple scenarios, and brainstorming [35]. One possible approach to the scenario formulation can be resumed with the following steps:

- Identify the driving factors.
- Combine the drivers in a viable way, understanding their relationship, such as mutual exclusivity, interdependence, independence, and so on.
- Draft a consistent number of possible scenarios.
- Streamline the scenarios to achieve an adequate number of plausible and probable scenarios.
- Hypothesise the possible implications for the future.

The driving factors are often selected by resorting to the Pareto principle [36], therefore identifying only the most influential. Analysing the relationship between the factors helps the analyst understand the possible scenarios, leading to eliminating a consistent number of unfeasible combinations. The evolution of the scenarios is defined, and streamlined techniques are used to shrink the number of plausible narrations. One of the most used techniques is the plausibility cone [37] and its extensions [38]. The cone of plausibility

(Figure 1.9) helps cluster the generated scenarios into different groups and identify the most probable, best case, worst case and least probable scenario [39]. Finally, some hypotheses about the further implications and outcomes of the scenarios, identifying the most critical.

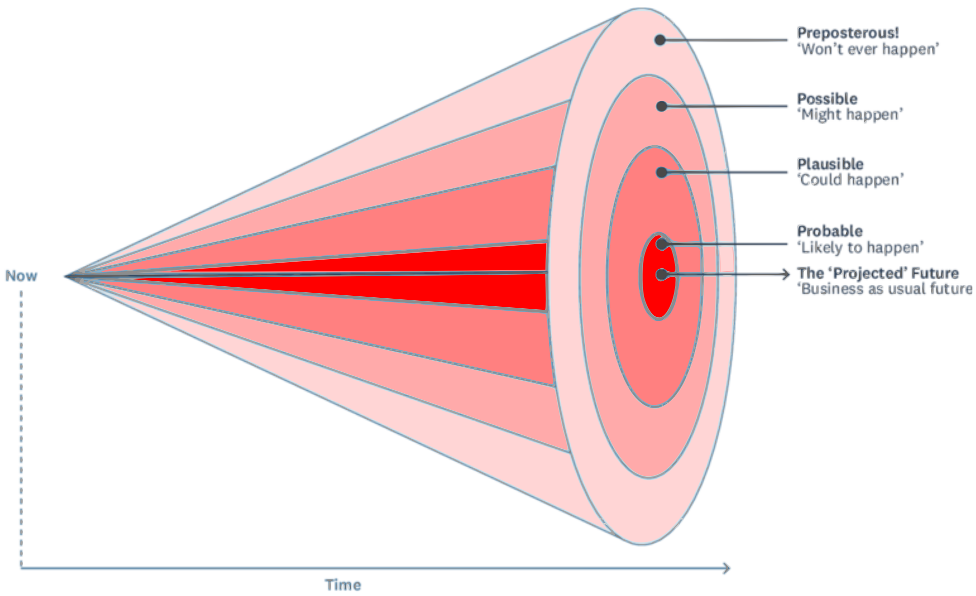

Figure 1.9 Plausibility cone representation

In conclusion, the systematic analysis of experts' judgments can be done using the Delphi method. The Delphi method and scenario planning are two prominent tools within this family commonly used for addressing such uncertainties. The Delphi Method formalize a methodology to generate discrete future histories resorting to experts' judges and opinions [40]. Scenario planning models uncertainty by defining a finite set of future scenarios that aim to encompass all possible evolutions of a given phenomenon. These scenarios incorporate future events and associated probabilities, which can be challenging to estimate accurately. Moreover, it is common for scenario planning to overlook particular possibilities, potentially neglecting crucial evolutions that may occur. Additionally, the just-described procedures are often utilized standalone in evaluating systems instead of including them in a more complex framework considering simultaneously different methods.

More details about this family of methods are provided in section 6.2 and in the case study of Chapter 6, in which it is applied.

1.2.10 Info-gap decision theory

Information-gap theory is widely used in decision-making under uncertainty [41]. It is one of the most suitable tools to model epistemic uncertainty or uncalculated probability. The primary assumption of this approach is that there is something unknown about the system under analysis, and this uncertainty can be managed as proposed by this theory [15].

Info-gap is a non-probabilistic decision theory that can prioritize options and make decisions in the face of deep uncertainty. An "info gap" is the discrepancy between what is known and what is necessary to know to make a correct decision. Info-gap models represent uncertainty in parameters and the forms of functional relationships. Robustness and opportuneness are two decision notions offered by info-gap decision theory. The robustness strategy, which differs from result optimisation, maximises immunity to error while satisfying the outcome. On the other hand, the opportuneness strategy looks for opportunities with the least amount of uncertainty [42, 43].

The info-gap theory requires three items: performance requirement, uncertainty model and system model. The system model contains all the factors and requirements of the actual system. The performance requirements are the duty, thus what the decision-makers want to achieve, like the minimum economic loss and similar stuff.

The uncertainty is modelled by resorting to subsets. These subsets are described by estimating the uncertainty parameter with a point value ($\tilde{u}$) and its deviation around its value (α). Equation 1.24 defines the subset.

$$U(a, \tilde{u}) = \{u : |u - \tilde{u}| \leq \alpha\tilde{u}\} \tag{1.24}$$

The robustness and opportuneness functions refer to how the deviation is set. The former represents the highest level of uncertainty, at which the performance is still satisfied. The latter is the favourable uncertainty that leads to better outcomes.

A possible procedure to model uncertainty sources with info-gap decision theory follows the subsequent steps.

1. Identify uncertainty sources by determining the variables and factors that contribute to uncertainty.
2. Define the range of possible values for each variable. These ranges are the uncertainty space that represents the gap in information.

3. Define the robustness function to describe the performance of a decision against variations for different points in the uncertainty space.
4. Define the maximum allowable level of uncertainty in the uncertainty space and select the robustness or opportuneness strategy.

Then, the performance of the decision will be evaluated by analysing them within the uncertainty space.

Ultimately, this theory is used when poor information is available or other probability theories are not viable or give imprecise information.

1.3 Use of uncertainty modelling methods

The methods mentioned above need to be configured before they can be used. For example, when probability theory and epistemic and aleatory uncertainty overlap, the values of the array X (Level I) that describe the parameters of the distributions need to be estimated. However, this estimation process may be subject to epistemic uncertainty, represented by the values in the array θ (Level II), which must also be calculated.

The problem can be divided into two subproblems: the estimation of X and the estimation of θ. However, this division is necessary only when considering the inclusion of epistemic uncertainty. The uncertainty can be modelled in a deterministic manner, in which the uncertain variables are represented by a fixed number of values or by an interval, or in a probabilistic/possibilistic/evidence approach, in which the probability density function, the probability and possibility values, or the plausibility/belief function must be estimated. The analyst can choose to consider only the I level of uncertainty or the II level as well. Table 1.2 shows the suggested methods according to the number of levels selected and the estimation steps required to achieve a robust model for the uncertainty sources, according to the considerations made by the authors of reference [4].

Suppose the analyst wants to represent only the I level of uncertainty and decides to model it deterministically. In that case, he starts from the available data and determines the appropriate range of variation for each variable, denoted as x, within the array X.

If the analyst wants to represent only the I level in a probabilistic way, it is necessary to estimate the probability density functions that describe the behaviour of the variables. Estimating probability density functions is a crucial step for obtaining a detailed description of the uncertain variable.

Suppose the analyst wants to represent both the I and II levels of uncertainty in addition to estimating the probability density function *pdf(X)* for the array X. In that case, the analyst is also required to estimate θ, which describes the epistemic uncertainty associated with the estimation of the array X. The estimation of θ involves utilizing statistical data and expert judgment from engineering sources. θ can be determined in a deterministic, probabilistic, or non-probabilistic manner, similar to the array of aleatory uncertainty.

Table 1.2 Suggested method to model uncertainty according to the number of levels of uncertainty considered and estimation steps [4]

Levels of uncertainty	**Suggested method**	**Estimation steps**
I level: Deterministic II level: Not considered	Scenario planning combined with Delphi Method	• Analyse theoretical constraints and expertise • Select the boundaries
I level: Probabilistic II level: Not considered	Probability theory	• Observe and collect data, expertise, and theoretical properties • Estimate pdf shapes and parameters.
I level: Probabilistic II level: Deterministic	Joint probability density function and scenario planning.	• Observe and collect data, expertise, and theoretical properties • Estimate pdf shapes and parameters
I level: Probabilistic II level: Probabilistic	Joint probability density function and joint probability density function	• Observe and collect data, expertise, and theoretical properties • Estimate pdf shapes and parameters

I level: Probabilistic II level: Evidence theory	Joint probability density function and plausibility/belief distribution	• Observe and collect data, expertise, and theoretical properties • Estimate pdf shapes and parameters

Table 1.3 shows some relevant strengths and weaknesses of the above-discussed uncertainty modelling methods. The suitability of each method is strictly related to context and the uncertainty source's nature.

Table 1.3 Strengths and weaknesses of uncertainty modelling methods

Approach	**Strengths**	**Weaknesses**
Probability Theory	• Rigorous framework for representing uncertain variables with known probabilities • Precise numerical measures and clear uncertainties representation	• Supposes deep knowledge of probability • Difficulties in managing deep uncertainty • Loss of some aspects of uncertainty sources • Requires good enough data
Bayesian Theory	• Uses prior knowledge combined with new evidence using Bayes' theorem • Formal approach for quantifying uncertainty • Requires small data and admits subjective belief	• Prior distributions strongly affect the performance • Computationally intensive • Loss of some aspects of uncertainty sources

		• Not fit all situations of uncertainty
Dempster-Shafer Theory	• Uses evidence from multiple sources • Establishes a formal framework for reasoning under uncertainty	• Belief definition might be subjective • Computationally intensive • Not fit all situations of uncertainty
Possibility Theory	• Uses imprecise or qualitative information • Not require precise probabilities	• Performs less than probability theory in quantifying uncertainty • Not provide numerical measures • Uses subjective assessments
Interval Analysis	• Copes with bounded uncertainty • Simplifies complex calculation • Uses imprecise information	• Might provide conservative results • Not handle complex forms of uncertainty • Not fit all situations of uncertainty
Stochastic Processes	• Model variables evolving over time and/or space • Simulate complex evolving uncertainties	• Computationally intensive • Require numerous pieces of data • Parameters choice strongly influences performance • Not fit all situations of uncertainty

Autoregressive Models	• Model time-dependent and sequential data • Provide a systematic approach for handling historical data	• Might assume linearity and stationarity in data • Order choice strongly influences performance • Require numerous pieces of data
Scenario planning	• Provides multiple potential futures • Enhances resilience and flexibility • Provides a proactive and adaptive approach for uncertainty handling	• Computationally intensive • Might not cover all possible scenarios • Uses subjective opinions • Might neglect critical factors
Info-Gap Decision Theory	• Handles severe uncertainty and limited information • Provides robust decisions against lack of information	• Allowable uncertainty level choice and gap definition strongly influence performance • Might provide conservative or risky results

Another issue that arises during uncertainty modelling is that some sources require different methods to be used simultaneously. Let us consider an uncertainty source that introduces point events in the future, which can happen with a specific probability and magnitude. This type of uncertainty source is discrete, and it is necessary to estimate the likelihood, time of occurrence, and magnitude of events to describe it. One viable solution is to combine discrete stochastic processes to model the probability of the date of occurrence of an event with other probability modelling techniques to represent the effect of that event. An example is the case of natural events like earthquakes. Indeed, to model this uncertainty, an analyst may combine the Poisson process to estimate the date of the event and probability density functions with probability theory to model the damage that the event causes on the system under analysis. However, beyond the example, as we will see in the following sections, this event is often modelled using fragility curves when these curves are available.

Chapter 2

System modelling and uncertainty propagation

In this chapter, an overview of the main existing system modelling methods will be provided. As a matter of fact, three different approaches will be described: analytical model, simulation model, and meta-model or surrogate model. Analytical models go deeper into the system, trying to model the relationships that lead the processes. Even if the analytical models are the most accurate and descriptive methods to represent the system under analysis, they can be highly costly from a computational point of view and modelling efforts. Moreover, analytical equations to represent the system are sometimes unavailable or cannot be validated for some reason. When these issues occur, other solutions are viable. These other methods comprise, e.g., simulation models. In the industrial plants sector, discrete events simulation models are widespread since they can be beneficial in modelling systems for which the equations that depict the processes are unknown. Additionally, since they are often equipped with an animation and visualization part, they are effortless to be understood also by practitioners and managers.

The system model is often designed with meta-models and surrogate models when the main issue is the computational power required. Several solutions rely, e.g., on response surfaces, machine learning, and artificial intelligence. With the meta-model approach, the system is treated like a black box.

On the other hand, in the second part of this chapter, some uncertainty propagation methods are discussed. They are introduced in the same chapter of the system model because how the model is represented strongly affects the applicable propagation methods. Actually, the propagation methods that can be used are also influenced by how the uncertainty sources are modelled. In particular, deterministic methods, analytical approaches, and sample-based approaches for uncertainty propagation will be reviewed.

2.1 System modelling approaches

Let us define a system as a group of components, or elements and entities, interdependent, that act together to achieve a prefixed objective. Instead, a model is a system representation that includes only the relevant aspects for the system's analysis or design. Therefore, the system will be described with a prefixed level of detail, including only the components and relationships that are considered relevant.

One of the most challenging tasks is building an accurate model of the system under analysis. For the sake of brevity, three different strategies will be considered.

- Analytical model.
- Simulation model.
- Meta-model.

2.1.1 Analytical model

The system model can take the form of either an analytical model, a simulation model, or a surrogate model. An analytical model is characterized by a set of equations that describe the system's behaviour and enable the output calculation based on the given input.

Generally, an analytical model comprises a set of equations that carefully explain the relationship between the variables that characterize the system under modelling. They are based on a mathematical solution of governing equations, including empirical and deterministic models [44]. They are primarily quantitative or computational in nature and represent the system in terms of a set of mathematical equations that specify parametric relationships and their associated parameter values as a function of time, space, and other system parameters [45]. Such models play a crucial role in answering certain questions or designing the system. Different models consider different system characteristics, such as performance, reliability, or mass properties. Additionally, an analytical model should be expressed with sufficient precision to analyse them formally [44].

The most straightforward approach is utilising an already validated system model. Several analytical systems design and evaluation models have been developed in the literature. These analytical formulations often rely on the equation taken from physics theory. It is common to find analytical models describing the system's thermodynamics, the loads, or fluid-dynamics interactions. Furthermore, some designing procedures are based on these physics equations. For instance, as we will see in Chapter 5, if the problem involves designing a shell and tube heat exchanger under uncertainty, the system can be effectively modelled using the Kern or the Bell-Delaware methods. By utilizing well-known and validated system models or design methods, it is possible to avoid the need for extensive model validation calculations. These methods have already been thoroughly studied and validated in the literature. However, there may be instances where the problem at hand requires considering specific characteristics that existing models do not fully address. In such cases, it becomes necessary to develop a new system model and subsequently validate it. An additional example of an analytical model will be provided in Chapter 6, where the analytical model for assessing the produced power of a wind turbine is briefly presented.

Another example of an analytical model of the system can be found in the queuing theory. These analytical models are often based on stochastic process theory, like birth-death processes, which are continuous-time Markov processes. The queueing theory is often used to evaluate the industrial system already designed in a deterministic manner to include variability.

Since analytical models deeply depict the interactions between the several variables that describe the system, they can determine the optimal solution for optimisation problems. In fact, the mathematical model provides a numerical solution to a problem.

However, in many cases, the actual systems are too complex to achieve a proper description of all the issues that characterise them. Indeed, developing an analytical model for an actual system can be critical, and the computational efforts to solve it may be very high.

2.1.2 Simulation model

On the other hand, a simulation model is constructed using techniques like Finite Element Method, Computational Fluid Dynamics, System Dynamics, Agent-based model, Discrete Event Simulation or similar approaches. Regardless of the chosen modelling approach, the ultimate goal is to assess the quantity of interest, representing the specific aspect or parameter being evaluated within the system.

Simulation models can be divided into static simulation models and dynamic simulation models. The former represents the system in a particular state or time, whereas the latter pertains to a system in evolution over time. Another classification distinguishes the simulation model into deterministic and stochastic. The first does not contain uncertainty and variability and gives a specific output for a given input. The second includes probabilistic elements; thus, both inputs and outputs are characterised by randomness.

Additionally, another clustering method groups the simulation models into continuous and discrete models. Continuous models are depicted by quantities that change continuously instead of discrete, in which the changes are not continuous. Generally, discrete simulation models are independent of time, and the system's status is associated with a simulation clock, a fictitious clock that advances when something happens. The latter are event-driven models. One of the main drawbacks of continuous simulation models is that they require differential equations to define the rates of change of the variables that describe the system. This implies that the computational and modelling complexity increases dramatically.

Finite Element Method

The Finite Element Method represents a general tool to find approximated numerical solutions of partial differential equations. Some of this method's most interesting areas of applicability are structural analysis, heat transfer, and mass transport. The basis of the approach to solving a problem is the discretization of a macroscopical continuous object into smaller, simple parts. The discretization of the space gives the mesh of the object representing the solution's space. Figure 2.1 [46] shows a mesh for a cylindrical cavity for nonlinear numerical simulation. Defining the problem's boundary and the expected loads, a system of equations will be obtained. Finally, the solution is found by minimising an associate error function.

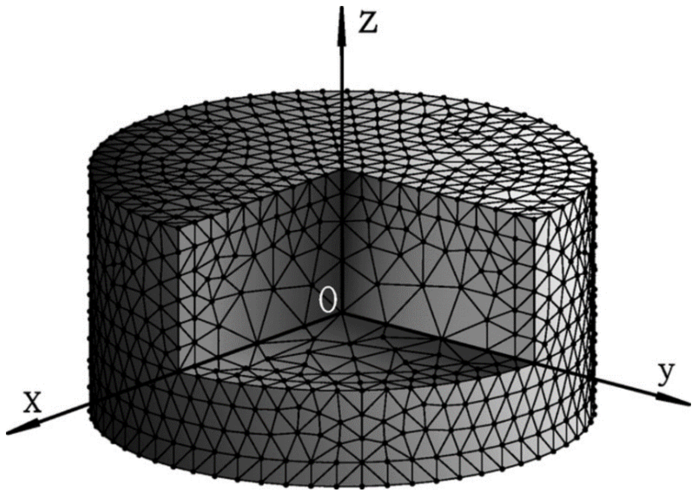

Figure 2.1 Scheme of the finite element mesh in a cavity for nonlinear numerical simulation [46]

The single element of the mesh must be small enough to accurately represent the geometry without neglecting local characteristics and dissimilar properties of materials that constitute the object under analysis [47].

Computational Fluid Dynamics

The Computational Fluid Dynamics method often resorts to Navier-Stokes equations since they define the single-phase fluid flows. Indeed, this approach is part of fluid mechanics, and like the Finite Element Method, it approximates reality to find a numerical solution to some problems. In this case, the problems of interest inquire about the interaction of the fluids with surfaces defined by boundary conditions. Figure 2.2 [48] shows the fluid flow simulation results for a shell and tube heat exchanger.

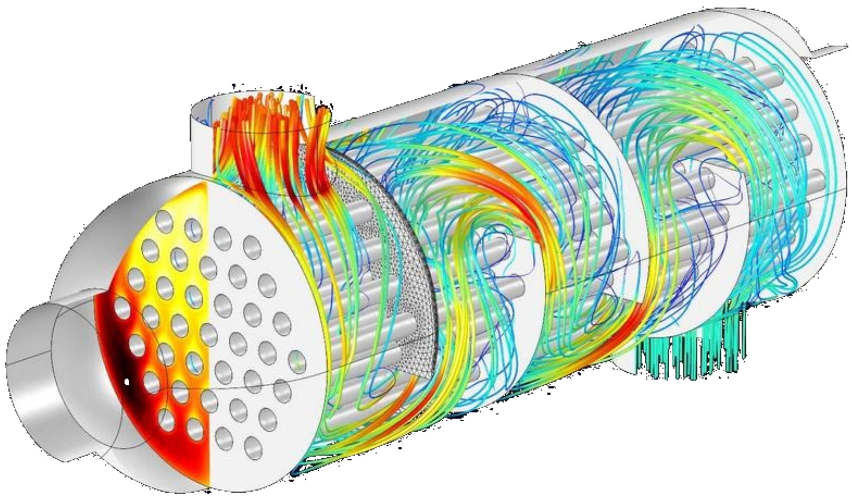

Figure 2.2 Fluid flow simulation for a shell and tube heat exchanger [48]

The first step of the analysis is the definition of the geometry of the problem. After that, the fluid volume is computed, and the Finite Element Method, or similar approaches, is used to obtain the mesh of the fluids. Then, resorting to the physical equations that describe the system's thermodynamics and dynamics, and with the definition of boundary conditions, the simulation is launched, and the equations are solved by discretizing the continuous time and space into steady states or transients. Finally, the results are post-processed to be analysed in a simple-to-read form [49, 50].

System Dynamics

This approach is aimed at modelling the dynamics of complex systems, resorting to feedback structures such as stock, flow diagrams, loops, and array variables,

As reviewed elsewhere [51, 52], system dynamics has been applied to several scientific fields, from water management to healthcare. Basically, this approach is suitable for all complex systems because it is based on the systems theory and is used to understand the behaviour of systems under analysis.

The system is represented as a causal loop diagram, a map linking the system components using arcs representing their interactions. Figure 2.3 [53] gives an example of a diagram and explains the different roles of the symbols. The structure of changing the system is captured by drawing the interactions between the elements.

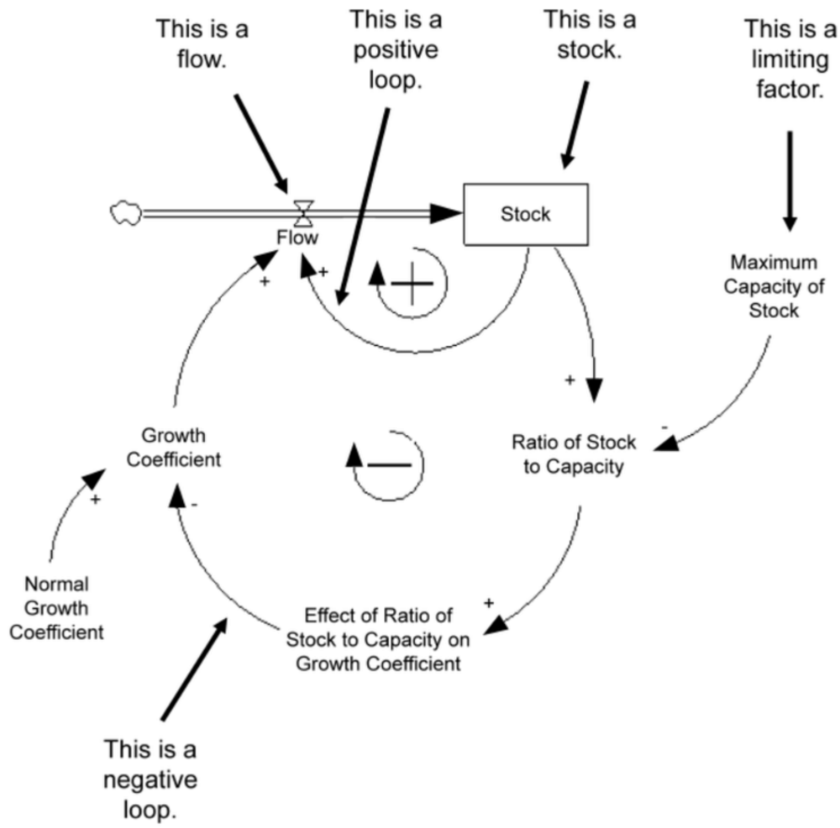

Figure 2.3 General casual loop diagram for system dynamics representation [53]

Additionally, quantitative analysis can be performed using stock and flow diagrams. The former represents something like a buffer, in which the entities are stocked, while the latter is the rate of change of the stock.

Finally, these diagrams can be transformed into equations. Once the equations are defined, it is possible to perform the simulation. Basically, the following steps are comprised. Firstly, the boundary, the stock and flows, the information affecting the flow behaviour, and the feedback loops are identified. Then, the diagram of the whole system is built, and the equations that describe the flows are written. Finally, the initial conditions defining the system's initial state are set, and the model is launched. After the simulation, the results can be analysed. For completeness, the equation can be written both in continuous and discrete time [54].

Agent-based model

The Agent-based models represent the interactions between autonomous agents. This modelling is necessary to understand the effects of the agents and their interaction on the whole system.

An agent is an entity that can make autonomous decisions based on predetermined rules. Some researchers affirm that this modelling technique is an alternative to traditional differential modelling. The point of view on the system is focused on the single elements that constitute it, and the single element can determine radical changes in the system itself.

The main advantages of this approach reside in the capability to observe emergent phenomena, to obtain a realistic description of the system, and its intrinsic flexibility. Since the primary assumption of the methods is that the whole is more than the sum of its parts, the interaction between the parts is the critical factor for capturing the unexpected and critical-to-predict phenomena. The realistic description of the system is due to each agent's decision-making capability. In this way, the model is closer to reality and represents the actual nature of the system under analysis. Instead, intrinsic flexibility resides in the simplicity of introducing new agents or rules of decisions without modifying the whole system.

Since the modularity and scalability of the approach, the most advanced models include Monte Carlo simulation for considering uncertainty, but also artificial neural networks, evolutionary algorithms, and other learning techniques. It is handy for modelling human systems [55].

Discrete-event simulation

The most exciting simulation approach from the perspective of this thesis is the Discrete-Event Simulation.

Discrete-event simulation models are dynamic and discrete-time simulation models in which the system is represented as a sequence of events over time [56]. These types of models can be divided into:

- Activity-oriented.

- Event-oriented.
- Process-oriented.

In the activity-oriented approach, the time is discretised into tiny incremental intervals, and the clock advances with each activity occurrence. To be sure that the increment does not neglect some events, it should be less than the minimum possible time of occurrence of an event that may change the system status. For instance, if the mean time between the occurrence of an event is 10 seconds, a plausible proper incremental time should be around 0.01 seconds. This way, the simulations have a substantial computational time because the code is scanned several times until the sequence's conditions are satisfied. The sequence's conditions are some conditions that need to be satisfied before moving from one activity to another. Therefore, most of the time, increments will not produce changes in the system's state, but the activity check is done every time [57]. The activity cycle diagram is a graphical modelling tool suited for activity-oriented discrete event simulation modelling.

The event-oriented approach is aimed at shortcutting the time of simulation, shifting the simulation clock of an interval equal to the time between now and the next event. For generalization, this way creates an event list in which the events are stored in the set of pending events. Each simulation iteration updates the simulation time to the minimum time among the subsequent scheduled events. The main advantages of this approach reside in the simplicity of implementation, the execution speed, and the flexibility of the model [57]. Figure 2.4 shows an event graph diagram for a system in which the entities enter the system, are loaded on a machining station, are processed, and finally unloaded from the machining station.

The process-oriented approach models the activity as a process. It is considered more elegant and easier to read. However, in the absence of available packages, it could be challenging to write and slow in the execution [57].

The functioning of discrete event simulation models is based on pseudorandom number generators. These tools are used to sample the values of the variables that describe the system. The state of the system is the picture of the values of the variables that describe the system at a specific time. The system's state does not change until something happens, so until an event occurs. The system's clock jumps from the time of the current event to the

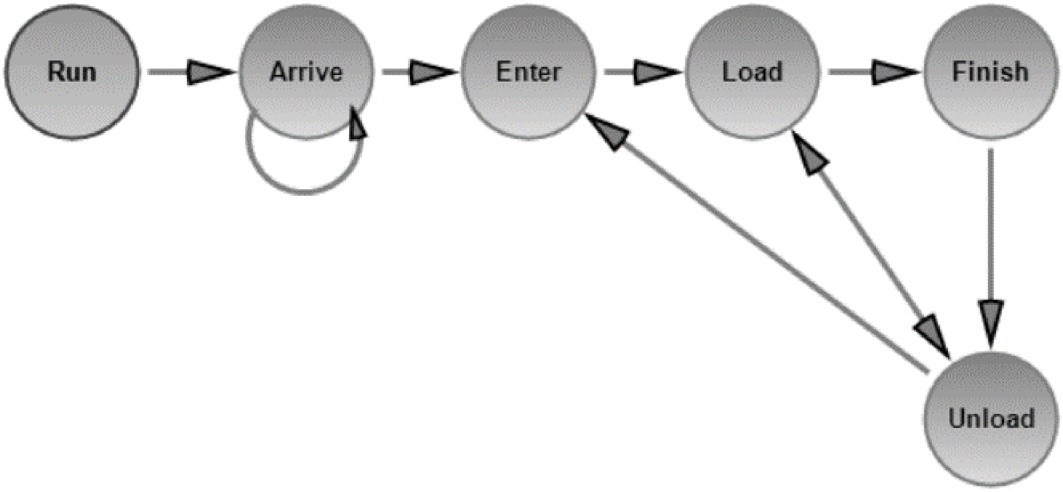

Figure 2.4 Event graph diagram for a generic process of loading, machining, and unloading of entities

time of the subsequent event. This operation mode is called incremental time progression. An event is everything that can happen that causes a change in the system status. It is described by a date and the changes it causes in the system. The events are stocked in the future event list, a buffer of events with a queue sorted by the event date. Since the structure of the model, they are often used to collect statistics to make decisions and understand the system's performances under analysis. The logic that stands under the conceptual design of a Discrete-event simulation model can be represented with easy-to-read flowcharts. As a matter of fact, some simulation software resorts to flowcharts to write the model's code. With these flowcharts, the logic behind a simulation model can be understood immediately.

Discrete-event simulation modelling is often used to include uncertainty in evaluating industrial systems or processes which have already been designed with deterministic methods. However, it is unsuitable for systems or processes in which the interest is the understanding of their behaviour over continuous time. Moreover, simulation models increase in complexity with the complexity of the system under-representation. Even if the computing power of computers is growing, a complex simulation model may require an enormous amount of time to perform a complete simulation.

2.1.3 Meta-model

Surrogate models and meta-models are viable solutions to replace the expensive system models. Indeed, simulation models have been widely used to understand systems' behaviour and analyse real-world systems. However, the model calibration and model parameters sensitivity analysis still remain a complex task [58]. In addition, computer code complexity grows with the complexity of the system. Therefore, surrogate models are mainly used to reduce the computational expenditure and to perform iterative simulations of the system model in a shorter time. They are known as approximation models now that they approximate the system's outputs with several approaches. For example, some of the leading tools used are polynomial response surface models, kriging models, neural network models, and radial basis function models [59].

One of the most challenging issues with surrogate models is their accuracy. In fact, the commonly adopted approach consists of drawing several meta-models based on input and output data from the simulation to evaluate the accuracy of these models and select the most proper for the problem under analysis. In literature, some authors have found that with slightly nonlinear responses in high dimensions, the kriging models are the proper instruments [60]. At the same time, radial basis functions perform better when highly nonlinear responses exist [61].

The testing of several methods in order to select the proper one for the system under analysis is a common approach but has established a substantial resource-consuming problem. Combining individual surrogate models is an alternative to reduce the error and save time. This combination can be done with a linear combination of the single surrogate models. Indeed, with this approach, the errors are reduced by their compensations. However, the selection of the weights of each model in the linear combination is an arduous task. As a matter of fact, literature has explored this issue. For example, the weights can be determined using a matrix method [62] or resorting to error minimisation [63]. Finally, a recursive algorithm has been proposed to minimise the assessed root mean square error by changing the weights [64].

Before reviewing some more common surrogate models, it can be interesting to understand the general modelling process [65], which differs enormously from the other two families of modelling methods we have seen in the previous paragraphs. Indeed, the objective is to find a function $y=f(x)$ that represents the system using data about the inputs x and the outputs y.

The first step of the modelling process is to collect data from the actual system and select a modelling approach between the set of existing surrogate models. One of the main challenging tasks in this part is understanding the inputs influencing the outputs of interest. The challenge of this step resides in the fact that the inputs can have interdependences, and the value of an input may change dramatically the effect of another input on the output. Once the relevant inputs are assessed, the fundamental goal is to build a comprehensive combination of input values to depict the design space but small enough to reduce the computational time. In this phase, we need to know the information about the output that the actual system gives when the selected inputs enter the system. Indeed, the outputs related to the selected inputs must be known to build pairs of known inputs-outputs. Basically, we know that our desired model will provide the output y_1 when the input x_1 is given. At this stage, a problem that often comes out is the overfitting. Prosaically, an overfitted model is a model that is too flexible and fits not only the data but also the noise related to these data.

The second step is to estimate the parameters and train the model. The parameters of the model (a) represent the way in which it is possible to obtain the function $f(x, a)$ that fits well with the results that the function $f(x)$, which is the system, would provide. Several estimation criteria are available in the literature, such as Maximum Likelihood Estimation [66] or Cross-Validation [67].

Finally, the model is tested using the actual output of the system and comparing it with the output the built model gives when the input related to the known output is provided. Generally, the indexes of the model's goodness of fit are the root mean square error (*RMSE*, 2.1) and the correlation coefficient (r^2, 2.2).

$$RMSE = \sqrt{\frac{\sum_{i=0}^{n_t}(y_i - \hat{y}_i)^2}{n_t}} \tag{2.1}$$

$$r^2 = \left(\frac{cov(y - \hat{y})}{\sqrt{var(y)var(\widehat{y})}}\right)^2 \tag{2.2}$$

Where n_t represents the size of the test data set, y is the real output of the system, and $\hat{y}$ is the output of the model. The lesser the *RMSE* and the higher the r^2, the better the fitting of the model of the actual system. A model with an r^2 of about 0.8 can be considered to have good predictive capabilities [65]. These quantitative measures of the model's goodness allow us to compare different models to select the best one. However, it may be helpful to obtain a visual understanding of the fitness properties of the model by contrasting the actual data and the curves or surfaces that the model draws.

Polynomial Response Surface Models [59]

This methodology uses regression and variance analysis to estimate the input and output relationship. Generally, experimental campaigns are conducted to estimate the coefficients of the model.

Let us define ϵ as the statistical error, x_i like one component of the predictor set with a size equal to m, and β_0, β_i, and β_{ij} are the parameters which are being estimated. In addition, the magnitude of the components' coefficient is used to judge the level of influence of each parameter on the response of the whole system. A general formulation of the model is equation 2.3.

$$f(x) = \beta_0 + \sum_{i=1}^{m} \beta_i x_i \sum_{i=1}^{m} \sum_{j>i}^{m} \beta_{ij} x_i x_j + \cdots + \epsilon \tag{2.3}$$

The most widely adopted polynomial response models have a low grade of the polynomial. Indeed, the surfaces most commonly used are of the second order due to their flexibility. The estimation is done by substituting the sample points at the relative components of the predictor. The fitting model for these second-order surfaces is shown in equation 2.4, where the symbol ^ represents an estimated value.

$$\hat{f}(x) = \widehat{\beta_0} + \sum_{i=1}^{m} \widehat{\beta_i} x_i \sum_{i=1}^{m} \sum_{j>i}^{m} \widehat{\beta_{ij}} x_i x_j \tag{2.4}$$

Even if this approach reduces the noise effect and is suitable for numerous cases, the fittings are not so accurate when nonlinear high-dimensional problems are considered. Indeed, an overfitting issue can occur because of the high order of the polynomials. However, a possible solution is to resort to a generalized polynomial response surface, which substitutes the polynomials with suitable functions applied to the predictor components.

Kriging Models

Especially for optimisation purposes, Kriging models are one of the best approaches. Basically, this approach is very similar to the Gaussian Process model [65]. The basis equation of the model is provided in 2.5.

$$\psi^{(i)} = \exp\left(-\sum_{j=1}^{k} \theta_j \left| x_j^{(i)} - x_j \right|^{p_j}\right) \tag{2.5}$$

In equation 2.5, θ is the vector that allows the basis function's width to vary from variable to variable, but often, it is constant for all dimensions, k is the size of the array, whereas $x_j^{(i)}$ are the training points. The Kriging exponent p typically is in the range [1,2]. For further detail on the mathematical formulation that goes beyond the scope of this work, the reader can refer to the reference [65].

This type of model can represent its own uncertainty [58]. This means that each prediction obtained by this type of surrogate model has an associated uncertainty, typically in the form of variance. The variance of predictions is strictly related to the accuracy of the prediction in front of training data but also to the shape of the approximation function. A set of multivariate random variables represents the output variables, whereas a parametric covariance function is built on the inputs. The closer the input, the higher the correlation between the outputs. Thus, the uncertainty associated with the model predictions is low if the estimations are close to the training points.

Neural Network Models [59]

The backpropagation neural networks are networks with several feedforward layers. Each layer is composed of nodes, and each node has an input.

The nodes of the first layer receive the input of the actual system, the hidden layers manipulate the data, and the output layer theoretically should give an output array close to the expected output, i.e., the output of the real system. The nodes, also called neurons, are fully connected to each other, and each node's output enters all the other nodes after it is changed with the effect of a weight.

The weights must be trained to allow the network to emulate the system behaviour in terms of given results given an input. To do so, the gradient descent method is used via backpropagation. The propagation of errors is performed, and the error feedback continuously suggests how to adjust the layers' weights in the reverse direction.

The training process ends when the network error is in the acceptable range, and other criteria are satisfied, e.g. the number of iterations is exceeded.

Even though each neuron of each layer is linked to each neuron of the subsequent layer, there is no connection between the nodes of the same layer. Figure 2.5 shows an example of a neural network with three layers.

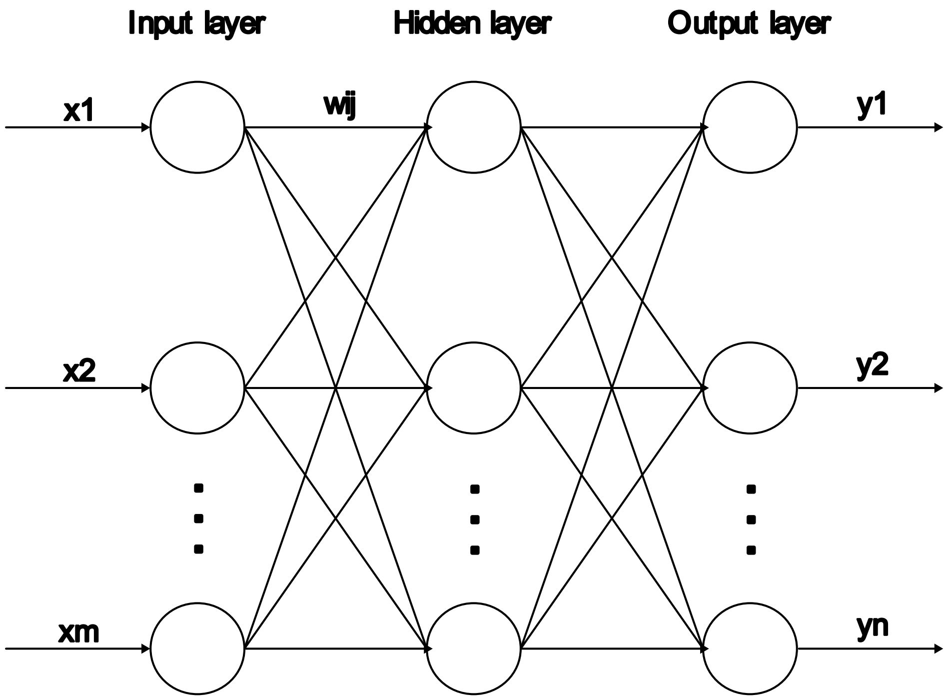

Figure 2.5 Example of a three layers artificial neural network

The neurons themselves process the input of the neurons with their activation function, which produces the output. Generally, each node of the same layer has the same activation function but differs from one layer to another.

Although this approach is used for high nonlinear and high-dimensional problems, one of the main issues is selecting the training set and test size because neural networks often suffer from overfitting.

Radial Basis Function Models [59]

The independent variable of a radial function is the distance between the point to be measured and the sample point. These models are widespread; for instance, discrete data interpolation and image processing extensively use them.

In most straightforward cases, this approach represents the estimating function as a linear combination of basis functions, representing the magnitude of the influence of the parameters on the output. The basis functions are one for each training point and depend only on the distance from the point being estimated to the training point for the model.

After selecting some sample points with experimental design, each sample is considered the centre, and its radial function is used as a basis function. These functions are then fitted to obtain the response value of the output to be measured.

Finally, the Euclidean distances between the sample point and the corresponding to be measured are combined as independent variables to transform the multidimensional problem into a simple one-dimensional one.

In conclusion, another approach to system modelling is to develop a meta-model. A meta-model is a mathematical function less computationally intensive than a full system model yet still provides similar results regarding the quantity of interest. The system is seen as a black box represented by a function or set of functions. The meta-model is constructed using an experimental design that approximates the training set consisting of real data and predicts the actual system's output. However, it is essential to note that the meta-model must also undergo validation, and it generally exhibits a more significant residual error than a traditional system model. Moreover, the meta-model may overestimate or underestimate the system output within some domain regions. Nevertheless, considering many problems, minimising variability to the minimum extent may not be necessary, and using a meta-model can still be a viable solution.

2.1.4 Use of system modelling methods

Regardless of the system being modelled, the system model itself introduces a new source of uncertainty related to epistemic uncertainty. Reducing this type of uncertainty can be highly challenging as the equations within the model serve as a representation of reality and may not capture all the intricacies of the actual system. When the system is modelled with a simulation model, assumptions and simplifications are needed to reduce the computational expenditure. Furthermore, if we consider surrogate models, they introduce estimation errors that must be addressed. Consequently, when propagating uncertainty, it is crucial to consider the epistemic uncertainty arising from the system modelling process. To address this uncertainty, a combination of approaches can be employed, including utilizing literature data, incorporating the calculated residual error, and relying on expertise in the field.

Additionally, whether the quantity of interest is purely technical is enough to model the system. When the quantity of interest pertains to economic aspects, developing an economic model in addition to the system model becomes necessary. For example, as demonstrated in Chapter 6, when assessing the net present value of a wind power system, the energy market is modelled to incorporate economic considerations. The economic model is often analytical in nature.

In any case, the requirement for model validation is crucial. The validation of a model can be achieved by establishing an acceptable level of confidence through a comparison between the model's results, generated when specific inputs are provided, and the real output data collected from the actual system under the same inputs. In other words, model validation involves comparing the system model to relevant information, data, or another validated model under specific experimental conditions. This comparison allows us to infer the validity of the system model within the given conditions. However, it is essential to note that a model cannot be fully validated but can be corroborated by available information or experts' judgments. The system model may still have residual errors when compared to the actual system. These residual errors are challenging to eliminate and persist even in validated or corroborated models.

Table 2.1 shows some relevant strengths and weaknesses of the above-discussed approaches.

Table 2.1 Strengths and weaknesses of system modelling approaches

Approach	**Strengths**	**Weaknesses**
Analytical models	• Quantitative and computational models • Deeply depiction of the interactions between several variables	• Hard to draw • Computational efforts may be very high • With complex systems, they may not be used

	• Capability to be optimised to find the optimum and suboptimum solutions	• Require a deep knowledge of the mechanics and dynamics laws that govern the actual system
Simulation models	• Easiness in reading and interpretation • Easiness in including uncertainty • Capability to model the system over time	• Increase in complexity dramatically with the complexity of the actual system • Complex simulations may require an enormous amount of time to be simulated
Surrogate models	• Easiness in developing • Less computational expenditure compared with other approaches • A practical approach to modelling	• Overfitting • Difficulty in deciding the proper number of training set • Hardness in selecting the proper surrogate model for the actual system • Higher residual errors than other approaches

2.2 Uncertainty propagation

Uncertainty propagation pertains to estimating the effects of the inputs' uncertainties on the outputs of the system model. The proper uncertainty propagation method selection depends on the uncertainty type, i.e. if it is epistemic, aleatory or both, and on the system model formulation [16].

Several methods can be employed to propagate uncertainty, and selecting a specific method depends on the characteristics of the uncertain variables, such as whether they are continuous or discontinuous. Additionally, the choice is influenced by the characteristics of the model, particularly the computational time required for simulation, as well as the type of variable of interest, whether the entire probability distribution or only specific parameters are required. Obviously, this thesis does not aim to review all uncertainty propagation methods comprehensively. However, the following methods will be briefly described as they will be utilized in the case studies presented in the subsequent chapters.

- Deterministic methods. Such as Design Of Experiments (DOE), worst/best case and scenario analysis [68, 69].
- Analytical approaches. For instance, Taylor approximation and First/Second order reliability method.
- Sampling-based approaches. Such as Monte Carlo sampling methods and adaptive sampling techniques.

The above three families of methods can be clustered into two different groups: deterministic setting, which includes deterministic methods, and probabilistic setting, which pertains to analytical and sampling-based approaches [4].

The output of the propagation in the model serves various objectives. For instance, it can be employed to assess risk by manipulating either the probability density function or the variable of interest, thereby assisting decision-makers (Chapter 6). Additionally, it can be used to provide optimisation algorithms with the variables to be optimised (Chapter 5). Further clarification regarding these applications will be provided in the case studies.

2.2.1 Deterministic methods

Deterministic methods for uncertainty propagation involve computing the performance of a system by analysing it for fixed values of the uncertain variables. After identifying the most influential variables, scenarios are selected, and the system is evaluated accordingly.

The most straightforward approach is to rely solely on worst-case analysis. In worst-case analysis, the assumption is that if the system performs well under the worst possible conditions in which it can operate, it will perform even better in all other scenarios. This assumption holds true in most cases; however, two distinct problems arise. Firstly, suppose the worst-case scenario selected is not truly the most severe condition the system can encounter. In that case, it may result in dangerous failures or failure to meet the specified requirements. Secondly, even if the worst case is accurately identified, designing the system to meet the specification under such extreme conditions may lead to oversizing or over-engineering. Indeed, if the worst-case scenario were probable, it would essentially become the nominal case. However, suppose the failure to meet specifications for a brief period in the lifespan of an industrial system is not dangerous or prohibitively expensive. In that case, the additional costs associated with oversizing the system may not be justified.

Scenario analysis is a highly intricate approach. The selection of the number of scenarios and their descriptions typically relies on expert judgments and opinions, which can vary significantly from one expert to another. Moreover, the critical issue lies in determining an adequate number of scenarios that accurately depict the most critical and probable conditions under which the system will operate. In any case, even if experts could determine the appropriate number of scenarios with great accuracy, estimating the probability of these scenarios remains a challenging and heuristic-driven task. Additionally, it becomes necessary to combine different scenarios in order to obtain a reliable estimation of the variables of interest.

The challenging task of assessing the probability of scenarios has been extensively explored in the literature. To aid decision-makers in clustering scenarios and identifying the most probable set, the concept of the plausibility cone has been developed [37, 70-72].

From an engineering perspective, one of the most interesting methods is the Design Of Experiments (DOE), a widely adopted approach in literature. This is a method used to understand which variables mainly affect the response and what the desired input values are to achieve prefixed outputs. The DOE is used to characterize or optimise a process propagating the uncertainty in a system model. The procedure involves the following steps [73].

- Problem definition.
- Factors, levels, and ranges selection.
- Variable of interest selection.
- Problem design selection.
- Performing the experiments.
- Statistical analysis of the data.
- Conclusions and recommendations.

The problem definition phase requires a critical analysis of the problem and understanding the inputs involved to address clearly the questions the experiments and simulations aim to answer.

The choice of factors, levels and ranges step concerns classifying the inputs into design and nuisance factors. Once the inputs are clustered, the analyst must select the levels at which the runs will be performed. In order to select the levels, it is necessary to identify the region of interest of each variable and then the number of levels that should be used.

The variable of interest selection phase is related to the output of the analysis and the performance of the system which wants to be assessed.

Several types of experimental designs are available in the literature. Each type of experimental design is related to the scope of the analysis, particularly to the questions defined at the initial stage. More details about this topic can be found in [73].

Suppose that a full factorial experimental design was selected. In the performing the experiment phase, the analyst will perform all the runs or experiments by permutating all the inputs' levels.

Finally, the results are statistically analysed to assess the uncertainty of the outputs and final remarks are drawn.

In conclusion, the Design Of Experiments is a preferred method when randomizing factors is impossible or costly and for the first screening of the most influential inputs.

2.2.2 Analytical approaches

Analytical approaches are rigorous and generally already validated. Additionally, they often yield transparent and easily interpretable results. The Taylor expansion formula for the moments of functions of random variables is a widely used tool for evaluating the moments of a function. It only requires partial characteristics of the inputs. For instance, when considering the second moment, the standard deviation of the output σ_y is estimated by combining the standard deviation σ_{xi} of the N inputs x_i (2.6).

$$\sigma_y = \sqrt{\sum_{i=1}^{N} \left(\frac{dy}{dx_i}\sigma_{xi}\right)^2} \qquad (2.6)$$

One of Taylor's approximation assumptions is that the uncertainty levels are small. For that reason, it is widespread in the metrological field [5].

In system models which suffer from uncertainty, there are known stochastic inputs. As the previous chapter shows, these inputs can be represented by a probability density function. Since the primary goal of the uncertainty propagation is to understand the effect of the uncertainty of the inputs on the output, it may be enough to compute low-order statistics, such as the mean (2.7), the covariance matrix, that are composed by the covariances values (2.8), and the variance of each component (2.9).

$$E[x] = \int_{low}^{up} pdf(x)dx \tag{2.7}$$

$$cov(x,y) = E[(x - E[x])(y - E[y])] \tag{2.8}$$

$$\sigma^2 = \int_{low}^{up} (x - E[x])^2 pdf(x)dx \tag{2.9}$$

Where *E[x]* is the expected value of the probability density function (*pdf(x)*) of the random variable x, σ is the standard deviation, and *up* and *low* are the upper and lower bound of the probability density function, respectively, and identify the probability space in which the *pdf* is defined.

Analytical methods are often based on moments. Indeed, methods for numerical integration, Taylor approximation, and methods based on stochastic development are focused on these uncertainty measures. However, deterministic methods and some analytical methods may be inappropriate if the interest is to obtain a specific confidence interval [4]. In contrast, stochastic development methods may give a variance matrix of the results [74].

The limitation of the analytical approach lies in the requirement to have knowledge of the output function and its derivatives. Consequently, this method can only be applied if the system model is provided in an analytical form or a validated meta-model is available. Furthermore, the output function must be sufficiently differentiable, and the moments of X must be finite. It is important to note that while this method allows for the estimation of the mean, standard deviation, and other characteristics of the output probability distribution, it does not provide the whole probability density function. Moreover, methods like numerical integration often require a considerable number of runs; thus, if the simulation time is ample, namely when the uncertain model inputs are more than six, they may not be viable [4].

The First-order reliability method (FORM) and Second-order reliability method (SORM) are analytical techniques used for estimating reliability and performing uncertainty analysis. These methods utilize the Taylor expansion of the output function and rely on the definition of the limit state of the functions and the distribution parameters. When estimating a low probability, the FORM-SORM methods are highly efficient compared to simulation methods. However, a limitation of these methods is that it is not possible to quantify their accuracy, as their approximations are based on deterministic calculations [4, 75].

2.2.3 Sampling-based approaches

Sampling-based approaches are the most prevalent family of probabilistic methods for propagating uncertainty. Nevertheless, they are mainly employed in three sectors: optimisation, numerical integration, and generating probability distributions [76]. Monte Carlo Sampling (MCS) techniques and all their variants undoubtedly dominate the stage of uncertainty propagation. These methods employ repeated pseudo-random sampling to estimate unknown parameters numerically [77]. In this thesis, one can find MCS in all the investigated case studies applied to various uncertainty sources modelled in different ways. For instance, in this work, MCS has been applied to joint probability distributions, probability boxes, numerical intervals, Autoregressive Integrated Moving Average (ARIMA), Markov Chain Monte Carlo, and so on. The capability of MCS methods to model complexity and assess the impact of risk is well-known, and they are widely used in approximating solutions to mathematical problems [78]. When a problem is not analytically solvable, numerical simulation aids in this task. The aforementioned references may assist the reader in delving deeper into the methodology.

Despite the high computational time required for the simulation, the Monte Carlo Sampling (MSC) method is one of the most popular methods for uncertainty propagation.

This family of methods resorts to repeated random sampling from predefined probability distribution on the input to obtain several values of a model's outputs by simulating the system model multiple times. Therefore, the uncertainty of the outputs is estimated by statistically analysing the obtained results.

Basically, the Monte Carlo Sampling is based on four steps.

1. The domain of the possible inputs is defined, resorting to available data.

2. The inputs are sampled several times over the domain.
3. The computation of the outputs is performed for each sample.
4. The results are aggregated and statistically analysed to assess the related uncertainty.

The sampling procedure resorts to normalized uniform random variables distributed uniformly between 0 and 1. Actually, the procedure resorts to pseudo-random number generators that are aimed to define a series of numbers included in the range [0,1]. One of the simplest adopted pseudorandom number generators is the linear congruential generator. Its recurrent relation is expressed in equation (2.10).

$$X_{n+1} = (aX_n + c)\ mod\ (m + 1) \tag{2.10}$$

X_{n+1} is the pseudorandom computed number, X_n is the number calculated at the previous recursion, a is the multiplier, c represents the increment, m is the modulus, and X_0 is the seed, i.e. the starting value. It is necessary to divide X_{n+1} by the modulus to obtain the number in the range [0,1]. Between the elements of equation 2.10 are the relationships expressed in 2.11, 1.12, 2.13, 2.14.

$$m > 0 \tag{2.11}$$

$$0 < a < m \tag{2.12}$$

$$0 < c < m \tag{2.13}$$

$$0 < X_0 < m \tag{2.14}$$

Since the sampling procedure may involve probability distributions which differ from the uniform one, the procedure requires computing the cumulative distribution of the probability density function under-sampling and then inverting the cumulative distribution to transform the uniformly distributed random variables along the cumulative distribution.

The Monte Carlo methods go almost surely to convergence for the strong law of large numbers, and its results are asymptotically Gaussian distributed. However, to increase the confidence level of results, the number of samples N of step two, which allows us to determine N values of the outputs to assess the uncertainty, must be carefully selected. Since the MCS provides the error associated with assessing the propagated uncertainty, it is possible to know the minimum number of runs necessary to get accurate results.

A possible approach to choosing the number of runs for a Monte Carlo simulation is to apply the formula proposed by Fenton and Griffiths (2.15) [79]. First, it is necessary to set the confidence level of the estimation error. Without loss of generality, the confidence level can be considered *(1-α)*.

$$N = \left(\frac{Z_{\alpha/2}\sigma}{e}\right)^2 \tag{2.15}$$

Where $Z_{\alpha/2}$ is the value of the standard normal variable with a cumulative probability equal to *(1-α/2)*, σ is the standard deviation of the mode output for uncertainty analysis, and e is the desired estimation error.

Another approach is based on the weak law of large numbers. The central assumption is that the larger the sample size, the lower the difference between the sample and population statistics. The practicability of this approach is that the minimum number of required simulations is chosen by observing the variation of model output statistics. Different simulations are carried out, with an increasing number of runs respectively. Once the differences between the output statistics are in a predefined acceptable range, i.e. when the statistics become stationary, the minimum number of runs is obtained [80].

Another issue concerning Monte Carlo sampling methods is the strategy of domain sampling. The most general approach has already been discussed, but when the domain increases in dimension, the required number of runs to cover all the solution space may be enormous. For that reason, different strategies for space sampling have been developed.

The variance reduction or accelerated sampling methods aim to reduce the number of simulations for a given accuracy or the variance for a given number of simulations. They are based on reducing the sampling domain by decomposing it into subregions. This decomposition helps achieve a more accurate space sampling than the simple sampling technique described above.

Latin Hypercube Sampling (LHS) splits the domain into disjoint subspaces of equal probability. Then, a simple sampling is performed in each subset [81]. In this way, it covers the whole area of definition. The LHS may perform several useless simulations if the goal is to estimate a rare probability because most samples will be outside the interesting region [5].

The stratified sampling technique divides the sample space into a collection of disjoint subsets. This means that the subsets are collectively exhaustive and mutually exclusive. Then, simple random sampling is performed simultaneously for each subregion [81]. Since the regions' importance can be decided by resorting to different weights from the original density, forcing the sampling procedure, applying these weights is possible to avoid useless simulations in the case of rare probability estimation.

Importance Sampling (IS), like stratified sampling, involves biased input distribution to intensify the sampling procedure in the region of interest. The weights of the estimator are changed each run to adjust the region of interest. It is often employed around the design point to deal with the time-consuming nature of modelling.

In conclusion, the primary drawback of MCS is the high computational time required for simulations. The use of meta-models has been widely adopted to reduce the implementation time.

2.2.4 Sensitivity analysis

So far, the presented methods are focused on the uncertainty propagation for the uncertainty analysis. The objective of the uncertainty analysis is to give a precise picture of the set of possible output outcomes and the associated probability distribution, moments, or indexes [82]. It focuses on uncertainty quantification and propagation. On the other hand, sensitivity analysis is a method for understanding the changes in the model output values that result from changes in the inputs [82].

Sensitivity analysis can be grouped into local or global sensitivity analysis. The former is often used to change the input value by small quantities around the selected design point to observe the changes in the output values, often with linear methods. Instead, the global one is focused on the model output variance related to the whole input space. Additionally, the global sensitivity analysis determines which parts of the output variance are related to different inputs [83].

Several methods are available for performing sensitivity analysis, and a non-exhaustive list is provided below:

- One-factor-at-time method.
- Derivate-based local methods.

- Regression analysis.
- Variance-based methods.

The above-listed methods work more or less in the same manner. Firstly, the input uncertainties must be quantified using one of the theories for uncertainty modelling according to the type of available data. Then, the model output of interest must be chosen. Subsequently, the system model is simulated or calculated several times, resorting to some sampling techniques or Design Of Experiments. Finally, the set model outputs are manipulated to obtain the desired measures of uncertainty.

Before reviewing the methods mentioned above by giving only some references and comments, it can be useful to understand how the sensitivity analysis results are presented. They can be provided either in graphical form, for instance, using a scatter plot or using different indexes expressing the output's dependence on several inputs. Some sensitivity indexes are cited below.

The Taylor-based linear sensitivity indices assume that the system response is acceptable linear; thus, the Taylor quadratic approximation generates the following elementary index (2.16).

$$s_i^{2\ Taylor} = \frac{\left(\frac{\delta G}{\delta x^i}\right)^2 var(X^i)}{\sum_j \left(\frac{\delta G}{\delta x^j}\right)^2 var(X^j)} \tag{2.16}$$

Where s_i is the sensitivity index corresponding to component x^i, i and j identify different inputs, $G(x,d)$ is the deterministic function that represents the model, X^i is the random variable associated with the i-input, x^i is the component i of the vector of the uncertain model inputs, and d is the vector of fixed input [5].

The Monte-Carlo sensitivity indices are defined as the normalised ratio of input-output Pearson (2.17) or Spearman (2.18) coefficients.

$$s_i^{2\ Pearson} = \frac{Corr(X^i, Z)^2}{\sum_{k=1,..,p} Corr(X^k, Z)^2} \tag{2.17}$$

$$s_i^{2\ Spearman} = \frac{Corr(r_{X^i}, r_Z)^2}{\sum_{k=1,..,p} Corr(r_{X^k}, r_Z)^2} \tag{2.18}$$

Where Z is the output array, *Corr* identifies the ratio between the covariance of the *i*-input and the output and the i-input variance multiplied by the output variance [5].

The three indexes exposed so far are viable under the hypothesis of linearity, monotonicity, and additivity of the model under analysis. Moreover, the input-output relation can be investigated only pairwisely, neglecting the interactions between inputs. The Sobol indices resolve these limitations. In the case of non-linearity, it is often solved using Monte-Carlo sampling instead of closed-form. The first-order indices (S_i) (2.19) investigate the relationship between a single input and the output without looking at the interactions.

$$S_i = \frac{var[E(G(X,d)|X^i)]}{var\ G(X,d)} \tag{2.19}$$

For each value of the *i*-th uncertain input, $E(G(X,d)|x^i)$ is the expected value for the uncertain output without other information about the system. S_i represents the proportion of output variance related to the *i*-th input output variance [5].

Finally, the second-order Sobol index (2.20, S_{ij}) pertains to the contribution to the output variance of the combined variation of the two inputs i and j [5].

$$S_{ij} = \frac{var[E(G(X,d)|X^i X^j)]}{var\ G(X,d)} - S_i - S_j \tag{2.20}$$

One-factor-at-time method [84, 85]

This method relies on defining the nominal value of each input and then moving one input at a time to upper and lower levels. In this way, the system's response to the change can be observed.

The sensitivity can be estimated by using partial derivatives or linear regression. However, the whole input space is not analysed, and the interactions between the inputs are neglected. This approach is similar to DOE, and it is also easy to understand by practitioners. Furthermore, it should be a viable solution when numerous inputs are involved. On the other hand, when there are critical problems under investigation, it may neglect important implications, thus leading to missing the optimal design factors. Another weakness is the high time required for performing the analysis due to the high number of runs required, especially when several inputs should be considered.

Derivate-based local method [86]

This approach is linked to the computation of the partial derivative of the model response to an input factor. Despite the possibility of building a matrix to show transparently all the sensitivity in a model, the derivate-base local method explores only tiny portions of the input space and often only small permutations, one input at a time.

Regression analysis [87, 88]

Regression analysis can be used only when the system response is linear. In fact, the coefficients of the regression, which measure the sensitivity of the system, are often linear due to difficulty in interpreting standardised coefficients with a grade higher than one. Nevertheless, this approach is transparent and requires a low computational expenditure.

Variance-based methods [89-91]

This is the family of Sobol's methods and indices, and it performs a global sensitivity analysis of the model under investigation. The inputs are considered independent of each other. As previously said, it is possible to estimate the effect of the single input on the output and the effect of the interactions.

2.2.5 Use of uncertainty propagation methods

With the assistance of references [4, 75], for the sake of clarity and completeness, Table 2.2 presents the prominent family of methods for uncertainty propagation and the variables of interest for which their use is suggested.

Table 2.2 Family of methods and measure of uncertainty

Family of methods	Measure of uncertainty	Source
Deterministic method	Range	[75]
Numerical integration	Moments of *pdf*	[92]
Taylor approximation	Variance of *pdf*	[93]
Monte Carlo Simulation	All probabilistic criteria	[76-78]
Variance reduction techniques	Exceedance probability	[94]

Stochastic development	Moments of *pdf*	[95, 96]
FORM/SORM	Exceedance probability	[94, 97]

Considering one as the maximum level and three as the lowest level of model complexity and computational time for the mainly used methods in uncertainty propagation, Figure 2.6 summarizes these two characteristics of the methods [75]. The axis ticks' labels represent the score of the method in the labelled feature. Although it has the maximum computational time, MCS is the most suitable family of methods to cope with highly complex models because of its low modelling complexity.

The worst-case scenario approach is risky if the selected scenario is not truly the most severe condition the system can encounter. Moreover, even if the worst case is accurately identified, designing the system to meet the specification under such extreme conditions may lead to oversizing or over-engineering.

Scenario analysis is a viable approach to exploit different futures. Nevertheless, the selection of the number of scenarios typically relies on subjectivity. Moreover, it is difficult to determine the appropriate number of scenarios to accurately depict the most critical conditions under which the system will operate. Finally, estimating the probability scenarios is a challenging and heuristic-driven task.

The Design Of Experiments is a practical solution when randomizing factors is impossible and for the first screening of the most influential inputs. However, the DOE standalone remains a deterministic method for uncertainty propagation.

Deterministic methods may not be practical when the objective is to achieve a certain confidence interval. In contrast, stochastic development methods may provide a variance matrix of the results.

Analytical approaches require to know the output function and its derivatives. Therefore, this method is viable when the system model is given in an analytical form or like a meta-model. Moreover, the output function must be sufficiently differentiable, and the random variable's moments must be finite. Additionally, it does not provide the whole probability density function.

Methods like numerical integration often need a consistent number of repetitions; therefore, if the simulation time is extensive, they may not be practical.

The main drawback of FORM/SORM methods is the inability to determine the accuracy of the results. However, when estimating a low probability, they are highly efficient compared to simulation methods.

Monte Carlo methods are very flexible, and empirical distributions can be handled. Furthermore, it can be easily extended and modified. Since the approach is often not provided like rigorous formulas, it can be helpfully understood by practitioners. However, the calculations can be larger than analytical models, and solutions are not exact. Indeed, the confidence level depends on the number of runs.

Commonly, sensitivity analysis is performed by resorting to sampling-based approaches or defining different levels of the inputs in which the system is tested. When the sample space is ample, the time required for the simulation can be extensive. The most adopted approaches suppose that the inputs are independent, but new methods for correlated input are under development in the literature. When the system model has a nonlinear response, it is common to use variance-based measures to avoid the sensitivity analysis approaches based on linear regression. Another issue related to sensitivity analysis methods is that they suppose a single univariate model output. Therefore, when the analyst is interested in understanding different outputs, he must perform several sensitivity analyses, one for each output. Despite this viable solution, the analysis results may be very complicated to understand when the model outputs are correlated.

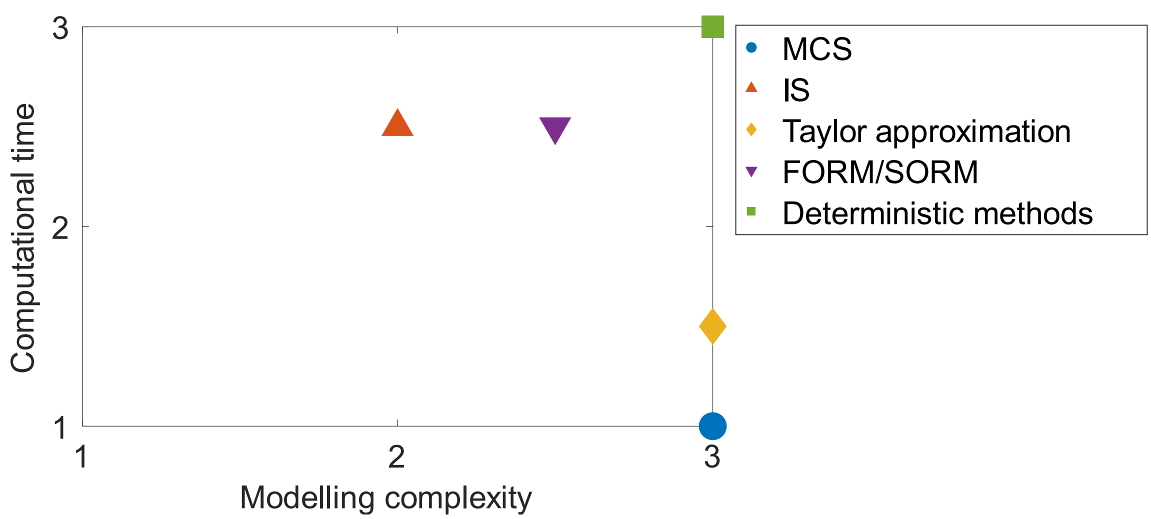

Figure 2.6 Modelling complexity score versus computational time score of the mainly used methods for the uncertainty propagation

Table 2.3 shows some relevant strengths and weaknesses of the above-discussed approaches.

Table 2.3 Strengths and weaknesses of uncertainty propagation methods

Approach	**Strengths**	**Weaknesses**
Deterministic Methods	• Provide precise solutions • Computationally efficient with simple problems • Trace the uncertainty influence on the output	• Assume known values and fixed parameters • Might neglect the variables' interactions • Suitable for low complex system and variability • Might provide overly optimistic or pessimistic results
Analytical Approaches	• Use analytical formulations of uncertainty propagation • Allow for precise mathematical formulations of uncertainties	• Might use simplifying assumptions or linear models • Might not be suitable for highly complex or non-linear systems • Might underestimate the uncertainty
Sampling-Based Approaches	• Cope with complex systems • Handle probabilistic uncertainties • Explore numerous outcomes using numerous samples	• Might be computationally intensive with complex problems and models • The number of samples strongly affects the

	• Do not use strong assumptions • Might be used with a large range of models	accuracy of the performance • Might not provide exact solutions, obtaining variable results
Sensitivity Analysis	• Assesses the impact of the uncertainty on the output • Identifies critical factors • Ranks variables by their influence • Helps in understanding models' behaviour	• Might assume that variables are independent • Might neglect potential interactions • Might not capture non-linear behaviour and higher-order interactions between variables • The selected method strongly influences the performance

Ultimately, deterministic and analytical methods might provide precise solutions but oversimplify uncertainty. Sampling-based approaches are computationally efficient when dealing with the same problems of deterministic and analytical methods but become computationally demanding when dealing with complex problems. Finally, sensitivity analysis captures the influences of different factors on the output but might neglect some interactions and dependencies.

Chapter 3

Industrial systems design and evaluation under uncertainty

Design and evaluation of industrial systems under uncertainty and variable operating conditions is a well-known problem in the literature. The main difference between the uncertainty and the variable operating conditions is that the former refers to the aleatory and epistemic uncertainty of the system input, the relationships used to model the system, and the uncertain parameters. In contrast, the latter pertains to the desired or undesired change in the operating condition. Indeed, e.g., a system can be designed to accomplish a specific objective with certain nominal conditions. However, in a further time, the desired specifications or nominal conditions can be changed for some causes. Moreover, the operating conditions may change for other reasons, e.g., changes in demand values, changes in uncontrollable inputs or similar issues. This change can be performed if the designers have considered this possibility, e.g., resorting to a flexible design or similar approaches.

Several contributions are available in the literature to cope with uncertainty during the design phase or to assess the systems' performances under variability. However, most works often include few sources of uncertainty or few methods to include them. Even though the proposed methods are frequently very advanced and complex and cover an extensive range of causes of uncertainty, they are often suited for specific applications instead of being general for a vast range of applicability fields because of the specific characteristics of different problems, which may require detailed and extensive frameworks to cover all of them.

This chapter describes the primary methodologies available in the literature for designing and assessing industrial systems under uncertainty. Furthermore, pieces of commercial software aimed at the same scopes are described. The first part of this chapter focuses on the existing methods for the designing phase and the different aspects that must be considered to achieve a well-performing design. Although there are several works which are suited for the design under uncertainty of specific families of products, processes, and systems, since the aim of this thesis is to provide a general framework to deal with uncertainty, only the contributions that propose general approaches are included in the analysis of the existing methods. The second part analyses existing methods for evaluation under uncertainty of completed designs.

3.1 Design under uncertainty

The effects of uncertainty influence the system throughout its entire life cycle. From the initial stages of the design phase, uncertainty plays a significant role in shaping the design decisions. Despite the well-established importance of this aspect, novel methods to address this challenge have not yet gained widespread adoption in the industrial sector. Consequently, developing strategies that can efficiently manage design problems under uncertainty is crucial.

Numerous fields have encountered the impact of uncertainty on industrial systems, yet researchers and practitioners frequently address specific sources of uncertainty while completely overlooking others. One of the crucial steps taken was to incorporate production scheduling under uncertainty during the design stage [98]. The authors aimed to discuss the challenges presented by multiproduct batch and continuous processes in chemical plants.

Production planning is one of the fields where the significance of uncertainty becomes evident, as it directly impacts system performance. It is crucial to explicitly consider uncertainty to generate efficient and effective planning decisions [99], and incorporating such decisions at the design stage makes industrial systems more capable of coping with these uncertainty sources. Non-probabilistic decision theory has been developed in past years to prioritize alternatives and facilitate decision-making under uncertainty [42], with more recent updates [43]. Furthermore, planning and scheduling under uncertainty pose practical challenges in various sectors. A literature review on applying multiple uncertainty approaches has highlighted the need for further research in this area [100]. One key factor in addressing uncertainty in engineering design problems is the incorporation of operational tolerances to account for deviations, which significantly impact resource planning and management [101].

In recent times, the vulnerability of supply chains has been extensively illustrated by various disruptive events, such as earthquakes, the COVID-19 pandemic, and emerging conflicts. Examining inventory and design decisions for highly perishable products assumes a crucial role in enhancing supply chain efficiency [102]. Indeed, the significance of incorporating uncertain events, including the impact of financial issues, in supply chain design under conditions of uncertainty has been widely acknowledged in the literature.

A sound industrial system and product design represent the most effective solution for mitigating the impact of uncertainty. This includes addressing technical aspects of the product, such as stress-based topology optimisation under uncertainty, which considers uncertainties in applied loads and material properties [103]. Additionally, it extends to functional aspects, such as characterizing input uncertainties in strategic energy planning models [104]. The significance of statistical theory in identifying sources of uncertainty during the design phase has been well-established in the literature.

The need to avoid rigid specifications and narrow forecasts has been recognized in the past year. Indeed, the trend towards designing flexible industrial systems has gained considerable credibility in engineering. The inability of a system to adapt to changing circumstances is one of the significant weaknesses of an industrial plant. Designing for flexibility significantly enhances the likelihood of success for industrial initiatives. Tools for reality analysis and modelling have been collected in [105].

On the other hand, robust design has also gained credibility in reducing the impacts of uncertainty. In fact, a robust system can maintain the desired specifications even when environmental conditions change [106]. A robust system minimises the variability of the response as input variability increases. The most widely adopted approach by practitioners to achieve robustness in design is to employ the design of experiments [107]. Indeed, uncertainty modelling is often neglected, resorting to linear and non-linear programming to obtain uncertainty-unsensible components [7]. The crucial problem is to find the region of admittable solution for the optimisation problem. Someone used the Monte Carlo simulation to identify the region's boundary [6]. However, identifying the non-admittable solution remains a critical issue that, in another work, was tried to be addressed [108]. This approach is viable for all problems with linearizable functions for performance evaluation [109]. The top-down approach, V-shape approach, and target cascading are the most used in the literature. In addition to robust design, resilient design aims to mitigate the effects of uncertainty resulting from disruptive events by minimising the recovery time required for the system to regain its total capacity after the event [110]. Additionally, the system can quickly adapt to different emerging contingent conditions.

Whatever strategy is adopted to design the system, optimisation problems arise. Robust optimisation emerges as a powerful approach to address optimisation problems that involve uncertainty. One of the pioneering works that thoroughly analyses this issue is [111]. Indeed, the proposed approach aimed to operate under information scarcity and formulate the problem in a solvable manner. The authors explored the potential use of worst-case analysis and uncertain linear programming to tackle design parameter uncertainty while probabilistically modelling the constraints. Furthermore, they developed a theory for resolving dynamic multistage problems.

The Integrated Design Automation Laboratory (IDEAL) of Northwestern University has investigated the design under uncertainty problem from the perspective of meta-model building, its validation and related uncertainty quantification, and the multidisciplinary design optimisation problem. Some of the most recent publications by the researchers of IDEAL are on the Bayesian optimisation for multiple models [112], adaptive batch sampling [113], stochastic non-linear analysis of fibre composites [114], and the reduction of optimisation time using adaptive sampling and heuristic-based strategies [115].

In any case, during the design phase, different strategies can be carried out to improve the ability of the system to operate under uncertainty, namely, simplify the tasks, reduce the uncertainty, and protect the system.

Simplifying the tasks means reducing the admissible product tolerances or extending the operations time to consider a time buffer to deal with unexpected events.

Reducing uncertainty stands for the mitigation strategies that can be adopted to reduce the probability of events or investigate the sources of epistemic uncertainty to reduce them.

Protecting the system pertains to the actions to do or elements to include in the design to reduce the system's sensitivity to uncertainty sources. The protection can be active or passive. The former refers to the design of a system that can change its configuration or way of working to adapt to changes, thus obtaining a flexible or reconfigurable system. On the other hand, the latter concerns the capability of the system to be insensitive to uncertainty without the need to change its configuration, therefore creating a robust system [116].

In the literature, there are reviews specifically focused on modelling, analysis, and optimisation under uncertainty. In a comprehensive review [75], design optimization methods under uncertainty have been deeply analysed, and a survey on the other issues pertaining to uncertainty modelling and propagation has been provided. However, it should be noted that design optimisation problems are frequently addressed using various methods depending on the system being optimised. Since in the previous chapters the uncertainty types, uncertainty modelling techniques and uncertainty propagation methods have been discussed, the following paragraphs will give more detailed information regarding the literature on design optimisation problems.

3.1.1 Common elements of designing under uncertainty methods

Design under uncertainty is not a straightforward task. Indeed, the literature has explored this field from several perspectives and faced the problem with several strategies. However, some general common elements can be identified as follows.

- Inputs and outputs definition.
- Constraints definition.
- Uncertainty modelling.
- System model definition.
- Uncertainty propagation.
- Risk assessment.
- Optimisation or risk mitigation strategy.

First of all, the inputs and outputs must be carefully identified. Indeed, as extensively discussed in the previous chapters, the designer should identify the system's inputs and select the outputs of interest. Inputs are independent design variables and uncontrollable parameters. The designer can govern the independent design variables, whereas the uncontrollable parameters are not under its control. Moreover, both the design variables and parameters can be uncertain or deterministic. The admittable values of the input array should be defined to avoid unfeasible solutions. When uncertainty is included, the outputs of interest suffer from uncertainty, too. Therefore, the designer has to decide how to represent the outputs. For instance, he can be interested in the outputs' whole distribution or only in some characteristics, like quantiles, exceedance probabilities, and similar indexes.

Then, the uncertain variables must be modelled. At this stage, the crucial task is to select the most appropriate theory to depict the random variable's behaviour and the parameters' epistemic uncertainty.

Subsequently, the designer should model the system. The system model types have already been discussed, and the designer should select the model type that accurately represents the actual system, saving computational time.

The uncertainty moves from the input to the output. The selection of the proper method for uncertainty propagation relies on the selected uncertain variables, the selected variable of interest, and how the system has been modelled.

Once the uncertainty is propagated and the variables of interest are modelled uncertainly, the risk is assessed. For instance, obtaining a probability density function or an exceedance probability after all the previously cited steps can be considered a risk assessment procedure.

Finally, the design can be optimised, resorting to the optimisation strategy suited for the application, or choices about risk mitigation strategies can be implemented.

One of the challenges is the consistency of the uncertainty model, system model, uncertainty propagation method, output representation and optimisation algorithm. Indeed, when the aforementioned decisions were taken, the decision-maker should carefully select all the models to avoid incompatible algebras.

3.1.2 Robust design

The main aim of robust design is to find the proper configurations of the design parameters for which the system response has the minimum dispersion around the desired output value, i.e. the specification.

In industrial practice, the statistical control of the production process is made online during the production phase. However, designing a process, a product or a system with high sensitivity to changing inputs may be a costly error. At the design stage of any process, several decisions must be made in the presence of uncertainty and imperfect knowledge. Taguchi’s system design method has been proposed to address the abovementioned problem in the past century.

The traditional Taguchi’s approach [117] is based on performing experiments on a system model or prototype to exploit the interaction between controllable and uncontrollable input variables which affect the model outputs to minimise the response variation of the system by selecting the proper design input. The method proposed by Taguchi can be summarized in the following steps. More details about each step can be found elsewhere [118].

1. Defining the problem.
2. Identifying the system and output of interest.
3. Identifying the most influential variables on the output.
4. Identifying the controllable variables, e.g. design variables and the admissible values levels.

5. Identifying the uncontrollable variables, e.g. noise factors, and their possible value levels.
6. Defining the conditions to perform the experiments and measurement methods.
7. Defining the experimental plan.
8. Doing the experiments and collecting the data.
9. Analysing the collected data, e.g. using the ANalysis Of VAariance (ANOVA) techniques.
10. Identifying the variables that lead the uncertainty propagation to the output.
11. Determining the best level conditions for the controllable variables, i.e., the values of design variables.
12. Forecasting the results with estimation models.
13. Verifying the estimations with control experiments.

As can be seen, the Taguchi method can be considered an extension of the DOE approach. In addition, Taguchi introduced the loss function ($L(y)$, Figure 3.1). At least three lost functions can be defined in the function of the objective of the design: nominal is better (3.1), lower is better (3.2), and higher is better (3.3).

$$L(y) = K(y - y_0)^2 \tag{3.1}$$

$$L(y) = Ky^2 \tag{3.2}$$

$$L(y) = K\frac{1}{y^2} \tag{3.3}$$

Where y is the random variable representing the system's output, in the Nominal better case, the loss function measures the distances between the actual value of the output and the specification y_0. K is a factor that converts the lower technical performance than the specification into a cost. This factor is often set to 0 before overcoming the maximum admittable displacement between the specification of the measured value of the output.

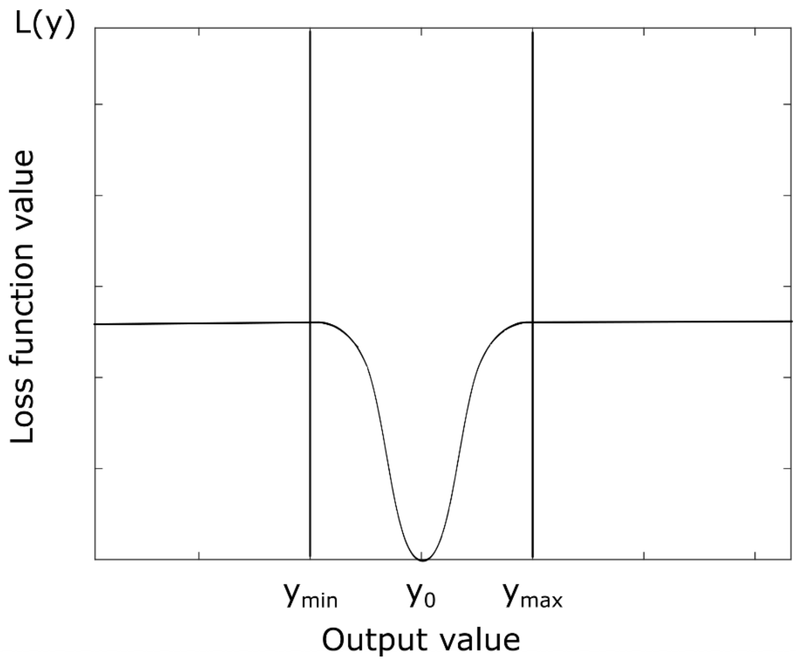

Figure 3.1 Taguchi loss function for Nominal better case

In any case, the concept of Robust Design has multiple interpretations in the literature due to the ample number of engineering fields in which it is applied. Indeed, as reviewed in [116], robustness can be considered like:

- A measure of performance variations [119].
- Insensitivity to known risks [120].
- Insensitivity to changes in the operating environment [121].
- Insensitivity to expected and unexpected variations [122].
- The ability of the system to operate appropriately across several operational conditions [123].
- The system's ability to maintain its performance level in the presence of fluctuations in the input or the environment [124].
- The system's ability to absorb change [125].
- Insensitivity to varying future scenarios [126].

Generally, two different criteria for judging a robust design can be derived: the decrease in performance variation and the handling of noise. In an available review [127], the authors analysed the existing approaches to determine the suitability for robust design, clustering them regarding transfer function and noise-behaviour model. The former shows the relationships between the inputs and outputs, whereas the latter shows the influence of the noise on the product behaviour. The results of their analysis are presented in Table 3.1.

Table 3.1 Transfer function and noise-behaviour models for determining the suitability of robust design [127]

Model	Characteristic	Use
Transfer Function	Exploiting flat sections of the function by shifting the working point	Optimise parameters
	Reducing/ eliminating variation in positioning	Use self-positioning; provide stop dogs
	Increasing product quality/ decrease in variation of product characteristics	With cast components, avoid vertical sections
	Exploiting elasticity	Apply the principle of elasticity
	Achieving independence of functions	Decouple functions
	Increasing predictability	Seek exactly constrained systems
	Increasing range of tolerance for performance variation	Change requirements
	Facilitating quality control	Change requirements
	Standardising of products and processes	Reuse models; use standard parts
	Reducing the potential for the occurrence of failures	Simplify the geometry; Reduce the number of parts
Noise-behaviour model	Reducing/ eliminating noise	Isolate heat source
	Reducing/ eliminating the influence of noise	Isolate component/product

Reducing/ eliminating the impact of noise	Use symmetric structure; apply the principle of self-help
Increasing future robustness	Increase modularisation

Robust design can operate on the output performances in three ways: reducing the reducible uncertainty (Figure 3.2), changing the slope of the transfer function that determines uncertainty propagation from the input to the output (Figure 3.3), i.e., changing the design architecture, and when the transfer function is non-linear, moving the design variables on a flatter portion of the curve (Figure 3.4).

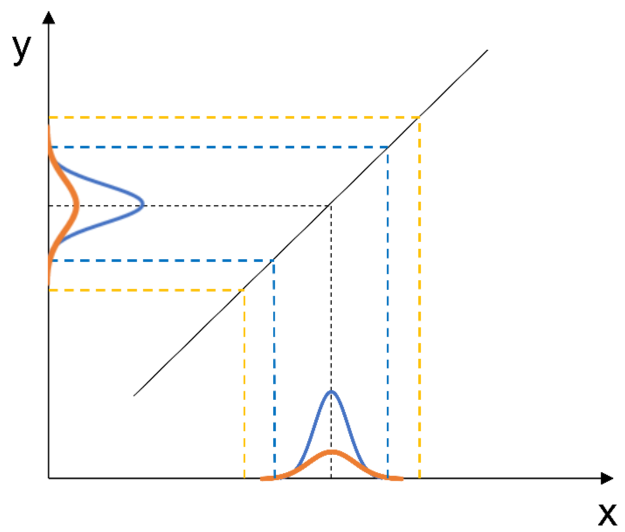

Figure 3.2 Robust design uncertainty mitigation: reducible uncertainty reduction [128]

The reducible uncertainty can arise from different sources, and specific sources require specific actions to be reduced. For instance, if the uncertainty is related to the sample size used to determine the value of a measure, increasing the number of experiments may shrink it. On the other hand, if the uncertainty pertains to the relationships used to model the system, a more detailed model may be a viable solution. In any case, these are only two examples to show that different sources require different actions. However, these approaches are still found on the assumption that the less variability enters the system, the less uncertainty will be in the outputs.

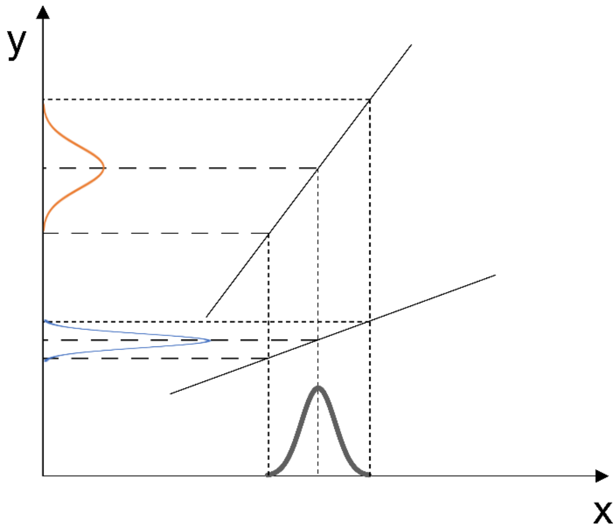

Figure 3.3 Robust design uncertainty mitigation: slope changing [128]

Since the uncertainty is propagated from the inputs to the outputs using a transfer function, an increase in robustness can be achieved by changing, for example, the architecture of the industrial equipment or system, as shown in Chapter 5. The slope change can influence the dispersion of the output around the mean value, as shown in Figure 3.3.

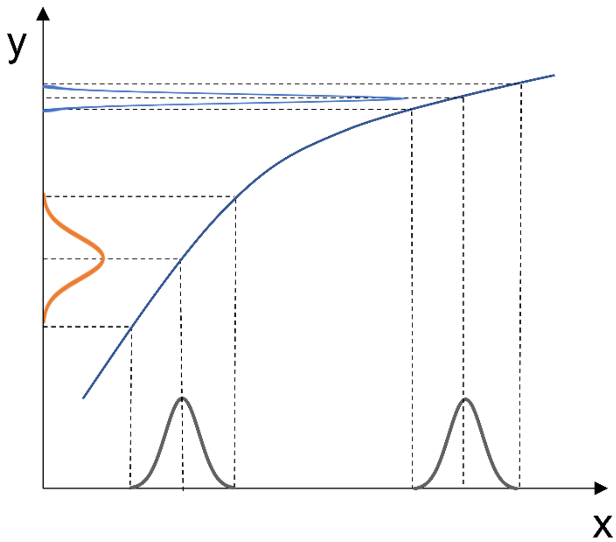

Figure 3.4 Robust design uncertainty mitigation: moving on a flatter portion of the curve [128]

Finally, when the transfer function is non-linear, the designer can select the independent design variables to operate in a flatter portion of the curve. However, this approach is constrained by the admittable region of the independent design variables and, therefore, is not always a viable solution.

Robust design optimisation

Let us define the function of the output y of the model that represents the system as $y=f(x, d)$, where x is the array of the independent design variables, and d is the array of other fixed and known parameters. The model $f(x, d)$ is obtained by resorting to some design procedure that, starting from the independent design variables and other parameters which are known and influence the design, allows the designer to compute the dependent design variables and the design architecture.

The general approach to robust design optimisation relies upon minimising the expected value of the loss function ($E(L)$). The expected value of the loss is expressed in equation 3.4.

$$E(L) = K[(\bar{y} - y_0)^2 + \sigma_y^2] \tag{3.4}$$

Where $\bar{y}$ is the average value of the actual model outputs, σ_y is their standard deviation, and y_0 is the specification. Reducing $E(L)$ by changing the design variables can simultaneously reduce the distance of the expected value of the output from the specification and the dispersion around the average value. The change of design variables can be done with different approaches, starting from the design of experiments to meta-heuristic algorithms. Whatever the selected method to pursue the design procedure, the result is an optimum or suboptimum design in which the probability density function of the output values is close to the specification and as narrow as possible.

The optimisation function can be applied to different performance measures and formulated differently. Whatever the formulation of the function under optimisation, if the goal is the robustness of the design, the function should consider both the expected value and some measure of the dispersion of the possible outcomes.

The general formulation of the robust design optimisation problem when uncertain variables are included can be expressed as follows (3.5) [129]:

$$\begin{cases} Min\, f(x, d, p) \\ S.t.: g_j(x, d, p) \quad j = 1, \dots, J \\ d_l \leq d \leq d_u \end{cases} \tag{3.5}$$

The objective is to minimise the performance function $f(x, d, p)$, where x is the vector of the random design variable, d is the vector of the deterministic design variable, and p is the vector of the random uncontrollable design parameters. The design variables x and d are changeable and controllable during the design process, whereas an uncontrollable design parameter is not. The vectors d_l and d_u are the vectors of the upper and lower bounds of deterministic design variables. Supposing that there are J constraints, g_j is the function of the j-th constraint. Often, in this type of problem, the decision variables are the mean of the random design variables and the actual values of the deterministic ones.

In the literature, robust design optimisation problems are solved by resorting to numerical integration, analytical methods, and simulation methods in function of the probability moment the designer is interested. Generally, multiobjective methods are involved in the optimisation to include the mean and dispersion of the random output simultaneously. Three of the most used are the weighted sum method, compromise decision support problem, and physical programming [130].

The weighted sum method defines a single objective function starting from multiple objectives. A possible formulation for the optimisation function is expressed in equation 3.6 [131-133].

$$f(x,d,p) = \alpha\left[\frac{E[f(x,d,p)]}{\mu^*}\right] + (1-\alpha)\left[\frac{\sigma(x,p,d)}{\sigma^*}\right] \tag{3.6}$$

Where μ^* and σ^* are normalisation's mean and standard deviation base values. Although some authors define this approach as inefficient [130], it is widely adopted due to its simple and easy application.

The compromise decision support problem is a type of hybrid optimisation problem. Indeed, the designer formulates the optimisation problem, including both mathematical and goal programming [134, 135].

Physical programming classifies and includes the objectives in the constraints set. The objective function can be easy, like the one in equation 3.6. However, whatever the objective function is, it must represent a preference function between the objectives.

More details about the Robust Design can be found in the reference [130].

3.1.3 Reliability-based design

Reliability-based design is focused on the integration of the concept of reliability during the design phase. This approach aims to maintain the reliability of the design during the operation, maintenance and decommission phases. Prosaically, one basic example of the reliability-based design is the attempt to ensure the system's reliability using safety factors for uncertainty accounting. Indeed, the safety factors method oversize, overengineer, or overdesign a system to ensure it almost surely meets the specifications.

The reliability analysis analyses the ability of the system to maintain its capability in achieving the tasks for which it was thought under certain conditions and over a fixed time. Basically, a state function of the system is defined (*g(x)*). This function considers the input variables (*x*) and informs about the system's success or failure to achieve its specifications or goals. The most straightforward criterion to understand whether a system is reliable is the Boolean one. If the system cannot meet the specifications, the state function gives a value above or below a specific threshold. The limit state of the function identifies the threshold. Commonly, the distinguishing between reliable and unreliable systems is made according to the zero point of *g(x)* (3.7). The judgment function *I(g(x))* gives the information in Boolean algebra [136].

$$I\big(g(x)\big) = \begin{cases} 1 & g(x) < 0 \quad reliable \\ 0 & g(x) \geq 0 \quad unreliable \end{cases} \tag{3.7}$$

Since the reliability analysis is strictly related to the uncertainty modelling methods of the inputs, it can be clustered into two groups: the probabilistic reliability analysis method and the fuzzy reliability analysis method. The former occurs when the random variables are modelled as a probability density function. Instead, the latter is carried out when fuzzy membership functions or fuzzy theory are used to describe the random variables [136].

The probabilistic reliability analysis can be grouped according to the used method in FORM and SORM, MC-based methods, performance measure approach, i.e. mean value, hybrid mean value, etc., and approximation model methods, like artificial neural networks and response surface methods. These methods approximate the computation of the failure probability P_f, which can be formulated as in equation 3.8.

$$P_f = \int \dots \int I(g(x)pdf(x)dx_1 \dots dx_n \tag{3.8}$$

Where n is the number of the inputs involved and *pdf(x)* is the joint probability density function of the array of random variables x.

The fuzzy reliability analysis is divided into based on fuzzy logic and based on fuzzy variables. However, this approach has already been not mature and thus is not used in engineering applications [136].

Design for Reliability (DfR) is a method rooted in reliability analysis that proposes an alternative approach to the test-analyze-and-fix philosophy [137]. The DfR procedure can be summarised as follows.

- Identify.
- Design.
- Analyse.
- Verify.
- Validate.
- Monitor and control.

The first stage is to represent quantitatively the reliability requirements of the system which is being designed. Several strategies can be used to carefully describe the requirements, such as developing metrics, benchmarking, and reliability program plan methods.

The design phase concerns the design of the system. Failure Modes and Effects Analysis (FMEA) is a common approach used in this phase.

In the analysis phase, the reliability analysis is performed. The identification of the most common failure modes is done, and their probability must be calculated. Some instruments, like the reliability block diagram, give an instantaneous idea about the reliability of a system.

The verify phase pertains to the iterative process in which the system is tested to check the compliance of the first estimation to the results obtained by experimentations or simulations. Then, the design or process is validated and, in some cases, starts the control phase, in which the system's performance is monitored over time.

The FMEA is a qualitative process in which the system is deeply studied to understand and classify the failure modes and their impact on the system. During the process, each subsystem in the whole system is investigated to list all possible failure modes, their causes, the possible defects, and the procedure for preventing or detecting the failures. The main goal of the process is to define three indices for each combination of failure modes: their probability of occurrence, the magnitude of the event, and their detection possibility. These indices are substantially rating scores which can assume a value on a prefixed scale, typically from one to ten. Their values are then multiplied to compute the risk priority index. The risk associated with the event is the product between the event's magnitude and the probability. The higher the index, the higher the priority of taking actions to mitigate the probability or the magnitude or to implement items to increase the possibility of detecting them. More details about FMEA theory and implementation have been reviewed elsewhere [138, 139].

The Failure Mode, Effects, and Criticality Analysis (FMECA) is an extension of the FMEA method. The main difference resides in the criticality analysis used to determine the magnitude of a failure and its probability of occurrence from a quantitative perspective. Indeed, the FMEA indices give only qualitative information, whereas FMECA indices are quantitative [140].

Reliability-Based Design Optimisation

Reliability-Based Design Optimisation (RBDO) is an optimisation approach in which uncertain factors are included, resorting to the probability theory. The factors' uncertainty impacts the functions of constraints, whereas the factors' mean values are included in the optimisation function. Since, in most engineering problems, the optimal solution is near the boundary, the uncertainty effect can cause the falling out of the design point from the feasibility region. Generally, the RBDO can consider the aleatory uncertainty or both aleatory and epistemic uncertainty. The optimisation problem is formulated as follows (3.9, 3.10) [75, 129, 136].

$$\begin{cases} \text{Min } f(d, E[x], E[p]) \\ S.t.\ \ P(g_u(d, x, p) < 0) \geq R_t \\ \qquad g_d(d) < 0 \\ \qquad d_l \leq d \leq d_u \\ \qquad x_l \leq E[x] \leq x_u \end{cases} \tag{3.9}$$

$$P(g_u(d, x, p) < 0) = \int_{g(d,x,p) \leq 0} pdf(x, p) dx dp \tag{3.10}$$

Where d and x are the vectors of deterministic and random design variables, respectively, $pdf(x, p)$ is their joint probability density function, d_l, d_u, x_l, and x_u are their lower and upper bounds, $E[.]$ identifies the expected value of a random variable, p is the vector of uncertain parameters, that includes the epistemic uncertainty, $g_u(.)$ and $g_d(.)$ are the deterministic and random constraints functions respectively, and R_t is the minimum allowable value of reliability. In this way, e.g., one can perform a cost minimisation considering the effects of the uncertainty on the system's reliability. The probabilistic constraint is the item that differentiates this type of optimisation problem from the deterministic one.

The optimisation process is often carried out by resorting to sampling techniques because of the difficulty or impossibility of solving in closed form equation 3.10.

In the end, a possible approach to the optimisation combines robust optimisation and reliability optimisation by utilizing as a performance function an objective function which simultaneously considers the mean and the standard deviation of the selected performance [129]. An example of this type of performance functions can be found in equation 3.6.

More details about more advanced models and methods for reliability-based design optimisation, like double loop reliability-based design optimisation, sequential optimisation and reliability assessment, and safety factor-based sequential optimisation and reliability assessment, can be found elsewhere [75, 129, 136].

3.1.4 Flexibility-based, reconfigurability-based, and resilience-based design

Resilience is the system's ability to recover its capacity or to return to its desired state after an expected event occurrence [141]. Resilience is often measured as the ratio between the area subtended by the capacity curve over time after a disruptive event and the time interval to reach the system's capacity before the event [142]. In any case, the strategies for increasing resilience are focused on redundancy, flexibility, and recoverability [143]. Design for Resilience has been intensely discussed elsewhere [144, 145]. Finally, a recent paper has defined resilience-based design starting from the reliability-based design theory [146].

Flexibility is commonly defined in literature as the ability of a system to respond to change [147]. Thus, this property of systems is another tool to cope with the uncertainty in industrial systems.

Even though the flexibility concept has been widely explored in the literature, several interpretations of the implications of this system's ability exist. Some authors tried to clarify the concept of flexibility with a deep literature review [148]. Their work identifies three ample application fields: decision theory, real options theory, and design flexibility. An emerging issue is the confusion that may occur when analysing the concept of robustness and flexibility. Robustness guarantees the satisfaction of specifications despite environmental, inputs and other changes. In contrast, flexibility is related to the will to satisfy changing requirements and adapt the system's way of working for this purpose once it has been fielded.

Since Real Option theory has its own paragraph, some comments on the flexibility of a design are briefly given in this part.

In the production system field, flexibility refers to the ability to change production volume to satisfy an uncertain demand for an item; the ability to process an item on different machines, therefore, to have general purpose resources; the possibility of a system to extend its productivity capacity; the ability to process several different products on the same system without major setup. For clarity, the main difference between volume and capacity flexibility resides in the fact that the former refers to a change in the scheduled volume. In contrast, the latter refers to the cap of the capacity level.

Whatever increases the above-cited abilities increases the flexibility of the industrial system. This means that, for example, a system designed with general-purpose machines, redundancy, speedy setup, and mixed model production line, similar to the Flexible Manufacturing System (FMS) [149], is designed according to the flexibility-based design approach.

More details about the flexible manufacturing system can be found elsewhere [149].

A reconfigurable manufacturing system has an open architecture that enables the adoption of new resources and layout changes very quickly to respond rapidly and economically to emergent increases in market demand [150]. Basically, the reconfigurability-based design can change both its hardware and software resources to adjust its structure to larger production capacity or new products in response to new market or regulatory requirements. The main characteristics of a reconfigurable system can be resumed as follows [151].

- Scalability. The capacity of cost-effective adaptation to market demand changes.
- Convertibility. The capability of adaptation to new products.
- Diagnosability. The possibility to monitor the real-time product quality and defects. This leads to increased system reliability.

- Customization. The system’s adaptability around a family of products.
- Modularity. The compartmentalization of systems to reconfigure and reallocate tasks to machines.
- Integrability. The possibility to include new modules effectively.

Further details on reconfigurable manufacturing systems can be found elsewhere [152]. For completeness, some authors proposed a decision support methodology to minimise the expected total cost of assembly systems with modular resources, including reconfiguration costs [153].

In the end, while flexibility pertains to changing and assuming different states to cope with changing requirements with short time, effort, cost, or performance degradation, reconfigurability regards adjusting the functionality and capacity at low cost and time [154].

3.1.5 Real options theory

The Real Options theory is widely used for economic evaluation [155]. This approach can enhance the flexibility of a system during the design phase [156], and, from the author's perspective, its most significant contribution lies in providing a new methodology for the economic evaluation of an investment. This theory enables estimation of the net present value of an economic initiative without resorting to the traditional approach while also allowing for increased resilience and mitigation of uncertainty effects during the design phase. This theory is based on financial derivatives known as options, which are utilized to mitigate the risk associated with fluctuations in the price of an underlying asset by paying a premium. In the case of a call option, the owner possesses the right, but not the obligation, to purchase an asset at a predetermined price on a fixed future date.

Conversely, a put option grants the owner the same right to sell an asset. The hedging strategy involves setting a lower or upper price limit the option owner establishes with their purchase. The types of real options are listed below.

- Option to expand. This refers to the opportunity to invest in the future to expand the current operational system, such as entering new markets or increasing market presence.
- Option to learn. This pertains to the possibility of increasing knowledge or understanding about a particular subject or area.
- Option to wait. This denotes the option to postpone a decision to a future time, such as delaying an investment or increasing production capacity at a later date.

- Option to contract. This represents the possibility of reducing the scale or scope of an investment, often in response to changing circumstances or market conditions.
- Option to abandon. This signifies the ability to terminate or shut down a project to minimise or mitigate economic losses.
- Option to switch. This refers to the capability of shutting down a project to minimise economic losses and subsequently restarting it when favourable conditions arise.

This theory can effectively address both epistemic and aleatory uncertainty, although pricing the option is not a straightforward process. Furthermore, the actions taken to mitigate uncertainty specifically focus on enhancing the system's flexibility [157]. Nevertheless, the approach generally involves four steps: problem description, data collection to implement the option evaluation model, reviewing the results, and making design changes as necessary. It is an iterative process that proves highly valuable in making strategic decisions within uncertain stochastic processes. Furthermore, it can be employed to simplify certain problems and reduce the computational power needed by combining it with uncertainty propagation techniques. As mentioned earlier, the most significant advancement of this theory lies in the assessment of the economic performance of a system. Real Options, in fact, can determine the risk-adjusted strategic value, providing a realistic estimation of the value of an investment or an organization, taking into account their guard against adverse events [158]. On the other hand, estimating the value of a real option is a highly complex task, and ongoing research is dedicated to addressing this challenge. For example, the author of [159] recently examined the valuation of mergers and acquisitions within the framework of Real Option theory.

3.1.6 Design optimisation and design-based risk mitigation strategies

After modelling the uncertainty sources and the system, propagating uncertainty through the system model, and assessing the risk, one has a complete picture of the system under analysis. At this point, the selected objective drives the subsequent steps. Theoretically, the decision maker has all the information required to make a conscious choice, but several things can be done.

One can perform different actions to act on the design of the system or on the system itself. In the first case, the system design can be optimised using various methods or algorithms to enhance the system's robustness, resilience, flexibility, or other characteristics, which aid in dealing with uncertainty. On the other hand, one can act on the system with risk-hedging actions to mitigate technical or economic risks.

Stochastic optimisation is a branch of optimisation methods. This approach uses random variables in formulating the objective function and constraints and can be divided into two groups: methods for stochastic functions and metaheuristic algorithms.

Methods for stochastic functions include stochastic approximation methods and scenario optimisation. The former is a group of iterative methods which resort to recursive update rules for solving linear systems or approximating extreme values [160, 161]. The latter investigates solutions for robust optimisation and constraints-based optimisation problems resorting to scenarios combination [162].

Metaheuristic algorithms are randomized search methods which use probabilistic techniques to approximate global optimisation. Indeed, this type of algorithm finds a sub-optimum solution, not the actual one. They can be used with analytical, surrogate, and simulation models. Several algorithms exist, and most of them are listed in Chapter 5. Since the functioning of these search methods is related to the one used, additional information about these issues can be found in the reference [163]. Additionally, a classification of more than eighty algorithms is provided in the review in reference [164].

The existing literature has extensively explored design optimisation under aleatory and epistemic uncertainty. As mentioned above, some authors have focused on optimising systems under aleatory uncertainty, while others have considered epistemic uncertainty. Only a limited number of contributions have tackled both types of uncertainty simultaneously. Furthermore, in many cases, only a few uncertainty sources are taken into account, resulting in designs that may not be as accurate. Nevertheless, in recent years, there has been a growing interest in optimisation under uncertainty, and knowledge in stochastic programming has been expanded [165]. This increasing interest suggests that researchers and practitioners recognise the importance of incorporating uncertainty into design optimisation to create more robust and reliable systems.

Analytical approaches to optimisation are suitable when the number of optimisation variables is small, and the involved function can be formulated analytically, particularly for non-linear optimisation problems. However, in cases where the optimisation problem is linear, analytical approaches can still be utilized. Nevertheless, in real-world scenarios, numerical optimisation methods are often more appropriate. In fact, they are preferred when dealing with problems involving many dimensions or when constraints cannot be easily formulated in closed form.

Simulation-based optimisation is widely utilised in the practical world when dealing with complex problems and real-world systems. Metaheuristic algorithms for global optimisation have been extensively investigated and classified, demonstrating their ability to solve a wide range of problems [166]. On the contrary to optimisation algorithms and iterative methods, metaheuristic algorithms do not guarantee the finding of the optimal solution. Nevertheless, some studies on the convergence and the possibility of finding the global optimum are underway. Despite the aforementioned drawbacks, metaheuristics may offer effective solutions to optimisation problems, particularly when there is incomplete information and the required computational time for optimisation tasks is substantial. The goal of this family of algorithms is to find a near-optimal solution. Due to their widespread use in the literature and their high capabilities in solving design optimisation problems under uncertainty, Chapter 5 will provide further information about the research on this topic. Additionally, the practical example in the case study will demonstrate the effectiveness of metaheuristic algorithms.

Beyond design optimisation, some actions can be taken by decision-makers and designers on both the design and the system itself. Design for X policies is widely implemented in the risk mitigation field. For instance, design for flexibility [149], resilience [144], modularity, and reconfigurability [152] are just a few examples of the strategies that can be implemented in the design. All these strategies share some aspects in common, such as equipment redundancy. Redundancy involves including multiple machines for each type to shift production if required. The machines must have relatively low utilization. Another vital element is the use of general-purpose machines. General-purpose machines can handle different products and perform various operations. Nowadays, the enhancement of the previously introduced system characteristics is influenced by the Industry 4.0 paradigm. The integration between cyber and physical systems using the Internet of Things enables the enhancement of flexibility, resilience, and reconfigurability of industrial systems.

When economic risk is involved, the most widely used practices are resorting to insurance and financial products like derivatives. More details on this topic will be provided in the literature review of Chapter 6.

To reduce the gap between scientific research and industrial application, some authors have proposed frameworks for categorizing the effects of uncertainty on the various aspects of decision-making, optimisation, and related topics. For instance, in an original work [17], a framework with three goals has been developed: assessment, adjustment, and abatement of uncertainty. Uncertainty assessment pertains to the effects on the feasibility, analysing the range of parameters, the constraints and the uncertainty effects on the objective functions. The uncertainty adjustment attempts to minimise the effect on feasibility and the objective functions, using the already introduced recursive algorithms and robust optimisation. Instead, uncertainty abatement refers to reducing the uncertainties and increasing the accuracy of the parameters and input data. The cited paper finds in the already explained approaches of continuous description of sampling space and discrete sampling two different strategies to reduce the optimisation problem complexity.

In conclusion, all the works and theories mentioned above have been considered to extend their applicability fields and to integrate the different approaches and methods in a single framework for uncertainty coping.

3.2 Industrial systems evaluation under uncertainty

Although most industrial systems are still designed neglecting uncertainty and resorting to nominal conditions or, in the best case, using discrete event simulation tools, after the design phase, the project is often evaluated using sensitivity analysis to understand which variables strongly influence its performance [167]. Additionally, one can usually evaluate the system under likely scenarios to observe the behaviour of the system in off-design conditions [168, 169].

Understanding the economic and technical performance of an industrial system under uncertainty is crucial for decision-makers, designers, managers, and practitioners. The literature has generally focused on a single or a few sources of uncertainty rather than simultaneously considering as many sources as possible. Nonetheless, there is significant attention given to this issue. For several years, researchers have been attentive to economic performance evaluation, adopting approaches that model uncertain discount rates in future scenarios and determine appropriate forward rates of discount [170, 171]. They have also taken into account the effect of climate change on discount rates. At the same time, other authors have considered the implications of high-impact catastrophes associated with climate change on the uncertainty of the economic environment [172].

Cost-benefit analysis is an established methodology used in various sectors, from the private to the public. In order to obtain credible results, it is crucial to take uncertainty into account. However, analysts often rely on heuristic rules and simple probabilities to deal with the uncertainty of cost-benefit estimations and derive a probability distribution of the outcomes, representing the associated risk [173]. Alternatively, analysts may employ Monte Carlo simulation and other types of sensitivity analysis to consider parameter uncertainties [174]. Nevertheless, a few structured approaches currently consider multiple sources of uncertainty simultaneously.

Decision-making becomes challenging when dealing with complex problems, particularly when multiple objectives are involved and trade-offs are necessary. A common approach is simplifying the problem into a single objective, such as maximising monetary return [175]. However, decision-makers often rely on rules of thumb to handle uncertainty [176]. In recent years, more structured approaches have been proposed. For example, the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) can assist decision-makers in prioritising the best choices, even in the presence of a multi-objective optimisation problem [177].

To the best of our knowledge and based on the literature analysis, it is apparent that scientific research has predominantly focused on specific sources of uncertainty rather than considering multiple sources simultaneously. There is a notable lack of research that addresses several sources of uncertainty in decision-making, design, and evaluation under uncertainty. Additionally, the existing works often focus on specific problems instead of frameworks of general applicability.

The following paragraphs review some of the available contributions in literature and commercial tools for evaluating different types of industrial systems under uncertainty.

3.2.1 Risk assessment

A potential source of damage or loss is known as a hazard. When this hazard is likely to have some effects on the system or the environment, the risk arises. Therefore, risk is the combination of an event that can occur and its probability of occurrence. This probability is strictly related to the uncertainty about translating the possible damage linked to the hazard to actual damage. When uncertainty may affect a system with undesired effects, evaluating risks and assessing is crucial to avoid incorrect or uninformed decisions.

A general approach to define safety barriers against possible consequences which may arise from the hazard is to identify the possible accident scenarios and to predict their consequences. Although a straightforward and common approach is to define the worst-case scenarios and protect the system against these events, this can lead to underestimating the risk associated with other events. Moreover, defining the worst-case scenarios is not straightforward and can lead to neglecting other relevant cases.

The Probabilistic Risk Assessment (PRA), or Quantitative Risk Assessment (QRA), is a framework that comprises the uncertainties about the events that can affect the system by considering three issues: the events that translate the hazard into actual damage, the probability of these events, and the consequences of them. Very often, the output of the process is the individual risk, which can be seen as the number of fatalities after an event, but also as the expected economic losses after it, or frequency-consequence curves, i.e. the expected number of accidents with at least a number of fatalities, which can be seen like a probability density function of expected loss.

The two predominant strategies of PRA are the frequentist and the Bayesian approach. The former is usually the first choice when ample data is available and uses statistical inference and probability models to estimate risk probability and effects. The latter resides in subjective probabilities and is often used when poor data is available. Basically, with the Bayesian approach, the analyst establishes the models to represent epistemic and aleatory uncertainty and then applies the law of total probability to assess the predictive distributions of the quantities of interest. Whatever the chosen approach, the risk analysis process starts with selecting the relevant hazards and scenarios, representing their uncertainty, assessing the risk, supposing action to mitigate the risk and finally assessing the residual risk. The procedure output is a series of events, associated probabilities, and expected consequences [178].

The main steps of risk assessment can be summarised as follows.

- System modelling.
- Uncertainty sources and hazards identification.
- Initiator events indentification.
- Events probabilities and consequences assessment.

- Risk assessment and decision-making process.

The system modelling and calibration pertains to the concepts expressed in section 2.1, as well as the sources of uncertainty identification and modelling of the issues described in section 1.2.

The selection of initiating events is made by analysing the data about hazards. The events which come out from the hazards, i.e. the event that starts the translation from the plausible to the actual event, should be classified using a risk matrix according to their criticality as acceptable, As Low As Reasonably Practicable (ALARP), and unacceptable.

The sequences of events which lead to the damage or loss have specific probabilities. These probabilities are estimated by combining each event's probabilities that belong to the specific sequence. Therefore, in the fourth step, the probability of sequences is assessed, e.g., by using the event tree method or fault tree analysis. The event tree method uses inductive logic by discretising the real accident evolution to individuate the accident sequence resulting from an initiating event. For further details, see reference [179]. On the other hand, fault tree analysis is a deductive technique to understand the causal relations which lead to an event. Further clarification about this method and its applications can be found elsewhere [180].

Finally, the risk assessment and decision-making process step estimate the possible outcomes and probabilities. Then, possible solutions to mitigate the effects of the events on the outcomes or their occurrence probabilities are drawn and eventually put into practice.

Even though the above discussion is mainly focused on failure and system damage, it can be extended to other variables of interest, as remarked when the concept of loss has been introduced. Indeed, the risk assessment is considered from various contributions in the literature similar to the uncertainty quantification process. An exhaustive contribution focused on uncertainty quantification and risk assessment can be found in the reference [181].

In conclusion, the risk assessment process passes by identifying the variable or variables of interest. As already said, the variable can be purely technical, economic, or a combination of these two distinct aspects. Additionally, the variable can be only one, like the outlet temperature of one fluid in a shell and tube heat exchanger (Chapter 5), or more than one, like the Net Present Value (NPV) distribution, the Value at Risk (VAR), and the probability of obtaining a NPV less than zero in an economic evaluation of an industrial initiative

(Chapter 6). Identifying the variable of interest is crucial in the risk assessment process. It plays a significant role in determining the most appropriate uncertainty propagation method (as shown in Table 2.2) and, eventually, the most suitable optimisation algorithm after its estimation.

Once the variable of interest has been selected, the focus must shift to the measure of uncertainty associated with that variable. Understanding the uncertainty is essential for making informed decisions or optimising the system. Some possible measures of uncertainty of the variable of interest are listed below.

- Wost-case scenario.
- Expected value of the variable of interest.
- Standard deviation of the variable of interest.
- Coefficient of variation of the variable of interest.
- High-level moments of the probability distribution.
- Confidence intervals of the variable of interest.
- Quantiles of the variable of interest.
- Probabilities of exceeding a threshold.
- Failure frequency.
- Ranges or maximal and minimal values of the variable of interest.
- Probability density function of the variable of interest.
- Cumulative belief in not having exceeded a threshold.
- Plausibility/belief functions of the variable of interest.
- Value At Risk (VAR).
- Risk-Adjusted Return on Capital (RAROC).

The aim of this thesis is not to review the risk assessment procedures. For that reason, further clarification is provided in references in the literature review section of case studies. Additionally, the application of this methodology can be seen in the subsequent chapter.

3.2.1 Literature-available uncertainty quantification frameworks

From the previous review, it emerges that the literature is often focused on specific topics, such as some uncertainty sources, methods, models, or systems, instead of addressing from a general perspective the problem of assessing industrial systems performance under uncertainty. Despite this fact being generally true, some works in the previous pages generalised the existing theories and systematised the existing approaches to face the uncertainty propagation problem or design under uncertainty from a general perspective. As a matter of fact, for instance, the reference [4] contributes significantly to conceptualising a framework for quantitative uncertainty assessment by addressing multiple sources simultaneously without focusing on a specific system. This paragraph summarises the work just mentioned to give a more comprehensive picture of state-of-the-art.

Even though the authors' proposal is suited explicitly for practitioners, they incorporated several concepts. Firstly, they employed an analytical model (paragraph 2.1.1) or adopted a surrogate model (paragraph 2.1.3) of the system to minimise complexity. Next, they characterised the uncertain inputs by employing probabilistic (paragraph 1.2.1) or possibilistic approaches (paragraph 1.2.4) to measure their associated uncertainty. Subsequently, they utilised the technical system model by considering fixed parameters and uncertain variables to evaluate the output uncertainty of the variable of interest. Finally, a sensitivity analysis (paragraph 2.2.4) was conducted to ascertain whether the decision criteria, which rely on the analysis objective, satisfy the specified requirements. If not, the authors recommended that decision-makers take action to mitigate uncertainty through system design modifications. A notable aspect is that the authors present the analysis results deterministically, ensuring practitioners can comprehend them.

The framework can achieve the following four distinct objectives.

- Understanding the impact of variability on the output.
- Validating a measurement or model.
- Selecting among various models or choices.
- Meeting prescribed standards and thresholds.

The approach is based on the forward process and the feedback process.

The forward process propagates the uncertainty from the input to the output and eventually assesses the risk.

On the other hand, the feedback process has different objectives in the function of the goal for which the framework is used. For the first two goals, it is used to improve the system or uncertainty model accuracy or reduce the models' complexity by changing their representation or introducing assumptions or simplifications. For the third objective, it is used to change the scenario in which the forward process is performed. Finally, when the fourth goal is ongoing, it is used to adjust the controlled variables or to improve the measurement to achieve the thresholds or criteria satisfaction.

Additionally, the authors deeply discussed the existing uncertainty models, deterministic and meta-models, several uncertainty propagation models, and the well-known problem of properly selecting the variables of interest. Furthermore, they discussed the applicability of methods in different cases and provided suggestions about the preferred method at given conditions. Figure 3.5 shows the cited uncertainty quantification framework.

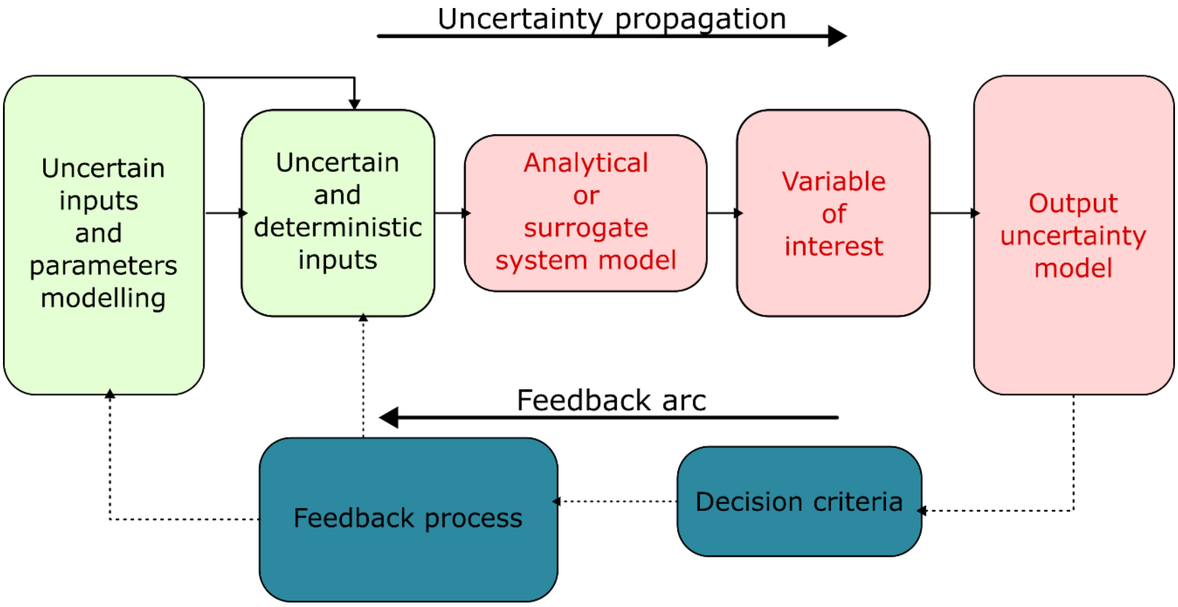

Figure 3.5 Literature-available framework for uncertainty quantification proposed by de Rocquigny et. al [4]

One of the authors of the aforementioned work also expanded the theoretical foundations of the framework by proposing additional mathematical and statistical tools to incorporate risk assessment and some economic items into the final evaluation [5].

3.2.2 Commercial software for uncertainty quantification

Several commercial tools for uncertainty quantification are available on the market. Despite most of them being specialised software, some others are general purpose. Some of these general-purpose pieces of software are briefly reviewed in the following to show their relevant features and capabilities. The information reported below is based on deep reviews available in the literature [16, 74].

- Dakota.
- PSUADE.
- OpenTURNS.
- Chaospy.
- QUESO.
- PyMC and PyMC3.
- Stan.
- UQ Tools.
- UQTk.
- OpenCOSSAN and COSSAN-X.

Dakota is an open-source software made by Sandia National Laboratories. It was born in 1994 as an optimisation tool but extended to include uncertainty quantification. Basically, it can automate variables and parameters changes to assess the risk. This allows the analyst to calibrate, optimise, and do sensitive analysis or uncertainty quantification, giving the software the response of a computational model. Then, it provides the new input to the model, and the process goes ahead iteratively.

The system model can be emulated resorting to surrogate models. Therefore, analytical and simulation models are not includible.

Dakota is focused on forward uncertainty propagation, and the aleatory uncertainty of inputs can be represented with eleven standard distribution types and five standard discrete distribution types. Although it also admits the correlation between the variables, the computation of partial correlation coefficients supposes the linear relationship between input and output. In contrast, the assessment of partial rank correlation coefficients assumes that the relationship between input and output is monotonic. On the other hand, epistemic uncertainty can be represented by continuous or discrete intervals, integers, strings, and real values.

The uncertainty propagation can be performed with sampling, stochastic expansion, and reliability methods. Additionally, it includes the theory of evidence and the interval methods for propagating epistemic uncertainty. A feedback process can be used to perform optimisation under uncertainty, mainly to achieve robust or reliable design.

PSUADE is a collection of mathematical techniques for uncertainty quantification and means Problem Solving Environment for Uncertainty Analysis and Design Exploration, and it was developed by Lawrence Livermore National Laboratory.

PSUADE encompasses several sampling approaches to perform uncertainty propagation, including aleatory and mixed aleatory-epistemic uncertainty propagation. Instead, purely epistemic uncertainty propagation techniques, such as Dempster-Shafer's theory, seem to be not currently included. The main features are uncertain parameter screening and dimension reduction, response surface analysis, quantitative uncertainty analysis, reverse uncertainty quantification with Bayesian theory, and optimisation under uncertainty.

PSUADE builds an internal surrogate model using Kriging methods, polynomial fits, and radial basis function expansions. Thus, system models built by the user are not admitted. Moreover, only basic probability distributions such as uniform, normal, lognormal, and triangular are available.

OpenTURNS is a Python module was made by a collaboration between academic institutions and Airbus Group, Électricité de France Research and Development, Phimeca Engineering, and Ingénierie Mathématique et Calcul Scientifique.

The uncertainty can be represented using more than forty parametric distributions, stochastic processes, and multivariate distributions.

Sampling methods, polynomial chaos and reliability methods perform the aleatory uncertainty propagation, while epistemic uncertainty seems not currently included. Bayesian model calibration allows the tool to address reverse uncertainty quantification problems.

The system model can be represented by polynomial chaos, Kriging methods or by an approximation of the computational model as an expansion on an orthogonal basis.

Beyond the absence of epistemic uncertainty, another limitation resides in that optimisation procedures cannot be performed.

Chaospy is a Python module that includes two uncertainty propagation methods: non-intrusive polynomial chaos and Monte Carlo sampling.

Some information about propagation outputs can be calculated, such as the moments of the outputs’ probability density functions.

The main goal of this tool is to generate a list of model inputs with random samples or quadrature points.

QUESO, PyMC, PyMC3, and Stan focus on Bayesian model calibration via Markov Chain Monte Carlo.

The Parallel C++ Statistical Library for Bayesian Inference (QUESO) is a collection of algorithms and tools to assist the research into uncertainty quantification and model prediction.

The primary objective of the QUESO library is to address the inverse uncertainty quantification problems using the Bayesian approach combined with Markov Chain Monte Carlo.

PyMC3 extends PyMC by including Hamiltonian Monte Carlo and determines the gradients needed for the Markov Chain Monte Carlo method. Furthermore, it also includes interfacing with external software.

Stan is very similar to the other two tools cited above and is a valid alternative to them.

UQTools is a MATLAB toolbox developed by NASA and suited for reliability methods.

It supports model emulation using polynomials and radial basis functions and has limited support for local sensitivity analysis.

UQ Toolkit (UQTk) is a collection of methods for uncertainty quantification. It was made by Sandia National Laboratories, and even though it is focused on polynomial chaos expansion, it can construct model emulators using Gaussian process regression, another approach that uses Bayesian model calibration with Markov Chain Monte Carlo Method.

Finally, it can perform global sensitivity analysis, and the capabilities of this tool are surrogate construction, sensitivity analysis and reverse problem.

OpenCOSSAN is an open-source MATLAB toolbox, and it is the computational part of the COSSAN-X software. COSSAN-X is an uncertainty quantification tool with a graphical user interface. It was developed by the Institute for Risk and Uncertainty at the University of Liverpool.

Rather than for industrial systems, COSSAN-X is designed for mechanical components and products. Indeed, it can interface with finite element solvers and other external simulation and designing tools to extend the range of applications. The software has several toolboxes, including aleatory uncertainty propagation, reliability approaches, robust and reliability-base optimisation, meta-modelling methods, stochastic finite elements methods, and local and global sensitivity analysis approaches.

It is a very comprehensive software. However, it is mainly focused on mechanical design, and the epistemic uncertainty can be modelled using intervals of fixed but unknown constants. Moreover, the model emulation uses either artificial neural network or polynomial fitting and the optimisation is mainly centred on structural and reliability-based optimisation.

3.2.3 Risk mitigation strategies

Risk mitigation strategies concern the impact of the specific event on the system and the expectation about its occurrence. Indeed, the risk can be defined as in equation 3.11.

$$R = P \cdot M \tag{3.11}$$

R is the risk associated with the actual event arising from a hazard. This event may happen with a probability *P* and with an impact on the system equal to the magnitude *M*. Therefore, the risk mitigation strategies concern both the reduction of the probability and the impact on the system. The actions which can be done can affect either the probability or the magnitude. However, in some cases, they can affect both quantities. Figure 3.6 classifies each risk with respect to the yet-cited characteristics.

The matrix of risk mitigation strategies suggests when doing what. Indeed, when the impact on the system is low, and the probability of occurrence of the hazard is low, the risk is neglectable, and the suggested strategy is to accept the risk as is. When the likelihood and impact on the system are high, it suggests doing something to reduce the probability of occurring or the potential damage to the system. Despite the utility of classifying the risk in that way, the matrix does not suggest anything if one between the likelihood and the impact is high and the other low. Indeed, only the result of quantitative risk assessment can provide transparent data which can be used to perform a decision-making process.

Additionally, each risk can be classified according to the knowledge that the analyst has on it. The matrix of identification and certainty can be defined. The identification pertains

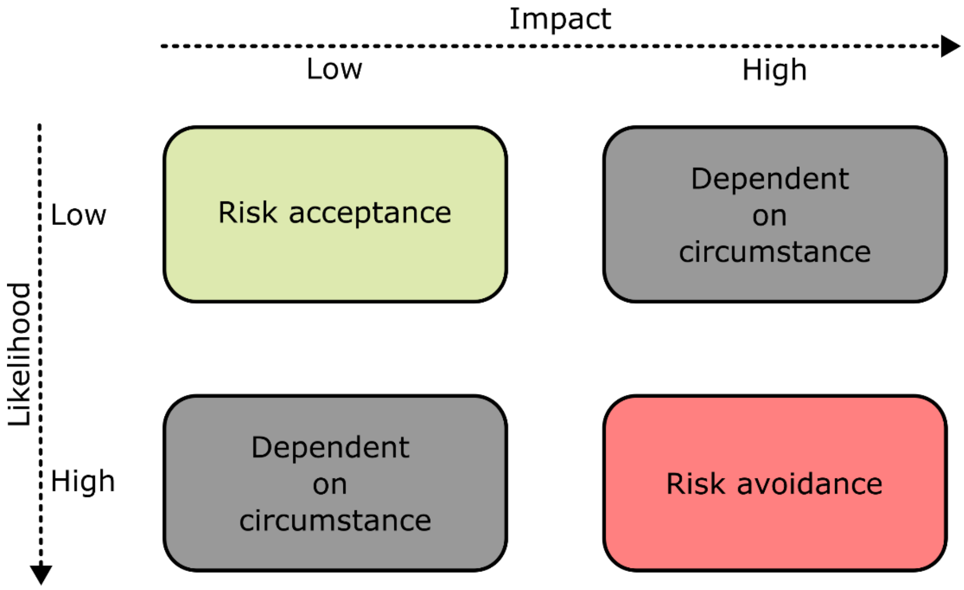

Figure 3.6 Matrix of risk mitigation strategies classified in respect of their likelihood and impact on the system

to the understanding of the event and its consequences. In contrast, certainty refers to the impact of the risk on the system and its occurrence. Both certainty and identification can be known or unknown. Therefore, four types of risk can be identified:

1. Identification: known; Certainty: known.
2. Identification: unknown; Certainty: known.
3. Identification: known; Certainty: unknown.
4. Identification: unknown; Certainty: unknown.

The type 1 is called identified knowledge. It is theoretically known risk because the events that may happen are, and also practically because the impacts and risk exposure can be described using evidence.

The type 2 is called untapped knowledge. The risk is less known abstractly, but the firm's experience suggests accepting the risk without managing it.

The risks of type 3 are the identified risk. Now that the analysts are not sure there is a concrete risk exposure, these risks should be addressed.

Finally, the type 4 are the unidentified risks. This group refers to possible risks which are not yet conceptualised and without knowledge about their possible impacts on the firm.

Despite the fact that numerous actions exist for each specific case, this work aims to provide a general-purpose approach. Therefore, the plausible actions will be clustered in general strategies. Although there are several strategies which decision-makers can adopt, four families of strategies can be defined: avoid, transfer, shrink, and accept.

Risk avoidance is an approach that tries to reduce the exposure to risk by reducing the magnitude of the impact on the system. This reduction is made using passive or active protections against the risks.

Transferring the risk means shifting the impact to a third party. Examples include financial products, such as insurance and derivatives.

Risk shrinking involves action to reduce the probability of hazard occurrence related to the risk being mitigated. Some possible actions are reducing the process complexity, selecting more stable suppliers, etc.

Accepting the risk is a passive strategy in which the decision-maker chooses to face the risk when the event occurs. Budgets' reserve and response activities to the event should be defined.

In conclusion, even if it is possible to make the aforementioned classification, the strategies tend to overlap. Indeed, taking out insurance or buying derivatives can be considered both a risk transfer and risk avoidance strategy since the impact on the firm is reduced and moved to a third party.

3.3 Final remarks

The previously exposed methods and approaches are advanced and sophisticated and underline several aspects of the criticalities which arise when uncertainty is considered during the design phase or in the evaluation of industrial systems.

Considering the design phase, with few exceptions, the available methods are focused on single aspects of the problem. For instance, there are methods for optimising the design under aleatory uncertainty and others under epistemic uncertainty. When both are considered, the problem is seen from a specific perspective, such as robustness or reliability optimisation. To the best of our knowledge, available literature contributions do not analyse the problem since the uncertainty modelling to the system optimisation but focus on a single step of the whole procedure.

Considering the uncertainty quantification, a very advanced contribution has been presented in the previous pages. However, even if not solely, the work mainly focuses on technical performances and the uncertainty propagation phase. Moreover, analytical and surrogate system models have been considered, but not often the simulation ones. In addition, optimisation and mitigation strategies have not been fully explored.

Some of the general-purpose available commercial tools include several methods for uncertainty modelling and propagation but often include only a surrogate model of the system instead of an analytical or simulation one. Therefore, this leads to the difficulty of including both technical and economic models of the system simultaneously. Some tools include only aleatory uncertainty and a small number of probability distributions. In addition, some pieces of software are suited for reverse uncertainty propagation problems. Moreover, only a few can perform optimisation under uncertainty, and it is mainly focused on robust or reliable optimisation. None of them includes risk mitigation strategies. Finally, the most advanced tools are focused on mechanical components and products rather than industrial systems.

This thesis aims to fix this literature gap by proposing a comprehensive approach that systematises and integrates the existing approaches for uncertainty modelling, system modelling, uncertainty propagation, risk assessment and quantification, design optimisation, and risk mitigation in a single framework. Furthermore, it includes modelling the technical system and the economic environment in which it operates simultaneously. The comprehensive framework is presented in Chapter 4. This way, it is possible to extend the applicability fields and to apply the existing methodology to address issues in systems which have never been studied from this perspective, as will be shown in Chapter 5 and Chapter 6. Furthermore, this work introduces a new uncertainty classification method. It combines scenario analysis with other uncertainty propagation methods to simultaneously consider the financial, political, market, and regulatory risks, randomness of input variables, and epistemic uncertainty of parameters and system models. Finally, it explicitly includes optimisation algorithms and risk mitigation strategies in the framework, such as financial instruments or redundancy. Framework's capabilities in assessing, risk-mitigating, and optimising are demonstrated with two case studies.

Chapter 4

General framework

This section presents the general framework for designing and evaluating industrial equipment, components, and systems under uncertainty and variable operating conditions [8]. This framework systematises the existing literature approaches and attempts to extend their fields of applicability. Indeed, the general idea is to integrate into a single framework the phases of understanding the uncertainty sources, classifying them, modelling these sources and the system, propagating the uncertainty, assessing the risk, optimising the design or taking risk mitigation actions. Additionally, when it is needed, the framework aims to consider both the system and the economic environment in which it operates. In this way, it is possible to extend the applicability fields and to apply the existing methodology to systems which have never been studied from the uncertainty perspective.

Furthermore, this framework introduces a new uncertainty classification method to help the analyst select the most proper method to represent different uncertainty sources according to their behaviour over time. The proposed approach combines scenario analysis with other uncertainty propagation methods to simultaneously consider the financial, political, market, and regulatory risks, randomness of input variables, and epistemic uncertainty of parameters and system models.

Finally, it explicitly includes optimisation methods for optimising under uncertainty and risk mitigation strategies, such as financial instruments or redundancy.

The literature about design and evaluation under uncertainty highlights the importance of considering uncertainty in several aspects of design and assessment processes. Nowadays, it is well known that moving under uncertainty is challenging in numerous fields, such as engineering, economics, and decision-making. The approach proposed in this study aims to fill the gaps discussed in the previous chapters, and the main advantage that it introduces is that several sources of uncertainty are simultaneously included in the design and evaluation process to help decision-makers achieve more conscious and aware choices.

The most relevant addressed gap falls in enhancing decision support systems for uncertainty management and design support systems for designing under uncertainty and extending the fields of applicability of existing methodologies. Indeed, two new applications will be presented in the following chapters. The former is focused on the design under uncertainty of shell and tube heat exchangers, which are widespread in industrial systems. The latter is the evaluation of renewable energy systems under uncertainty, and the results show the importance of considering uncertainty to avoid wrong investment decisions.

As explained subsequently, the general framework can include several types of uncertainty.

- Aleatory uncertainty.
- Epistemic uncertainty.
- Model uncertainty.
- Parameter uncertainty.
- Processes uncertainty.
- Boundary uncertainty in optimisation problems.

Additionally, to model these different clusters of uncertainty, the approach can adopt several methods to represent and propagate the uncertainty. The uncertainty propagation approach should be selected according to the adopted uncertainty representation method to avoid incompatible algebras.

- Probabilistic and possibilistic approaches.
- Bayesian methods.
- Stochastic processes.
- Interval analysis.
- Probability boxes.
- Fuzzy sets.
- Autoregressive models.
- Scenario building and planning.
- Info-gap decision theory.
- Sampling-based approaches for uncertainty propagation.
- Deterministic approaches for uncertainty propagation.
- Analytical approaches for uncertainty propagation.
- Sensitivity analysis.

Furthermore, when the objective is to optimise the design, it is possible to resort to several optimisation methods.

- Robust optimisation.
- Stochastic optimisation.
- Reliability-based optimisation.
- Lattice methods.
- Multi-objective optimisation.
- Heuristic optimisation.

Finally, the following methods can be used to help decision-makers take actions to mitigate the risk.

- Decision trees.
- Multi-criteria decision-making.
- Real option analysis.

4.1 General framework description

In order to address the research questions mentioned in the Introduction and driven by the motivation of this thesis, a comprehensive framework for design optimisation and project evaluation under uncertainty that systematises and integrates existing approaches is presented. Figure 4.1 schematically illustrates the overall framework.

The proposed framework consists of multiple blocks, each of which can be activated or deactivated to achieve different objectives. Different goals require different paths across the framework, as subsequently explained. However, it is essential to have at least one block to model uncertainty, as well as the blocks for system modelling and risk assessment, which must always be activated. The two main objectives that can be achieved are the optimisation of the design before its conclusion and the evaluation after its conclusion.

The framework is horizontally divided into two groups. The blue bracelet represents the design feedback actions, while the red represents the space for the analysis and design forward actions.

The following four different paths can be identified in the framework.

- The black path or uncertainty propagation path.
- The green path or designing path.
- The red path or design optimisation path.
- The olive path or risk mitigation strategies path.

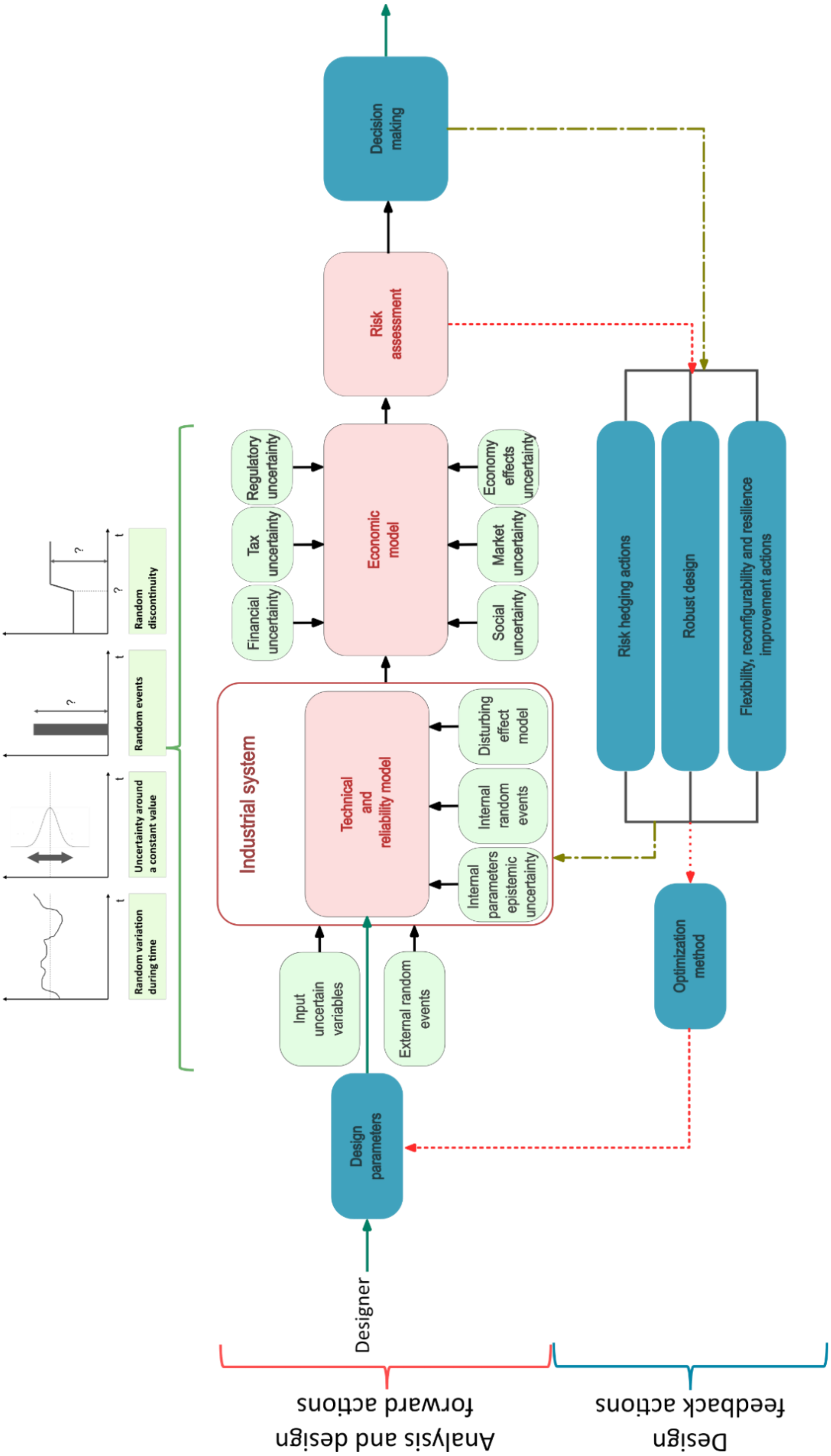

Figure 4.1 General Framework schematization

The black path is common to all the others, and it is necessary to include the uncertainty propagation method. Thus, to link the inputs to the outputs.

Once the black path is activated, the green path, which is the design one, can be switched on. Whether the green path works, it allows the red and olive paths. These last two can be used simultaneously or stand-alone.

Only the uncertainty propagation path works if the goal is to assess the risk. On the contrary, if the objective is to design the system, the green path is activated, and the design obtained with the proposed variables' value can be evaluated. This evaluation permits the decision-maker to accept the design solution or repeat the design procedure. In addition, decision-makers can activate the risk mitigation strategies path to include risk hedging actions.

Finally, suppose the designer wants to optimise its design. In that case, he can resort to the red path, selecting the type of optimisation, the objective functions, the constraints, and the optimisation method or algorithm, which autonomously acts on the design variables.

The grey lines are shared between the red and the olive paths. Additionally, the red and olive paths can be activated simultaneously to include both design optimisation and risk mitigation strategies.

The single design evaluation, that is, without the red path, can be considered as an evaluation of a design after its conclusion with a design routine that substitutes the completed system model. This way, one can also operate risk-hedging actions on a completed design. However, only actions which do not influence the system configuration.

The green bracelet symbolizes the space in which uncertainty is modelled and propagated. The types of uncertainty considered are categorized as depicted in the four images above the green bracelet. These categories include random variation during time (e.g., the electricity price), uncertainty around a constant value (e.g., the actual value of the power coefficient), random events (e.g., components failures), and random discontinuity (e.g., changes in regulatory prescriptions).

The green blocks represent the sources of uncertainty, which can be modelled as explained in the following subsections. The red blocks represent the models or surrogate models that need to be developed to describe the behaviour and characteristics of the industrial system, the economic environment, and the risk assessment procedure. The blue blocks represent the fixed inputs, the risk mitigation strategy, the design optimisation processes, and all the decisions made by the designers and decision-makers in general.

The red line around the industrial system represents the uncertainties and elements within the system. It encompasses the endogenous uncertainties, as well as the resources and relationships that characterize the system under analysis.

In the next subsections, the elementary blocks that comprise the framework will be thoroughly described, emphasizing the strong correlation between different blocks and the potential for establishing an automated iterative loop process for designing and implementing strategies for risk mitigation based on its estimation.

4.1.1 Proposed uncertainty classification

Although in section 1.1, it is shown that there are numerous classifications of uncertainty, this thesis introduces a novel categorization of uncertainty [8]. These newly identified clusters aim to assist designers and analysts in selecting the appropriate method for modelling uncertainty sources by examining their temporal and spatial behaviour. Uncertain variables can be categorized based on their inherent characteristics, as depicted in Figure 4.2, where the following classifications are identified:

- Type I variability is characteristic of variables that randomly change their value over time. This behaviour can be represented using models such as time series and random processes. For example, in the case of wind power systems, Type I variability can be observed in the fluctuation of wind speed and direction over time, as well as in the variation of electricity sales price.
- Type II variability is characteristic of variables that assume an unknown value, which can be described using a predefined probability density function. Examples of Type II variability include the uncertainty associated with interest rates or the efficiency value in a conversion system.
- Type III variability is characterized by the random occurrence of point events with either known or unknown intensity. Examples of Type III variability include internal equipment failures or external natural events that have the potential to cause significant disruptions to system operations. Random processes can also be employed for modelling purposes in such cases.
- Type IV variability is characterized by random discontinuities, where one or more variables experience a random step change in value at an unpredictable time. This

type of variability is often observed in economic, political, and regulatory scenarios throughout the lifespan of a system.

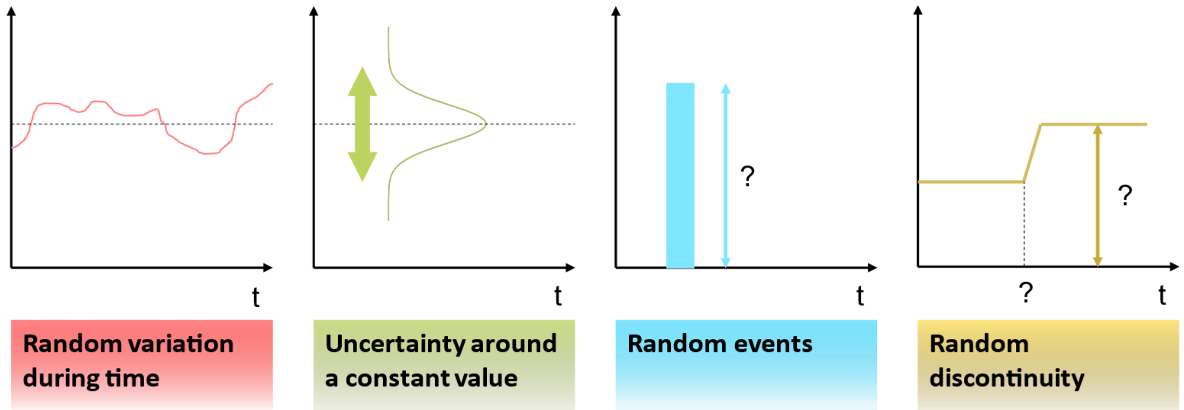

Figure 4.2 Proposed uncertainty classification

This classification assists in the identification of suitable tools for modelling uncertainty, considering the various theories available in the literature (section 1.2). Table 4.1 suggests uncertainty modelling methods according to the uncertainty type. For the sake of remark, the table contains only suggestions, and other techniques can be selected.

Table 4.1 Suggested uncertainty modelling methods according to the uncertainty classification

Type of uncertainty	Description	Suggested modelling methods
Type I	Random variation during time	• Stochastic processes • Autoregressive models • Probabilistic approaches • Scenario planning
Type II	Uncertainty around a constant value	• Possibilistic approaches • Interval analysis • Fuzzy sets • Probability box

		• Scenario planning • Info-gap decision theory
Type III	Random events	• Probabilistic and possibilistic approaches • Stochastic processes • Fuzzy sets • Scenario planning • Bayesian methods
Type IV	Random discontinuity	• Scenario planning • Stochastic processes • Probabilistic and possibilistic approaches

4.1.2 Uncertainty blocks

After selecting the objective, which includes both the level of detail of the modelling and the blocks of the framework to be utilized, it is crucial to identify the most influential uncertain variables affecting the output of interest. Each uncertain variable describes at least one aspect of uncertainty sources (Figure 4.3). To appropriately represent the variability and uncertainty of the inputs, one can refer to the uncertainty description provided in previous subsections [2, 4, 75].

Identifying the uncertainty sources strongly affecting the system is one of the most challenging tasks. Indeed, the number of sources is generally enormous and modelling them all can be very time-consuming and computationally expensive. Moreover, the output of interest may not suffer an ample range of sources of uncertainty which can be identified within and without the system.

The green blocks in Figure 4.3 represent only some families of uncertainty sources which affect industrial and economic systems.

Input uncertain variables from outside the system comprise the variables under the designer's control and the uncontrollable ones. Some authors refer to the uncontrollable variables by calling them parameters. In any case, the input uncertain variables are the

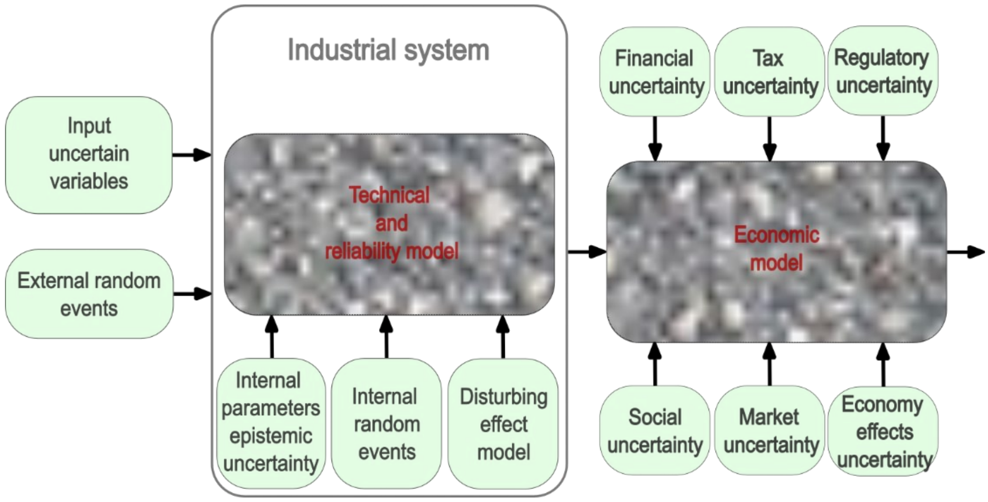

Figure 4.3 Uncertainty blocks schematization

elements of the environment that, for some reason, enter the technical system. If they are controllable, such as the natural variability of products from another system or epistemic uncertain variables, their variability can be reduced before entering the system.

External random events pertain to the perturbations which can hit the system. For instance, disruptive natural events represent this group of uncertainty sources.

On the other hand, uncertainty sources also arise within the system. Internal random events are mainly components' failures, whereas the internal parameters' epistemic uncertainty comes from the mathematical formulas or the data used to build the system model. The disturbing effect model mainly depicts the noises affecting the system and the data used. It can be interesting to underline that several uncertainty modelling approaches coexist in this framework. For instance, we can represent the failures with fuzzy theory, internal parameters epistemic uncertainty with probability boxes, and stochastic processes for the disturbing effects model. These different methodologies can be integrated by selecting the proper uncertainty propagation method, typically sampling-based approaches.

Financial, tax, social, regulatory, market and economy effects uncertainty are all uncertain sources affecting the economic model. Therefore, the investment cost model, the revenues model or both.

These sources of uncertainty can be modelled by using all the theories collected in section 1.2.

4.1.3 System models

Another challenging task is the building of an accurate model of the system (Figure 4.4) under analysis. These models can be the technical and reliability model of the system and the economic model. The economic model can be present or not, in function of the goals of the analysis and the variables of interest.

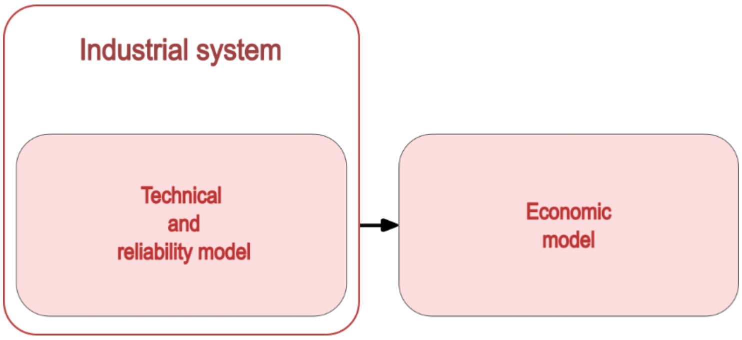

Figure 4.4 System model schematization

The technical model can be a design routine that calculates the system's theoretical configuration or a model of an already existing system. The design routines are often analytical. They allow the designer to obtain one possible architecture of the system. On the contrary, when the system already exists, the model is often a simulation or surrogate model. In some cases, when the system under analysis is easy enough to model with analytical formulas, the suggestion is to use this depiction to reduce the effects of epistemic uncertainty. Indeed, since the model only represents the system and is not the actual one, another source of uncertainty is introduced. The more detailed the system, the less the introduced epistemic uncertainty. However, the more complex the relations between the variables and the computational expenditure for propagating the uncertainty and simulating the model.

The economic model is often the investment cost model and uses information about the technical system model. This way, the data of the technical model are used in the cost computation routine with the information and formulas about the unitary cost of materials, works, engineering activities, and similar elements. The revenues and net present value models are often near the cost model. Indeed, including data about the market in which the system operates makes it possible to combine several pieces of information to estimate the profitability of the investment. Also, the economic model introduces epistemic uncertainty because the prices and demands are volatile. In addition, the formulation of the economic model introduced epistemic uncertainty due to the relations used to model the economy effects and link the unitary costs to the design architecture. Actually, several pieces of information will be estimated, for example, the time to manufacture or assemble some components or the efficiencies of some processes.

As already mentioned, the system can be modelled with different mythologies (section 2.1). However, the most straightforward approach is utilising an already validated system model. Indeed, to validate a new design routine or a new system model involves a considerable quantity of data, information, and time. Moreover, expert judgments and numerous experiments are needed to assess the epistemic uncertainty, requiring many modelling efforts.

4.1.4 Uncertainty propagation process and risk estimation

This subsection aims to elucidate the interaction between the uncertainty blocks and the system model. The uncertainty, modelled to depict the various sources of uncertainty and variability, is propagated throughout the system model (red arcs in Figure 4.4). As can be seen, the designer's input and risk assessment output also concern the uncertainty propagation process.

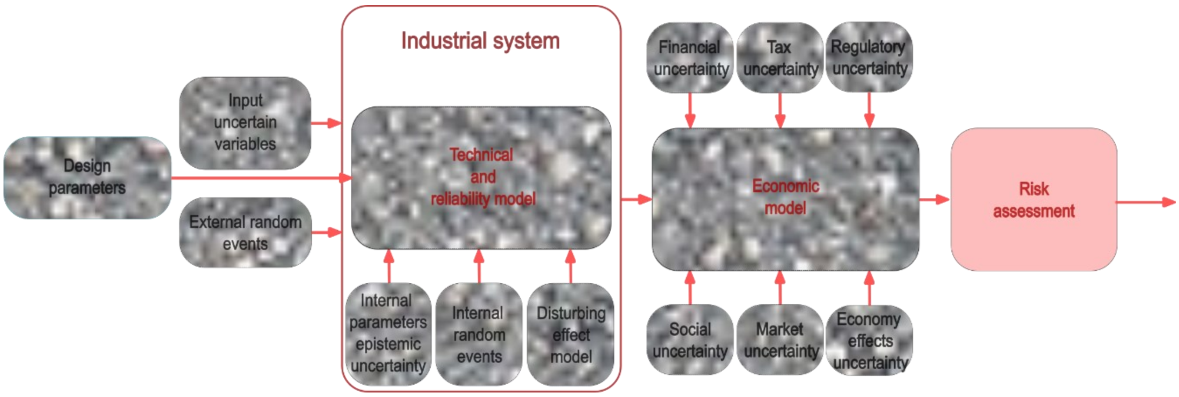

Figure 4.5 Uncertainty propagation schematization (red arcs)

Although all the methods mentioned in section 2.2 can be adopted to assure the propagation of the input uncertainty to the outputs of interest, since the uncertainty can be modelled with different approaches, the selection of the uncertainty propagation method is crucial to allow the input uncertainties enter the models and describe the variable of interest.

When different algebras are employed to represent the uncertainty sources, one commonly adopted approach is to recur to sampling-based methods. Indeed, this way, it is often possible to obtain real numbers which enter the various models to obtain the desired results.

In any case, because the uncertainty propagation methods can be considered as the language with which the various blocks communicate, the experience and knowledge of the analyst are essential to avoid modelling errors, which can lead to the inoperability of the framework.

In addition, the analyst will select the uncertainty propagation model according to the available computational power, time, and the searched characteristics which describe the uncertainty of the variables of interest.

The risk estimation is strictly linked to the variables of interest. This is another crucial block of the framework because it provides information about the quantities of interest, i.e. the uncertainty measures. Firstly, the analyst or decision-maker fixed a variable or some variables of interest. Subsequently, he should decide the quantity or quantities of interest in which he is interested. These quantities are used in the decision-making process. Therefore, they should give enough knowledge about the variables which lead to the decision. Unfortunately, the more the pieces of information and the detail level required about a variable, the fewer the suitable uncertainty propagation methods that can be used. This issue entails the mandatory selection of modelling approaches for the system, uncertainty sources, and uncertainty propagation methods. Further details about this problem have already been discussed in section 2.2.5.

4.1.5 Feedback actions arcs

The feedback arcs identify the optimisation process and the risk mitigation counteractions. Whether the goal is risk assessing, they are switched off. Whether the goal is to design a system, only the green and the black paths work. On the contrary, the optimisation path, that is, the red one, can be used by the designer to establish an iterative process to search for optimal or sub-optimal solutions to accomplish some optimisation objectives. On the other hand, the risk mitigation strategies path, that is, the olive one, can be used by designers and decision-makers to include designing strategies which change something within the industrial system or financial instruments to translate the risk. As mentioned, the red and the olive paths can be used stand-alone or simultaneously. Indeed, one can want to optimise the design, include risk mitigation counteraction, or both simultaneously.

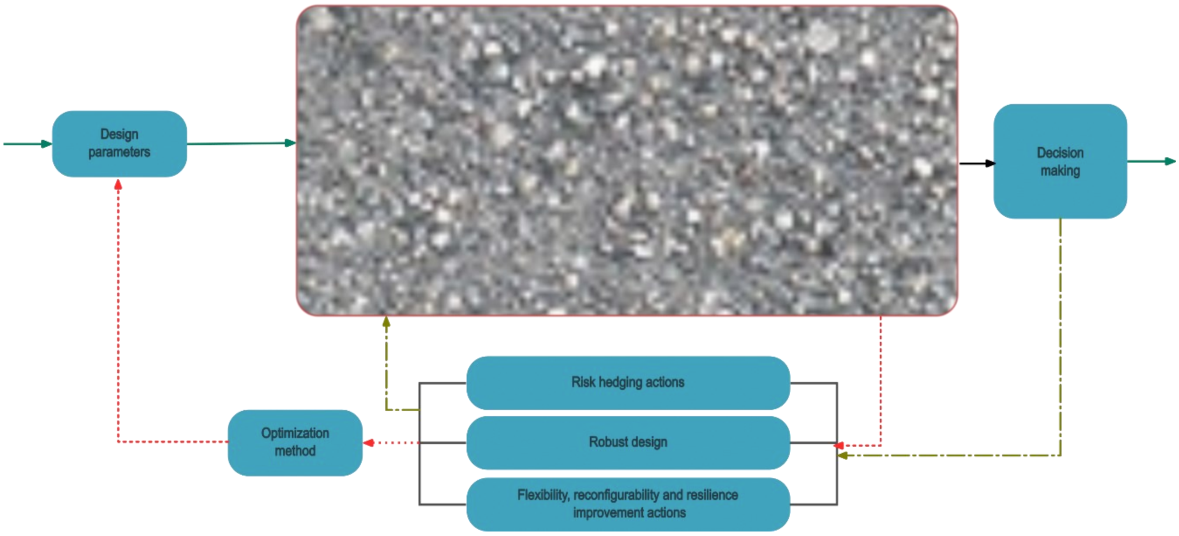

Figure 4.6 Design optimisation and risk mitigation schematization

Once a design procedure is started, the olive and red paths can work. The grey line that links the concept of risk hedging actions, robust design and flexibility, reconfigurability and resilience improvement actions are shared between the risk mitigation and optimisation paths.

The risk mitigation counteractions can be used to change the system's architecture to pursue the strategies described in section 3.1. Furthermore, other common strategies which do not act directly on the design configuration but transfer or mitigate the risk can be adopted, as described in paragraph 3.2.3.

The optimisation path can be used to achieve an optimal or sub-optimal array of the input controllable parameters' values. The optimum can be obtained according to robust, reliable, reconfigurable, flexible, and resilient design concepts, as discussed in sections 3.1.2, 3.1.3, 3.1.4, and 3.1.6. The designer should select the objective or performance function and constraints by including uncertainty measures in one or both. The performance function should consider the design's evaluation criteria chosen by the decision-maker. The constraints must be carefully defined to avoid all the inadmissible solutions. Finally, the selection of the proper optimisation method is crucial. Indeed, the optimisation method should be chosen according to the methods used to represent the system and to perform the uncertainty propagation. Even though iterative methods and algorithms are suitable for the purpose, the first can operate with specific classes of problems. For that reason, very often, the adopted methods are metaheuristic optimisation algorithms.

4.2 Methodologies developed and adopted for the framework application

The previous section described the general framework. This one provides how the blocks are specifically modelled in this thesis. Although the application to the specific system is in the subsequent chapters, the general methods adopted and developed in this thesis may deserve a description.

The economic and technical models are built by adopting already validated analytical formulations and surrogate models available in the literature. At the same time, the design procedures are also built by retrieving available models and relationships from the literature.

The risk assessment procedure was conducted in two ways depending on the uncertainty propagation methods used.

- Assessing a probability density function based on the frequency of occurrence of the output values obtained by combining the results of different runs performed with Monte Carlo simulation.
- Combining the results obtained from the experiments, defined as explained below, using their associated probability. Thus, the combination of the results allows the author of this thesis to assess the probability density function of the variable of interest.

Therefore, resorting to those distributions, coefficients of variation, quantiles and thresholds were computed and used as risk indexes.

Given the several methods used to model the uncertainty and the adopted uncertainty propagation methods, the meta-heuristic algorithm seemed to be the most suited approach for optimisation purposes. Therefore, the genetic algorithm provided by MATLAB has been used.

The adopted hedging techniques rely mainly on financial instruments. In particular, financial derivatives were used to mitigate the economic risk that arises from market uncertainty. The relationships for forward contract pricing were retrieved from the literature.

The following pages describe the approaches to the scenario analysis and combination, the uncertainty modelling and propagation, the external random events modelling, the internal random events modelling, and the failures calendar and availability array.

4.2.1 Scenario analysis and combination

In the literature, scenario planning (section 1.2.9) is a widely adopted approach to explore the possible evolutions of macroscopic variables over medium and long time horizons. Below, the methodology adopted is described.

First of all, the study's object and the analysis's time horizon must be defined. This initial step is critical and encompasses both defining the system and the environment. Then, given the environment, one must state the changes in the environmental conditions the analyst intends to describe. For instance, for the sake of clarity, the author will consider an analysis of possible changes in climatic conditions. Additionally, the time horizon must be set to define the time boundary of changes. In the example, the analyst declares the year 2050 as the time limit.

The adopted method follows the subsequent steps.

- Selecting scenario variables.
- Identifying the driving forces.
- Defining the possible events.
- Defining the variables' values.
- Conducting a cause-effect analysis.
- Conducting a cross-impact analysis.
- Combining the variables' values to obtain the scenarios.

The first step concerns the scenario's variables selection. Identifying the influential scenario variables is strictly related to the changes that the scenario analysis would depict. Indeed, the analyst must identify which variables influence the changes it wants to study. In the example, suppose they identify the green gas emission and the deforestation level. Then, in step 2, the driving forces must be identified. Each driving factor affects the relative variable in function of the event that will happen in the future. Each variable can assume different values according to the event which will happen. Therefore, in the example, suppose that the main driving factor for the green gas emission variable is the green technology adoption level, and for the deforestation level variable, the regulatory policies.

Steps 3 and 4 aim to identify the possible events and the relative variables' values. Firstly, the analyst identifies the possible events which can happen. Subsequently, they will estimate the effects of the events on the scenario variables. In the example, they indicate three possible events for the green gas emission variable: high adoption, medium adoption, and low adoption. This means that three different levels of emissions might happen in the future: x, y, and z. Similarly, they indicate two events for the deforestation level, namely increasing and decreasing, declaring two levels of deforestation that may happen in the future: k, j.

Step 5 concerns performing the cross-impact analysis. This step is crucial to understand whether and how a variable affects another. This way, one can suppose a correlation matrix, which transparently defines the probability of an event or a value once another happens. In the example, there are no relationships between the two variables.

After this procedure, the scenarios are obtained by permutating the level of each variable. In the example, six scenarios will be identified.

In order to select the more plausible scenario, the author integrates the plausibility cone concept into the method [37, 70].

Since the framework aims to include the higher number of uncertainty sources necessary to depict the uncertain behaviour of systems in a sufficiently accurate manner, another new feature has been introduced. In the literature, as explained in the previous chapters, scenario analysis is often performed stand-alone. Adopting sampling-based approaches for uncertainty propagation makes it possible to perform scenario analysis, including the variability inside the scenarios. Indeed, at the beginning of the propagation, a scenario can be sampled from a set of predefined scenarios. These scenarios can have an associated probability of occurring. Whether they do not have an associated probability, the uncertainty is propagated in each scenario by considering one at a time. Instead, when they have an associated probability, the analyst can do two things alternatively to combine the results. The first follows the subsequent steps.

1. Select the number of runs.
2. Sample from the discrete distribution one scenario according to their probability of occurring.
3. Propagate the uncertainty of the sources with the condition of the sampled scenario.

4. Store the value of outputs of interest in an array or matrix and repeat step 2 many times equal to the runs' number.
5. Analyse statistically the array or matrix of the outputs.

Alternatively, the analyst can perform the analysis with the following step.

a. Propagate the uncertainty with the condition of one scenario.
b. Store the value of the outputs of interest and repeat step a for each scenario.
c. Combine the outputs of interest obtained in different scenarios.
d. Analyse statistically the combined results.

Therefore, the sampling-based approaches are used in this framework to establish a series of nested sampling-based approaches to combine scenario analysis with the uncertainty sources modelled with different methods.

More details about scenarios combination are provided in section 6.2 and in the case study of Chapter 6, in which it is applied.

4.2.2 Uncertainty modelling and propagation

Although all the methods described above can be used to depict uncertainty sources, in this work, some of them have been selected to be used practically.

Since each uncertainty source claims for best-suited methods in function of its nature and of the goal of the analysis, the aleatory uncertainty of input uncertain variables has been modelled with the following methods.

- Probability theory.
- Markov chain.
- ARIMA time series.

The probability density functions of the variables have been obtained in two ways: by retrieving them from the literature and estimating them from the available data sets. The estimation has been done using available tools, mainly the distribution fitter of MATLAB.

Markov chains, particularly the birth-and-death Markov process, have been constructed by resorting to literature-available historical time series. The historical time series needs to calculate the number of possible states and the transition rates of the Markov process. The maximum and minimum values of the time series define the range of admittable values. On the other hand, the permanence time in a specific state is helpful to assess the probability of that particular state and compute the transition rates.

ARIMA time series also uses historical time series data to perform regression analysis and obtain coefficients for the model. The regression was performed using the available routines provided by MATLAB.

The epistemic uncertainty of the economic model and parameters, internal parameters, and relationships to represent the technical model has been modelled using the probability theory. When no information about the uncertainty distribution has been known, uniform distribution is used. On the contrary, triangular distribution centred in the computed value has been used when the uncertain parameters have been estimated using relationships. However, the ranges of uncertain parameters have been retrieved from the literature.

The uncertainty has been propagated by adopting the following three approaches.

- Design of Experiments.
- Taylor expansion formula for the moments of functions of random variables.
- Monte Carlo methods.

Design of Experiments has been used to conduct full factorial experiments for combining the possible levels of factors. The levels represent the possible values that a random variable can assume, and they have been determined by following the subsequent steps.

1. Retrieve the probability density function of the random variable.
2. Set the sample size.
3. Discretise the probability density function into a number of intervals equal to the sample size and equally spaced.
4. Associate the centre of each interval to a possible level.
5. Calculate the probability of that level by integrating the probability density function in the interval.

In function of the number of factors, i.e., the random variables, the above procedure is repeated for each variable, and the full factorial experiment is written. Then, the probability of each experiment, i.e., a combination of factors, is calculated. Using the probability associated with each factor, each combination of factors has an associated probability equal to the product of the probability associated with each factor. Finally, the system is simulated in each experiment, and the results have their probability of occurring.

The Taylor expansion formula for the moments of functions of random variables is used by applying it to the relationship that links the standard deviation of the output of interest to the uncertain variables that contribute to the output uncertainty.

Finally, Monte Carlo methods have been used to sample the probability density function of uncertain variables, simulate the ARIMA process, and obtain possible evolutions of the Markov Chain. The number of runs has been selected to obtain the statistical significance of the estimation. Monte Carlo simulation has been performed using the available routine provided by MATLAB.

4.2.3 External random events modelling

This thesis with external random events mainly refers to disruptive events which may impact the system. With the term “disruptive events”, the author refers to external natural events (i.e. earthquakes, storms, rogue waves, impact with icebergs, etc.) or even man-made events, such as terrorism acts or collisions with ships, which could impact the system structure and causing a damage. Different types of systems have different plausible disruptive events.

Generally, a library of disruptive events should be built and included in the simulation according to the location and the type of system.

The adopted procedure is described in the following, considering a generic external random event. The approach resorts to hazard curves or the probability of occurrence of the event. A hazard curve (e.g., Figure 6.3) describes the annual probability of an event occurring at a specific location in relation to its magnitude.

The procedure is developed by generalizing an approach proposed in the literature for seismic events, as cited below (6.3.5). In order to calculate the date of the event and its magnitude, the hazard curve is discretized into a user-defined number of magnitude classes. For each magnitude value, the annual probability of occurrence is thus obtained. These data pieces can also be provided in terms of event magnitude and probability without recurring to the discretization of the hazard curve. Since each different magnitude class occurs at a fixed constant rate, the distribution of the time between events is considered exponentially distributed. The procedure to obtain a list of events’ dates and their magnitude, given pairs of magnitude and probability of each magnitude class, follows the subsequent steps.

1. The plant life is defined.
2. The event date is set to zero.
3. Following the descending level of magnitude classes, the next magnitude class is selected by considering its annual probability of occurrence.

4. Using the exponential distribution of the time between events, the time to the next event is obtained by resorting to Monte Carlo sampling.
5. The event date is stored in the events list, paired to the magnitude level, and added to the current event date.
6. Steps 4 and 5 are repeated until the end of plant life.
7. Return to step 2 until all the magnitude classes have been selected.
8. The list of events' dates and magnitudes is stored, and the procedure stops.

After the above-mentioned procedure, the events calendar is known, but none of their effects on the system. Fragility curves are used to estimate the damage the system suffers after each event. Given the event's magnitude, the fragility curve provides the probability of exceeding a predetermined damage state, i.e., failure modes. The limit load the system can support before failure occurs is considered to be a random variable log-normally distributed, and the system will fail if its supporting capacity is less than or equal to the magnitude level corresponding to the chosen intensity measure. The cumulative distribution function of the probability of exceeding a fixed damage state (*cdf*$_f$) conditional on a magnitude level (*ML*) is given by (4.1).

$$cdf_{f(ML)} = \Phi\left(\frac{1}{\beta} ln \frac{ML}{\mu}\right) \tag{4.1}$$

Where Φ is the standard normal cumulative distribution, μ the mean of the distribution and equal to $a \cdot ML \cdot b$, a and b being experimentally derived constants, and β the standard deviation of the distribution.

Fragility curves can be retrieved from the literature for many sets of events, damage states' components, systems and plants. However, they can also be constructed using simulation procedures (e.g. Finite Elements Simulation).

Several damage levels can be selected. The more levels there are, the more accurate the description of possible damage will be. Each damage level is associated with a specific time to repair and cost, which is considered as a percentage of the investment. The highest damage level is associated with destructive damage, i.e. the interruption of system life and the impossibility of restoring it. If the probability distributions of repair time and cost are known, it is possible to consider their uncertainty using Monte Carlo sampling.

For the determination of the damage level, the procedure follows the subsequent steps.

1. The event list is retrieved.
2. Following the chronological order of events, the next event is selected.
3. Following the descending order of severity of damage levels, the next damage level is selected.
4. A random number between 0 and 1 is sampled.
5. The random number is compared with the cdf_f value associated with the event's magnitude.
6. If the random number is less or equal to that value and the highest damage level is being analysed, the system life is interrupted at the date associated with that event, and jump to step 10. Otherwise, go to step 7.
7. If the random number is less or equal to that value, damage occurs, the event is included in the list of failures with their date, time to repair, and cost, and return to step 2. Otherwise, go to step 8.
8. If the random number is greater than the cdf_f value, return to step 3 until all occurrences of damage states are verified. If the random number is greater than all cdf_f values, the event does not lead to a fault.
9. Return to step 2 until all the events on the events list are considered.
10. The list of failures is stored, and the procedure stops.

At the end of this procedure, the output is a list containing the occurrence date, downtime and expected cost of all disruptive events that will occur.

4.2.4 Internal random events modelling

This work considers internal random events as components' failures. Generally, a system can be decomposed into several components or subassemblies. Each component or subassembly has several failure modes, which can determine different types of intervention. This thesis considers three types of interventions: minor repair, major repair, or replacement. The components can be in series, so when a single element fails, the whole system fails and production stops, or in parallel, in this case, the system can operate while the fault component is under restoring. This work considers that all components are in series. For each failure mode of each component, a specific mean failure rate, time to repair, and expected restoration cost (i.e., material replacement cost, subsequently utilized to compute the repair cost) must be defined.

For each j-th component, an overall constant failure rate λ_j and the frequency distribution f_i of the three i-th failure modes are known.

The procedure follows the subsequent steps.

1. The actual failure rate of each component failure mode is computed as $\lambda_k = \lambda_j f_i$. As failures occur at a constant rate, the distribution of their time to failure (*TTF*) will be exponential. All subsequent failures of the same type will occur after a certain random *TTF*, calculated from the last time the same type of failure occurred. The *TTF* is to be considered as a net time, i.e. excluding plant shutdowns due to further failure types occurring in the meantime. The different failure types, being conceptually independent of each other, will not affect the timing of the failure sequence of the other categories.
2. For each fault type, generate a *TTF* sequence by repeatedly randomly sampling its distribution. In practice, having extracted a random number $R \in [0,1]$, the *m*-th TTF of the *k*-th fault type will be $TTF_{km} = - \lambda_k \ln (R)$.
3. Repeat the procedure until the sum of the TTF_{km} generated for the fault type considered is at least equal to the nominal life of the installation, so as to generate a random sequence of faults of the same type covering the entire life of the installation.
4. For each *k*-th fault type, the theoretical date of occurrence of the *m*-th fault (assuming a zero time to repair, *TTR*) will be equal to the sum of all previous *TTF*s (TTF_{km}) times *m,* ranging from 1 to *m*-1.
5. Repeat steps 2 to 4 for each type of failure, obtaining as many independent sequences of timed failures.
6. Combine the obtained sequences into a single sequence by sorting the faults by increasing dates. This would be the timetable in which the various faults would hypothetically occur if repairs were instantaneous or occurred in negligible time.
7. Starting with the first fault in the sequence, add the random *TTR* generated for the repair of the fault under consideration to the current dates of all subsequent faults. The number of required technicians for the repair is sampled from a standard distribution centred on the mean number of required technicians and with a user-given standard deviation. The restoration cost is sampled from a triangular distribution centred on the mean value of the restoration cost and with minimum and maximum values a percentage of the mean value. The repair cost is calculated by

multiplying the hourly cost of the technicians, the number of required technicians, and restoring time and adding the cost of materials.

8. Repeat step 7 sequentially for all scheduled faults, updating the attempted occurrence date of all subsequent faults each time. This gradual shift allows the net *TTF* value of each fault to be maintained with respect to the previous occurrence of the same type of fault, net of interruptions for the repair of other faults occurring in the meantime. When the date of failures following the current one, as a result of this forward shift sequence, becomes greater than the nominal life of the system, these failures will be ignored because they will not occur.
9. When the *TTR* has also been added for the penultimate fault in the sequence (and thus the date of the next fault has slipped), the actual occurrence date of all faults is obtained.
10. The list containing all events and occurrence dates, ordered over time, their time to repair, the required number of technicians for the repair and their restoration cost is stored and the procedure is stopped.

4.2.5 Failures calendar and availability array

One of the goals of the events list generation is to assess the availability of the system. This thesis resorts to the so-called availability array to represent the amount of time in which the system operates. In order to obtain the availability array, the failures calendar must be produced following the subsequent steps.

1. Retrieve the internal random events list and the failures list due to external random events that have been developed using the procedure described above.
2. Add all the internal random events to the failures calendar.
3. Add to the failures calendar the next external event that leads to a failure, starting from the nearest event date and arriving at the farthest.
4. If the event is of the type which destroys the system without the possibility of restoring it, the procedure stops. Otherwise, go to step 5.
5. If the event date falls in a downtime period, the fault restoration process is interrupted, and the system restoration from the disruptive event starts. Therefore, the *TTR* of the internal event is shortened to the event date of the considered external event, and its restoration cost is proportionally shrunk, net of materials cost. Otherwise, go to step 6.

6. Shift all the events with an occurrence date greater than the one of the considered event of a quantity equal to its time to repair.
7. Delete from the list all the events with an updated occurrence date greater than the plant life.
8. Return to step 3 until all the events have been considered.
9. Store the failures calendar, which is a time phase list containing all events and occurrence dates, ordered over time, their time to repair, the required number of technicians for the repair, their restoration cost over the entire plant life, and the procedure stops.

After obtaining the failure calendar, the availability array can be built following the subsequent procedure.

1. Select a value for the unit time intervals.
2. Subdivide the whole system life into unit time intervals.
3. Associate a Boolean state variable at each unit time interval.
4. Set the state variable's values to 1, meaning the system is up.
5. Following the chronological order of events, select the next event.
6. Starting from the event date, set the value of the state variable associated with the unit time intervals related to the repair time of that event to 0. This means that the system is down.
7. Return to step 5 until all the events have been considered.
8. Store the availability array, and the procedure stops.

The availability array is a practical tool to depict the time in which the system produces and when it is under maintenance.

4.3 Final remarks

In this chapter, the systematic General Framework developed to design and manage industrial equipment, components, and systems under uncertainty has been presented. Additionally, a new classification of the types of uncertainty has been provided to define a novel clustering method based on the behaviour of the variables over time and space. Thanks to this classification, selecting the appropriate method to model the uncertainty of variables becomes more straightforward. The literature review in the field of design and management under uncertainty has revealed the necessity to develop new strategies to cope with the growing number of uncertainty sources that affect an industrial system. This General Framework is designed to be as comprehensive as possible, aiming to cater to a wide range of systems. In order to maintain its generality, the framework has been composed of several modular blocks and paths that can be activated or deactivated based on specific objectives. This approach allows for flexibility in tailoring the framework to meet different objectives without sacrificing its overall applicability. Although there may be several types of goals, the primary ones are design optimisation and system performance assessment. The evaluation process is a forward process, whereas the design optimisation and action for mitigating the risk have a forward and feedback process. In order to address this distinction, the framework environment has been divided into two distinct parts, each associated with the direction of the process. For the sake of clarity, different paths have been identified, one for each macroscopic task. Subsequently, the blocks are clustered and briefly described by introducing the most relevant issues for modelling them or accomplishing specific tasks. This allows for a clear delineation of functionalities and facilitates the utilisation of appropriate tools by the analysts and designer. Furthermore, when feasible, specific instructions and suggestions regarding the most suitable methods to use under given conditions have been provided. The objective of this thesis is not to exhaustively review all the methods to model the blocks. However, the literature focusing on the cited methodologies and tools has been referenced to guide the reader to explore the topics more comprehensively.

In conclusion, the first objective of this Doctoral Project, which is the literature focus on dealing with uncertainty systematisation and the conceptualization of the systematic general framework, has been carried out. Now, in order to address the research questions mentioned earlier, it is essential to employ this common general framework. The subsequent chapters will present two distinct case studies, each corresponding to one of the two goals, and will showcase an escalating level of system complexity.

Chapter 5

Framework application to equipment design optimisation

In the previous chapter, the General Framework for designing and evaluating industrial components, equipment, and systems under uncertainty has been presented. This section adapts the framework to address the optimisation objective under uncertainty.

To address the three research questions from an optimisation perspective, the selected case study is the shell and tube heat exchanger (STHE) design. Shell and tube heat exchangers are the most common type of heat transfer equipment used in process plants. HEs play a key role in feedstock transformation, efficient energy utilisation, and economic savings. These goals are achieved by providing and removing heat to and from process streams and allowing heat recovery and energy integration. However, several sources of uncertainty and the variability of the fluids' characteristics affect HEs in actual plants, making the design of this type of equipment rather complex despite their apparent structural simplicity.

From the relevant literature on the design and optimisation of STHE, a lack of papers assessing the capability of objective functions (OF) to obtain realistic and practicable heat exchangers (HE) is clear. Indeed, most of the contributions in this field focus on the capabilities of the algorithms to optimise the HEs, but none on the OF. This issue causes a lack of consistent basis to compare different algorithms. Also, it leads to a poor comprehension of the implications of optimising an OF on the other relevant elements that characterise the STHE. For example, some authors optimise the effectiveness of the STHE, neglecting the HE's surface, thus not considering the required pumping power and total costs.

First, an analysis of the capabilities of different OFs to obtain a practicable STHE with good performance is conducted. This analysis allows us to clarify the considerations made in section 3.1.1 from a practical perspective. Subsequently, the problem of heat exchanger design under uncertainty is presented by using a literature review. Then, the framework application for optimising STHE's design under uncertainty is presented. The literature about optimal heat exchanger design is reviewed first, including the case of uncertainty quantification and equipment design under uncertainty. Subsequently, the design problem under uncertainty of heat exchangers is stated, identifying five possible alternative approaches, including robust design. Afterwards, a numerical experiment is carried out to consistently compare the five methods and analyse their performances, applicability domains and limitations. This is the first time alternative methods for heat exchanger design under uncertainty are compared, and another novelty is to examine the possibility of designing robust shell and tube heat exchangers adopting a metaheuristic optimisation method based on a Genetic Algorithm (GA). In this case, the GA is used to determine the required equipment configuration to minimise the distance of output stream temperature from the specification. Guidelines are derived to help designers select the best approach according to the specific problem instances. The section is concluded by discussing its limitations and planning future research work.

The framework application allows us to address the research questions in the Introduction. Indeed, this approach is used to compare several designs obtained with different methods; to do this, they are evaluated under uncertainty conditions. Furthermore, the framework is used to propose a new method for STHE optimisation. Finally, final remarks are provided to underline the most important findings.

Two publications have been developed from the studies conducted to produce this chapter [128, 182].

5.1 The problem of selecting the proper performance measure: the case of shell and tube heat exchangers

STHEs are widespread in industrial systems and are critical equipment in many production processes. Furthermore, their use in heat recovery applications contributes to resource conservation. While the traditional STHE design procedure is well established, its non-automated application is time-consuming owing to its iterative nature, and it is strongly affected by the designer's subjective choice of controllable parameters' values. Numerical optimisation approaches have been applied to STHE design to automate and improve the design process.

Although some researchers are sceptical about the possibility of adopting precise optimisation methods in heat exchanger design [183], a vast number of optimisation algorithms has been applied in the literature, as reviewed elsewhere [184-186], and an extensive range of objective functions (OF) have been suggested.

The optimisation algorithm selection is a relevant problem since it mainly influences the efficiency and effectiveness of the search procedure within the design space. However, the choice of the OF is crucial, as it leads to the architecture of the HE and the quality of the resulting “optimal” design. In this regard, the care to objective function selection has been relatively scarcer, establishing confusion in the designer, who has no guidelines when choosing this. Therefore, many different OFs are used in the literature despite the lack of studies comparing the performances of OFs.

The literature is unclear about the reasons for choosing a particular function, and the authors often do not provide an explanation for their choice and refrain from discussing the impact of their choice on the resulting equipment configuration. Moreover, an ambiguous similarity among several OFs also boosts uncertainty. Generally, OFs are connected either to a cost minimisation or some technical performance measure to be optimised. Nevertheless, when resorting to a cost OF, the capital investment is often computed in a trivial way using simple parametric functions related to the overall heat exchange surface. This approximation causes the incapability of these OFs to obtain detailed design. In fact, the total exchange area is not linked to changes in the equipment architecture. The architecture of the equipment strongly impacts the manufacturing cost, as discussed by Caputo et al. [187]. On the other hand, OF based on thermos-physical performances may lead to equipment configurations that are apparently optimised but not practicable because of their numerous drawbacks or unfeasibility. Therefore, many authors do not show nor explain the actual architecture of the equipment obtained by their selected OF.

As previously said, selecting the variable of interest plays a significant role in applying the proposed general framework. In this section, a critical comparison of objective functions is carried out to show the effect of the variable of interest on the optimised design.

The contents presented in this section allow practitioners and researchers to select the OF to be used with any optimisation approach consciously. A critical literature review was carried out to show the most common OFs for optimising HE, and eight OFs were used to assess their impact on the geometric, thermal, and economic performances of STHE. A numerical application was made to compare the optimised designs obtained with different objective functions in a realistic case under consistent assumptions. The comparison was made both using single and multi-objective OFs, highlighting their merits, drawbacks, and limitations.

5.1.1 Literature review

About 120 research papers on STHE optimisation are available in the literature from 2005 to 2021. Additionally, the number of yearly new papers has increased until 2021. From the analysis of these contributions, the most adopted design procedures are Kern and Bell-Delaware methods, and most works focus on mathematical optimisation techniques. The main difference between these documents resides in the selected numerical method [185]. Table 5.1 collects a non-exhaustive list of the algorithms used to optimise the STHEs. Note that the most used are at the top of the list.

Table 5.1 Optimisation algorithm used in STHE optimisation

Algorithm	***References***
Genetic Algorithm	[186-218]
Non-dominated Sorting Genetic Algorithm-II	[219-231]
Particle Swarm Optimization	[198, 206, 229, 232-237]
Multi-Objective Genitic Algorithm	[238-242]
Firefly Algorithm	[201, 204, 243, 244]
Cuckoo Search	[204, 245-247]
Monte Carlo Simulation	[210, 229, 248]
Elitist Jaya Algorithm	[249-251]
Differential Evolution Algorithm	[252, 253]
Heat Transfer Search Algorithm	[254, 255]
Modified Teaching Learning-Based Optimization	[256, 257]
Grey Wolf Optimizer	[254, 258]
Symbiotic Organism Search	[254, 259]
Multi-Objective Particle Swarm Optimization	[260, 261]
Passing Veichle Search	[254]

Artificial Forage Optimization	[254]
Salp Swarm Algorithm	[254]
Electro-Search Algorithm	[254]
Grasshopper Optimization Algorithm	[254]
Ant Lion Optimizer	[254]
Alfa Tuning Elephant Herding Optimization	[262]
Differential Evolution Based ABC	[263]
Branch-And-Reduce Optimization Navigator	[264]
DIscrete and Continuous OPTimizer	[264]
Exhaustive Search	[229]
Crow Search algorithm	[229]
Bacteria Foraging Algorithm	[265]
Multi-Objective Self-Adaptive Multi-Population-Jaya algorithm	[266]
Adaptive Range Genetic Algorithm	[267]
Simulated Annealing Algorithm	[215]
Falcon Optimization Algorithm	[268]
Brute Force Algorithm	[210]
Cohort Intelligence	[269]
Delayed Rejection Adaptive Metropolis hasting	[270]
Multi-Objective Heat Transfer Search	[271]
Tsallis Differential Evolution	[272]
Bat Algorithm	[273]
Predator-Prey Algorithm	[228]
Electromagnetism-like Algorithm	[274]
Gravitational Search Algorithm	[275]
Hybrid Particle Swarm Optimization and Ant Colony Optimization	[205]
Distributed Multistart Ant Colony Optimization	[276]

Particle Swarm Local Optimization	[276]
Improved Intelligent Tuned Harmony Search algorithm	[277]
Hybrid Differential Evolution and Ant Colony Optimization	[278]
Biogeography-Based Optimization	[279]
Imperialist Competitive Algorithm	[280]
Quantum Particle Swarm Optimization and Zas Lavskii Chaotic Map Sequences	[281]
Algorithm Of Changes	[282]
Artificial Bee Colony	[283]
Harmony Search Algorithm	[284]
Others	[285-300]
Reviews	[184, 185]

In several instances, authors claim superior performances for their algorithm. However, this superiority is doubtful because results are often neither fully comparable nor discussed. This issue appears from the non-declaration of some problems and the non-consistency of problem formulation or materials and methods involved [184]. Moreover, some used optimisation algorithms are designed to search efficiently over large design spaces, whereas in HE designs, the feasibility region is not too large. Indeed, the multiple interdependencies between variables and the fact that they can often assume only a small set of discrete values shrinks the solution space. Thus, while the computational advantage in using advanced search algorithms may often be slight with STHE design optimisation, the OF selection plays a key role in the implication of the technical and economic viability of the equipment.

From the aforementioned literature, cost optimisation, in a broad sense, is the most often set goal. However, heat transfer area, pressure drop, energy disruption, exergy, entropy, ensergy and heat transfer rate have been used as objective functions. Recently, multi-objective optimisation has increased its diffusion in this field, and it is used to combine thermal and economic performance. In particular, cost and effectiveness are frequently simultaneously optimised. In recent years, the minimisation of pressure drop has become increasingly important to implement novel geometric baffle configurations that increase the overall heat transfer rate. However, these new baffle layouts raise the necessary pumping power. Although minimisation of energy dissipation has also been used, some papers have shown that its mathematical formulation cannot achieve viable architectures.

Researchers have attempted to build a consistent basis to compare different algorithms by adopting cost-oriented objective functions. This cluster of OFs has a traditional formulation based on the heat exchange surface to estimate the capital cost and pressure drop to assess the operational cost. Indeed, not-so-more detailed models have often been introduced to evaluate investment and operating costs.

Table 5.2 shows a non-exhaustive list reporting several OFs and the relative number of occurrences in single and multi-objective problems available in the literature.

Table 5.2 Number of occurrences of different OFs in literature in single and multi-objective optimisation

	Number of occurrences		
OF	**Single-OF**	**Multi-OF**	**TOT**
Total cost	52	15	67
Total annual cost	10	7	17
Investment cost	1	1	2
Operating cost	0	1	1
Area	6	5	11
Weight	1	0	1
Effectiveness	2	10	12
Heat Transfer rate	1	11	12
Pressure drop	1	15	16
Exergy disruption	1	5	6
Entropy generation unit	2	2	4
Fouling resistance	1	1	2
Entransy	2	2	4
Global heat transfer coefficient	0	1	1

The OFs division into single and multiple objective optimisations is crucial to understanding which specific performances can be used stand-alone and which should be used only in multi-objective optimisation problems, in conjunction with other OFs that lead the optimised design to viable architecture. Indeed, only some OFs directly or indirectly consider design issues that lead to a useful, practical, and realistic solution. For that reason, a pervasive multi-objective function combines costs and thermal effectiveness.

Regarding single-objective optimisation of STHE, the objective functions can be clustered into four groups:

- Geometric functions.
- Fluid-dynamic and energy-related functions.
- Weighted average of different performance measures.
- Cost functions.

Single objective optimisation

The crucial role of geometric functions in cost reduction, agile transportation, and straightforward arrangement of equipment within densely packed plants is demonstrated by the high level of attention that the literature gives to the optimisation of geometric equipment dimensions [186, 212, 253, 264, 285, 286, 288, 300]. However, looking for compact equipment is often an indirect cost-reducing procedure. Indeed, even though the weight was considered in a paper [186], the widely adopted geometric measure to be minimised is the overall heat transfer area. The use of different meta-heuristic algorithms [253, 286], Taguchi design approach [212], and Mixed Integer Linear Programming (MILP) [288] have been explored to achieve the minimisation of the heat transfer surface constrained to a heat transfer rate. Yang et al. examined different strategies for heat transfer enhancement with the aim of reducing equipment surface area and Investment Cost (IC) [264, 300]. Even though a smaller surface area usually means lower IC, it also means smaller tube diameter and shorter length. Therefore, it means a more significant pressure drop, which increases Operating Costs (OC). The reduction of the Total Cost (TC) is strictly related to the trade-off between IC and OC. This fact is shown in the literature [285] using the comparison of surface area and Total Annual Cost (TAC) as OFs of a MILP.

Fluis-dynamic and energy-related functions are linked to input and output temperatures, that is, the process parameters' values, rather than the actual equipment's geometry. Several thermal-performance measures, such as exergy, efficiency, entropy generation, entransy dissipation and effectiveness, have been considered. Even though many references have adopted this type of functions [193, 195, 201, 204, 208, 211, 217, 243, 289, 292, 301, 302], since their non-direct relations with the equipment architecture, they do not help in equipment design. Indeed, several designs with non-equivalent relevant characteristics may share the same level of thermal performance. Thus, if they are used as single OF, their optimisation may lead to unfeasible or economically viable geometrical configurations.

Beyan [301] has introduced the entropy generation number that seemed suitable as OF for optimising STHE since it also accounts for pumping power. However, the “entropy generation paradox” implies that economic savings from irreversibility reduction are compensated by higher costs caused by lower thermal efficiency. Indeed, several authors underlined that minimising entropy generation may not lead to thermal efficiency maximisation. Some have introduced a different formulation of the entropy generation number to deal with the entropy generation paradox [195]. Moreover, a recently published work demonstrated that the main effect of entropy generation minimisation is on pressure drop rather than on heat loss [243].

The relationship between thermo-economical performances and shell-side field synergy number were explored [193], as well as the integration between exergy destruction cost and TC by presenting the exergetic cost minimisation [217, 289]. In past years, the concept of entransy has been introduced [302]. It is a new thermodynamic function that represents the ability to transfer heat while reducing its dissipation, thus preserving the reversibility of the transformation, and that can be used for optimising HE. For HE optimisation purposes, it was used resorting to the number of entransy dissipation [211] and the entransy dissipation resistance [208] minimisation.

On the other hand, Effectiveness optimisation maximises the exploitation of all thermal energy of both fluids [201, 204]. However, it may lead to non-viable final equipment configuration from the perspectives of surface requirements and economic performances. Indeed, effectiveness maximisation brings the exchanged heat as close as possible to the maximum exchangeable heat quantity, which is not always advisable of feasible from a practical perspective. For example, in considering counter-current design, this can imply that the hot fluid outlet temperature is lower than the cold stream’s outlet temperature. Therefore, it requires an unacceptable value of heat transfer area and related pressure losses.

One of the main issues of STHE is the fouling resistance, which is highly impacted by the fouling film. This latter is significantly affected by the geometry of the equipment. Since this problem is well-known, a MILP for fouling resistance minimisation constrained to heat duty and pressure drop was proposed. This approach allows the authors to reduce the shell-side fouling resistance by 17% and the tube-side by 48% compared to literature-available designs [292].

The weighted average of multiple performance measures (WAMPM) concerns combining different objectives in a single function using their weighted sum [210, 229, 248]. The substantial difference between this approach and the usage of multiple objective functions pertains to the fact that multiple-objective methods usually lead to a Pareto optimality frontier and require specific solution algorithms. Applying WAMPM requires the adimensionalisation of each considered performance measure and allows us to optimise a single compound performance index. However, this performance index has no physical meaning and does not give information about equipment configuration or functionality. There is no link between the OF and physical HE characteristics. On the other hand, the advantage of combining different performances entails the possibility to optimise several characteristics. For instance, it was recently applied to optimise equipment sustainability [248]. Additionally, it was used to consider the impact on the labour force, carbon plant, costs and several other KPIs with different meta-heuristic algorithms to optimise social, environmental, and economic sustainability [210]. Other authors used WAMPM for achieving a better management of project sustainability [229]. Nevertheless, the impact evaluation of each performance measure and the weights selection are not straightforward problems and are still under investigation.

Cost functions are the most used in STHEs optimisation problems statement [187, 188, 190, 192, 194, 196-198, 200, 203, 205-207, 232, 234-236, 244-247, 249, 251, 252, 254, 255, 258-260, 262, 263, 265, 267-270, 272, 274-284, 287, 290, 296, 298, 299]. They can be clustered into Total Cost and Total Annual Cost functions, and both sets simultaneously include capital investment and operating costs. The former minimisation is usually pursued by minimising the surface area, whereas the latter minimising the pumping costs. Their coexistence in a single OF requires methods for discounting or levelising cash flows.

In one of the first contributions [298], authors resort to a TAC formulation including pumping power and thermal loss for accounting of OC for STHE optimisation. On the other hand, the IC was assessed using Hall's method, thus expressing the investment cost as $IC=a_1+a_2A^{a_3}$. This equation includes the heat transfer area A and the coefficients a_1, a_2, and a_3, allowing them to consider surface range, the HE construction material and type, and the scale economy, respectively. This IC estimation overlooks the geometrical configuration of the equipment. Indeed, the same transfer area can be obtained with several architectures, leading to different manufacturing cost values. For that reason, a more recent work [187] detailed the cost estimation of STHEs analytically, explicitly considering the manufacturing processes and geometrical parameters' values. Since the size of pumps strictly depends on the HE's pressure losses, and they contribute to the total investment cost, some authors include both the capital cost of HE and pumps [249, 278].

Additionally, other authors integrated operating costs by including indirect manufacturing costs [270]. Instead, in other papers, the problem of operating costs was addressed. Indeed, Selbaş et al. [188] modelled the maintenance cost considering an annual percentage increment of OC. In contrast, others explored different HE surfaces to reduce fouling factors' effect and model IC with the Purohit expression [190]. Since the performance functions are closely linked to design variables values, the Global Sensitivity Analysis (GSA) was used to identify the most influential variables on costs. Their optimisation procedure was attempted to reduce computational complexity [284]. Finally, different optimisation algorithms were compared consistently in the literature, assuming a total cost-based objective function [254, 296].

As previously mentioned, one of the problems in comparing papers focused on OFs is that there are often inconsistent bases. Even though authors generally used the Kern or Bell-Delaware methods as STHEs design procedure, others used constructal theory [196, 200, 203] or modified-existing methods for using a non-traditional optimisation approach [290].

Although maintenance and reliability considerations were often made [251], e.g. restraining a coefficient of increase of surface into a given interval [255], an analytical formulation for optimising the maintenance schedule was proposed only in an article [197].

Since someone affirmed the importance of including thermal performances, in reference [246], the TC was constrained to an effectiveness level. Other authors [247] consider some penalties associated with TC optimisation by defining some threshold performance values, such as a minimum effectiveness value, which affect the performance when not met. This approach does not merely discard solutions that do not meet some constraints but penalises them by linearly increasing the TC with the level of constraint violation.

For compact STHEs, a new TC mathematical formulation was proposed, including the uncertainty of correlations and inlet quantities: the best HE was chosen, resorting to multi-criteria decision-making under uncertainty [260].

Beyond the issue of OF selection stands the problem of constraints formulation. Design correlations have validity ranges, which are not always accurately respected [184]. Additionally, constraints can be used to achieve a reasonably feasible equipment architecture. Even though some constraints can pertain to design formulas, parameters, and system type, each objective function requires specific constraints. For instance, an explicit constraint on maximum allowable pressure drop may be needed if they are not yet in the OF, e.g. considering IC or heat transfer area instead of TC. The analytical formulation of constraints may not be easy and may influence the selection of the optimisation algorithm or vice versa. This issue is sometimes addressed by forcing the optimisation algorithm to accomplish some constraints or not directly including them but resorting to a post-processing procedure after solving the optimisation problem. Indeed, in some cases, tuning the theoretical optimum solution into a more feasible sub-optimal solution is possible.

Using multi-objective optimisation formulations may address the problem of constraints' selection by providing a set of equipment performances and obtaining a non-dominated solution. The problem here is choosing one solution within the set of non-dominated ones.

Multi-objective optimisation

Multi-objective optimisation (MOO) is extensively studied in the STHEs area, despite many studies being more concerned with the performance of MOO algorithms than with the choice and justification of OFs. Although a performance used as a single OF can be deceptive or unhelpful for equipment design, its combination with others may be helpful. Indeed, this approach is essential for simultaneous optimisation of the trade-off suggested by economic and thermal performances [220, 225, 250, 256, 261, 273]. Decision-makers now have the option of choosing the preferable configuration on the Pareto efficient frontier, which represents the set of non-dominated options, without having to settle for sub-optimal designs.

For instance, as was already mentioned, thermal effectiveness maximisation results in a rapid rise in TC due to increased surface area. This is due to the simultaneous reduction of the Logarithmic Mean Temperature Difference (LMTD), as fluids' outlet temperatures should be roughly the same, and of the LMTD correction factor, which, below the 0.8 threshold, rapidly declines and becomes uncertain.

Effectiveness is sometimes substituted with exergy efficiency to achieve comparable effects [221]. Ozcelik [191] made one of the first MOO attempts with a formulation of exergetic cost. Exergy disruption [224], entransy dissipation theory, and TAC were applied in the double OFs optimisation of exergy efficiency [230]. To comprehend the significance of minimising the influence of the irreversible transformation from friction and heat transfer points of view, effectiveness, TC, pressure drop, and entropy generation units were simultaneously optimised [271].

It was frequently thought to maximise heat transfer rate (Q) while minimising total cost (TC) [199, 237, 240]. For various STHEs in terms of baffle types, such as segmental, helical, disc, and doughnut [223], Q and pressure drop were also correlated using Computational Fluid Dynamics simulation with Taguchi experimental design [291] and Artificial Neural Network (ANN) [209, 213, 218]. Helical baffle and coiled wire insert technology [214], the addition of nanofluid [238] and segmental porous baffles were also explored with GA-ANN [216] and Multi-Objective Genetic Algorithm (MOGA) [239] for Q enhancement.

Since fluids' velocities affect the overall heat transfer rate and pressure drop, establishing a trade-off, the Pareto frontier, is very useful in selecting the best solution [241]. Applying the response surface method and MOGA was found helpful for increasing thermal performance, i.e., shell-side Nusselt number, and reducing friction loss in STHEs with fold baffles [242].

TC can be optimised using the MOO problem by including both IC and OC as OFs [227]. However, the widespread use of Hall's correlation has limited the accuracy of estimating IC in calculating the equipment area and OC in pressure drop evaluation. For this reason, another formulation can be optimised to manage the uncertainty of cost coefficients' selection by simultaneously minimising the exchange surface and pressure loss [222, 228, 295]. Further considerations about equipment surface and TAC can be found in Elsays et al. [233].

Optimisation of ecological impact was also considered for MOO with the minimisation of TC and the entransy dissipation, aiming to exploit the whole thermal energy of the fluids and reduce pumping energy consumption [231]. From a similar perspective, but allowing for maintenance consideration, energy efficiency and fouling rate support were studied with ANN [293].

Agarwal and Gupta [219] optimised the TAC and mass flow rate of service fluid, considering a case where, after passing through the STHE, the outlet cooling water was recycled into a cooling tower. Reducing water consumption is crucial not only for its economic value but also because of availability concerns.

In the end, Lambert and Gosselin [202] considered epistemic uncertainty and minimised at the same time the TAC and its standard deviation. This approach is critical to get the impact of uncertainty on the equipment design, and it is not entirely investigated on STHEs design.

In general, multi-criteria decision-making methods can assist in choosing the weights within the OF for selecting the preferred equipment configuration agreeing to user preferences. A MOO computer tool for STHEs was also developed in [257].

The above-presented discussion leads to the following considerations.

The scientific community has not already achieved a standardisation of OFs. Indeed, a large number of optimisation problem formulations have been proposed. However, most authors do not motivate the OF selection.

Even though a consensus around cost-related OFs seems to be established, energy-related OFs also occur, especially in MOO problems.

Since, in some papers, the proposed optimal solution may be unfeasible or non-realistic (e.g., HE with colossal surface area or high total cost), some authors are sceptical of the literature results [183].

The main difference between cost or geometry OFs and energy-related ones is that the former has a straightforward meaning because architecture or operational aspects are concerned. In contrast, the latter does not define transparently an equipment configuration and may be unhelpful if the goal is to produce a piece of "well-designed" equipment. Indeed, energy-related functions lead to several HEs with the same energy performance. Moreover, good thermal performance does not necessarily imply good performance in other crucial aspects. Since the thermal performance measures optimise mainly the process parameters and, in some cases, may be assessed neglecting the equipment's geometric configuration, they should not be used as single OF but paired to other OFs in multiple objectives design optimisation.

On the other hand, cost performance measures have practical implications for geometric or thermal performances. For example, a piece of low total-cost equipment has a geometry reducing the surface area while preserving the heat transfer efficiency (transferred heat per unit area) and pressure losses. Thus, it simultaneously considers several categories of design goals. Multiple-objective OFs address two necessities, i.e. the true blue need of optimising simultaneously two or more performance characteristics and the ought to get an effective and viable geometrical design when considering non-geometry-related performance measures such as the energy-related ones, which would be steady with an uncertain set of alternative geometrical designs.

5.1.2 Research methodology

Although often neglected, the literature review underlines that the performance measure's choice for heat exchanger design optimisation is a sensitive matter. STHEs optimisation can be aimed at different goals, but it should always be considered that the ultimate scope of HE is heat transfer to be obtained with a "well-designed" piece of equipment.

This section aims to assess the design implications of the OF choice. The following will consistently compare optimal designs achieved by adopting different OFs. Firstly, single-objective optimisation is carried on, and MOO is subsequently considered. For optimisation purposes, the Matlab library of GA and MOGA algorithms is used to perform computations, together with the design procedure described in [192]. The description of the selected OFs, the comparison methodology and the reference case study, are also available in the already published author's work [182].

Single-objective functions selection for STHEs design comparison

Eight OFs were selected to provide an extensive comparison of optimised designs. Four geometric objective functions were chosen for achieving equipment compactness. Three OFs were used to optimise energy-related performances, and a single objective function was used to consider the TC.

<u>OF1: Heat transfer area *A*</u>

$$\min (A) = Nt\pi d_o L \tag{5.1}$$

A minimisation aims to reach a compact heat exchanger. Compactness is a required characteristic, and it leads to lower *IC*.

OF2: Area Footprint *AFP*

$$\min(AFP) = LD_s \tag{5.2}$$

The rectangular ground footprint of the equipment measures the land occupation in an industrial plant. The occupied area is considered as the tubes' length L times the shell diameter D_s and could represent an opportunity cost.

OF3: Tubes length *L*

This is merely an OF trying to reduce the equipment size by shortening the length of its tubes (min(L)).

OF4: Volume Footprint *VFP*

$$\min(VFP) = \frac{\pi {D_s}^2}{4} L \tag{5.3}$$

This is the same as *AFP* but extended to the equipment volume, to be used when available volumetric space represents, at the same time, a constraint and an opportunity cost.

OF5: Pumping power *P*

$$\min(P) = \left(\frac{1}{\eta}\right) \cdot \left[\left(\frac{m_t}{\rho_t}\right) \cdot \Delta P_t + \left(\frac{m_s}{\rho_s}\right) \cdot \Delta P_s\right] \tag{5.4}$$

Where η is the pump efficiency and ρ_T and ρ_S are the density of tube and shell side fluids, respectively.

This is an OF related to a fluid dynamics perspective. Its minimisation's importance resides in its effect on pressure drop on both the shell side (ΔP_s) and tube side (ΔPt). Pressure drop minimisation also influences pump sizing and operating costs from a practical point of view.

From a thermal perspective, instead, effectiveness (ε, equation 5.5 [303]) and number of entransy dissipation units (g, equation 5.6 [211]) are used. The literature shows that g could be optimised in two different ways, with constant Q and so optimising the mass flow rate or outlet temperature of service fluid and computing the other from the energy balance or resorting to ε-NTU method [304] for sizing the STHE, whereas ε with only the latter. The first manner for g optimisation is not a real optimisation because when Q is constant, the thermal performance of the HE remains the same and only pressure drops are optimised. In this case, the optimisation algorithm merely makes the outlet service fluid temperature equal to the outlet process fluid temperature, reaching a value of g near 0.5. In addition, the pressure drop contribution to g is about three orders of magnitude less than the thermal contribution, so the OF is not too sensitive to frictional loss.

<u>OF6: Heat exchanger effectiveness *ε*</u>

$$\max(\varepsilon) = \frac{2}{(1+C^*) + (1+C^{*2})^{1/2}\coth\left(\frac{NTU}{2}(1+C^{*2})^{1/2}\right)} \tag{5.5}$$

Where Number of Thermal Units (*NTU*) is the product of the HE surface and global heat transfer coefficient divided by the smallest of the two fluids stream heat capacity rates, while C^* is simply the ratio of the smaller to larger heat capacity rate.

<u>OF7: Number of entransy dissipation unit *g*</u>

$$\min(g) = g_{\Delta T} + g_{\Delta P} = \\ = \frac{\frac{1}{2}(mc_p)_h\left(t_{h,i}{}^2 - t_{h,o}{}^2\right) + \frac{1}{2}(mc_p)_c\left(t_{c,i}{}^2 - t_{c,o}{}^2\right) + m_h \frac{\Delta P_h}{\rho_h}\frac{(t_{h,o}-t_{h,i})}{\ln\left(\frac{t_{h,o}}{t_{h,i}}\right)} + m_c \frac{\Delta P_c}{\rho_c}\frac{(t_{c,o}-t_{c,i})}{\ln\left(\frac{t_{c,o}}{t_{c,i}}\right)}}{Q(t_{h,i}-t_{c,i})} \tag{5.6}$$

Where $g_{\Delta T}$ is the thermal dissipation contribution and $g_{\Delta P}$ the fluid-dynamic dissipation contribution. m and c_p are mass flow rate and specific heat, respectively, of hot fluid (h) and cold fluid (c). Q is the heat transfer rate, whereas t represents temperatures: subscript i identifies inlet, o outlet, c and h cold and hot fluids.

From an economic point of view, the selected objective function is *TC* (equation 5.7). The total discounted HE cost is computed as the sum of investment cost (equation 5.8), resorting to Hall correlation, and the present worth of pumping cost (*DOC*, equation 5.9).

<u>OF8: Total cost *TC*</u>

$$\min(TC) = IC + DOC \tag{5.7}$$

$$IC = a_1 + a_2 S^{a3} \tag{5.8}$$

$$DOC = \sum_{N=1}^{Ny} \frac{P}{(1+i)^n} \cdot Cen \cdot H \tag{5.9}$$

Economic values and parameters for cost evaluation are shown in Table 5.3. Please refer to the nomenclature of this section in the List of Symbols section for the meaning of symbols.

Table 5.3 Parameters used to assess the investment and operating costs

a_1	a_2	a_3	η	*H (h/y)*	*i (%/yr)*	*Ny (yr)*	*Cen (€/kWh)*
8000	259.2	0.91	0.7	7000	10	10	0.12

Multi-objective functions selection for STHEs design comparison

In the case of MOO, the following OFs are used.

OF1 = Heat transfer area *A* and Total Cost *TC*

OF2 = Area footprint *AFP* and Total Cost *TC*

OF3 = Thermal effectiveness *e* and Total Cost *TC*

The analysis of multi-objective optimisation is not carried out to introduce a new optimisation method or new objective functions but to consistently compare different combinations of objective functions and emphasise the effect of combining several objective functions in comparison with using them stand-alone. Whereas OF1 may be found in [233] and OF3 is widely used in the literature ([220, 225, 226, 256, 257, 261, 273]), AFP, namely

OF2, is a new objective function introduced by the authors, the combination with total cost should be considered as a new formulation.

Reference case

In order to compare in a consistent manner the equipment configurations resulting from the above objective functions, the Kern method [305] for HE sizing is used in a reference application case. An exception is made for OF7 and OF8, where the ε-NTU design method is utilized.

In this manner, the outlet temperatures of fluids are computed, and only inlet temperatures and mass flow rates are assigned. Moreover, we assume that heat exchanger must be designed to cool a process fluid, and both fluids' nominal flow rates, temperatures and thermophysical properties are available in Table 5.4. Obviously, outlet temperatures must not be considered when using the ε-NTU method.

Table 5.4 Nominal conditions and thermophysical properties of the two fluids.

Fluid	m (kg/s)	t_i (°C)	t_o (°C)	ρ (kg/m3)	c_p (kJ/kg K)	μ (Pa s)	λ (W/m K)	Rf (m^{2}K/W)
methanol	27.8	95	40	750	2.84	0.00034	0.19	0.0002
seawater	68.9	27.5	40	995	4.2	0.0008	0.59	0.00033

Considered design and optimisation variables are shell diameter (Ds), baffles spacing (B), tubes' diameter (do), number of tube-side passages (n), tube-side fluid and tubes' pattern for the Kern method. At the same time, the tubes' length (L) is also included for the ε-NTU method. Problem constraints include a maximum allowable pressure drop of 70 kPa, length-to-shell diameter ratio in the range of 3-15, and tube-side and shell-side fluid velocity in the range of 0.6-2.5 m/s and 0.4-1.5 m/s, respectively. The latter two lower bounds are introduced to reduce the fouling effect.

Comparison methodology

In order to compare different optimal designs obtained by the optimisation of previous OFs, each STHE will be optimised by referring to a j-th OF (j=1…8) and evaluated concerning eight performances p - namely A, AFP, L, VFP, P, ε, g, TC - identified by subscript i=1…8.

Then, a relative performance index I_{ij} (equation 5.18) is introduced, measuring the relative difference between the value of p assumed from the j-th design and its optimum value.

$$I_{ij} = \frac{p_{ij} - p_{ii}}{p_{ii}} \tag{5.10}$$

p_{ij} is the i-th performance value in the case of optimisation with respect to j-th OF. In contrast, p_{ii} is the performance value of equipment optimised precisely for that performance.

5.1.3 Results discussion

Single-objective optimisation results

At first, single-objective optimisation results are considered. The resulting optimal equipment configurations are shown in Table 5.5, while Table 5.6 shows the corresponding equipment performances, and Table 5.7 shows the value of the index I_{ij}. In the Tables, each column is associated with a distinct *j-th* OF, namely *A, AFP, L, VFP, P, ε, g, TC*.

Table 5.5 Optimised shell and tube heat exchanger configuration

OF	***A***	***AFP***	***L***	***VFP***	***P***	***ε***	***g***	***TC***
D_s	0.7	0.8	0.8	0.8	1.0	1.2	1.4	0.9
L	4.3	2.4	2.4	2.6	4.3	10.0	9.1	2.7
B	0.5	0.5	0.5	0.5	0.4	0.7	0.5	0.9
n	4	6	6	6	2	8	8	4
do	0.012	0.012	0.012	0.012	0.02	0.012	0.022	0.012
Pattern	Square	Triang	Triang	Triang	Square	Triang	Triang	Square
Tube side	Methanol	Methanol	Methanol	Methanol	Water	Methanol	Methanol	Methanol
Pt	0.015	0.015	0.015	0.015	0.025	0.015	0.0275	0.015
Cl	0.003	0.003	0.003	0.003	0.005	0.003	0.006	0.003
Nt	1116	2085	2086	1873	1148	6828	2032	2311
v_t	1.84	1.47	1.47	1.64	0.60	0.60	0.60	0.89
Re_t	38871	31202	31187	3474	11941	12706	23294	18772
Pr_t	5.1	5.1	5.1	5.1	5.7	5.1	5.1	5.1
h_t	4314	3619	3617	3944	3248	1764	1562	2410
ΔP_t	69996	47656	47619	61046	4302	37427	18381	13503
D_e	0.012	0.009	0.009	0.009	0.020	0.009	0.016	0.012
v_s	0.96	0.93	0.92	0.93	0.40	0.42	0.50	0.43
Re_s	14249	10004	9932	10006	17461	4493	9795	6331
Pr_s	5.7	5.7	5.7	5.7	5.1	5.7	5.7	5.7
h_s	6152	6931	6904	6932	1280	4463	3737	3937

ΔP_s	69999	69990	68604	69998	10209	70000	70000	8044
U	969	935	934	960	562	661	607	739
S	179	186	186	181	309	2574	1280	235
IC	37130	38089	38107	37359	55797	337078	182300	45253
OC	8932	7937	7820	8534	811	7479	6632	1269
DOC	54885	48774	48056	52438	4987	45960	40754	7799
TC	92015	86863	86163	89797	60784	383038	223054	53052
ε	0.79	0.79	0.79	0.79	0.79	0.87	0.87	0.79
$t_{h,o}$	40.0	40.0	40.0	40.0	40.0	34.4	34.4	40.0
$t_{c,o}$	40.0	40.0	40.0	40.0	40.0	41.5	41.5	40.0
g	0.5011	0.5007	0.5007	0.5009	0.5001	0.4493	0.4491	0.5002
$g_{\Delta P}$	0.0011	0.0007	0.0007	0.0009	0.0001	0.0005	0.0002	0.0002
$g_{\Delta T}$	0.5000	0.5000	0.5000	0.5000	0.5000	0.4488	0.4489	0.5000
AFP	2.83	1.86	1.86	1.94	4.48	11.98	12.66	2.42
VFP	1.47	1.15	1.15	1.15	3.68	11.26	13.80	1.71
P	10.6	9.4	9.3	10.2	1.0	8.9	7.9	1.5

Table 5.6 Performance values for each optimised design

Objective function (j)

Performance (i)	A	AFP	L	VFP	P	ε	g	TC
A	179	186	186	181	309	2574	1280	235
AFP	2.83	1.86	1.86	1.94	4.48	11.98	12.66	2.42
L	4.3	2.4	2.4	2.6	4.3	10.0	9.1	2.7
VFP	1.47	1.15	1.15	1.15	3.68	11.26	13.80	1.71
P	10.6	9.4	9.3	10.2	1.0	8.9	7.9	1.5
ε	0.79	0.79	0.79	0.79	0.79	0.87	0.87	0.79
g	0.5011	0.5007	0.5007	0.5009	0.5001	0.4493	0.4491	0.5002
TC	92015	86863	86163	89797	60784	383038	223054	53052

Table 5.7 Indexes I_{ij} values for different OF and performance measure

Objective function (j)

Performance (i)	A	AFP	L	VFP	P	ε	g	TC
A	0.00	0.04	0.04	0.01	0.72	13.36	6.14	0.31
AFP	0.52	0.00	0.00	0.04	1.41	5.44	5.80	0.30
L	0.80	0.00	0.00	0.08	0.81	3.23	2.86	0.14
VFP	0.28	0.00	0.00	0.00	2.20	8.79	11.00	0.49
P	10.00	8.78	8.63	9.51	0.00	8.22	7.18	0.56
ε	0.09	0.09	0.09	0.09	0.09	0.00	0.00	0.09

g	0.12	0.11	0.11	0.12	0.11	0.00	0.00	0.11
TC	0.73	0.64	0.62	0.69	0.15	6.22	3.20	0.00

The substantial differences in optimal configurations prove the importance of OF selection.

Looking at Table 5.5, it is straightforward that each adopted OF minimises (or maximises, if it is the case) the performance included in OF formulation. For example, using A as OF, it is possible to find that the heat exchange surface reaches the minimum value, but such objective function (like AFP, L and VFP) neglects operating cost. For this reason, the pressure drop on the tube and/or shell side is close to the maximum allowable value of 70 kPa.

Using P as OF, the other heat exchanger performances are neglected, giving minimum values for pumping power on both sides. However, at the same time, values of surface A, equipment footprint AFP, equipment length L and volume footprint VFP are more significant than the minimum values.

OFs ε and g lead to equipment having heat exchange surface and investment cost an order of magnitude bigger than other OFs and, at the same time, high values of pressure drop.

Figure 5.1 summarizes I_{ij} values resorting to spider plots, highlighting the relative performances of optimal design configurations with respect to all selected performance measures. In particular, each graphic of Figure 5.1 refers to a specific *j-th* OF, and the plotted points depict the corresponding I_{ij} index values showing the relative performance of that optimal exchanger as compared to the corresponding performance of an HE optimised for each *i-th* performance measure. Obviously, a hypothetical HE having the best performance in all the considered performance measures would have a spider plot where all points would collapse at the origin of the graph.

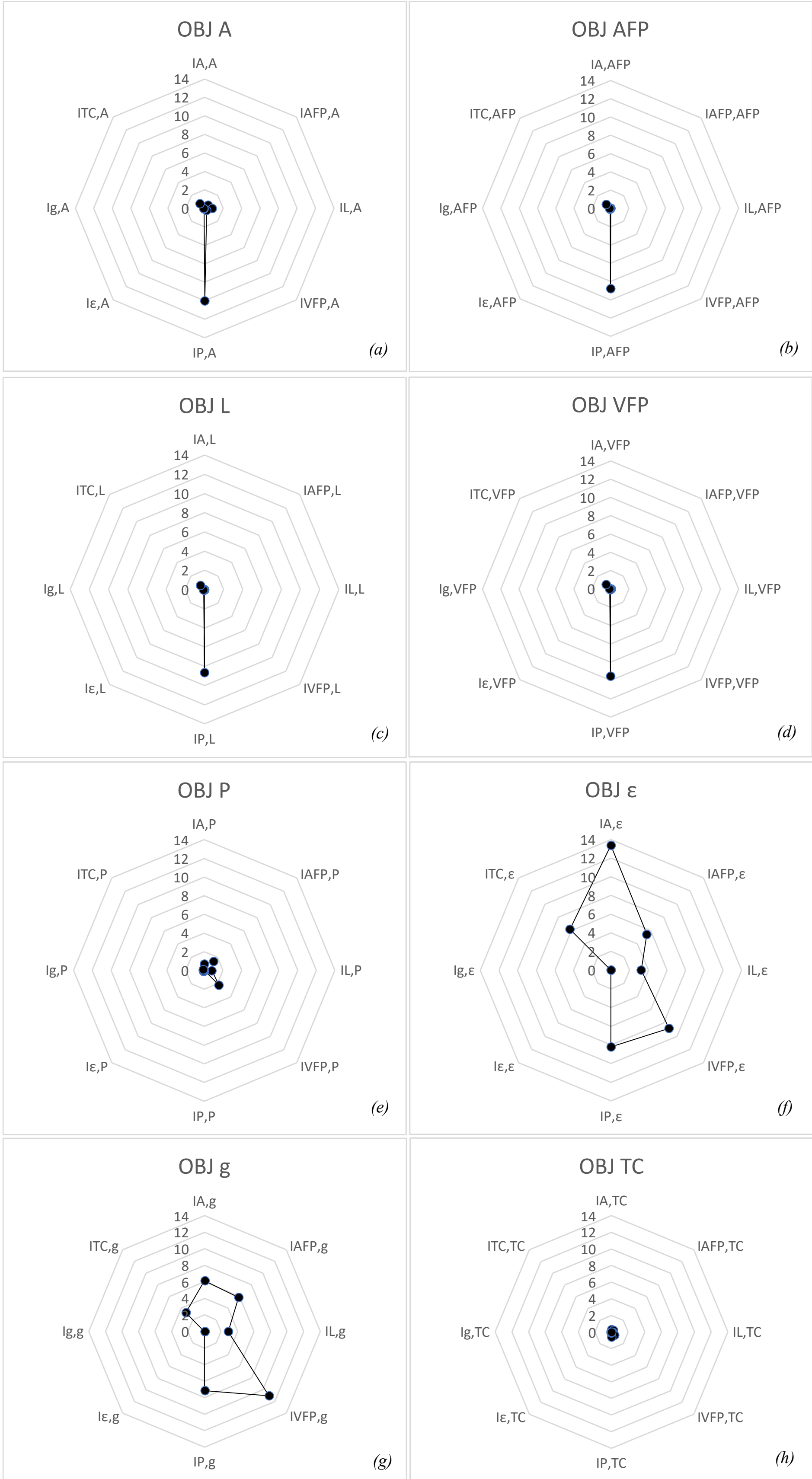

Figure 5.1 STHE design performance comparison

Graphs 3a to 3d show very well that geometric optimisation, being not sensitive to pressure drop, leads to a consistent increase in pumping power. *P* increases by about ten times in comparison to *P*-optimised design. Passing to this latter case (Fig. 3e), as *P* directly influences *OC* and the geometry of HE, *TC* is "only" about two times bigger than *TC*-optimised one, and in general, *P*-optimised configurations are pretty good overall performance measures.

Effectiveness maximisation leads to a configuration affected by noticeable degradation in all other performance measures (Fig. 3f). STHE surface increases fourteen times if compared to *A*-optimised HE, and even pumping power and *TC* grow up. The heat exchange area increases because the hot fluid outlet temperature is kept lower than the cold fluid outlet temperature to exploit the whole thermal power of fluids. Hence, the corrective factor of *LMTD* falls under the 0.8 threshold.

In the case of the Number of entransy dissipation units (Fig 3g), the above considerations are confirmed by experimental results. Outlet temperatures are the same as the ε-optimised design, so effectiveness was maximised from the thermal point of view. Pressure drop is contained by $g_{\Delta P}$, but it is three orders of magnitude minor than $g_{\Delta T}$, and the final effect is that *g* is not too sensitive to its contribution.

Researchers have often exempted themselves from showing the final HE configuration obtained with their optimisation, and in their works, only optimum values of optimisation variables are shown. Using these values, in some cases, final configurations do not have a practical use for their dimensions or cost, which could be much lower, giving up little percentage of thermal performance.

The design that performs better in all indices, obviously the second in every p_{ij} only after the p_{ii}, is obtained with *TC* minimisation. This is easy to understand because geometric indexes are small thanks to the *IC* minimisation, which drives towards small exchange areas, and *OC* minimisation, which acts directly on pumping power. Effectiveness and *g*, even show good values. In fact, ε and $g_{\Delta T}$ are small because outlet temperatures of fluids are equal in specifications, and $g_{\Delta P}$ is reduced by *OC*. However, *TC*-minimisation performed by adopting a simplified cost correlation has two critical problems. Firstly, cost is estimated using the overall surface area only, neglecting manufacturing processes, and geometrical allocation of the area is also neglected, as the same *A* could be obtained with different *L*, *do*, *B*, D_s, *n* and tubes' patterns.

Overall, in single-objective optimisation, economic functions demonstrate their superiority in optimising STHE in terms of realisable architecture and general performances. Considering thermal performances could be necessary for some problems, but an economic quantification of them leads to good results. Anyway, even though monetary analysis is easy to understand, the challenge is to formulate OFs which include all important costs directly dependent on HE geometric configuration and which could include other performances that could be of interest in different cases.

Multi-objective optimisation results

Using the same case study above and considering the OFs declared in paragraph 5.1.2, a MOO is performed using the MOGA of Matlab, obtaining a Pareto efficient frontier. In Figure 5.2, the results of *A* - *TC* (a) and *AFP* - *TC* (b) optimisations are depicted. In Figure 5.3, the Pareto front for effectiveness maximisation and total cost minimisation is instead shown. Decision-making techniques or weighted sum of two OFs allows decision-makers to select the preferred trade-off point on the frontier.

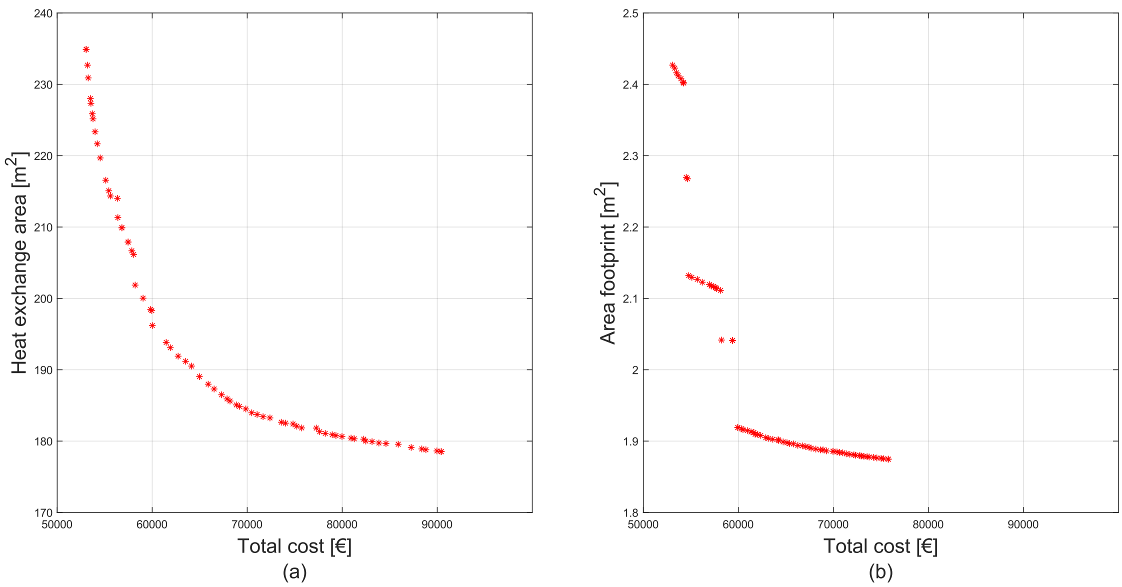

Figure 5.2 Pareto front of optimised heat transfer area and total cost (a) and optimised area footprint and total cost (b)

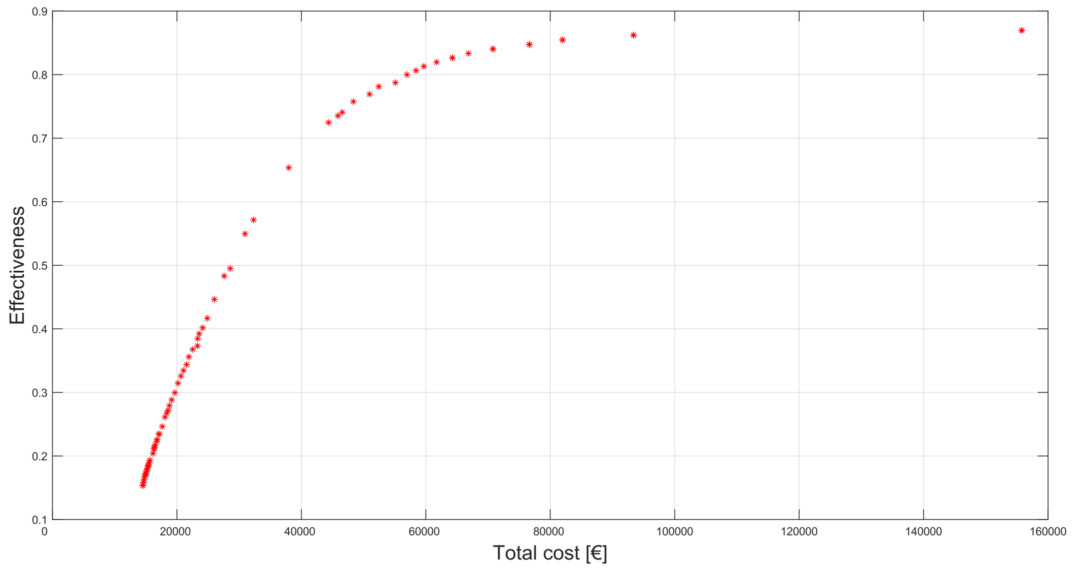

Figure 5.3 Pareto efficient frontier for effectiveness and TC optimisation

In Figure 5.2, it can be noticed that when the HE area decreases, the total cost increases owing to higher fluid velocity and pressure drop. The same occurs in area footprint minimisation.

Even if the only interest of the designer is HE area minimisation, the use of MOGA allows the designer to include *TC* as well in the configuration decision so that a good solution is always obtained. In fact, the minimum heat transfer surface found on the frontier is at least one of the least expensive. Including *TC* also allows for suitable configurations when a thermal performance measure is optimised (Figure 5.3) without incurring the unfeasible configuration typical of stand-alone thermal OF optimisation.

As noticeable from the above results, the same maximum effectiveness of single optimisation is obtained ($\varepsilon = 0.87$), although *TC* values are quite different. In fact, in the single OF optimisation, *TC* is 383038 €, whereas in MOO, it is 155773 €. The *TC* still remains high in absolute terms (as compared to about 53000 € of the *TC*-optimised exchanger), and the equipment configuration remains quite cumbersome. However, a significant improvement was obtained compared to sole effectiveness-based optimisation. It should also be noted that further increasing effectiveness above the threshold of 0.75 is hard to do (in the literature, typical effectiveness values are always taken between 0.5 and 0.7) owing to a rapid cost increase determined by much higher exchange areas. In this case, MOO, including total cost, proves to be quite valuable.

Overall, MOO, apart from the difficulty in choosing the preferred point on the Pareto frontier, has three main following advantages.

- Pareto frontier represents the best obtainable solutions space in which the designer can move to make decisions.
- Given the optimum value of a function, the other OF has the better obtainable value: being the point of the Pareto-efficient frontier, neither value can be improved without worsening the other one.
- It is possible to minimise/maximise OFs non-optimisable with single objective optimisation without reaching unfeasible solutions (e.g., thermic performances).

5.1.4 Remarks and limitations

As claimed in the previous chapters, it was shown that the choice of the OF is not indifferent, as it heavily impacts the equipment configuration and the "engineering" quality of the resulting design. The consequences of choosing specific kinds of OF were shown and discussed.

Evidence was provided that geometry-based OFs, aimed at pursuing equipment compactness and/or reduction in capital investment, are generally penalised by excessive pressure drop levels and consequent operating costs.

OFs which minimise pressure drop are able to strike an excellent overall trade-off between thermal, geometrical and economic performances.

OFs based on thermal performances are not advisable because thermal performance by itself does not define a geometric configuration (i.e. does not help the designer in determining a viable equipment configuration) and, from a practical engineering point of view, generally delivers scarcely viable solutions, which are affected by high costs.

The best solution appears to directly choose a total cost-based OF, as this implicitly dives towards a compromise between area minimisation and pressure loss reduction, delivering an excellent overall design that is also cost-effective. In this respect, the designer is advised to include in a cost-based OF definition as many elements as possible amenable to economic quantification (i.e. footprint, maintenance costs, thermal efficiency through economic evaluation of the exchanged energy, etc.) as this is an effective manner to include other design objectives having a physical meaning in a balanced design which is also cost-effective. Finally, utilization of economic OFs also simplifies the problem of setting design constraints which, when based on physical parameters, may be difficult to explicit in analytical form manageable by the optimisation algorithms. In fact, violation of physical constraints would generally result in equipment configurations with poor cost-effectiveness, which are promptly discarded by using an economic OF. This allows us to obtain a good engineering design without explicitly imposing a predefined threshold on the design parameters.

Finally, MOO was shown to be useful in tackling intrinsically multidisciplinary design problems (such as sustainability optimisation) and reducing the risk of scarcely viable design when solely thermal performances are used to drive design optimisation.

This section showed that the choice of the optimisation objective is relevant as it can strongly affect the cost-effectiveness and engineering viability of the obtained equipment configuration. Comparison of the performances of different objective functions is made possible by carrying out a consistent analysis based on a specific design instance. Different objective functions were optimised with the same procedure regarding the processor, metaheuristic algorithm and mathematical formulation. Optimal designs were evaluated by resorting to a new evaluation index to compare differences from different optimal designs.

Results show that pressure loss minimising and, above all, total cost minimising objective functions strike the best trade-off in equipment performances. Caution is mandatory when thermal performances are only being optimised, as this can give rise to unviable and economically unsustainable equipment configurations. Multi-objective optimisation assures that competing designs do not dominate the thermal optimum from an economic perspective. Economic functions are the most used and interesting from an industrial plant's point of view. Indeed, they are easy to implement and understand. The importance of thermal and geometrical performances is not to be neglected, but the possibility of giving economic value to these aspects is advised.

All results have been obtained referring to a single application example. The analysis should be extended to a wide range of alternative problem instances to confirm the validity of the results. Therefore, we do not make any claim of generalization, even if results appear to be generalizable based on engineering reasoning. Only eight objective functions and corresponding performance measures were explored. The analysis could be extended to other performance measures and objectives of interest to the designers. Finally, the analysis is limited to shell and tube heat exchangers, while other equipment configurations could be taken into account.

5.2 Shell and Tube Heat Exchanger under uncertainty: an overview

As said in section 5.1, shell and tube heat exchangers are the most frequent type of heat transfer equipment utilized in process plants. However, many external and internal sources of uncertainty and variability affect heat exchangers' operations in actual plants, making this kind of equipment's thermal and mechanical design rather complex despite their apparent structural simplicity. Among external sources of variability, either deterministic or random changes in input streams' conditions may occur, namely variation in hot and cold stream flow rate and temperature, changes in their composition and uncertainty in the fluids' physical properties. Internal sources of variability include uncertainty deriving from imprecise heat transfer and pressure drop correlations, flow maldistribution effects, and fouling phenomena [306].

Sources of uncertainty are often beyond the designer's control (section 1.1.4) and could affect different aspects [307].

- Variations of the environmental and operating condition: whereas some quantities could be assumed as deterministic and constant during the design phase, their value could change during the operating time. This is the case of input parameters and different noise signals influencing the system's performance.
- Manufacturing tolerances: some design solutions may be affected more or less than others by the departure from the geometrical theoretical configuration.
- Output evaluation: the model and the equations used to evaluate the equipment's performances are not the exact description of the reality. In fact, assumptions and simplifications necessary to reduce the modelling effort could introduce other types of uncertainty and neglect some phenomena.
- Constraint uncertainties: the feasibility space, i.e. the set of possible solutions, could be smaller than the one theoretically envisaged due to the model's incapability to determine the actual feasibility region.

Furthermore, uncertainty can be divided into a) aleatory uncertainty and b) epistemic uncertainty (section 1.1.1). The former comes from the random variability of the input, and it is not reducible. In contrast, the latter is imputable to non-perfect knowledge of the physical phenomena and unperfect correlations and is theoretically reducible.

Traditional design methods ignore variability in that they assume constant and known values of process conditions, namely the temperature and flow rate of input process streams, their composition and thermophysical properties, as well as heat transfer and pressure loss coefficients obtained from empirical correlations. Equipment design is based on nominal operating conditions, often assuming average values if a variability range is expected and providing ex-post verification that minimum heat duty specifications are satisfied when operating parameters are changed within a likely range. Nevertheless, uncertainty propagation and sensitivity analysis in heat exchangers is a topic that has gathered some attention from academics. Statistical methods to understand equipment behaviour have been known and used since '50 [308]. In particular, methods for assessing internal parameters' uncertainty and the capability of designs to satisfy requirements are available [309]. In order to protect against uncertainty and obtain a desired degree of confidence in satisfying specifications, design handbooks suggest additional pressure drop and surface area to be factored in as a safety factor, determined by a statistical combination of the variance of uncertain factors [306, 310]. Otherwise, the design is made assuming worst-case conditions. This may lead to excessively conservative design, with equipment oversizing or failure to meet design specifications under some operational conditions.

To counter uncertainty reactively, one could design the equipment incorporating some structural flexibility (section 3.1.4) to be used if and when necessary (i.e. a bypass stream or additional heat transfer area to be put into service on request). However, this may be often unpractical given that heat exchangers are designed with a predefined structural architecture when the geometrical parameters are fixed in the design phase and can not be changed during operation. Alternatively, some kind of equipment regulation and control could be allowed. Another approach could be to design allowing output variability, i.e. allowing operational states where specifications are not strictly met, provided that some performance measure is optimised.

When the above options are not feasible, the goal of designing a robust heat exchanger may be sought (section 3.1.2). Robustness is the ability of the equipment to maintain its operational capability and meeting design specifications under different operating circumstances. Technically, it involves a design able to optimise the mean response and reduce output variability in the face of input variability and noise factors by preventing variability propagation rather than reducing the input variability [311]. Therefore, robustness is a manner of passively managing uncertainty by choosing an equipment architecture that ensures adequate performance over a wider range of conditions [312]. However, while methods to assess the effects of uncertainty propagation in heat exchangers' performances are available in the literature, methods for robust design of heat exchangers under uncertain operating conditions are scarce.

Overall, as shown in the subsequent literature review, optimal heat exchangers' design methods, in general, neglect variability and uncertainty. Manual methods, instead, address uncertainty in empirical manners or by adopting penalising approaches such as design for average conditions, worst-case design or oversizing. However, no sound justification is offered to support their utilization. Most papers addressing uncertainty in heat exchangers focus on uncertainty propagation instead of design methods to counter uncertainty. The designer is left without guidance about how to deal with uncertainty. Therefore, a knowledge gap exists as far as equipment design under uncertainty is concerned.

5.2.1 Literature review

The literature on STHEs' optimisation has been analysed in the previous section. However, the design of processes under uncertainty is a research field in itself, extensively studied for a long time [313], especially in chemical process plant design and process synthesis, as reviewed elsewhere [165, 314].

However, Costa and Bagajewicz [315] point out that despite advances in computational tools, the basic design of process equipment is still carried out in industry by resorting to trial-and-verification procedures guided by heuristic rules. This is mainly imputable to the circumstance that the academic literature about process design under uncertainty is dominated by mixed-integer nonlinear models (for instance [316, 317]) which, regardless of the utilized solution techniques (i.e. stochastic or mathematical programming-based), have practical limitations that have restrained practitioners from abandoning the time tested heuristics and simplified computer-aided tools.

Nevertheless, the literature specific to heat exchanger design under variable operating conditions and parameters uncertainty is comparatively scarce and mainly focused on either assessing the equipment performance variation under uncertainty [318], the effect on designs [310] or suggesting guidelines to account for variability [309], rather than in providing optimal design solutions and methods. However, it can be argued that general methods developed for optimal probabilistic design of processes could also be applied to equipment design. In particular, Haseler et al. [319], as well as Clarke et al. [320], investigated the sensitivity of the overall heat exchanger calculations and operational performances to uncertainties in individual fluid properties, also using Monte Carlo techniques. However, they did not consider the uncertainties' effects on process specifications or address any optimisation problem. This kind of analysis was also extended to cross-flow heat exchangers [321]. The Monte Carlo method was also used by Affan Badar et al. [322] and Mahbub Uddin and Bell [310] to appraise the impact of uncertainties on the heat transfer coefficient. Prasad and Bharadwaj [323] analysed the performance of a counterflow concentric tube heat exchanger, estimating the uncertainties in the temperature response caused by uncertainties in the fluids' inlet temperatures and the overall heat transfer coefficients using a two-point distribution technique. Kayansayan [324] developed an analytical method to estimate the thermal behaviour of heat exchangers in off-design conditions. Knetsch and Hauptmanns [325] investigated the dynamic response of heat exchangers under process and parameters' uncertainty by resorting to a Monte Carlo variability propagation. Lambert and Gosselin [326] explored the impact of correlations' uncertainty on heat exchangers sizing and cost. Bounds on thermal systems' performances when operating in uncertain conditions were investigated by Taylor, Hodge and James [327]. Abdelaziz and Radermacher [328] investigated the effect of manufacturing tolerances and flow maldistribution on the performance of compact heat exchangers. Specific investigations on uncertainties in heat exchangers' performances owing to fouling phenomena have been carried out by Khan and Zubair [329, 330], Zubair and Qureshi [331], while Yeap et al. [332] develop specific heat transfer and pressure drop fouling models to allow estimation of cost-effective extra area to heat exchangers. Lemos et al. [333, 334] included velocity-dependent fouling factors and a threshold fouling model in a design optimisation procedure.

From the design point of view, Buckley [308] was the first to use a statistical approach to the sizing of process equipment. Starting from a design based on nominal values of design parameters and assuming a normal distribution of uncertain parameters, he combined the impact of the standard deviation of each variable parameter to determine the overall variability of the required transfer surface area of the heat exchanger. Then, he fixed the oversizing level to obtain the desired confidence level. A similar design approach based on specifying the probability of meeting a prescribed duty in case of process uncertainty, using the root sum squares method, is described by Cho [309] and Affan Badar et al. [322], but without attempting an optimal solution. As far as optimal exchanger design under uncertainty is considered, Caputo et al. [335, 336] optimised shell and tube exchangers' design considering variability in the input streams conditions (flow rate and temperature) or uncertainties in the heat transfer coefficient, adopting an economic objective function. Saldanha et al. [260] used multi-objective particle swarm optimisation and scenario construction to optimise shell and tube heat exchangers considering uncertainties in the tube-side inlet and outlet temperatures, pressure drop factor, friction factor, Nusselt number, as well as shell-side heat transfer coefficient and pressure drop while the objective function minimised heat transfer area and pressure drop.

Finally, a risk assessment method to evaluate the consequences of process uncertainties is provided by Shilling et al. [337]. An application of the robust design of a heat exchanger in the automotive sector is given by Arner [107]. Design under uncertainty was also applied to heat exchangers network, HEN, [338]. More recently, Al Khulaifi and Al Mutairi [339] developed a method for optimal synthesis of HENs, while Floquet et al. [340] presented a method to assess the robustness of a HEN.

Overall, the literature review shows that the research on heat exchanger design has been more focused on assessing the impact of uncertain parameters and estimating uncertainty propagation. This allows researchers to rate the goodness of an equipment configuration but does not directly help in designing the exchanger. The established research stream on optimal heat exchanger design generally neglects variability and uncertainty. Statistical design methods aimed at ensuring a desired confidence level on expected performances have been suggested, but empirical manual methods based on nominal condition design with verification for off-design conditions or empirical techniques based on worst-case conditions, safety factors and oversizing are used in practice. No justification for such empirical methods has been elaborated.

Methods for optimal stochastic design of heat exchangers are quite scarce. Overall, the heat exchangers design community lacks a consistent comparison of design methods addressing uncertainty and guidelines helping to choose the proper design method.

5.2.2 Methods for heat exchangers' design under uncertainty

As shown in Figure 5.4, variability associated with input variables, random events, and internal parameters uncertainty propagate through the system, making the output performance measures variable as well. The output variability may exceed some acceptability ranges bounded by predefined performance levels' thresholds. As an example [325], when a stream feeding a catalytic reactor exceeds a maximum threshold, the catalyst may be damaged. In contrast, if it drops below a minimum threshold, the required quality of the effluent is not guaranteed. Risk quantifies the system output deviation from the expected value in terms of frequency of occurrence and magnitude of consequences.

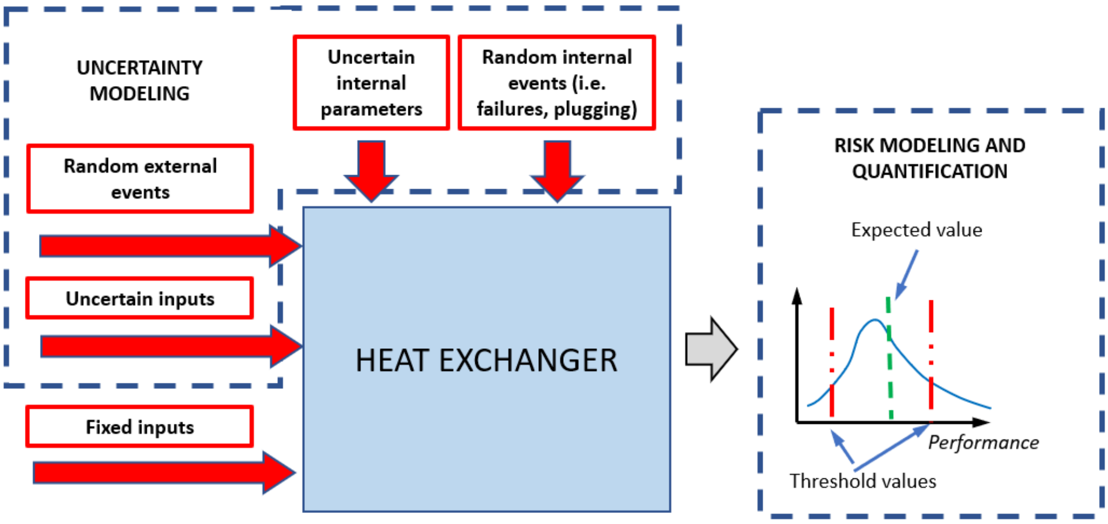

Figure 5.4 Conceptual schematization of system response under uncertainty

One possible general formulation of a process design under uncertainty [341] is the following.

$$
\begin{aligned}
Max \quad & f\,(u,q,x,\theta) \\
s.t. \quad & e(u,q,x,\theta) = 0 \\
& g(u,q,x,\theta) \leq 0 \\
& g_q(y,y^*) \leq 0 \\
& u \in U, q \in Q, x \in X, y \in Y, \theta \in \Theta
\end{aligned} \tag{5.11}
$$

Where f is a scalar function representing the performance measure to be optimised, u, q, x, θ are the vectors of design, control, state variables, and uncertain parameters, respectively;

y is the vector of quality-related variables, having desired values y^*, while e represent the model equations, g_q the quality constraints and g other constraints.

According to the literature [116, 312], there are basically three methods to protect a system against uncertainty, namely a) reducing and controlling input variability; b) active protection by making the system flexible. i.e. able to adapt to changing conditions [148]; c) passive protection so that the system is able to withstand the influence of uncertainty. This, in turn, may be pursued by resorting to two opposite approaches, namely c1) including reserves and redundancy in system design (i.e. oversizing or designing for the worst case), e.g., as a cushion to buffer variability, or c2) building robustness in the system as means of reducing the propagation of uncertainty from input to the output. Robustness criteria can be incorporated into the design problem by penalising the output, including a quality cost term [341] based on the offset between the expected value and the nominal one and the variability around the expected value. This can be made, for instance, through penalty functions, such as Taguchi's loss functions (which typically account for nominal-the-best, larger-the-better and smaller-the-better conditions), or by imposing explicit restrictions over robustness metrics of quality-related variables such as their variance or other moments [311, 342]. Robust optimisation problems are reviewed, for instance, by Bertsimas et al. [343], Gorissen et al. [344], Dellino et al. [345] and Beyer and Sendhoff [307]. At the same time, advances in sensitivity analysis are resumed by Borgonovo and Plischke [88].

In the case of heat exchangers, solution a) is often unfeasible. Indeed, although many industrial processes are designed to operate in steady-state conditions, many other processes instead work in intrinsically unsteady conditions owing to periodic or batch operations. Moreover, even processes designed to operate under steady-state conditions are subject to random perturbations or occasional changes in production rates. Therefore, they need to be associated with a control system able to regulate process parameters, limiting their excursion to respect target values. Furthermore, auxiliary plants, such as heat recovery systems, are often associated or slaved to process plants, but are not strictly regulated as this could interfere with the operations of the main process. Therefore, it is frequent that such heat recovery systems, utilising heat exchangers as the means of energy transfer, are fed by sources with a time-varying energy content. Moreover, fluid composition and physical properties are subject to changes during operation, which are difficult to estimate. From the design point of view, equipment designers use empirical correlations to estimate heat transfer and pressure drop coefficients, or fouling rates, which have an intrinsic uncertainty range (often up to ±15% error range), while the designer may not oversee fabrication to ensure that built equipment is consistent with specifications and complies with stated tolerances. Finally, the time trend of equipment degradation during operation, i.e. accumulation of fouling deposits which affect fluid dynamics and heat transfer, is difficult to estimate and influenced by external events such as the timing of maintenance cycles.

Moreover, the performance variations of a heat exchanger when the values of inlet process variables change are not always intuitive. For instance, let us assume that the mass flow of the hot fluid increases, whereas, for the sake of simplicity, the cold fluid has constant mass flow and inlet temperature. In this case, being fixed the equipment architecture, the hot fluid heat transfer increases but, at the same time, the thermal power to be removed increases too. If the hot fluid were the controlling one, the former statement would suggest that the hot stream output temperature will decrease and the latter that it will increase. The coexistence of the two phenomena, with their own influence and magnitude, may determine a non-linear trend in the output of the heat exchanger. Overall, the possible non-linear response of the equipment makes it strongly susceptible to uncertainty in process conditions as far as performance estimation is concerned, and small simultaneous variations of process variables may have a relevant amplification effect. This, apart from making the behaviour of the equipment not readily intuitive, may prevent it from meeting design and operational specifications.

As far as strategy b) is concerned, it is not feasible to build heat exchangers with a modular or changeable structure in order to gain operational flexibility. Therefore, the active uncertainty protection frequently adopted is regulation through the installation of a control system [346, 347]. However, while this represents an added cost and increased system complexity, the range of allowed stream regulation may be somewhat limited.

For instance, considering that the transferred heat may be expressed as $Q \sim S\ U\ LMTD$, the most frequently applied regulation strategies try to modify the effective log-mean temperature difference $LMTD$ by acting on the flow rate of the controlling stream or modifying the overall heat transfer coefficient U by acting on the flow rate of the controlled stream. Another option is to bypass a portion of the controlled stream flow rate and let it mix downstream the exchanger with the remaining portion of the stream that has passed through the equipment. In the case that the controlling stream is a condensing fluid, a fourth control method would be to allow partial condensation on the tube bank in order to modify surface area S.

In greater detail, when a service fluid is available, and the heat exchange is between a process and that service fluid, without phase change, three main regulation strategies are possible. However, it must be pointed out that only one of the two outlet temperatures may be controlled. In fact, once the inlet and outlet temperatures and mass flow of one fluid are assigned, the heat exchanger duty is determined.

Let be t_{PI} and t_{PO} the process fluid inlet and outlet temperature, respectively, t_{SI} and t_{SO} the service fluid inlet and outlet temperature, respectively, and m_P and m_S the corresponding mass flows, being t_{PO} the process variable to be controlled. A first control strategy (Figure 5.5) is to measure the process fluid outlet temperature by a temperature indicator (TI) and adjust its value by acting on a valve able to manipulate the mass flow of the service fluid.

Modifying m_S, the service fluid convective coefficient and the outlet service fluid temperature change, determining new values for the driving forces and t_{PO}. Even if the control scheme shown in Figure 5.5 is frequent, when the service fluid convective coefficient is not the controlling one, the change in the overall heat transfer coefficient is very small and the regulation may be non-effective.

A possible alternative is the regulation scheme shown in Figure 5.6, where the measurement of the controlled variable determines a modification of the process fluid's mass flow rate. In this case, if an excessively high value of t_{PO} is measured, the control valve is opened. Consequently, a bigger m_P flows through the equipment, and the output temperature reduction is obtained as a net result of the (possible) increment of the overall heat transfer coefficient and the reduced heat amount transferred to the unit of mass flowing. Generally, the output temperature change per unit change of mass flow is small and may be non-linear.

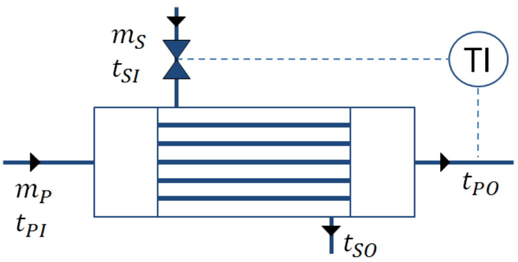

Figure 5.5 Regulation on service fluid mass flow

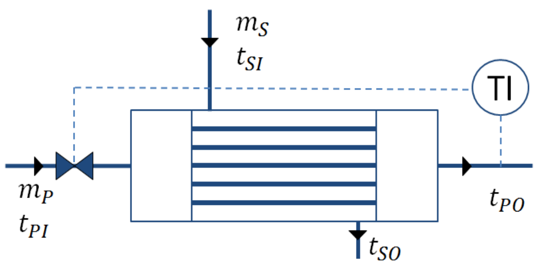

Figure 5.6 Regulation on process fluid mass flow

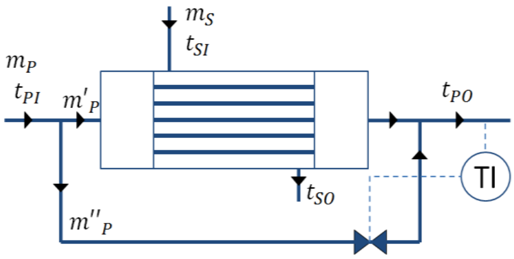

Figure 5.7 By-pass control scheme

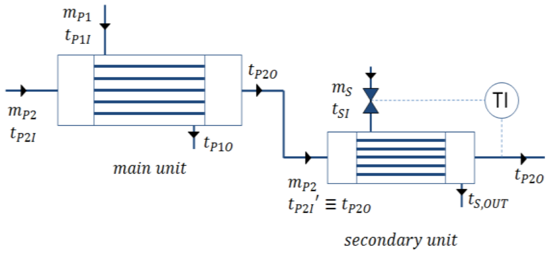

Figure 5.8 Regulation scheme for process/process heat exchangers

The third control strategy is depicted in Figure 5.7, where the heat exchanger is overdesigned. At the exit of the equipment, the process flow temperature is higher (if the unit has to warm up the process fluid) or lower (if the unit must reduce the temperature of the process fluid) with respect to the specified value. The prescribed value of t_{PO} is then achieved by blending the main stream passing through the heat exchanger and a bypass stream of the same process fluid.

A different scenario is also possible when the heat exchange is between two process fluids for energy-saving purposes. Namely, the first fluid has a mass flow rate m_{p1} and the second one m_{p2}, while the inlet temperatures are t_{P1I} and t_{P2I}, respectively (see Figure 5.8).

In this case, both outlet temperatures are relevant, and the action on only one of the two mass flows is not always possible. This is why the system is sometimes made by two or more heat exchangers in series. The first one is the main unit and couples the two process steams obtaining output temperatures which are different from the respective specified values. Secondary units are arranged in series to the main unit in order to reach the specified output temperature by resorting to a service stream. In the simple scheme of Figure 5.8, the main unit is actually without any control system, and the temperature of the mass flow rate m_{P2} is tuned by resorting to the secondary unit.

As a concluding remark, the actual variations of operating conditions cannot be neglected when designing a heat exchanger expected to operate in non-stationary conditions, irrespective of the installation of a process control system.

As far as solution c) is concerned, alternative c1) is most often practised either by directly increasing the surface area or, indirectly, by increasing the design fouling factors or lowering the adopted heat transfer coefficients. Nevertheless, alternative c2), i.e. designing a robust exchanger which can accommodate changes in input streams and uncertainty in internal parameters without excessively penalising the output performance, would be an attractive solution and possibly superior to the alternative of using extra surface area and allowing for extra pressure loss.

Based on the above discussion, it can be stated that the utilized methods for heat exchanger design under uncertainty either fall into one of the following categories.

Method 1) Neglect uncertainty. The exchanger is designed for nominal conditions, and uncertainty is neglected. In this case, Polley and Pugh [348] suggest sizing the equipment according to nominal operating conditions, i.e. referring to a nominal "design point" and then evaluating the responses of the exchanger to changed conditions. In case the obtained performances fall outside an accepted interval, the "design point" is changed in order to obtain an alternative equipment configuration. However, one problem of a design based on average values of input conditions derives from the consideration that excursions of input process parameters above and below the nominal value will not be compensated, as the same percentage changes of opposite sign in input variables are likely to determine output effects having different magnitude owing to the possible nonlinear behaviour of the equipment. The basic conceptual flaw inherent in designing for average input values is a well-known example of the so-called Jensen's Law [349], also known as the "Flaw of Averages", which, roughly speaking, states that exceptions made for linear functions, the average of all the possible outcomes associated with uncertain parameters is generally not equal to the value obtained from using the average value of the parameters" [105]. Finally, it should also be noted that the economic effect of unmet specification in the value of a controlled process parameter may be quite different in case the specification is not met in excess or in defect of the nominal desired value. Furthermore, if changes in input parameters above and below their respective average value do not have the same probability of occurrence their impact can be even stronger. For instance, in a heat recovery contexts a heat recovery amount higher than the nominal value could be useless, while one lower than the nominal value would shut down the process or require an auxiliary heating. Imagine, for instance, the case where a hot stream should be cooled at least to a threshold temperature level T_{th}. Then, exceeding the threshold (i.e. having an output temperature $T < T_{th}$) does not have a significant economic benefit, while not meeting the target cooling level (i.e. having $T > T_{th}$) might imply additional cooling expenses. This means that deviations of the same magnitude but of a different sign with respect to the average may have different economic values, so the economic effects do not compensate by designing the equipment according to average process values.

Method 2) Design for worst case. It is a classic example of "overdesign", where the reference design point is chosen assuming the (most credible) worst conditions likely to be expected. When average operating conditions instead of extreme ones are experienced most of the time, this design may prove to be uneconomical and unsatisfying from the thermal performance point of view. It is important to highlight that the worst-case definition is not straightforward when several physical quantities are involved and interdependent. For example, the growth of process fluid's mass flow rate increases the quantity of heat to be transferred but, at the same time, increases the velocity of the fluid and, consequently, the heat transfer coefficient. Therefore, the worst-case definition is difficult under uncertainty.

Method 3) Accommodate uncertainty through the use of design margins. This alternative overdesign method implies designing for the nominal design point but adding some "design margin", i.e., the addition of extra surface area [348]. A proper way of adopting a safety margin is to obtain the probability density function of the heat transfer area required to meet specifications under the various operating conditions, often assumed to be Gaussian, and then specify the oversizing level in terms of multiples of the standard deviation in order to obtain a prescribed probability of satisfying the specifications [308, 309]. Nevertheless, in practice, this merely means that the heat exchange area computed for nominal design conditions, neglecting uncertainties, is multiplied by a safety factor (from 15% to 100%) chosen relying on the designer's experience ([306], page 193). This is rather equivalent to design for worst-case conditions, but it may have strong drawbacks from the financial and operational point of view. For instance, in the words of Polley and Pugh [348], "It can give rise to control problems. It can give rise to operability problems. It can promote fouling. It can result in under-performance of heat exchanger networks."

Method 4) Design to optimise a prescribed performance measure. In this method, the output variability is accepted, but the equipment is designed in order that, considering the actual performances resulting from off-design operation, a specific goal is met. This, in general, is obtained by optimising an assigned objective function (i.e. the net economic value including capital and operating costs, the value of economic performance *EP* of exchanged or recovered energy and possibly penalties for not meeting specifications).

For instance, such an objective function (OF, €/yr) could be expressed as the net economic result.

$$OF = \pm C_I \tau \pm \sum_{j=1}^{N} P_j C_{en} H p_j \pm C_{pe} \pm \sum_{j=1}^{N} C_{TE}\left(t_{jo}\right) \Delta T_j m_j C_p H p_j \tag{5.12}$$

Where the signs of the various terms depend on whether a minimisation or maximisation of OF is sought and whether the economic value of exchanged heat, represented by the latter term at the right-hand member, is revenue or an operating cost. In the above equation, C_I is the capital investment, τ the capital recovery factor, j $\in$ (1 to N) the index representing the j-th operating condition, C_{en} (€/kWh) is the electric energy unit cost, P_j is the required fluid pumping power in the j-th operating condition, H the yearly operating hours, p_j the probability of the j-th operating condition, C_{pe} a penalty value in case any of the design constraints is violated, $C_{TE}(t_{jo})$ a user-defined function specifying the unit value of exchanged energy (€/kJ) as a function of the actual outlet temperature t_{jo} of the reference stream in the j-th operating state, ΔT_j the difference between t_{jo} and the desired goal temperature for the reference outlet stream in the j-th operating state, m_j the mass flow rate of the reference stream in the j-th operating state, C_p the constant pressure specific heat of the stream.

Adopting this approach, Caputo et al. [335, 336] optimised shell and tube exchangers' design by considering both deterministic and random changes in the input streams' conditions (flow rate and temperature) and uncertainties in the overall heat transfer coefficient. In both papers, a GA optimisation algorithm used previously for optimal design in deterministic conditions [192] and to include fouling effects [197] was utilized. This approach proved to be superior to Methods 1, 2, and 3.

Method 5) Design for robustness. This means designing an exchanger with the explicit goal of minimising the variability of the actual output with respect to a reference nominal output when factoring in changes in the input streams' process conditions and/or internal parameters' variations. The first general mathematical formulation of robust design was done by Taguchi, introducing a quadratic loss function, giving a quantitative interpretation of the quality cost. Firstly, he remarked on the importance of the type of specification (bilateral or unilateral) and then gave three different formulations for the computation of the expected quality loss: nominal is better, more is better, and less is better. While the first considers both the standard deviation and the mean of the quantity of interest, the remaining two formulations consider only the distances of the mean from the specification.

As mentioned in section 3.1.2, robust design can act on the output performances of interest in three different ways: *a)* reducing the reducible uncertainty, *b)* changing the slope of the transfer function that determines uncertainty propagation from the input to the output and *c)* when the transfer function is non-linear, moving the design point on a flatter portion of the curve (Figure 5.9).

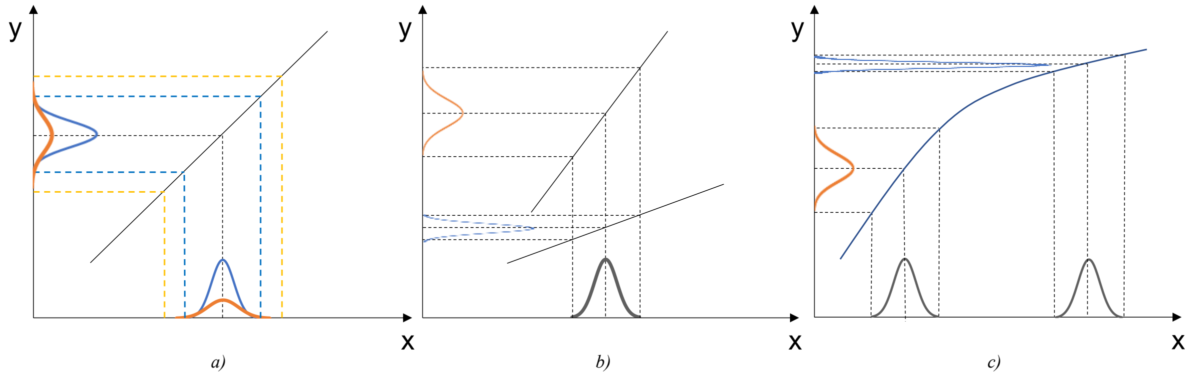

Figure 5.9 Robust design uncertainty mitigation: a) reducible uncertainty reduction, b) slope changing and c) moving on a flatter portion of the curve

For heat exchangers, specifications may be assigned in three different ways.

- A single value of outlet temperature is used when uncertainty is not considered, and the problem is formulated in a deterministic manner. In this case, uncertainty is not allowed.
- More/less is better, meaning that the specification is achieved if the outlet temperature is at least equal to a defined value, and the lower (or higher) the best. The uncertainty may be considered;
- Nominal is better, meaning that the specification is met when the outlet temperature falls in a specified range around a defined value, and the closer the value is to the target, the better. The uncertainty may be considered.

In robust design literature, the design problem is thus formulated as expressed in section 3.1.2 [106, 350, 351].

A different formulation which assigns different weights to minimising the mean and the standard deviation in the objective function is also proposed by Doltsinis et al. [350] (equation 5.13).

$$
\begin{array}{lll}
\text{find} & x & \\
\text{minimising} & f = (1-\alpha)E(f(x,y))/\bar{x} + \alpha\sigma(f(x,y))/\sigma^{*} & \\
\text{subject to} & E\big(g_i(x,y)\big) + \beta_i\sigma\big(g_i(x,y)\big) \leq 0 & (\text{i}=1,2,\ldots,\text{k}) \\
 & \sigma\left(c_j(x,y)\right) \leq \sigma^{+}{}_{j} & (\text{j}=1,2,\ldots,\text{l}) \\
 & x^{-}{}_{a} \leq x_a \leq x^{+}{}_{a} & (\text{a}=1,2,\ldots,\text{n}) \\
 & 0 \leq \alpha \leq 1 &
\end{array}
\qquad (5.13)
$$

E(f), that is, the expected value of the performance function, and its standard deviation *σ(f)* are both minimised. β_i is a flexibility index for the i-th constraint that represents the maximum acceptable probability of not satisfying the i-th constraint, and c_j is the structural performances function that imposes an upper limit on standard deviation at $\sigma^{+}{}_{j}$.

However, no research explicitly focused on a formally robust exchanger seems to be available.

5.3 Framework application for optimising STHEs

This section provides the application of the framework presented in Chapter 4 to the case of shell and tube heat exchanger design under uncertainty. The framework application is made to answer the following research questions: should uncertainty always be considered when designing heat exchangers, or can it be neglected? Are the available approaches for designing shell and tube heat exchangers effective when uncertainty is not included still effective when considered? Which is the preferred method to be applied in specific problem instances?

The application procedure involves the following steps.

- Uncertainty sources identification.
- Uncertainty sources modelling.
- Performance measure selection.
- Design routine selection.

- Independent Design Variable identification.
- Uncertainty propagation method selection.
- Optimisation method selection.
- Objective function formulation.

Figure 5.10 shows the application results, in which the unused blocks have been blackened.

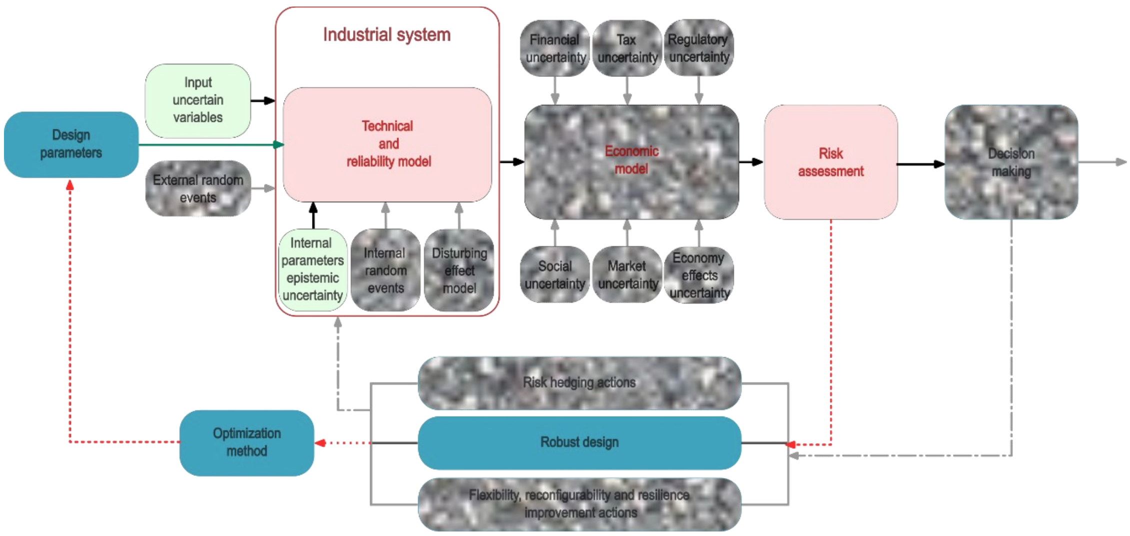

Figure 5.10 General framework applied to the STHE optimisation with blackened unused blocks

The aleatory uncertainty is considered by including the variability of the input streams' conditions. Indeed, the variability of temperatures and mass flow rates of both cold and hot fluids are considered. The epistemic uncertainty is included by considering the uncertainty in the correlations used to assess the heat transfer coefficients and the fouling resistances. Additionally, the failures may be included by considering the clogging of tubes by fouling.

The modelling of aleatory uncertainty is performed by resorting to probability theory. The fluids' inlet mass flow rates and temperatures are represented by normal probability density functions centred on their nominal values. Then, the probability distributions are discretised in several equally spaced samples.

The modelling of epistemic uncertainty is made using probability theory, too. Indeed, a uniform probability density function is defined for each epistemic uncertain internal parameter. These distributions are built around the assessed nominal value of each parameter and then discretised in several equally spaced intervals.

The performance measure choice is a challenging task, as amply discussed in section 5.1. However, since the goal of heat exchangers is to transfer heat, and a deliverable is to preserve cost-effectiveness, the equipment is evaluated on the probability of satisfying the specification and expected total cost. The former is achieved by comparing the probability density function of the outlet temperatures with the specification. In contrast, the latter is calculated by resorting to Hall's correlation, in which the required pumping power is computed using the expected pressure drop of the designed equipment.

The system model, which includes the design routine and the evaluation model, comprises Kern's design routine for achieving the architecture of the STHE and the ε-NTU for evaluating the outlet temperatures. Kern's design routine calculates the dependent design variable starting from the independent ones.

The independent design variables are selected according to the design procedure used. They are the shell diameter, the baffle spacing, the outlet tubes' diameter, the number of tube passages, the selection of the fluid that flows through tubes, the pattern of tubes and a fictitious value for reference process condition to be used for design purposes, that are, cold mass flow rate, inlet hot fluid temperature, inlet cold fluid temperature.

The uncertainty is propagated through the model resorting to the design of experiments. A full factorial experiment is performed by permutating all the values of all uncertain variables and parameters obtained by their distributions' discretisation. Additionally, the uncertainty is also propagated in the designed equipment by using the Taylor expansion formula for the moments of functions of random variables.

The optimisation process is made using the genetic algorithm, a meta-heuristic algorithm widely adopted in the literature for STHE optimisation purposes. At each iteration, the algorithm changes the values of the independent design variables, the design routine computes the dependent design variables, and the evaluation procedure assesses the performance of the current design through the fitness function calculation. It stops when the number of maximum iterations is reached or when convergence in a local minimum is found, that is, when, for a number of iterations, the value of the fitness function does not change.

Several objective functions, also called fitness functions, are suitable for this optimisation process. For that reason, two of them are chosen. The former concerns the probability of satisfying the specification in the three most common cases, that are, nominal is better, more is better, and less is better. The latter is a function for robust design and optimises simultaneously the difference between the mean of outlet temperature and its specification and its standard deviation.

Figure 5.11 shows the yet-described framework more concisely. The framework is used to evaluate or optimise the design. While the former task is addressed, the feedback optimisation arc does not work. The evaluation is used to assess the performance of the different design methods exposed in the previous section and to compare them with the ones obtained using this framework for optimisation purposes, too.

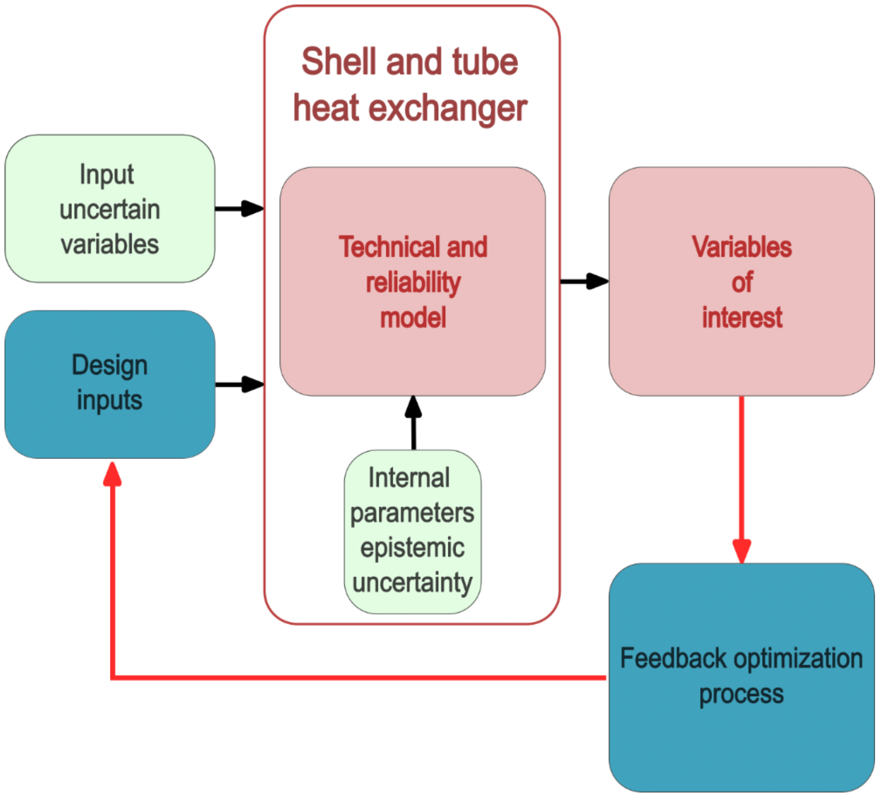

Figure 5.11 Framework for STHE optimisation under uncertainty

5.3.1 Assessing the performance of different design methods for STHEs under uncertainty: a case study

In order to answer the research questions introduced in the introduction and to show the capabilities of the framework, a comparison in a consistent manner of the above five design methods will be made using a common case study. Methods 1, 2, and 3 are surely effective when uncertainty is not propagated in the obtained design, but are they yet when this is done?

Therefore, two different problem instances will be considered to focus on both random and epistemic uncertainty. Case study 1 will examine the circumstance where uncertainty exists in the input streams' conditions (i.e. external random variability). In contrast, Case 2 will examine the impact of uncertainties in the design correlations (i.e. internal epistemic uncertainty).

In Case 1, the author assumes that a countercurrent heat exchanger has to be designed to cool a process fluid and that the nominal flow rates, temperatures and thermophysical properties of both fluids are shown in Table 5.8.

Table 5.8 Nominal conditions and thermophysical properties of the two fluids for Case 1

Fluid	m (kg/s)	t_i (°C)	t_o (°C)	ρ (kg/m^3)	Cp (kJ/kg K)	μ (Pa s)	λ (W/m K)	Rf (m^2 K/W)
methanol	25	95	40	750	2.84	0.00034	0.19	0.0002
seawater	74.38	27.5	40	995	4.2	0.0008	0.59	0.00033

As explained in the previous section, here, the author will only consider the thermal performance as objective, while economic evaluation will be used only to compare the obtained alternative design solutions.

For the sake of cost comparison, the total discounted heat exchanger cost is computed as the sum of investment cost (equation 5.14) and the present worth of pumping cost (*DOC*, equation 5.15). Economic values and parameters for the case studies are shown in Table 5.9. For symbols' meanings, please refer to the nomenclature of this section in the List of Symbols section at the end of the thesis.

$$IC = a_1 + a_2 S^{a3} \tag{5.14}$$

$$DOC = \sum_{n=1}^{Ny} \frac{\left[\left(\frac{1}{\eta}\right) \cdot \frac{\left(\frac{m_T}{\rho_T}\right) \cdot \Delta P_T + \left(\frac{m_S}{\rho_S}\right) \cdot \Delta P_T}{1000}\right] \cdot Cen \cdot H}{(1+I)^n} \tag{5.15}$$

Table 5.9: Parameters used to assess the investment and operating costs

a_1 (€)	a_2 (€/$m^{2 \cdot a_3}$)	a_3	η	H (h/yr)	I (%/yr)	Ny (yr)	Cen (€/kWh)
8000	259.2	0.91	0.7	7000	10	10	0.12

In order to evaluate the impact of aleatory uncertainty on equipment design, both *more is better* (MisB) and *nominal is better* (NisB) specifications are compared. Aleatory uncertainty of inputs has been modelled in the way shown in Table 5.10, assuming that all variables have a normal probability density distribution.

Table 5.10 Probability distributions of flow rates and temperatures of inlet fluids

	t_{hi} (°C)	m_h (kg/s)	t_{ci} (°C)	m_c(kg/s)
E[x]	95	25	27.5	75
σ	2.14	0.83	1.25	0.83
CV	0.02	0.03	0.05	0.01

Where the operator *E[x]* is the expected value of each *x-th* process parameter labelled in the columns, σ is the standard deviation, and $CV = \sigma/E[x]$ is the coefficient of variation.

The design campaign has been carried out as follows.

1. *Nominal design* is done by mimicking the traditional design process by manually changing the following design variables: outer diameter of tubes, fluids side pass, shell diameter, baffle spacing, number of tube side passes and tube pattern, until all constraints are satisfied and suitable cost reduction is obtained.
2. *Worst-case design* scenario is carried out considering the lowest logarithmic mean temperature difference and the higher value of duty.
3. *Safety factor design* is carried out considering a safety factor with a value of 1.5. The value has been chosen to reach a probability approximately 100% of meeting specification for more is better design. However, in the following, even the values of 1.25 and 1.75 will be considered in order to perform a sensitivity analysis.
The effect of safety factor use is an increase in the exchanger's length and, consequently, in the heat exchange surface.
4. *Objective function optimised design*. In this case, two alternatives are considered depending on NisB or MisB specifications. For the NisB case, the objective function *OF* is to maximise the probability of obtaining a temperature in a range of ±2 °C across the specification (equation 5.16). For the MisB case, the adopted objective function is to

maximise the probability of having an exit temperature lower than the specification (equation 5.17).

$$OF = \max \ \mathrm{P}\left[(t_o - 2) < Tout_i < (t_o + 2)\right] \tag{5.16}$$

$$OF = \max \ \mathrm{P}\left[Tout_i < t_o\right] \tag{5.17}$$

Where *P[..]* is the probability of obtaining the wanted result, $Tout_i$ is the actual outlet temperature when scenario i is under analysis, and t_o is the specification.

5. Robust design. Regardless of traditional formulations of robust design, which usually include the average and standard deviation of the performance measure in the objective, here the objective is pursued by minimising the expression in equation 5.18, i.e. centring the outlet temperatures distribution on the specification and reducing its standard deviation. Moreover, although the usual formulation for robust design resorts to economic penalties to asses a solution, here, no economic penalty is included in the objective function to guarantee more consistency with the other design methods. In fact, here, the author is more interested in minimising the distance from the specification regardless of the economic consequence of an unmet specification.

The proposed objective function (*OBJ*) simultaneously minimises the difference between the mean of outlet temperature and the specification and its standard deviation.

$$OBJ = \min \sqrt{\sum_{i=1}^{ns} (Tout_i - t_o)^2 \cdot p_i} \tag{5.18}$$

Where ns is the number of considered scenarios, and p_i is the probability of the *i-th* scenario.

This novel formulation differs from the traditional Taguchi formulation, which separately minimises deviation and standard deviation by resorting to penalty cost factors. Compared to other objective functions found in the literature, the rather simple structure of the chosen function is justified by considering that the goal of this design approach is to reduce uncertainty propagation, which merely implies minimising output variability in the face of input variability.

In order to globally evaluate the behaviour of obtained designs, each configuration has been assessed in a set of possible operating conditions, including all possible permutations of discretized probability density functions of each aleatory process quantity (m_h, t_{hi}, m_c, t_{ci}). In order to build the design scenarios, a six-sigma truncated Gaussian distribution is used, and five equally spaced samples are taken, thus generating 625 combinations. The pdf of the mass flow rates is included to correctly size the pumping system and avoid excessive pressure drops.

It should be noted that design Methods 1), 2), and 3) do not utilize any optimisation procedure. Therefore, obtained solutions are not necessarily the best, while Methods 4) and 5) seek optimisation of the above-stated objective functions.

The adopted optimal design procedure for Methods 4) and 5), based on a GA, is shown in Figure 5.12.

The procedure starts with specification definition (outlet temperature of one of the two fluids) and data collection (fluids' chemical composition, computation of thermophysical properties μ, λ, ρ, *Cp* at mean temperature, *Rf*, *HE type* – fixed tube sheet, U-tube, split ring floating head and others - and choice of probability density function for process variables m_c, m_h, t_{ci} and t_{hi}). The second step of the adopted procedure builds scenarios containing expected operating conditions. Each scenario is obtained by permuting discretized pdf, previously identified. The next step is managed by an optimisation algorithm (GA), which selects initial values of Independent Design Variables (IDV, namely D_s, B, *do*, N_{tp}, *Tube side* (fluid that flows through tubes), *Pattern* and a fictitious value for reference process condition to be used for design purposes m_c, t_{hi}, t_{ci}). Such values are supplied to a design routine using Kern relations [305] to determine Dependent Design Variables (DDV, namely fictitious m_h and Q, v_s, v_t, h_S, h_T, U_{dirt}, d_i, *Pt*, *Cl*, N_{tt}, L_{tt}, *S*). "Fictitious" means that values of temperatures and mass flow rates selected by GA are used for design purposes but do not correspond to nominal values of process parameters. The use of a fictitious design point is required because it is not assured, given the variability of actual streams' conditions and Jensen's inequality, that designing the equipment with a deterministic algorithm (Kern method) for the nominal design point delivers an equipment configuration which optimises the selected objective function [335]. In fact, Jensen's inequality suggests that mean values of temperatures and mass flow rates are not always the best choice for equipment design. The use of a GA assigning fictitious values to the input process conditions, to be used as the reference nominal operating point for design purposes, frees the designer from assuming an average design point or choosing an arbitrary design point in case of process conditions variability.

The obtained equipment configuration is evaluated in the Performance Evaluation step over the entire range of actual operating conditions described by the assumed scenarios, determining the expected value of pressure drop *E[ΔP]*, operating cost *E[OC]* and discounted operating cost *E[DOC]*, expected total cost *E[TC]* and fluids outlet temperatures' probability density functions. Based on the obtained equipment configuration and the scenario values of the input process variables, the corresponding output temperature values are computed by resorting to the ε-NTU method.

During Constraint Violation Analysis, a penalty cost is considered if some constraint is violated (e.g. use of a correlation out of its validity range), rejecting unsuitable equipment. Each feasible design found is saved. GA acts iteratively by modifying IDV and supplying them to the design routine, looking for alternative designs. The adopted optimisation tool, provided by Matlab, uses traditional genetic algorithm tools – elite count, crossover, mutation and migration. The procedure stops when the best current value is maintained for a defined number of iterations or when a maximum number of runs is reached.

No explicit validation of the design procedure and obtained results is provided, given that the adopted method iteratively utilizes an established and well-proven design algorithm from the literature (Kern and efficiency method). The numerical implementation was validated in previous works of the same author utilizing the same code. The optimisation algorithm was taken from the widely utilized MATLAB library.

For each solution, the expected values of outlet temperatures are computed by resorting to ε-NTU method across all scenarios. Possible constraint violation is checked before comparing a solution with others found by GA. Solutions not respecting constraints are disregarded. The constraints are the maximum allowed pressure drop of 70 kPa for both shell and tube sides, Reynolds number > 300 shell side or 10.000 tube side, and tube length to shell diameter ratio in the range 3 to 15. The Reynolds number is computed according to Kern's method [305] using the equivalent hydraulic diameter corresponding to the adopted tubes' pattern and the flow velocity evaluated referring to the shell free pass area along the diametral plane.

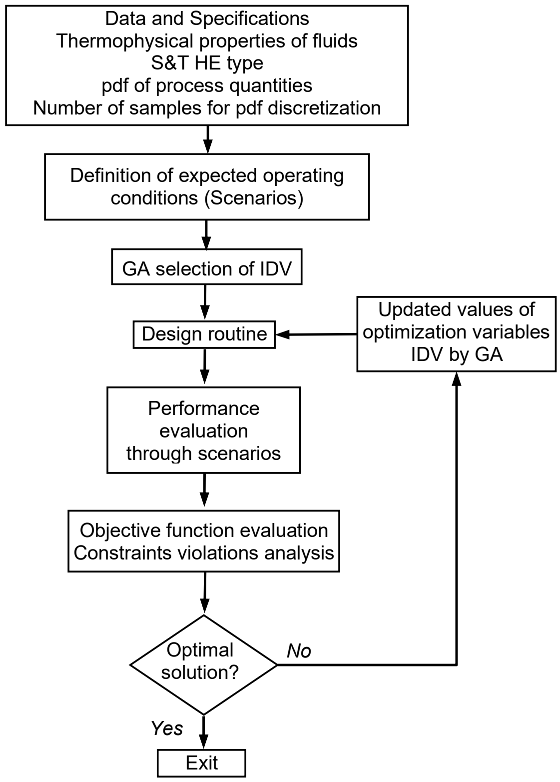

Figure 5.12 Optimised design procedure considering operating variable conditions

In Case 2, the influence of epistemic uncertainty on the performance of the equipment is instead investigated. Input variables are fixed at their nominal values while the uncertainty of heat transfer coefficients correlations and fouling resistances' values are accounted for. In particular, nominal values of heat transfer coefficients are computed with deterministic correlations (equations 5.19, 5.20) [305], whereas fouling resistances by resorting to commonly used values [305].

$$h_S = 0.36(\lambda_S/D_e)({Re_S}^{0.55}{Pr_S}^{1/3})(\mu_S/\mu_{wS})^{0.14} \tag{5.19}$$

$$h_T = 0.027(\lambda_T/d_i)({Re_T}^{0.8}{Pr_T}^{1/3})(\mu_T/\mu_{wT})^{0.14} \tag{5.20}$$

Then, to model epistemic uncertainty and to evaluate the effect of low and high levels of uncertainty, their actual values are changed in the range ±20% and ±40% of the respective nominal value, assuming a uniform distribution. For each variable, the range is divided into eight equally spaced intervals. All the 4096 admissible permutations are considered.

5.3.2 Results discussion

Comparison of design solutions under Aleatory Uncertainty

Design results for the NisB (Case 1A) and MisB (Case 1B) for each of the five design methods are shown in Table 5.11 and Table 5.12. Please note that in the Tables, results related to Methods 1,2, 3 and 5 are the same for both NisB and MisB cases because the procedure is unchanged, and the only difference is in the probability of meeting the specification. Results for Method 4 instead are different due to the change in the objective function. Relevant geometric characteristics and outputs of interest are printed in bold typeface.

Table 5.11 Different designs obtained by different design modes and performance evaluations for nominal is better specification

Name	***[-]***	***Case 1A***				
Design type	[-]	Nominal	Worst Case	Safety factor	Objective function	Robust design
t_{hi}	[°C]	95.0	101.4	95.0	96.3	94.6
t_{ho}	[°C]	40.0	40.0	40.0	40.0	40.0
m_h	[kg/s]	25.0	27.5	25.0	25.9	27.3
t_{ci}	[°C]	27.5	31.3	27.5	25.9	25.2
t_{co}	[°C]	40.0	40.0	40.0	40.0	40.0
m_c	[kg/s]	74.4	130.6	74.4	70.1	68.1
Q	[kW]	3905	4798	3905	4136	4222
LMTD	[°C]	28.7	27.0	28.7	30.4	30.4
F	[-]	0.81	0.82	0.81	0.81	0.81
HE type	[-]	SRFH	SRFH	SRFH	SRFH	SRFH
Tube Side	**[-]**	**Cold fluid**	**Cold fluid**	**Cold fluid**	**Hot fluid**	**Hot fluid**
$\boldsymbol{D_s}$	**[m]**	**0.9**	**1.0**	**0.9**	**1.0**	**1.0**
B	**[m]**	**0.4**	**0.3**	**0.4**	**0.8**	**0.5**
do	**[m]**	**0.02**	**0.02**	**0.02**	**0.0318**	**0.04**
$\boldsymbol{N_{tp}}$	**[-]**	**2**	**2**	**2**	**4**	**4**
N_{tt}	[-]	918	1191	918	345	258
$\boldsymbol{L_{tt}}$	**[m]**	**4.2**	**4.0**	**6.4**	**8.1**	**8.7**
v_s	[m/s]	0.52	0.53	0.52	0.42	0.72
v_t	[m/s]	0.81	1.10	0.81	0.79	0.70
Re_S	[-]	16701	17200	16701	16391	25956
Pr_S	[-]	5.1	5.1	5.1	5.7	5.7
Re_T	[-]	16109	21813	16109	44163	49453
Pr_T	[-]	5.7	5.7	5.7	5.1	5.1
h_S	[W/m^2 K]	1709	1737	1709	2507	3513

h_T	[W/m^2 K]	4126	5259	4126	1803	1569
U_{dirt}	**[W/m^2 K]**	**684**	**720**	**684**	**598**	**602**
S	**[m^2]**	**244**	**299**	**367**	**279**	**284**
L/D	[-]	4.74	4.00	7.10	7.94	8.36
ΔP_T	[Pa]	25331	29610	37996	9371	56752
ΔP_S	[Pa]	7373.7	12421	9757	10092	7168
OBJ Value	**[°C]**	**1.27**	**2.03**	**3.73**	**1.25**	**1.24**
$E[\Delta P_T]$	[Pa]	7487	4493	9905	9492	6045
$E[\Delta P_S]$	[Pa]	25355	24840	38032	10631	66712
Pattern	[-]	Triang	Triang	Triang	Square	Triang
OBJ Value norm	[-]	3.17%	5.08%	9.33%	3.12%	3.09%
$MAX[\Delta P_T]$	[Pa]	7857	4714	10388	10939	6973
$MAX[\Delta P_S]$	[Pa]	29214	28620	43821	11161	70040
IC	[€]	46618	54459	63851	51590	52213
OC	[€/yr]	1675	2299	2395	1244	5378
E[OC]	[€/yr]	1686	1397	2410	1333	6226
E[DOC]	[€]	10359	8582	14807	8193	38257
DOC	[€]	10290	14124	14717	7646	33043
TC	[€]	56908	68583	78567	59236	85257
E[TC]	[€]	56976	63040	78658	59783	90470
Probability to satisfy the specificication NisB	**[-]**	**89%**	**61%**	**12%**	**90%**	**90%**
σT_{hout}	[°C]	1.27	1.26	1.24	1.25	1.24
$E[T_{hout}]$	**[°C]**	**39.9**	**38.4**	**36.5**	***40.0***	**40.0**
CV	[-]	3.17%	3.27%	3.40%	3.12%	3.09%
OBJ Value norm $E[T_{hout}]$	**[-]**	**3.18%**	**5.29%**	**10.24%**	**3.12%**	**3.09%**

Table 5.12 Different designs obtained by different design modes and performance evaluations for more is better specification

Name	***[-]***	***Case 1B***				
Design type	[-]	Nominal	Worst Case	Safety factor	Objective function	Robust design
t_{hi}	[°C]	95.0	101.4	95.0	101.3	94.6
t_{ho}	[°C]	40.0	40.0	40.0	40.0	40.0
m_h	[kg/s]	25.0	27.5	25.0	27.5	27.3
t_{ci}	[°C]	27.5	31.3	27.5	31.3	25.2
t_{co}	[°C]	40.0	40.0	40.0	40.0	40.0
m_c	[kg/s]	74.4	130.6	74.4	130.4	68.1
Q	[kW]	3905	4798	3905	4791	4222
LMTD	[°C]	28.7	27.0	28.7	27.0	30.4
F	[-]	0.81	0.82	0.81	0.82	0.81
HE type	[-]	SRFH	SRFH	SRFH	SRFH	SRFH

Tube Side	[-]	Cold fluid	Cold fluid	Cold fluid	Hot fluid	Hot fluid
D_s	**[m]**	**0.9**	**1.0**	**0.9**	**0.8**	**1.0**
B	**[m]**	**0.4**	**0.3**	**0.4**	**0.5**	**0.5**
do	**[m]**	**0.02**	**0.02**	**0.02**	**0.0127**	**0.04**
N_{tp}	**[-]**	**2**	**2**	**2**	**6**	**4**
N_{tt}	[-]	918	1191	918	2151	258
L_{tt}	**[m]**	**4.2**	**4.0**	**6.4**	**2.7**	**8.7**
v_s	[m/s]	0.52	0.53	0.52	1.50	0.72
v_t	[m/s]	0.81	1.10	0.81	1.26	0.70
Re_S	[-]	16701	17200	16701	17094	25956
Pr_S	[-]	5.1	5.1	5.1	5.7	5.7
Re_T	[-]	16109	21813	16109	28285	49453
Pr_T	[-]	5.7	5.7	5.7	5.1	5.1
h_S	[W/m^2 K]	1709	1737	1709	8794	3513
h_T	[W/m^2 K]	4126	5259	4126	3161	1569
U_{dirt}	**[W/m^2 K]**	**684**	**720**	**684**	**918**	**602**
S	**[m^2]**	**244**	**299**	**367**	**235**	**284**
L/D	[-]	4.74	4.00	7.10	3.25	8.36
ΔP_T	[Pa]	25331	29610	37996	179170	56752
ΔP_S	[Pa]	7373.7	12421	9757	37451	7168
OBJ Value	**[°C]**	**1.27**	**2.03**	**3.73**	**2.38**	**1.24**
$E[\Delta P_T]$	[Pa]	7487	4493	9905	31427	6045
$E[\Delta P_S]$	[Pa]	25355	24840	38032	64428	66712
Pattern	[-]	Triang	Triang	Triang	Triang	Triang
OBJ Value norm	[-]	3.17%	5.08%	9.33%	5.94%	3.09%
$MAX[\Delta P_T]$	[Pa]	7857	4714	10388	36201	6973
$MAX[\Delta P_S]$	[Pa]	29214	28620	43821	67641	70040
IC	[€]	46618	54459	63851	45236	52213
OC	[€/yr]	1675	2299	2395	17570	5378
E[OC]	[€/yr]	1686	1397	2410	7037	6226
E[DOC]	[€]	10359	8582	14807	43237	38257
DOC	[€]	10290	14124	14717	107962	33043
TC	[€]	56908	68583	78567	153199	85257
E[TC]	[€]	56976	63040	78658	88473	90470
Probability to satisfy the specificication MisB	**[-]**	**53%**	**89%**	**100%**	**95%**	**52%**
σT_{hout}	[°C]	1.27	1.26	1.24	1.24	1.24
$E[T_{hout}]$	**[°C]**	**39.9**	**38.4**	**36.5**	**38.0**	**40.0**
CV	[-]	3.17%	3.27%	3.40%	3.27%	3.09%
OBJ Value norm $E[T_{hout}]$	**[-]**	**3.18%**	**5.29%**	**10.24%**	**6.26%**	**3.09%**

Geometrical differences between the optimised equipment (Methods 4 and 5) and the non-optimised ones reside mainly in the larger length of the firsts and in the number of tube passes, that are doubled. Significant differences in baffle spacing and shell diameter are not detectable. The outer diameter of tubes doubles in Method 5 as compared to the others. The hot fluid pass in the optimised design is tube side. This choice can be explained by the greater simplicity in reaching the goal for the algorithm thanks to the larger number of degrees of freedom offered by passing in the tube side. Being the probability density function of the inlet temperature centred on the specification, the nominal design (Method 1) has high performances, comparable with those of optimised equipment, but this does not happen for worst-case design (Method 2) and safety factor (Method 3) because the higher heat exchange area increases the difference between the expected value of the outlet temperature and the specification. Robust design (Method 5) has the best performance in this case, achieving the lowest standard deviation of the output and the same probability to meet the specification of the Method 4 design. Expected total cost is computed resorting to the probability density function of pumping costs, as affected by the pressure drops and the investment cost, but does not consider any cost or revenue coming from meeting or not the specification. From this point of view, the Robust design is the most expensive while the nominal design is the least expensive, but it is comparable with the optimised design obtained from Method 4.

It can be noticed that in the MisB case, Method 3 (safety factor) performs as well as optimisation Method 4 because it directly acts on the surface area. Conversely, Method 4 indirectly tries to correct the *LMTD* by changing the input reference conditions (i.e. fluid mass flow rates and temperatures) but always within the variability range imposed by the assumed probability distribution functions. This constraint is included to prevent the optimisation algorithm from selecting fictitious conditions leading to excessive pressure drops or oversizing. However, the safety factor method should be used with caution. In fact, while it can ensure total satisfaction of specifications, this may be obtained at the expense of excessive oversizing, whereas other methods can reach a more effective compromise design. For instance, Method 4 reduces by 5% the probability of meeting the specifications but allows a 30% reduction of heat exchange surface, although, in this case study, suffering a pressure drop increase.

The poor performance of robust design in MisB case, similar to Method 1 design, is justified considering that reducing the variability of the output is not the objective of this kind of problem.

In Figure 5.13 and Figure 5.14, the relevant results, namely the probability of satisfying the specification and the obtained value of the objective function (equation 5.18), are shown. The lower the value of the objective function and the higher the probability of meeting the specification, the better the obtained exchanger. A low value of the objective function means outlet temperature distributions with low standard deviation and centred on the specification, while a high probability to meet the specification means the correct sizing of the equipment. The usage of safety factor and of the worst-case scenario is useful when the assigned specification is MisB, but leads to inferior solutions when the problem is NisB as the distribution of the outlet temperature is not centred on the specification. For the perfect centring, the robust design results in the best solution.

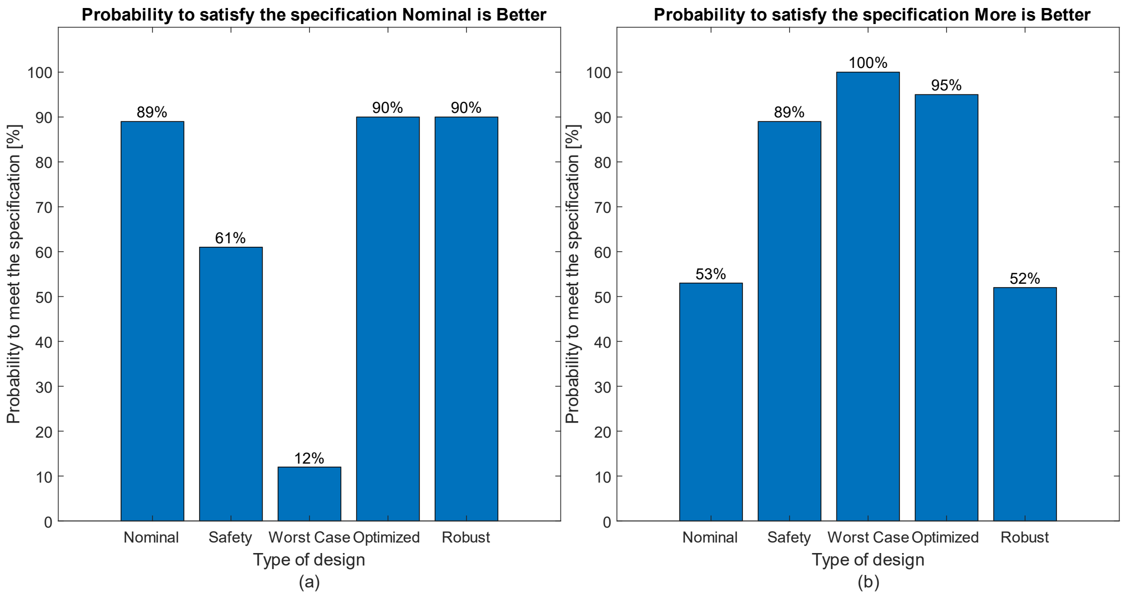

Figure 5.13 Probability to satisfy the specification under NisB (a) and MisB (b) for different design methods

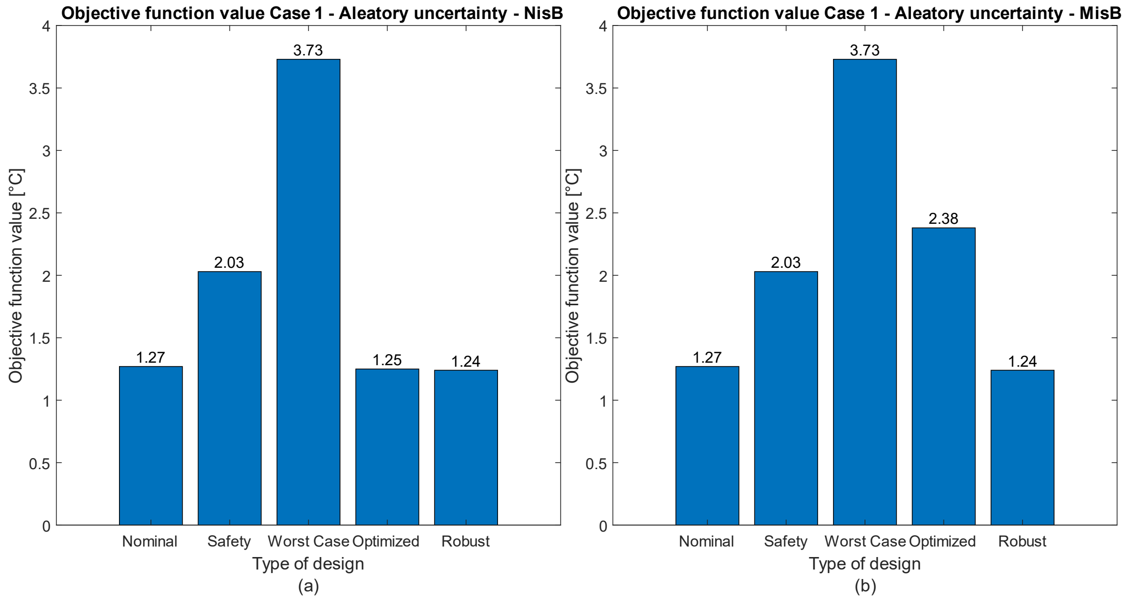

Figure 5.14 Objective function value under NisB (a) and MisB (b) specification fo different design methods

In order to find dominating solutions, it is useful to represent the obtained equipment configurations in terms of total cost and probability to meet the specifications as made in Figure 5.15.

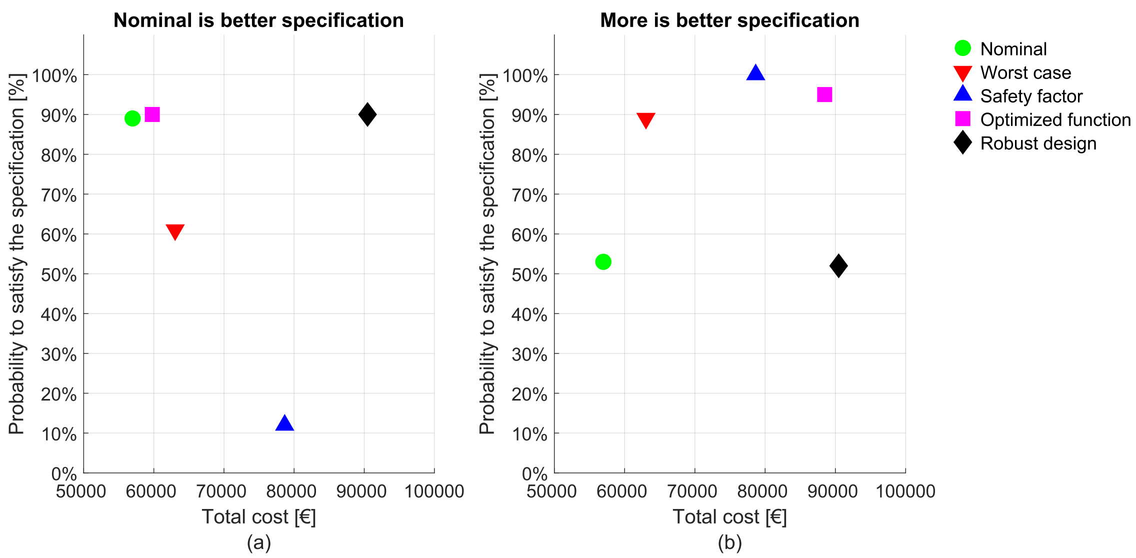

Figure 5.15 Probability to meet the specification and expected total cost of designs in Case 1A (a) and 1B (b)

In the case of NisB specification, and when the standard deviation of the output is neglected, Method 1 provides the lowest cost and a probability of satisfying the specification comparable with the optimised approaches (Methods 4 and 5).

However, it should be borne in mind that the cost shown neglects the economic effect of failing to meet the specification. When such effects are accounted for, on a case-specific basis, the solutions comparison could lead to significantly different results.

Sensitivity analysis on Safety factor effect

To show the impact of the safety factor (SF), three different values, namely 1.25, 1.5, and 1.75, are assumed, and the resulting equipment configurations are shown in Table 5.13, while in Figure 5.16 the comparison of probability to meet the specification NisB and MisB cases and expected total cost of designs obtained with different safety factor values is shown.

Table 5.13 Safety factor selection effect on performances and designs configuration

Name	***[-]***	***Safety factor effect***		
Safety factor value	[-]	1.25	1.5	1.75
t_{hi}	[°C]	95.0	95.0	95.0
t_{ho}	[°C]	40.0	40.0	40.0
m_h	[kg/s]	25.0	25.0	25.0
t_{ci}	[°C]	27.5	27.5	27.5
t_{co}	[°C]	40.0	40.0	40.0
m_c	[kg/s]	74.4	74.4	74.4
Q	[kW]	3905	3905	3905
LMTD	[°C]	28.7	28.7	28.7
F	[-]	0.81	0.81	0.81
HE type	[-]	SRFH	SRFH	SRFH
Tube Side	**[-]**	**Cold fluid**	**Cold fluid**	**Cold fluid**
$\boldsymbol{D_s}$	**[m]**	**0.9**	**0.9**	**0.9**
$\boldsymbol{B}$	**[m]**	**0.4**	**0.4**	**0.4**
do	**[m]**	**0.02**	**0.02**	**0.02**
$\boldsymbol{N_{tp}}$	**[-]**	**2**	**2**	**2**
N_{tt}	[-]	918	918	918
$\boldsymbol{L_{tt}}$	**[m]**	**5.3**	**6.4**	**7.4**
v_s	[m/s]	0.52	0.52	0.52
v_t	[m/s]	0.81	0.81	0.81
Re_S	[-]	16701	16701	16701
Pr_S	[-]	5.1	5.1	5.1
Re_T	[-]	16109	16109	16109
Pr_T	[-]	5.7	5.7	5.7

h_S	[W/m^2 K]	1709	1709	1709
h_T	[W/m^2 K]	4126	4126	4126
U_{dirt}	**[W/m^2 K]**	**684**	**684**	**684**
S	**[m^2]**	**305**	**367**	**428**
L/D	[-]	5.92	7.10	8.29
ΔP_T	[Pa]	31663	37996	44328
ΔP_S	[Pa]	8565	9757	10948
OBJ Value	**[°C]**	**2.62**	**3.73**	**4.36**
$E[\Delta P_T]$	[Pa]	8696	9905	11114
$E[\Delta P_S]$	[Pa]	31694	38032	44371
Pattern	[-]	Triang	Triang	Triang
OBJ Value norm	[-]	6.55%	9.33%	10.91%
DELTA	[-]	-	-	-
$MAX[\Delta P_T]$	[Pa]	9122	10388	11653
$MAX[\Delta P_S]$	[Pa]	36518	43821	51125
IC	[€]	55312	63851	72261
OC	[€/yr]	2035	2395	2755
E[OC]	[€/yr]	2048	2410	2772
E[DOC]	[€]	12583	14807	17032
DOC	[€]	12503	14717	16930
TC	[€]	67815	78567	89191
E[TC]	[€]	67895	78658	89293
Probability to satisfy the specificication MisB	**[-]**	**97%**	**100%**	**100%**
Probability to satisfy the specificication NisB	**[-]**	**40%**	**12%**	**4%**
σT_{hout}	[°C]	1.25	1.24	1.23
$E[T_{hout}]$	**[°C]**	37.7	36.5	35.8
CV	[-]	3.32%	3.40%	3.44%
OBJ Value norm $E[T_{hout}]$	**[-]**	**6.95%**	**10.24%**	**12.18%**

As can be seen in Figure 5.16, in NisB case, it is not useful to adopt the safety factor method because the total cost rises and the probability of meeting specification lowers when the value of SF increases. This happens because in Method 3, the equipment is first designed according to Method 1 procedure, and then the surface area is increased by a safety factor. Thus, the pdf of the outlet temperature, which is centred on the nominal specification in Method 1, when applying the surface extension, is shifted towards lower temperatures.

Instead, when the specification is MisB, the growth of SF increases the expected total cost but also improves the performance. Caution must be applied in choosing SF value because it has a decreasing marginal return. In fact, when it grows from 1.25 to 1.5, a gain of only 3% is obtained in the probability to meet the specification, and there is no gain in rising SF from 1.5 to 1.75.

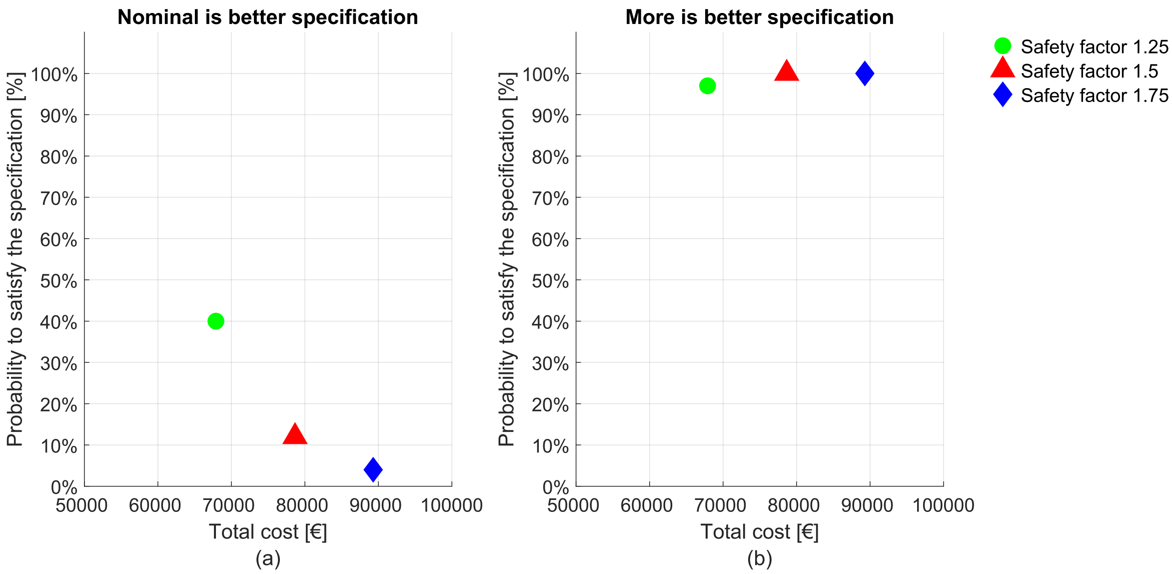

Figure 5.16 Comparison of probability to meet the specification NisB (a) and MisB (b) and expected total cost of designs obtained with different safety factor values

Comparison of design solutions under Epistemic Uncertainty

As previously stated, in this section, attention is focused on the impact of epistemic uncertainty only. This refers to "internal" variability imputable to unperfect knowledge of heat transfer and fouling phenomena through empirical correlations.

In this section, an exchanger designed for nominal operating conditions (Method 1) will be used as a reference case and compared to the robust design (Method 5) configuration by observing the resulting output variability.

In practice, the shell side and tube side heat transfer coefficients (equation 5.19 and 5.20) and fouling factors will be computed resorting to widely accepted literature correlations in nominal operating conditions and the obtained values will be then changed in the +/- 40% range with a more detailed analysis focused on +/- 20% variations using uniform distributions.

In particular, possible variation of heat transfer coefficients over such a wide range may determine the shift of controlling film from tube side to shell or vice-versa. Moreover, the change of the heat transfer coefficients when the heat exchange area was assigned would modify the outlet temperatures, thus shifting their probability distribution.

However, here, heat transfer coefficients' variation is caused only by epistemic uncertainty instead of by changes in fluids' flow rates or thermophysical properties.

Figure 5.17 shows both the probability of satisfying the specifications (outlet hot fluid temperature of 40 +/-2 °C) and the weighted average dispersion of outlet temperature around the specification (i.e. the objective function value, equation 5.18).

In general, an increase in objective function value, as well as a decrease in the probability of satisfying the specification, is observed when the uncertainty in heat transfer coefficient calculation and fouling factor increase. This is caused by the structure of the input/output temperature transfer function, as shown below. However, resorting to robust design (Method 5), better results can be obtained compared to nominal design (Method 1), with gains increasing when the uncertainty level increases. In fact, when the uncertainty range increases from +/- 20% to +/-40%, the output temperature variability reduction in Method 5 compared to Method 1 grows from 7% to 11%.

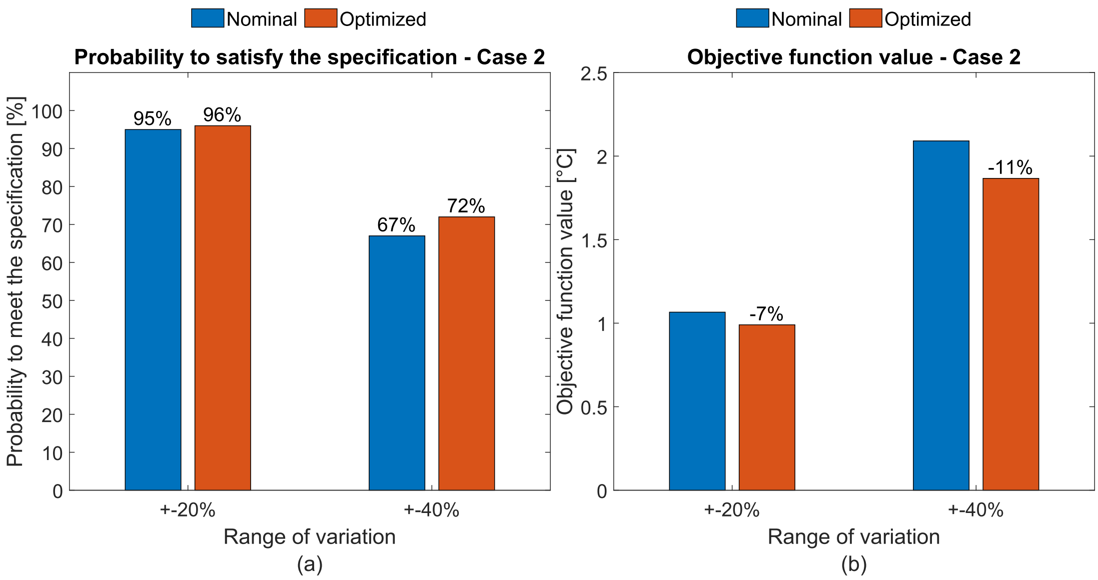

Figure 5.17 Probability to satisfy the specification NisB (a) and Objective Function values (b) under epistemic uncertainty effect

Obtained design configurations and their performances are shown in Table 5.14. The optimised designs (Method 5) are more compact than the equipment designed according to Method 1. In particular, the outer diameter of tubes and of the shell decrease, while the length is similar. The number of tube passages increases, and the final result is that the fluid velocity both in the shell and tube side increases. Results suggest that robust design can be effective in countering epistemic uncertainty, albeit to a minor extent.

Table 5.14 Nominal design evaluation and optimised heat exchanger design under epistemic uncertainty effect

Name	*[-]*	*Nominal*		*Optimised*	
Design type	[-]	-0.2	-0.4	-0.2	-0.4
t_{hi}	[°C]	95.0	95.0	95.0	95.0
t_{ho}	[°C]	40.0	40.0	40.0	40.0
m_h	[kg/s]	25.0	25.0	25.0	25.0
t_{ci}	[°C]	27.5	27.5	27.5	27.5
t_{co}	[°C]	40.0	40.0	40.0	40.0
m_c	[kg/s]	74.4	74.4	74.4	74.4
Q	[kW]	3905	3905	3905	3905
LMTD	[°C]	28.7	28.7	28.7	28.7
F	[-]	0.81	0.81	0.81	0.81
HE type	[-]	SRFH	SRFH	SRFH	SRFH
Tube Side	[-]	Cold fluid	Cold fluid	Hot fluid	Hot fluid
$\boldsymbol{D_s}$	**[m]**	**0.9**	**0.9**	**0.8**	**0.6**
$\boldsymbol{B}$	**[m]**	**0.4**	**0.4**	**0.8**	**0.6**
do	**[m]**	**0.02**	**0.02**	**0.018**	**0.012**
$\boldsymbol{N_{tp}}$	**[-]**	**2**	**2**	**6**	**4**
N_{tt}	[-]	918	918	726	1026
$\boldsymbol{L_{tt}}$	**[m]**	**4.2**	**4.2**	**4.8**	**4.5**
v_s	[m/s]	0.52	0.52	0.55	0.91
v_t	[m/s]	0.81	0.81	1.69	1.80
Re_S	[-]	16701	16701	12088	13425
Pr_S	[-]	5.1	5.1	5.7	5.7
Re_T	[-]	16109	16109	53716	38030
Pr_T	[-]	5.7	5.7	5.1	5.1
h_S	[W/m^2 K]	1709	1709	3747	5954
h_T	[W/m^2 K]	4126	4126	3726	4239
$\boldsymbol{U_{dirt}}$	**[W/m^2 K]**	**684**	**684**	**846**	**959**
$\boldsymbol{S}$	**[m^2]**	**244**	**244**	**198**	**174**
L/D	[-]	4.74	4.74	5.81	7.03
ΔP_T	[Pa]	25331	25331	14068	53992
ΔP_S	[Pa]	7374	7374	69992	69986

OBJ Value	**[°C]**	**1.07**	**2.09**	**0.99**	**1.87**
Pattern	[-]	Triang	Triang	Square	Square
OBJ Value norm	[-]	2.66%	5.23%	2.48%	4.67%
IC	[€]	46618	46618	39816	36379
OC	[€/yr]	1675	1675	4062	7643
DOC	[€]	10290	10290	24957	46961
TC	[€]	56908	56908	64773	83340
Probability to satisfy the specificication NisB	**[-]**	**95%**	**67%**	**96%**	**72%**
σT_{hout}	[°C]	1.05	1.98	0.98	1.80
E[T_{hout}]	**[°C]**	**40.2**	**40.7**	**40.2**	**40.5**
CV	[-]	2.61%	4.86%	2.43%	4.43%
OBJ Value norm E[T_{hout}]	**[-]**	**2.65%**	**5.14%**	**2.46%**	**4.61%**

Comparison of aleatory and epistemic uncertainty impact

In order to compare the relative impact of epistemic and aleatory uncertainty, the standard deviation of outlet temperature σ_y is evaluated by resorting to the Taylor expansion formula for the moments of functions of random variables.

$$\sigma_y = \sqrt{\sum_{i=1}^{N} \left(\frac{dy}{dx_i}\sigma_{xi}\right)^2} \tag{5.21}$$

In equation 5.21 *N* is the number of variables affected by uncertainty (i.e. mass flow rates and temperatures when aleatory uncertainty is under investigation, and the heat transfer coefficients and fouling resistances when epistemic one is considered), being σ_{xi} is the standard deviation of the i-th input variable x.

In Figure 5.18, the standard deviation of the hot stream outlet temperature is shown when uncertainty is propagated in an optimised design (Method 5) and a nominally designed (Method 1) exchanger. This result is computed assuming for each i-th variable $\sigma_i = z \cdot E[x_i] \cdot CV_i$, where *z* is a scaling factor, *E[x]* and *CV* are, respectively, the expected value and coefficient of variation of the assigned variables' distribution. The same factor *z* (0.5, 1, 1.5, 2) is used to scale each process variable in the same manner.

Overall, the outlet temperature variability increases linearly with the inlet temperature variability but less than proportionally with the mass flow rates' variability. This linear growth of output also means that the possible compensation effects occurring when homogeneous variables assume opposite values are not able to significantly reduce the outlet variability.

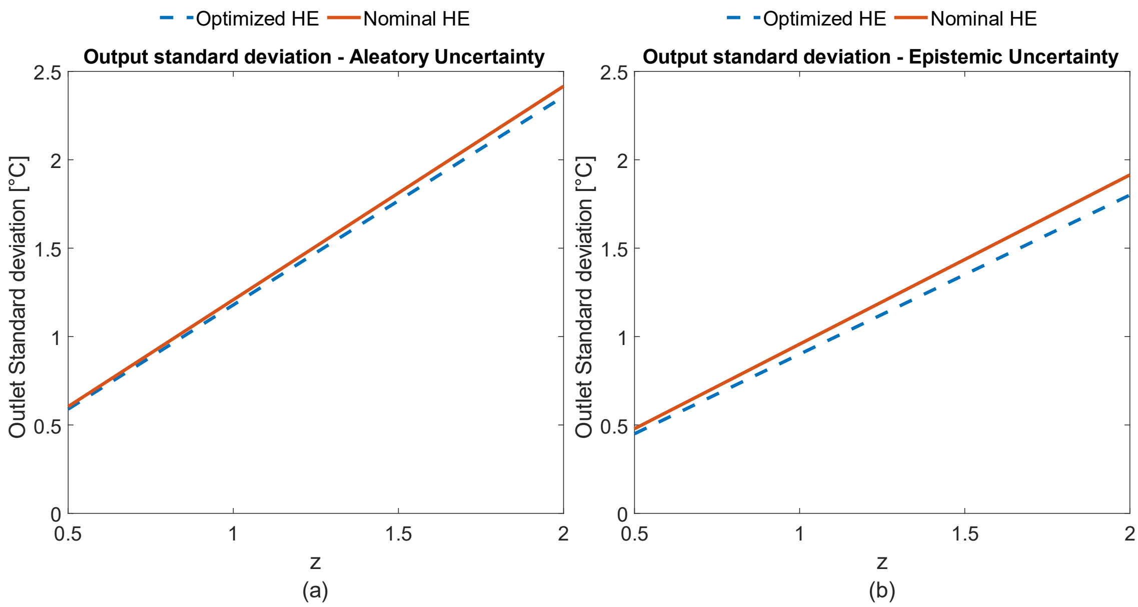

Figure 5.18 Output standard deviation under aleatory (a) and epistemic(b) uncertainty computed with uncertainty propagation formula applied on a robust optimised and a non-optimised HE

Findings and results discussion

Although the above results were obtained referring to a single specific numerical experiment, there are some findings which appear to be somewhat generalizable in order to provide some guidelines for designers, as summarized below.

1. The input uncertainty is linearly propagated in output uncertainty. The linear correlation implies that if inlet uncertainty increases, the difference in performance between the robust heat exchanger (Method 5) and a piece of equipment designed for nominal conditions (Method 1) becomes more significant.
2. Aleatory uncertainty has a higher impact than epistemic uncertainty on the performances of the exchanger. In fact, the variations of mass flow rates and

temperatures influence the log mean temperature difference and even the heat transfer coefficients, while epistemic uncertainty only affects the latter.

3. A symmetric change in homogeneous variables does not necessarily lend itself to effective variability compensation.
4. As far as random variations of external process variables are concerned, optimisation methods, including robust design, generally lead to more compact equipment in terms of surface area, albeit with a smaller number of longer and larger diameter tubes and more tube passes. In the case of NisB specification, a nominal point design provides performances comparable to optimal design, while safety factor and worst-case design deliver poor performances as the distribution of the outlet temperature is not centred on the specification. This suggests that in NisB cases with symmetrical variations of process parameters around their average, a simple design based on average conditions neglecting uncertainty can be acceptable. The worst-case design and safety factor method is not effective with symmetric variations of process parameters because it leads to a higher heat exchange area, increasing the gap between expected performance and the design specification and also lowering the probability of meeting the specification. In MisB situations, the latter method can ensure satisfaction of specifications over a wide range of operating conditions but at the expense of excessive oversizing. Caution must be applied in choosing the safety factor value as it has a decreasing marginal return. Robust design performs as poorly as the nominal design point method, as reducing the variability of the output is not the design goal in this type of application.
5. In case of epistemic uncertainty of internal parameters, the robust design method can be slightly superior to nominal point design and also provide a piece of more compact equipment.
6. Robust design appears to be effective in compensating both aleatory and epistemic uncertainty, although in a minor manner. In fact, with a given inlet uncertainty, some configurations amplify the uncertainty while others dampen it, so it is, in theory, possible to optimise the HE and obtain a more robust design, but in practice, the behaviour difference is not really significant. Moreover, a heat exchanger is characterized by a geometrically fixed physical structure, making the equipment hardly adaptable to changing operating conditions.

Based on the above findings, Table 5.15 can be built to provide suggestions for choosing the preferable design method to address uncertainty. This table is to be intended as a starting reference only. We do not make a claim of its absolute validity, and the designer is encouraged to explore alternative methods as it is hard to predefine which is the best method in a specific instance.

Table 5.15 Suggested STHE design approaches for addressing uncertainty

Type of uncertainty	Bilateral specifications (Nominal is Better)	Unilateral specifications (More is Better)
Random variation of external process conditions	I, IV, V	II, III, IV
Epistemic uncertainty of internal parameters	V	

Legend: I) design for nominal reference condition; II) worst case design; III) use of safety margins; IV) objective function optimisation; V) robust design.

5.3.3 Remarks and limitations

The purpose of this section was to discuss the existing methods to cope with uncertainty in shell and tube heat exchangers' design, understand the influence of uncertainty on the thermal performances of the equipment and explore the potential of applying the proposed framework for optimal robust design of exchangers under uncertainty.

The main proposed novelty resides in the direct and consistent comparison of alternative design methods under uncertainty that was not performed earlier, and no detailed analysis of their effectiveness is available. Moreover, to the best of our knowledge, this is the first time that the robust design of heat exchangers has been practically considered as a tool to address uncertainty.

Results show that different methods may give different results, and they are not exchangeable. There is no preferred method to deal with the uncertainty, but the best solution is not to neglect it. In fact, variations in mass flow rates could lead to errors in pumping system sizing and to unexpectedly high-pressure drop values, with correspondingly high pumping costs, while changes in inlet temperatures could dramatically reduce the driving force. The application of the uncertainty propagation formula through Taylor expansions shows that in shell and tube heat exchangers, uncertainty in the input propagates to the output in a linear manner. Different geometric configurations of the equipment could reduce the proportionality constant, but not in a significant manner. Aleatory uncertainty has the greatest impact on the output. In fact, it influences the heat transfer coefficient with the mass flow rates and with inlet temperatures the log-mean temperature difference, while the epistemic one influences only the first one. As practical advice, at first, it is necessary to understand the nature of the problem. In fact, when NisB specifications apply, results suggest avoiding Worst-Case scenario and Safety factor methods and preferring Objective function optimisation and Robust optimisation. In MisB case, the Safety factor method with the correct selection of safety factor value, as shown, can lead to superior performances, while Robust optimisation has no benefit.

The main limitation of the study is that a single objective function is considered, that economic consequences of failing to meet specifications are not considered and that results refer to a single, although extensive, numerical experiment. The generality of findings must be verified by resorting to a more extensive experimental campaign.

Now that the framework has been applied to this case study, it is possible to address the research questions proposed in section 5.3. Even though when the probability density functions or ranges which represent the variability of the temperatures and mass flow rate of the inlet fluids, as well as the epistemic uncertainty, are centred in the mean value of the quantities, the uncertainty may be neglected by resorting to the Method 1, some issues related to the pressure drop can arise. Indeed, in some cases, they may exceed the upper bound, causing severe problems to the mechanical structure or the operability of the equipment. Therefore, uncertainty should be considered to avoid this kind of problem, but also to ensure the specification is achieved when the distributions or ranges are not centred in the mean value of the quantities. The available approaches, which lead to performing design in the absence of variability, do not perform well when uncertainty is included, as has been demonstrated. Finally, at the end of section 5.3.2, a resume of the preferred methods in specific problem instances has been provided.

In future works, the use of Method 4 will be examined in greater detail by exploring the impact of different objective functions, including both thermal and economic parameters and the value of exchanged heat. Moreover, the combined effect of both aleatory and epistemic uncertainty will be explored.

Overall, based on the findings of the approach application, designers of shell and tube heat exchangers can gain greater awareness of when and why uncertainty should be accounted for and can be assisted in choosing with greater confidence the proper design approach for heat exchangers operating under uncertainty.

5.4 Final remarks

In this Chapter, the framework proposed in Chapter 4 has been applied to the STHE design evaluation and optimisation under uncertainty.

Since selecting the proper variable of interest and objective function is a crucial task and the literature was scarce in comparing different OFs for optimising STHEs, a literature review and a comparison of several OFs on a consistent basis have been carried out. The results allow us to produce a brief guide to understand the effects of different OFs on the final design configuration. Additionally, it has been found that caution is mandatory when thermal performances are only being optimised, as this can give rise to unviable and economically unsustainable equipment configurations. Multi-objective optimisation assures that competing designs do not dominate the thermal optimum from an economic perspective. Economic functions are the most used and interesting from an industrial plant's point of view. Indeed, they are easy to implement, understand and use, and their results are straightforward to compare. The importance of thermal and geometrical performances is not to be neglected, but the possibility of giving economic value to these aspects is advised.

Then, considering that equipment operates in actual plants, i.e. without constant conditions, a literature review of the design and evaluation of STHEs under uncertainty has been carried out. The literature on STHEs' design often overlooks the effects of the uncertainty. Therefore, the aforementioned general framework has been applied to STHEs' design optimisation and evaluation, and a case study in which several existing designing approaches were compared on a consistent basis was shown.

The results allow us to address the subsequent research questions.

- Should uncertainty always be taken into account when designing heat exchangers, or can it be neglected?
- Are the available approaches for designing shell and tube heat exchangers effective when uncertainty is not included still effective when it is considered?
- Which is the preferred method to be applied in specific problem instances?

Firstly, it can be stated that uncertainty should be considered to ensure the achievement of the specification and the respect of constraints when the distributions or ranges are not centred in the mean value of the quantities. Additionally, the available approaches, which lead to performing design in the absence of variability, may not be effective when the uncertainty is included. Finally, a brief guide to selecting the proper methods in specific problem instances has been provided.

Chapter 6

Framework application to industrial systems assessment

This Chapter adapts the General Framework presented in Chapter 4 to address the industrial systems assessment goal. In order to show the capabilities of the approach, the considered system is rather complex than the equipment faced in Chapter 5. Indeed, the selected systems are offshore wind power systems.

Other features of the framework are also used, which in the equipment design optimisation problem were neglected. The blocks of uncertainty that enter the economic model and the external disruptive events that were before switched off are now used to perform the risk assessment procedure. Furthermore, the feedback arc is used for including risk mitigation actions on an already concluded design, i.e. for market risk mitigation purposes.

Some sources of deep uncertainty involving the environment in which the system operates are included using scenario analysis. The applied scenario analysis procedure will be described in the following, and the literature and references used to build scenarios will be described.

Before beginning, an explanation of why the selected systems are offshore wind power plants may be helpful.

Exploiting renewable energy sources is a fundamental aspect of the decarbonization and energy transition strategies enforced to counteract climate change and secure energy supply. While wind energy is a mature technology, offshore wind power systems are experiencing notable growth in developing novel technical solutions and in the global installed power base. Offshore wind power plants have several advantages over their land-based counterparts, especially considering the higher available wind speeds owing to the absence of terrain obstacles, the lack of land consumption, and the lower visual impact, which allows wider acceptance from the public opinion. Nevertheless, offshore wind power plants are penalized by higher installation and operational costs owing to logistic issues, the necessity of transferring the produced energy on land, and the severity of the operating environment, causing much higher maintenance expenses.

However, renewable energy systems are subject to several sources of uncertainty, both epistemic and aleatory, impacting system profitability and generating technical and economic performance variability, resulting in investment risk and financial risk [352]. This could even be hedged by new financing instruments [353] but requires a thorough consideration during the design, planning and assessment phases.

In wind power systems, uncertainty does not only arise from imprecise turbine design relationships and variability of wind speed and sales price of produced energy but also from downtime and costs deriving from random failure of internal components [354-356] as well as from disruptive external events deriving by natural hazards and man-made events (i.e. ships collisions, rogue waves, earthquakes, etc.) which threat to destroy the entire system truncating its useful life.

However, while previous literature focused on analysing specific uncertainty issues of wind power systems, such as wind speed of energy price forecasting [357-360], an overall model incorporating and integrating all variability sources [361, 362] is still lacking. Moreover, available economic assessment models for wind power plants, both on-land and offshore, usually only allow a deterministic analysis of a sensitivity analysis by changing the value of variables one at a time. When a random variation of parameters is included, it is usually made considering the economic effect of just a few variables, thus preventing a comprehensive assessment of the effect of uncertainties on investment profitability and risk.

The framework is adapted to this type of energy conversion system to give a contribution to fill this gap and to address the following research questions. Considering a profitable offshore investment system evaluated on mean values, is it still economically effective when the risk assessment procedure considers numerous sources of uncertainty? Does the economic performance of these systems significantly change when uncertainty is included in the evaluation procedure? Since the energy market is volatile, is it possible to include effective financial instruments for mitigating the market risk? Should scenario analysis be considered to include the changes in the environment in the long term? Is combining different scenarios by using their associated probability a viable solution to assess a single performance instead of several performances, one for each scenario?

The general framework adaptation produces a new general method for risk analysis and economic performance assessment of renewable energy systems, particularly offshore wind power plants. This methodology simultaneously considers the main sources of epistemic and aleatory uncertainty, allowing us to estimate the net present value probability distribution and some associated risk measures. The developed approach can be useful for a more detailed and risk-aware assessment of offshore wind power investments, providing a useful decision-making tool for designers, managers, and investors.

As will emerge from the following literature review, no papers focus on the economic evaluation of offshore power systems under uncertainty. Secondly, in the literature, some articles focus on the power system evaluation under uncertainty, considering only the aleatory uncertainty of wind speed (renewable energy load) or a few other variables. This thesis considers the random uncertainty related to wind source availability, the economic market scenarios, as well as the impact of random failures and disruptive events. Furthermore, this framework includes epistemic uncertainty related to the non-perfect ability of the mathematical model to represent the system and the epistemic uncertainty of the system's characteristics (e.g., power curve, gearbox efficiencies, etc.). Finally, climate change is also considered.

The Chapter is organized as follows. Firstly, a literature review is carried out to assess the state of the art in economic evaluation and uncertainty propagation in (offshore) wind power systems. The general framework adaptation to assess the economic performance of renewable energy systems under uncertainty is presented. Subsequently, three possible scenarios for the evolution of the environment in which the system operates are presented. Next, a detailed model focused on offshore wind power systems is developed. Finally, a case study is presented to show the model's capabilities and demonstrate the importance of considering uncertainty during the economic performance assessment of offshore wind power systems. In conclusion, a discussion of the model limitations and perspectives for future work are provided.

The studies carried out to write this chapter produced the four papers in references [363-366].

6.1 Offshore wind power systems economic evaluation under uncertainty

Historically, energy power plants' technical feasibility and economic viability have been assessed by resorting to deterministic analysis assuming average and nominal values of input parameters. In order to account for uncertainty, a sensitivity analysis is often made. While sophisticated global sensitivity analysis techniques are available (e.g., the Sobol method), these are computationally intensive. Consequently, one often finds simplified analyses where the value of one parameter at a time is changed, and the resulting impact of the chosen performance measure is observed. As a step further, Monte Carlo analysis techniques have often been used to generate random scenarios. This can be performed by simultaneously changing around the mean in a random manner multiple variables value, or, in more sophisticated cases, by reproducing specific structure (by means of marginal characteristics and dependence properties). As an alternative, a substantially deterministic analysis can be performed accompanied by a dynamic analysis factoring in the random uncertainty of relevant time-dependent parameters such as electricity market price evolution and wind speed changes. However, the above approaches neglect a thorough analysis of all variables' uncertainty propagation issues, resulting in erroneous performance estimation and poor risk assessment.

In recent years, some authors have begun to study the problem of uncertainty in renewable energy systems. In traditional and renewable energy systems, short- and long-term decisions must be made under uncertain conditions. Thus, methods for modelling uncertainty in decision-making under uncertainty in the energy sector have been reviewed [367]. Since energy supply and demand are strongly affected by uncertainty, an optimisation strategy was proposed for the operating schedule [368]. A multi-criteria decision-making problem under uncertainty was developed to select the most appropriate renewable energy system at a specific site [369]. A generic stochastic simulation-optimisation framework for deploying financially viable systems has been proposed [370]. This framework includes the uncertainty of energy sources and model elements but does not directly consider failures, disruptive events, financial risk, and fiscal policy risk. The failures and maintenance uncertainty greatly affect the system's economic performance, so a method focusing on modelling the uncertainty of reliability costs and failures has been proposed [371].

The most studied type of uncertainty in the wind power sector is aleatory uncertainty. In fact, most papers available in the literature focus on wind speed and power forecasting.

One of the most widely used approaches for wind speed prediction consists of constructing a Weibull probability density function from historical wind speed data [358, 359, 372-377]. Probabilistic forecasting methods are also used to identify the most suitable type of predictive distribution [378], demonstrating the maturity of this research field. The use of the Markov chain in short-term prediction has also been explored in order to reduce restricted assumptions on wind speed probability distribution [379]. Other works have focused on forecasting wind power produced by incorporating the temporal and spatial dependence structure [380] or adopting other solutions, which are reviewed elsewhere [381].

Another source of aleatory uncertainty in the economic evaluation of renewable power plants stems from the electricity sale price. The energy price can be analysed as a stochastic process by employing ARIMA [382, 383], ARMA and ARMAX [384] models.

Table 6.1 compares how uncertainty has been accounted for in the relevant literature. The table excludes articles focusing only on energy price prediction [382, 384-392] and wind speed prediction [31, 393, 394] not applied to a wind system.

Table 6.1 Comparison of wind energy systems uncertainty modelling in the literature

	Type of model (Technical/Economic)	**Uncertainty modelling**			
References	**Included**	**Energy price**	**Wind speed**	**Technical model**	**Failures**
[395]	Yes/Yes	No	No	No	No
[396]	Yes/Yes	No	No	No	No
[397, 398]	Yes/Yes	No	Yes	No	No
[399]	Yes/No	No	Yes	No	No
[400]	Yes/No	No	Yes	No	No
[360]	Yes/No	No	Yes	Wind Power forecasting	No
[401]	Yes/No	No	Yes	Power Curve	No
[402]	Yes/No	No	Yes	Manufacturing tolerance and insect contamination	No
[357]	Yes/Yes	Yes	Yes	No	No
[370]	Yes/Yes	Yes	Yes	Power Curve	No
[403-405]	Yes/No	No	No	No	Yes
[358, 406]	Yes/Yes	No	Yes	No	No
[407, 408]	Yes/No	No	Yes	No	Yes
[409]	Yes/No	No	No	No	Yes

[410]	Yes/No	No	Yes	Wake effect, internal wind farm collector system, unavailability of wind turbine	No
This work	Yes/Yes	Yes	Yes	See Table 6.3	Yes

Note that authors of papers [357] and [395] use commercial software, EViews and RETScreen, respectively, to conduct their analysis. Although the most popular methods for dealing with uncertainty, especially epistemic uncertainty, are Monte Carlo sampling from a predefined probability density function and, especially for aleatory uncertainty, stochastic models, the above works deal with stated sources of uncertainty by different methods, e.g. using Markov chains and ARIMA and SARIMA methods for aleatory uncertainty. With the exception of this work, only three papers in the table above include failures, and none assesses the economic performances of wind turbines. Considering the epistemic uncertainty of relations and the effectiveness of the WT model, only four papers include these sources of uncertainty but not failures.

There are several computer tools, some purely deterministic, others considering uncertainty, for analysing the integration of renewable energies in various energy systems. energyPro [411] was developed for the technical and financial analysis and optimisation of thermal generation, renewable generation and energy storage systems, but it is a deterministic tool and only admits sensitivity analysis. Hybrid Optimisation of Multiple Energy Resources [412] is another tool that can simulate different system solutions and admits optimisation and sensitivity analysis. The availability and load of the energy resource can be generated synthetically by taking variability into account, or time series can be imported by the user. Scheduled maintenance activities can be defined, but random failures cannot be included in the analysis. Grid outages can be scheduled or random. Disruptive events can be considered, but they can occur at most once a year and their duration and start date are constant, which can only be randomised during the sensitivity analysis. The change in loads, prices and costs is only considered with a percentage change from one year to the next. RETScreen [413] provides both sensitivity and risk analysis. The risk analysis is performed for the financial feasibility indicator selected by the user, but only using the Monte Carlo simulation. The user obtains the probability distribution of the selected indicator, but only a small number of key input parameters can be changed. Moreover, component efficiency, system life cycle and other important sources of epistemic uncertainty are not included. The random uncertainty of failures and disturbance events is neglected. Finally, SAM [414] is designed to facilitate decision-making in the renewable energy sector. It can perform parametric analysis, exceedance probability analysis and stochastic analysis. With stochastic analysis, it is possible to include uncertainty by estimating the effect of variability of inputs on an output variable by using Latin hypercube sampling. The shortcoming of this tool is its inability to include changes in the primary source over the years, random failures and other sources of uncertainty that change during the life cycle years. Therefore, it calculates the energy produced using coefficients to consider system availability, ageing of components and other losses. In this way, not only failures are neglected, but also disruptive events.

Overall, to the best of our knowledge, a general framework for evaluating the economic performance of renewable energy systems which simultaneously includes all sources of uncertainty is still lacking, and this thesis is the only one that considers a wide range of uncertainty sources to evaluate economic performances of offshore wind energy systems.

6.1.1 A common external disruptive event: ship collision

Some papers in the literature have focused on the ship collision analysis on offshore wind turbines. The majority of works have considered fixed-bottom structures. Indeed, monopile foundations for offshore wind turbines' response to ship collision have been tested both with a striking rigid body ship and a deformable body [415]. Another work considers the deformation of jacket foundation under ship collision, including different scenarios of the ship's speed, collision direction and angle [416]. The previous papers conclude that the ship collision may cause plastic deformation, leading to wind turbine collapse. The effects of collision increase when the wind load is considered in the analysis, reducing the needed impact energy for the turbine's collapse [417]. The risk of collision is higher in considering service vessels during maintenance operations. Some authors have demonstrated that even if the vessel speed is low, the wind turbine structure can be affected by the impact, resulting in structural damage [418]. In the same work, the authors show that 20% of the ship-turbine strikes are on approach, while 80% are on drift. Therefore, this means that 80% of collisions happen with a speed of 0.3-2.8 m/s. Indeed, the most frequent speed is 1.2 m/s. The relevance of offshore maintenance in fixed-bottom wind turbines has been extensively reviewed in a contribution [419]. Therefore, the risk of collision with a maintenance vessel increases due to the high number of interventions. The authors of [420] consider the collision of a barge and a bulk ship with different loads with a fixed-bottom offshore wind turbine. The combination of the results they obtained allows them to provide two fragility curves, one for each type of ship. The driving factor of the fragility curves is the speed of the ship now of the strike. When considering floating offshore wind turbines, the literature is scarce. In recent years, intending to fill this gap, a contribution proposes an initial step for analysing the effects of ship collision on a spar floating offshore wind turbine [421]. The results indicate that the mass and the initial velocity lead the deformation process. Furthermore, there is an elastic response of the overall structure which reduce the total effect of the impact in comparison with a fixed turbine type at the same speed. For the floating spar, a strike with a speed of about 5 m/s may seriously damage the system. Indeed, the failure analysis of a spar buoy structure shows that crash with vessel is a relevant event, with a probability of about 10^{-6} events per hour. The consequences of these events have been considered severe. The dynamic and damage analysis carried out in a recent paper allow us to understand how severe are the consequences of the collision of a ship with a spar buoy [422]. Finally, the combination of collision load and wind-wave-mooring loads have been investigated [423]. The analysis of the literature suggests that:

- The ship collision impacts the floating structures less than the bottom-fixed ones.
- The wind and wave load decrease the critical speed, leading to the wind turbine's collapse.
- Most collisions happen between small service vessels with a load ranging from 125 to 850 tons. Collision with a bulk ship with a mass of 30,000 tons is rarer but may happen.
- 20% of the collisions happen on approach at high speed, while most happen on drift with a low speed in the range of 0.3-2.8 m/s.
- Speed collision higher than 5/6 m/s may be critical and can damage the spar structure.
- Only fragility curves for the ship collision between a barge and bulk ship and fixed-bottom structure are available in the literature.

6.1.2 Climate change effects on wind power systems

Climate change affects weather conditions, and the fact that renewable energy systems suffer from this issue is well-known. Wind energy systems are one of the instruments used to mitigate climate change and produce green energy. However, wind energy systems suffer from climate evolution, and climate change may negatively impact wind farms' production. Indeed, in the future, some regions of the world may experience a reduced wind speed, whereas others may experience an increase. A deep review of climate change's impact on wind energy has been proposed in the literature [424]. The authors focused on the variability of the wind resource in northern Europe, considering also the effects of climate change on the maintenance of wind farms. Indeed, they considered extreme wind speed, icing, sea ice and permafrost, and also air density. They concluded that the wind speed will increase in some regions of north and central Europe, but undesirable weather-critical events will also increase. Other authors focused on changes in wind speed and direction at 10 m worldwide due to anthropogenic climate change [425]. They showed that global warming impacts the future of wind resources, underlined the possible increase of extreme wind speed probability due to tropical cyclones, and proposed a map for further studies. A recent work studied the evolution of wind speed in Chile to evaluate its impact on optimal power system expansion plans [426]. They analysed three different scenarios of concentration of greenhouse gasses and concluded that even though mean wind speed will slightly increase in the next years, its variability will increase too. Another work deeply analysed future wind speed probability distribution [427]. The authors resorted to several circulation models and simulated wind speed at 10 m under the representative concentration pathway (RCP) RCP 8.5 condition. The RCP 8.5 scenario supposes that emissions will continue to increase during the 21st century. It is often taken as the worst-case climate change scenario. It hypothesises that the global mean temperature will increase by 5°C in 2100 compared with its value in the pre-industrial era. The sea level will also increase by about 0.63 m [428, 429]. The simulation about the near-surface wind speed showed that the most significant wind speed decrease will be in Eastern Russia and the USA. The authors analysis provided fitting distribution, accuracy, mean value, and standard deviation of current wind speed and the simulated wind speed in the near, midterm, and far future. Even though they said that, in some world regions, wind speed changes will be marginal, a slight change strongly affects the extracted power from the wind. Since the wind farm of the numerical example is located in Italy, a study on the impacts of climate change on power generation in Italy is considered [430]. The paper studied wind resource availability in Italy for short, until 2050, medium, until 2080, and long, until 2100, term. Two scenarios were analysed: the RCP 8.5 and the RCP 4.5. The RCP 4.5 supposes that the emissions peak in 2040 and then decline. It is often considered the most probable baseline scenario in which the increases in temperature in 2100 will be about 2.5-3 °C, and the sea level increases of about 0.47 m compared to the data of the pre-industrial baseline. They assessed wind producibility as the ratio between the produced power per hour and the installed power. The results showed that in both scenarios, the wind producibility will increase in the short period in the plant region of the numerical study of about 3-4%. However, in other regions of Italy the producibility will decrease.

6.2 The future of offshore wind power systems in Italy: scenarios description

In the literature, scenario planning (section 1.2.9) is a widely adopted approach to explore the possible evolutions of macroscopic variables over medium and long time horizons. As a matter of fact, several reviews are available on this topic [431-433]. This approach focuses on the complexity and uncertainty of the environment. Indeed, its primary goal is not to forecast variables' values but to depict several different futures. The uses of scenario planning relies on defining plausible and possible description of the future. Even though various methods exist, most of them have a high implication of subjective judgments. Therefore, the scenarios' making process is often low replicable. Indeed, all the three most important techniques of scenarios, that is, Intuitive logic methodology, La prospective methodology, and Probabilistic modified trends methodology, are based on experts' judgments [434]. Generally, scenarios are produced by analysing reality and identifying the most influential variables on future development. Then, it is crucial to determine the driving forces which cause the changes in the future-influent variables. Basically, the scenario planning includes the following steps.

1. Defining the objective of the study. The output of this step is the system selection, the study's time horizon, the geographic boundaries, and the stakeholders.
2. Collecting data. Resorting to the specifications obtained in step 1, it is possible to collect the data collection about all relevant issues necessary to describe the events which affect the factors and variables which lead to the future's development.

3. Understanding trends and uncertain elements. The identified factors and variables are studied to understand their influence on the system under analysis, the range of their variability over time, and trends. Additionally, their number is streamlined by conducting uncertainty analysis or similar approaches.
4. Understanding the interdependence between the events, the factors, and variables value. This step is crucial to understand whether and how a variable affects another. This way, one can suppose a correlation matrix, which transparently defines the probability of an event or a value once another happens.
5. Building the scenarios. Combining different trends and uncertainty allows us to describe several scenarios, which are then reduced in number by using expert judgments and available data, establishing a subjective procedure.

Analysts and decision-makers often suppose strategies to cope with the consequences of realising different scenarios. For the sake of completeness, also more quantitative approaches to scenario planning exist. They are based mainly on the combination of analytical formulation, sampling methods, and the contribution of experts. For instance, the Interactive Cross Impact Simulation uses Monte Carlo simulation, combining data and experts' opinions [435]. On the other hand, Trend impact analysis resorts to historical trend interpolation and opinions to set the probabilities and impacts of future events [436].

Steps 2 and 3 are often carried out using cause-effect analysis [437, 438]. This approach often gives a cause-effect matrix in which the rows are the variables, whereas the columns are the outputs. In the intersections, there is a qualitative or quantitative measure of the effect that a variable has on the output.

Step 4 often uses the cross-impact analysis, which is a widely adopted tool for understanding the interdependences between events [439, 440]. It is used to analyse if and how much the occurrence of an event influences the probability of occurrence of another event. Typically, the output of the procedure is a cross-impact matrix. The cross-impact matrix is a matrix in which each row and each column represent a variable. In the intersections is a qualitative or quantitative value describing the interdependence level. The qualitative can be, for instance, a plus, neutral or minus symbol. In contrast, the quantitative measure can be the value of reduction of the probability of occurrence of the event in the column once the event in the row has occurred. This approach allows futurists to build consistent and plausible scenarios.

Thus, based on the aforementioned studies, scenario analysis seems to be a suitable tool to capture the effects of long-term electricity prices, investment cost reductions, and subsidy policy changes on the economic performance of offshore wind power systems.

The adopted method follows the subsequent steps.

- Selecting scenario variables.
- Identifying the driving forces.
- Defining the possible events.
- Defining the variables' values.
- Conducting a cause-effect analysis.
- Conducting a cross-impact analysis.
- Combining the variables' values to obtain the scenarios.

This approach used and analysed scenarios to model social, political, and regulatory risk and understand their effect on the NPV distribution. As will be seen in the case study, it is supposed that the plant, including several wind generators, will start its production in 2030 to evaluate cost reduction effects over the years.

The first step concerns the scenario's variables selection. Three scenario variables were selected: the long-term energy price, the investment cost reduction, and the subsidy policy. Then, in step 2, the driving forces must be identified. These variables have three different driving forces: geopolitical relationships, European energy policy, and Italian energy policy, respectively. Each driving factor affects the relative variable in function of the event that will happen in the future. Each variable can assume three different values according to the event which will happen.

Steps 3 and 4 were carried out to identify the possible events and the relative variables' values, as described below.

Starting from the World Energy Outlook report [441], long-term energy price values were defined according to [442]. Three distinct events were considered, namely Relief (R), Central (C), and Tension (T). In addition to considering traditional energy market drivers, the analysis also incorporates the geopolitical situation. Event R assumes a relaxation of tensions between the USA, Europe, Russia, and China in the coming years. It anticipates a continued import of fossil fuels from Russian pipelines, resulting in a reduction in energy prices. However, there is an ongoing effort to reduce dependence on Russia, leading to a decrease in natural gas imports compared to the pre-2021 levels. The renewable energy targets recently adopted will remain in place. In event C, Europe will cease importing Russian pipeline gas by 2027, and there will be a smooth increase in the utilization of renewable resources in subsequent years. Natural gas is gradually replaced by synthetic fuels such as green hydrogen. To maintain competitiveness, the price of natural gas falls. Furthermore, there is an increase in the utilization of heat pumps, and by 2060, electric vehicles and trucks in Europe will account for 95% of the market. In event T, the current tensions between Russia and the West persist and escalate in the coming years, leading to a rise in energy prices. Europe immediately halts the importation of Russian pipeline gas, and European consumers find themselves in competition with Asian markets for energy resources.

The events are related to three variables' values, namely Relief (R), with a mean variable value of 60 €/MWh; Central (C), with a mean variable value of 79 €/MWh; and Tension (T), with a mean variable value of 100 €/MWh.

Investment cost reduction is modelled by the offshore wind power learning rate [443, 444], which is considered fixed and equal to 9%. This data was combined with events about the offshore wind power installed capacity in Europe in 2030 [445], which may be 40.5, 70.2 and 98.93 GW. The three values of the scenario's variables considered are High Investment Cost Reduction (H), Medium Investment Cost Reduction (M), and Low Investment Cost Reduction (L). The extent of investment cost reduction is influenced by the projected installed capacity in 2030. As already said, a fixed learning rate of 9% is assumed, while the global European installed capacity can vary, with values of 40.5 GW, 70.2 GW, and 98.93 GW for the L, M, and H scenarios, respectively, based on the forecasted developments in the energy economy over the coming years. In the L event, limited progress is made in electricity interconnections between European states, unfavourable national policies regarding permitting and planning in high-potential markets persist, and the European renewable energy target is not achieved. In the M event, regional cooperation mechanisms are established, the renewable energy directive is implemented, and national policies promoting wind energy are strengthened. Additionally, there is an intensification of power interconnection infrastructures. In the H event, the European targets for renewable energy sources (RES) are increased to 35%. The power transmission network is intensified beyond the initial target of 15%, and there is an acceleration in new installations due to favourable policies implemented by member states.

The higher the installed capacity in 2030, the higher the percentage of investment cost reduction. This combination leads to three variable values, namely High Investment Cost Reduction (H), with a reduction of 23%; Medium Investment Cost Reduction (M), with a reduction of 17%; and Low Investment Cost Reduction (L), with a reduction of 12%.

Regulatory risk is included in considering subsidies. Although there are currently no subsidies for offshore wind power plants at the time of this study, the Italian government is considering the introduction of a subsidy plan. Three events have been considered: feed-in tariff (F), feed-in premium tariff (P), and no subsidies (N). In the feed-in tariff event, the lack of available data led to the setting of the tariff at 187 €/MWh, based on the historical levelized cost of energy for offshore wind power systems [446]. If this event occurs, the time series of electricity prices has no influence on the Net Present Value (NPV) since the power generated is sold at a fixed price. In the feed-in premium tariff event, a fixed tariff of 31 €/MWh is applied. In this case, the selling price is calculated by adding the feed-in premium value to the current market price of energy. In the no-subsidies event, the selling price is solely based on the current energy market price, without any additional subsidies or premiums.

Step 5 concerns performing the cross-impact analysis. In this work, since the driving forces are assumed to be independent, the events are considered independent. Thus, it was supposed that the variables did not impact each other.

Table 6.2 provides a resume of the considered scenario's variables, the driving forces, the events, and the variables' values.

Table 6.2 Values of scenario's variables

Scenario's variable	Driving force	Events	Variable's value
Long-term energy price	Geopolitical relationships	Tension	100 €/MWh
		Central	79 €/MWh
		Relief	60 €/MWh
Investment cost reduction	European energy policy	High	23%
		Medium	17%
		Low	12%
Subsidy's policy	Italian energy policy	Feed-in	187 €/MWh
		Feed-in premium	31 €/MWh
		No subsidies	-

It is important to note that if the Feed-in Tariff subsidy is selected, the NPV probability density function is not influenced by the energy price but is still influenced by the investment cost reduction. Therefore, the consistent and possible scenarios obtained by combining all the scenario variables' values are 21. Each scenario is represented by two or three letters corresponding to the evolution story of the associated variables. More details about the selected scenarios can be found in reference [364].

Even if assessing the probability of scenarios is challenging, to help decision-makers select the more plausible scenario, the author tries to contribute critically by using the plausibility cone concept [37, 70]. Scenarios were clustered into four groups: preferable, possible, plausible, and probable. Subsidies policy around the world is heading towards a feed-in premium tariff. Therefore, despite scenarios HF, MF, and LF being preferable from the wind power investor perspective, they are not in the probable group. Daily news about relationships between West and Est countries yields only possible scenarios with take relief assumptions (R). Other scenarios with no subsidies (N) are plausible, but Italian politicians wanted to pursue a subsidy policy, especially for wind and solar energy. Thus, scenarios with feed-in premium subsidies are in the probable group. Ultimately, the continuous investment in wind power systems worldwide, especially in Europe, makes the high investment cost reduction the most probable hypothesis. Therefore, the author believes HTP and HCP are the most probable futures.

Finally, a simplified procedure for scenarios combination (section 4.1.4) has been developed. This procedure was used to include the effect of possible changes of a scenario variable over time (type IV uncertainty, section 4.1.1) and follows the subsequent steps.

1. Defining a set of probable scenarios.
2. Associating a probability to each scenario resorting to experts' judgments.
3. Assessing the performance of the system in each scenario.
4. Combine the results, resorting to the supposed scenarios' probabilities.

One possible approach to Step 4 is using a weighted sum, which weighs the scenarios' probabilities. In the case study, more details on the application of the procedure will be provided.

6.3 Framework application for evaluating wind power systems under uncertainty

This section provides the application of the framework presented in Chapter 4 to the case of wind power systems evaluation under uncertainty. The framework application is made to demonstrate the model's applicability to several fields, address the assessment goal, and answer the above-expressed research questions. For symbols' meanings, please refer to the nomenclature of this section in the List of Symbols section at the end of the thesis.

The application procedure involves the following steps.

- Uncertainty sources identification.
- Uncertainty sources modelling.
- Performance measure selection.
- Technical model formulation.
- Economic model formulation.
- Uncertainty propagation method selection.
- Scenarios analysis.
- Risk mitigation strategy selection.
- Risk assessment.

For renewable energy systems, and specifically offshore ones, nine families of uncertainty sources can be identified.

- Input uncertain variables, such as the availability and intensity of energy sources, represented by stochastic processes.
- External random events, such as disruptive events, for example, earthquakes, ships or iceberg collisions, storms, rogue waves, etc.
- Internal parameters epistemic uncertainty, such as the uncertainty related to components' efficiencies values or to the inaccurate values given by the relationships used to design the system.
- Internal random events, for example, components' failures.
- Financial risk, that is settled, e.g., in cost of debt or, in general, in cost of capital.
- Tax risk, arising from changes in tax policies of countries.

- Social risk, for example, the resistance of the population to the construction of a plant or the change in environmental laws and energy policies of governments, which might allow support for renewable energy production.
- Market risk, i.e. the risk associated with changes in the selling price of energy or changes in the value of demand.

As far as wind energy systems are concerned, the reference [361] provides a comprehensive list of specific sources of variability and literature contributions addressing each source.

In this application, we include the sources of uncertainty indicated in Table 6.3, where is indicated the affected variable, its variability type, the nature of uncertainty (Epistemic, E, or aleatory, A), as well as the adopted modelling approach.

Table 6.3 Considered sources of uncertainties

Variable	**Uncertainty nature**	**Variability type**	**Modelling approach**
Bank interest rate	E	II	Monte Carlo sampling from predefined pdf
Investment cost	E	II	
Plant nominal life	E	II	
Self-interest rate	E	II	
Power coefficient	E	II	
Gear box efficiency	E	II	
Generator efficiency curve	E	II	Monte Carlo sampling from a predefined pdf centred on the nominal performance curve
Power electronic efficiency curve	E	II	
Number of required technicians for system restoring	E	II	
Repair costs	E	II	
Disruptive external events	A	III	Monte Carlo sampling from hazard curve and random generation of failure severity level from fragility curve
Components failures	A	III	Monte Carlo sampling of Time to failure pdf and Monte Carlo sampling of time to repair pdf
Wind speed	A	I	Markov chain
Electricity price	A	I	ARIMA time series
Wind direction	A	I	Monte Carlo sampling from predefined pdf
Wake effect	E	II	

Regulatory risk	A	IV	
Long-term market risk	A	IV	Scenario analysis
Investment cost-related risk	A	IV	

The sources of uncertainty stated above are the inputs to the technical, reliability (i.e., the probability that a product will properly operate for a design life under the specified environmental or operating conditions [447]) and economic model and are used to assess the risk of the investment. As well known, risk refers to the uncertainty of outcome, of actions and events, and it represents uncertainty about and severity of the outcomes of an activity [448].

The technical model consists of mathematical formulations representing the system and the relationships used to assess its power output considering the wind variability and the wind turbine conversion efficiency. The reliability model is used to assess the availability of the system and determine production interruption periods caused by internal and external failure events. The economic model is used to evaluate costs, revenues and, thus, the required performance indicators of the economic result.

The model is conceived with a modular blocks structure, so that the specific manner to model the variables' uncertainties can be changed in order to utilize the one better suited to specific situations, and new modules can be added to model additional uncertainties.

Market risk is described by the electricity price variability. An ARIMA model is adopted, as motivated in section 6.3.7. Given that in long-term analysis, the electricity price could change seriously under different scenarios, a trend parameter is included in the model to increase or decrease the price of a fixed or random percentage every year. Financial risk, such as interest rate variability, is simulated by Monte Carlo sampling from a predefined probability density function.

The random discontinuities of social risk, political risk, and regulatory risk are included by using a scenario analysis module. The uncertainty of plant life duration is accounted for by Monte Carlo sampling from a predefined probability distribution.

The flowchart in Figure 6.1 shows the logical sequence of the computational procedure in the proposed framework. Basically, a Monte Carlo analysis approach is adopted where a sequence of random instances of the system life is simulated through a predefined number of iterations. At first, wind turbines' type and location are chosen. Environmental data are

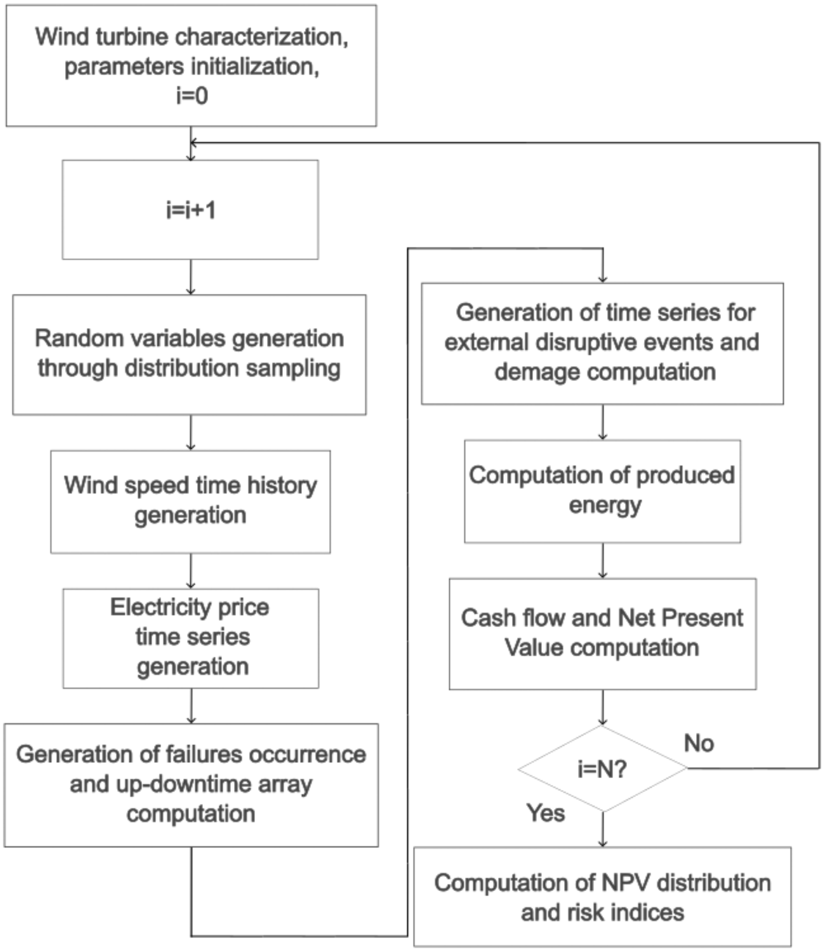

Figure 6.1 Flowchart of the framework adapted for offshore wind power systems

gathered, and the turbine technical characteristics and farm layout are input to the program data set. The number of runs, the expected life years of the system, and all other constant input data are declared, and the simulation is started. In each iteration, the value of variables subjected to epistemic uncertainty is generated by sampling the corresponding probability distributions. Then, for each year, the hourly time series of wind speed (section 6.3.3) and electricity prices (section 6.3.7), as well as the calendar or randomly occurring components faults (section 6.3.6), are generated through simulation of the corresponding stochastic processes. This allows us to compute the net annual energy production. Subsequently, the annual cash flows are computed by resorting to the economic model, and the Net Present Value (NPV) is computed. After the predetermined number of runs is terminated, the resulting set of NPV values is used to build the NPV frequency distribution histogram.

In the end, risk is assessed with the following three risk indicators.

- The NPV Coefficient of Variation *CV = σ[NPV] / E[NPV]*.
- The probability that $NPV < 0$.
- The Value-at-Risk (*VaR*) at 5%.

For computational purposes, the algorithm is based on four data vectors updated in each iteration. The adopted vectors *WS*, *EP*, *NPP*, and *A* represent, over the system life span, the annual sequence of wind speed, electricity price, nominal produced power and availability array with a time discretization chosen by the user, respectively. In this work, a 1-hour time discretization is adopted. The availability array values are the instantaneous system binary state variable d_{yh} = 1 or 0, representing whether the system is up or down according to failures and the subsequent restoration downtime. The *y* subscript represents the simulated year, and *h* is the current hour within the year. The same subscripts notation is also used to denote elements of *EP*, *WS*, and *NPP* elements.

Figure 6.2 shows the framework application to offshore wind power systems.

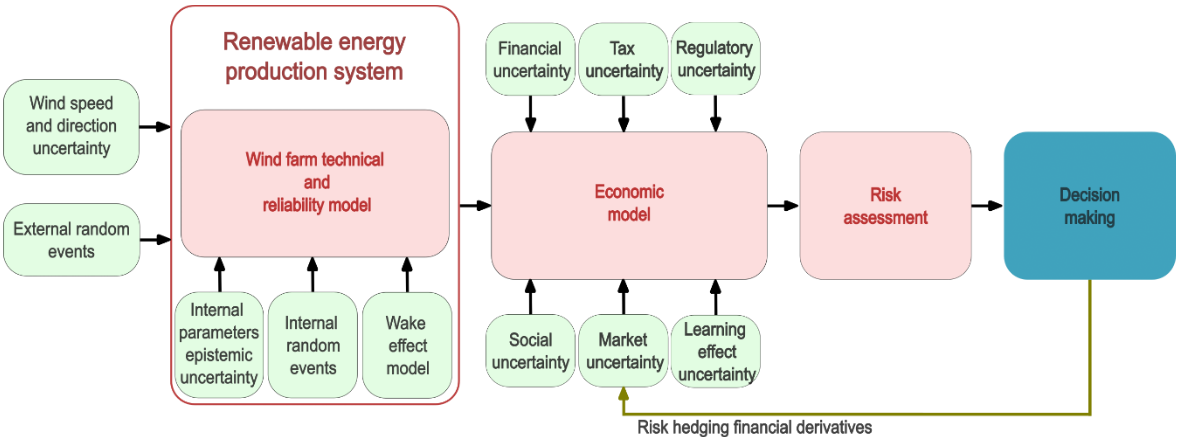

Figure 6.2 Proposed general framework for economic performance evaluation of renewable energy system

6.3.1 Wind farm technical and reliability model

The technical and reliability model enables the computation of power extracted by a horizontal-axis wind turbine based on the instantaneous wind velocity value, as described by Mathew [449]. This allows us to compute revenues from energy sales in order to assess investment profitability. Power *P* (MW) extracted by a horizontal axis turbine from the undisturbed flow of wind is expressed in (6.1).

$$P = \frac{1}{2} c_p \rho S U^3 \eta_g \eta_{gb} \eta_{pe} \cdot 10^{-6} \tag{6.1}$$

Where U is the undisturbed wind speed, S is the rotor swept area, and ρ air density, c_p is the turbine-specific power coefficient [449], and η_{gb} the wind speed-dependent efficiency of the gearbox, η_g of generator and η_{pe} of power electronics. As well-known, the power coefficient and efficiency values suffer from epistemic uncertainty, while the wind speed suffers from aleatory uncertainty, as explained subsequently.

One of the most important sources of uncertainty is component failures, which strictly affect the availability of the wind turbine and its actual power output. In order to account for equipment outages, an hourly availability array A_{yh} is generated as described subsequently. The hourly availability array stores a sequence of 0 (systems in the down state) and 1 (systems in the operational state) for each hour of the entire life of the system. An hourly wind speed array WS_{yh} stores instead the generated time series of wind speed and, using the power curve of the WT, it is transformed into the Nominal Produced Power array (NPP_{yh}). Finally, the hourly produced energy array (6.2) is obtained by multiplying elementwise the NPP_{yh} and the availability array.

$$HP_{yh} = NPP_{yh}(\cdot)A_{yh} \tag{6.2}$$

The assessment of produced energy becomes more complex when passing from a single wind turbine to a wind farm owing to the so-called wake effect, which determines a power loss in downstream turbines operating in the wake of an upstream generator [450]. In fact, when the wind passes through the turbines located upstream in a wind farm, the extraction of energy by the initial row of turbines and the turbulent motion of the rotating blades causes the flow to weaken and become disturbed. Consequently, the power generated by the first row of turbines located downwind is significantly lower compared to the upwind turbines. This deficit pattern persists for all subsequent turbines following the initial wake field. In certain cases, particularly in large-scale wind farms, the power deficit can range from 20% to 40% [451]. As a result, the annual energy production may suffer losses of up to 15% [452]. Additionally, rotor-induced turbulence increases the dynamic mechanical loading on downwind turbines. Thus, the wake effect not only diminishes the productivity and economic viability of the wind farm but also imposes limitations on the lifespan of the wind turbines, as indicated in [453].

The minimisation of wake effects calls for the layout optimisation of the wind farm [454]. While numerous models exist to represent the wake effect in wind farms [455] and research is underway to investigate wake losses [456], in this work, Jensen's wake model [457, 458] has been adopted as it has been recognized as a suitable choice in layout optimisation studies [459] due to its simplicity and relatively high accuracy when compared to other widely adopted wake models.

According to Jensen's model [458], the wind speed deficit (*ΔU [m/s]*) is computed as in (equation 6.3) where U_a *[m/s]* is the undisturbed wind speed at the up-wind wind turbine *a*, C_t is the thrust coefficient, and it is also a function of wind speed, X_{ab} *[m]* the horizontal distance between the wind turbines, *k* is the wake decay constant, A_b *[m^2]* is the rotor swept area, D_a *[m]* is the wind turbine diameter and A_{ab} *[m^2]* is the overlapped area between the up-wind and down-wind wind turbines.

$$\Delta U = U_a\left(1 - \sqrt{1 - C_t}\right)\left(\frac{D_a}{D_a + 2kX_{ab}}\right)^2 \frac{A_{ab}}{A_b} \tag{6.3}$$

If the distance between the two centres of the rotor on the plane orthogonal to the wind direction of the two considered wind turbines (*d*) is lower than the wind turbine diameter and higher than zero, the overlapped area can be calculated resorting to (equation 6.4), where R_a and R_b are the radii of the two wind turbines, *d* (equation 6.5) is the distances between the centre of the two rotors with coordinates *(x_a, y_a)* and *(x_b, y_b)*, respectively, on the plane orthogonal to the wind direction, *x* is calculated with the (equation 6.6), and *y* is computed resorting to (equation 6.7).

$$A_{ab} = R_a^2 \sin^{-1}\left(\frac{y}{R_a}\right) + R_b^2 \sin^{-1}\left(\frac{y}{R_b}\right) - y(x + \sqrt{R_b^2 - R_a^2 + x^2}) \tag{6.4}$$

$$d = \sqrt{(x_b - x_a)^2 - (y_b - y_a)^2} \tag{6.5}$$

$$x = \frac{R_a^2 - R_b^2 + d^2}{2d} \tag{6.6}$$

$$y = \sqrt{R_a^2 - x^2} \tag{6.7}$$

If the distance between the two centres of the rotor on the plan orthogonal to the wind direction of the two considered wind turbines is equal to zero, the overlapped area is equal to the rotor swept area. If the distance between the two centres of the rotor on the plan orthogonal to the wind direction of the two considered wind turbines is higher than the wind turbine diameter, the overlapped area is equal to zero.

As wind turbine rotors dynamically adjust their positions to maximise energy capture, the interaction between upwind and downwind turbines is not static. Consequently, the overlapped area between two turbines can vary from 0 to the rotor swept area (A_b), leading to a corresponding variation in the ratio from 0 to 1. This dynamic nature implies that the wind speed deficit is not constant. To accurately determine the overlapped area, it is necessary to have knowledge of the wind direction and the overall layout of the wind farm. This indicates that certain wind farm configurations can result in minimal wake losses. Furthermore, a trade-off arises between space utilization, which affects costs associated with cabling and movements required for maintenance and inspections, and the distances between wind turbines aimed at reducing their mutual interaction. In any case, as per the findings presented in [460, 461], it is commonly recommended that a safe distance for installing new turbines should be approximately 7-10 times the diameter of the turbine blades when positioned downstream. For turbines installed orthogonal to the prevailing wind direction, a distance of around three-five times the turbine blade diameter is typically considered safe.

The first step in the power computation process is to acquire accurate time series data for the wind direction. These data can either be readily available or obtained by combining the two components, x-axis and y-axis of the wind speed time series, respectively. In order to capture the variability of wind direction, Monte Carlo sampling is performed using a Kernel distribution [462]. This allows to better match experimental data which may not adequately fit a predetermined parametric density function. Experimental data is fitted by considering the conditional probability of wind direction and wind speed. This means that a particular wind direction is only considered valid if it corresponds to an acceptable level of wind speed from that direction. This approach allows for a more realistic representation of the relationship between wind direction and wind speed in the modelling process. Subsequently, the process continues as follows:

1. The coordinates of the wind turbines' location in the wind farm are provided.
2. The matrix of distances X_{ab}, between each pair of wind turbines is computed. The dimensions of this matrix correspond to the number of turbines present in the wind farm.

3. For every wind direction, the system is rotated to align orthogonally with the wind direction under consideration.
4. The overlapped area (A_{ab}) for each wind turbine is evaluated. It is important to note that a wind turbine can be influenced by multiple other turbines or none at all. Therefore, a matrix of values A_{ab}, for each wind turbine, with dimensions equal to the number of turbines, is created. Each element of the matrix represents the extent to which wind turbine a is affected by wind turbine b.
5. By utilizing the wind speed associated with the wind direction of each specific hour, and hence the corresponding overlapped area values, the power extracted by each wind turbine during a specific hour is calculated. This results in a structure comprising matrices, one for each wind turbine, representing the extracted power for each hour throughout the year.

Following this, the aforementioned data is integrated with the up-time and down-time array of each turbine, as detailed in subsequent sections [363]. When constructing these arrays, a notable distinction from the case in which only a single piece of equipment is considered is that each wind turbine will possess its own individual failure history and energy production record. As a result, each turbine will contribute to the overall revenue by selling the energy it generates. Once one has the actual hourly produced power of each turbine, they can be summed up to obtain the whole hourly produced electricity of the farm.

6.3.2 Economic model

The economic model encompasses both cost computation and revenue computation, as it was shown.

The cost items, as summarized in Table 6.4, are taken into account during the cost computation process. The adopted cost model is extensively described in the reference [463]. The author resorts to [464] for estimating the floating platform cost and to [465] for the installation procedure. The evaluation of corrective maintenance costs and the revenue computation have been carried out as explained in the following [363], accounting for the presence of multiple turbines.

Table 6.4 Cost model items

Cost Item	Sub-items	Literature source
Investment cost	Wind turbine and floating platform purchase (wind turbine, floating platform, cables and transmission system, mooring and anchoring systems)	[463]
	Wind turbine and floating platform installation (loading onto a vessel, sea transport, mooring, electrical cable lying, onshore cable installation) and rent of the shipyard	
Operating cost	Grid access fees, insurance costs, and seabed rental	
	Maintenance cost (preventive)	
	Maintenance cost (corrective)	See text [363]

It is important to note that when the wind farm is considered, the array cables cost increases dramatically and always determines a relevant percentage of the investment. In fact, in the optimisation of the wind farm layout, there is a trade-off between the spacing between the turbines, which increasingly reduces the wake effect, and the space consumption, which increasingly causes the growth of the investment cost due to the cable arrays and, generally of all transmission system. Additionally, the operation cost is affected by the farm layout.

Since the annual failure list is computed resorting to the methodology discussed in section 6.3.6, the annual cost of corrective maintenance encompasses the cost of each failure ReC_i (equation 6.8). Material costs, also called restoration costs, are also factored in, drawing from relevant data found in Carroll et al. [356].

$$ReC_i = C_t N_t RT_i + RC_i \tag{6.8}$$

Where C_t is the hourly cost of technicians, RT_i is the recovery time of the failure, N_t is the number of technicians required for operations, and RC_i is the cost of the materials used for the activities. The costs of external random events are estimated as expressed in section 6.3.5. In any case, a brief recap is made here. The restoration cost is taken from the literature [356] and has a different value for each component depending on the failure mode. There are three failure modes, i.e., minor repair, major repair, and major replacement. Finally, the costs of restoring the equipment damaged by a disruptive event, based on the generated disruptive events list, are calculated as a percentage of total investment for low and medium damage levels as the external event impacts the entire system instead of on a single component. For a high damage level, on the other hand, the wind turbine's life is interrupted because the system cannot be restored. The revenues of the y-year R_y are computed according to equation 6.9 through elementwise multiplication of the vector of hourly produced electricity HP_{yh}, which represents the production of the whole wind farm, and the hourly electricity price vector EP_{yh} and summation over the yearly hours.

$$R_y = \sum_{h=0}^{8760} HP_{yh}(\cdot)EP_{yh} \tag{6.9}$$

Where h identifies the specific hour, and EP_{yh} is the simulated hourly electricity price vector, as explained subsequently.

6.3.3 Wind uncertainty modelling

While the literature commonly relies on sampling Weibull probability distributions based on historical data to address this uncertainty [359, 373, 376], this approach can result in unrealistic sudden changes in speed and direction values. In order to mitigate this issue, this work adopts a Markov chain method, following the approach outlined by Negra et al. [31], to generate hourly time series of wind speeds over the entire lifespan of the plant. This methodology relies on the historical hourly wind speed data at the selected site. Given that available weather data refer to wind speed at 10m above sea level, to assess the wind speed values at the height of the turbine's hub, the log law is used [466]. In greater detail, the adopted method sets up a birth-and-death Markov process using the historical time series to calculate the number of possible states and the transition rates of the Markov process. The calculation of the number of possible states and the transition rates are strictly related to the maximum and minimum values of wind speed of the training time series and the time of permanence in certain states, respectively. This approach allows us to consider both statistical parameters of the past values of wind speed and its randomness, generating a time-series of wind speed values for each run, to be stored in the hourly wind speed array WS_{yh}. The number of possible states and the transition rates depend on the maximum and minimum values.

6.3.4 Epistemic uncertainty of internal parameters

Within the model, the epistemic uncertainty of internal parameters is associated with the efficiency of components and model simplifications. To model this type of uncertainty, a probability density function is utilized, centred around the mean value of the quantities and bounded by their maximum and minimum values. The considered sources of epistemic uncertainty related to the technical model are namely the power coefficient, gear box efficiency, generator efficiency curve, and power electronic efficiency curve.

The selected wake effect model suffers from epistemic uncertainty, also in single wake conditions, that has been investigated in literature [467]. While at the wake centre, Jensen's model is one of the most accurate models, and it is the most accurate model for wind speeds lesser than 8.5 m/s, it was found that it underestimates the wake loss of about 2-5%, and considering the entire wake cone the model overestimates the wind speed reduction. The maximum differences between the predicted wind speeds after the wake effect and the measured ones are observable at low distances. In fact, for a downstream distance ranging from 2.55 diameters to 3.75 diameters, the measured average wind speed is higher than the predicted one of about 14%-12%. Approaching from a downstream distance of about 5.1 diameters to 7.3 diameters, the error changes from 12% to 7%. Although there is a conservative aspect in this underestimation, the model proposed in this work tries to cope with the real uncertainty of the system. For that reason, the assessed value of the wind speed after the decay due to the wake effect computed by Jensen's model is adjusted by sampling a value from a uniform distribution ranging from 0.07 to 0.12.

6.3.5 External random events

With the term "disruptive events", the author refers to external natural events (i.e. earthquakes, storms, rogue waves, impact with icebergs, etc.) or even man-made events, such as terrorism acts or collisions with ships, which could impact the wind turbine structure causing a damage. The sensitivity of a wind turbine's structural integrity to natural hazards depends on the type of platform. For instance, monopile and tripod foundations, being bottom-supported, may be affected by earthquakes, while floating structures would remain unaffected.

This modelling framework is suitable for various wind turbine support structures. e.g. spar buoy, tension leg platform, semi-submersible platform, monopile or tripod structure. Monopile and tripod foundations are fixed and limited to shallow water (i.e. <50m), but they are widespread [468], while floating structures are used for deep water.

This means that a library of disruptive events models should be built and included in the simulation according to the site and the considered support structure.

A possible model for earthquakes is described in the following. It is assumed that a hazard curve (Figure 6.3) is available to describe the annual probability of a seismic event occurring at a specific site in relation to its magnitude, expressed in terms of peak ground acceleration (PGA).

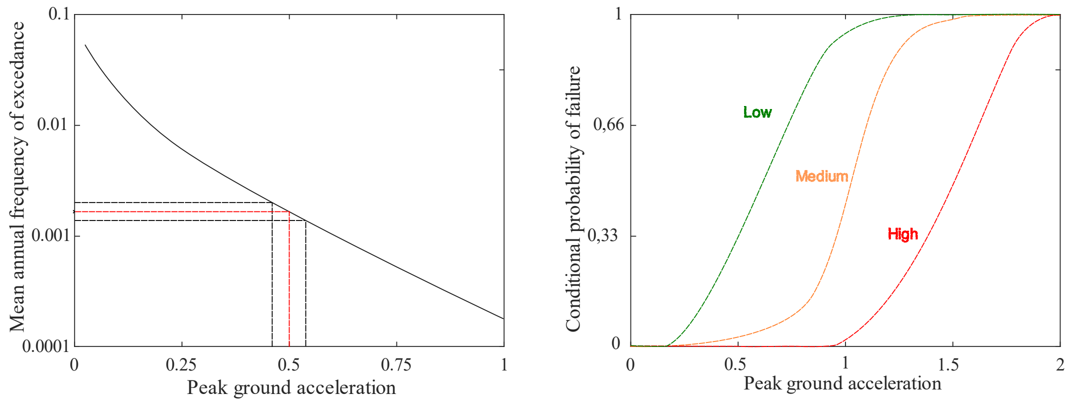

Figure 6.3 Example of hazard curve discretization and example of fragility curves

According to [469], to calculate the date of the event and its magnitude, the hazard curve is discretized into a user-defined number of magnitude classes. For each magnitude value, the annual probability of occurrence is thus obtained. Since each different magnitude class occurs at a fixed constant rate, the distribution of the time between events is exponentially distributed. Monte Carlo sampling is used to determine the time to the next event and added to the current event date. The procedure is repeated until the end of plant life is reached, and the process is replicated over all magnitude classes in order to obtain a list of events' dates and their magnitudes.

In order to estimate the damage the system suffers after each event, fragility curves are used [469]. Given the magnitude of the event (e.g. PGA), the fragility curve provides the probability of exceeding a predetermined damage state, i.e. failure modes. The limit seismic load before failure occurs is a random variable log-normally distributed, and the system will fail if its seismic capacity is less than or equal to the ground motion level corresponding to the chosen intensity measure. The cumulative distribution function of the probability of exceeding a fixed damage state (cdf_f) conditional on a PGA is given by (6.10).

$$cdf_{f(PGA)} = \Phi\left(\frac{1}{\beta} ln \frac{PGA}{\mu}\right) \tag{6.10}$$

Where Φ is the standard normal cumulative distribution, μ the mean of the distribution and equal to $a \cdot PGA \cdot b$, a and b being experimentally derived constants, and β the standard deviation of the distribution.

Fragility curves are available in the literature for many pairs of damage states' components, systems and plants, but they can also be constructed using simulation procedures (e.g. Finite Elements Simulation). With regard to bottom-fixed offshore wind power plants, fragility curves are available for monopile [470-472] and jacket foundations [473] subjected to seismic loading, the combination of aerodynamic and seismic loads [474, 475] and hurricane and seismic load [476], as well as electrical grid damages [477, 478]. While [474, 476] refer to land-based wind turbines, their results are easily applied to bottom-fixed offshore wind systems.

Three different damage levels are considered here, namely low, medium, and high. Each damage level is associated with a specific time to repair and cost, which is a percentage of the investment. The highest damage level is associated with destructive damage, i.e. the interruption of turbine life and the impossibility of restoring it. If the probability distributions of repair time and cost are known, it is possible to consider their uncertainty using Monte Carlo sampling.

For the determination of the damage level, for each turbine, a random number between 0 and 1 is sampled for each event, starting from the highest damage level and arriving at the lowest. If the random number is less or equal to the cdf_f value associated with the PGA of the event, damage occurs. If the random number is greater than the cdf_f value, it is compared with another damage level until all occurrences of damage states are verified. If the random number is greater than all cdf_f values, the event does not lead to a fault.

The disruptive events that do not lead to a failure are neglected, while the others are included in the list of failures with their date, time to repair and cost.

At the end of this procedure, the output is a list containing, for each turbine, the occurrence date, down time and expected cost of all disruptive events that will occur in the current run.

Additionally, another model to account for ship collision is described. The ship collision event simulation and the relative damage assessment are developed following a procedure that is like the disruptive events simulation procedure proposed above. Based on the literature review, the whole ship collision probability, that is, 10^{-6} events per hour, is divided into low-speed, medium-speed, and high-speed collision. The low-speed collisions represent 50% of the events, the medium-speed collisions are 30% of the events, and the high-speed collisions are 20% of the events. The speeds are 1 m/s, 2.8 m/s, and 6 m/s respectively.

The size of the ship which strikes the wind turbine structure is divided into three classes. The 10% of the events are caused by a heavy bulk ship and cause disruptive events that lead to the collapse of the structure. The 36% of the events are caused by a medium-sized ship that causes medium damage to the turbine. The 54% of the collision is caused by a light service vessel that leads to a little damage to the turbine. The three sizes are associated with three supposed different estimated fragility curves with a mean of log(1.48) m/s, log(3.88) m/s, and log(4) m/s and a standard deviation of 0.23 m/s, 0.55 m/s, and 0.55 m/s respectively. Figure 6.4 shows the fragility curves of the wind turbine.

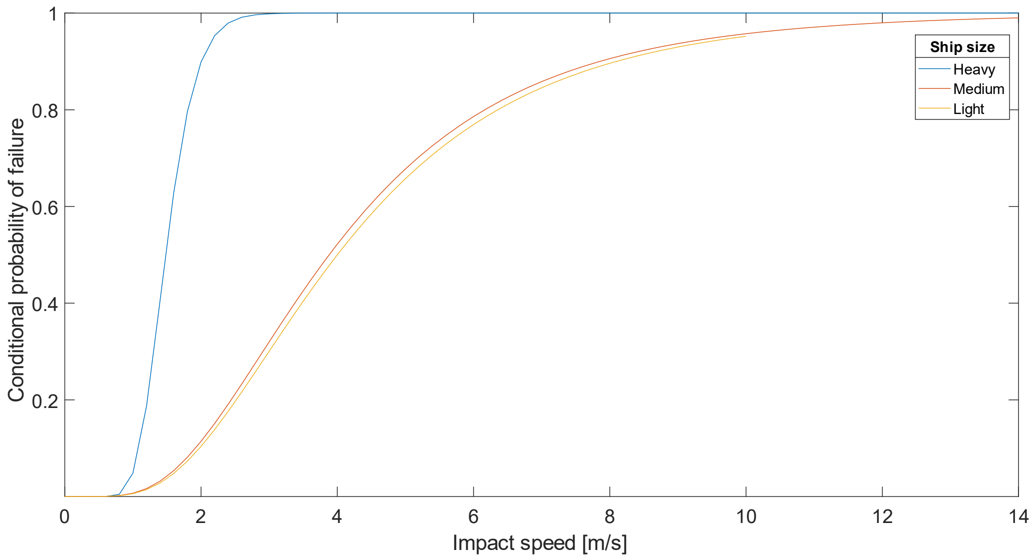

Figure 6.4 Fragility curves of the wind turbine for different ship sizes

The fragility curves have been supposed by comparing the data about the expected deformation of the fixed-bottom wind turbine under different wind speed impacts, for which the fragility curves are available in the literature, and the data on the expected deformation of the spar buoy platform under the same wind speed impact. The impact of a heavy bulk ship leads to the disruption of the structure, whereas with the medium to a restoring cost and production loss of 30% of the investment cost. Finally, the impact of the light service vessel is associated with an economic loss of 10% of the investment cost. For each turbine, the procedure follows the subsequent steps.

1. For each impact speed, the event date is sampled from an exponential distribution build with the events/year rate associated with each impact speed. Therefore, three event types are possible: low, medium, and high impact speed.

2. The event date is summed with the time now, the event speed that identifies the event type, and the date is added to the event list, and the simulation clock jumps to the event date.

3. Step 2 is repeated until the simulation clock reaches the plant years life. If the time now exceeds the plant's life, the event is neglected, and the event list is concluded.

4. Starting from the event with the nearest date and arriving at the farthest, a random number between 0 and 1 is sampled and compared with the lowest probability value associated with the ship size. If the random number is lesser than the probability, the event is associated with that type of ship; if not, the next higher probability is considered, and the procedure is repeated. Finally, if the random number is higher than all the probability associated with the ship type, the smallest ship is selected.

5. Starting from the event with the nearest date and arriving at the farthest, a random number between 0 and 1 is sampled and compared with the ship size cumulative distribution function value associated with the impact speed. Suppose the random number is lesser than the probability value. In that case, damage occurs, and the economic loss associated with the event type is added to the list of economic losses due to ship collision. If the event is an impact with a heavy bulk ship, the wind turbine collapses, and it cannot be recovered. The event does not lead to a fault if the random number is greater than the cumulative distribution function value associated with the impact speed.

At the end of the procedure, for each turbine, an event list with event date, impact speed, ship size, and economic loss is obtained. This list enters the technical model to change the farm layout if an impact with a bulk ship occurs and always the economic model to concur in the net present value assessment.

6.3.6 Internal random events

It is assumed that the wind turbine system can be decomposed into the following components or subassemblies [479]: pitch and hydraulic system, generator, gearbox, blades, grease/oil/cooling liquid substitution, electrical components, contractor/circuit breaker, controls, safety, sensors, pumps/motor, hub, heaters/coolers, yaw system, tower/structure, power supply/converter, service, transformer and other. Each component or subassembly has three different failure modes, which determine a minor repair, a major repair, or a replacement. The components are considered in series, so when a single element fails, the whole system fails and production stops. Each failure mode of each component is associated with a specific mean failure rate, time to repair and expected restoration cost (i.e. material replacement cost, subsequently utilized to compute the repair cost).

Although the adopted procedure has already been shown in section 4.2.4, it is reported here for the sake of readability.

For each j-th component, an overall constant failure rate λ_j is known, as well as the frequency distribution f_i of the three i-th failure modes.

For each turbine, the algorithm to generate the failures events list includes the following steps:

1. The actual failure rate of each component failure mode is computed as $\lambda_k = \lambda_j f_i$. As failures occur at a constant rate, the distribution of their time to failure (*TTF*) will be exponential. All subsequent failures of the same type will occur after a certain random *TTF*, calculated from the last time the same type of failure occurred. The *TTF* is to be considered as a net time, i.e. excluding plant shutdowns due to further failure types occurring in the meantime. The different failure types, being conceptually independent of each other, will not affect the timing of the failure sequence of the other categories.
2. For each of the fault types, generate a *TTF* sequence by repeatedly randomly sampling its distribution. In practice, having extracted a random number $R \in [0,1]$, the *m*-th TTF of the *k*-th fault type will be $TTF_{km} = - \lambda_k \ln (R)$.
3. Repeat the procedure until the sum of the TTF_{km} generated for the fault type considered is at least equal to the nominal life of the installation, so as to generate a random sequence of faults of the same type covering the entire life of the installation.
4. For each *k*-th fault type, the theoretical date of occurrence of the *m*-th fault (assuming a zero time to repair, *TTR*) will be equal to the sum of all previous *TTF*s (TTF_{km}) times *m,* ranging from 1 to *m*-1.
5. Repeat steps 2 to 4 for each type of failure, obtaining as many independent sequences of timed failures.

6. Combine the obtained sequences into a single sequence by sorting the faults by increasing dates. This would be the timetable in which the various faults would hypothetically occur if repairs were instantaneous or occurred in negligible time.
7. Starting with the first fault in the sequence, add the random *TTR* generated for the repair of the fault under consideration to the current dates of all subsequent faults. The number of required technicians for the repair is sampled from a standard distribution centred on the mean number of required technicians and with a user-given standard deviation. The restoration cost is sampled from a triangular distribution centred in the mean value of the restoration cost and with minimum and maximum values a percentage of the mean value (e.g. 90% and 110%). The repair cost is calculated by multiplying the hourly cost of the technicians, the number of required technicians, and restoring time and adding the cost of materials (equation 6.8).
8. Repeat step 7 sequentially for all scheduled faults, updating the attempted occurrence date of all subsequent faults each time. This gradual shift allows the net *TTF* value of each fault to be maintained with respect to the previous occurrence of the same type of fault, net of interruptions for the repair of other faults occurring in the meantime. When the date of failures following the current one, as a result of this forward shift sequence, becomes greater than the nominal life of the system, these failures will be ignored because they will not occur.
9. When the *TTR* has also been added for the penultimate fault in the sequence (and thus the date of the next fault has slipped), the actual occurrence date of all faults is obtained.

The time-phased lists of external disruptive events and components' failures are then merged in order to obtain, for each turbine, a global list containing all events and occurrence dates, ordered over time, their time to repair, the required number of technicians for the repair and their restoration cost over the entire plant life.

If the disruptive event date falls in a down-time period, the fault restoration process is interrupted, and the system restoration from the disruptive event starts. The events' dates of the failures following a disruptive event are shifted, as explained in the above algorithm, while the event date of a disruptive event remains unchanged.

At the end of the events generation procedure, the entire system life span is subdivided into unit time intervals Δt (here Δt = 1 hr). For each time interval, the system state variable *d* is defined, assuming value 0 if the system is down and 1 if the system is up. The values of the state variable are stored in an hourly availability array A_{yh} where subscripts represent the y-th year of equipment life and the h-th hour.

6.3.7 Economic model uncertainty

This section and the subsequent one include all uncertainties affecting the economic and financial parameters, i.e. electricity price variability, the uncertainty of capital investment, including learning effects, tax policy etc. Additionally, the sources of epistemic uncertainty in the economic model are bank interest rate, investment cost, plant nominal life, and self-interest rate.

The computation of investment costs introduces epistemic uncertainty due to the relationships utilized. In order to address this, the value is sampled from a probability distribution constructed based on the computed expected value. On the other hand, revenue calculation involves multiplying the hourly produced power by the hourly energy price while disregarding any downtime periods. Market risk is primarily considered through the modelling of hourly energy prices. Historical time series data is used as input to perform regression analysis and obtain coefficients for an autoregressive integrated moving average (ARIMA) model. These parameters are then utilised to simulate, using Monte Carlo simulation, 1000 paths for each run, and the middle time series is selected from the set for revenue computation in the current run. Additionally, scenarios on the forecasted mean electricity price are used to set the mean value over that will be constructed the time series to include long-term variability. Since the coefficients of the ARIMA model change depending on the provided data, for the sake of example in (equation 6.11) the structure of the adopted ARIMA(1,1,1) equation is shown.

$$y_y = (1 - \phi_1)m + (1 + \phi_1)y_{t-1} - \phi_1 y_{t-2} + e_t + \theta_1 e_{t-1} \tag{6.11}$$

Where y is the variable under regression, m is the drift term, Φ_1 is the auto-regressive coefficient, θ_1 represents the moving average coefficient, e is the error term, and the subscript t identifies the reference time period.

In order to incorporate financial risk, Monte Carlo sampling is employed, drawing from a predefined probability density function of the plant's nominal life, bank investment cost, and self-interest rate.

6.3.8 Long-term scenario effects (type IV uncertainty)

To the best of our knowledge, previous works have never accounted for Type IV uncertainty, which represents random discontinuities arising from factors such as economic, political, and regulatory scenario variations combined with all the other sources of uncertainty. This omission hinders a comprehensive assessment of the system's economic viability. In the proposed method, scenarios' effects are taken into account by modelling the long-term trend of average electricity price, the impact of learning effects on capital investment and the changes in subsidies' policies.

In greater detail, the market risk itself encompasses both short-term, specifically modelling the fluctuations in energy prices over a brief period, and long-term changes that may occur under various scenarios. When considering future wind farm investments, it also becomes appropriate to incorporate the risk associated with potential reductions in investment costs due to the learning rate, called investment cost-related risk in Table 6.3. Additionally, given the substantial role subsidies play in this sector, it is crucial to model the potential changes that may arise over an extended period due to political decisions. The latter source of risk is called regulatory risk in Table 6.3.

The model incorporates the concept of investment cost reduction by utilizing the offshore wind power learning rate, as documented in the studies by Fortes et al. (2015) and Shields et al. [443, 444], where authors consider a constant learning rate of about 9%. This value is combined with scenarios concerning the projected installed capacity of offshore wind power in Europe by 2030, as presented by Nghiem and Pineda [445]. Figure 6.5 shows the resulting learning effect curve. The curve represents the price per megawatt installed in the function of the year of installation, considering the cumulative growth of installed capacity over the years.

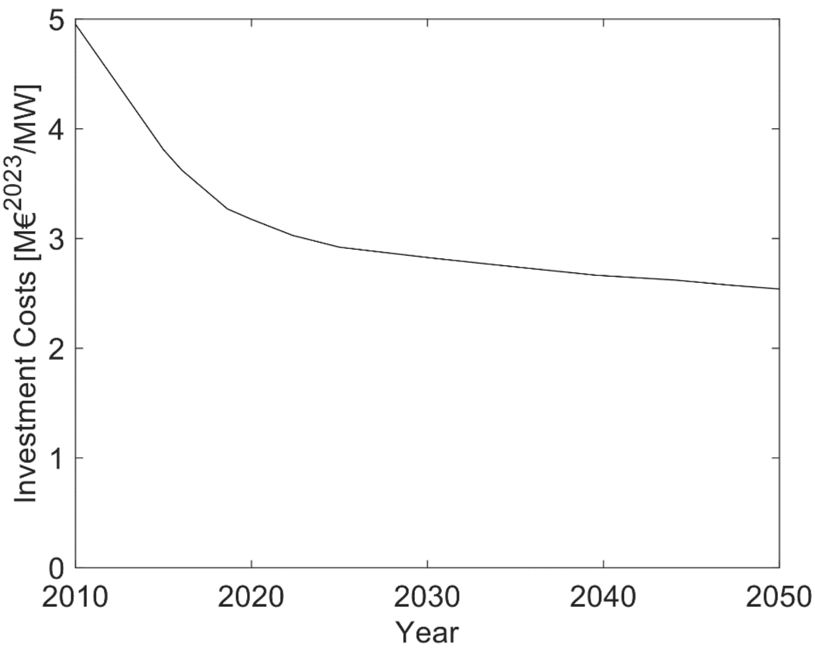

Figure 6.5 Learning rate curve: investment costs of offshore wind power system per MW installed during the years

The values of scenarios' variables have already been defined in section 6.2, and their number reduction has been discussed. Furthermore, the scenarios' combination procedure has been introduced. Despite that, a brief recap is made in the following.

Commonly adopted scenarios' variables have been taken from the literature to consider the long-term market risk and regulatory risk [442]. In literature, reports on the possible evolution of the mean electricity price and its volatility are widespread. One can select the report that most fits its requirements and the boundary condition of the case study. The short-term variability of the energy price is then simulated starting from the expected yearly energy price found in the considered scenarios. Regulatory risk can be modelled by considering possible strategies of subsidies. Indeed, nowadays, countries basically adopt three different policies: no-subsidies, feed-in tariff, and feed-in premium tariff. A Feed-in tariff consists of a fixed price paid for the generated power without the influence of the current market price. Instead, the feed-in premium tariff consists of an extra-price paid by summing the subsidy value to the current market price.

If variables (e.g., the electricity price, the investment cost reduction, and subsidies policy) have different driving factors and the assumptions are not mutually exclusive, they can be combined to obtain new and more comprehensive scenarios. During the reports' selection, this issue must be carefully considered.

One significant drawback of scenario analysis is the challenge it poses in decision-making under deep uncertainty, primarily due to the absence of assigned probabilities to scenarios. While assigning probabilities to scenario occurrences can be a complex task, there are certain variables for which such probabilities can be defined. For instance, by analysing political interests and opinions regarding renewable energy sources, it becomes possible to make assumptions about the evolution of subsidy policies.

By assigning realistic probabilities to the best and worst-case scenarios, it becomes possible to use the mid-case scenarios as representative probabilities for each scenario. With sufficient information available, it is feasible to perform accurate estimations of scenario probabilities and associate credible probabilities with each scenario. In this study, a four-step process is followed to integrate various scenarios and evaluate a single net present value probability density function for the investment. Firstly, scenarios pertaining to regulatory, long-term market, and investment cost-related risks are constructed, and the most probable scenarios are selected, as exposed in section 6.2. Next, the net present value probability density function is assessed for each scenario individually. Then, these functions are multiplied by their corresponding probabilities and subsequently aggregated by summation. The procedure is demonstrated in the case study example.

6.3.9 Climate change effect

In this work, climate change is considered an almost surely event, which affects the environment and the weather year after year. According to the literature, the inclusion of climate change is performed considering the expected percentual changes in wind speed producibility in the region of the location of the wind turbine. The wind producibility is expressed as produced power per hour divided by the rated power of the wind turbine. For instance, in the numerical example, the increase of 4% at the end of the plant's life of wind producibility is considered for the location of the wind turbine. The percentual increase has been supposed to be linear. Therefore, starting from 0% and arriving at 4% each year of the plant life presents a percentual increase of 0.2%. The expected percentual changes increase or decrease the hourly produced power of the plant. Therefore, the adjusted produced power enters the economic model and the simulation proceeds.

6.3.10 Risk assessment

As a measure of investment profitability, the Net Present Value (*NPV*) of cash flows over the project life span is adopted here. NPV is affected by all the above-discussed sources of uncertainties with their propagation effects. Therefore, in the NPV computation procedure, there are several nested uncertainty models. Each run of the simulation procedure ends with a specific value of computed NPV. To do this, the investment cost I_0 must be computed as shown above. Then, I_0 is reduced according to different scenarios related to the learning effect, and finally, it is sampled by a triangular distribution centred in its model-calculated nominal value using Monte Carlo simulation. Revenues are affected by the uncertainty of energy prices and the produced power. Moreover, the produced power is affected by the random uncertainty of the wind speed (modelled resorting to Markov processes) and by the epistemic uncertainty of the internal parameters (Monte Carlo sampled from a distribution centred on their nominal values). The random and disruptive events lists and the sample-based computation of corrective maintenance costs directly affect the operating cost. Furthermore, bank and self-interest rate suffers from epistemic uncertainty, which is modelled using Monte Carlo sampling. The weighted average cost of capital uncertainty affects the NPV values acting on the discounting operation but also on the loan instalment, which influences taxes.

To begin, the user selects a location and wind turbines' type, and the program populates the data set with the turbine's technical specifications and relevant environmental data. Once all constant input data, including the number of runs, projected system lifespan years, and other necessary details, are declared, the simulation is initiated.

During each run, the values of variables affected by epistemic uncertainty are determined by sampling the relevant probability distributions throughout each cycle. Subsequently, through simulation of the corresponding stochastic processes, annual time series of failures, wind speed, and electricity prices are generated. This enables the calculation of annual net produced energy, disregarding downtime periods. Subsequently, the economic model is utilized to calculate annual cash flows and determine the NPV, resulting in an NPV frequency distribution histogram computed over the entire number of performed runs.

Risk assessment involves computing the probability density function of the NPV, evaluating the probability of obtaining an NPV lower than zero, and assessing the Value at Risk (*VaR*), assumed to be the maximum economic loss over the entire life of the system, with a confidence level of 95%. Additionally, the coefficient of variation of NPV is assessed as a measure of its variability.

The NPV is computed according to (equation 6.12), where I_o is the investment cost, Y is the expected life of the plant expressed in years, CF_y represents the cash flow related to the y-th year, and $WACC$ (equation 6.13) is the weighted average cost of capital.

$$NPV = -I_0 + \sum_{y=1}^{Y} \frac{CF_y}{(1+WACC)^y} \tag{6.12}$$

$$WACC = c_0\left(\frac{I_0 - V_0}{I_0}\right) + c_d\left(\frac{V_0}{I_0}\right) \tag{6.13}$$

Where V_0 stands for the debt, c_d represents its cost, and c_o is the cost of equity. Considering the yearly revenue, the yearly operating cost (OC_y) and taxes (T_y), the cash flow related to the y-th year is calculated as shown in (equation 6.14).

$$CF_y = R_y - OC_y - T_y \tag{6.14}$$

Taxes can be expressed by (equation 6.15) considering the tax rate (a), the share interests of the debt (q_y), and the depreciation charge (AMM).

$$T_y = a[R_y - OC_y - q_y - AMM] \tag{6.15}$$

The loan instalment L (equation 6.16) is supposed to be constant; therefore, if V_{y-1} is the outstanding debt from the year y, the shared interest is computable with (equation 6.17).

$$L = V_0 \frac{c_d(1+c_d)^n}{(1+c_d)^n - 1} \tag{6.16}$$

$$q_y = c_d V_{y-1} \tag{6.17}$$

Where n is the number of years of repayment of the financed capital, which is set according to the loan agreement.

6.3.11 Risk hedging

Given that uncertainty can negatively affect the profitability of the investment, financial tools can be employed to hedge risk and are included in the risk assessment model. In particular, financial derivatives can be used for speculative purposes or for risk hedging. In the case of renewable energy projects, investors typically aim for the latter. Different energy markets require different risk hedging strategies, which is why practical guides are available to manage market uncertainty [480]. Electricity and weather-based swap and forward contracts are commonly utilized for risk mitigation. This involves resorting to a fixed price per MWh for a predetermined energy amount [481, 482]. Additionally, more complex financial instruments, such as vanilla plain options and exotic energy derivatives, have been explored [483]. Given the market's volatility, strategies for accurately pricing wind power future contracts [484] and power forward contracts [485] are already under investigation. As energy forecasting is a challenging task, addressing prediction errors can assist in risk mitigation. This is why weather derivatives based on forecast errors have been developed [486]. Real options theory has also been explored in the feasibility study of wind farms [487].

In order to streamline the computational burden of the simulation tool and maintain simplicity, an over-the-counter (OTC) contract was selected for inclusion in this thesis, despite the availability of other appropriate financial instruments for mitigating electricity price risk. The framework's modular nature allows for easy modification of this specific block (depicted as the feedback arc in Figure 6.2) to accommodate an expanded range of contracts, both in number and type.

The implemented model incorporates a forward contract as the chosen financial instrument, which entails a fixed volume (V) representing the total MW of power sold to a single client at a predetermined price, called strike price (St). The mathematical formulation of the forward price F, considering that the electricity is not storable, is in (6.18).

$$F = V \cdot St \cdot e^{r \cdot t} \tag{6.18}$$

Where r is the risk-free rate of the investment and t *is* the delivery date in years. Generally, the forward power price is often a biased forecast of the future spot price. The forward premium decreases with the expected variance of wholesale spot prices and increases with the expected skewness of wholesale spot prices. In equilibrium, F is the expected value of the spot price minus the expected variance of spot prices multiplied by a positive parameter (k) plus the skewness of spot prices multiplied by a positive parameter (γ), as shown in (6.19) [488]. These two parameters are usually selected to take into account the risk aversion of the investors.

$$F = E(St) - k \cdot var(St) + \gamma \cdot skew(St) \tag{6.19}$$

The negative impact of expected spot price variance on forward premiums is rooted in the risk-averse behaviour of producers who seek to mitigate price risk through forward contracts. Conversely, a positive skewness implies a higher likelihood of significant upward price spikes, prompting risk-averse retailers to hedge against spot price risk. Consequently, the risk-related hedging actions of both producers and retailers exert downward and upward pressure on forward prices as a means to safeguard against spot price uncertainty. In any case, the previous equations are used to estimate the price of the forward, but generally, the buyer and the seller arrive at different estimations. In fact, the buyer assumes that the price will increase, whereas the seller assumes that it will decrease.

Through this instrument, the seller effectively hedges against the risk of a decrease in the energy price, while the buyer hedges against the risk of an increase in the energy price. The buyer benefits when the fixed price exceeds the prevailing market price, whereas the seller benefits in the opposite scenario. The contract establishes a mandatory obligation for the seller, who is the energy producer, to supply a fixed quantity of energy to the buyer and to the buyer to buy it. The contracted energy must be delivered on an hourly basis, with each hour's amount determined by the ratio between the total volume of the contract and the total number of hours within the interval that spans from the contract's start date to its expiration date. In the case of a contract duration exceeding one year, the price must be adjusted by capitalizing it using the market-free risk cost of capital. In situations where the energy producer is unable to meet the required delivery quantities due to factors such as a lack of wind or the unavailability of certain wind turbines, they are obliged to supply all the available produced energy and compensate the buyer with a penalty as predetermined in the contract. This penalty is proportional to the amount of undelivered power. The computational procedure of the producer cash flow related to the forward contract (*FC*) is shown in equation 6.20.

$$\begin{gathered} if\ HP_{yh} \geq V_{yh} : FC_y = FP \cdot V_{yh} \\ else : FC_y = FP \cdot HP_{yh} - FP_P(V_{yh} - HP_{yh}) \end{gathered} \tag{6.20}$$

Where V_{yh} is the due hourly volume, *FP* is the contracted electricity price per MWh, and FP_P is the contracted penalty. Following the determination of the total energy generated by the farm within a specific hour, if the quantity is less than or equal to the fixed quantity stated in the contract, all the energy is sold at the predetermined strike price, and the corresponding penalty is calculated and paid to the buyer. However, if the generated energy exceeds the contractually obligated amount, only the energy specified by the contract is sold at the strike price, while the remaining power is sold at the prevailing market price.

The financial instrument is integrated into the revenue computation process.

6.4 Assessing the performance of wind farms under uncertainty: a case study

In order to show its capabilities, the model was implemented in MATLAB environment and applied to the example of a 20 turbines wind farm located 5 kilometres off the port of Brindisi, Italy, at coordinates latitude 40.68, longitude 18.06 degrees (Figure 6.6). The water depth is approximately 400 metres. The expected date for the investment is the year 2030.

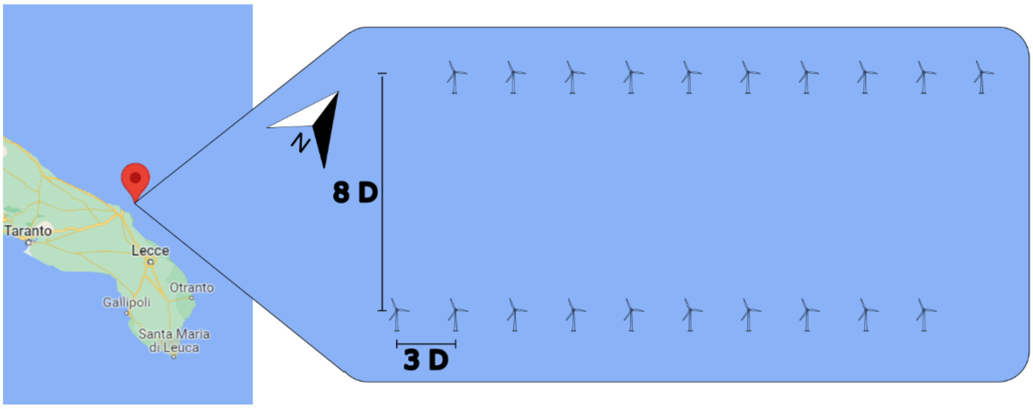

Figure 6.6 Site location and wind farm layout

The following description applies to each wind turbine within the farm. Based on the specific site characteristics, a horizontal axis NREL 5-MW reference wind turbine [489] was selected. It is installed on a SPAR platform. The wind turbine is designed for a rated wind speed of 11.4 m/s (with cut-in and cut-off wind speeds at 3 and 25 m/s, respectively). The wind turbine features a rotor diameter of 126 meters and a hub height of 90 meters. It utilizes a geared drive train and operates with pitch regulation. The power curve and the power coefficient of this turbine are presented in Figure 6.7.

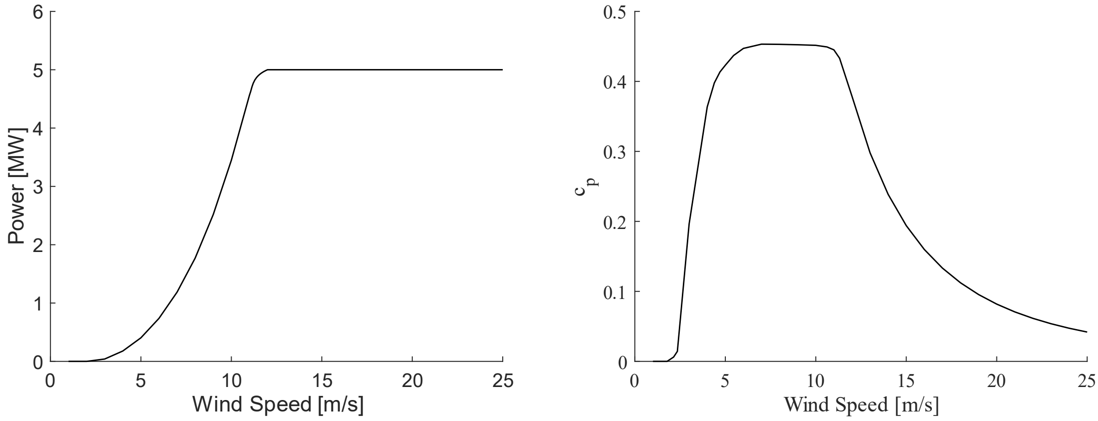

Figure 6.7. 5 MW Wind turbine power curve and power coefficient

The farm arrangement is based on adopting twenty turbines arranged in two rows, with a horizontal spacing of 3 diameters and a vertical spacing of 8 diameters. The adopted layout has been selected according to the indication provided in references [460, 461] to reduce the wake effect impact on the produced energy.

To illustrate the dynamic behaviour of the wake area, Figure 6.8 presents the percentage of waked area for the adopted reference wind turbine type as a function of wind direction, assuming it is the fifth of the front row, exposed to the north. When the wind originates from the south, it is overshadowed by the turbines in the second row, and when the wind comes from the east or west, it is affected by the turbines within the same row.

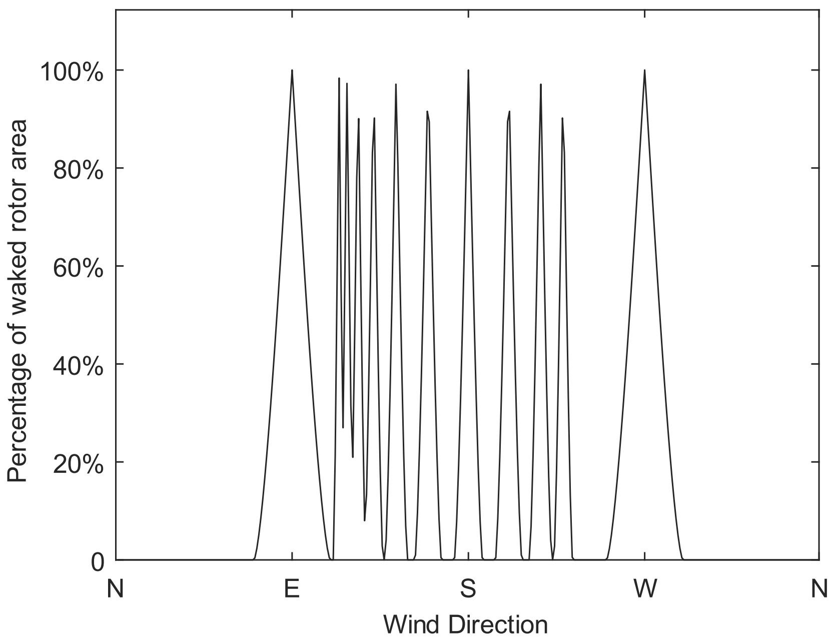

Figure 6.8 Percentage of waked rotor area in the function of wind direction

The site-specific wind direction distribution is represented by the wind rose shown in Figure 6.9.

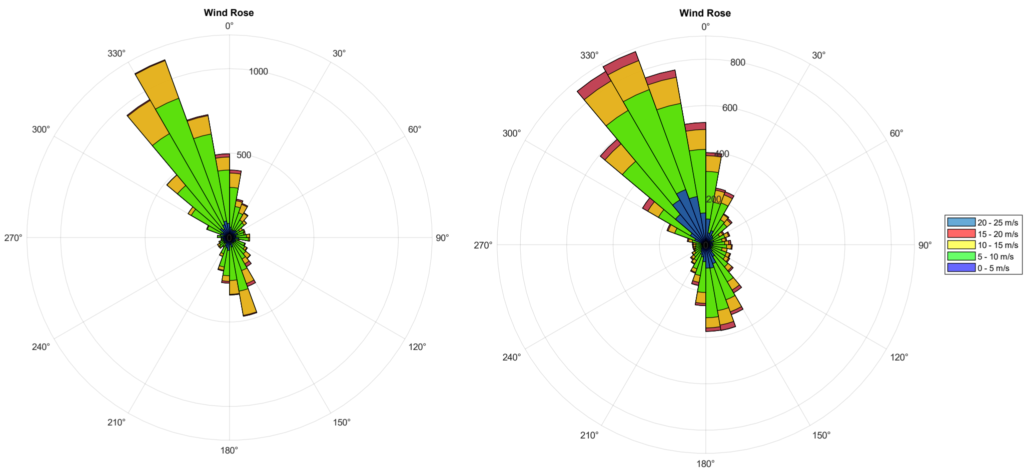

Figure 6.9 Real data wind rose (left side) and simulated data wind rose for the first year of a generic run (right side)

The ECMWF (European Centre for Medium-Range Weather Forecasts) provided ERA5-Land hourly wind data spanning from 1950 to the present. From this dataset, the hourly time series of wind speed and wind direction at the height of 10 meters were extracted for the period between 2015 and 2019, and used for defining states and transition rates of the Markov chain. These, which are employed to generate synthetic wind speed values throughout the operational life of the wind plant, are to be adjusted to the hub height using a logarithmic law.

The average wind speed during the twenty years of operation is 5.89 m/s, the same as the historical series, and the coefficient of variation of the historical time series is 0.55, while the one of the synthetic time series is 0.5. In addition, the maximum value of the speed is 18 m/s, the same as the historical time series. Figure 6.10 shows a sample wind speed time series compared with actual data.

Based on the simulated wind speed, the instantaneous power output is computed according to equation 6.1, assuming the power curve and power coefficient curves of the readopted reference turbine type shown in Figure 6.7. Furthermore, the produced power is

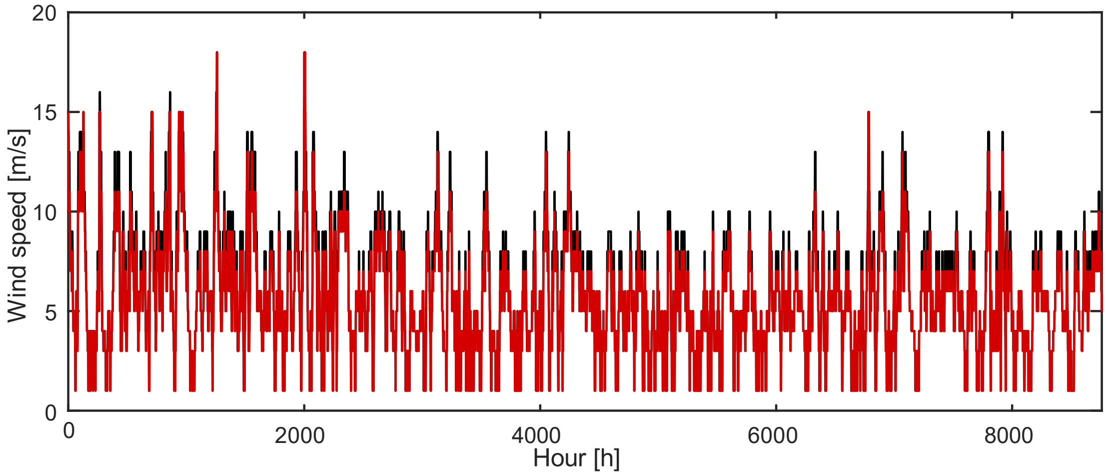

Figure 6.10 Real wind speed data (red line) compared with simulated wind speed time series for a generic year of the simulation.

adjusted to consider climate change effects by adopting the procedure and data explained in section 6.3.9.

In order to estimate structure costs, all geometrical and construction data for the Spar floating platform were sourced from Castro-Santos [464], employing the adopted cost model. The same model was used for estimating the wind turbines' cost, resorting to the above-declared data. For the distance-related costs, the wind farm layout and location were considered. The main results of the cost estimation are resumed in Table 6.5.

The expected investment cost is computed according to 2013 values. Table 6.5 costs have been adjusted by applying the current EU producer price index (PPI) to account for present value considerations. The European PPI in 2013 was 103.7, and at the beginning of 2023 was 133.6 [490]. This correction leads to an increase of about 30%.

Table 6.5 Main items costs calculated by the model

Cost item	**Nominal value**
Wind turbines	157.4 M€
Floating platforms	92.0 M€
Transmission systems	29.3 M€
Mooring and anchoring systems	36.5 M€
Wind turbines installation	13.0 M€
Floating platforms installation	13.9 M€
Mooring and anchoring systems installation	1.4 M€
Transmission systems installation	3.5 M€
Total Investment Cost	347 M€

Additionally, to better account for investment cost-related risk, three different learning effect values were considered. This allows us to include the effect of capital cost reduction in case the investment is delayed.

In section 6.2, the possible events related to the investment cost reduction have already been discussed (Table 6.2). Therefore, as a result of the aforementioned assumptions, the investment cost reductions for events H, M, and L are respectively about 23%, 17%, and 12% based on the assumed learning curve discussed in section 6.3.8.

As far as electricity sale revenues are considered, a time series of energy prices must be generated.

The hourly time series of the Italian energy price in 2021, obtained from the GME (Italian Power Exchange) database, is employed to estimate the parameters of the ARIMA regression model. This model has been used to simulate the wind speed values throughout the operational lifespan of the wind plant. In addition to capturing short-term variability, which is shown, for instance, in Figure 6.11, a long-term trend component that affects the average base price is also incorporated, assuming the three values of the scenario's variables exposed in section 6.2, and shown in Figure 6.12. The behaviour of the electricity price is similar to the real-time series behaviour in terms of mean and maximum and minimum values.

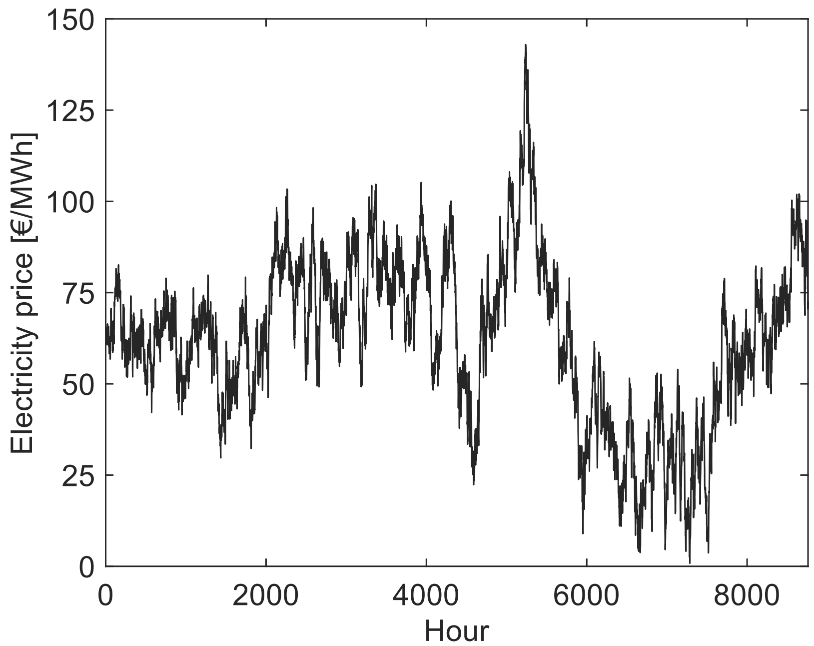

Figure 6.11 Simulated time series of electricity price for one year of plant's life

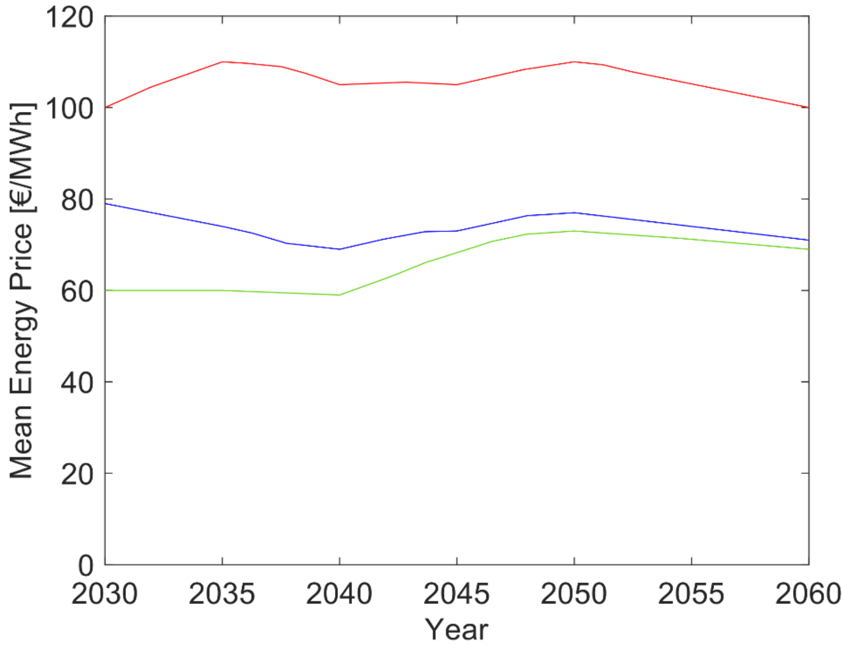

Figure 6.12 Mean energy price during years according to the T value of scenario's variable (red line), C value (blue line) and R value (green line).

In section 6.2, the possible values of the scenario's variable subsidy policy have been fixed in feed-in, feed-in premium, and no subsidies, as summarised in Table 6.2.

The scenarios' variables are grouped into three categories, one for each scenario driver (i.e., mean electricity price, subsidies, and learning effect), and, within each group, they are mutually exclusive. It is important to note that if the Feed-in Tariff subsidy is selected, the NPV probability density function is not influenced by the energy price but is still influenced by the investment cost reduction. This results in a total of twenty-one possible scenarios when considering all the permissible permutations. The energy price events and investment cost events are based on the European energy scenarios for 2050. The energy price scenarios are primarily driven by the relationship between West and East countries, while the investment cost scenarios are influenced by the internal policies of European member states. On the other hand, the subsidy scenarios are primarily influenced by the internal policy of Italy. These assumptions allow for the assumption of independence among the different variables' evolutions and enable the consideration of all possible permutations.

Recalling the consideration made in section 6.2, in order to demonstrate the model's capabilities and streamline the number of scenarios, a scenario reduction process was conducted by utilizing the concept of the plausibility cone [37, 70-72]. The plausibility cone concept allows us to establish a narrowed range of scenarios that are deemed plausible within a certain context.

The author has categorized the assumed scenarios into four groups: preferable, possible, plausible, and probable. While scenarios HF, MF, and LF may be considered preferable from the perspective of a wind power investor, they do not fall into the probable group. This is because the trend in subsidies policies worldwide is shifting towards a feed-in premium tariff rather than a feed-in tariff. However, among the set of three scenarios, LF remains the most plausible option. This is because if the investment cost reduction is lower, the regulator may adopt a more effective subsidies policy. Moreover, the current daily news on the geopolitical situation suggests a non-relief scenario between West and East countries, indicating that scenarios assuming relief (R) are only possible rather than probable. Given that the worst-case tension scenario (T) serves as one of the boundaries for the analysis, the central scenario (C) becomes the most probable option. While scenarios with no subsidies (N) are plausible, it appears that Italian politicians are inclined towards implementing a subsidies policy, particularly for wind and solar energy. Therefore, scenarios involving feed-in premium subsidies fall into the probable group. Furthermore, considering the ongoing investments in wind power systems worldwide and in Europe, it is highly probable that a significant reduction in investment costs will occur. Consequently, in the author’s opinion, the High Investment Cost Reduction (HCP) scenario represents the most probable future outcome. Based on the statements and projections made by the European and Italian governments regarding renewable energy sources and the expected advancements in wind power technology, four distinct narratives on subsidies policy development were considered (this defines the treatment of Type IV uncertainty considered in this application example). Simulation results were then combined by taking into account their respective probabilities to obtain a consolidated probability density function for the NPV. The NPV density function for each scenario was evaluated individually and then multiplied by its associated probability. Finally, these individual results were summed together to derive the overall NPV probability density function. In order to capture the varying stages of the plant's life cycle, it was divided into six time spans. For each time span, a specific percentage change in the Feed-in Premium tariff value was assigned, as detailed in Table 6.6.

Table 6.6 Time span percentage change in feed-in premium tariff value

Probability	Time span					
	1	2	3	4	5	6
35%	0%	0%	0%	0%	0%	0%
5%	5%	10%	15%	20%	25%	25%
20%	-5%	-30%	-50%	-60%	-70%	-70%
40%	0%	0%	-70%	-70%	-70%	-70%

In order to account for epistemic uncertainty in each variable, Monte Carlo simulation is employed using symmetrical triangular distributions [min, nominal, max]. The minimum and maximum values in the distribution are determined as the nominal value ± (PD × nominal value), where PD represents the percentual deviation. However, for bank interest rate and self-interest rate, epistemic uncertainty is not described by a percentage deviation but by an absolute deviation. The bank interest rate is set as (6 ± 4)%, while the self-interest rate is (4 ± 2)%. Nominal values and the adopted PD, based on references [491, 492], can be found in Table 6.7. Additional assumed parameters for the analysis include a financial loan duration of 10 years, with 50% of the investment cost being financed. The tax rate is set at 35%, the hourly cost for technicians is 50 €/hour per person, and the yearly percentage of amortization is 7%.

Table 6.7 Parameters for variables showing epistemic uncertainty

Variable	Nominal value	PD
Power coefficient	See curve in Figure 6.7	± 1 %
Generator efficiency	See curve in Figure 6.13	± 1 %
Power electronic efficiency	See curve in Figure 6.13	± 1 %
Gearbox efficiency	98 %	± 1 %
Restoration Cost	[356]	±·10 %
Investment cost	350 M€	±·30 %
Plant years life	20 (nominal)	±10 %

In order to model failures, data on the average failure rate, average repair time, average cost, and the average number of technicians classified according to main components and damage level were taken from [356] and used to generate failure histories according to the method described above. Since in Carroll et al. [356] the failure and restoration data were referred to 2-4 MW wind turbines, the values of restoration cost were increased by 10% to account for a higher power turbine and adjusted with the European Producer Price Index

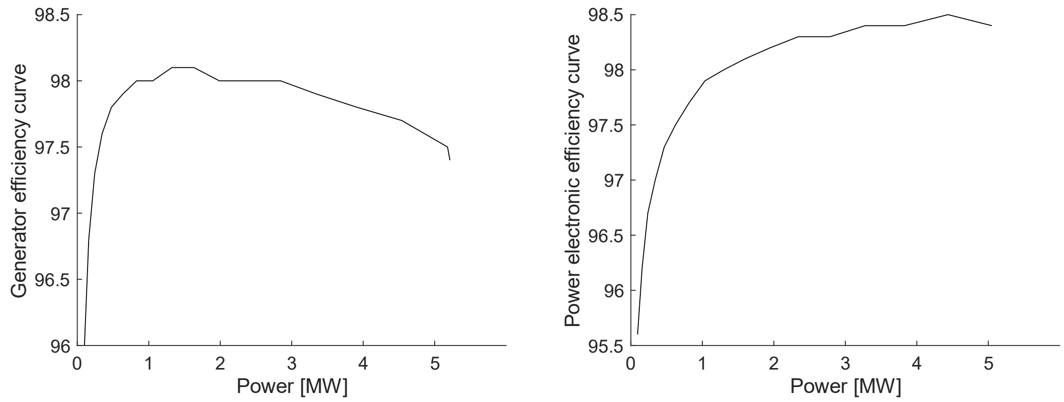

Figure 6.13 Generator and power electronic efficiency curves

with the aim to consider inflation. Considering the site location and the floating platform type, earthquake-disruptive events were neglected because of the very low probability and effects of their occurrences. However, ship collisions events are included by following the procedure and data reported in section 6.3.5.

As far as the risk hedging is concerned in the examined scenarios, Table 6.8 provides the main assumptions on the forward contract.

Table 6.8 Forward contract

Expiring Date	2042
Starting date	2030
Strike price	130 €/MWh
Yearly volume	50 GWh
Risk-free rate	1.5%
Penalty per MWh	20 €/MWh

The system analysis was performed, including 1000 iterations. The obtained frequency distribution of the Net Present Value is shown in Figure 6.14. The NPV average value is about 8 M€ and a standard deviation of 11 M€. In fact, its maximum value is 43 M€, whereas its minimum is -18 M€. The *VaR* at 5% of probability of occurrence is equal to -9 M€, so only with a probability lesser than 5% will there be a loss bigger than 9 M€. However, the probability of the NPV being less than 0, resulting in economic loss, is 24%. Table 6.9 provides some information on the NPV and other risk parameters.

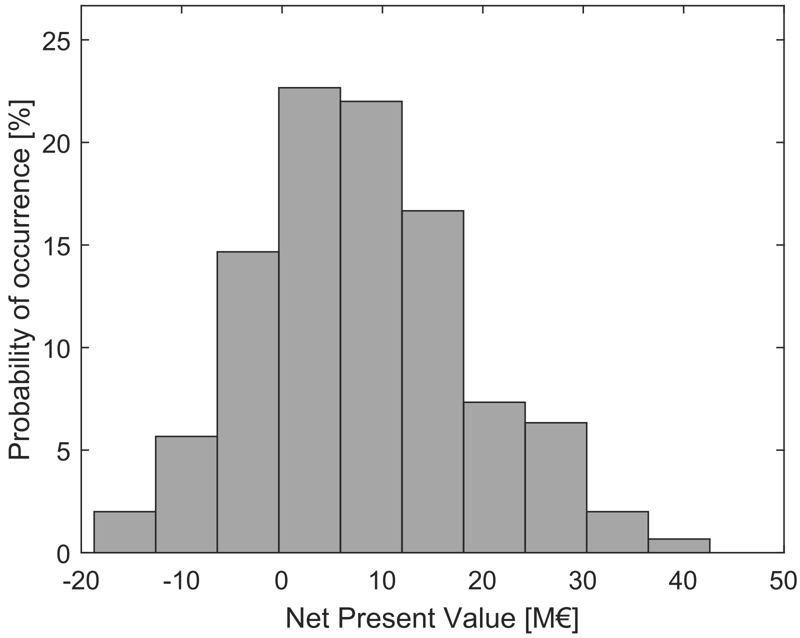

Figure 6.14 Net present value frequency distribution of wind farm.

Table 6.9 Profitability and risk analysis results

Min Data Value	$-1.87 \cdot 10^{7}$ €
Max Data Value	$4.26 \cdot 10^{7}$ €
E[NPV]	$7.99 \cdot 10^{6}$ €
σ	$1.09 \cdot 10^{7}$ €
CV	1.37
P(NPV<0)	24.00 %
VaR 5%	$-9.04 \cdot 10^{6}$ €

Figure 6.15 shows the net present value distribution and the cumulative probability of a wind power system composed of a single wind turbine as compared to the *NPV* distribution and cumulative probability of the 20 units wind farm. The aforementioned data are still adopted for the comparison, but the future contract yearly volume underwent a twenty-fold reduction to account for the change in the number of wind turbines between the two systems considered. These distributions are obtained by resorting to the distribution fitter of MATLAB using a confidence level of 95%. Due to the low average wind speed that characterized the wind of the Mediterranean sea, a single wind turbine investment is not cost-effective. In fact, the expected value of the NPV is -2.2 M€ in front of an adjusted investment of about 25.5 M€. The scale economies and the higher availability of the system, which arise from the bigger number of independent wind turbines, more than compensate

the wake effect. Nevertheless, in spite of low average wind speeds, the wind farm design leads to a cost-effective investment.

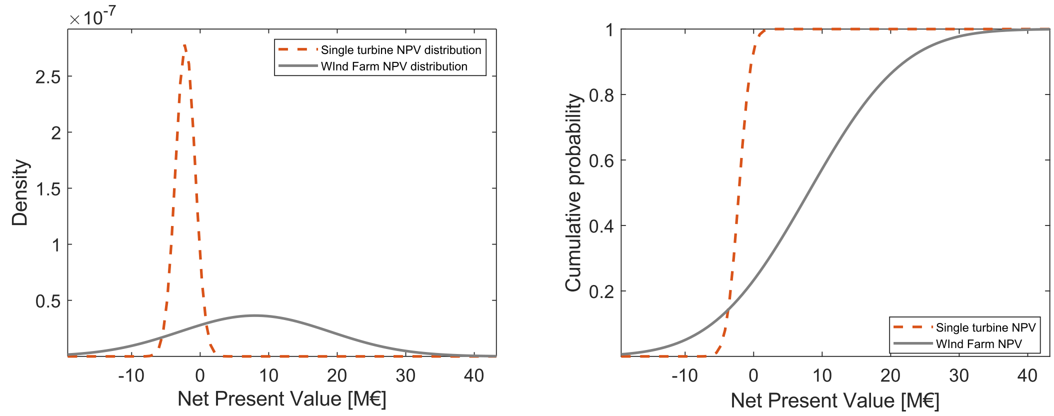

Figure 6.15 Net present value probability distribution (left side) and cumulative probability of net present value (right side)

6.5 Final remarks

This chapter presented the adaptation of the general framework introduced in Chapter 4 for economic evaluation and economic risk assessment of industrial systems. The blocks of uncertainty that enter the economic model and the external disruptive events have been used to perform the risk assessment procedure. Furthermore, the feedback arc has been used for including risk mitigation actions on an already concluded design, i.e. for market risk mitigation purposes. Some sources of deep uncertainty involving the environment in which the system operates have been included using scenario analysis.

The selected industrial system was offshore wind farms, and by using the framework, their evaluation and risk assessment under uncertainty have been carried out. By addressing this topic, the author aims to fill a significant gap in the existing literature where uncertainty is often overlooked or dealt with using simplified methods such as static Monte Carlo simulation or one parameter at a time sensitivity analysis. Moreover, previous studies have typically focused on considering uncertainty in only a limited number of influencing variables, such as wind speed and electricity price, without taking into account the broader range of uncertainties. The first step that acknowledges the importance of considering several sources of uncertainty simultaneously in this context can be found in reference [363], and it solely focuses on a single wind turbine, disregarding crucial factors in wind farms like wind direction and the wake effect. Furthermore, that work does not account for type IV uncertainty sources, nor does it propose or provide any risk mitigation measures. By contrast, this part of the thesis addresses these limitations and provides a more comprehensive approach to the economic evaluation and risk assessment of offshore wind farms. A broader set of influencing variables has been considered, including wind direction and wake effect, climate change, ship collisions, and accounting for type IV uncertainty sources, such as political, regulatory, and technology development risk. Additionally, this work suggests and offers potential risk mitigation instruments to enhance decision-making in this field.

The proposed model encompasses several notable features that contribute to its novelty and advancement in the field. Specifically, it introduces the following key elements in greater detail. Firstly, this model is the first attempt towards an integrated evaluation of uncertainty propagation, encompassing various types of variability sources within both short and long-term time horizons for wind farms. This comprehensive approach sets it apart from previous models that often focused on isolated aspects of uncertainty. Moreover, the model incorporates the economy of scale effects into the estimation of capital investment, and it accounts for the interference caused by the wake effect in energy production, an important factor that affects overall performance and efficiency. Furthermore, the model demonstrates its versatility by incorporating the capability to model scenario changes throughout the system's life cycle and the effects of climate change. Lastly, the model includes the consideration of financial derivatives as risk-hedging instruments. By integrating these instruments into the analysis, the model offers a more comprehensive perspective on risk management and enables stakeholders to make more informed decisions.

The numerical application showed the model capabilities and demonstrated the importance of considering uncertainty propagation when assessing the profitability and investment risk of wind energy systems. In fact, despite the average value of the NPV amounting to 8 million euros, which represents the value obtained under the assumption of all nominal values for variables, the application of this uncertainty propagation method reveals concerning insights. Specifically, there is a 5% probability of incurring losses exceeding 9 million euros and a 24% chance of experiencing some level of loss.

The current model at present is limited to a single elementary financial instrument, although it is feasible to incorporate more sophisticated tools. In addition, only electricity market risk hedging is included. Moreover, only earthquakes and ship collisions are considered as external disruptive events. As a future work, the model will be extended in order to include a wider library of risk hedging instruments modelling, such as swaps and futures contracts, also including weather risk hedging. Furthermore, the model will incorporate additional types of disruptive events, such as rogue waves and hurricanes. Moreover, although the model has encompassed long-term phenomena associated with climate change, it neglected extreme weather events. They will be included, enabling a more comprehensive evaluation of the risks involved. It is worth noting that the installation of offshore wind turbines can influence the precipitation patterns in nearby onshore locations. The extraction of kinetic energy from the airflow by wind turbines introduces convergence upstream and divergence downstream, which appears to reduce precipitation near the shore [493]. Further studies are required to assess the environmental impact of this renewable energy system. Moreover, the presence of offshore platforms introduces new risks to maritime traffic, thus necessitating quantitative risk assessments for specific shipping routes [494].

The model serves as a valuable decision support tool specifically designed for the planning phase of offshore wind investment projects. Its primary objective is to facilitate a risk-aware profitability evaluation, providing stakeholders with crucial insights to inform their decision-making processes. Additionally, the model's capability to assess the outcomes of alternative design choices throughout the project's life cycle makes it a valuable resource for designers. They can utilize the model to compare and evaluate various technical solutions, considering factors such as performance, cost-effectiveness, and risk implications. This feature enables designers to make informed decisions by weighing the trade-offs associated with different design options. Moreover, due to its modular architecture, the model can be employed during the operations phase as well. For example, it can be utilized to test alternative maintenance policies or production control strategies by leveraging real-time wind and energy price forecasts. By selectively turning off certain modules, short-term simulations can be performed to evaluate the effectiveness and efficiency of different operational approaches. Overall, the suggested approach not only contributes to a more detailed and comprehensive assessment of offshore wind farm investments but also supports risk-aware decision-making throughout the project's life cycle.

Therefore, recalling the research question mentioned in the introduction of Chapter 6, one can affirm that uncertainty strongly influences the economic evaluation of wind power systems, and an economically effective investment evaluated without including uncertainty may no longer be effective when uncertainty is included. Furthermore, since the high volatility of the energy market, risk mitigation strategies can be used to reduce, with great results, the effect of market uncertainty. The scenario analysis is crucial to include long-term changes in the environment in which the system operates because they seriously affect the system's performance, as can be seen in the numerical example. Finally, since simulating different scenarios leads to different economic results, the proposed procedure for combining the scenarios helps in estimating a single performance measure instead of several performances, which are hard to understand.

In the end, the use of the general framework to address the performance assessment under uncertainty of an industrial system has been shown.

Conclusions

Industrial systems are subject to various sources of uncertainty, which significantly impact their design and assessment. Indeed, the performance of components, equipment, and systems is strongly affected by uncertainty and the variability of the operating conditions. While this is widely recognised in the literature, it often still lacks the ability to address the inclusion of uncertainty during the design and evaluation phases. Although the industrial environment is characterised by a VUCA context, that includes market volatility, weather fluctuations, customer behaviour, and other factors, the complexity of modelling multiple uncertain and variable processes, inputs, and parameters involved in designing and evaluating industrial systems, as well as the ambiguity inherent in representing reality through models, are often streamlined, or overlooked. Since industrial designers and managers operate within a VUCA context, the necessity of proposing new methods to navigate this dynamic environment arises.

Starting from the existing frameworks and methods available in the literature reviewed in Chapter 1, Chapter 2, and Chapter 3, this thesis aims to provide a comprehensive framework for designing and evaluating industrial systems under uncertainty, presented in Chapter 4. Numerous existing approaches have been systematised to produce a general framework that represents the uncertainty sources, propagates the uncertainty in the system model, assesses the technical and economic risk, and optimises the design or mitigates the risk. Additionally, a novel uncertainty sources classification method has been proposed. It clusters the uncertainty into four groups by analysing the variables' behaviour over time. According to this method, the uncertainty sources can be variables changing their value randomly over time, variables assuming an unknown value which is described according to a predefined probability density function, random occurrence of point events of either known or unknown intensity, and a random discontinuity where one or more variables occur a random step change in value at a random time. This classification is helpful in selecting the proper method for uncertainty representation and propagation. This way, selecting the proper system model is easier, too.

The incorporation of uncertainty in the design and evaluation of industrial systems showed that it is crucial to avoid erroneous or not enough conscious decisions.

The application of the framework in two case studies, presented in Chapter 5 and Chapter 6, has shown that the framework is general because of the differences between the investigated systems. The industrial systems of case studies have never been studied from the comprehensive uncertainty perspective proposed in this work. In particular, the study of designing shell and tube heat exchangers under uncertainty and variable operating conditions fills a literature gap, as most papers have neglected the uncertainty sources, and highlighted that uncertainty should be included during their design phase. Indeed, a heat exchanger that is able to meet the specifications when evaluated in nominal conditions may not meet them when uncertainty is considered. Furthermore, the application of the framework to the problem of evaluating offshore wind power plants fills the literature gap related to addressing this issue and demonstrates that a system that is economically effective when evaluated by neglecting uncertainty may not be effective when included.

This new approach has the potential to describe and better understand the actual performance and behaviour of industrial systems, and the case studies are just two examples that demonstrate the benefits of including uncertainties and support the hypothesis that motivated this thesis. The analyses conducted with the framework support are more conscious of the reality, so the designs and evaluations can provide a more realistic forecast and representation of the performance.

The proposed general framework and the case studies carried out allow the author to address the research questions that have been stated in the Introduction.

Firstly, the additional modelling efforts required by the proposed general framework are justified in terms of achieving a more realistic assessment of the techno-economic performance of a design, improving the performance by adopting optimisation algorithms under uncertainty, and enabling a more accurate evaluation of economic performance. Indeed, the equipment design considering uncertainty has shown superior performance in comparison with pieces of equipment designed neglecting it. Furthermore, the more well-modelled uncertainty sources are considered, the greater the accuracy of the risk assessment procedure. This results in an economic and technical benefit in considering uncertainty during the design and evaluation of equipment and industrial plants.

Then, the inclusion of the uncertainty of correlations, components' failures, disruptive events, and similar elements strongly affect the technical and economic performance of an industrial system. Indeed, the analysis of the distribution of the outlet temperature of the shell and tube heat exchanger and the net present value distribution of the offshore wind farm have shown that the dispersion of the values around the expected one is not neglectable in order to achieve a proper risk assessment. Considering simultaneously the uncertainty sources, their effect may be accurately assessed.

Finally, the analysed case studies have shown that an economically or technically viable system under deterministic conditions may not be viable when uncertainty is included.

The general framework for designing and evaluating industrial systems under uncertainty has been developed, and its application has shown the vital role of uncertainty in determining industrial systems performance.

Although the main objective of the thesis has been achieved, some limitations need to be pointed out. Firstly, although some suggestions have been provided, the user must manually select the required blocks and all the modelling methods without a procedure that helps in this decision-making process. Moreover, only two application examples have been carried out, thus resulting in a non-fully generalisation of the framework. Additionally, only market risk mitigation strategy capabilities have been shown. Finally, the lack of a manufacturing plant case study limits the current applicability of the framework to equipment and process plants.

Future works

Future works should address the limitations mentioned above. In particular, the lack of a procedure to help select the proper number of blocks and modelling methods makes this task difficult. Addressing the aforementioned issues allows researchers to comprehend whether it is possible to produce an automatic procedure for selecting the proper number of blocks of the framework and proper modelling methods.

Then, other case studies should be analysed, with particular attention to manufacturing plants, which involve an enormous number of sources of uncertainty. Moreover, they are influenced by both continuous quantities and discrete uncertain variables. The present framework can cope with the uncertainty affecting equipment and process plants. However, it will be understood whether it is able to deal with the various sources of uncertainty which affect manufacturing plants.

Eventually, other risk mitigation strategies should be tested and include real-time data to dynamically adapt and select risk mitigation instruments to specific instances.

At present, risk mitigation strategies for market risk have been successfully implemented. The effect of including other risk mitigation strategies to reduce the effects of other risks should be investigated.

Finally, the possibility of including real-time data to help the dynamic adaptation of risk mitigation tools to specific instances should be addressed.

List of symbols

Section 5.1

Symbol	Unit	Caption	Symbol	Unit	Caption
A	[m^2]	Heat transfer area	*L*	[m]	Tube length
a_1	[-]	Numerical constant	*m*	[kg/s]	Mass flow rate
a_2	[-]	Numerical constant	*n*	[-]	Number of tube passages
a_3	[-]	Numerical constant	*Nt*	[-]	Tubes number
AFP	[m^2]	Footprint in plant	*Ny*	[yr]	Equipment life
B	[m]	Baffle spacing	*NTU*	[-]	Number of thermal units
C^*	[-]	Ratio of capacity rates	*OC*	[€/yr]	Operating cost
Cen	[€/kWh]	Energy cost	*P*	[kW]	Pumping power
Cl	[m]	Clearance	*Pattern*	[-]	Tubes pattern
c_p	[kJ/kgK]	Specific heat	*Pr*	[-]	Prandlt number
De	[m]	Equivalent diameter	*Pt*	[m]	Tube pitch
do	[m]	Tube outer diameter	*Q*	[W]	Duty
DOC	[€]	Discounted operating cost	*Re*	[-]	Reynolds number
D_s	[m]	Shell diameter	*Rf*	[m^2 K/W]	Conductive fouling resistance
F	[-]	Temperature difference corrective factor	*S*	[m^2]	Heat exchanger surface
g	[-]	Number of entransy dissipation units	*TC*	[€]	Total cost
H	[h/yr]	Annual operating time	*t*	[°C]	Fluid temperature
h	[W/m2K]	Heat transfer coefficient	*Tube Side*	[-]	Fluid tube side passage
i	[%/yr]	Annual discount rate	*U*	[W/m^{2}K]	Global heat transfer coefficient
IC	[€]	Investment cost	*VFP*	[m^3]	Volumetric footprint
L/D	[-]	Length diameter ratio	*v*	[m/s]	Fluid velocity
LMTD	[°C]	Logarithmic mean temperature difference			
	Subscripts			***Greek symbols***	
c	**[-]**	Cold fluid	*ΔP*	[Pa]	Pressure drop
h	**[-]**	Hot fluid	**ε**	**[-]**	Effectiveness
i	**[-]**	Inlet	*η*	[-]	Overall pumping efficiency
o	**[-]**	Outlet	**λ**	[W/mK]	Thermal conductivity
s	**[-]**	Shell side	*μ*	[Pa s]	Viscosity
t	**[-]**	Tube side	*ρ*	[kg/m^3]	Density

Section 5.3

Symbol	Unit	Caption	Symbol	Unit	Caption
B	[m]	Baffle spacing	*Max ΔP*	[Pa]	Maximum value of pressure drop
Cen	[€/kWh]	Energy cost	*m*	[kg/s]	Mass flow rate
Cp	[kJ/kgK]	Specific heat	*Nb*	[-]	Baffle number
CV	[-]	Coefficient of variation	*Pr*	[-]	Prandlt number
do	[m]	Tube outer diameter	*Re*	[-]	Reynolds number
d_i	[m]	Tube inner diameter	N_{tp}	[-]	Number of tube passages
DOC	[€]	Discounted operating cost	N_{tt}	[-]	Tubes number
D_e	[m]	Shell side equivalent diameter	*Ny*	[yr]	Equipment life
D_s	[m]	Shell inner diameter	*OC*	[€/yr]	Operating cost
E[x]		Expected value of *x*	*Pattern*	[-]	Tubes pattern
F	[-]	Temperature difference corrective factor	*Q*	[W]	Duty
H	[h/yr]	Annual operating time	*Rf*	[m^2 K/W]	Conductive fouling resistance
HE type	[-]	Heat exchanger type	*S*	[m^2]	Heat exchanger surface
h	[W/m^2K]	Heat transfer coefficient	*TC*	[€]	Total cost
I	[%/yr]	Annual discount rate	*t*	[°C]	Fluid temperature
IC	[€]	Investment cost	*Tube Side*	[-]	Fluid tube side passage
L/D	[-]	Length diameter ratio	U_{dirt}	[W/m^2K]	Global heat transfer coefficient
LMTD	[°C]	Logarithmic mean temperature difference	*v*	[m/s]	Fluid velocity
L_{tt}	[m]	Tube length			
Subscripts			***Greek symbols***		
c	Cold fluid		*ΔP*	[Pa]	Pressure drop
h	Hot fluid		λ	[W/mK]	Thermal conductivity
i	Inlet fluid		η	[-]	Overall pumping efficiency
o	Outlet fluid		μ	(Pa s)	Viscosity
S	Shell side fluid		ρ	[kg/m^3]	Density
T	Tube side fluid		σ		Standard deviation

Section 6.3

Symbol	Unit	Caption	Symbol	Unit	Caption
A	[-]	Availability	$O\&M$	[€/y]	Managing and preventive maintenance cost
AMM	[€/y]	Depreciation charge	OC	[€/y]	Operating cost
AP	[MWh/y]	Annual produced energy	P	[W]	Power
CF	[€/y]	Cash flow	$P(x)$	[-]	Occurrence probability of x
C_t	[€/h]	Hourly cost of technichans	q	[-]	Share interest debt
c_p	[-]	Power coefficient	R	[€/y]	Revenue
CV	[-]	Coefficient of variation	RC	[€]	Restoration cost
$E[x]$	[-]	Expected value of x	ReC	[€]	Repair cost
EP	[€/MWh]	Hourly electricity price	RT	[h]	Recovery time
HP	[MW]	Hourly produced energy	S	[m^2]	Swept area
FC	[€]	Forward contract's cash flow	T	[€/y]	Taxes
FP	[€/MWh]	Contracted electricity price	U	[m/s]	Wind speed
FP_P	[€/MWh]	Contracted penality	V	[MWh]	Duty volume
I_0	[€]	Investment cost	V_0	[€]	Debt
L	[€/y]	Loan instalment	VaR	[-]	Value at risk
NPP	[MW]	Nominal produced power	$WACC$	[-]	Weighted average cost of capital
NPV	[€]	Net Present Value	WS	[m/s]	Wind speed
N_t	[-]	Number of required technicians	Y	[-]	Plant years life
Subsctipts			***Greek symbols***		
Symbol	**Unit**	**Caption**	**Symbol**	**Unit**	**Caption**
y		Year	σ	[€]	Standard deviation
h		Hour	ρ	[kg/m^3]	Air density
-	-	-	η_g	[-]	Generator efficiency
-	-	-	η_{gb}	[-]	Gearbox efficiency
-	-	-	η_{pe}	[-]	Power electronic efficiency

List of acronyms

ALARP: As Low As Reasonably Practicable

ANN: Artificial Neural Network

ANOVA: ANalysis Of VAriance

AR: AutoRegressive

ARIMA: AutoRegressive Integrated Moving Average

ARMA: AutoRegressive Moving Average

ARMAX: AutoRegressive Moving Average with eXogenous inputs model

CDF: Cumulative Distribution Function

CFD: Computational Fluid Dynamics

CV: Coefficient of Variation

DDV: Dependent Design Variable

DfR: Design for Reliability

DOE: Design Of Experiments

DST: Dempster-Shafer Theory

ECMWF: European Centre for Medium-Range Weather Forecasts

EU: European Union

FEM: Finite Element Method

FMEA: Failure Modes and Effects Analysis

FMECA: Failure Mode, Effects, and Criticality Analysis

FMS: Flexible Manufacturing System

FORM: First-Order Reliability Method

GA: Genetic Algorithm

GBM: Geometric Brownian Motion

GME: Gestore dei Mercati Energetici

GSA: Global Sensitivity Analysis

HE: Heat Exchanger

HEN: Heat Exchanger Network

IC: Investment Cost

IDEAL: Integrated Design Automation Laboratory

IDV: Independent Design Variable

IS: Importance Sampling

KPI: Key Performance Indicator

LHS: Latin Hypercube Sampling

LMTD: Logarithmic Mean Temperature Difference

MCS: Monte Carlo Sampling

MILP: Mixed Integer Linear Programming

MisB: More is Better

MOGA: Multi-Objective Genetic Algorithm

MOO: Multi-Objective Optimisation

NASA: National Aeronautics and Space Administration

NisB: Nominal is Better

NPV: Net Present Value

NREL: National Renewable Energy Laboratory

OC: Operating Cost

OF: Objective Function

OTC: Over-The-Counter

PD: Percentual Deviation

PDF: Probability Density Function

PGA: Peak Ground Acceleration

PPI: Producer Price Index

PRA: Probabilistic Risk Assessment

PROMETHEE: Preference Ranking Organization Method for Enrichment Evaluation

PSUADE: Problem Solving Environment for Uncertainty Analysis and Design Exploration

QRA: Quantitative Risk Assessment

RAROC: Risk-Adjusted Return on Capital

RBDO: Reliability-Based Design Optimisation

RCP: Representative Concentration Pathway

RES: Renewable Energy Sources

RMSE: Root Mean Square Error

SAM: System Advisor Model

SARIMA: Seasonal AutoRegressive Integrated Moving Average

SD: System Dynamics

SF: Safety Factor

SORM: Second-Order Reliability Method

STHE: Shell and Tube Heat Exchanger

TAC: Total Annual Cost

TC: Total Cost

TI: Temperature Indicator

UQTk: Uncertainty Quantification Toolkit

USA: United States of America

VaR: Value at Risk

VUCA: Volatility Uncertainty Complexity Ambiguity

WAMPM: Weighted Average of Multiple Performance Measures

WT: Wind Turbine

CFD: Computational Fluid Dynamics

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