UNIVERSITÀ DEGLI STUDI
DI BERGAMO

UNIVERSITÀ DEGLI STUDI
DI BRESCIA

Ph.D. Program in

Computational Methods for Forecasting and Decisions in Economics and Finance

Session XXV

Title of the Thesis:

Optimal Allocation of Physical Assets in the Railway Sector

Advisor:

Prof. Maria Grazia Speranza

Doctoral Candidate:

Francesco Piu

To Cinzia

Acknowledgements

First and foremost, I would like to express my gratitude and my sincere thanks to my advisor Professor Maria Grazia Speranza from the University of Brescia. I am grateful to her for the knowledge I gained from her, for the trust she placed in me and for her invaluable guidance. Her insights and knowledge, stimulating suggestions and encouragement were of great value to the development of this research. She is a wonderful person and has been a wonderful mentor.

I am also honored to have Professor Marida Bertocchi from the University of Bergamo as Ph.D. Program Director. I am grateful to her for the support she gave me, for her great availability and for the great growth opportunities I have received from the Ph.D. Program. I would like to express my deep sense of gratitude to both of you for the fantastic learning experiences in Bertinoro 2010, 2012 and in Rome 2012.

I am deeply indebted to Professor Michel Bierlaire for welcoming me at the TRANSP-OR Laboratory, EPFL, for ten months. He offered me the opportunity to work as a lecturer and to have a great researching experience. His courses, meetings and conferences exposed me to advanced topics and his kindness, natural teaching ability, and intelligence were especially memorable.

I also wish to express my gratitude to Dr. V. Prem Kumar, in few words, a man hardly ever to be found nowadays from all aspects. His door was always open to discuss and advice, his suggestions helped to enhance several aspects of

Abstract

This Thesis analyzes the class of planning and scheduling problems generally named *Locomotive Assignment Problem* (LAP) and proposes a methodological innovation in the solution of this class of problems.

The LAP represents a class of planning and scheduling problems solved assigning a fleet of locomotives to a network of trains optimizing one or more crucial objectives and satisfying a rich set of constraints (first and before all others the motive power constraints).

The first part of the Thesis presents a comprehensive survey of the optimization models developed to solve the LAP. This survey shows that the optimization models are gaining more and more importance in solving large size complex planning and scheduling problems that characterize the management of freight train transport services. This class of problems, that were historically solved by simulation, can now be (approximately) solved using mathematical optimization techniques. Large-scale very complex freight rail activities impose to separate the LAP in three distinct phases (or problems): the locomotive planning, the locomotive scheduling and the locomotive routing phases. Namely, we have to solve the *Locomotive Planning Problem* (LPP), the *Locomotive Scheduling Problem* (LSP), and finally the *Locomotive Routing Problem* (LRP) in which the refueling of diesel locomotives has to be guaranteed.

The separation of the LAP leads to definitely suboptimal solutions. Thereby,

there is a strong incentive to concurrently solve locomotive planning, scheduling and routing problems. However, a structural integration of these three phases in a model that encompasses the LPP, the LSP and the LRP is prohibitive due to the size and complexity of real problems. The aim of the second part of this Thesis is to introduce a methodological innovation able to (partially) integrate the planning and the routing of *consists*. North American freight trains are generally very heavy and a single locomotive is often not sufficient to pull this kind of trains. Therefore two ore more diesel locomotives are combined to form a consist (a group of linked locomotives) that provides the required motive power performance. Our objective is to obtain LPP solutions that make the routing phase easier to handle and more economical. We pursue this objective first considering the LPP in its *Consist Flow Formulation* in which a set of consists (assembled before solving the LPP) is assigned to trains, and second exploiting information on consists range and fuel capacity exploitation not featured in the previous studies. In the previous studies the set C of the consists types that are initially available to solve the LPP were taken as given in terms of consists types (usually railroad companies provide C to researchers). This study does not take C as given and proposes an integer optimization model named *consists selection* that identifies the set C of consists types (available to solve the LPP) maximizing the consists range and the consists efficiency in the fuel tank capacity exploitation. The last part of the Thesis describes the creation of a simulation program able to generate realistic train schedules. The assessment of savings offered by the adoption of the consists selection in the LPP solution procedure relies on the realism of these train schedules.

iv

Contents

Contents

List of Figures

List of Tables

List of Tables

Part I

The Locomotive Assignment Problem: a survey on optimization models

F. Piu,   M. G. Speranza

Department of Quantitative Methods, University of Brescia, C. da S. Chiara 50, Brescia, Italy

Introduction Part I

The strong competition among railroads and the growing role of the private sector (specially in Europe) imply that railroads are paying more and more attention on operating cost, punctuality and performance, which affect customers satisfaction. The U.S. freight transportation system is one of the best example of the effects of the competition among transportation companies. The whole system (highways, waterways, airways and railways) offers the best service and rates in the world, and the freight rail element of this system is critical to the competitiveness of many industries and the economies of many states (Grenzeback et al. [2008]). America's freight railroads span 140,000 miles and form the most efficient and cost-effective freight rail system in the world (Thompson [2007]). Historically, U.S. and Canada present the set of railways companies offering the most competitive rate in the world. Many of these companies have invested and continue to invest in the creation of simulation tools and optimization models to support their decision processes. One of the most important decision problems is the Locomotive Assignment Problem (LAP), a class of planning and scheduling problems that involves very expensive assets and huge numbers (large railroad companies assign thousands of locomotives to thousands of trains daily). The LAP is solved assigning a fleet of locomotives to a network of trains optimizing one or more crucial objectives (costs, profit, fleet size, level of service) and satisfying a rich set of technical and budget constraints.

List of Tables

This first part of the thesis presents a survey on optimization models developed to solve the LAP.

The LAP optimization models may vary depending on the scheduling problem characteristics (application field, planning level, optimization objectives) and may require different solution methodologies and algorithms. Not surprisingly, many optimization models for the LAP have been developed by North American research centers and focus on real problems faced by U.S. and Canadian companies.

In the last decades, however, an increasing interest in optimization models for this class of planning and scheduling problems emerged among others, for instance, European, Australian, Indian and Brazilian railroad companies.

These aspects are reviewed and are involved in the classification proposed for the considered LAP optimization models.

1 LAP optimization models

1.1   Tonnage-based versus schedule-based approach: the role of the optimization models

The increased computational power allows the tractability of more complex models and bigger instances. Consequently, the unavoidable complexity and size of the real life problems may be captured and managed more effectively leading to the creation of valuable decision-support tools for realistic applications. The increasing interest in optimization models may not be completely explained by the increasing computational power and modeling ability. In the last three decades, passenger and freight movement over the transportation system have increased significantly in both developed and emerging countries. The U.S. rail freight transportation system represents a significant example: the ton-miles of rail freight (a ton-mile represents one ton of freight carried over one mile) moved over the national rail system have doubled since 1980, and the density of train traffic measured in ton-miles per mile of track has tripled since 1980 (Grenzeback et al. [2008]). Despite the fact that the rail share of the total freight transportation market is moderate (14 percent of total tons carried, 25 percent of total ton-miles) and that the rail market share is also declining, the current

demand for rail freight transportation is pressing the capacity of the rail system (Grenzeback et al. [2008]). Until very recently, the investment in new freight rail capacity has not been sufficient to keep pace with the growth of the economy and the demand for rail freight services. This partially explains the reducing market share. However, rail market share is declining also because of structural changes in the economy. The major buyers of freight rail service (manufacturing, agriculture and mining) remain crucial in the U.S. economy but the economic growth over the last decades has been fueled by the service industries that usually ship more high-value-added, lighter and time-sensitive products by air and trucks (Grenzeback et al. [2008]).

Still, the demand for rail freight transportation is increasing, and the request to reduce greenhouse gas emissions (like CO_2) will probably further increase this demand because the freight rail service is very fuel-efficient and generates less air pollution per ton-mile than trucking (Grenzeback et al. [2008]). In fact, rail companies face a rapidly increasing demand with a slowly increasing rail capacity since the creation of new freight rail capacity involves huge investments. Given the demand for freight transportation, usually expressed in terms of weight (tonnage), a railroad company establishes a policy for the routing of trains. If the demand for freight transportation from a specific origin to a specific destination is high enough, direct trains are used. On the other hand, if the demand does not justify the cost of a direct train, the freight may be shipped through a sequence of links and intermediate nodes. Alternatively, trains have to wait at the origin node until a sufficient tonnage has been accumulated. In both cases delays are inevitable. This policy (running trains only when they have enough freight) has been traditionally practiced by North American railroad companies and is named tonnage-based dispatching. In a tonnage-based approach, the company holds all trains until they have enough tonnage. A train may be scheduled every day, but

it may be delayed or cancelled, depending on the achieved tonnage.

The idea underlying the tonnage-based approach is simple: to minimize the total number of operating trains by maximizing the train size in order to (theoretically) minimize the crew costs and maximize the track capacity.

However, in practice, there are some limitations and shortcomings:

(i) Operating costs may increase due to an increased idling cost and relocation cost of equipments and crews.

(ii) Tracks used to load/unload or store railcars and locomotives (i.e. yards) cannot optimize their operations relying on repetitive schedules and may require more storage capacity and railcars, crew and locomotives to deal with traffic variability.

Moreover, the tonnage-based approach implies an unreliable and poor service for the customers that in many cases could lead to a shift in the consumer preferences and the abandon of the rail transport in favor of alternatives like trucks. Then, the tonnage-based approach was and remains a good strategy for bulk goods like coal, but it has proven to be a poor strategy for most other goods. Although the tonnage-based approach is still common in North America, it is rarely used in the European context where freight trains typically operate according to schedules (like passenger trains): this is the schedule-based approach. In the schedule-based approach trains run as scheduled, even when a train has not achieved a sufficient tonnage.

Historically, North American railways avoided the schedule-based approach, partly because the demand level did not justify the cost of low tonnage trains, partly because of the complexity involved in this approach (Ireland et al. [2004]). The schedule-based strategy implies that the schedule should be adapted depending on the forecast of the traffic and requires advanced computers and operations

research tools to conduct deep analyses of different alternatives in short times. As reported in Ireland et al. [2004], the schedule-based strategies recently have gained favor in U.S. and Canada where several railroad companies have adopted this more disciplined approach to obtain cost-effective and customer-effective operating plans. The increase in customer demand for freight rail transport and the recent availability of advanced computers and OR software push several North American railways to change the paradigm of their operations passing to a schedule-based strategy.

Canadian Pacific Railway (CPR), Norfolk Southern (NS) and Canadian National (CN) have made resolute changes to shift to the schedule-based strategy. CPR in 1997 was one of the first companies that explored the possibility of running a scheduled railway. It was one of the first railroads to adopt a true scheduled railroading, and the paradigm shift produced huge impacts in operations and capital investments (Ireland et al. [2004]).

At the beginning of the century CPR obtain more than 500 million (Canadian \$) of annual operating costs savings thanks to the improvements in labor productivity, locomotive productivity, fuel consumption and railcar velocity by 40%, 35%, 17% and 41% respectively (Ireland et al. [2004]). These savings are generated by the ability to better execute the plan through daily repetition and to better manage crews and equipment (faster railcars, improved locomotive utilization). In addition to cost savings, running on a schedule has allowed CPR to recapture traffic from the trucks. The new schedule-based approach has allowed CPR to think and act like truckers (Cambridge Systematics [2005]). In the last years all North American Class I railroads have followed the example of CPR, NS and CN, switching most of their services to run on a scheduled operating plan. Also CSX Transportation and FEC have adopted the scheduled railroading philosophy (Cambridge Systematics [2005]).

The success of the new Operations Research tools used by CPR has overturned the old paradigm that tonnage-based plans are more efficient. Supporting the historical role of simulation tools, optimization models are gaining more and more importance in solving large size complex scheduling problems that characterize the schedule-based approach in real life applications. Tables 1.1 and 1.2 show that the number of optimization models for the LAP has significantly grown after the year 2000.

Table 1.1: LAP Researches in U.S. and Canada

Authors	Country	Institution	Railway company
Charnes and Miller [1956]	U.S.	Purdue University	n.a.
Florian et al. [1976]	Canada	Université de Montréal	Canadian National
Ziarati et al. [1997]	Canada	École Polytechnique de Montréal, Ad Opt Technologies Inc	Canadian National
Ziarati et al. [1999]	Canada	École Polytechnique de Montréal, Northeastern University	Canadian National
Cordeau et al. [2001]	Canada	École Polytechnique de Montréal,	Canadian National
Cordeau et al. [2000]	Canada	École des Hautes Études Commerciales de Montréal	Canadian National
Cordeau et al. [2001]	Canada	École des Hautes Études Commerciales de Montréal, Ad Opt Technologies Inc	Canadian National
Lingaya et al. [2002]	Canada	École Polytechnique de Montréal, École des Hautes Études Commerciales de Montréal	VIA Rail Canada
Powell et al. [2002]	U.S.	Princeton University	n.a.
Powell et al. [2001]	U.S.	Princeton University	n.a.
Powell and Topaloglu [2003]	U.S.	Princeton University	n.a.
Powell [2003]	U.S.	Princeton University	n.a.
Ireland et al. [2004]	Canada	Canadian Pacific Railway, MultiModal Applied Systems	Canadian Pacific Railway
Ziarati et al. [2005]	Canada	Shiraz University (IRN)	Canadian National
Ahuja et al. [2005a]	U.S.	University of Florida	CSX
Ahuja et al. [2005b]	U.S.	University of Florida, École des Hautes Études Commerciales de Montréal	CSX
Marar et al. [2006]	U.S.	University of Florida, Massachussets Institute of Technology, CSX Transportation	CSX
Ahuja et al. [2006]	U.S.	University of Florida, Innovative Scheduling Inc.	CSX
Powell and Bouzaiene-Ayari [2006]	U.S.	Princeton University	n.a.
Powell et al. [2007]	U.S.	Princeton University	n.a.
Powell and Bouzaiene-Ayari [2007]	U.S.	Princeton University	n.a.
Vaidyanathan et al. [2008a]	U.S.	University of Florida, Innovative Scheduling Inc.	Norfolk Southern
Vaidyanathan et al. [2008b]	U.S.	University of Florida, Innovative Scheduling Inc.	CSX
Marar and Powell [2009]	U.S.	Massachussets Institute of Technology, FedEx Express - Operations Research	CSX

Table 1.2: LAP Researches outside U.S. and Canada

Authors	Country	Institution	Railway company
Booler [1980]	United Kingdom	Salford University	n.a.
Ramani [1981]	India	Indian Institute of Management	Indian Railways
Wright [1989]	United Kingdom	University of Lancaster	n.a.
Forbes et al. [1991]	Australia	University of Queensland	n.a.
Booler [1995]	United Kingdom	Salford University	n.a.
Brannlund et al. [1998]	Sweden	Royal Institute of Technology - Stockholm, Linköping University	Banverket S.N.R. Admin.[a]
Scholz [2000]	Sweden	Swedish Institute of Computer Science	SJ Swedish State Railways[b]
Noble et al. [2001]	Australia	Staffordshire University (GBR), Swinburne University of Technology (AUS), CSIRO Mathematical and Information Sciences (AUS)	Public Transport Corporation
Lütbecke and Zimmermann [2003]	Germany	Braunschweig University of Technology	VPS[c] EKO Trans[d]
Brucker et al. [2003]	Germany	University of Osnabrück (DEU), University of Twente (NLD)	n.a.
Maróti and Kroon [2005]	Holland	Centrum Wiskunde & Informatica, Utrecht University and Erasmus University	Nederlandse Spoorwegen
Illés et al. [2005]	Hungary	Eötvös Loránd University of Sciences, Szent István University	MÁV[e]
Illés et al. [2006]	Hungary	Eötvös Loránd University of Sciences, Szent István University	MÁV[e]
Baceler and Garcia [2006]	Brazil	Universidade Federal do Espírito Santo, Companhia Vale do Rio Doce	Companhia Vale do Rio Doce
Fügenschuh et al. [2006]	Germany	Technische Universität Darmstadt, Deutsche Bahn AG	Deutsche Bahn AG
Paoletti and Cappelletti [2007]	Italy	Models and Decisional Systems - Trenitalia	Trenitalia
Fügenschuh et al. [2008]	Germany	Technische Universität Darmstadt, Deutsche Bahn AG	Deutsche Bahn AG
Sabino et al. [2010]	Brazil	Pontifícia Universidade Católica do Rio de Janeiro	Tubaro Railroad Terminal
Keisuke and Fukumura [2010]	Japan	Railway Technical Research Institute	Japan Freight Railway Company
Ghoseiri and Ghannadpour [2010]	Iran	Iran University of Science and Technology, University of Maryland (USA)	n.a.

[a]Banverket Swedish National Railway Administration: the Swedish company that owns the tracks but not the trains
[b]Stateiis Järiivägar Swedish State Railways: the Swedish company that owns the trains but not the tracks
[c]Verkehrsbetriebe Peine–Salzgitter GmbH
[d]EKO Transportgesellschaft GmbH, Eisenhüttenstadt, Germany
[e]Magyar Államvasutak (MÁV): the Hungarian State Railway Company

1.2 LAP planning levels and application fields

The LAP is one of the most important classes of problems in railroad scheduling because it involves very expensive assets and huge numbers. Every year, large railroad companies invest billions of dollars acquiring, managing and fueling locomotives. Every day they assign thousands of locomotives to thousands of trains. Due to the size of real life problems, even a small percentage improvement toward a better efficiency in the use of locomotives may lead to significant economic savings.

The locomotive scheduling may be studied at three levels: strategic, tactical and operational in accordance with the length of the planning horizon and the temporal impact of the decisions. At the strategic level only the number of locomotives and their type matter, the specific ID of each locomotive is not considered and locomotives of the same type are completely equivalent. In the strategic version of the LAP, for each train we determine the type and the number of locomotives assigned to that train. In the strategic LAP the train schedule is given and cannot change (delays or disruptions are not considered).

The tactical and operational LAP introduce many aspects not considered in the strategic version. These additional aspect are crucial because we deal with specific locomotives and not just with locomotive types. More precisely, we have to assign locomotive ID codes (an ID is unique for each specific locomotive) to trains. This means that we have to solve a locomotive routing problem while honoring the constraints of the planning phase and new operational constraints (like fueling constraints and maintenance constraints). Moreover, the train schedule may be affected by delays and disruptions events.

1.2.1 Freight and passenger railway transportation

Passenger and freight trains have different characteristics. Passenger trains always run according to a fixed schedule while freight trains may operate without schedules and simply depart when they have accumulated a sufficient tonnage. Passenger trains are more time sensitive and thus have higher priority whenever they share the same rail network with freight trains (a common occurrence in U.S., Canada, Europe, Australia and in many developing countries). Typically, passenger trains are lighter than freight ones since they use a small number of cars coupled with one or two locomotives while freight trains generally contain a large number of cars coupled with several locomotives. For passenger trains the maximum gross weight is known in advance with a small uncertainty while the weight of freight trains may change unexpectedly for both scheduled and not scheduled services.

There are significant differences in complexity and modeling of the strategic LAP in the passenger and freight frameworks. Very often a single locomotive is sufficient to pull a passenger train (and therefore the load of the train is not relevant). When a single locomotive is not sufficient, locomotives are combined to form a *consist* (a group of linked locomotives) that provides more pulling force (and horse power). Usually, to pull a passenger train no more than two locomotives of the same type are needed when a single locomotive is not sufficient. According to Noble et al. [2001], in the first case the problem is modeled assuming several classes of locomotives but a single pulling locomotive (multi-class single-locomotive problem), in the second case the train is pulled by a multi-locomotive consist (multi-class multi-locomotive problem). In both cases the reduced size of passenger trains and consists make the problem more tractable with respect to the freight version. Thus, it is possible to assign simultaneously both locomotives and cars to the passenger trains (Cordeau et al. [2000], Cordeau et al. [2001],

Lingaya et al. [2002]), while for freight trains these two assignments are managed separately.

As reported in Cordeau et al. [1998], few works focusing on the management of passenger railway locomotives may be found in the operations research literature. Ramani [1981] focuses on the problem faced by Indian Railways, Cordeau et al. [2000], Cordeau et al. [2001], and Lingaya et al. [2002] treat the problem of simultaneous locomotive and car assignment at VIA Rail Canada, Illés et al. [2005] and Illés et al. [2006] treat the locomotive assignment at Magyar Államvasutak (MÁV, the Hungarian State Railway Company), Maróti and Kroon [2005] study the maintenance routing of trains at NS Reizigers (the main Dutch operator of passenger trains), Paoletti and Cappelletti [2007] present a decision support system developed by the Models and the Decisional Systems Department of Trenitalia (the main Italian operator of passenger trains) to aid the locomotive fleet planning.

A large number of papers focuses on the more complex freight railway locomotive assignment. Tables 1.3 and 1.4 report a list of the researches inspired by real LAP applications in passenger and freight train services.

Table 1.3: Researches in passenger trains locomotive management

Authors	Railway company
Ramani [1981]	Indian Railways
Cordeau et al. [2000]	VIA Rail Canada
Cordeau et al. [2001]	VIA Rail Canada
Lingaya et al. [2002]	VIA Rail Canada
Illés et al. [2005]	Magyar Államvasutak
Illés et al. [2006]	Magyar Államvasutak
Paoletti and Cappelletti [2007]	Trenitalia

Table 1.4: Researches in freight trains locomotive management

Authors	Railway company
Florian et al. [1976]	Canadian National
Ziarati et al. [1997]	Canadian National
Ziarati et al. [1999]	Canadian National
Ziarati et al. [2005]	Canadian National
Ireland et al. [2004]	Canadian Pacific Railway
Ahuja et al. [2005a]	CSX Transportation
Ahuja et al. [2005b]	CSX Transportation
Ahuja et al. [2006]	CSX Transportation
Vaidyanathan et al. [2008a]	CSX Transportation
Vaidyanathan et al. [2008b]	CSX Transportation
Powell and Bouzaiene-Ayari [2007]	Norfolk Southern
Brannlund et al. [1998]	Banverket Swedish National Railway
Scholz [2000]	Stateiis Järiivägar Swedish State Railways
Noble et al. [2001]	Public Transport Corporation
Baceler and Garcia [2006]	Companhia Vale do Rio Doce
Fügenschuh et al. [2006]	Deutsche Bahn AG
Fügenschuh et al. [2008]	Deutsche Bahn AG

The following list reports some critical aspects that imply the increased complexity of the strategic LAP in freight trains.

a. The number of active locomotives in freight trains is often two or three times that required in passenger trains (consist may be constituted by 4 or more pulling locomotives).

b. The number of active and passive locomotives attached to freight trains may be significantly higher than the number of locomotives attached to passenger trains (to give an example, CSX permits up to 12 locomotives per train).

c. There are many different types of freight trains, belonging to (three) different classes (intermodal, auto and merchandize), that require very different consists, thereby it is more difficult to reduce the size of such a heterogeneous set of consist.

d. There are more train to train connection possibilities to be considered for freight trains, more constraints (like locomotive versus train compatibility constraints) and complications like *consist busting*.

The consist busting is the operation of merging locomotives from inbound trains and regrouping them to make new consists. The consist busting typically entails the breaking up of an incoming consist at a station and the assignment of the locomotives in it to more than one outgoing train.

1.2.2 Yard switching and in-plant railroad LAP

Railroad yards are a complex series of railroad tracks for storing, sorting, loading or unloading railroad cars and locomotives and represent a crucial component of a railroad network. They are the points of origin and destination of shipments and freight movements. In a yard, inbound trains are disassembled, unloaded and

inspected. After that (when needed) cars and locomotives are sent to cleaning and maintenance facilities (shops). Finally, they are loaded and reassembled forming new outbound trains.

As reported in Sabino et al. [2010], yard activities are an important part of freight transportation operations since the delays associated with these activities represent a large portion of the transit time for rail freight. Yard locomotives are often called switch engines, they move cars and locomotives within the railroad yard. The solution of the LAP helps to minimize the costs of the switch operations optimizing the fleet size of the switch engines that greatly affects these costs (see Sabino et al. [2010] for more details).

Lübbecke and Zimmermann [2003] report another particular real life application of the LAP. Large industrial plants in the automobile, chemical, and steel industry transport freight from production to storage or shipping terminals that are often spread over large areas. In order to preserve a timely production process it may be useful to have a private railroad system which manages these tasks (often a subsidiary and a distinct legal entity). An industrial in-plant railroad has to be managed minimizing operational costs and the assignment of locomotives has to be solved efficiently. There are very few studies dedicated to this particular version of the LAP. Charnes and Miller [1956] is one of the first, more recently Lübbecke and Zimmermann [2003] presented a real application of the LAP at Verkehrsbetriebe Peine-Salzgitter GmbH and EKO Transportgesellschaft GmbH.

2 Problem types

The locomotive assignment problems may be classified in several ways. For instance, problems may be classified considering the objective pursued by the modeler. Some classical objectives are the minimization of operating costs (maximization of profits) or the minimization of the fleet size. Another more specific objective may be the minimization of deadheading times. Active locomotives pull trains but locomotives may also move in a passive way: *deadheading* locomotives are attached to trains as passive rolling stock elements and are moved like wagons in order to be repositioned, *light-travelling* locomotives form a group where only the leading locomotive is active and pulls the remaining locomotives attached as passive rolling stock elements. Another possibility is to classify problems looking at the *planning level* and thus the problem may be a strategic, tactical or operational locomotive assignment.

From a modeling perspective, a first important classification may be obtained considering the maximum number of pulling locomotives a train may require. If each train needs a single pulling locomotive then the problem is modeled by a *single locomotive model*. If some trains require more than one pulling locomotive then the problem is modeled by a *multiple locomotive model*.

18

2.1 Single locomotive models

Ceteris paribus[1], the problems in the single locomotive category are easier to solve. It is natural to proceed further in the classification considering how many locomotive types the model requires. According to Forbes et al. [1991], if the problem is modeled assuming only one type of locomotive, then it becomes similar to the single depot bus (vehicle) scheduling problem (SDVSP), while if several locomotive types are required, then the problem is similar to the multiple depot bus (vehicle) scheduling problem (MDVSP). The former version may be modeled as a minimum cost flow problem whose solution is achievable for very large scale instances as remarked in Ziarati et al. [1997]. This version may be solved efficiently by polynomial or pseudo-polynomial algorithms, for instance by the so called Hungarian Method as reported in Fügenschuh et al. [2006] (see also Ahuja et al. [1993] for details about the Hungarian Method).

Booler [1980] considers a one day cyclic train schedule with possibly variable trains departure times and proposes a model based on multi-commodity flows. The objective is to find a minimum cost set of locomotive schedules to pull a given set of trains. Booler proposes a heuristic method based on a linear programming model since the direct application of methods suitable for ship scheduling problems (embedded networks, compact inverse methods, methods based on decomposition) leads to significant integrality gaps. Booler tests the method on small instances (10 ÷ 50 trains) and Wright [1989] points out that this approach does not produce good solutions for more realistic instances (100 ÷ 500 trains).

Wright [1989] seems to be the first author able to find a valid solution for large-scale instances. He considers a cyclic one day train schedule and obtains the solution through a heuristic procedure. Three algorithms are used to solve the

---

[1]all other things being equal

problem: the first is a deterministic algorithm that provides a feasible solution, the second is a stochastic algorithm, and the third is a simulated annealing algorithm. Wright tests the procedure on several instances ($25 \div 200$ trains) and shows that the stochastic algorithm outperforms the deterministic one and that the simulated annealing algorithm is the best of the three. The solution procedure does not take into account the fleet size constraints. For this reason, Wright does not recommend the use of this procedure for real life applications. Forbes et al. [1991], inspired by the work of Wright, obtain an exact solution for the locomotive scheduling problem. They transfer to the locomotive scheduling problem a solution procedure they developed for the MDVSP in a previous work. The model is based on an integer linear program equivalent to a multi-commodity flow formulation where each commodity represents a locomotive type. This method represents a significant improvement over the method proposed by Wright, mainly because Forbes et al. are able to take into account the fleet size constraints, not included in the model of Wright. Testing the procedure on the same dataset used by Wright, Forbes et al. solve several moderately large scale instances (25 to 200 trains) on a daily cyclic train schedule framework. Booler [1995] proposes also a Lagrangian relaxation approach to improve the solution method proposed in Booler [1980], but still the tests were conducted only on small instances (14 trains, 3 locomotives types).

More recently, Fügenschuh et al. [2006] followed a path similar to the one adopted in Forbes et al. [1991]. Starting from their experience on multi-depot multi-vehicle-type bus scheduling problems, they extend their solution methodologies to the locomotive scheduling problem. As done by Forbes et al., Fügenschuh et al. point out the extra difficulties of locomotive scheduling problems due to several new aspects taken into account: cyclic departures of trains, time windows on starting/arrival times, transfer of wagons among trains. The model is formulated

as a linear integer programming problem, in two different versions: with fixed and with flexible starting/arrival times.

The fixed starting time version of the problem is called *capacitated cyclic vehicle scheduling problem* (CVSP) due to the cyclic character of the locomotives schedules. The flexible starting time version is called *cyclic vehicle scheduling problem with time windows* (CVSPTW). The CVSPTW is further specialized in two sub-versions. The first considers constant traveling times while in the second the driving time depends on the total network load. This takes into account the fact that often freight and passenger trains share the same tracks and thus at daytime a freight transport may wait for the passenger transport, and then the average traveling speed may be much lower than the one at nighttime. Fügenschuh et al. consider the strategic locomotive scheduling problem for freight trains on a one day cyclic scheduling framework. Their work aims to improve the simulation tool used by the Deutsche Bahn AG (the largest German railway company) supporting the strategic simulations of the future network load in freight transport. Their model is based on a multi-commodity min-cost flow formulation and is solved as a linear integer programming problem. In both versions, CVSP and CVSPTW, the objective is to minimize the total cost. In the former, the total cost is given by the active locomotive costs and the deadheading costs (the shorter the deadheading trip the lower the cost), while in the second also the idling costs are considered. The CVSP and the CVSPTW problems are formulated as integer programming problems and commercial IP solvers (ILOG CPLEX 10) are used to compute feasible/optimal solutions. The CVSP is solved with both finite and infinite capacity, whereas the CVSPTW is solved only with infinite capacity. Fügenschuh et al. are able to solve instances of the CVSP up to 1537 trips and 4 locomotive classes while for the CVSPTW they consider up to 120 trips and 4 locomotive classes and time windows length ranging from ± 10

to ±120 minutes intervals around the pre-scheduled starting time. The CVSP is solved to optimality with computation times ranging from 1 second for the 42 trips, 3 classes case to 9537 seconds for the larger instance with 1537 trips and 4 classes. The CVSPTW presents optimality gaps that range from 0.00% for the 42 trips, 3 classes instance to 79.06% for the 120 trips, 4 classes instance, with larger gaps where the trip time is network load dependent. Observing these gaps the authors consider that a heuristic approach could be fruitful for the CVSPTW. That heuristic approach is introduced in Fügenschuh et al. [2008]. In this study the authors propose the same results for the CVSP and extend their research on the CVSPTW considering some additional more complex instances (up to 340 trips, 6 locomotive classes and ±120 minutes intervals or up to 727 trips, 6 locomotive classes and ±30 minutes intervals). More important, while in Fügenschuh et al. [2006] the authors solve the CVSPTW using a branch-and-cut method implemented in a general purpose solver (CPLEX), they introduce a new heuristic solution approach to obtain better results (smaller gaps) and solve some new bigger instances of the CVSPTW. Namely, the new solution approach hinges on a randomized parameterized greedy (PGreedy) heuristic that acts in two phases: in the first phase it identifies a feasible solution that synchronizes train connections minimizing the number of missed car transfers among trains (i.e. minimizing idling car costs), in the second one it seeks a minimum number of locomotives and a minimum total length of all deadhead trips. Further, the authors implement a special purpose reformulation and resolving technique (as well as the inclusion of valid cutting planes) to improve the formulation of the problem before applying the CPLEX general purpose branch-and-cut algorithm. A comparison between the solutions obtained with the new heuristic solution approach and the ones obtained with CPLEX shows the performance of the new methodology in terms of gaps reduction and ability to solve bigger instances.

Illés et al. [2005] and Illés et al. [2006] treat the locomotive assignment at Magyar Államvasutak (MÁV, the Hungarian State Railway Company). They model a problem in which a single type train is pulled by a single type engine and solve the problem for real data. They introduce a simplified version of the problem that does not contain the maintenance conditions and may be solved in polynomial time through combinatorial optimization techniques.

Like Charnes and Miller [1956], Lübbecke and Zimmermann [2003] treat the in-plant railroad locomotive scheduling and routing problem, a subject that has not been extensively discussed in the operations research literature. They describe the mathematical and algorithmic solutions proposed to in-plant railroad companies as decision support tools for scheduling and routing problems. The minimization of the total deadheading and waiting time is considered as an example of practically relevant objective function. The problem is related to the multiple-vehicle pickup and delivery problem, and two formulations of the problem are considered: a mixed integer and a set partitioning programs. The linear programming relaxation of the set partition model is solved by column generation. Computational experiments are conducted on both artificial and real life data obtained from three different German plants (VPS, EKO and SOL).

Sabino et al. [2010] propose an ant colony optimization algorithm to assist railroad yard operational planning operations. Given the information about the railroad yard layout, the switch engines available and a detailed specification of all pending planned switch orders, the goal is to determine a switch engine schedule. The project is developed together with professionals from Tubaro Railroad Terminal (the largest railroad yard in Latin America), it is focused on the creation of an algorithm designed for real life application able to generate a solution in a predefined processing time and in accordance with railroad yard operational policies. The proposed ant colony optimization algorithm tries

to minimize a multi-objective function that considers both fixed and variable transportation costs involved in moving railroad cars within the railroad yard area. More specifically, the authors implement a CompetAnts algorithm that significantly outperforms the traditional ant system algorithm for problems with multi-objective function characterized by two conflicting sub goals. A railroad yard operations simulator is developed to create artificial instances in order to tune the parameters of the algorithm.

Ghoseiri and Ghannadpour [2010] develop a hybrid genetic algorithm to solve a multi-depot homogeneous LAP with time windows. The problem is to assign a set of homogeneous locomotives, initially located in a set of dispersed depots, to a set of scheduled trains to be serviced in pre-specified time windows. The problem is formulated as a vehicle routing problem with time windows (VRPTW): the trains act as customers of the VRPTW that should be serviced in their time windows. Each customer has two coordinates (origin and destination), and the existing depots (say P depots) are considered as central zones that provide the neighbouring zones (current customers) with locomotives. A cluster-first, route-second approach allows the authors to treat the multi-depot LAP as a set of single depot problems solved independently. Thereby, at first stage trains are assigned to the existing P depots (following a priority principle) obtaining P clusters. After that, each single depot problem (each cluster) is solved heuristically by a hybrid genetic algorithm characterized by a Push Forward Insertion Heuristic (used to determine the initial solution) and by a neighbourhood search and improving method. A medium sized numerical example (84 nodes and 42 trains per day in a weekly planning horizon) with four different scenarios is presented. To test the quality of solutions of the hybrid genetic algorithm, some small and medium-sized instances are created and solved by branch-and-bound technique (exact solution available up to 16 nodes).

2.2 Multiple locomotive models

The most complete version of the LAP occurs when consists (instead of single locomotives) are linked to trains, and there is more than one locomotive type involved. Thus a single train may be linked with several locomotives of different types. This is the LAP with heterogeneous consists.

Florian et al. [1976] analyzed a freight train problem for the Canadian National Railways (CN) and were among the first to deal with this version of the problem. The problem is formulated as an integer program based on a multi-commodity network flow formulation. The objective is to minimize the capital investment and the maintenance costs over a long planning horizon selecting an optimal number of (mixed) locomotive types that satisfy the motive power requirements of each train. The motive power requirement constraints are determined according to train weight, train length (number of cars) and geography (slope of the traveled tracks).

They propose a solution based on a Benders decomposition method and conduct their computational experiments using the weekly train schedule for the Atlantic region of the CN. Their implementation does not converge rapidly so the problem could not be solved to optimality, and the size of the optimality gaps was considered acceptable for medium-sized problems but not for large ones. It should be noticed that the limited computational power at that time imposed to run the algorithm for less than 30 iterations, different convergence result could be probably obtained with the present computers.

Ziarati et al. [1997] extended the formulation proposed in Florian et al. [1976] to include many of the operational constraints encountered at CN (e.g. deadheading, scheduling of the maintenance intervals of the locomotives, noncyclic trains schedules with fixed starting and ending times). Ziarati et al. propose a space-time network approach for the operational version of the LAP with a heterogeneous

fleet. The problem is formulated as a mixed integer linear program corresponding to a multi-commodity network flow problem with supplementary variables and constraints. The objective is the minimization of the total operational costs. They consider a week as time horizon. However, in the solution of very large instances the time horizon is divided into a set of rolling overlapping time windows (two or three days each) that involve fewer trains services (500 / 1000 each). Every time slice is then optimized using a branch-and-bound procedure in which the linear relaxations are solved with a DantzigWolfe decomposition. The solution of the problem for a slice determines the initial conditions for the following problem associated to the next slide. Computational experiments are conducted on real life data (26 stations, 164 yards, 18 shops, 1988 train services, 1249 locomotives, 26 locomotive types). As in Florian et al. [1976], optimality has not been reached, with gaps ranging from 3% to 7%. Results are very promising using slices of three days. In this case the authors obtain a 7.53% improvement in locomotive reduction (a 1% improvement corresponds to a \$4 million annual saving) though nearly 21 hours of CPU time were necessary.

To reduce the optimality gaps, Ziarati et al. [1999] strengthen the previous formulation with specific cutting planes, additional cuts that are based on the enumeration of feasible assignments of locomotive combinations to trains. They report an average reduction of the integrality gaps of about 33% for instances of one, two, and three days time slices. The use of these cuts jointly with the new branching strategy (named branch-first, cut-second approach) consistently improves the solution quality with a modest increase in computation time.

Cordeau et al. [2000] describe a decomposition method for the simultaneous assignment of locomotives and cars in the context of passenger transportation. Compatible equipment types (locomotive and car types) may be joined to form a train. More precisely, a train is obtained joining some car types with just

one locomotive type chosen among the available compatible equipment types. The compatibility constraints are imposed defining the set of all accepted train types (i.e. the set of all accepted collections of compatible equipment types containing one locomotive type and some car types). The authors propose an integer programming formulation in which each train type corresponds to a different commodity, and the problem is modeled as a multicommodity flow on a space-time network where nodes denote events i.e. arrivals, departures and repositioning of a unit (arrival node and repositioning node are located within the same station), and arcs are divided in (train) sequence arcs, repositioning arcs and waiting arcs. The simultaneous assignment of locomotives and cars requires a large integer programming formulation. Cordeau et al. propose an exact algorithm, based on Benders decomposition approach, that exploits the separability of the problem. The authors evaluate the performance of this solution method performing computational experiments on a set of 9 instances obtained from VIA Rail Canada (the most important passenger railway in Canada). The company uses six equipment types: two types of locomotives and two types of first-class and second-class cars, which may be combined in three different ways. The demand for first-class cars is either 0 or 1, whereas the demand for second-class cars lies between 2 and 8 cars (a very reduced train size with respect to freight trains). Most trains require a single locomotive, only few require two, leading to a multiple locomotive problem. A part of the computational experiments focuses on the performance comparison of the proposed Benders decomposition approach to those of three other solution methods, namely Lagrangian relaxation, a simplex-based branch-and-bound algorithm and a DantzigWolfe decomposition (column generation). The authors show that the method based on the Benders decomposition approach finds optimal solutions within a short computation time and outperforms the other considered approaches. In particular, Cordeau et al.

[2000] argued that a straightforward implementation of DantzigWolfe decomposition was not appropriate to solve their formulation because of the large size of the resulting master problem. Nevertheless, in Cordeau et al. [2001], the authors propose several refinements that make the problem more tractable and show that column generation can indeed be a very effective solution approach.

The model in Cordeau et al. [2000] is well suited for a Benders decomposition approach. However, although it was tested on real-life data and produced optimal solutions in reasonable computation times, the model is probably not sophisticated enough to be used in practice. The model introduced in Cordeau et al. [2001] is characterized by a broader range of refinements captured by its formulation, it incorporates a much larger set of constraints and possibilities which are required in a commercial application. A first example of these refinements is the ability to take substitution possibilities (among car types) into account. Other examples are the possibility of performing maintenance during the day (and not exclusively at nighttime), the minimization of switching operations, the possibility of choosing the combination of equipment to be used on certain train legs in a long-term planning framework. The authors obtain a large-scale integer programming model and propose a heuristic approach based on column generation. Namely the model is solved by a heuristic branch-and-bound method in which the linear relaxation lower bounds are computed by column generation. The authors perform computational experiments on a set of 6 instances (each one is solved in three different scenarios) concerning the trains operated by VIA Rail in the Québec-Windsor corridor (the number of train legs in each instance varies from 326 to 348, six types of equipment, two types of locomotives, a complete fleet composed by more than 130 units). The algorithm has been successfully implemented at VIA Rail, it finds good quality solutions in a few hours of computation on a Sun Ultra 3 computer (300 MHz), a satisfactory

performance in a long-term planning framework.

In Lingaya et al. [2002], the same research group addresses the operational car assignment problem (OCAP), a short-term planning problem that arises at VIA Rail Canada. The authors propose a model for supporting the operational management of locomotive-hauled railway cars. They describe a modeling and solution methodology for a car assignment problem that arises when individual car routings that satisfy all operational constraints must be determined. As in Cordeau et al. [2001], cars may be switched on or off the train at various locations in the network, thereby locomotives and cars must be assigned simultaneously to the scheduled trains because the minimum connection time between two consecutive trains covered by the same locomotives depends on whether cars need to be switched during the connection (the model assumes that for each train a successor train has already been specified). Moreover, the switching time (and so the connection time) depends on the position of the switched cars within the train since switching cars located in the middle (i.e. in the body) of the train requires more time with respect to the cars located at its end. This represents the first approach that explicitly considers the order of the carriages in the trains, a choice that increases the complexity of the problem but that is necessary because of the dependence of the minimum switching times on the positions of the switched cars. The model deals also with the effects of a varying passenger demand and with the consequent altered timetable and rolling stock schedules (trains may be canceled, added or simply rescheduled to account for changes in the demand). The objective of this model is to maximize anticipated profits i.e. anticipated revenues minus operational costs (while seat shortages and the number of composition changes are not minimized). The solution approach is based on a Dantzig-Wolfe reformulation solved by column generation techniques and followed by a branch-and-bound procedure applied heuristically to obtain

good integer solutions. The authors perform computational experiments on a set of 140 instances obtained from a combination of 10 test instances with 7 scheduling horizons and 2 scenarios. The test instances stem from a weekly schedule used in a particular season. For this specific weekly schedule, the authors determine locomotive and car cycles using the solution approach introduced in Cordeau et al. [2001] for the first phase of the planning process. Then, they create a large number of instances by randomly generating demand revisions for first-class and second-class cars. The algorithm has been successfully implemented at VIA Rail, it finds good quality solutions in a few minutes of computation on a Sun Ultra-10 computer (440 MHz) depending on the considered scheduling horizon (typically less than 1 minute for 1 day scheduling and less than 15 minutes for 7 days scheduling).

Scholz [2000] investigated a locomotive scheduling problem for the Swedish railway system. The problem involves a set of trips that have to be covered by locomotives, and the objective was to run the same set of trips with as few locomotives as possible. Every trip is characterized by a start location, an end location and a total travel time required. Interestingly, there are no specific departure times associated with the trips but each trip has a departure time window, and the trips have to depart during that time window. Trip schedules are represented in a Gantt chart format, and the problem becomes similar to a bin packing problem with additional constraints. Each logical locomotive is displayed in the Gantt chart vertical axis against time on the horizontal axis, each trip forms a rectangle in the Gantt chart, the length of each rectangle expresses how long the trip is. Thereby, to efficiently use locomotives to run the trips, one must rearrange the rectangles of the Gantt chart so that as little space as possible is taken along the vertical axis i.e. a bin packing problem. Scholz's solver also had to choose the route that a locomotive could take to get from a

trip start location to its end location taking into account the time needed for a possible passive transfer and avoiding collisions in single-laned tracks.

Noble et al. [2001] study a locomotive scheduling problem faced by the Australian State of Victoria's Public Transport Corporation (PTC). PCT has to decide which locomotives to allocate to a set of long-trip train services so that the total power allocated results greater than the load to be pulled, and the overall cost is minimized. The authors consider 26 outward and return journeys and 6 types of locomotives. The problem is simplified by the fact that, since trips are long and repetitive, once a locomotives is assigned to a service it remains with that service. Noble et al. initially proposed a straightforward pure integer program formulation of the problem. As optimality was impossible to achieve, the authors change the model reformulating the constraints and replacing every integer variable with a linear sum of a special ordered minimal covering set of binary variables. Adopting this new formulation it was possible to achieve optimality in negligible computation time.

Ziarati et al. [2005] propose a multi-commodity flow formulation for a cyclic heterogeneous locomotive scheduling problem. The main objective of this problem is to assign a sufficient number of locomotives to pull all the trains using the minimum number of available locomotives over a time horizon of one week. The problem requires a cyclic solution that may be used every week. The problem is solved by a heuristic genetic algorithm (no information on dual bounds is provided). The data instance is from Canadian National North America Company and consists of up to 1629 train services, 93 stations, 1182 available locomotives divided in 7 types. This algorithm is able to cover all 1629 trains with only 738 locomotives providing a solution after 20 hours of computation time on a 1GHz Pentium-III platform.

Baceler and Garcia [2006] study a locomotive scheduling problem faced by the

Vitoria-Minas Railroad (EFVM), owned by Companhia Vale do Rio Doce. The authors used real EFVM data based on a schedule of train trips in a two days period and worked with 138 locomotives (divided in five types) and 390 trains passing by 35 stations. The research developed successfully a mathematical model that represents a real-life problem of Brazilian Railways. The authors showed that the locomotive scheduling determined by the use of operational research in the EFVM Railroad is better than the locomotive assignment currently conducted by EFVM employees without specialized tools. Using a two days period, it was possible to save almost 19% of the entire locomotive fleet used in this period, which means a saving of 20.65% of the HP available. In terms of money, this part of the fleet represents nearly 63 million of 2010 US dollars in investments.

Paoletti and Cappelletti [2007] present a decision support system developed by the Models and the Decisional Systems Department of Trenitalia (the main Italian operator of passenger trains) to aid the locomotive fleet planning. The planning and the sizing of all the rolling stock types that are used to cover all the rosters (i.e. the service sequences to be executed) has been realized through the development of a Fleet Rostering model that builds the daily rosters for each locomotive (for a day that statistically represents the observed timetable). The locomotive rostering model takes into account the timetable planned services and assigns to each train the necessary traction group. This model has to build the employment roster for each used locomotive. The rosters are cyclic, and the locomotive, at the end of the roster, has to go back to the station of roster origin. A further element of complexity is represented by the great size of the problem: more than 4000 locomotives divided in 50 types, the possible traction groups (single or composed) are more than 200, the timetable presents 9000 daily services and there are 109 maintenance plants. The authors develop a minimum

cost multicommodity flow model. The specific heuristic algorithm, developed to search the minimum cost paths tree, reaches acceptable quality solutions in an acceptable time for the company.

An alternative approach to solve complex combinatorial problems has been proposed in Powell et al. [2001], and is based on the approximate dynamic programming (ADP) framework.

The idea proposed by Powell et al. is to formulate the original problem as a dynamic programming problem and solve, through ADP, a sequence of small sub-problems that can be managed optimally using commercial solvers (like CPLEX). This approach permits to deal with uncertainty in a general way allowing the modeling of a wide class of uncertainties even in complex real life combinatorial problems. The ADP framework has been extensively described in many papers (Marar et al. [2006], Marar and Powell [2009], Powell [2003], Powell and Topaloglu [2003], Powell et al. [2001, 2002, 2007]), technical reports (Powell and Bouzaiene-Ayari [2006]), conference proceedings (Powell and Bouzaiene-Ayari [2007]) and in a book (Powell [2007]). The LAP is often formulated as a Mixed Integer Programming (MIP) problem, a class of problems which is treated for instance in Powell et al. [2002], Powell and Topaloglu [2005], Topaloglu and Powell [2006]. Powell et al. apply the ADP framework to several real life railways problems including the LAP. Namely the LAP has been covered, with different degrees of detail, in several documents (papers, conference proceedings and technical reports) such as Henderson et al. [2007], Marar et al. [2006], Marar and Powell [2009], Powell [2003], Powell and Bouzaiene-Ayari [2006, 2007], Powell and Topaloglu [2003, 2005], Powell et al. [2001, 2007]. Moreover, Powell et al. apply their approach to the solution of a real life LAP. Focusing on a recent project, in 2006 they develop an application, sponsored by the Norfolk Southern Railroad

and Burlington Northern Sante Fe Railroad. This application was claimed to solve the problem of assigning locomotives to trains over a planning horizon (a week for a real-time planning, a month for a strategic planning) capturing a high level of detail (about locomotives and trains) as well as a variety of complex business rules. Notably, the application simultaneously handled the problem of routing locomotives to shops (maintenance centers). In 2007 this application was still in development in collaboration with Norfolk Southern Railroad. Finally, in 2009 the work of Powell et al. produced an application named Princeton locomotive and shop management system (PLASMA) which completed the user acceptance test at Norfolk Southern as a strategic planning system. PLASMA has been used to assist the (strategic) decision making in the 2009 locomotive road fleet requirement.

An important improvement in the realism of the LAP models has been provided in Ahuja et al. [2005b]. Ahuja et al. study a real life locomotive scheduling faced by CSX Transportation Inc., a Class I U.S. railroad company. Following the requests of the managers of CSX, who sponsored the research, Ahuja et al. focus on a weekly schedule and on the strategic version of the corresponding locomotive assignment problem. Ahuja et al. [2005b] propose a MIP formulation in which each locomotive type corresponds to a different commodity, and the problem is modeled as a multicommodity flow with side constraints (the number of locomotives of each type is limited) on a space-time network where arcs denote trains and nodes denote events i.e. arrivals and departures of trains and locomotives (for a review of the network models and their application in locomotive and train scheduling see for instance Ahuja et al. [2005a]).

The total cost is defined as the sum of ownership, active, deadheading, light-

traveling and consist busting costs plus the penalty for the use of single-locomotive consists. The objective is to minimize the total costs while finding:

  (i) the active locomotives and deadheaded locomotives for each train;

 (ii) the light-traveling locomotives;

(iii) the train-to-train connections.

Starting from the data provided by CSX, Ahuja et al. consider an instance of the LAP with 538 trains (running with different weekly frequencies), 119 stations and 5 types of locomotives. In a week, the total number of trains which differ at least for the running day is 3324 and the resulting weekly space-time network consists of 8798 nodes (events) and 30134 arcs (train trips).

The proposed formulation does not consider some real life constraints like the weekly consistency constraint (i.e. the same train running on different days should have the same locomotive assignment) and the train to train connection consistency (i.e. the same train to train connection should be adopted for each pair of connected trains). Even without these constraints (which would increase dramatically the problem size), the MIP formulation consisted of 197424 variables and 67414 constraints and could not be solved to optimality or near-optimality using a commercial software like CPLEX, even considering the linear programming relaxation of the problem. In order to deal with this large size instance, Ahuja et al. propose a decomposition-based heuristic approach that allows (using CPLEX) near-optimal solutions for real life instances in moderate computation times and implicitly accounts for the consistency constraints. The first step of this heuristic approach transforms the weekly scheduling problem in a daily scheduling one. This is done passing from the actual set of weekly frequencies to the following binary set: cancel trains running less than 5 days a week (weekly frequency equal to zero) and set to 7 the frequency of the remaining trains. This simplification

35

works because in the specific dataset provided by CSX the 94% of trains run at least 5 days a week. Even if the daily space-time network is significantly smaller, it contains 1323 nodes and 30034 arcs and finding an integer optimal solution is still very problematic. Ahuja et al. identify in the fixed-charge variables (cost of consist busting and light-travelling) the principal obstacle that prevents the optimal (or near-optimal) solution of the daily problem. Consequently, the following three-step heuristic approach is implemented to eliminate fixed-charge variables:

(i) Select among the admissible train to train connections the ones with the lower impact on the cost function; the impact is assessed solving the linear programming relaxation of each problem obtained fixing the connections one by one.

(ii) Identify a small but potentially useful set of light-travel arcs and, as for train to train connections, fix the light-travel arcs one by one and select them relying on the impacts on the cost functions.

(iii) Once the fixed-charge variables are eliminated through the two previous steps, solve the integer program for the daily locomotive assignment without the fixed-charge variables obtaining a high-quality solution (in short time).

Ahuja et al. obtain an integer high quality solution for the daily scheduling problem in 15 minutes with CPLEX 7.0. The procedure is completed using this solution as the starting point for a very large-scale neighbourhood (VLSN) search algorithm. This algorithm stars from this initial feasible solution and repeatedly replaces it by an improved neighbour until a local optimal solution is obtained. The solution of the daily problem is then heuristically adapted displacing locomotive from the fictitious trains to the actual trains respectively

inserted and cancelled in the daily schedule by the frequency quantization. Thereby a modified MIP flow formulation of the weekly problem is obtained from the solution of the daily problem resorting the original weekly frequency distribution. Anyway this modified weekly problem still requires excessive computation time. Then the corresponding multicommodity flow problem is heuristically converted into a sequence of single commodity flow problems with side constraints, one for each locomotive type. Finally, a VLSN search algorithm is applied to improve the feasible integer solution of the weekly locomotive scheduling problem obtained in the previous step. Computational tests were conducted on a real life scenario: 3324 trains originating from and terminating at 119 stations and 3316 locomotives belonging to five locomotive types. The algorithms made extensive use of CPLEX 7.0. and were tested on a Pentium III 750 MHz. The solution obtained in Ahuja et al. [2005b] is substantially superior to the one provided by the software developed at CSX: the total cost is substantially reduced, and the number of locomotives used dramatically decreases (by $350 \div 400$ units, depending on the scenario).

A technical document (Ahuja et al. [2006]) was prepared to introduce some possible extensions of the model, e.g. CAB signal requirements, optimal routing of locomotive to fueling stations and shops to satisfy fueling and maintenance constraints. The same research group prepared a more detailed presentation of these and other extensions (Vaidyanathan et al. [2008a]) considering a generalized version of the LAP. Vaidyanathan et al. [2008a] extended the previous planning LAP model in several ways by incorporating in the strategic problem all the real-world constraints needed to generate a fully implementable solution and by developing additional formulations necessary to the transition of the LAP solutions to the real life practice.

Vaidyanathan et al. propose two alternative formulations for the generalized

planning LAP: the *consist flow formulation* and the *hybrid flow formulation*. The consist flow formulation (CFF) is an extension of the locomotive flow formulation (LFF) described in Ahuja et al. [2005b]. In the CFF locomotive types are replaced by the consist types, and each consist type is defined to be a single commodity routed on the train network. In the LFF, single locomotives are assigned to trains and consists are the result of this assignment. In the CFF the solution is obtained starting from a set of consists already assembled. The optimal set of assembled consists is determined heuristically. The hybrid formulation allows the assignment of both assembled consist and single locomotives. Focusing on the CFF, Vaidyanathan et al. point out that performance critically depends on the number and types of consists. As expected, the greater the number of consists with different horsepower and tonnages, the better the quality of the solution. Vaidyanathan et al. proposes essentially the same multi-step solution approach adopted in Ahuja et al. [2005b]. The use of assembled consist restricts the solution space and may lead to a loss in optimality. Nevertheless, several computational tests performed by Vaidyanathan et al. show that the optimal objective function value in the CFF may be just 5% higher than the one obtained in the LFF. The correct identification of the set of assembled consists is crucial to reduce as much as possible the optimality gap. This (small) optimality gap is highly compensated by many benefits:

a. The LFF could not converge to a feasible solution in more than 10 hours, while the CFF optimally solves the same instances within a few minutes.

b. The CFF allows the model to implicitly handle many constraints that were explicitly used in the LFF, offering shorter computation and rapid convergence.

c. Complex rules on the allowed consist classes (locomotive types combinations), impossible or hard to impose in the LFF, are easy to enforce in the CFF.

d. Consist busting (and its corresponding cost) is reduced to a large extent.

In fact, great improvement in solution speed and robustness, significant consist busting reduction and easy implementation of complex constraints, make the consist flow formulation superior.

Some important real life constraints cannot be inserted in the planning phase and the models proposed in Ahuja et al. [2005b] and Vaidyanathan et al. [2008a] did not account for the fueling and servicing feasibility of individual locomotive units. The fueling and servicing constraints have to be imposed to specific locomotive units, not to locomotive types. This may be done in the locomotive routing phase, that follows the planning and the scheduling phases. Vaidyanathan et al. [2008b] developed methods that allow the routing of locomotive units on fueling and servicing friendly routes while honoring the constraints seen in the planning phase. Tables 2.1 and 2.2 present the classification of the optimization models reviewed.

Table 2.1: Classification of the LAP optimization models — Part A

Authors	Problem type	Planning level	Objective function	Model structure	Solution method
Booler [1980]	Single locomotive	Tactical	Min operating costs	Multicommodity	Heuristic
Wright [1989]	Single locomotive	Strategic	Min operating costs	Assignement problem	Heuristic
Forbes et al. [1991]	Single locomotive	Tactical	Min operating costs	Assignement problem	Branch-and-bound
Booler [1995]	Single locomotive	Tactical	Min operating costs	Assignement problem	Heuristic
Cordeau et al. [2000]	Locomotives & cars	Tactical	Min operating costs	Multicommodity	Benders decomposition
Cordeau et al. [2001]	Locomotives & cars	Tactical	Min operating costs	Multicommodity	Heuristic
Lingaya et al. [2002]	Locomotives & cars	Operational	Min operating costs	Multicommodity	Heuristic
Lübbecke and Zimmermann [2003]	Single locomotive	Operational	Min deadheading and waiting time	Set partitioning	Price-and-branch
Illés et al. [2005]	Single locomotive	Strategic	Min operating costs	Assignement problem (Circulation problem)	Goldberg-Tarjan algorithm
Illés et al. [2006]	Single locomotive	Strategic	Min operating costs	Assignement problem (Circulation problem)	Goldberg-Tarjan algorithm
Fügenschuh et al. [2006]	Single locomotive	Strategic	Min operating costs	Multicommodity	Branch-and-cut
Fügenschuh et al. [2008]	Single locomotive	Strategic	Min operating costs	Multicommodity	Heuristic
Sabino et al. [2010]	Single locomotive	Operational	Min operating costs	Assignement problem	Heuristic
Ghoseiri and Ghannadpour [2010]	Single locomotive	Operational	Min operating costs	Assignement problem (Vehicle routing)	Heuristic

Table 2.2: Classification of the LAP optimization models — Part B

Authors	Problem type	Planning level	Objective function	Model structure	Solution method
Florian et al. [1976]	Multiple locomotives	Strategic	Min investment and maintenance	Multicommodity	Benders decomposition
Ziarati et al. [1997]	Multiple locomotives	Operational	Min operating costs	Multicommodity	DantzigWolfe decomposition
Ziarati et al. [1999]	Multiple locomotives	Operational	Min operating costs	Multicommodity	Branch-and-cut
Scholz [2000]	Multiple locomotives	Strategic	Min used locomotives	Multicommodity	Heuristic
Noble et al. [2001]	Multiple locomotives	Strategic	Min operating costs	Multicommodity	Heuristic
Powell [2003]	Multiple locomotives	Operational	Min operating costs	Multicommodity	Approximate dynamic programming (ADP)
Powell and Topaloglu [2003]	Multiple locomotives	Operational	Min operating costs	Multicommodity	Approximate dynamic programming (ADP)
Ahuja et al. [2005b]	Multiple locomotives	Strategic	Min operating costs	Multicommodity	Heuristic
Ziarati et al. [2005]	Multiple locomotives	Strategic	Min operating costs	Multicommodity	Heuristic
Baceler and Garcia [2006]	Multiple locomotives	Strategic	Min operating costs	Multicommodity	Branch-and-cut
Paoletti and Cappelletti [2007]	Multiple locomotives	Operational	Min operating costs	Multicommodity	Heuristic
Powell and Bouzaiene-Ayari [2007]	Multiple locomotives	Operational	Min operating costs	Multicommodity	Approximate dynamic programming (ADP)
Powell et al. [2007]	Multiple locomotives	Operational	Min operating costs	Multicommodity	Approximate dynamic programming (ADP)
Vaidyanathan et al. [2008a]	Multiple locomotives	Strategic	Min operating costs	Multicommodity	Heuristic

41

Conclusions Part I

This survey presented a review of the recent optimization models proposed to solve the Locomotive Assignment Problem (LAP). The application of optimization models in the LAP solution received an increased attention in the last years that is attested by the growing number of research contributions in this field. The increasing interest in optimization models may be explained to some extent by the choice of the principal North American railways to change the paradigm of their operations passing to a schedule-based strategy that requires advanced Operations Research software. These railways companies follow the path delineated by the Canadian Pacific Railway (CPR) that implemented with success the schedule-based strategy at the end of the past century. CPR overturned the old paradigm that tonnage-based plans are more efficient and recaptured traffic from the trucks thinking and acting like truckers.

Recent LAP optimization models are developed to capture and manage more effectively the unavoidable complexity and size of the real life locomotive scheduling problems. These models represent a significant improvement in terms of realism over older models that were often built on basic approximations of real systems. These improvements are made possible by the increased modeling ability and by the constant growth in computational power that makes sophisticated models and bigger instances tractable. Simulation techniques remain a very useful tool to support decision making. Nevertheless, problems that were only solvable by

simulation can now be (approximately) solved using mathematical optimization. Supporting the historical role of simulation tools, optimization models are gaining more and more importance in solving large size complex scheduling problems that characterize the schedule-based approach in real life applications.

Although the improved realism of recent optimization models allows the tractability of realistic freight rail transport instances, we still observe a separation of the locomotive scheduling and routing problems. Large-scale very complex freight rail activities impose the separation of the locomotive planning, scheduling and routing phases and cause the adoption of definitely suboptimal solutions. Thereby, there is a strong incentive to concurrently solve locomotive planning, scheduling and routing problems due to the crucial links between these decision phases. Future research should concentrate on the integration of the (so far) distinct models of the locomotive planning, scheduling and routing problems.

Part II

Exploiting Homogeneity Aspects for Locomotive Scheduling Problems

F. Piu[a],   V. Prem Kumar[b],   M. Bierlaire[b],   M. G. Speranza[a]

[a]Department of Quantitative Methods, University of Brescia,
C. da S. Chiara 50, Brescia, Italy

[b]TRANSP-OR Laboratory, École Polytechnique Fédérale de Lausanne,
Station 18, Lausanne, Switzerland

Introduction Part II

The LAP is solved assigning a fleet of locomotives to a network of trains usually minimizing the total operational cost and satisfying a rich set of constraints. Large-scale very complex freight rail activities impose to separate the LAP in three distinct problems:

1. Locomotive Planning Problem (LPP).

2. Locomotive Scheduling Problem (LSP).

3. Locomotive Routing Problem (LRP).

The LPP, the LSP and the LRP are solved sequentially. At the beginning of the solution sequence we consider the available locomotive types (in the LPP) while at the end (in the LRP) we route specific locomotive units to fueling and maintenance stations imposing the required fueling and maintenance stops (i.e. honoring the fueling and maintenance constraints).

The separation of the LAP leads to definitely suboptimal solutions. To achieve optimality a model should encompass LPP, LSP and LRP. Such a structural integration is not practicable due to the size and complexity of real problems.

This second part of the thesis focuses on the planning versions of the LAP i.e. the LPP. In the LPP for each train we determine the *type of consist* (a combination of locomotive types) assigned to that train. The set C of the consist types that are initially available to solve the LPP is generally taken as given in terms of consist

types (railroad companies provide C to researchers). Given C, the LPP solution determines the number of consist units used for each consist type. This research does not take C as given, we introduce an integer optimization model (called *consist types selection* or shortly *consists selection*) to identify the consist types included in C. The consists selection precedes the LPP solution and determines the consist types that form C and are available to solve the LPP. We select the consist types minimizing the active and ownership costs but also the number of fueling events and the inefficiencies in the consist fuel capacity exploitation. This selection leads to LPP solutions that produce savings in terms of overall fueling cost and are easier to handle in the routing phase. The consists selection is a methodological innovation able to partially integrate planning and routing phases accounting (indirectly) for the fueling constraints in the LPP. Solving several realistic instances we show that we may obtain yearly savings up to US\$ 110000 (210 fueling events, 985 servicing hours) for a set of 229 trains.

3 The Locomotive Planning Problem

The Locomotive Assignment Problem may be studied at three levels: planning (or strategic), tactical and operational, in accordance with the length of the respective planning horizon and the temporal impact of the decisions. The three notions identify the planning activities in the long, medium and short term, respectively. At the planning level only the number of locomotives and their type matter, the specific tail number of each locomotive is not considered and locomotives of the same type are completely equivalent. The solution of the LPP determines, for each train, the type and the number of locomotives assigned to that train. Usually, in the LPP the train schedule is given and cannot change (delays and disruptions are excluded). On the contrary, the tactical and the operational LAP introduce many aspects not considered in the planning version. This is necessary because we deal with specific locomotives and not just with locomotive types. More precisely, we have to assign locomotive tail numbers (unique for each specific locomotive) to trains and solve a locomotive routing problem while honoring the constraints of the previous planning phase and new operational constraints (like fueling constraints and maintenance constraints). North American freight trains are generally very heavy and a single locomotive is often not sufficient to satisfy the required motive power performance. Therefore

a suitable *consist* (two or more linked locomotives) has to be chosen from a set of locomotives with different characteristics to provide the requested motive power performance.

3.1 Definitions

Before continuing, we provide a more precise characterization of locomotives and trains and we introduce some useful definitions.

A *locomotive* may be characterized by its:

1. Maximum Horse Power (HP).

2. Maximum pulling force or Tractive Effort (TE).

3. Range (i.e. fuel tank capacity and fuel consumption rate).

The term *train* indicates a train service characterized by:

1. ⟨departure time, departure station⟩ and ⟨arrival time, arrival station⟩.

2. TE requirement (depends on train weight and track geometry).

3. HP requirement (imposed by train speed).

Active locomotives pull trains but locomotives may also move in a passive way:

1. Deadheading locomotives are attached to trains as passive rolling stock elements and are moved like wagons in order to be repositioned.

2. Light-travelling locomotives form a group where only the leading locomotive is active and pulls the remaining locomotives attached as passive rolling stock elements.

Chapter 3. The Locomotive Planning Problem

Freight trains may be classified in fast and slow trains. According to AREMA [2003], HP and TE are related via the maximum speed achievable by a train, namely speed $\propto \frac{HP}{TE}$. Consequently, high HP consists are suitable for fast freight trains (intermodal and auto trains) while low HP consists are suitable for slow freight trains (merchandise and bulk trains).

Since the reduction in operations costs is primarily pursued by minimizing the number of used locomotives, it is important to promote *train to train connections*: when a train service ends at its arrival station (say station $\mathcal{S}$) its consist is assigned to a compatible outbound train (whose departure station is $\mathcal{S}$) in its entirety. The reassignment of a consist in its entirety would avoid *consist busting* operations. The consist busting is the operation of merging locomotives from inbound trains and regrouping them to make new consists to be assigned to outbound trains. The consist busting typically entails the breaking up of an incoming consist at a station and the assignment of the locomotives in it to more than one outgoing train. According to Vaidyanathan et al. [2008a], consist busting are characterized by labor, cost and time intensive activities (each consist busting requires between two to six additional hours per locomotive within the station).

The ownership and the active utilization of a consist have costs that are specific for each consist types. Hereinafter we shortly indicate the sum of Active and Ownership costs for a given consist type as *ActOwn*.

A primary part of the information sources exploited in this research reports several locomotive and train costs in terms of US\$ in 2008 (*2008US\$*). For this reason we have expressed all the monetary values in terms of 2008US\$ throughout all the current study.

3.2 The state of the art in the LPP solution

The most complex version of the LAP is solved when trains are pulled by consists obtained joining several locomotives of different types.

Ahuja et al. [2005b] significantly improve the realism of the LPP models studying a weekly locomotive scheduling problem faced by CSX Transportation Inc. (a Class I railroad). Ahuja et al. [2005b] propose a MIP formulation and model the problem as a multicommodity flow (each locomotive type correspond to a different commodity) with side constraints (the number of locomotives of each type is limited) on a space-time network where arcs denote trains, and nodes denote events i.e. arrivals and departures of trains and locomotives. Having defined the total cost as the sum of ownership, active, deadheading, light-traveling and consist busting costs plus the penalty for the use of single-locomotive consists, the objective is to minimize the overall costs identifying active, deadheading, light-traveling locomotives and train-to-train connections. Vaidyanathan et al. [2008a] propose the *Consist Flow Formulation* for the LPP. The LPP may be solved starting from a set of locomotive types not already assembled in consists or may be solved starting from a set C of consist types fixed ex-ante. The *Locomotive Flow Formulation* (LFF) described in Ahuja et al. [2005b] defines each locomotive type as a commodity while the Consist Flow Formulation (CFF) replaces locomotive types with consist types and each consist type is defined to be a single commodity. In the LFF, single locomotives are assigned to trains, and the consists are the result of these assignments while in the CFF the solution is obtained starting from a set of consists already assembled. As expected, the solution quality critically depends on the number and types of consists: a greater number of consists types leads to a higher solution quality. The use of assembled consist restricts the solution space leading to a loss in optimality. Nevertheless, computational tests performed by Vaidyanathan et al. [2008a] show that the

optimal objective function value in the CFF may be just 5% higher than the one obtained in the LFF. The correct identification of the set of assembled consist is crucial to reduce as much as possible the optimality gap. This small optimality gap is highly compensated by improvements in solution speed, significant consist busting reduction, implementability of complex constraints that make the CFF superior. Some important real-life constraints cannot be inserted in the LPP, so the models proposed in Ahuja et al. [2005b] and Vaidyanathan et al. [2008a] did not account for the fueling and maintenance constraints that are honored in the locomotive routing phase (Vaidyanathan et al. [2008b] developed methods that allow to route locomotive units on fueling and maintenance friendly routes while honoring the constraints seen in the planning phase).

4 The current study

The literature survey shows the lack of studies focused on the integration of planning, scheduling and routing phases, which could be an extremely complex task. The three phases are solved sequentially: the solution of the LPP is the starting point for the subsequent scheduling and routing problems. Important constraints (like fueling and maintenance constraints) are relegated in the routing phase because they rely on locomotive tail numbers that are not considered in the LPP.

This study proposes a methodological innovation able to partially integrate planning and routing phases accounting (indirectly) for the fueling constraints in the CFF LPP.

In the previous studies, the set C of available consist types were assumed as given in terms of its qualitative composition. This means that the consist types that are available for the LPP optimization are determined by the expertise of locomotive managers. Subsequently, the LPP solution determines the number of consist units needed for each consist type in C.

Our objective is to define a preliminary optimization program (called *consist types selection* or shortly *consists selection*) that determines the qualitative composition of the set C identifying the consist types initially available for the

solution of the LPP. The consists selection indirectly accounts for the fueling constraints minimizing the number of fueling events. This phase could identify consist types that are not captured by a purely cost-oriented consists selection but that may be useful in the routing phase, where a reduced number of fueling events could simplify fueling routing and produce savings that could not be achieved using (apparently) more economical consist types.

Finally, we exploit in the consists selection the concept of consist fueling homogeneity that allows the identification of consist types that exploit efficiently their fuel capacity and reduce the fueling costs.

4.1 Consists Selection: concepts and methodology

The locomotive fueling and maintenance constraints are not considered in the LPP model and are relegated in the routing problem because they rely on specific locomotive tail numbers. Inspired by the CFF of the LPP proposed in Vaidyanathan et al. [2008a], we introduce an optimization program that precedes the LPP optimization and selects the initially available consist types among all the possible consist types. We call this preliminary optimization program as *consists selection*.

The aim of the consists selection is to identify the composition of the consist types set C i.e. to define the consist types initially available for the solution of the LPP. The actual number of units for each consist type (i.e. the weights of the consist types inside C) will be precisely determined after solving the LPP. Our objective is to identify a set C that gives LPP solutions easier to handle when fueling constraints are satisfied. Implementing the consists selection and solving the LPP, we may find solutions that are not necessarily optimal for the LPP alone. However, these solutions reduce the number of fueling stops in the

routing phase and may result more economical when we consider the planning and the routing phases altogether.

The set C obtained from the consists selection depends on the set of trains and on the set of available locomotive types. Given a set of trains and a fleet of locomotives, we determine the consist types that generate a fleet of consist units able to minimize the overall cost while servicing all the trains. In this study we consider 229 trains of three speed classes and 7 locomotive types that generate 288 consist types from which we extract the set C.

4.1.1 The actual number of fueling stops

To reduce the total fueling cost we could diminish the *fueling stops cost* (fsc) reducing the total number of fueling events. Given a locomotive type, the actual number of fueling stops is greater than the one calculated relying on the range of that locomotive type because railroads have to prevent out of fuel events. According to Ahuja et al. [2006] railroads have been found to have several of these out of fuel events in a day. Out of fuel events have severe costs, US\$ 8000 each in 2000 according to GE Harris Energy Systems [2000] (equivalent to 2008US\$ 9995). These cost could be avoided measuring electronically the fuel level. However, according to Lindsey [2007], in 2008 nearly the 90 percent of the locomotives were still without electronic fuel measurement.

Lindsey [2007] reports that railroads adopt very conservative practices to avoid out of fuel events, information confirmed also by GE Harris Energy Systems [2000] (locomotives are refueled when their fuel tanks are still 60% full) and by Ahuja et al. [2006] (the average fuel dispensed per event is only one third to half the locomotive tank capacity). The range of each locomotive type depends on its consumption rate and on its actually exploitable fuel tank capacity. These very conservative policies reduce the actually exploited fuel tank capacity increasing

the number of fueling events (and the overall fueling cost). According to GE Harris Energy Systems [2000], for each locomotive type this study assumed the actually exploitable fuel tank capacity equal to the 40% of the nominal tank capacity. Hereinafter, for each locomotive type, the term tank capacity refers to the actually exploitable fuel tank capacity of that locomotive type (while the term nominal tank capacity refers to the nominal volume of the tank).

4.1.2 The fueling stop cost

According to Unkle and Roddy [2004], a locomotive may be serviced in (at least) three different types of sites:

1. Run-through tracks, where simple processes may be executed.

2. Service tracks, where locomotives are isolated from the main line, and more complex and lengthy processes (like repairs) may be undertaken.

3. Main shops where locomotives may be even disassembled.

The train delay due to the time spent refueling strongly depends on the site on which the fueling stop occurs. Fast refueling events (including on-road refueling operations performed by fueling trucks) are typically associated to run-through tracks while refueling events on service tracks and main shops require more time. Raviv and Kaspi [2012] assume that the train delay cost caused by refueling operations is equal to 2010US$ 250 (2008US$ 246.75) for each fueling event. This assumption is the same adopted in the problem solving competition "Locating Locomotive Refueling Stations" organized in 2010 by Railway Applications Section of INFORMS, and won by Raviv and Kaspi. The assumption is reasonable under the framework adopted in the competition:

1. The only source of fueling are the fueling trucks.

2. All the trains are pulled exactly by one locomotive.

3. Assume instantaneous refueling time.

4. A train incurs a fixed cost if it is refueled.

The fueling stop cost is determined by various characteristics of the train being delayed and of the yard. According to Schafer and Barkan [2008] the industry expert opinion is that the cost of delay for a single train is in the range of 2006US\$ 200 to 2006US\$ 300 per hour (2008US\$ 213.4 to 2008US\$ 320.12 per hour). The cost of 2008US\$ 246.75 assumed in Raviv and Kaspi [2012] seems plausible for on-road refueling events performed by fuel trucks. The characteristics of the train and the time spent refueling (and waiting to be refueled) determine the fueling stop cost. BNSF Railway Twin Cities division [2006] reports that refueling can take up to 10 hours in some congested rail yards (like the ones in Pasco-Washington, Seattle or Vancouver). For this reason BNSF (a U.S. Class I railway company) has invested and continue to invest in new fueling facility that are able to refuel a train in less than one hour (the station in Minot should be able to refuel a train in about 45 minutes). Souten et al. [2008] indicate an average refueling time of 1.5 hours for the BNSF yard located in San Bernardino. According to Gannett-Fleming [2008], estimates provided by Norfolk Southern (another U.S. Class I railway company) indicated that the fueling operation typically takes 3 hours at the Dillerville Yard (Lancaster County, Pennsylvania). The uncertainty about the fueling stop cost is further increased by the different characteristics of trains, in particular by their priority. Given the same refueling time, high priority trains (being associated to a higher value of time) have a higher fueling stop cost with respect to low priority trains.

This study assumes that all the trains have the same priority and that the fueling stop cost is uniquely determined by the the amount of time spent refueling (and

waiting to be refueled). We also assume for the fueling events a hourly cost equal to the one adopted for the idling events that is 2008US$ 111.51 according to Wilbur Smith Associates [2010]. According to GE Harris Energy Systems [2000], the 80% of the locomotive fleet units are refueled on service tracks where each stop takes on average 6 hours, while the remaining 20% are refueled on run-through tracks, where each stop takes on average 30 minutes. Equivalently, we may assume that each fueling event takes on average 4.9 hours and has a fueling stop cost of 2008US$ 546.4. Figure 4.1 reports the number of fueling stops (left y axis) and the corresponding costs (right y axis) of 288 consist types (the numbers in the x axis) working 52 weeks, 50 hours per week.
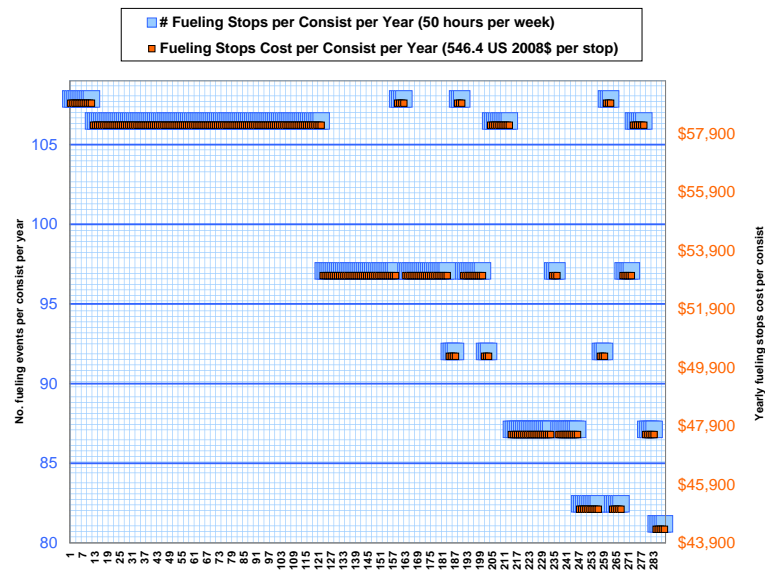

Figure 4.1: Yearly fueling events and costs for a single consist

4.1.3 The fueling homogeneity

Each consist type may present a certain grade of homogeneity according to one or more parameters used to characterize the locomotive types joined inside

that consist type. Given the operative conditions, each locomotive type is characterized by its range or equivalently by the number of fueling stops required over a fixed time horizon (frequency of the fueling events). The frequency of the fueling events for a consist type is determined by the locomotive type with the shortest range (locomotives cannot run out of fuel). The locomotive types that form a consist type could have similar or dissimilar ranges. In a fueling heterogeneous consist, i.e. built using locomotives with dissimilar ranges, the locomotives with the longer ranges exploit their fuel capacity inefficiently. In a fueling heterogeneous consist a portion of the fuel remains unused in the locomotives tanks. Thus, the money value of the fuel is not productively invested causing an opportunity cost that we denote as heterogeneity fueling cost (hfc). On the contrary, a group of locomotives types characterized by similar ranges has a low hfc and exploits the fuel tank capacity more efficiently. We may shortly define *perfectly homogeneous* a consist type characterized by an $hfc = 0$. The hfc of a consist is closer to zero the more *homogeneous* it is.

4.2 The heterogeneity fueling cost

Consider a locomotive type X (long range), joined with a locomotive type Y (short range) in a XY consist type. Since Y cannot run out of fuel, a portion of the fuel stored in the tank of X will be not exploited generating a *heterogeneity fueling cost (hfc)*.

The hfc introduced in this study concurs in the consists selection process though active and ownership costs are dominant. Referring to 2008US\$ we have:

1. The highest consist hfc is US\$ 0.89 per day.

2. The lowest consist ownership cost is US\$ 31.28 per hour.

3. The lowest consist active cost cost is US\$ 80 per hour.

The hfc may become relevant when we compare consist types with almost equivalent $ActOwn$ cost (active + ownership cost).

4.2.1 Neglecting locomotive passive movements

The consist type has a crucial role during the active part of a consist unit service while it is not relevant during passive movements (deadheading and lightraveling). The objective function of the LPP accounts for unused locomotives (savings) and costs due to (Ahuja et al. [2005b], Vaidyanathan et al. [2008a]):

1. Active locomotives.

2. Ownership.

3. Deadheading and Light-travelling locomotives (passive movements).

The objective function of the consists selection should consider only fueling costs, active and ownership costs since the choice of the consist types is done looking at the motive performances requested during active movements (TE and HP constraints). Moreover, according to Ahuja et al. [2002] the time spent by locomotives in deadheading and ligh travelling movements represents a small portion of the locomotive service time. Given a real-life weekly LPP proposed by CSX (3324 trains, 119 stations, 3316 locomotives, 5 locomotive types), Ahuja et al. [2002] solve the weekly LPP developing a software called Advanced Locomotive Scheduling (ALS). The solution provided by the ALS shows its superiority over the one obtained by the CSX software called LSM (Locomotive Scheduling Model). Table 4.1 shows the breakdown of the locomotive service time according to the ALS and LSM solutions. Table 4.2 (taken from John and Ahuja [2008]) confirms that for each locomotive type the active cost is significantly greater than the deadheading cost that, as expected, is the same for all the locomotive types (i.e. locomotive type is irrelevant during passive movements).

Table 4.1: Deadheading and light traveling in percentage terms
over the total locomotive service time

Service Time	ALS solution	LSM solution
Idling time	46.70%	49.10%
Active time	44.40%	31.30%
Deadheading time	8.10%	19.60%
Light traveling time	0.8%	0%

Table 4.2: Active and deadheading costs comparison

Locomotive class	Active cost per hour (2008US$)	Deadheading cost per hour (2008US$)
AC4400CW	155	9
C40-8/C40-8W	125	9
SD40/SD40-2/SD40-3	105	9
ES44DC	125	9
GP40/GP40-2	80	9

For all these reasons, the active and the ownership costs represent the dominant parts of the overall cost, and passive movement costs are considered not relevant in the consists selection.

4.2.2 Neglecting train to train connections

The train to train connections hold a crucial role in the LPP optimization but they are neglected in the consists selection. In a train to train connection, we

use the same consist to serve several trains. In a sequence of trains, the train with the highest HP/Tonnage requirements determines the minimal performance of the shared consist. The performance of the chosen consist is suited for some trains of the sequence and excessive for others. In this study, we identify for each train the best suited consist type respecting the fleet size constraints and neglecting the train to train connections.

Figure 4.2 (taken from Ahuja et al. [2005b]) shows the space-time network structure including ground nodes, ground arcs and connection arcs that are essential to model deadheading, ligh-traveling and train to train connection in the LPP, while Figure 4.3 shows the space-time network structure adopted in the consists selection model.
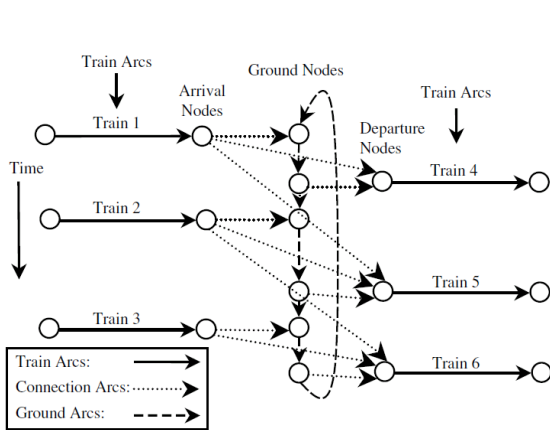
Figure 4.2: Structure of the space-time network in the LPP (Ahuja et al. [2005b])
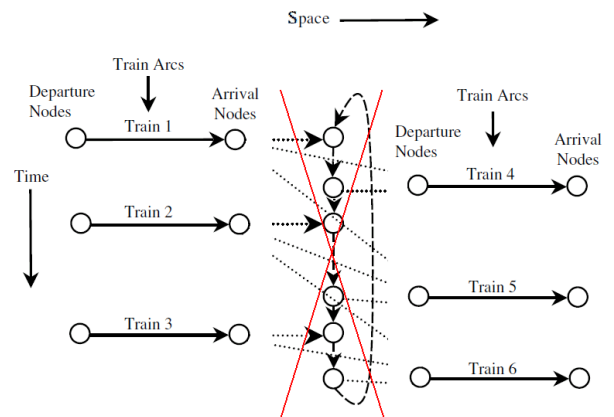
Figure 4.3: Structure of the space-time network adopted in the consists selection

5 Models and Data

The consists selection model solves the weekly assignment of consists by neglecting passive movements (deadheading and light traveling) and train to train connections. To estimate the potential savings made by the adoption of the consists selection, we create realistic locomotives specification, trains specifications and schedules datasets. We apply the preliminary consists selection to some realistic scenarios and instances obtained from these datasets.

5.1 Selection phase mathematical modeling

We model the weekly consists selection as an integer multicommodity flow problem with side constraints on a spacetime network. Each consist type defines a commodity in this network.

Neglecting locomotive passive movements and train to train connections we have a space-time network $G = (N, A)$ in which arcs denote trains and nodes denote events (departures and arrivals of trains).

The set of arcs A coincides with the set of train arcs $TrArcs$.

The set of nodes N is formed by the two subsets:

1. Arrival nodes ($ArrNodes$).

2. Departure nodes ($DepNodes$).

Each train l is characterized by the following attributes:

1. dep-time(l), the departure time of a train l;

2. arr-time(l), the arrival time of a train l;

3. dep-station(l), the departure station of a train l;

4. arr-station(l), the arrival station of a train l;

5. T_l, the tonnage requirement for a train l;

6. HP_l, the HP per tonnage requirement for a train l.

Three different sets of locomotives may be associated to each train l:

1. MostPreferred[l], the preferred locomotive types.

2. LessPreferred[l], the accepted (paying a penalty) locomotive types.

3. Prohibited[l], the locomotive types not permitted.

Given the set of all locomotive types K, k denotes a particular locomotive type belonging to K.

Every locomotive type k $\in$ K is characterized by the following attributes:

1. h^k, the horsepower (HP) of a locomotive of type k;

2. b^k, the number of axles on a locomotive of type k;

3. G^k, the ownership cost of a locomotive of type k;

4. B^k, the fleet-size of a locomotive of type k;

5. c_l^k, the cost of assigning an active locomotive of type k to a train l.

The model relies on the following definitions:

1. α^{ck}, the number of locomotives of type $k \in K$ in a consist $c \in C$;

2. $I[i]$, the set of arcs entering in the node i;

3. $O[i]$, the set of arcs leaving the node i;

4. C, the set of consist types available for assignments;

5. $c \in C$ denotes a specific consist type;

6. c_l^c, the cost of assigning an active consist of type $c \in C$ to a train arc l;

7. e_l^c is the heterogeneity fueling cost of a consist c that pulls the train l for its entire travel time;

8. f_l^c is the fueling stops cost of a consist c that pulls the train l for its entire travel time.

The decision variables are the following:

1. z^c, a binary variable which takes value 1 if a consist type $c \in C$ is used;

2. x_l^c, a binary variable which takes value 1 if a consist type $c \in C$ flows on arc $l \in TrArcs$.

The model is inspired by the model adopted in Vaidyanathan et al. [2008a] (the LPP model in its CFF). We solve a weekly consist assignment with a fixed number p of maximum available consist types. The value of p should be low to have LPP solutions manageable and useful in real-life applications.

$$min : w = \sum_{l \in TrArcs} \sum_{c \in C} c_l^c x_l^c + \sum_{l \in TrArcs} \sum_{c \in C} \sum_{k \in K} \alpha^{ck} x_l^c G^k + \sum_{l \in TrArcs} \sum_{c \in C} [e_l^c x_l^c + f_l^c x_l^c]$$

$$\text{(5.1a)}$$

subject to

$$\sum_{c \in C} \sum_{k \in K} \alpha^{ck} t_l^k x_l^c \geq T_l, \quad \forall \, l \in TrArcs \tag{5.1b}$$

$$\sum_{c \in C} \sum_{k \in K} \alpha^{ck} h^k x_l^c \geq HP_l, \quad \forall \, l \in TrArcs \tag{5.1c}$$

$$\sum_{c \in C} x_l^c = 1 \tag{5.1d}$$

$$z^c \geq x_l^c, \quad \forall \, l \in TrArcs, \; c \in C \tag{5.1e}$$

$$\sum_{c \in C} x_l^c b^c \leq 24, \quad \forall \, l \in TrArcs \tag{5.1f}$$

$$\sum_{l \in S} \sum_{c \in C} \alpha^{ck} x_l^c \leq B^k, \quad \forall \, k \in K \tag{5.1g}$$

$$\sum_{c \in C} z^c \leq p, \; p = 3, 5, 7, \dots, 17 \tag{5.1h}$$

$$x_l^c \in 0, 1, \quad \forall \, l \in TrArcs, \; c \in C \tag{5.1i}$$

$$z^c \in 0, 1, \quad \forall \, c \in C \tag{5.1j}$$

5.2 Assessment of savings achievable introducing the consists selection

In the previous studies the LPP optimization was performed taking the set C of available consist types as given. Our objective is to asses the savings achievable introducing the consists selection before the LPP optimization. Given a train network and a consist fleet, the consist assignment provided by the consists selection generally differs from the one provided by the LPP since in the consists selection we neglect train to train connections. Neglecting train to train connections we cannot serve two or more train with the same consist, thereby in the consists selection problem each consist will serve a unique train. Consequently, the total number of consist units required in the solution of the consists selection will be higher with respect to the one required in the LPP. Given an instance of the LPP, the exact valuation of the achievable savings (provided by the consist selection) may be obtained after solving the LPP (and determining the train to train connections) and finally updating the LPP solution to honor the fueling constraints in the routing phase. Moreover, according to Nahapetyan et al. [2007], the train to train connections obtained from the LPP solution are often not respected. Trains are often delayed and sometimes are canceled altogether. As a result, terminals might not have enough locomotives to depart outbound trains. There are usually unanticipated, unscheduled trains that require locomotives not listed in the LPP solution. Nahapetyan et al. [2007] valuate some important measures of the overall performance of the locomotive assignment procedure at CSX. To obtain this valuation Nahapetyan et al. use the Locomotive Simulator/Optimizer (LSO) a decision support system (developed by Innovative Scheduling Inc.) that simulates the movement of locomotives across a railroad network. Simulations rely on historical train data to model

train delays, historical locomotive data to model locomotive breakdowns and historical data of maintenance centers (shops) to model repair and maintenance of locomotives at CSX. The simulations reported in Nahapetyan et al. [2007] show that the percentage of trains that does not depart with a set of locomotives specified in the LPP solution oscillates between about 30% and about 40% (and the percentage of trains that arrive ontime is around 50%). Thus, train to train connection may be higly modified or canceled, it is then quite difficult to valuate the actual savings achievable introducing the consists selection even after having solved the LPP.

In fact, the actual savings achievable introducing the consists selection may be valued only after having solved the LPP and the LRP (in which fueling constraints are honored). We do not solve the LPP and LRP (also because of the lack of essential information about the fueling stations network). This study introduces a methodological innovation in the LPP solution procedure and limits the analysis to the consists selection in which train to train connections are not considered. It is worth nothing that, given a set of trains, to identify the fleet of the best suited consists (i.e. the composition of the ideal fleet of consists) we may serve the trains assuming an unlimited availability of consist units for each consist type (i.e. we neglect the fleet size constraints). Neglecting the fleet size constraints we may divide the train set in two groups:

1. Trains that may concur in a train to train connection sharing the same consist.

2. Trains that cannot concur in a train to train connection.

If the fleet size constraints are neglected, the assignment of consist types to trains may be conducted for the entire set of trains in one step or may be equivalently obtained in two steps assigning independently the consist types to the two groups

because the assignment of the first group of trains do not impact the second group (thanks to the unlimited consist availability). The consists selection alone may provide a reliable valuation of the achievable savings for a train schedule that does not allow us to exploit train to train connections. This valuation may also be considered an approximation of the actual savings since usually train to train connections involve only a part of the scheduled trains (the lower the number of train to train connections the better the estimate of actual savings). To summarize, our objective is to asses the potential savings achievable adopting a consist types set C obtained accounting for the $ActOwn$, the hfc and the fsc with respect to a consist types set C obtained selecting the consist types considering only the active and ownership costs ($ActOwn$). To achieve this objective we solve a reference model in which the consists selection is performed considering only the $ActOwn$. The reference model is named *model M1* and the consists selection model is named *model M2*.

In the reference model (model M1) the objective function accounts only for the $ActOwn$ (i.e. $\sum\limits_{l \in TrArcs} \sum\limits_{c \in C} c_l^c x_l^c + \sum\limits_{l \in TrArcs} \sum\limits_{c \in C} \sum\limits_{k \in K} \alpha^{ck} x_l^c G^k$).

In the consists selection model (model M2) the objective function accounts also for the hfc and fsc terms (i.e. $\sum\limits_{l} \sum\limits_{c} [e_l^c x_l^c + f_l^c x_l^c]$).

Objective function for the model M1:

$$min : w = \sum_{l \in TrArcs} \sum_{c \in C} c_l^c x_l^c + \sum_{l \in TrArcs} \sum_{c \in C} \sum_{k \in K} \alpha^{ck} x_l^c G^k \tag{5.2a}$$

Objective function for the model M2:

$$min : w = \sum_{l \in TrArcs} \sum_{c \in C} c_l^c x_l^c + \sum_{l \in TrArcs} \sum_{c \in C} \sum_{k \in K} \alpha^{ck} x_l^c G^k + \sum_{l \in TrArcs} \sum_{c \in C} [e_l^c x_l^c + f_l^c x_l^c]$$
$$\tag{5.2b}$$

The constraints are the same for the two models.

The assessment of savings is completed solving these two models and comparing the two respective overall cost $(ActOwn + hfc + fsc)$.

The objective value of M2 represents an overall cost (since the hfc and the fsc are present in the objective function). To obtain the overall cost of M1 we add the objective value of M1 (i.e. the $ActOwn$) with the hfc and the fsc that correspond to the M1 solution.

The difference between this M1 overall cost and the objective value of M2 provides the weekly savings obtained accounting for the hfc and the fsc in the optimization program.

The model M2 may have several optimal equivalent solutions, all characterized by the same overall cost (that coincides with the M2 objective value). On the contrary, M1 may have several optimal solutions that are all equivalent in terms of optimal M1 objective value but may present different $[hfc + fsc]$ values (and so different overall costs) since the hfc and the fsc are not accounted in M1 optimization (they are calculated ex-post once we know the M1 solution).

The solution of the consists selection is obtained through a three step procedure. In the first step we solve the models M1 and M2: the optimal M2 solutions are characterized by the minimum achievable overall cost $(ActOwn + afc + fsc)$ while, for each instance, solving the model M1 we do not identify an unique M1 overall cost. For each instance, in general the optimal M1 solution is not unique and we found a set of optimal equivalent solutions characterized by the same $ActOwn$ cost (same optimal objective value) but different hfc and fsc (not considered in the model M1).

In the second step, for each instance, we identify the optimal M1 solutions characterized by the highest $[hfc + fsc]$. Then, for each instance, we calculate the overall cost as the sum of the optimal M1 objective value $ActOwn$ and the highest value of $[hfc + fsc]$ (we refer to this sum as the M1 overall cost).

In the third step, for each instance, we calculate the difference between the M1 overall cost (previously calculate in step 2) and the M2 overall cost obtaining the maximum weekly savings achievable adopting homogeneous (fueling) consists.

5.3 The dataset

Vaidyanathan et al. [2008a] solve the LPP implementing the consist flow formulation in two different scenarios (with similar size) provided by CSX:

$\langle$388 trains, 6 locomotive types$\rangle$ and $\langle$382 trains, 6 locomotive types$\rangle$

For each scenario the LAP is solved finding the total number of locomotives used in 8 sub-scenarios identified by 8 different consist types sets C (their size varies from 3 to 17 consist types).

Railway companies do not provide such kind of detailed data without a partnership. Nevertheless, a deep search on scientific publications, economic and technical reports, manuals and other freely available sources, give us the realistic data needed for our analysis. The information retrieved may be grouped in four categories:

1. Locomotives and rolling stock data (train cars data).

2. Train data.

3. Consist data.

4. Tracks data.

To obtain a realistic set of consist types C, the proportion of train types in the set of train services matter more than the number of train services: a set of 1000 grain trains (a flat, dull train services set) would produce an unrealistic

composition of C. Thereby, we create a set of 229 train services characterized by a realistic proportion of the following 3 different train classes:

1. Auto trains (10 trains).

2. Intermodal trains (65 trains).

3. Merchandize and Bulk trains (154 trains).

The 229 train services are created to represent a realistic set of train for a typical East-coast railway company (it may be CSX for instance). On average, a West-coast company would have longer routed distances, higher travel times, higher weights of the trains and a different distribution of trains among the three classes Auto, Intermodal and Merchandize.

Table 5.1 lists the information sources exploited. Figures 5.1, 5.2 and 5.3 report the histograms for the travel time, the routed distance and the gross weight respectively, for the 154 Merchandize (and Bulk) trains, the 65 Intermodal trains and the 10 Auto trains.

Table 5.1: Data sources

Locomotives and train cars data	Train data	Consist data	Tracks data
GE Harris Energy Systems [2000]	Tolliver and Bitzan [2002]	Liu [2003]	Unkle and Roddy [2004]
Bitzan et al. [2002]	Liu [2003]	Ahuja et al. [2005b]	Ammah-Tago [2006]
Tolliver and Bitzan [2002]	Holowaty et al. [2004]	John and Ahuja [2008]	Cramer [2007]
Liu [2003]	Dirnberger [2006]	Vaidyanathan et al. [2008a]	ICF International [2009]
Ahuja et al. [2005b]	BNSF Railway Twin Cities division [2006]	Innovative Scheduling [2009]	
CSX Corporation [2005]	Cambridge Systematics [2007]		
Parajuli [2005]	Lai et al. [2008]		
Schonfeld [2005]	Gannett-Fleming [2008]		
Ammah-Tago [2006]	Schafer and Barkan [2008]		
CSX Corporation [2006]	Souten et al. [2008]		
Hawthorne et al. [2006]	Brosseau and Ede [2009]		
Cambridge Systematics [2007]	CSX Corporation [2009]		
Cramer [2007]	ICF International [2009]		
Ireson [2007]	Innovative Scheduling [2009]		
Lindsey [2007]	Roucolle and Elliott [2010]		
Sylte [2007]	Nourbakhsh and Ouyang [2012]		
John and Ahuja [2008]	Raviv and Kaspi [2012]		
Vaidyanathan et al. [2008a]			
Brosseau and Ede [2009]			
CSX Corporation [2009]			
ICF International [2009]			
Innovative Scheduling [2009]			
Metrolinx [2010]			
Wilbur Smith Associates [2010]			
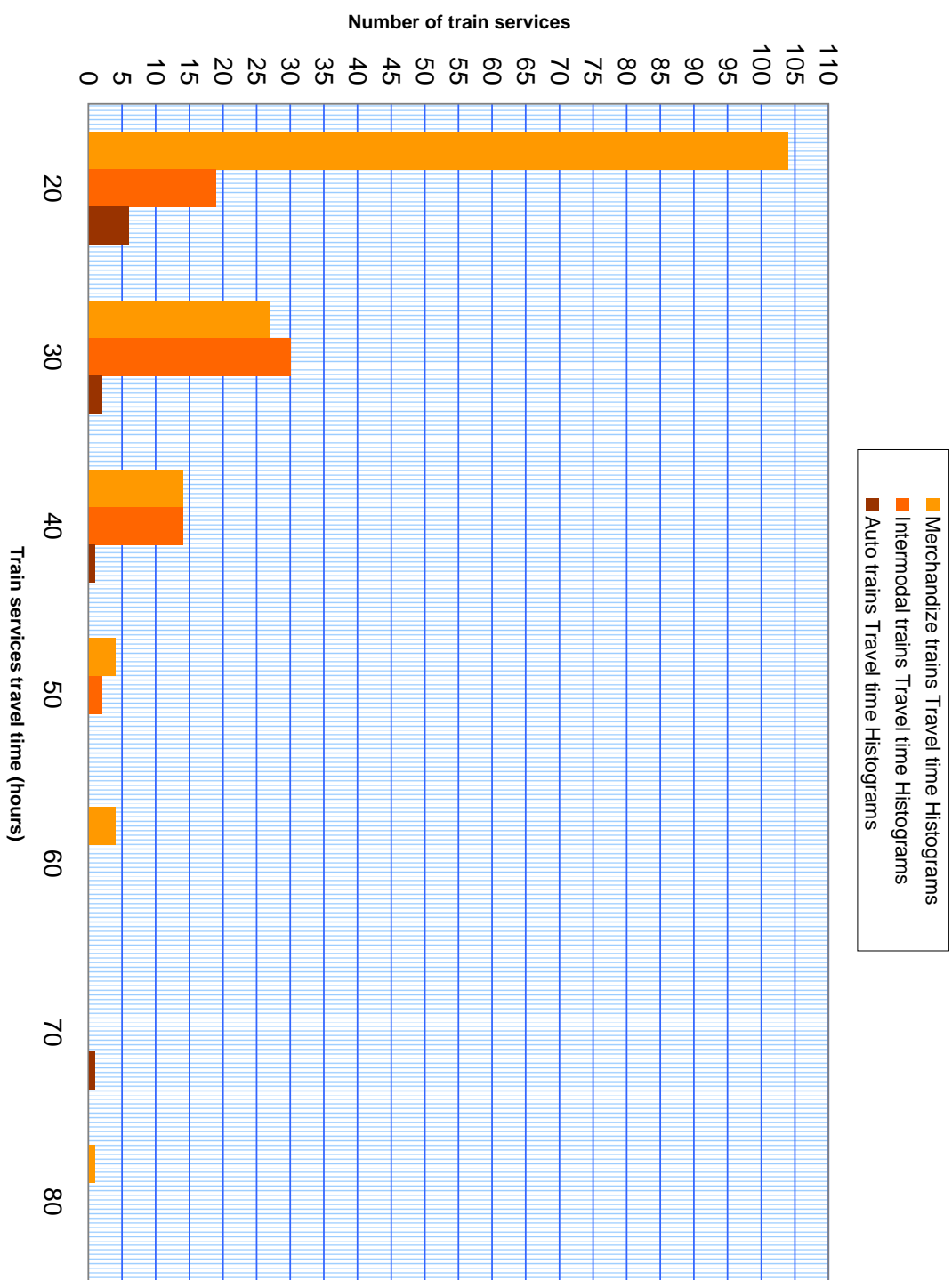
Figure 5.1: Travel time histograms (154 Merchandize trains, 65 Intermodal trains, 10 Auto trains)
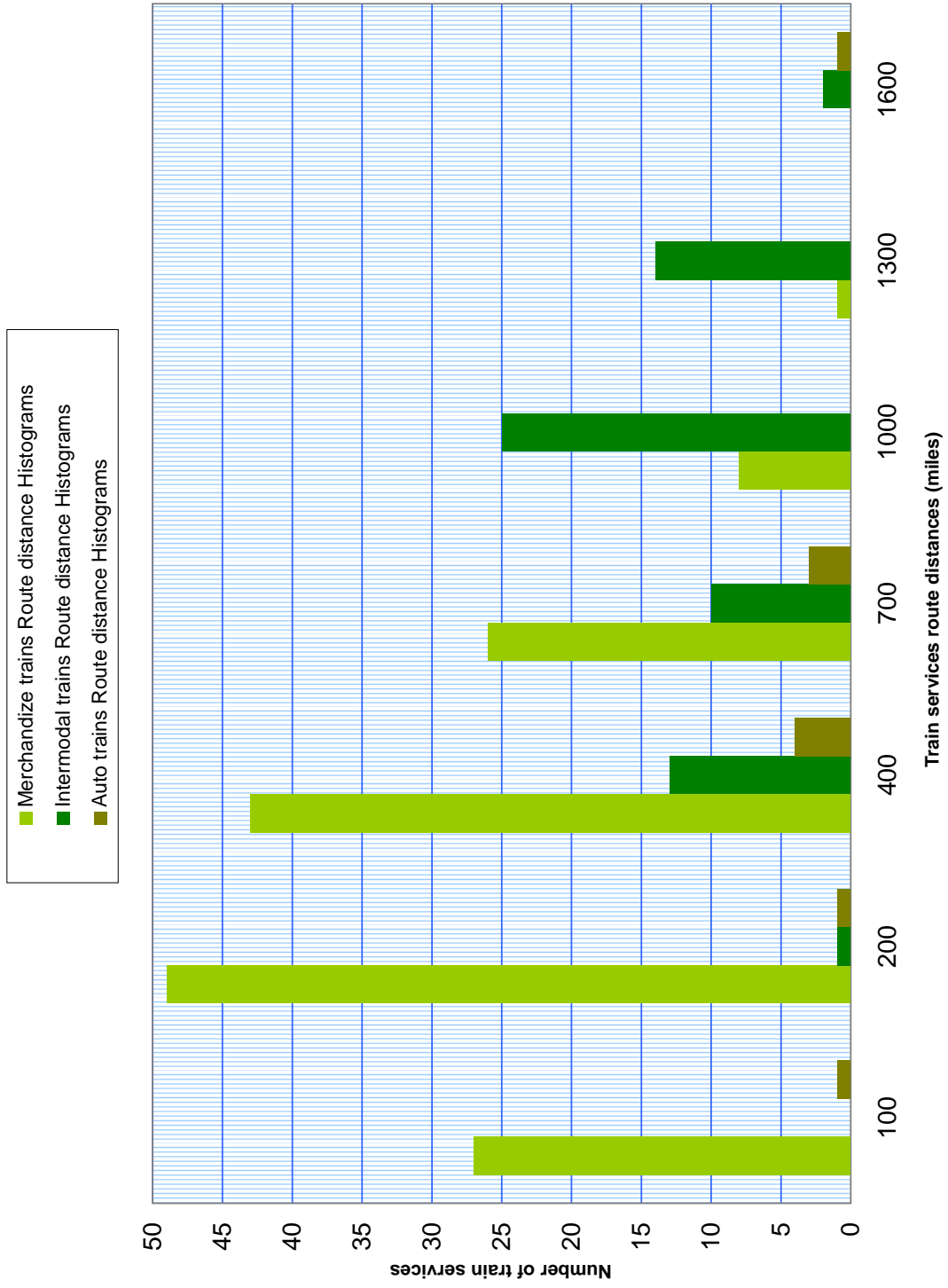
Figure 5.2: Routed distances histograms (154 Merchandize trains, 65 Intermodal tranis, 10 Auto trains)
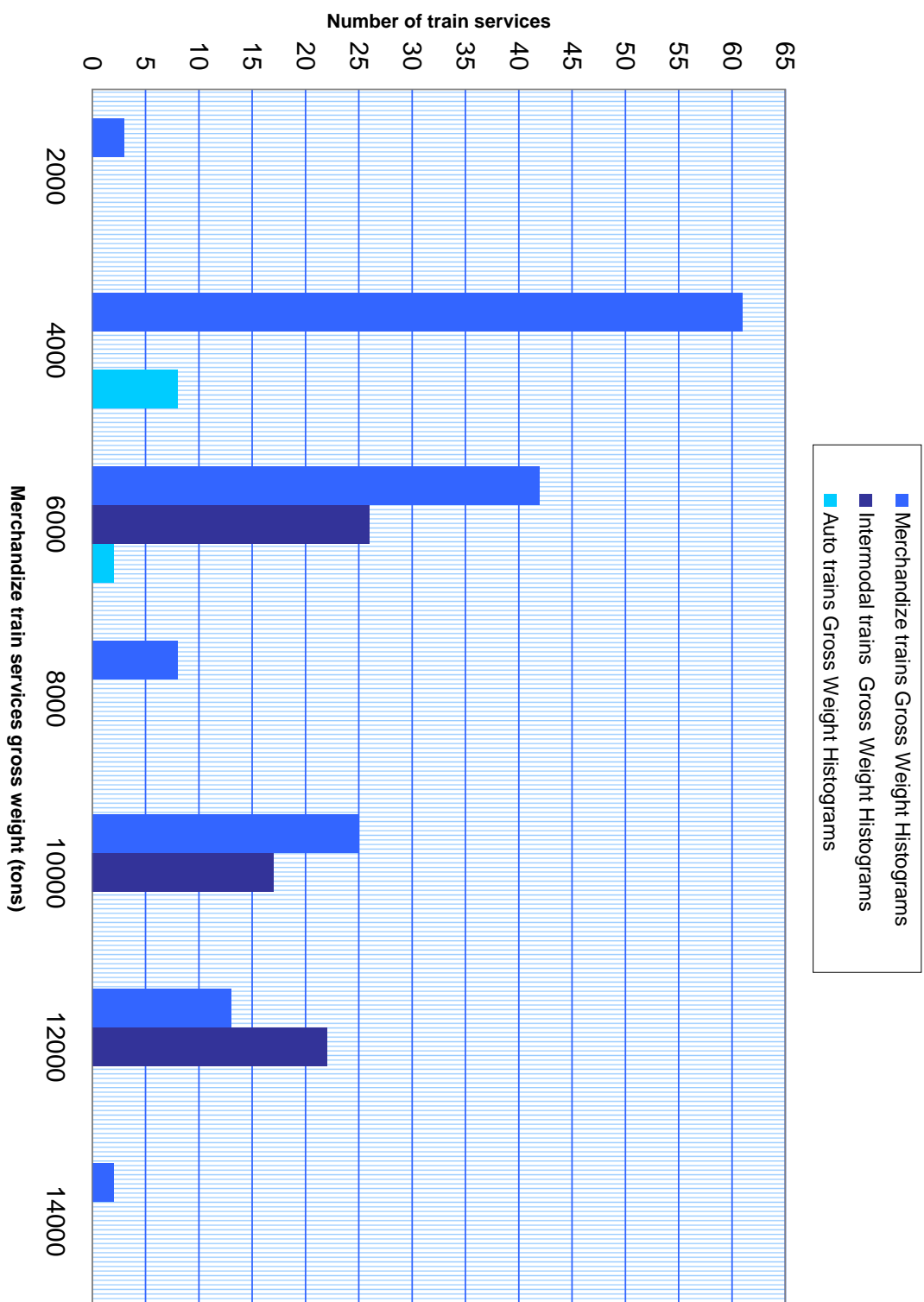
Figure 5.3: Gross weight histograms (154 Merchandize trains, 65 Intermodal tranis, 10 Auto trains)

Our instances are generated considering two set of locomotive types, the first one is the same adopted by Vaidyanathan et al. [2008a] and includes 6 locomotive types (AC4400CW, AC6000CW, C40-8, GP40-2, SD40-2, SD60I), the second one is obtained adding the locomotive type ES44DC to the previous group of 6 locomotive types.

Each locomotive type may be a preferred, accepted or prohibited choice for the 3 different train classes and Innovative Scheduling [2009] offers a realistic reference on this subject. Knowing the preferred, accepted and prohibited ⟨train class, locomotive type⟩ connections, we may build the set of allowed consist types for each train speed class. Combining up to 7 locomotive types, we obtain 288 valid consist types and the corresponding prohibited connections:

1. 36 consist types are prohibited for Merchandise and Bulk trains;

2. 218 consist types are prohibited for Auto trains;

3. 249 consist types are prohibited for Intermodal trains.

The data extracted from the selected information sources have been integrated in a simulation program used to generate our instances. Table 5.2 reports some relevant CSX locomotive data.

Table 5.2: Locomotive types characteristic data

Locomotive type	Locomotive type alpha code	HP	Active cost[a] (US \$ per hour)	Lease cost[a] (US \$ per hour)	Ownership cost[b] (US \$ per hour)	Itermodal trains[c]	Auto trains[c]	Merchandize, Bulk trains[c]
AC4400CW	A	4400	155	28	43.792	1	1.2	Prohibited
AC6000CW	B	6000	155	28	43.792	1	1.2	Prohibited
C40-8	C	4000	125	26	40.664	1.2	1.2	1.2
ES44DC	D	4400	125	29	45.356	1.2	1.2	1.2
GP40-2	E	3000	80	20	31.28	Prohibited	Prohibited	1
SD40-2	F	3000	105	20	31.28	Prohibited	Prohibited	1
SD60I	G	3800	117	24	37.536	Prohibited	1.2	1.2

[a] 2008US\$, John and Ahuja [2008], figures for $AC6000CW$ and $SD60I$ are a guesswork

[b] estimated values, derived from the lease cost according to Wilbur Smith Associates [2010]

[c] the additional 20% of penalty cost is applied if an accepted connection is used instead of a preferred one, Liu [2003]

The Table 5.3 reports (in the last three columns) the active costs multiplication factors of the preferred and accepted connections between locomotive types and train speed classes. The basic active costs (reported in the fourth column) multiplied by these coefficients provides the actual active cost per hour (in 2008US\$). To facilitate the description of the consist types we adopt an alphabetic code for each locomotive type (as reported in the second column).

From the dataset that is used to generate the train schedules, we extract 32 different instances. These instances are grouped in four different scenarios (we have 8 instances in each scenario), each scenario is characterized by three

different parameters:

1. Number of available locomotive types (6 or 7).

2. Single locomotive consists (allowed or prohibited).

3. Size of the locomotives fleet (actual fleet size or reduced fleet size).

The actual locomotive fleet size is the one of the 2011 CSX locomotive fleet (Table 5.3) while the reduced fleet size is obtained considering the 25% of the actual size (for each one of the 7 locomotive type groups the reduced sizes are rounded suitably).

Table 5.3: The 7 locomotive types in the 2005, 2006 and 2011 CSX fleets

Locomotive class	Units 2005[a]	Units 2006[b]	Units 2011[c]
AC4400CW	593	593	621
C40-8/C40-8W	532	532	529
SD40/SD40-2/SD40-3	404	402	529
AC6000CW	116	117	117
ES44DC	0	100	302
SD60I/SD60/SD60M	90	90	94
GP40/GP40-2	0	0	416

[a] CSX Corporation [2005]
[b] CSX Corporation [2006]
[c] 2011 data source: www.thedieselshop.us/CSX.HTML (accessed April 2011)

Due to the risk of track block, CSX strongly discourage the assignment of consists composed by only one locomotive (single locomotive consist), and a penalty for this kind of assignment is adopted in Ahuja et al. [2005b]. In the solution obtained

by Vaidyanathan et al. [2008a] the single locomotive consists are not adopted. In this study we consider two dichotomous alternatives: single locomotive consists are allowed without any penalty or are not allowed at all.

The four scenarios considered in this study are the following:

1. 6 locomotive types; single locomotive consists prohibited; actual fleet size;

2. 6 locomotive types; single locomotive consists prohibited; reduced fleet size;

3. 7 locomotive types; single locomotive consists allowed; actual fleet size;

4. 7 locomotive types; single locomotive consists allowed; reduced fleet size.

6 Numerical results and Discussion

This section shows the potential savings achievable by implementing the preliminary consists selection (we report the savings in terms of money, number of fueling stops and servicing hours saved).

A primary part of our information sources describes the locomotive fueling and management costs in terms of US$ in 2008 (2008US$). Thus, in accordance with these information sources we have always expressed the monetary values in terms of 2008US$ throughout all the current research.

6.1 Results

The results obtained by us rely on some simplifying assumptions. The locomotive types ranges are calculated relying on the locomotive utilization profile (the breakdown of locomotives activity within a 24-hour period). More precisely, we rely on the partition of the engine operative service time, i.e. the percentage of time that the diesel engine is turned on and consumes fuel, within a representative (based on yearly averages) 24-hour period.

We focus on the locomotive *duty cycle* i.e. the profile of the different locomotive power settings (Idle, Notch levels 1 through 8) as percentages of the engine

operating time. To figure out the fsc, we assume that each locomotive type has the same duty cycle of a representative Class I mainline freight locomotive reported in Railway Association of Canada [2008]. This representative duty cycle is determined by evaluating the time spent at each power notch level for a statistically significant sample of locomotives. In other words, we assume that all the locomotive types spend their operative service time at each engine power level (notch level) in the same manner of the representative Class I mainline freight locomotive. Moreover, for each locomotive type, we associate each notch level with the corresponding fuel consumption rate that is specific for each locomotive type (Seedah and Harrison [2010], ENVIRON International Corporation [2007]).

The yearly opportunity cost due to the unexploited fuel is calculated as the yearly total return that a railways company would obtain investing the value of the fuel (immobilized in the tanks of the consists) at the beginning of the year. Namely, we assume an annual real total return equal to 6.5%, this value is in line with the average of the Barclays Capital U.S. Aggregate Bond Index in the period 1982-2008 (9.45% according to Barclays Capital [2011]) discounted by an average inflation of about 3% (see for instance http://www.multpl.com/inflation/table). Figure 6.1 shows that the oil price and consequently the diesel fuel price were exceptionally high in 2008. To avoid opportunity cost overvaluation, we adopt the average price of diesel fuel in the period January 2008—August 2012 (2008US\$ 2.68 according to CSX Corporation [2011a], CSX Corporation [2011b], CSX Corporation [2011c], CSX Corporation [2011d] and http://www.eia.gov/petroleum/gasdiesel/).
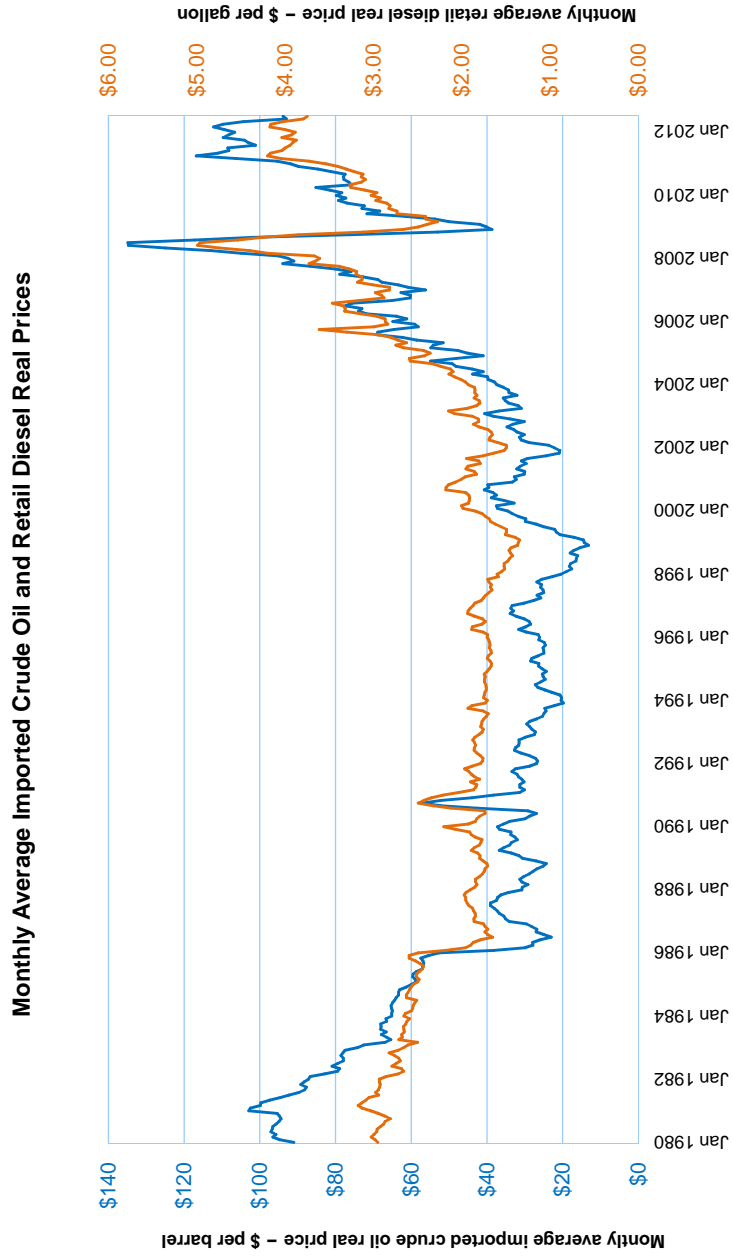
Figure 6.1: Average U.S. crude oil and diesel retail prices in the period 1980 - 2012

Having calculated the fsc and the hfc for each consist type, we implement the consists selection solving the two models M1 and M2 in the four scenarios with 8 instances for each scenario (associated with the 8 values of $p \leq 3, 5, \ldots, 17$ in the constraint 8.1h). To identify the 64 possible solutions (32 for each model M1 and M2) we adopt a compact notation, for instance M1No_25%-03 means: consists selection solution obtained applying the model 1 (M1) to the scenario with 6 locomotive types and single locomotive consist prohibited (No to the ES44DC type and No single locomotive consist), with the reduced fleet size (25% of the actual fleet) and with $p \leq 3$. Analogously M2Yes_100%-17 means model 2 (M2), 7 locomotives types (type ES44DC permitted) and Yes to single locomotive consist, actual fleet size available (100% of the fleet) and $p \leq 17$.

The models have been solved with CPLEX 12.2 on a Core 2 Quad Q9550 2.83 Ghz and 4 Gb RAM. Figures 6.2 and 6.4 report the maximum achievable yearly savings (in US2008$) while Figures 6.3 and 6.5 show the number of locomotives and consists required in the Yes and No scenarios respectively. In Figures 6.3 and 6.5, the left y axis refers to the number of used consist types, while the right one refers to the number of used locomotive units (that form the consist units).
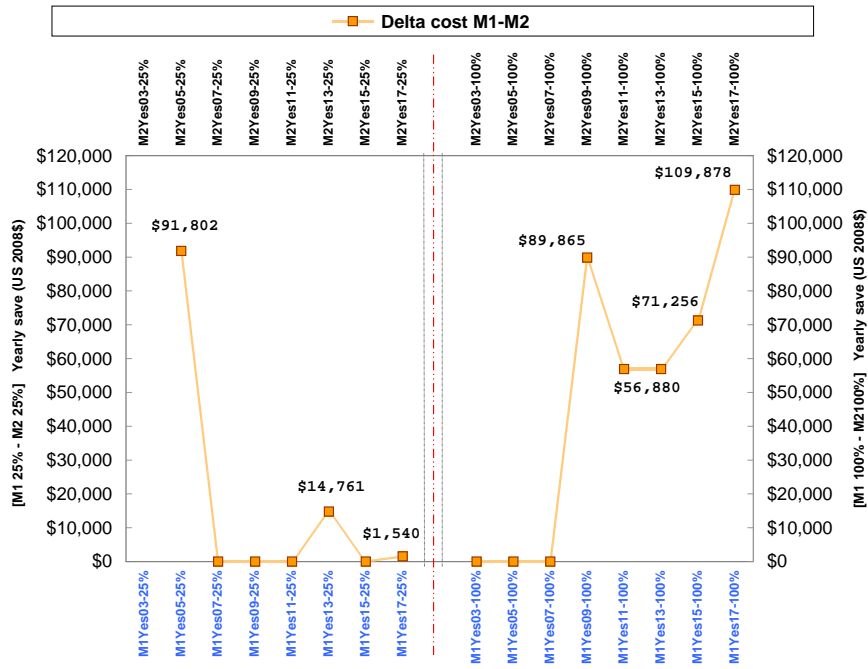
Figure 6.2: Yearly savings M1 VS M2, Yes single locomotives & Yes ES44DC type
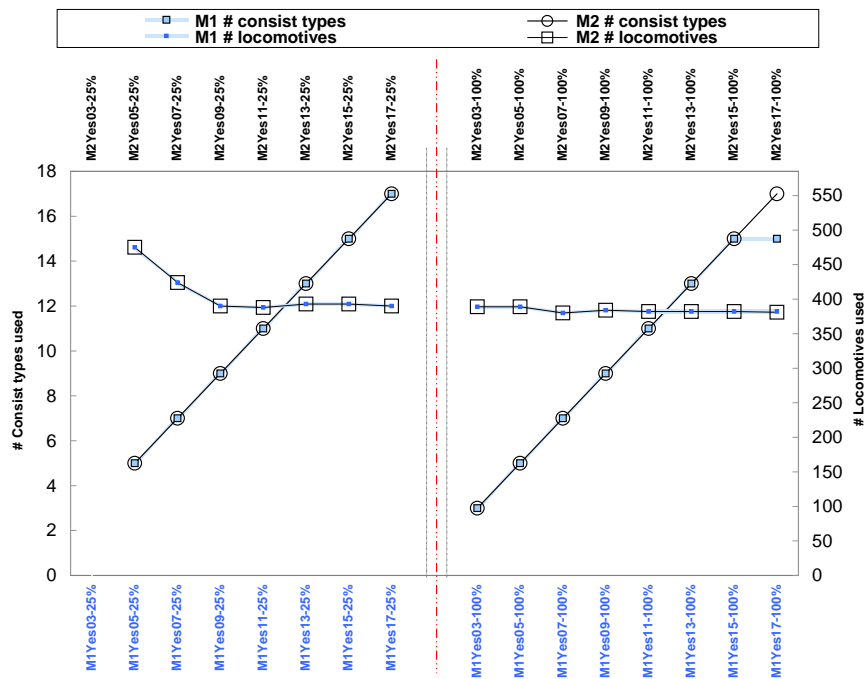
Figure 6.3: # Consists and Locomotives used M1 VS M2, Yes single locomotives & Yes ES44DC type
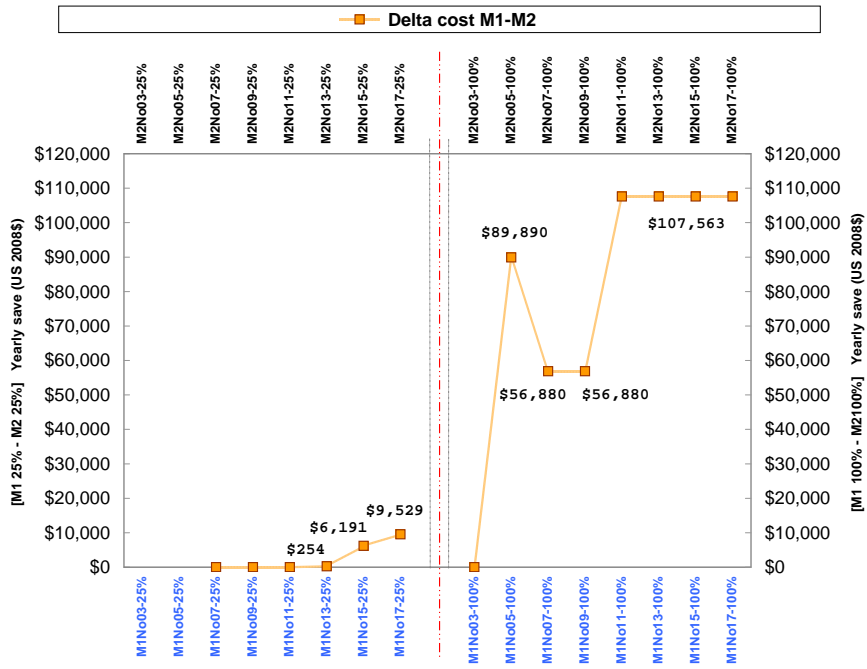
Figure 6.4: Yearly savings M1 VS M2, No single locomotives & No ES44DC type
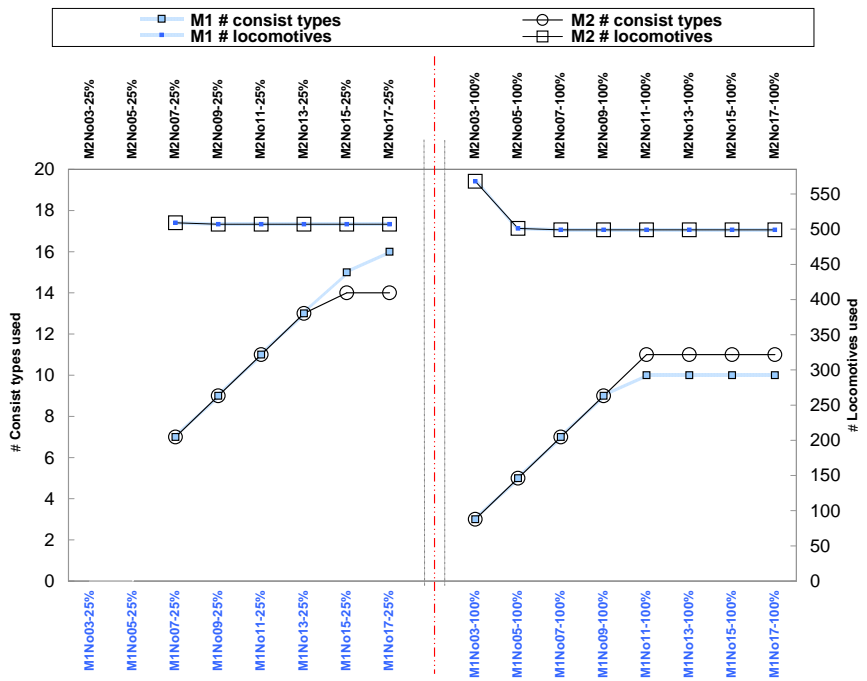
Figure 6.5: # Consists and Locomotives used M1 VS M2, No single locomotives
& No ES44DC type

Considering the 100% of the actual fleet size, for the instances characterized by 7 locomotive types and single locomotive consists allowed (M1Yes, M2Yes) we may observe the following:

1. M1 and M2 produce essentially the same requirement in terms of fleet size; the only difference is between M1Yes17-100% and M2Yes17-100% (382 and 381 locomotives respectively).

2. All the considered instances have a feasible solution.

3. The number of used locomotives remains stable ranging from 380 for $p \leq 17$ to 389 for $p \leq 3$.

4. The number of used consist types coincides with its maximum permitted value for both M1 and M2 except for M1 when $p \leq 17$, in this case it is equal to 15.

5. The maximum achieved yearly savings is approximately 2008US\$ 110000.

In the same scenario (M1Yes, M2Yes), if we consider the 25% of the actual fleet size we observe the following:

1. M1 and M2 produce the same requirement in terms of fleet size.

2. The instances with $p \leq 3$ is infeasible.

3. The number of used locomotive varies ranging from 388 for $p \leq 17$ to 475 for $p \leq 5$.

4. The number of used consist types coincide with its maximum permitted value p and is the same for M1 and M2.

5. The maximum achieved yearly savings is approximately 2008US\$ 92000.

Chapter 6. Numerical results and Discussion

We do not observe any effect of the consists selection on the fleet size in the 25% scenario and very small effect in the 100% scenario (a small difference between M1Yes17-100% and M2Yes17-100% i.e. 382 and 381 used locomotives respectively). Thus, as expected, the consideration of the fueling cost terms fsc and hfc in the LPP optimization essentially does not impact the number of used locomotives.

In the 25% scenario, for both models M1 and M2, the number of used consist types coincides with the maximum permitted value also when $p \leq 17$: the reduced availability of the best choices imposes the utilization of second choices (exploiting all the 17 available consist types).

In the same way, we resume the results for the instances characterized by 6 locomotive types and single locomotive consists prohibited (M1No, M2No). If we consider the 100% of the actual fleet size we observe the following:

1. M1 and M2 produce the same results in terms of fleet size.

2. The number of used locomotives decrease passing from 568 to 499 when p increases.

3. The number of used consist types does not coincide with its maximum permitted value when $p \leq 11, 13, 15, 17$ being equal to 10 an 11 for M1 and M2 respectively.

4. The maximum achieved yearly savings is approximately 2008US$ 108000.

If we consider the 25% of the actual fleet size we observe that:

1. M1 and M2 produce the same results in terms of fleet size.

2. The instances with $p \leq 3, 5$ are infeasible.

3. The number of used locomotives remains almost constant passing from 509 to 507 when p increases.

4. The number of used consist types coincides with its maximum permitted value for both M1 and M2 except when $p \leq 15, 17$; when $p \leq 15$ it is equal to 15 for M1 and 14 for M2, when $p \leq 17$ it is equal to 16 for M1 and 14 for M2.

5. The maximum achieved yearly savings is approximately 2008US\$ 9529.

Again, we do not observe effects of the consists selection on the fleet size. This is exactly what we expect because the *ActOwn* (that depends on the number of used locomotive units) dominates fsc and hfc.

Comparing the Yes and the No scenarios, we observe that in the No instances the absence of single locomotive consists reduces the LAP optimization possibilities and the solution flexibility leading to:

1. An increased average consist size $\Rightarrow$ increased number of used locomotives.

2. An increased consist size constraints tightness $\Rightarrow$ more infeasible solutions.

3. A reduced consist types availability $\Rightarrow$ reduced number of (useful and) used consist types.

4. Smaller savings when fleet size constraints are tight (25% scenario).

5. Consistently bigger savings when fleet size constraints are loose (100% scenario).

The differences are even greater comparing the 100% and the 25% scenarios, we observe that in the 25% instances the strongly reduced availability of locomotives reduces the optimization possibilities:

1. The best consist types are used up rapidly $\Rightarrow$ utilization of second choices that increases the number of used consist types.

2. Utilization of second choices (costly consist types) $\Rightarrow$ higher average size of consists i.e. more used locomotives.

3. Significantly smaller savings.

Figures 6.6, 6.7, 6.8, and 6.9 report the distribution of savings among the three different train classes (auto, intermodal, merchandize) in the four scenarios Yes100%, Yes25%, No100%, and No25%.

Comparing the yearly savings distribution that characterize the Yes and No instances we observe several similarities between the Yes100% and No100% histograms while these similarities disappear in the Yes25% and N0%25 histograms. The differences in the yearly savings distributions are even more evident among the 100% and 25% instances. This fact evidences that the tight size constraints impact the solution (and the savings opportunities) more than the unavailability of the sigle locomotive consists and of the consist type ES44DC.
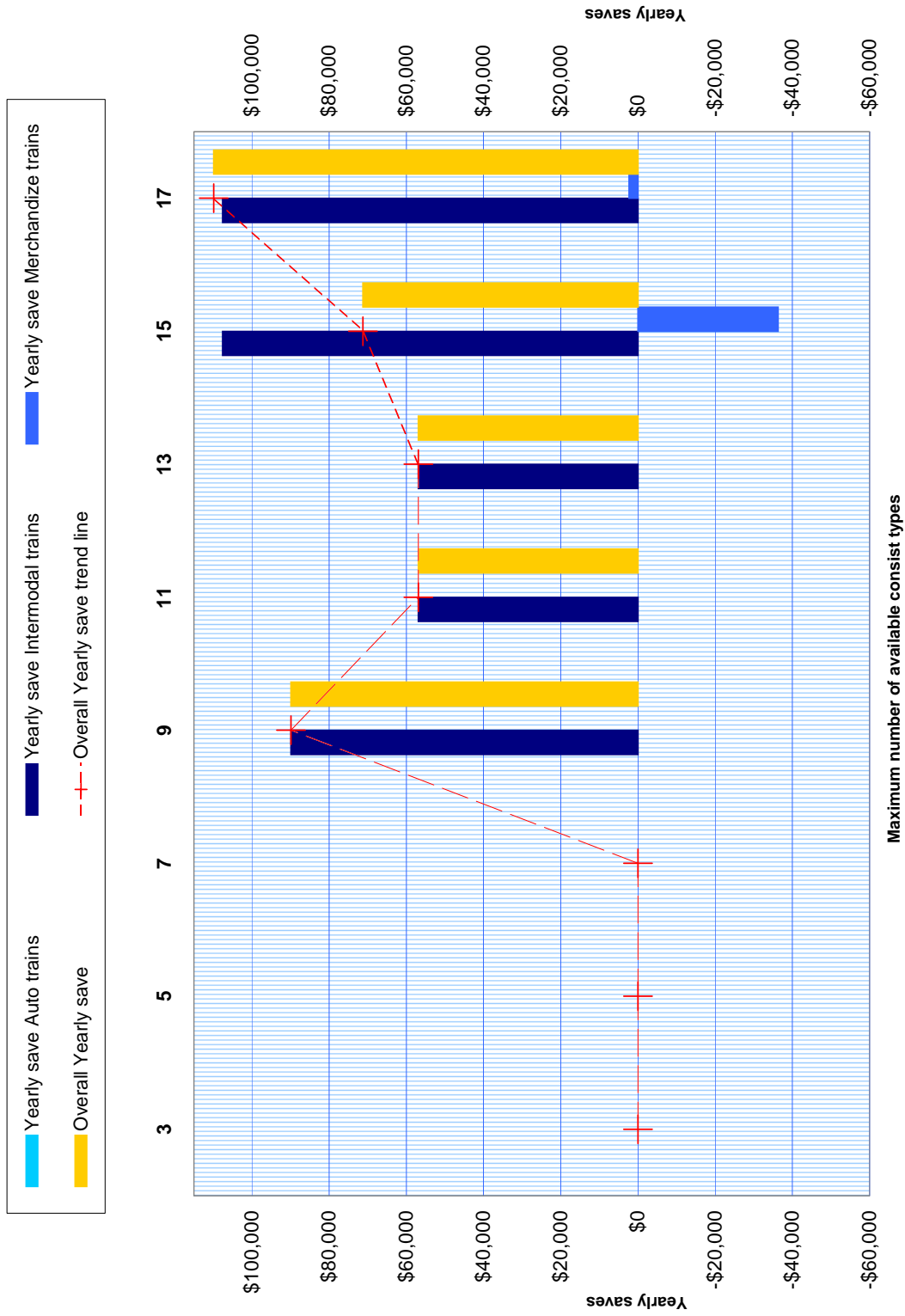
Figure 6.6: Yearly savings histograms for the Auto, Intermodal and Merchandize trains in the Yes100% instances
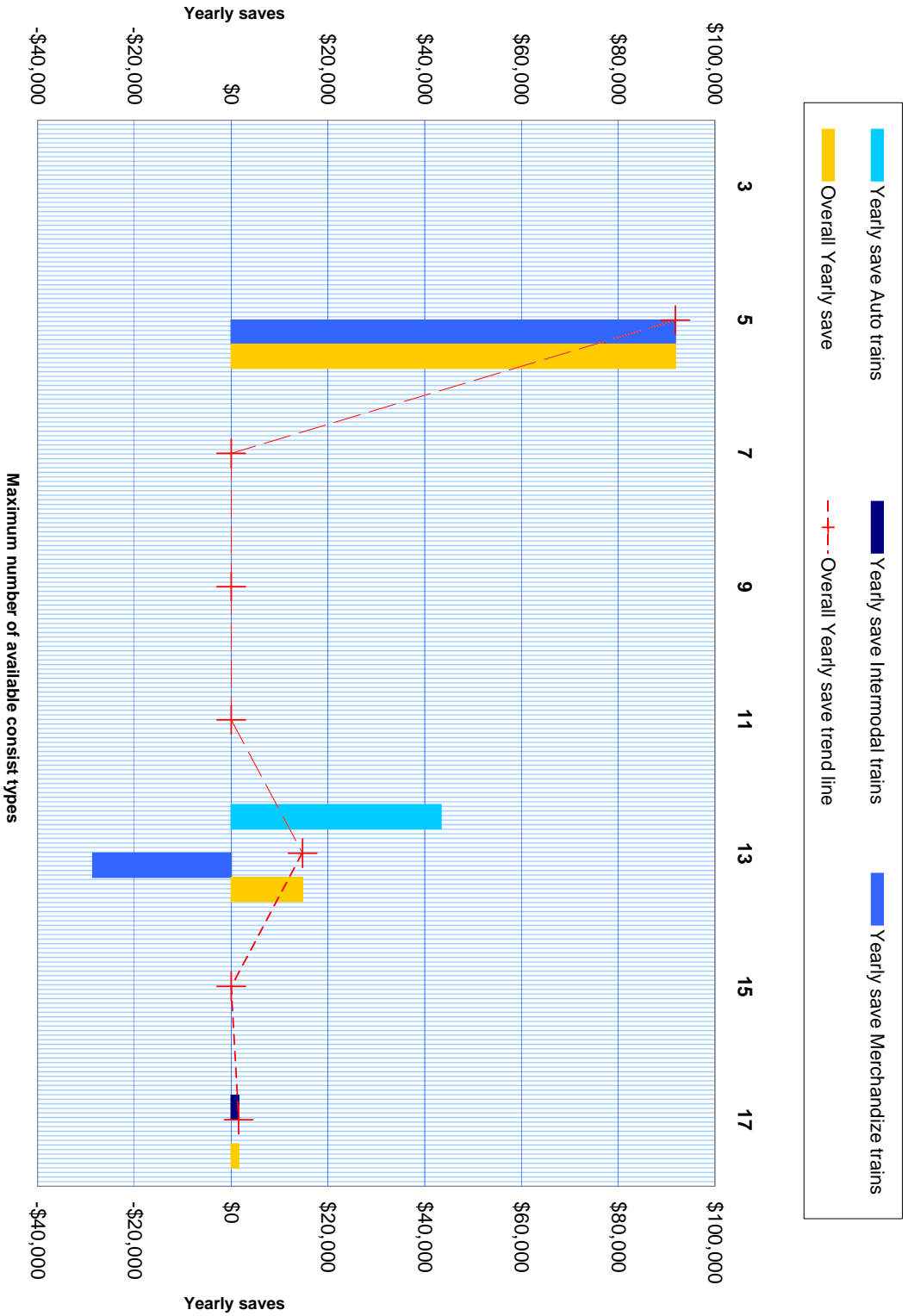
Figure 6.7: Yearly savings histograms for the Auto, Intermodal and Merchandize trains in the Yes25% instances
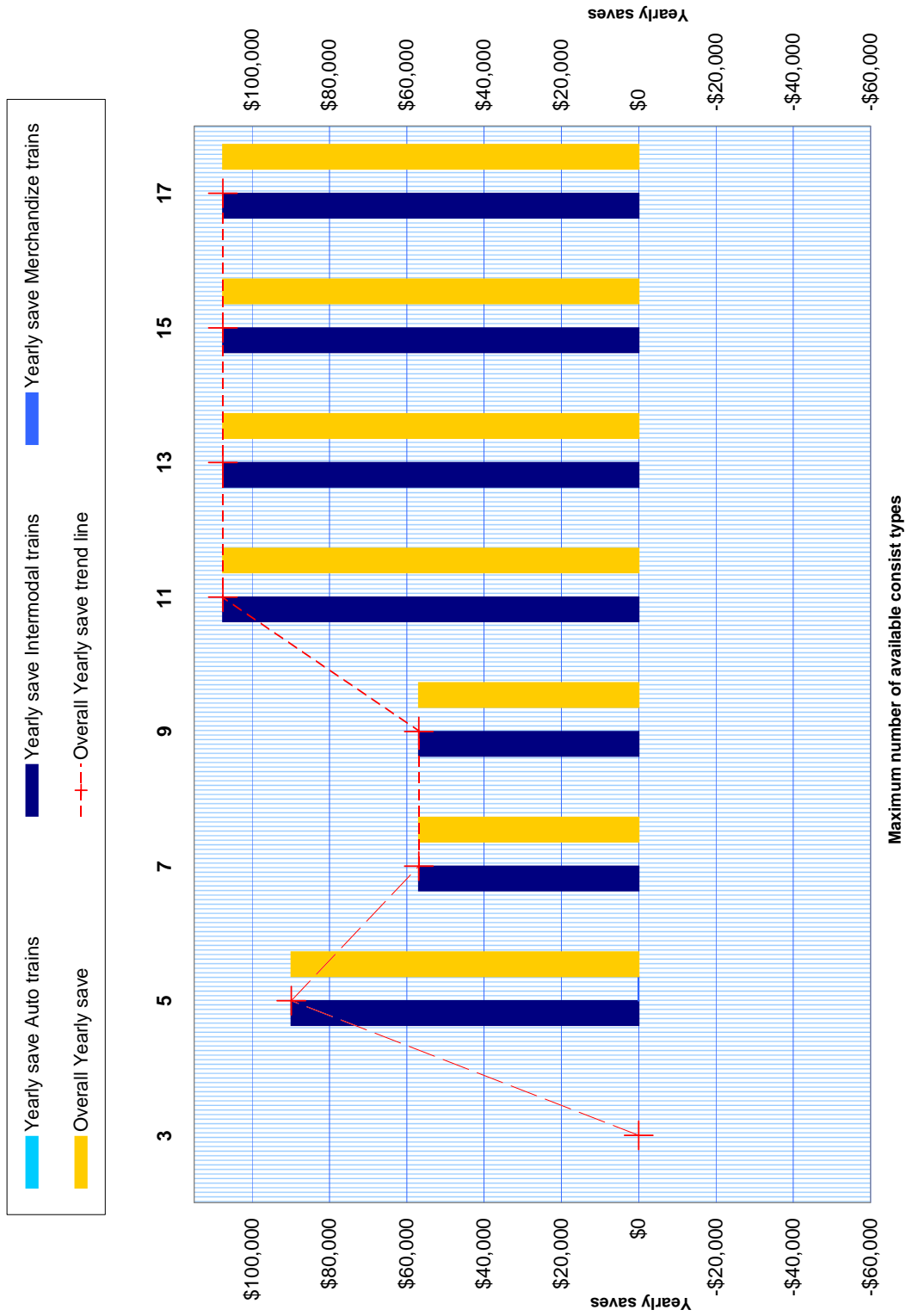
Figure 6.8: Yearly savings histograms for the Auto, Intermodal and Merchandize trains in the No100% instances
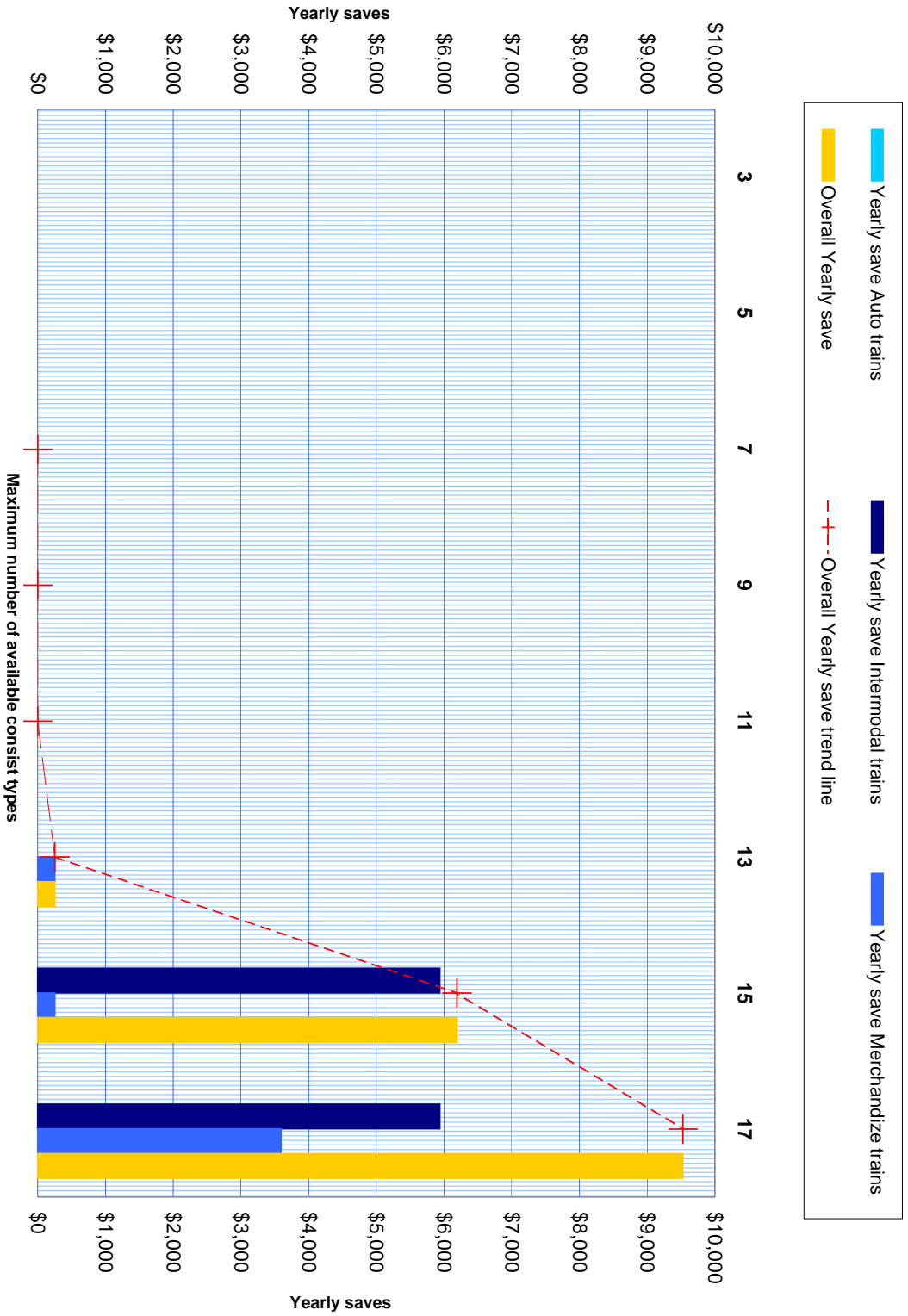
Figure 6.9: Yearly savings histograms for the Auto, Intermodal and Merchandize trains in the No25% instances

Observing the consist type changes that characterize the passage from the M1 to the M2 solutions, we may divide the consist type changes in two groups:

1. Consist type changes that save money.

2. Consist type changes that lose money.

Table 6.1 reports the consist type changes evidencing the two groups.

Table 6.1: Consist type changes associated with savings and losses (savings < 0)

Savings > 0 Changes	All Count	All Percent.	100% Count	100% Percent.	25% Count	25% Percent.	Yes Count	Yes Percent.	No Count	No Percent.
BC→AC	165	42.42%	163	65.46%	2	1.43%	70	30.70%	95	59.01%
BCC→ACC	84	21.59%	84	33.73%	0	0.00%	28	12.28%	56	34.78%
EFF→EEF	47	12.08%	0	0.00%	47	33.57%	47	20.61%	0	0.00%
D→C	8	2.06%	0	0.00%	8	5.71%	8	3.51%	0	0.00%
CF→FF	3	0.77%	0	0.00%	3	2.14%	0	0.00%	3	1.86%
D→F	2	0.51%	0	0.00%	2	1.43%	2	0.88%	0	0.00%
AC→CC	1	0.26%	0	0.00%	1	0.71%	1	0.44%	0	0.00%
AA→AC	1	0.26%	0	0.00%	1	0.71%	1	0.44%	0	0.00%
C→G	1	0.26%	0	0.00%	1	0.71%	1	0.44%	0	0.00%
CC→GG	1	0.26%	0	0.00%	1	0.71%	0	0.00%	1	0.62%
EF→EE	1	0.26%	0	0.00%	1	0.71%	0	0.00%	1	0.62%
Count	314		247		67		158		156	
Savings < 0 Changes	All Count	All Percent.	100% Count	100% Percent.	25% Count	25% Percent.	Yes Count	Yes Percent.	No Count	No Percent.
E→F	57	14.65%	0	0.00%	57	40.71%	57	25.00%	0	0.00%
CE→DE	8	2.06%	0	0.00%	8	5.71%	8	3.51%	0	0.00%
CF→CC	3	0.77%	0	0.00%	3	2.14%	0	0.00%	3	1.86%
AC→AA	2	0.51%	0	0.00%	2	1.43%	2	0.88%	0	0.00%
EEE→CD	1	0.26%	1	0.40%	0	0.00%	1	0.44%	0	0.00%
CG→CC	1	0.26%	1	0.40%	0	0.00%	1	0.44%	0	0.00%
EF→FF	1	0.26%	0	0.00%	1	0.71%	0	0.00%	1	0.62%
G→C	1	0.26%	0	0.00%	1	0.71%	1	0.44%	0	0.00%
GG→CC	1	0.26%	0	0.00%	1	0.71%	0	0.00%	1	0.62%
Count	75		2		73		70		5	
Total	389		249		140		228		161	

The presence of consist type changes that produce losses is justified by the scarcity of specific consist types: without fleet size constraints, i.e.unlimited locomotive availability, the optimization program would not consider this disadvantageous changes. In fact, these changes are exploited to free up some specific locomotive types to be used in the creation of profitable consist changes (otherwise impossible) that off set the losses of the disadvantageous changes and produce savings.

We note that on a total number of 389 consist changes we have only one occurrence of a consist change that involves consists with a different size (EEE→CD), this fact confirms what we expect: the consists selection optimization program does not consider consists with equivalent performances but different sizes as substitutes due to the relevant active and ownership costs for each single locomotive.

As before, the differences among the scenarios are particularly marked between the 100% and the 25% specially for the distribution of consist changes with savings < 0. For instance, on a total of 75 consist changes that cause a monetary loss, 73 of these changes are distributed among the instances of the 25% scenario. Figure 6.10 shows an example of savings and losses of the two groups of consist changes along with the travel time (to enhance the readability of the chart we have excluded the four less numerous consist changes in each group).

We conclude the results section with the Table 6.2 that reports the savings in terms of number of fueling stops and servicing hours.
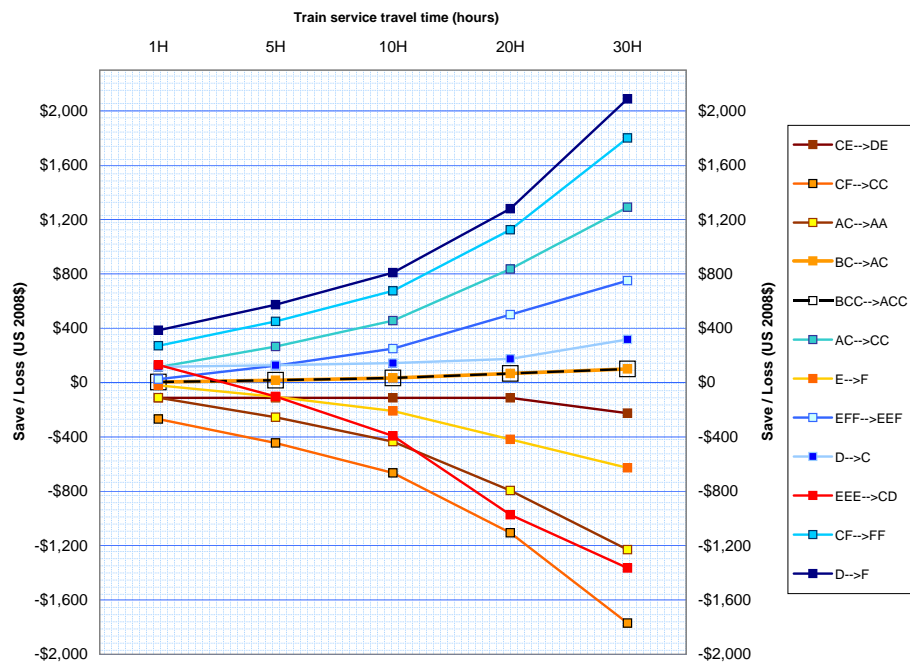
Figure 6.10: An example of savings and losses achievable with different consist changes in different travel times

Table 6.2: M1 vs M2 yearly savings in 2008US$, fueling hours and fuel stops

M1 vs M2 Instances	Yearly savings (2008US$)	Yearly savings (2008US$)	Yearly hours saved	Yearly Fuel stops saved
No_25%-03le	infeasible	infeasible	infeasible	infeasible
No_25%-05le	infeasible	infeasible	infeasible	infeasible
No_25%-07le	0	0	0	0
No_25%-09le	0	0	0	0
No_25%-11le	0	0	0	0
No_25%-13le	4.89	254.26	2.28	0.47
No_25%-15le	119.05	6190.61	55.52	11.33
No_25%-17le	183.24	9528.62	85.45	17.44
No_100%-03le	0	0	0	0
No_100%-05le	1728.65	89889.71	806.11	164.51
No_100%-07le	1093.84	56879.93	510.09	104.1
No_100%-09le	1093.84	56879.93	510.09	104.1
No_100%-11le	2068.51	107562.58	964.6	196.86
No_100%-13le	2068.51	107562.58	964.6	196.86
No_100%-15le	2068.51	107562.58	964.6	196.86
No_100%-17le	2068.51	107562.58	964.6	196.86
Yes_25%-03le	infeasible	infeasible	infeasible	infeasible
Yes_25%-05le	1765.43	91802.3	823.27	168.01
Yes_25%-07le	0	0	0	0
Yes_25%-09le	0	0	0	0
Yes_25%-11le	0	0	0	0
Yes_25%-13le	283.87	14761.4	134.55	27.46
Yes_25%-15le	0	0	0	0
Yes_25%-17le	29.61	1539.75	14.03	2.86
Yes_100%-03le	0	0	0	0
Yes_100%-05le	0	0	0	0
Yes_100%-07le	0	0	0	0
Yes_100%-09le	1728.17	89864.63	805.89	164.47
Yes_100%-11le	1093.84	56879.93	510.09	104.1
Yes_100%-13le	1093.84	56879.93	510.09	104.1
Yes_100%-15le	1370.31	71255.98	639.01	130.41
Yes_100%-17le	2113.04	109877.93	985.36	201.09

6.2   Discussion

Figure 6.10 confirms the conjecture: the longer the travel, the higher the number of fueling events, the higher the achievable savings. Another aspect emerges analyzing the results: working with a suitable consists fleet (100% scenario), the savings concentrate on a small number of consist changes (BC→AC and BCC→ACC, the *ActOwn* costs of A and B are equal while the $[hfc + fsc]$ of A is lower) and on a specific train service class (intermodal trains). The changes BC→AC and BCC→ACC are the most present because these consist types are higly interchangeable. Their *ActOwn* costs are equal and the perfomance differences between the locomotives AC4400CW and AC6000CW (A and B respectively) are small enought to keep satisfied (for a large part of the train set) the train service requirements. It is less evident why these savings concentrate on intermodal trains.

Each consist type has different ownership and active hourly costs. Considering the preferred consist type for each train type (preferred connection) we may identify the minimum possible active cost that characterize each consist type. Summing this active cost with the ownership cost we obtain the minimum active and ownership cost per hour (*ActOwn* minimum cost per hour). Figure 6.11 shows how the performance of a consist in terms of TE and HP vary along with the *ActOwn* minimum cost.

The TE diminishes slowly and remains quite stable while the HP diminishes more rapidly when the *ActOwn* minimum cost decreases. Thus, if a wide range of HP performance is acceptable (as for slow trains), we could reduce the *ActOwn* cost preserving very similar performance in terms on TE. In this case several consist types with different *ActOwn* costs may be considered perfect substitutes, and the differences in terms of *ActOwn* cost may be very high and dominate the (much smaller) savings achieved by a long range homogeneous consists fleet.
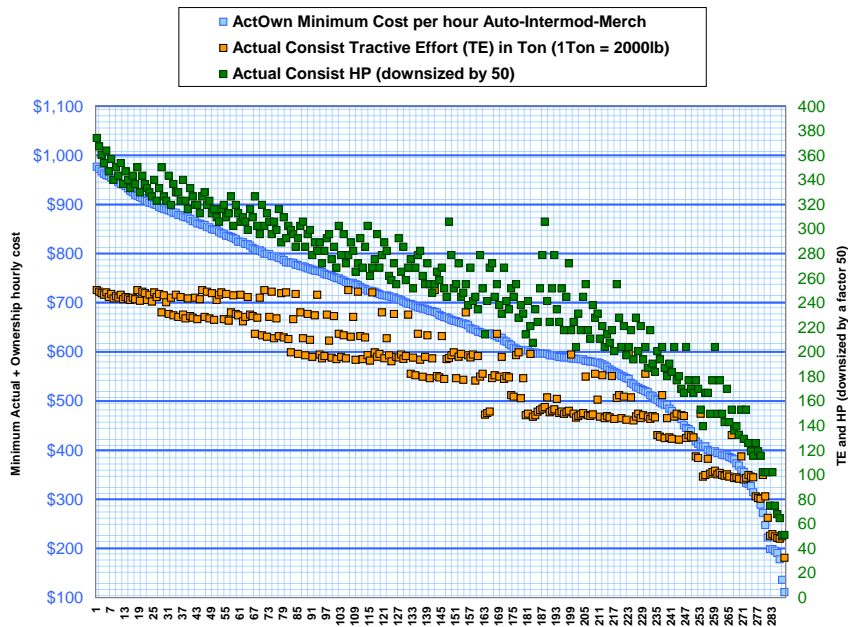
Figure 6.11: TE and HP versus (Actual + Ownership) hourly cost

However, if the HP performance is critical (as for fast trains, like intermodal that are the faster ones) we expect that only consist with similar HP (and so similar *ActOwn* cost) are perfectly interchangeable. Thereby, differences between interchangeable consist in terms of *ActOwn* are small, and savings offered by long range homogeneous consists become significant.

A fleet of consist may offer significant savings just replacing the locomotive type B with the A (whenever possible). Furthermore since savings concentrate on (long travel) intermodal trains these changes are even more easy to implement because they involve only a portion of the consist fleet (the part that serves these specific trains) reducing the cost of the fleet renovation.

7 Conclusions and future work

In this study we propose a methodological innovation that is able to partially integrate LAP planning and routing phases. Our objective is to obtain LPP solutions that make the routing phase easier to handle and more economical. We pursue this objective considering the LPP in its consist flow formulation and accounting for information about consist characteristics, such as ranges and efficiency in the exploitation of fuel capacity, not featured in the previous studies. We focus on the identification of the set of initially available consist types to be used in the LAP optimization. This set were typically assumed as settled in terms of consist types (that is its qualitative composition) by the expertise of locomotive managers and the LPP were solved to identify the quantitative composition of the set. In this study, we propose an optimization program (*consists selection*) to identify the qualitative composition of the set of consist types to be used in the LPP optimization. We introduce the concept of consist fueling homogeneity, and we implement the preliminary consists selection that precedes the LPP optimization. This phase could identify consist types that are not captured by a purely cost-oriented consists selection but that may reduce the opportunity costs linked with the unexploited portion of the fuel stocks and simplify the fueling routing reducing the number of fueling stops (and the

102

corresponding costs).

We consider several realistic instances, and we obtain yearly savings up to 2008US\$ 110000 (210 fueling events, 985 servicing hours). We found that when a suitable consist fleet size is available, savings strongly concentrate on (long travel) intermodal trains and that to obtain significant savings only a small number of consist types changes are sufficient. The future studies should include other homogeneity parameters in the implementation of the consists selection. Along with the fueling homogeneity we suggest to build consists considering the maintenance homogeneity too. According to the U.S. Federal Railroad Administration requirements, each locomotive must undergo preemptive maintenance at some designated shop on (or before) 92 days have elapsed since its last maintenance. Thereby, locomotives are sent to maintenance centers (*shops*) every 92 days (Nahapetyan et al. [2007], Illés et al. [2006]), and a locomotive becomes critical when its maintenance is scheduled within 7 days. In general, the residual time to the next maintenance event (hereinafter *rtm*) is different for each locomotive inside each consist, thereby consist are in general heterogeneous with respect to the *rtm* parameter. This fact has two important consequences in the routing phase:

1. Heterogeneous consists are busted to maintain critical locomotives.

2. Critical locomotives are highly dispersed over many different stations.

The *rtm* heterogeneity may cause many consist bustings (needed to send critical locomotives to the shops) and the dispersion of critical locomotives, and may increase:

1. The number of travels toward the shops $\Rightarrow$ high travel costs.

2. The organizational/logistic complexity.

103

3. The operational risks for crews and equipment.

Building consists considering the *rtm* parameter permits to obtain homogeneous consist with the following positive impacts in the routing phase:

1. Critical locomotives are grouped in critical consists, minimizing the number of stations where critical locomotives are located (low dispersion).

2. A critical consist may be sent to the shop in its entirety, thereby avoiding a busting operation.

The trivial example depicted in Figure 7.1 exemplifies the reduction of both travels toward shops and consist busting.

Figure 7.1: *rtm* heterogeneity versus *rtm* homogeneity example

Working with locomotives grouped in *rtm* homogeneous consists could require an increased locomotive fleet size to guarantee the turnover and preserve the feasibility of the weekly plan. Contrary to the fueling homogeneity, the maintenance homogeneity policy affects the consist fleet size and consequently the LPP solution. For this reason, to obtain an evaluation of the cost-benefit ratio of the maintenance homogeneity policy future studies should solve the consists selection jointly with the LPP optimization.

Part III

Simulation of Realistic Freight Train Schedules

F. Piu

Department of Quantitative Methods, University of Brescia,

C. da S. Chiara 50, Brescia, Italy

Introduction Part III

The assessment of savings offered by the introduction of the consists selection in the LPP solution procedure relies on the realism of LPP scenarios and instances. This study attains the realism of scenarios and instances retrieving reliable locomotives specifications, consists specifications, train and tracks data and a set of realistic train schedules from scientific publications, economic and technical reports, manuals and other freely available sources. All these data are aggregated and exploited in a simulation program that generates the instances used to assess the savings offered by the adoption of the consists selection.

8 Datasets and data aggregation

Railway companies do not provide detailed information needed to solve the consists selection (and the LPP) without a partnership. Therefore, this study required a deep search on scientific publications, economic and technical reports, manuals and other freely available sources, to obtain the necessary reliable data.

8.1 Data classification

The information retrieved may be grouped in the following five categories:

a. Train data.

b. Rolling stock data (train cars data).

c. Tracks data.

d. Locomotives data.

e. Consists data.

Train schedules provide the information that defines the train services characteristics:

108

- Transported freight type (commodity category).

- Train weekly frequency.

- Departure and Arrival times.

- Departure and Arrival stations.

- Travel characteristics (overall idling time, train speed).

- Train load status (empty or loaded).

- Train tonnage.

The freight type strongly affects all other information, for instance a train service focusing on fresh food moved in refrigerated box cars has very different weekly frequency, idling time, speed and weight with respect to a train service focusing on coal transportation. According to Ammah-Tago [2006, Figure 2], the average length of the haul depends on the commodity/freight type. Even tracks characteristics could change along with freight type: coal trains could use low speed tracks, whereas highly valuable freight should travel on high speed corridors.

This study considers the following train cars information to describe each train car model:

- Freight train cars type.

- Tare weight.

- Maximum payload.

- Mean gross weight.

- Car empty return ratio.

Chapter 8. Datasets and data aggregation

To describe the path associated with a couple ⟨departure station, arrival station⟩ we need information about intermediate segments that compose the path (length of each segment, specific slope of each segment, maximum train speed allowed on each segment). In this study we use only aggregated information about the tracks associated with the schedule. Thereby we consider only the following information about tracks:

- Average track grade (slope of the track).

- Average track length.

This study retrieves the following information about locomotives:

- Locomotives types considered (locomotives classes).

- CSX locomotives fleet composition.

- Locomotives nominal and effective HP.

- Locomotives nominal and effective TE.

- Locomotives types vs trains types preferred/accepted/prohibited connections.

- Penalty for accepted locomotives types vs trains types connections.

- Locomotive hourly active cost.

- Locomotive hourly ownership cost.

Finally, the information about consists used in this study is the following:

- Valid consists types.

- Maximum number of active axles in a consist.

8.2 Freight train schedules and timetables

To build a realistic space-time network, actual updated train service schedules are crucial. It is hard to obtain updated train schedules since they are not publicly available (due to security reasons). Nevertheless, some (outdated) CSX train schedules and timetables were available on Internet at the beginning of this research. These schedules and timetables were not available anymore at the end of the research period; some sites removed the data (like in the case of the site http://www.trainweb.org/csxtimetables/) other sites (like http://www.georgiarailfan.net/csxtrains/freights.html) were not accessible anymore. The retrieved schedules, although unofficial and not updated, provide a useful framework and reference being a plausible proxy of the (old) CSX schedules. To be more precise, the retrieved schedules contain a list of 1150 train designation codes (CSX train codes are composed by a letter followed by a three figures number) along with the corresponding weekly frequency, departure and arrival stations, departure and arrival times (it is named *List A*).

We exclude train designation codes associated with:

- turns job;

- reroute (detours) and service commitment trains;

- incomplete information;

- yard switchers;

- helpers, pushers, road shifters;

- foreign road trains;

The remaining valid codes amount to 755.

Some data about CSX trains are still available and offer useful information about

111

train frequency, departure and arrival stations, commodity carried.

These data are reported in a second different list (named *List B*) of 859 train designation codes (http://railroadfan.com/wiki/index.php/CSX_Train_Symbols) along with the corresponding freight type (commodity carried). Again, only the appropriate designation codes are selected and the valid designation codes amount to 691. Crossing the two list and considering common elements, we obtain a set of complete train schedules and from that set we extract 229 train services that represent quite well the several types of possible train services.

8.3   Freight types and train types

Realistic TE requirements are crucial to avoid dull scenarios and obtain useful indications from the selection phase. To obtain a variegated realistic set of TE requirements, we start specifying for each train service the type of freight carried. Freight type is our starting point since several important information about trains and train cars rely on the type of freight carried by train cars. Since these information are taken from several different sources, the list of freight types is obtained merging the different commodity types lists such that, the resulting list resumes and encompasses all the relevant commodity categories. The information merged are the following:

a. Commodity types found in the *List B*.

b. Commodity macro categories described in Hidayat [2005].

c. Standard Classification of Transported Goods (SCTG) list.

The commodity level of detail is the 2-digit SCTG, the one used in the Freight Analysis Framework (FAF) (the commodity flow database developed by the Federal Highway Administration in cooperation with the Bureau of Transportation

Statistics). The SCTG list is described with different levels of aggregation in ICF International [2009], Cambridge Systematics [2007], Ammah-Tago [2006] and AAR Policy & Economics Department [2008]. The final result of our synthesis links the train types reported in the *List B* with the freight macro categories proposed in CSX Corporation [2009] and with an aggregated version of the SCTG commodities groups. This aggregation procedure permits to exploit several information sources about trains and train cars (that refer to the SCTG commodity classification) in the characterization of CSX trains (that are associated with the freight macro categories proposed in CSX Corporation [2009]). Table 8.1 resumes the commodity class aggregation procedure.

Chapter 8.   Datasets and data aggregation

Table 8.1: Freight Types

List B	CSX Corporation [2009]	Aggregated SCTG[a]
Sources		
Auto	Automotive	Automobiles, Motor vehicles parts and equipment
Coal, Mine	Coal	Coal
Coke	Coke and Iron Ore	Coke
Dirt, Mud, Scrap, Trash	Emerging markets	Dirt (mud), Iron scrap, Trash, Waste
Divisional local freights	Mixed freight	Mixed freight
Ethanol	Agricultural Products	Ethanol
Grain	Agricultural Products	Corn, Farm Products, Grain, Wheat
Iron (scrap)	Emerging markets	Dirt (Mud), Iron scrap, Trash, Waste
Juice (Tropicana)	Food and consumer	Food, Juice, Kindred products, Refrigerated boxes
Mixed freight	Mixed freight	Mixed freight
Motorized vehicles	Automotive	Automobiles, Motor vehicles parts and equipment
Ore	Coke and Iron Ore	Metallic ores
Phospate	Phosphates and Fertilizers	Phospate
Pipe	Metals	Metal products, Pipes
Refrigerated boxes	Food and consumer	Food, Juice, Kindred products, Refrigerated boxes
Rock	Emerging markets	Cement, Clay, Non-metallic ores, Rock, Sand, Stone
Salt	Food and consumer	Salt
Stone	Emerging markets	Cement, Clay, Non-metallic ores, Rock, Sand, Stone
Wheat	Agricultural Products	Corn, Farm products, Grain, Wheat

---

[a]The aggregation of the SCTG stems from the analysis of the following sources:
ICF International [2009], Cambridge Systematics [2007], Ammah-Tago [2006], AAR Policy & Economics Department [2008]

114

8.4 Freight types and train cars types

The link among *List B* train types, CSX freight macro categories and aggregated
SCTG permits to associate the freight types (*List B*) with the appropriate car
types through the aggregated SCTG commodity groups. Table 8.2 resumes the
car types aggregation procedure. The adopted car types are identified crossing
the information retrieved from [ICF International, 2009, Exhibit J-1] (reported
in column C1 in Table 8.2), Cambridge Systematics [2007, Table A.1] (column
C2 in Table 8.2) that reports the car types considered in the URCS, U.S. Army
Corps of Engineers - Engineering and Construction Division [2000, Table 2-2]
(column C3) and finally from CSX Corporation [2009, p. 20] (column C4). Once
again, the list of train car types adopted in this study is obtained aggregating and
adapting these data. The elements in gray represent information not available
(n.a.) or repeated information inserted to take into account the different sizes of
lists in columns C1, C2, C3 and C4.

Table 8.2: Aggregated train cars types

C1	C2	C3	C4	Aggregated train car types
Boxcar	Box 40foot	Box 40T	Box car	**Box cars**
Boxcar refrigerated	Box equipped	Box 50T	Box car	**Box cars**
Boxcar for packaged items	Box 50foot	Box 70T	Box car	**Box cars**
Bulkhead flat cars (plates)	Flat other	Flat 40T	Flat car	**Flat cars**
Flat Car	Flat general	Flat 50	Flat car	**Flat cars**
Flatbed	Flat other	Flat 80T	Flat car	**Flat cars**
Flatbed with sides with sides	Flat other	Flat 100T	Flat car	**Flat cars**
Coil car (coiled sheets)	Flat other	Flat 140T	Gondola coil/sheet steel	**Flat cars**
Container / Van	Flat other	COFC 70T	Flat car	**Flat cars**
Double-stack car	Flat multilevel	COFC DoubleStack	Multi-level flat car	**Multi-level flat cars**
TOFC (trailer on flat car)	Flat intermodal	TOFC 70T	Flat car intermodal	**Flat cars**
TOFC refrigerated	Reefer (Refrig. car)	TOFC 70T	Flat car	**Flat cars**
Low side gondola	Gondola plain	Gondola 40T	Gondola	**Gondolas**
Low side gondola	Gondola equipped	Gondola 50T	Gondola coil/sheet steel	**Gondolas**
Tanker truck	Tank <22000gall	Tank 7500gall	n.a.	**Tanks < 22K**
Tank car	Tank <22000gall	Tank 10000gall	n.a.	**Tanks < 22K**
Tank car	Tank <22000gall	Tank 20000gall	n.a.	**Tanks < 22K**
Tank car	Tank >=22000gall	n.a.	n.a.	**Tanks > 22K**
Covered hopper	Hopper covered	Hopper 50T	Covered hopper	**Small covered hoppers**
Covered hopper	Hopper covered	Hopper 70T	Covered hopper	**Small cov. hoppers**
Covered hopper large	Hopper covered	Hopper 100T	Jumbo covered hopper	**Jumbo covered hoppers**
Covered hop. large	Hopper covered	Hopper 120T	Jumbo cov. hop.	**Jumbo cov. hoppers**
Covered hop. large	Hopper covered	Hopper 125T	Jumbo cov. hop.	**Jumbo cov. hopppers**
Open top hopper	Hopper open top	n.a.	Open-top hopper	**Open top hoppers**
Open top hopper	Hopper o. t. special	n.a.	Open-top hopper	**Open top hoppers**
Bi-level rack (vans, trucks)	Other Cars	n.a.	Bi-level rack (pickup, truck)	**Autoracks**
Tri-level rack (cars)	Other Cars	n.a.	Tri-level rack (sedan, auto)	**Autoracks**

8.5 Train cars weight

In the next step the tare weight, the mean achieved payload, the mean gross weight and the car empty return ratio are identified for each train car type adopted in this study. The AAR Manual of Standards and Recommended Practices provides weights, dimensional limits and other design constraints for cars that may be freely interchanged among North American railroads (Hawthorne et al. [2006]). According to Bitzan et al. [2002], the industry standard of 263000 pounds cars is being replaced with an industry standard of 286000 pounds cars but many short-line railroads cannot handle these larger cars. Most of the US rail traffic travels on high-density mainline tracks, however a large portion of this traffic originates on light-density branch-lines (often operated by short-line railroads). The American Short Line and Regional Railroad Association (ASLRRA) is an active trade association and lobbying group separated from the AAR and represents over 400 of the smaller US firms. In 2005, only an estimated 43% of short line and regional railroad tracks were capable of handling 286000 pounds cars (Cramer [2007]). From U.S. Army Corps of Engineers - Engineering and Construction Division [2000, Table 2-2] and ICF International [2009, Exhibit A-1] we obtain information about car tare weight, car maximum wheel load (i.e. maximum gross weight, once we know the number of car axles) and average payload. Namely, we use the data retrieved from U.S. Army Corps of Engineers - Engineering and Construction Division [2000, Table 2-2] to estimate the tare weight and the maximum gross weight of a fully loaded train car for each train car type used in this study (see the column "Aggregated train car types" of Table 8.2). The maximum payload for these train cars types is obtained subtracting the tare weight from the maximum gross weight. In the light of the uncertainty about the maximum car weight allowed on the tracks, some values obtained in this manner appear quite high. Moreover, it seems unrealistic that, in a

117

schedule-based approach, all the cars are fully loaded. As pointed out in Tolliver and Bitzan [2002], fully loaded cars could be usual for long unit trains (like coal or grain trains) while are in general less frequent for other kind of trains.

For all these reasons, instead of the maximum gross weight, an average car gross weight should be used to compute a realistic train TE requirement. ICF International [2009, Exhibit A-1] provides reliable average values of the actual achieved payload associated with the different car types and so we use these values as a reference. Considering the 75% of the maximum gross weight (estimated from U.S. Army Corps of Engineers - Engineering and Construction Division [2000, Table 2-2]), the obtained cars gross weights are very similar to the average values found in ICF International [2009, Exhibit A-1]. Table 8.3 resumes these findings.

Table 8.3: Train cars tare, mean actual payload and mean gross weights (in short tons)

CSX car types	Car type ID	Tare	Mean payload	Mean gross weight
Auto rack	Au	50	20	70
Box	Bo	46	60	106
Flat	Fl	49	88	137
Jumbo covered hopper	Ju	43	115	158
Gondola	Go	27	45	72
Multi-level flat car	Mu	56	120	176
Open top hopper	Op	23	120	143
Small covered hopper	Sm	30	60	90
Tank < 22000 gall	T1	35	48	83
Tank > 22000 gall	T2	60	120	180

To estimate the weight of a train and calculate the corresponding TE requirement, it is important to define the composition of the train in terms of cars. Some types of cars are used exclusively for a very specific freight (for instance auto racks), other types are very flexible and are used to move several types of freight. Given the freight transported by a train, it is essential to define which type of cars are adopted by that train and how many cars compose the train. The overall weight of a train depends on the gross weight of its train cars (and on the weight of the consist that pulls the train). Thereby, the weight of a train depends on its exact composition in terms of train car types (overall tare weight) and on the freight carried by cars (overall actual payload). It is possible to retrieve the associations between trains and freight macro categories from the *List B*. To make an example, a train may transport commodities like cement, clay, non-metallic ores, sand, rock, dirt (mud), iron scrap and trash. CSX inserts all these commodities in the freight macro-class named *Emerging Markets*. This kind of commodities may be transported using Sm covered hoppers, Op open hoppers or Go gondolas. For instance, a train transporting cement and stones may use Sm covered hoppers for cement (to protect it from adverse weather conditions) and Op open hoppers for stones. Nevertheless, the exact composition of trains in terms of train cars types is not available. In the previous example the only information available is that the train transports Emerging Market commodities, the number of Sm, Op and Go cars, and the exact freight and payload carried by train cars are unknown. This lack of information represents a problem that may compromise the realism of the motive power constrains associated with trains. The next chapter is focused on the solution of this problem. Table 8.4 is inspired by ICF International [2009, Exhibit A-1] and CSX Corporation [2009, p. 20] and describes which cars types are allowed for each aggregated SCTG freight type.

Table 8.4: Train cars types and freight types

CSX freight types	Aggregated SCTG	CSX cars types
Agricultural Products	Corn, Farm Products, Grain, Wheat	Ju
Agricultural Products	Ethanol	T1, T2
Automotive	Automobiles, Motor vehicles parts and equipment	Au, Bo, Mu
Coal	Coal	Op
Coke and Iron Ore	Coke	Op
Coke and Iron Ore	Metallic ores	Op
Emerging markets	Cement, Clay, Non-metallic ores, Rock, Sand, Stone	Go, Op, Sm
Emerging markets	Dirt (Mud), Iron scrap, Trash, Waste	Go, Op, Sm
Food and consumer	Food, Juice, Kindred products, Refrigerated boxes	Bo
Food and consumer	Salt	Ju
Forest Products	Paper	Bo
Forest Products	Wood	Fl
Metals	Metal products, Pipes	Fl, Go
Phosphates and Fertilizers	Phospate	Ju

9 TE and HP requirements

Each train imposes specific motive power constraints that depends on its TE and HP requirements which in turn depend on the train weight and speed. This chapter focuses on the identification of realistic TE and HP requirements for the set of trains adopted in this study.

9.1 Train types and train cars types

Freight trains do not always travel with train cars fully loaded. Typically, the train cars are unloaded at some intermediate stops or at the end of the trip (final arrival station), thereby they may spend part of their travel time moving void train cars. Some freight trains start from the departure station fully loaded, afterward they discharge all the train cars at the arrival station (end of the first trip) and make an empty return trip (second trip) to reach again the initial departure station in order to load the train cars and repeat the train service. A typical example is represented by coal trains that load all the cars at a mine (initial departure station), void all the cars at one or more plants (end of the first trip) and make an empty return trip (second trip) to reach again the mine and repeat the service. Clearly, the motive power constraints for loaded trains and void trains are very different (because of the difference in their weights). The

121

fully loaded train that makes the first trip and the void train that makes the second trip are identified by two different designation codes because they are two different trains. Thereby, it is important to define the load status (loaded or empty) for each one of the 229 trains in order to obtain realistic motive power constraints (it is very unrealistic to consider all the trains as fully loaded). This kind of information is not available in *List A* and *List B*, however Cambridge Systematics [2007, Table A.1] provides an average *empty return ratio* (defined as total traveled miles divided by loaded miles) for the different train cars types. To exploit this information, it is necessary to assume that each train is composed by train cars of the same type. This assumption is an approximation for trains like intermodal trains but is a realistic description of several freight trains like Auto trains, Grain trains, Ethanol trains, Chemicals trains and several others.

9.2 Mixed freigh trains

In the retrieved train schedules (lists A and B), some trains have a clear description of the commodity class transported while other ones are described as mixed freight trains (or equivalently merchandise trains). In the set of 229 train services, 138 train services are marked as mixed freight trains. To deal with these undefined mixed freight trains we decide to assign to that trains a specific commodity class type following a suitable proportion among the possible commodity classes. The used proportions stem from CSX Corporation [2009, p. 38] that report the volume of unit loads (in thousands of cars) broken up by commodity classes. To be more precise, we adopt these proportions for 120 out of 138 mixed freight trains while we associate the remaining 18 trains to ethanol transport (9 on T1 cars and 9 on T2 cars). Given the specific commodity classes for the 229 trains it is possible to associate one or more train cars types to each train.

Let M and W be two set of trains associated with two different freight macro-classes and let m be the number of trains in M. This study assumes that:

a. each train ℓ is associated with one (and only one) CSX freight macro-class
   $\implies M \cap W = \emptyset \ \forall M, W$;

b. a set M contains all the train cars types needed to carry the commodities that belong to the freight macro-class associated with M (see the first and the third columns in table 8.4).

Another assumption concerns the distribution of train cars units (that compose the trains that belong to M) among the different train cars types included in M; this distribution is essential to determine the motive power requirements for a train ℓ. For each train ℓ belonging to M, the number m is used to determine the distribution of cars units among the different cars types. To make an example, let m be equal to 23 and let M be the set of trains associated with the Emerging Markets freight macro-class (i.e. associated with all the commodities included in the Emerging Markets macro-class). Given 23 Emerging Markets freight trains and assuming that each Emerging Markets freight train is composed by 86 cars, the total number of train cars units is 1978. The 1978 train cars may be distributed among Op, Sm and Go cars in the following manner:

- 602 Op cars

- 688 Sm cars

- 688 Go cars

This distribution may be obtained dividing the set M in three subsets of trains M_{Op}, M_{Sm}, M_{Go} that include trains composed by train cars of the same type. Namely, M_{Op} contains 7 trains composed by 86 Op cars, M_{Sm} contains 8 trains

composed by 86 Sm cars and M_{Go} contains 8 trains composed by 86 Go cars. The number of trains in each subset M_{Op}, M_{Sm}, M_{Go} is determined dividing the number of trains m by the number of cars types (and rounding suitably). This study associates to each train set M (i.e. to each freight macro-class) an average (integer) number of train cars units u_M per train. It is then assumed that each train $\ell \in M$ has a number of train cars units equal to u_M. It is also assumed that each train $\ell \in M$ is composed by train cars of the same type such that the set M may be divided in homogeneous subsets $M_{s1}, M_{s2}, \ldots, M_{sn}$ where $s1, s2, \ldots, sn$ are the n different cars types needed to carry the commodities associated with M. Finally, it is assumed that the distribution of train cars units among the n cars types, is the one that leads to subsets $M_{s1}, M_{s2}, \ldots, M_{sn}$ with almost the same number of elements. In other terms, if $\frac{m}{n}$ is an integer number, the subsets $M_{s1}, M_{s2}, \ldots, M_{sn}$ contains exactly the same number of trains equal to $\frac{m}{n}$, otherwise the number $\frac{m}{n}$ is rounded suitably such that $|\#M_{si} - \#M_{sj}| \leq 1, \quad \forall i, j$ where $\#M$ is the cardinality of the set M. In the previous example $\frac{m}{n} = \frac{23}{3}$ thereby the cardinalities of M_{Op}, M_{Sm}, M_{Go} are 7, 8, 8 (clearly this is an arbitrary choice, they may be 8, 7, 8 or 8, 8, 7). All these assumptions are introduced to overcome a lack of information that may invalidate the realism of motive power constraints (as said it is not realistic to consider all the trains as fully loaded). High capacity tank cars (T2) are used only for agricultural products (ethanol), T1 cars are used for ethanol and chemical products. Ethanol trains composed by T1 or by T2 cars represent the same type of train (same commodity), thereby the 36 trains associated with the freight macro-class *Agricultural Products* are equally divided in a group of 18 grain trains composed by Ju cars and 18 ethanol trains composed by tank cars (9 T1 and 9 T2). Table 9.1 resumes the train set composition (Coal, Coke and Iron Ore trains are excluded from our analysis since they are not scheduled and run only with a sufficient tonnage).

Table 9.1: Train types, mixed freight trains and freight types

CSX freight macro-class	Commodity class	Car	# trains	% total	% mixed
Mixed freight trains					
Food & Consumer	Food, Juice, Kindred products, Refrigerated boxes	Bo	3	1.31%	2.50%
Forest Products	Paper	Bo	8	3.49%	6.67%
Metals	Metal products, Pipes	Fl	8	3.49%	6.67%
Forest Products	Wood	Fl	9	3.93%	7.50%
Emerging Markets	Cement, Clay, Non-metallic ores, Sand, Rock, Dirt (Mud), Iron scrap, Trash	Go	8	3.49%	6.67%
Metals	Metal products, Pipes	Go	9	3.93%	7.50%
Food & Consumer	Salt	Ju	3	1.31%	2.50%
Agricultural Products	Grain	Ju	18	7.86%	15.00%
Phosphates & Fertilizers	Phospate	Ju	14	6.11%	11.67%
Emerging Markets	Cement, Clay, Non-metallic ores, Sand, Rock, Dirt (Mud), Iron scrap, Trash	Op	7	3.06%	5.83%
Emerging Markets	Cement, Clay, Non-metallic ores, Sand, Rock, Dirt (Mud), Iron scrap, Trash	Sm	8	3.49%	6.67%
Chemicals	Chemicals	T1	25	10.92%	20.83%
	Total mixed freight trains		120		100%
Bulk / Unit trains					
Agricultural Products	Ethanol	T1	9	3.93%	
Agricultural Products	Ethanol	T2	9	3.93%	
Automotive	Automobiles, Vehicles parts/equipment	Au	10	4.37%	
Divisional / local trains		Go	16	6.99%	
Intermodal trains					
Intermodal		Bo	32	13.97%	
Intermodal		Fl	33	14.41%	
	Total freight trains		229	100%	

9.3 Freight trains weight

9.3.1 Train class and the number of train cars

The number of cars that compose a train varies along with the train type. Intermodal trains are composed by a large number of cars (often more than 100) while other trains like auto trains have a smaller number of cars. To define the length of trains, the different train types are grouped in four different train classes:

1. Auto trains

2. Divisional / Local trains

3. Merchandise and bulk trains

4. Intermodal trains

All the mixed freight trains and the ethanol train are grouped under the Merchandise and bulk trains class. ICF International [2009, Exhibit A-1] provides a reference for the average length (in number of cars) of several train classes. It is assumed that the length of trains is fixed inside each train class. The following list resumes the number of cars for each train class.

1. Auto trains, 57 train cars

2. Divisional / Local trains, 82 train cars

3. Merchandise and bulk trains, 86 train cars

4. Intermodal trains, 110 train cars

9.3.2 Loaded trains and empty return ratios

An important parameter that varies along with the car type is the *empty return ratio* (defined as total miles divided by loaded miles). Cambridge Systematics [2007, Table A.1] reports the empty return ratio for the cars types considered in the Uniform Railroad Costing System (URCS). It provides the empty return ratios (valid in 2005) for several railroad companies including CSX. To calculate the motive power constraints it is essential to assign to each train the label "empty" or the label "loaded". This objective may be achieved exploiting the information available about the train cars empty return ratios. Since each train is composed by train cars of the same type, it is possible to:

1. group trains looking at the car types obtaining 9 groups of trains (Au, Bo, Fl, Ju, Go, Op, Sm, T1 and T2 trains);

2. calculate the total miles traveled by trains in each one of these 9 groups.

Since the number of traveled miles is known for each train, it is possible to divide each one of these 9 groups in the two subsets "empty trains" and "loaded trains" counting the loaded miles and calculating the corresponding actual empty return ratios $= \frac{\text{Total miles}}{\text{Loaded miles}}$. The division proposed in this study obtains actual empty return ratios that are very close to the ones reported in Cambridge Systematics [2007] and preserve the realism of the empty and loaded trains groups (both groups contains trains associated with long and short trips).

Table 9.2 resumes the empty return ratios reported in Cambridge Systematics [2007] and the actual empty return ratios obtained from the division in empty and loaded trains of the previously described 9 groups of trains.

Table 9.2: Train cars expected and actual empty return ratios

CSX car type	Car type ID	Expected empty return ratio	Actual empty return ratio
Auto rack	Au	1.94	1.950
Box	Bo	1.68	1.682
Flat	Fl	1.15	1.148
Jumbo covered hopper	Ju	1.94	1.935
Gondola	Go	1.89	1.892
Open top hopper	Op	1.95	1.897
Small covered hopper	Sm	1.94	1.964
Tank $<$ 22000 gall	T1	1.97	1.961
Tank $>$ 22000 gall	T2	2.01	2.011

9.3.3   Weights distributions in the train classes

Given a train class (Auto, Local, Merchandise, Intermodal), the number and the type of train cars that compose a train are identified (as described) inside each class. Using the average mean gross weight reported in Table 8.3, it is possible to calculate the average gross weight for a train inside each class. In this case, each train class may be perfectly represented by a single train since all the trains have the same number of cars which in turn have all the same weight (the average mean gross weight). In fact, the distribution of weights in each train class would be an (unrealistic) uniform distribution. To add more realism to the train set (keeping fixed the number of train cars inside each class) it is possible to consider the variability that characterize the train cars gross weights. Starting from the average mean gross weight reported in Table 8.3, it is possible to generate a distribution of train cars weights accounting for the variability of train cars load. According to Brosseau and Ede [2009], the train cars gross weight data may

be fitted very well by a normal distribution. The data is obtained from the observation of 221311 train cars belonging to three US Class I Railroads, two West-Coast (BNSF Railway and Union Pacific Railroad) and one East-Coast (Norfolk Southern Railway) companies. Brosseau and Ede [2009] reports two train cars gross weights distributions, the first is for a general freight car while the second relies on a subset of 12791 bulk train cars. The general freight car gross weight distribution is a normal distribution with a standard deviation equal to 10% of the central value (the average train cars gross weight) and refers to a set of cars that includes the empty cars. In the present work the standard deviation refers only to loaded cars (empty cars have a fixed weight, the tare in Table 8.3) and it is expected to be lower than 10%. Let W and w be the weights of the heaviest and the lightest trains of the same type in the same train class, then $\frac{W-w}{w}$ identifies the maximum gross weight percentage variation in that class of trains. Lower standard deviations are sufficient to have substantial $\frac{W-w}{w}$ (see Table 9.3).

Table 9.3: Train cars gross weights Normal distributions

Train class	Car type ID	Mean of the Normal	Standard deviation of the Normal	$\frac{W-w}{w}$
Auto trains	Au	70 ton	0.81533 ton (1.165% of the mean)	7.1%
Intermodal trains	Bo	106 ton	1.23464 ton (1.165% of the mean)	5%
Intermodal trains	Fl	137 ton	1.59572 ton (1.165% of the mean)	8.8%
Divisional / Local trains	Go	72 ton	2.45213 ton (3.405732% of the mean)	7.4%
Merchandise and bulk trains	Bo	106 ton	3.61008 ton (3.405732% of the mean)	21.95%
Merchandise and bulk trains	Fl	137 ton	4.66585 ton (3.405732% of the mean)	24.78%
Merchandise and bulk trains	Go	72 ton	2.45213 ton (3.405732% of the mean)	25.3%
Merchandise and bulk trains	Ju	158 ton	5.38106 ton (3.405732% of the mean)	24.18%
Merchandise and bulk trains	Op	143 ton	4.87020 ton (3.405732% of the mean)	14.65%
Merchandise and bulk trains	Sm	90 ton	3.06516 ton (3.405732% of the mean)	16.98%
Merchandise and bulk trains	T1	83 ton	2.82676 ton (3.405732% of the mean)	20.11
Merchandise and bulk trains	T2	180 ton	6.13032 ton (3.405732% of the mean)	17.86%

9.3.4 Slope of the track an grade resistance

The previous sections describe the procedures and the assumptions adopted to obtain realistic train weights and consequently realistic motive power requirements (TE and HP requirements). The TE needed to pull a train (along with the stress on couplers) increases rapidly with the track slope (grade). According to Cramer [2007] and to U.S. Army Corps of Engineers - Engineering and Construction Division [2000], an additional pulling force of 20 lbs is needed for each ton of train and percent of grade. Grades from 0.0 to 0.4% are considered light, from 0.4% to 1.0% moderate, from 1.0% to 2.0% steep, from 2.0% to 3.0% very steep (to be avoided). A detailed description of the tracks geographic characteristics and train dynamics is out of scope. It is then assumed an average grade equal to 0.5% for the entire track network.

9.3.5 Tracks lengths and trains speeds

Since we do not have detailed data on railroad tracks, the average track length is a very useful reference in order to avoid unrealistic associations between the couple of times ⟨departure time, arrival time⟩ and the train speed allowed on the associated path ⟨departure station, arrival station⟩. ICF International [2009, Exhibit A-1] provides this reference through a set of railroad route distances for the East region (CSX, NS and CN railroads). By taking the rail distances between stations pairs, and dividing it by the travel time, one can approximate the average train speed. This study assumes three train speed classes (similar speed values are reported in Roucolle and Elliott [2010] and Dirnberger [2006]):

a. 32 mph for all the Intermodal trains

b. 22 mph for all the Auto trains

c. 17 mph for all the Merchandise and Local trains

9.4 Freight trains tonnage

The weight of a train calculated in the previous sections is needed to identify the pulling force required to move the train. However the train weight does not embody all the factors that generate the total train resistance. The total resistance of a railway vehicle R_{tot} is the sum of two components:

1. Grade resistance R_g (due to the slope of the track).

2. Dynamic resistance R_d (the resistance acting on a moving vehicle).

The grade resistance (in lb) of a vehicle is given by $R_g = W \cdot grade \cdot 20 \frac{lb}{ton}$ where W is the weight of the vehicle (in tons) and the grade is a value related to the slope of the track, this study assumes a positive grade $= 0.005$ (0.5%). Note that grade forces may resist or assist train movements depending on whether the slope of the track is positive or negative.

The dynamic resistance of a vehicle with n axles and a weight W (in tons) may be calculated using the Davis formula (Tolliver and Bitzan [2002], Gould and Niemeier [2009], Davis [1926])

$$R_d = \kappa \cdot (1.3 + \frac{29}{\omega} + b \cdot \nu + \frac{\zeta \cdot A \cdot \nu^2}{\omega \cdot n}) \tag{9.1a}$$

where

$R_d = $ unit $(\frac{lb}{ton})$ resistance acting on a moving vehicle

$\kappa = $ coefficient that adapts the formula to better represent the modern equipment

$\omega = \frac{W}{n} = $ load per axle (in tons)

$b = $ coefficient that defines the speed-dependent resistance

$\nu = $ vehicle speed in mph

$\zeta = $ streamlining coefficient that defines the resistance that varies with ν^2

$A = $ frontal cross-sectional area of the vehicle

131

The values for A, b, and ζ reported in Tolliver and Bitzan [2002] for locomotives and cars are the following.

Locomotives:

1. A = 120;

2. b = 0.03;

3. ζ = 0.0017.

Train Cars:

a. A = 125;

b. b = 0.045;

c. ζ = 0.0005.

The locomotives that compose the consist need to provide enough power to overcome the resistance of the railway cars and the locomotives themselves. Given a train, the procedure adopted to calculate the train TE requirement is the following:

1. Identify the grade of the track.

2. Identify the train speed.

3. Identify the consist weight W_c.

4. Identify the total weight of cars W_s.

5. Calculate the consist grade resistance $R_{cg} = W_c \cdot grade \cdot 20\frac{lb}{ton}$.

6. Calculate the cars grade resistance $R_{sg} = W_s \cdot grade \cdot \frac{lb}{ton}$.

7. Calculate the consist dynamic resistance R_{cd} through the Davis formula.

8. Calculate the cars dynamic resistance R_{sd} through the Davis formula.

9. Calculate the train total resistance $R_T = R_{cg} + R_{cd} + R_{sg} + R_{sd}$.

9.5 Train TE and HP requirements and Consists performance

A locomotive is propelled by its driving wheels (or drivers) i.e. the wheels driven by the pistons to propel the locomotive. The adhesion is the amount of force required to slide the wheels of a locomotive, and it expresses the ability of the steel wheels of a locomotive to have grip on the steel rails and to prevent the spinning or sliding of the wheels. The adhesion factor μ is the ratio of the adhesion to the weight of a locomotive. The maximum tractive force (Tractive Effort, TE) that can be developed by a locomotive depends on the weight on drivers multiplied by the adhesion factor. According to AREMA [2003], this study assumes an adhesion factor equal to 0.25, thereby given a consist characterized by a weight W_c, the consist maximum available TE is calculated as $TE = W_c \cdot 0.25$. This is a conservative valuation for some modern locomotive models characterized by $\mu \geq 0.25$.

A consist may pull a train if the consist available TE is sufficient to satisfy the train TE requirement. The consist available TE is inversely proportional to the train speed. When the train speed increases, the TE provided by a consist decreases. According to AREMA [2003], the consist TE and HP performance,

and the train speed are related as follow:

$$TE = \frac{HP \cdot 550 \cdot \eta}{speed \cdot 1.47} \tag{9.2a}$$

where

TE is expressed in lb

HP is expressed in horse power (1 hp $= 550 \; \dfrac{ft\,lb}{sec}$)

$speed$ is expressed in mph (1 mph $= 1.47 \; \dfrac{ft}{sec}$)

η is the locomotive efficiency

Given the grade and the weight of a train it is possible to:

  (i) identify the train grade resistance R_g;

  (ii) exclude the consists types that do not provide a TE sufficient to move the train when is standing.

The train HP requirement is the second information needed to identify the consist types suitable for the considered train. In other terms, given the grade, the train weight and the travel speed requested by the train service it is possible to exclude the consists that do not provide sufficient TE and that do not have a sufficient HP. The speed at which the consist TE equals the train total resistance R_T is called *balanced speed*. The balanced speed is the maximum possible speed for a train given a specific set of conditions.

$$speed_{max} = \frac{HP \cdot 374.15 \cdot \eta}{R_T} \qquad\qquad (9.3a)$$

where

TE is expressed in lb

HP is expressed in horse power $(374.15 = \dfrac{550}{1.47})$

$speed_{max}$ is expressed in mph

η is the locomotive efficiency

According to Parajuli [2005] and AREMA [1983] for diesel-electric locomotives the efficiency η is in the range of 0.80 to 0.85 and varies with the track speed of the locomotive. Other authors (like Schonfeld [2005]) suggest a value of 0.83 while Metrolinx [2010] reports η in the range of 0.87 to 0.90. This study assumes $\eta = 0.85$ (a conservative value for modern AC locomotives). Therefore the actual HP of a consist is obtained multiplying the nominal consist HP by 0.85. Knowing weight and speed of trains it is possible to select the suitable consist types looking at the actual consist TE and HP.

9.5.1 Valid consist types

A final consideration on consist types is that CSX imposes a maximum number of 24 active axles (48 driving wheels) per consist (constraint 5.1f, page 66). Since the number of axles per locomotive may be 4, 6 or 9, the maximum number of locomotive per consist is 6. Another aspect that reduces the set of accepted locomotive combinations (consist types) is represented by the prohibited ⟨train class, locomotive type⟩ connections. The three train speed classes Intermodal trains, Auto trains, and Mercandise trains, determine the prohibited

⟨train class, locomotive type⟩ connections that reduce the number of valid consist types. For instance, the locomotive type F is prohibited for Intermodal and Auto trains and is allowed for Merchandise trains while the locomotive type A is allowed for Intermodal and Auto trains and is prohibited for Merchandise trains. Consequently, each consist type that contains both the locomotive types A and F, cannot be assigned to trains and is useless. Considering all these restrictions, it is possible to obtain a set of 288 valid consist types to be analyzed in the consists selection phase.

Appendix

A Locomotive Planning Problem optimization model

The model proposed by Vaidyanathan et al. [2008a] may be considered the state of the art in the LPP optimization and represents a reference for our own study. It relies on a space-time network $G = (N, A)$ with nodes N and arcs A divided in different groups. The nodes N are grouped in:

a. Arrival nodes ($ArrNodes$), they model the train arrival events.

b. Departure nodes ($DepNodes$), they model the departure events.

c. Ground nodes ($GrNodes$), they allow the flow of consist from inbound trains to outgoing trains.

The ($GrNodes$) allow to model easily train to train connection, light-travel and idling of consist in stations.

Arcs A belong to four different sets:

a. Train arcs $TrArcs$, they connect ($DepNodes$) and ($ArrNodes$).

b. Ground arcs $GrArcs$, they connect ($GrNodes$) to ($GrNodes$) (train is idling in a station).

c. Light-traveling arcs $LiArcs$, they connect ($GrNodes$) to ($GrNodes$) (train is light-traveling).

d. Connection arcs $CoArcs$, they represent the train to train connections.

The model assumes that the light-travel possibilities are given.

Each arrival node $\in ArrNodes$ has a corresponding arrival ground node $\in$ $GrNodes$, the same holds for departure nodes, connection arcs $CoArcs$ connect arrival nodes $\in ArrNodes$ to the corresponding arrival ground nodes $\in GrNodes$ and the same holds for departure nodes. For each station the last ground node of the week is connected to the first ground node of the week of that station, through a ground arc such that the ending inventory of locomotives becomes the starting inventory in the next time period. This permits to count the locomotives used during the week, evaluating the flow of locomotives on arcs that cross the time line at midnight on Sunday (Sunday midnight is the check time, at this time there are no arrival or departure).

Three different sets of locomotives are associated to each train l:

- MostPreferred[l], the preferred locomotive types.

- LessPreferred[l], the accepted (paying a penalty) locomotive types.

- Prohibited[l], the locomotive types not allowed.

Each train l is characterized by the following attributes:

- dep-time(l), the departure time of a train l;

- arr-time(l), the arrival time of a train l;

- dep-station(l), the departure station of a train l;

- arr-station(l), the arrival station of a train l;

- T_l, the tonnage requirement for a train l;

- HP_l, the HP per tonnage requirement for a train l;

- E_l, the penalty for using a single locomotive consist on a train l.

Given the set of all locomotive types K, k denotes a particular locomotive type belonging to K. Every k ∈ K is characterized by the following attributes:

- h^k, the horsepower (HP) of a locomotive of type k;

- b^k, the number of axles on a locomotive of type k;

- G^k, the ownership cost of a locomotive of type k;

- B^k, the fleet-size of a locomotive of type k;

- c_l^k, the cost of assigning an active locomotive of type k to a train l;

- d_l^k, the cost of deadheading a locomotive of type k on a train l;

- t_l^k, the tonnage provided by a locomotive of type k to a train l.

The model relies on the following definitions:

- C, the set of consist types available for assignments;

- $c \in C$ denotes a specific consist type;

- F_l, the fixed cost for using a light arc l;

- c_l^c, the cost of assigning an active consist of type $c \in C$ to a train arc l;

- α^{ck}, the number of locomotives of type $k \in K$ in a consist $c \in C$;

- $I[i]$, the set of arcs entering in the node i;

- $O[i]$, the set of arcs leaving the node i;

Appendix A. Locomotive Planning Problem optimization model

- S, the set of overnight arc crossing the Sunday midnight timeline.

Given a consist of type $c \in C$, the parameter d_l^c defines:

a. The cost of assigning a deadheading consist if the train arc $l \in TrArcs$.

b. The cost of assigning a light-traveling consist if the train arc $l \in LiArcs$.

c. The idling cost if the train arc $l \in CoArcs \bigcup GrArcs$.

The decision variables are the following:

a. s^k, an integer variable indicating the unused locomotives of type $k \in K$;

b. z_c, a binary variable which takes value 1 if a consist type $c \in C$ is used;

c. z_l, a binary variable which takes value 1 if at least one consist flows on arc $l \in LiArcs$;

d. x_l^c, a binary variable which takes value 1 if a consist type $c \in C$ flows on arc $l \in TrArcs$;

e. y_l^c, an integer variable indicating the number of non-active consists (deadheading, ligh-traveling or idling) of type $c \in C$ flowing on arc $l \in AllArcs$, where $AllArcs = TrArcs \bigcup GrArcs \bigcup LiArcs \bigcup CoArcs$.

142

The weekly CFF LAP with a fixed number p of available consist types is:

$$min : w = \sum_{l \in TrArcs} \sum_{c \in C} c_l^c x_l^c + \sum_{l \in AllArcs} \sum_{c \in C} d_l^c y_l^c + \sum_{l \in LiArcs} F_l z_l - \sum_{k \in K} G^k s^k \quad \text{(A.1a)}$$

subject to

$$\sum_{c \in C} \sum_{k \in K} \alpha^{ck} t_l^k x_l^c \geq T_l, \quad \forall\, l \in TrArcs \quad \text{(A.1b)}$$

$$\sum_{c \in C} \sum_{k \in K} \alpha^{ck} h^k x_l^c \geq HP_l, \quad \forall\, l \in TrArcs \quad \text{(A.1c)}$$

$$\sum_{c \in C} x_l^c = 1 \quad \text{(A.1d)}$$

$$\sum_{c \in C} \sum_{k \in K} \alpha^{ck} (x_l^c + y_l^c) \leq 12, \quad \forall\, l \in TrArcs \quad \text{(A.1e)}$$

$$\sum_{l \in I[i]} (x_l^c + y_l^c) = \sum_{l \in O[i]} (x_l^c + y_l^c), \quad \forall\, i \in AllNodes,\ c \in C \quad \text{(A.1f)}$$

$$\sum_{c \in C} \sum_{k \in K} \alpha^{ck} (y_l^c) \leq 12 z_l, \quad \forall\, l \in LiArcs \quad \text{(A.1g)}$$

$$\sum_{l \in S} \sum_{c \in C} \alpha^{ck} (x_l^c + y_l^c) + s^k = B^k, \quad \forall\, k \in K \quad \text{(A.1h)}$$

$$\sum_{l \in S} (x_l^c + y_l^c) \leq M z_c, \quad \forall\, c \in C,\ M \text{ is a sufficiently large number} \quad \text{(A.1i)}$$

$$\sum_{c \in C} z_c = p \quad \text{(A.1j)}$$

$$x_l^c \in 0, 1, \quad \forall\, l \in TrArcs,\ c \in C \quad \text{(A.1k)}$$

$$y_l^c \geq 0, \quad and\ integer,\ \forall\, l \in LiArcs,\ c \in C \quad \text{(A.1l)}$$

$$z_l \in 0, 1, \quad \forall\, l \in LiArcs \quad \text{(A.1m)}$$

$$z_c \in 0, 1, \quad \forall\, c \in C \quad \text{(A.1n)}$$

$$s^k \geq 0, \quad and\ integer,\ \forall\, k \in K \quad \text{(A.1o)}$$

Bibliography

AAR Policy & Economics Department. Class I railroad statistics. Tech report, Association of American Railroads, 2008. URL `http://www.aar.org/PubCommon/Documents/AboutTheIndustry/Statistics.pdf`. Accessed Mar. 31, 2011.

R. K. Ahuja, T. L. Magnanti, and J. B. Orlin. *Network flows: theory, algorithms, and applications.* Prentice-Hall, Englewood Cliffs, NJ, 1993.

R. K. Ahuja, J. Liu, J. B. Orlin, D. Sharma, and L. A. Shughart. Solving real-life locomotive-scheduling problems. Tech report, MIT Sloan School of Management, 2002. URL `http://dspace.mit.edu/bitstream/handle/1721.1/1799/4389-02.pdf?sequence=2`. Accessed Mar. 31, 2011.

R. K. Ahuja, C. B. Cunha, and G. Sahin. Network models in railroad planning and scheduling. *TutORials in operations research*, 1:54–101, 2005a.

R. K. Ahuja, J. Liu, J. B. Orlin, D. Sharma, and L. A. Shughart. Solving real-life locomotive-scheduling problems. *Transportation Science*, 39:503–517, 2005b.

R. K. Ahuja, L. A. Shughart, J. Liu, and B. Vaidyanathan. An optimization-based approach for locomotive planning. Tech report, Innovative Scheduling, 2006. URL `http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.122.7865&rep=rep1&type=pdf`. Accessed Mar. 31, 2011.

F. Ammah-Tago. Freight in America: a new national picture. Tech report, U.S. Department of Transportation Research and Innovative Technology Administration, Bureau of Transportation Statistics, 2006. URL `http://www.bts.gov/publications/freight_in_america/pdf/entire.pdf`. Accessed Mar. 31, 2011.

AREMA. Arema manual for railway engineering. Tech report, American Railway Engineering and Maintenance-of-Way Association (AREMA), 1983.

AREMA. *Chapter 2 Railway Industry Overview*, pages 33–57. American Railway Engineering and Maintenance-of-Way Association (AREMA), Lanham, MD, 2003. URL `http://www.arema.org/publications/pgre/index.aspx`. Accessed Apr. 30, 2011.

A. Baceler and A. Garcia. An optimization approach to the locomotive scheduling problem in Brazilian railways. In R. Ravitharan, editor, *Rail Achieving Growth: Conference Proceedings*, Melbourne, 2006. RTSA.

Barclays Capital. U.S. Aggregate Bond Index. Tech report, Barclays Capital, 2011. URL `https://ecommerce.barcap.com/indices/index.dxml`. Accessed Apr. 27, 2012.

J. Bitzan, D. Tolliver, and D. Benson. Small railroads - Investment needs, finacial options, and public benefits. Tech report, Upper Great Plains Transportation Institute, North Dakota State University, 2002. URL `http://www.ugpti.org/pubs/pdf/DP145.pdf`. Accessed Dec. 05, 2011.

BNSF Railway Twin Cities division. Northern ligth, April 2006. URL `www.newslink.com/pubs/NTLT/NTLT0604.pdf`. Accessed Apr. 27, 2012.

Bibliography

J. M. P. Booler. The solution of a railway locomotive scheduling problem. *Journal of the Operational Research Society*, 31:943–948, 1980.

J. M. P. Booler. A note on the use of Lagrangean relaxation in railway scheduling. *Journal of the Operational Research Society*, 46:123–127, 1995.

U. Brannlund, P. O. Lindberg, A. Nou, and J. E. Nilsson. Railway timetabling using Lagrangian relaxation. *Transportation Science*, 32:358–369, 1998.

J. Brosseau and B. M. Ede. Development of an adaptive predictive braking enforcement algorithm. Tech report, U.S. Department of Transportation, Federal Railroad Administration, 2009. URL `http://www.fra.dot.gov`. Accessed Apr. 30, 2011.

P. Brucker, J. Hurink, and T. Rolfes. Routing of railway carriages. *Journal of global optimization*, 27:313–332, 2003.

Cambridge Systematics. 2004 Freight rail component of the Florida rail plan. Tech report, Florida Department of Transportation, 2005. URL `www.dot.state.fl.us/rail/Publications/Plans/2004/FreightComponentFull.pdf`. Accessed Mar. 31, 2011.

Cambridge Systematics. National rail freight infrastructure capacity and investment study. Tech report, Association of American Railroads, 2007. URL `http://www.aar.org/~/media/aar/Files/natl_freight_capacity_study.ashx`. Accessed Mar. 31, 2011.

A. Charnes and M. H. Miller. A model for the optimal programming of railway freight train movements. *Management Science*, 3:74–92, 1956.

J. F. Cordeau, P. Toth, and D. Vigo. A survey of optimization models for train routing and scheduling. *Transportation Science*, 32:380–404, 1998.

J. F. Cordeau, F. Soumis, and J. Desrosiers. A benders decomposition approach for the locomotive and car assignment problem. *Transportation Science*, 34: 133–149, 2000.

J. F. Cordeau, G. Desaulniers, N. Lingaya, F. Soumis, and J. Desrosiers. Simultaneous locomotive and car assignment at VIA Rail Canada. *Transportation Research Part B: Methodological*, 35:767–787, 2001.

B. E. Cramer. *North American freight rail: regulatory evolution, strategic rejuvenation, and the revival of an ailing industry*. Ph.d. thesis, University of Iowa, 2007.

CSX Corporation. Csx corporation 2004 corporate profile. Tech report, CSX Corporation, 2005. URL `http://idc.api.edgar-online.com/EFX_dll/EDGARpro.dll?FetchFilingHtmlSection1?SectionID=3847768-5067-127634&SessionID=FwUbHHC7QJSIcP7`. Accessed Apr. 30, 2011.

CSX Corporation. Csx corporation 2005 corporate profile. Tech report, CSX Corporation, 2006. URL `http://idc.api.edgar-online.com/efx_dll/edgarpro.dll?FetchFilingConvPDF1?SessionID=wx5cHZteg0JJ5qf&ID=4483224`. Accessed Apr. 30, 2011.

CSX Corporation. Csx corporation 2009 annual report. Tech report, CSX Corporation, 2009. URL `http://www.annualreports.com/HostedData/AnnualReports/PDFArchive/csx2009.pdf`. Accessed Apr. 30, 2011.

CSX Corporation. 2011 first quarter earnings conference call. Tech report, CSX Corporation, 2011a. URL `http://phx.corporate-ir.net/External.File?item=UGFyZW50SUQ9OTAwNTh8Q2hpbGRJRD0tMXxUeXBlPTM=&t=1`. Accessed Apr. 27, 2012.

Bibliography

CSX Corporation. 2011 second quarter earnings conference call. Tech report, CSX Corporation, 2011b. URL `http://phx.corporate-ir.net/External.File?item=UGFyZW50SUQ9MTAwMTIzfENoaWxkSUQ9LTF8VHlwZT0z&t=1`. Accessed Apr. 27, 2012.

CSX Corporation. 2011 third quarter earnings conference call. Tech report, CSX Corporation, 2011c. URL `http://phx.corporate-ir.net/External.File?item=UGFyZW50SUQ9MTEwOTY4fENoaWxkSUQ9LTF8VHlwZT0z&t=1`. Accessed Apr. 27, 2012.

CSX Corporation. 2011 fourth quarter earnings conference call. Tech report, CSX Corporation, 2011d. URL `http://phx.corporate-ir.net/External.File?item=UGFyZW50SUQ9MTIzNDQ1fENoaWxkSUQ9LTF8VHlwZT0z&t=1`. Accessed Apr. 27, 2012.

W. J. Davis. Tractive resistance of electric locomotives and cars. *General Electric Review*, 29:685–708, 1926.

J. R. Dirnberger. Development and application of lean railroading to improve classification terminal performance, 2006. URL `http://ict.illinois.edu/railroad/cee/pdf/thesis/ms\%20thesis\%20jeremiah\%20dirnberger\%20v\%20\%208\%20_5_.pdf`. Accessed Apr. 29, 2011.

ENVIRON International Corporation. Port of [o]akland 2005 seaport air emissions inventory. Tech report, Port of Oakland, 2007. URL `www.portofoakland.com/pdf/airEmissions_complete.pdf`. Accessed Apr. 27, 2012.

M. Florian, G. Bushell, J. Ferland, G. Guerin, and L. Nastansky. The engine scheduling problem in a railway network. *INFOR*, 14:121–138, 1976.

148

M. A. Forbes, J. N. Holt, and A. M. Watts. Exact solution of locomotive scheduling problems. *Journal of the Operational Research Society*, 42:825–831, 1991.

A. Fügenschuh, H. Homfeld, A. Huck, and A. Martin. Locomotive and wagon scheduling in freight transport. In R. Jacob and M. Müller-Hannemann, editors, *ATMOS 2006 - 6th Workshop on Algorithmic Methods and Models for Optimization of Railways*, Zürich, 2006. Internationales Begegnungs und Forschungszentrum für Informatik (IBFI).

A. Fügenschuh, H. Homfeld, A. Huck, A. Martin, and Z. Yuan. Scheduling locomotives and car transfers in freight transport. *Transportation Science*, 42: 478, 2008.

Gannett-Fleming. Dillerville rail yard consolidation project lancaster county, pennsylvania. Tech report, Gannett-Fleming, 2008. URL `https://edisk.fandm.edu/occ/community/hhra_report.pdf`. Accessed Apr. 27, 2012.

GE Harris Energy Systems. RSSI locomotive tracking white paper. Tech report, GE Harris Energy Systems, 2000. URL `http://www.arema.org/files/library/1999_Conference_Proceedings/00051.pdf`. Accessed Apr. 30, 2011.

K. Ghoseiri and S. F. Ghannadpour. A hybrid genetic algorithm for multi-depot homogenous locomotive assignment with time windows. *Applied Soft Computing*, 10:53–65, 2010.

G. Gould and D. A. Niemeier. Review of regional locomotive emission modeling and the constraints posed by activity data. *Transportation Research Record: Journal of the Transportation Research Board*, 2117:24–32, 2009.

Bibliography

L. Grenzeback, D. Hunt, J. Bryan, B. Muten, D. Simpson, and D. Jacoby. Rail freight transportation bottom line report. Tech report, American Association of State Transportation and Highway Officials, 2008. URL `http://www.dot.state.oh.us/`. Accessed Mar. 14, 2011.

V. T. Hawthorne, K. L. Hawthorne, E. T. Harley, C. M. Smith, R. B. Watson, and C. A. Woodbury. *Section 11 Transportation, Subsection 11.2 Railway Engineering.* Kluwer Academic Publishers, Norwell, MA, 2006.

S. G. Henderson, B. Biller, M. Hsieh, J. Shortle, J. D. Tew, R. R. Barton, and W. B. Powell. Approximate dynamic programming for high-dimensional problems. In S. G. Henderson, M. H. Biller, B. Hsieh, J. Shortle, J. D. Tew, and R. R. Barton, editors, *Proceedings of the 2007 Winter Simulation Conference.* OMNIPress, 2007.

R. Hidayat. Optimising locomotive requirements for a pre-planned train schedule. 2005.

M. C. Holowaty, R. U. Cogswell, and N. E. Moyer. Technical monograph: Transportation planning for the RichmondCharlotte railroad corridor - volume i. Tech report, Parsons Transportation Group, 2004. URL `http://www.fra.dot.gov/downloads/rrdev/rich_vol_1.pdf`. Accessed Aug. 06, 2011.

ICF International. Comparative evaluation of rail and truck fuel efficiency on competitive corridors. Tech report, U.S. Department of Transportation, Federal Railroad Administration, 2009. URL `http://www.fra.dot.gov/Downloads/Comparative_Evaluation_Rail_Truck_Fuel_Efficiency.pdf`. Accessed Apr. 30, 2011.

T. Illés, M. Makai, and Z. Vaik. Railway engine assignment models based on combinatorial and integer programming - operations research report 2005-04. Tech re-

port, Eötvös Loránd University of Sciences - Operations Research Department, 2005. URL `http://www.cs.elte.hu/opres/orr/download/ORR05_4.pdf`. Accessed Mar. 31, 2011.

T. Illés, M. Makai, and Z. Vaik. Combinatorial optimization model for railway engine assignment problem. In L. G. Kroon and R. H. Möhring, editors, *5th Workshop on Algorithmic Methods and Models for Optimization of Railways*. Internationales Begegnungs und Forschungszentrum für Informatik (IBFI), 2006.

Innovative Scheduling. Ilpo: Innovative locomotive planning optimizer - an optimization based tool for locomotive planning. Tech report, Innovative Scheduling, 2009. URL `http://www.innovativescheduling.com/Files/WhitePapers/IS_ILPO_WhitePaper.pdf`. Accessed Apr. 30, 2011.

P. Ireland, R. Case, J. Fallis, C. Van Dyke, J. Kuehn, and M. Meketon. The Canadian Pacific Railway transforms operations by using models to develop its operating plans. *Interfaces*, 34:5–14, 2004.

R. G. Ireson. Air quality technical report for the ictf modernization project. Tech report, Sierra Research Inc., 2007. URL `http://www.scribd.com/doc/18647661/`. Accessed Apr. 29, 2011.

A. John and R. K. Ahuja. Locomotive models at CSX Transportation. Tech report, Innovative Scheduling, 2008. URL `http://www.innovativescheduling.com/Files/Presentations/ConferencePresentation3.pdf`. Accessed Apr. 30, 2011.

S. Keisuke and N. Fukumura. Freight locomotive rescheduling and uncovered train detection during disruption. In J. M. Viegas and R. Macário, editors, *Selected Proceedings of the 12th World Conference on Transport Research*

Bibliography

Society, 2010. URL `http://www.civil.ist.utl.pt/wctr12_lisboa/WCTR_General/default.htm`. Accessed Mar. 31, 2011.

Y. C. Lai, C. P. L. Barkan, and H. Önal. Optimizing the aerodynamic efficiency of intermodal freight trains. *Transportation Research Part E: Logistics and Transportation Review*, 44:820–834, 2008.

R. A. Lindsey. An analysis of the opportunities for wireless technologies in passenger and freight rail operations. Tech report, Federal Railroad Administration, Department of Transportation, 2007.

N. Lingaya, J. F. Cordeau, G. Desaulniers, J. Desrosiers, and F. Soumis. Operational car assignment at VIA Rail Canada. *Transportation Research Part B: Methodological*, 36:755–778, 2002.

J. Liu. *Solving Real-Life Transportation Scheduling Problems*. PhD thesis, University of Florida, 2003.

M. E. Lübbecke and U. T. Zimmermann. Engine routing and scheduling at industrial in-plant railroads. *Transportation Science*, 37:183–197, 2003.

A. Marar and W. B. Powell. Capturing incomplete information in resource allocation problems through numerical patterns. *European Journal of Operational Research*, 197:50–58, 2009.

A. Marar, W. B. Powell, and S. Kulkarni. Combining cost-based and rule-based knowledge in complex resource allocation problems. *IIE (Institute of Industrial Engineers) Transactions*, 38:159–172, 2006.

G. Maróti and L. Kroon. Maintenance routing for train units: the transition model. *Transportation Science*, 39:518–525, 2005.

Metrolinx. Appendix 7 Conceptual design of electrification system. Tech report, Metrolinx, 2010. URL `http://www.gotransit.com/electrification/en/current_study/Appendix\%20Files/Appendix\%207.pdf`. Accessed Apr. 27, 2012.

A. Nahapetyan, R. K. Ahuja, F. Zeynep Sargut, A. John, and K. Somani. 17. a simulation/optimization framework for locomotive planning. In C. Liebchen, R. K. Ahuja, and J. A. Mesa, editors, *ATMOS 2007 - 7th Workshop on Algorithmic Approaches for Transportation Modeling, Optimization, and Systems*, Dagstuhl, Germany, 2007. Internationales Begegnungs- und Forschungszentrum für Informatik (IBFI), Schloss Dagstuhl, Germany. URL `http://drops.dagstuhl.de/opus/volltexte/2007/1182`. Accessed Apr. 27, 2012.

D. H. Noble, M. Al-Amin, and R. G. J. Mills. Production of locomotive rosters for a multi-class multi-locomotive problem. *Journal of the Operational Research Society*, 52:1191–1200, 2001.

S. M. Nourbakhsh and Y. Ouyang. Optimal fueling strategies for locomotive fleets in railroad networks. Tech report, University of Illinois at Urbana-Champaign, 2012. URL `http://ict.uiuc.edu/railroad/CEE/William\%20W.\%20Hay/Spring2012presentations/Feb17_fueling-RR_Seminar_02-2012.ppt`. Accessed Apr. 27, 2012.

B. Paoletti and S. Cappelletti. *The optimization model for locomotive rostering in the fleet planning project*, pages 362–365. Institute of Electrical and Electronics Engineers - IEEE, Beijing, Cina, 2007. URL `http://ieeexplore.ieee.org/xpl/freeabs_all.jsp?arnumber=4281679`. Accessed Mar. 31, 2011.

A. Parajuli. Modeling road and rail freight energy consumption: a comparative

Bibliography

study, 2005. URL `http://eprints.qut.edu.au/16193/1/Ashis_Parajuli_Thesis.pdf`. Accessed Apr. 30, 2011.

W. B. Powell. Dynamic models of transportation operations. *Handbooks in Operations Research and Management Science*, 11:677–756, 2003.

W. B. Powell. *Approximate dynamic programming: solving the curses of dimensionality*. Wiley-Interscience, New York, 2007.

W. B. Powell and B. Bouzaiene-Ayari. Approximate dynamic programming for locomotive optimization. Tech report, Princeton University, 2006. URL `http://academic.research.microsoft.com/Paper/4518847`. Accessed Mar. 31, 2011.

W. B. Powell and B. Bouzaiene-Ayari. Approximate dynamic programming for rail operations. In C. Liebchen, R. K. Ahuja, and J. A. Mesa, editors, *ATMOS 2007 - 7th Workshop on Algorithmic Approaches for Transportation Modeling, Optimization, and Systems*. Internationales Begegnungs und Forschungszentrum für Informatik (IBFI), 2007.

W. B. Powell and H. Topaloglu. Stochastic programming in transportation and logistics. *Handbooks in Operations Research and Management Science*, 10: 555–636, 2003.

W. B. Powell and H. Topaloglu. Fleet management. *Applications of stochastic programming*, page 185215, 2005.

W. B. Powell, J. A. Shapiro, and H. P. Simo. A representational paradigm for dynamic resource transformation problems. *Annals of Operations Research*, 104:231–279, 2001.

154

W. B. Powell, J. A. Shapiro, and H. P. Simo. An adaptive dynamic programming algorithm for the heterogeneous resource allocation problem. *Transportation Science*, 36:231–249, 2002.

W. B. Powell, B. Bouzaiene-Ayari, and H. P. Simo. Dynamic models for freight transportation. *Transportation*, 14:285–365, 2007.

Railway Association of Canada. Locomotive emissions monitoring program 2008. Tech report, Railway Association of Canada, 2008.

K. V. Ramani. An information system for allocating coach stock on indian railways. *Interfaces*, 11:44–51, 1981.

T. Raviv and M. Kaspi. The locomotive fleet fueling problem. *Operations Research Letters*, 40(1):39–45, 2012.

G. Roucolle and J. P. Elliott. Comments on transport Canadas review of Canadian Rail logistics. Tech report, Oliver Wyman, 2010. URL `http://www.tc.gc.ca/media/documents/policy/133-a-oliver-wyman-eng.pdf`. Accessed Apr. 27, 2012.

J. A. Sabino, J. E. Leal, T. Stützle, and M. Birattari. A multi-objective ant colony optimization method applied to switch engine scheduling in railroad yards. *Pesquisa Operacional*, 30:486–514, 2010.

D. H. Schafer and C. P. L. Barkan. A prediction model for broken rails and an analysis of their economic impact. In *Proceedings of the American Railway Engineering and Maintenance of Way Association (AREMA) Annual Conference*, 2008. URL `http://www.arema.org/files/library/2008_Conference_Proceedings/A_Prediction_Model_for_Broken_Rails_and_`

Bibliography

an_Analysis_of_Their_Economic_Impact_2008.pdf. Accessed Apr. 27, 2012.

V. Scholz. Knowledge-based locomotive planning for the Swedish Railway. Tech report, Swedish Institute of Computer Science (SICS), 2000. URL `http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.34.7764`. Accessed Mar. 31, 2011.

P. Schonfeld. *Transportation Systems - Section 85*. The engineering handbook second edition, CRC Press, 2005.

D. Seedah and R. Harrison. Export growth, energy costs, and sustainable supply chains. Tech report, Center for Transportation Research, University of Texas at Austin, 2010. URL `http://d2dtl5nnlpfr0r.cloudfront.net/swutc.tamu.edu/publications/technicalreports/476660-00069-1.pdf`. Accessed Apr. 27, 2012.

D. Souten, C. Lindhjem, and S. Seum. San Bernardino TAC emissions inventory. Tech report, Environ International Corporation, 2008. URL `http://www.arb.ca.gov/railyard/hra/env_sb_eirpt.pdf`. Accessed Apr. 27, 2012.

W. Sylte. Port of Oakland 2005 seaport air emission inventory. Tech report, ENVIRON International Corporation, 2007. URL `http://www.portofoakland.com/pdf/airEmissions_complete.pdf`. Accessed Apr. 29, 2011.

L. S. Thompson. *Conclusions: competitive tendering in railways - what can we learn from experience?*, volume 2007, pages 209–245. OECD (Organisation for Economic Co-operation and Development) Publishing, Paris, 2007.

D. Tolliver and J. Bitzan. Analysis of revenues and costs for wheat shipments originated in north dakota on the bnsf railroad. Tech report, North Dakota

State University, Upper Great Plains Transportation Institute, 2002. URL `http://www.ugpti.org/pubs/pdf/DP144.pdf`. Accessed Apr. 30, 2011.

H. Topaloglu and W. B. Powell. Dynamic-programming approximations for stochastic time-staged integer multicommodity-flow problems. *INFORMS Journal on Computing*, 18:31, 2006.

C. R. Unkle and N. E. Roddy. Method and apparatus for diagnosing difficult to diagnose faults in a complex system, April 2004. URL `http://books.google.com/patents/US20040073844.pdf`.

U.S. Army Corps of Engineers - Engineering and Construction Division. Railroad design and rehabilitation. Tech report, U.S. Army Corps of Engineers - Engineering and Construction Division, Directorate of Military Programs, 2000. URL `http://www.hnd.usace.army.mil/techinfo/ti/850-02.pdf`. Accessed Apr. 30, 2011.

B. Vaidyanathan, R. K. Ahuja, J. Liu, and L. A. Shughart. Real-life locomotive planning: new formulations and computational results. *Transportation Research Part B: Methodological*, 42:147–168, 2008a.

B. Vaidyanathan, R. K. Ahuja, and J. B. Orlin. The locomotive routing problem. *Transportation Science*, 42:492–507, 2008b.

Wilbur Smith Associates. Niagara frontier urban area freight transportation study - Technical memorandum No. 5, Economic impact analysis. Tech report, Greather Buffalo-Niagara Regional Transportation Council, 2010.

M. B. Wright. Applying stochastic algorithms to a locomotive scheduling problem. *Journal of the Operational Research Society*, 40:187–192, 1989.

Bibliography

K. Ziarati, F. Soumis, J. Desrosiers, S. Gelinas, and A. Saintonge. Locomotive assignment with heterogeneous consists at CN North America. *European journal of operational research*, 97:281–292, 1997.

K. Ziarati, F. Soumis, J. Desrosiers, and M. M. Solomon. A branch-first, cut-second approach for locomotive assignment. *Management Science*, 45:1156–1168, 1999.

K. Ziarati, H. Chizari, and A. Nezhad. Locomotive optimization using artificial intelligence approach. *Iranian Journal of Science & Technology, Transaction B, Engineering*, 29:93–105, 2005.