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I, Sin-Yeung Yoo, declare that the work presented in this thesis is, to the best of knowledge and belief, original, except as acknowledged in the text, and that the material has not been submitted, either in whole or in part, for a degree at this or any other university.

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Abstract

The aim of this work was to provide a survey of recent contributions about freight and passenger transportation. Whereas passenger optimization models considered problems such as line planning, train timetabling, platforming, rolling stock circulation, shunting and crew scheduling, freight transportation dealt with issues concerning car blocking, train makeup, routing, and empty car distribution.

The field of rail transportation has clearly received attention resulting in a diversity of literature contribution. As it was difficult to handle the large amount of papers, this work is trying to give a short review of some important contributions made in recent years.

Due to the increase in more sophisticated mathematical techniques, constant refinements in development of the models were made that were able to deal with larger problems. In addition, a trend towards more efficient transportation support systems was observed taking robustness into account. In addition, solution approaches that can deal with larger disturbances of the rail environment in a considerable speed and time, have received attention. Thus, future research can be done to develop more integrated models of scheduling and routing problems of train and passenger transportation to provide robust solutions and problem solving methods that handle disturbances of rail environment.

Zusammenfassung

Das Ziel dieser Arbeit war es, einen Überblick über die aktuellen Beiträge der Literatur in den Bereichen der Eisenbahnlogistik sowohl im Güter- als auch im Personenverkehr zu geben. Während sich der Güterverkehr mit Problemen der Zusammenstellung der Züge und Waggons beziehungsweise der Verteilung der Leerfahrzeuge auseinander setzte, beschäftigte sich die Eisenbahnlogistik im Bereich des Personenverkehrs mit Optimierungsmodellen bezüglich Eisenbahnlinienplanung, Erstellung eines Fahrplanes, Inbetriebnahme von Fahrzeugen und Besatzungs- und Einsatzplanung.

Die Bereiche der Eisenbahnlogistik haben in der Literatur eindeutig an Aufmerksamkeit gewonnen. In der Folge war es schwierig eine Auswahl aus dieser Vielfalt an Beiträgen zu treffen. Deshalb versucht diese Arbeit nur einen kurzen Einblick über einige wichtige Beiträge der letzten Jahre im Bereich der Eisenbahnlogistik zu geben. Aufgrund hochentwickelter mathematischer Techniken und deren Lösungsmöglichkeiten, die in den letzten Jahren aufgekommen sind, war es nun möglich die komplizierten Modelle der Eisenbahnlogistik in einer vernünftigen Zeit zu lösen. Darüber hinaus wurde ein Trend zur Entwicklung effizienterer entscheidungsunterstützender Hilfsprogramme für reale Gegebenheiten der Eisenbahnlogistik beobachtet. Im Großen und Ganzen sollten in Zukunft stärker integrierte Modelle der Eisenbahnplanung und Routenplanung entwickelt werden um robuste Lösungen und Methoden zu fördern.

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1. Introduction

Railroads play an important role in case of freight and passenger transportation. In Austria, for example, a total of 107.7 million tons of freight and a total of 242.1 million passengers were transported on local rail network by domestic and foreign railway companies in 2010 [1, 2].

However, due to severe competition from alternative transportation modes, the rail industry is eager to improve its planning and operational processes [3]. In general, rail operating policies may face a sequence of decisions to meet demand by allocating resources and facilities available. In case of freight transportation demand expressed in terms of tonnage of certain commodities has to be moved between a given origin-destination pair [4, 5].

Rail transportation problems can be classified in terms of planning horizon, whereas three levels of decision making can be distinguished: (i) At the strategic level, decisions will be made according to resource acquisition over a long time horizon, whereas (ii) tactical decisions based on medium and short term issues focus on allocating of existing resources. In contrast to tactical decisions, where operating policies are updated every few month, (iii) operational decisions deal with day-to-day activities of the railroad trying to respond to a detailed and dynamic environment [5].

Strategic issues in passenger railway systems are related to the service level to be supplied to the customers and the capacity of resources to meet these services. The service level is defined in terms of number of direct links, frequencies, and reliability, whereas resources are railway infrastructure, rail equipment (rolling stock) and the crew. Furthermore, it is difficult to solve strategic planning issues by applying optimization approaches due to long time horizons. This indicates the importance of forecasting models which take uncertainties into account, such as demand for rail transportation in the long run [6]. In contrast to strategic planning, which considers rolling stock management, crew management and line planning, tactical planning focuses on timetabling, platforming and rolling stock assignment. At the operational level further details are planned based on the information provided by tactical models. To respond to dynamic changes of the environment, timetabling, rolling stock circulation, crew scheduling and shunting problems are considered in detail [3, 7].

In case of freight rail transportation, changes of rail network structure and the location or extension of classification yards are considered as strategic planning issues. Furthermore, freight rail network models operate generally on the tactical level (Figure 1), which includes freight routing, blocking, train routing, makeup, scheduling, and the basic locomotive assignment problem [3, 8].

Finally, operational decisions deal with empty car distribution, engine and crew scheduling, timetable settings and dispatching policies [3].

Strategic	"Planning direction"			Tactical			Operational
	Freight routing	**Blocking**	**Train routing**	**Makeup**	**Schedule**	**Locomotive assignment**	Empty cars dispatching, classification schedules, fitting of trains into timetable
	Route cars through network Distribute classification work among yards	Shipment → blocks (at each yard)	Route trains through network	Block to train blockless: Car to train	*Coarse*: Frequency of trains *Fine*: Arrival and departure of trains	Engines → trains	

Figure 1. Mid- and short-term planning operations in freight transportation **[8]**

Starting with an overview about definitions regarding to rail systems, this work tries to review recent contributions in literature for rail transportation concerning operating policies for both freight and passenger transportation.

The following chapter 2 considers first of all train routing problems, whereas chapter 3 is trying to explore scheduling problems. While chapter 2 is considering rail network routing models and freight car models, chapter 3 is divided into four sections: (i) Line planning, (ii) train timetabling, (ii) train dispatching and (iii) locomotive assignment models. The last chapter of this work is going to review recent contributions of passenger rail optimization models including train platforming, shunting, rolling stock circulation and crew planning.

1.1. Background

Railway systems can be seen as a network, where arcs refer to lines of track on which trains carry freight or passengers, and nodes refer to yards or stations. In case of freight transportation, nodes represent classification or marshaling yards, where cars are sorted and combined on tracks according to their outbound destination. This classification of cars into blocks (groups) allows railroads to take advantage of the economies of full train shipments. The decision about the grouping of cars are called blocking policy. Cars, with different destinations but sharing some initial path of their subsequent trip out of the yard, are usually blocked together and have to be split at a later yard and reassigned. In this case, cars have to pass a number of intermediate yards which results in delays. Two types of classification yards are used for sorting cars in the same group. In hump yards, cars roll down an incline and are subsequently assigned to the appropriate track. In contrast, flat yards are using locomotives (engines) to move cars onto the tracks. Next, a take-list of potential blocks that may go into an outbound train, in the order of preference, is defined by the makeup policy. Thus, the decision about the train formation follows the take-list of blocks until an acceptable trainload is achieved. During these processes, a car may suffer various departure delays: (i) In case a car has to wait for the next outbound train to arrive, it is called connection delay. (ii) If the train's departure is dependent on the accumulation of a sufficient number of cars, accumulation delay occurs [3].

However, all these operations performed in a yard are called yard activities, whereas line activities refer to movements of cars or trains on tracks and interact with routing decisions that determine the flow of traffic on a rail network. A line can be defined as a direct connection between two end stations that is operated with a certain frequency and with a certain train type [7]. This line can be made of a single track, as it is often in North America, or contain two or more tracks. In case of a single track line, sidings (short track sections) are located at regular intervals along the lines, to allow trains to travel in both directions and to overtake, if a fast train wants to pass a slower one [5]. Line policies include scheduling and timetabling [3]: (i) Scheduling problems are dealing with the temporal dimension of railroad operations. It defines the service level and frequency of routes in a rail network. These scheduling activities are dependent upon the availability of rail equipment (rolling stock), such as locomotives and cars that are needed to operate trains [5]. A related scheduling problem that considers the use of rail equipment is the basic locomotive assignment problem. A locomotive is a railway vehicle that provides the power unit of a train. Given a planned train schedule, the locomotive assignment problem consists of assigning a set of locomotives to scheduled trains at minimum cost by satisfying some side constraints expressed as a number of locomotives or as a measure of pulling power needed (i.e. tonnage) [5]. (ii) A train timetable provides arrival and departure times for each yard or station in a train's route. Two different types of timetables exist in rail transportation: (a) in a cyclic timetable each period is the same, where a cycle time is denoted by T. This means, if a trip between two stations s_1 and s_2 leaves at time t_1 and arrives at time t_2, the next trip will be denoted with a departure time, $t_1 + kT$, and an arrival time, $t_2 + kT$, for integer values of k. In contrast to the cyclic timetabling problem, (b) the non-cyclic timetabling problem is mainly relevant for heavy-traffic, long-distance corridors, where the capacity is limited due to greater traffic density. The advantage of cyclic timetables is that it is easy to remember. On the other hand, this system is expensive to operate, because even in periods between peak hours with low travel demand, the system is operating with the same timetable used during peak hours with higher travel demand. Therefore, the capacity between peak hours and off-peak hours should be distinguished by modifying the length of the train, which results in different rolling stock and variable crew costs [6]. Although train timetabling is performed at the tactical planning level, real time operations need to synchronize freight and passenger operations on the lines of a rail network. Given a train timetable, the train dispatching problem denotes a feasible plan of meets and overtakes of trains and specifies the actual movements of trains [5].

Besides yard and line activities, network-wide policies consider the network as a whole, interacting with both yard and line policies. First of all, routing decisions have to be made that determine the flow pattern of traffic between origin-destination (OD) pairs. Secondly, it is necessary to consider the sequence of blocks to build up a train, since common blocks share certain legs of their flow paths on the network and split up when they have reached their destinations. These decisions are fully specified by network-wide blocking policies. Another network-wide problem in railroad operations is car and locomotive distribution. The basic issue is to redistribute empty cars and locomotives from locations with surplus to those with insufficient supply to meet demand of customers and passengers [3].

However, as mentioned above, this work deals with recent contributions of passenger and freight railway transportation. Optimization models were analyzed in both cases. Whereas in case of passenger transportation, operational planning problems, like line planning, train timetabling, train platforming, rolling stock circulation, train unit shunting, and crew planning, play an important role, problems of rail freight transportation are car blocking, train makeup, train routing and empty car distribution [6].

Several surveys about rail transportation were contributed over the last years. While Assad [3] and Cordeau et al. [5] reviewed optimization models for both, passenger and freight transportation, Caprara et al. [6] and Huisman et al. [7] provided an overview about passenger railway issues. However, the next section of this chapter is going to give a brief description of the definitions occurring during this work.

1.2. Problem definition

The rail transportation problem can be classified into three levels: train routing, scheduling and dispatching. At the strategic level the train routing problem decides which routes to take for a given OD pair of a train. At the tactical level the train scheduling problem determines suitable timetables which specify arrival and departure times at each train station. At last, given a train timetable, the dispatching problem specifies the actual movements of a train [9]. The most common approach to represent the rail transportation system is a network. It consists of nodes that represent yards or stations and arcs that represent tracks on which trains carry passengers or freight. One may distinguish between local problems where only one node or arc of the network is involved and global problems involving multiple entities [5]. However, the following two sections are going to deal with definitions concerning routing and scheduling problems.

1.2.1. Scheduling

The scheduling problem deals with line planning, train timetabling, dispatching and locomotive assignment problems. For the line planning problem (LPP), one has to choose a set of operating lines and its frequency in a network of tracks, such that the supplied transportation capacity is sufficient to satisfy all travel demands. Objectives could be maximizing passenger service while minimizing the operational costs of the railway system. Scheduled trains can be split into a number of subsets of trains, also called lines. Trains in each subset have the same routes, but different arrival and departure times. The frequency of a line denotes the number of trains that run in each direction in an hourly cycle time. A cycle time is denoted as the difference of departure or arrival times of two consecutive trains in the same subset and direction for each station. The passenger service level is often defined by maximizing the number of direct passengers. Direct passengers are passengers that can travel from their origin to their destination without changes of trains. The more direct connections are provided, the longer a line. As a consequence, this leads to transfer delays and may prevent an optimal allocation of rolling stock. Therefore, a solution may be provided through a robust and cost-optimal line system where lines are short and force passengers to transfer from one train to another very often. Thus, to obtain an optimal line system a trade-off between these two objectives has to be made. The line system has following options to provide enough capacity for the passenger‘s transportation: A line can either operate with high frequency and with trains with low capacity, or with low frequency and with trains with high capacity [6].

However, once the line system has been designed, a timetable for its train lines can be constructed [10]. The train timetabling problem (TTP) specifies a timetable which denotes arrival and departure times for each train at each station. For a given timetable, the dispatching problem denotes the actual movements of trains, whereas the aim is to optimize total train travel time by minimizing train delays and deviations from the planned train schedule. In addition collisions and deadlocks have to be avoided. A deadlock denotes the situation when a train blocks the movement of another train when it tries to crossover a junction (railroad hub) from one line to another. Therefore the number of tracks can have an effect on the dispatching policy. In case of a single track, network sidings are used to overtake trains or wait for trains to pass from the opposite direction. In contrast to the single track network, no sidings are used for multiple track networks. Because the movement of trains is related to their operating speed, the train dispatching model takes velocity into account. Each track has different limitations on train speed. In addition, passenger and freight trains can have different maximum speed although there are routed on the same track. Speed limit at a junction will be considered, if a train crosses a junction by moving from one line to another. At last, the dispatching policy has to consider train characteristics such as train priority, speed, length, and acceleration and deceleration rate. In general, passenger trains have higher priorities than freight trains, i.e. freight trains have to wait if passenger trains want to share the same track. Acceleration and deceleration rates are used to increase or decrease the train speed without violating speed limits. Sometimes trains cannot be operated with their maximum speed because of track speed limitations [5, 9].

Finally, the assignment of locomotives and cars to scheduled trains is a complex task for most railway providers. Locomotives are power units that pull trains that consist of cars [11]. In freight transportation, the assignment of cars to trains and the locomotive planning problem (LPP) is treated separately to supply enough power to pull the assigned cars of each scheduled train. In passenger transportation, however, both the assignment of locomotives and cars is considered simultaneously. That is because the same set of trains is operated in a given period with a similar number of cars. In addition, the smaller number of cars makes it easier to treat the LPP and car assignment problem simultaneously. Given a periodic train schedule and fleet, the objective is to find a set of rolling stock cycles that cover a list of scheduled trains at minimum cost. In addition, some operational constraints have to be considered such as maintenance requirements and equipment switching penalties [12].

Two kinds of locomotive assignment models can be distinguished as one has to determine the types and number of locomotives and cars for each scheduled train: (i) Single locomotive planning models consider only one engine for each train whereas (ii) multiple locomotive planning models may require more than one engine expressed as the number of engines needed for each train. These models can be formulated as a multi-commodity network flow problem with linking constraints that ensure that each train is covered exactly once. The most difficult version of this problem occurs when multiple engine types has to be considered and each train may require more than one engine to pull a train expressed in terms of motive power [5, 6].

In contrast to locomotives, some trains have self-propelled cars (train units). That is increasingly common in passenger rail transportation, but unusual for freight trains. The reason is that the turnaround process by changing the direction of a train can be easily carried out by self-propelled cars having driver's seats on both sides of the unit. In addition, shunting (switching) processes is easier for self-propelled cars than for locomotive hauled cars [13]. Shunting considers the process of sorting rolling stock into trains on a shunting area. In addition, several related processes such as routing rolling stock between the station and shunting area and maintenance issues are considered in the shunting process. Thus, the train unit shunting problem (TUSP) consists of matching the arriving and departing train units, as well as to sort these train units on tracks, such that total shunting costs including routing and penalty costs are minimized [6].

Various versions of the rolling stock circulation problem (RSCP) arise depending on the rail network and equipment used. The RSCP is an important task for train operators as they are responsible for timetables, rolling stock and crew management. Considering the acquisition, operational and maintenance costs of the rolling stock used, a train operator has to consider the type and the number of rolling stock units per scheduled train. In addition, variations in passenger's seat demand have to be considered. This leads to changes in train's composition by removing or adding equipment to trains. These coupling and uncoupling processes are usually penalized with switching costs and restricted by the available time at the station. The available time at a station is denoted by the waiting time between two consecutive trips of the train. The time required to carry out shunting operations is dependent on the available rolling stock. As mentioned earlier two cases of rail equipment can be distinguished: (i) locomotives and cars, and (ii) train units. Concerning the rail network, two different cases can be characterized as well: (i) Sparse networks consist of long distances, and thus, have long travel times and low frequencies of trains. In addition, a seat reservation system often exists and maintenance checks of the equipment are considered into the basic rolling stock circulation. In contrast to sparse networks, (ii) dense networks have relatively short distances with higher frequencies of trains. This result in different maintenance checks based on an ad hoc basis rather than incorporated in the basic RSCP. In addition, passenger seat reservation usually does not exist and only expected numbers of passengers are known [6].

In addition to rail equipment needed, crew planning has to be considered to run a rail system. The crew planning problem (CPP), considered by train operators, is concerned with planning a work schedule for train drivers and conductors needed to cover a given timetable for train services. A train service includes both the actual passenger and freight travel and empty rolling stock movements. It has to be performed every day in a given time horizon and contains a sequence of trips which has to be serviced by the same crew. CPP usually consists of crew scheduling and crew rostering: (i) Crew scheduling considers short-term issues where a set of duties (pairings) covers all the trips and (ii) crew rostering is showing a list of final duties to be attended. A duty indicates a sequence of trips to be covered by a single crew member within a given planning horizon. A crew member is located in a crew depot which denotes the starting and ending point of a work segment [6].

However, in addition to the scheduling problems, routing problems should be considered simultaneously. In fact, it is difficult to solve these problems simultaneously due to the complexity and size of problems. Nevertheless, the next section of this chapter will give a brief overview of the routing issues, considered in rail freight and passenger transportation.

1.2.2. Routing

Problems concerning routing issues are: blocking, makeup and train routing models. The grouping of different shipments into cars is called blocking [14]. A classification yard is a place where cars are separated, sorted and recombined to form a block [9]. In freight transportation, a shipment containing commodities consists of one or more cars with the same OD pair. It may pass through several classification yards on its route. The blocking capacity at each yard is determined by available yard resources, i.e. working crew, the number of classification tracks and switching engines. It denotes the maximum number of blocks and maximum number of cars or car size that each yard can handle. The aim of the blocking problem is to deliver the total traffic, i.e. the set of all shipments with minimum handling and delay costs. This can be reached by delivering a set of shipments with the fewest possible classification. The blocking path of a shipment denotes the sequence of blocks to which one shipment is assigned along its physical route [15].

A car is a rolling stock for freight transportation and has to be delivered between an origin and a destination point within a rail network. While large customers with a large amount of shipment may need to order a complete train, smaller customers order single cars. These cars are assigned to trains along with other cars demanded by other small customers and grouped together to an intermediate destination (shunting yard). A shunting yard is a place where trains are split up and reassembled into new trains. The train which consists of several cars, and has its origin and destination, and arrival and departure time, is called a trip. Trip duration is the time difference between starting and arrival time. The average travel speed of freight trains is lower than of passenger trains, especially at daytime. This results in trip durations up to three days. However, trains have different length and weight and thus need a certain number of locomotives with sufficient pulling power. At the start, the locomotive is attached (coupled) to the train and then detached (uncoupled) at the destination. For both coupling processes, a certain amount of time has to be considered for maintenance issues, such as technical checks and refueling of diesel [16]. Two different classes of locomotives can be distinguished, electrical and diesel. Furthermore, a locomotive is either active (pulling a train) or deadheading (driving without pulling a train). In addition, light deadheading, also called light travel or passive deadheading occurs when a locomotive is a part of a train just like a car. In case of passive deadheading the costs are lower, because crew and fuel costs are saved. A deadhead trip occurs when a locomotive is travelling from the destination station of a train to the departing station of another train [16].

However, locomotives and cars are important rolling stocks for rail transportation. Cars that share the same partial routes are blocked together in order to save costs. Whereas, the blocking model decides which cars should be combined to which blocks at which yards, the makeup model assigns blocks to trains. At last, network routing models determine the routing and the number of trains for that route to satisfy demands at various destinations [9]. In the following two chapters, research contribution of routing and scheduling models will be introduced in more detail.

2. Routing Problems

Operating plans for rail freight transportation include the allocation of train connections, the blocks to be built in each yard, and the makeup problem while satisfying a set of constraints on train and yard capacity. In addition, train timetables, which specify train arrival and departure times, should be determined simultaneously to ensure an efficient way of traffic delivery while using the track capacity optimally. However, because of the complexity of the rail freight transportation problem, a sequential model is often developed. Furthermore, operating plans are usually updated every few month with weekly or daily adjustments taking the demand variability into account [5].

However, most optimization models for rail routing problems are defined over a network where nodes refer to origins, destinations or intermediate transfer points, and lines refer to tracks where traffic has to be routed [5].

The following section contains a short description about network routing models including blocking and makeup models and will conclude with examples of freight car models.

2.1. Network Routing Models

Railway systems can be seen as a network whose nodes represent yards or stations and arcs represent tracks on which trains transport passenger or freight. The optimization model for train and freight routing consists of assigning freight to cars, cars to trains, and determining the routing and frequency of trains [5, 10]. Therefore this chapter is going to review recent publications about models concerning the blocking policy, followed by train routing and makeup models.

2.1.1. Blocking Models

Within the rail network cars have to be delivered between an OD pair. While large customers with a large amount of shipment may need to order one single train or block train, smaller customers order single cars. These cars are assigned to trains along with cars demanded by other customers and grouped together at classification yards, where cars are separated and reassembled only after they have reached the destination of the block [16]. Ideally, each shipment should be assigned to a block whose OD pair is the same, to avoid delays and unnecessary classifications. In practice, this is limited by the blocking capacity at each yard defined by the available resources such as working crew, the number of classification tracks and switching engines [15]. The railroad blocking problem is a very large-scale, multi-commodity flow, network design, and routing problem with billions of decision variables. This results in excessively high running times and thus is suitable only for small networks. As a consequence of these considerations, railroad companies would use manual decision-making processes with higher transportation costs and intensive time requirements rather than using optimization-based approaches [17].

However, the blocking network graph G = (N, A) consists of a set of nodes N representing yards where a set of shipments K originate, terminate, or are swapped. A set of arcs A represents blocks that can be built from node i to node j. A simplified example of the blocking network can be seen in figure 2 [17].

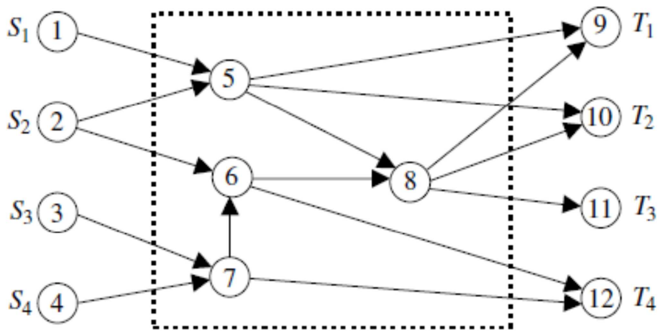

Figure 2. A railway blocking network: Nodes representing yards and arcs representing blocks **[17]**

The blocking problem can be formulated as a mixed integer programming (MIP) model. It has two sets of binary decision variables:

(i) $yij = 1$, if arc $(i, j) \in A$ is built, and is 0 otherwise.

(ii) $x_{ij}^{k} = v_k$, if shipment k flows on arc $(i, j) \in A$, and is 0 otherwise.

The parameter v_k denotes the number of cars in shipment $k \in K$.

The objective function is to minimize total handling and shipping cost. The handling cost includes the cost of reclassification h_i of a shipment at a yard, whereas the shipping cost deals with transportation cost of a shipment m_{ij} from its origin to its destination. The following three main capacity constraints have to be considered: (i) Each block is built on separate tracks. The blocking capacities of yards are limited because of the number of tracks each yard can provide. (ii) Each yard of the network can handle a limited number of cars. The car handling capacity constraint of yards is important to avoid congestions and breakdowns of operations. (iii) The flow capacity constraint of blocks determines a specified number of cars a block can carry [17].

The first successful attempt to solve a blocking optimization model appears in Bodin et al. [18]. They developed a commercial software system to solve a mixed integer nonlinear programming (MINLP) formulation. The objective of the underlying multi-commodity flow problem was to minimize shipping, handling and delay costs. The side constraints include capacity constraints at each yard in terms of maximum number of blocks and car size [15].

In the last fifteen years the railroad blocking problem was researched among others, by Newton et al. [19], Barnhart et al. [15] and Ahuja et al. [17]. Newton et al. [19] formulated the network design problem (NDP) as a MIP model in which yards are represented by nodes and blocks by arcs. They developed a strategic decision support tool based on column generation and branch and bound in which attractive paths for each shipment were generated by solving a shortest path problem. The objective of the underlying railroad blocking problem was to minimize the total miles, handling and delay cost by choosing which blocks to build at each yard, and to assign sequences of blocks to deliver each shipment. The model was applied on test instances based on an aggregate network with 150 nodes and 1300 commodities. The data included shipment volumes for peak periods, blocking capacities for each station and the structure of the rail system [15, 19].

Further contributions about railroad blocking problems were introduced by Barnhart et al. [15]. Compared to Newton et al. [19], they represented a similar model in which the Lagrangian relaxation technique was proposed to decompose the problem into two sub-problems, such as the flow and block problem. While the multi-commodity flow problem was solved by using linear programming combined with column generation due to the exponentially large number of potential blocking paths, the block sub-problem was solved by using a branch-and-cut algorithm due to the large number of connectivity constraints added to the problem [15]. However, their approach focused on determining a near-optimal solution with not scalable computing times as the problem increased in size. This inhibits their use in practice unless shipments are limited to follow a number of predetermined paths [10].

Ahuja et al. [17] presented a MIP model and solved the problem to near-optimality by using the very large-scale neighborhood (VLSN) search. This algorithm was also able to handle a variety of practical and business constraints that are necessary for solving a real-life railroad blocking problem.

Recent contributions of the railroad blocking problem have been presented by Yaghini et al. [20] and Yue et al. [21]. Yaghini et al. [20] formulated a MIP model and provided a metaheuristic algorithm based on ant colony optimization (ACO) to solve the railroad blocking problem within a short time. This approach was then experimentally applied to small test problems and compared to solutions generated with CPLEX. The solution method was also applied on a real-world blocking problem of the Iranian railways. Yue et al. [21] provided a similar

solution approach in comparison to [20] by proposing a model for a multi-route rail blocking problem and by solving the underlying integer programming formulation with an ACO algorithm.
An overview about blocking models discussed is shown in table 1.

Blocking Models

Authors	Problem type	Planning Horizon	Objective Function	Model Structure	Solution approach
Bodin et al. (1980)	Blocking	Tactical	Min shipping, handling and delay costs	Nonlinear MIP	Heuristic
Newton et al. (1998)	Blocking	Strategic	Min shipping and handling costs	Linear MIP	Column generation, Branch and Bound
Barnhart et al. (2000)	Blocking	Tactical	Min operating costs	MIP	Lagrangian Relaxation and Decomposition
Ahuja et al. (2007)	Blocking	Tactical	Min shipping and handling costs	MIP	Very large scale neighborhood search
Yaghini et al. (2011)	Blocking	Tactical	Min delivering costs	MIP	ant colony optimization
Yue et al. (2011)	Blocking	Tactical	Min operating costs	MIP	ant colony optimization

Table 1. Blocking Models

2.2.2. Routing and Makeup Models

While blocking models deal with freight routing and distribution among classification yards of a network, routing and makeup models determine the routing and frequency of trains and the assignment of blocks to trains [5]. Assad [4] was the first one who provided a combined makeup and routing model and proposed a multi-commodity network flow model to solve this problem.
In a series of two papers Marín and Salmerón [22, 23] studied the tactical planning of rail freight networks by applying local search heuristics such as simulated annealing, tabu search and descending heuristic. The problem was to decide the optimal assignment of the trains to the service network and simultaneously assign the demand of cars to the routes. The objective was to minimize car costs, train costs, and investment costs. As mentioned before, several heuristic methods have been proposed to decompose the global problem into two sub-problems: (i) car routing, when the train frequency is known in advance and (ii) car grouping to trains, when car routes are known. For small size networks a reformulation of the problem as a linear program led to the exact solution provided by a branch and bound algorithm that were used to compare the heuristic approaches. In contrast to smaller networks, only heuristics were used to solve the problem for larger networks. Computational

results show that simulated annealing obtains the best solutions in terms of solution quality, but require more time than other heuristics [22].

Jha et al. [24] provided two different multi-commodity network flow models for the block-to-train assignment problem: an arc-based and a path-based formulation. They proposed exact and heuristic algorithms including Lagrangian relaxation and greedy heuristic algorithm to solve the path-based problem.

In real world, however, uncertainties occur related to the amount of commodity or transportation cost. Yang et al. [25] analyzed the railway freight transportation planning problem under the mixed uncertain environment of randomness and fuzziness. It was solved by a hybrid genetic algorithm whereas the aim was to determine the optimal path, the amount of commodity flow on each path, and the service frequency for each origin-destination pair in a given network such that the total relevant cost was minimized [25].

Recently, Yaghini et al. [26] provided a train formation plan (TFP) which determined routing and frequency of trains and assigned the demands to trains. An improved local branching algorithm was proposed to solve the MIP model and was applied to real-world problems.

2.2.3. Compound Routing and Scheduling Models

Compound models attempt to integrate scheduling models into routing models of freight transportation. Therefore, service reliability and costs can be improved.

While Gorman [27] used a combination of genetic algorithm (GA) and tabu search (TS) algorithm to solve the joint train-scheduling and demand-flow problem, Newman and Yano [28] proposed a heuristic solution method based on Lagrangian relaxation and benders decomposition for the underlying integer programing model. They proposed a model which determined day-of-week schedules for direct and indirect trains and allocated containers to trains for the rail portion of the intermodal trip to minimize operating costs while meeting on-time delivery requirements. Intermodal rail operations differ in several aspects from conventional rail operations. First, intermodal networks have few widely spaced terminals, because of the high cost of container handling equipment, where economies of scale can be realized for container handling and in train movements from terminal to terminal. Second, a container makes only few stops or is transferred between trains a few times on its journey, because of the distances between intermodal terminals. As a result, blocks do not have to be considered. Finally, shorter delivery times are considered for intermodal freight with a greater need to schedule trains to achieve the desired levels of customer service. In comparison to conventional rail operations, freight has to wait while enough railcars accumulate to form a block. Intermodal rail operations indicate a reduction of the number of decisions required, but increase the need for train scheduling and routing decisions. The differences between Gorman's model and Newman's is that Gorman considered additionally linking constraints to enforce yard and line capacity in an aggregate way and focused on multiple routes between a single origin-destination pair. After the implementation of a tabu search enhanced genetic algorithm, Gorman applied his approach to a problem with multiple interdependent origins and destinations with significant improvements in cost and customer service [28]. To summarize, Newman and Yano [28] considered a problem where train schedules and container routes for each day over a short horizon has to be determined to achieve on-time delivery at minimum total cost. The objective is to minimize fixed charge per train, a variable transportation cost per container, handling costs per container dependent upon the location, and inventory holding costs for containers at any terminal to be held before their arrival at the destination.

2.2. Freight Car Models

The service of a freight car starts when a customer orders empty cars from a nearby yard and compatible car types are selected and moved to a loading point. Once loaded, they are taken to classification yards where they are assigned to blocks and put onto outbound trains. When a car reaches its final destination, it is unloaded and used for a new shipment. Very often, however, empty cars have to be repositioned to a different location where a request must be fulfilled. Because demand for transportation is not known in advance, the railroad must forecast future demands and manage its fleet accordingly [5].

Several models for fleet management and distribution of empty freight cars have been proposed in the literature. Recent contributions about this topic were provided by Joborn et al. [29] and Narisetty et al. [30]. Joborn et al. [29] analyzed the economy-of-scale effect for the distribution cost of empty freight cars in a scheduled railway system over a given train timetable. In addition to the cost proportional to the number of cars moved, there is a cost related to car-handling operations at yards, which depends on the number of car groups that are handled. Thus, if fewer and larger groups of cars are built, the total distribution cost could be decreased. The model was formulated as a capacitated, multi-commodity network flow optimization problem with fixed costs associated with arcs and included a time dimension by providing a model with multiple time periods. To find a good-quality solution in reasonable computing times for the underlying complex model, the TS algorithm was applied to solve the problem.

An optimization model for real-life decision support system was proposed by Narisetty et al. [30]. They developed a model for assigning empty freight cars based on customer demand with the objective to reduce overall transportation costs and to improve delivery times and customer satisfaction. A traditional repositioning strategy usually consists of returning each unloaded freight car to its original loading point [5]. This results in higher transportation costs due to the fact that most requesting customers are distant from the location of cars. In addition, the supply of available cars is often much smaller than the corresponding demand. Finally, car assignments are difficult because some business standards have to be met to provide customers with service at minimum operating cost. Prior to this research, car distribution managers had to decide about assigning cars to customers [30]. To ease their decision-making process, the concept of carpooling has been introduced where railroads and shippers agreed, that unloaded cars can be sent to any of a given set of loading points [5]. Because of the complexity of the problem, it was difficult to obtain high quality solutions manually. This resulted in higher costs and lower customer service level. Therefore an automated decision support system was provided by the rail company [30].

3. Scheduling Problems

In contrast to routing models discussed in chapter 2, scheduling models deal with the temporal dimension of railroad operations. Coordination of available resources is necessary due to the large number of trains provided in a rail network [5].

The aim of this chapter is to provide a short outlook of different approaches for railway scheduling problems according to timetabling and real time traffic management. The TTP considers the process of constructing a robust and optimized schedule for a number of trains on a certain part of the railway network, while in real time the already existing schedule has to be modified due to timetable disturbances.

However, this chapter intends to review some of the recent contributions dealing with optimization models for train scheduling problems for both freight and passenger trains. Section 3.1. deals with line planning models, while section 3.2. is referring to train timetabling problems followed by dispatching problems in section 3.3. The final part is focusing on locomotive assignment problems.

3.1. Line Planning Models

The LPP, faced by train operators, is a strategic planning problem, since the line is the basis of railway services. The basic input of the LPP is the railway infrastructure and the expected passenger travel demand represented by a given origin-destination matrix. Furthermore, in practice travel demand is not constant or symmetric: there exist peak hours and off-peak hours, where in case of peak hours the travel demand has a dominating direction. However, the line system (set of all lines) is symmetric in practice. This means, for each pair of stations s_1 and s_2, the number of direct trains is equal to the number of direct trains from s_2 to s_1. In addition, peak hours are interesting for train operators to manage, since they are the bottlenecks in a railway system. Therefore, capacities of trains should be able to handle peak flows, usually occurring in the morning and afternoon. Thus, if $d^m_{s1,s2}$ and $d^m_{s2,s1}$ denote the passenger travel demand per hour between station s_1 and s_2 in the morning, and $d^a_{s1,s2}$ and $d^a_{s1,s2}$ denote the demand during the afternoon peak, then the lines and the corresponding capacities should be such that passengers with travel demand

$$\boldsymbol{d_{s1,s2} = d_{s2,s1} = max\left\{d^m_{s1,s2}, d^m_{s2,s1}, d^a_{s1,s2}, d^a_{s2,s1}\right\}}$$

can be transported for each pair of stations and during the peak hours. Further assumptions for the LPP are that each passenger uses a pre-specified path through the network. This is easy to estimate as each path is specified by the ticket regulation. Each passenger is supposed to travel along the shortest distance path from their origin to their destination. Next, passenger flows are usually assumed to be split per line type. As a consequence different line types can be considered [6]. Examples for line types are: (i) Intercity (IC) trains for longer distances and larger stations, (ii) the interregional (IR) trains for intermediate distances, and aggloregional (AR) trains for short distances and smaller stations [31]. Finally, lines are assumed to be single track lines, where each line is defined to be a path in a rail network [6].

The LPP for a single line type can be described as follows [6]:

$$\max \omega_1 \sum_{l \in L} \sum_{p \in P} d_{lp} - \omega_2 \sum_{i \in I} k_i x_i \qquad (1)$$

subject to

$$\sum_{i \in I: l_i = 1} x_i \leq 1 \qquad \forall l \in L \qquad (2)$$

$$\sum_{i \in I: e \in E_{l_i}} f_i c_i x_i \geq d_e \qquad \forall e \in E \qquad (3)$$

$$\sum_{p \in P: e \in E_p} d_{lp} \leq \sum_{i \in I: l_i = l} f_i c_i x_i \qquad \forall l \in L, e \in E_l \qquad (4)$$

$$\sum_{l \in L: E_p \in E_l} d_{lp} \leq d_p \qquad \forall p \in P \qquad (5)$$

$$x_i \in \{0,1\} \qquad \forall i \in I \qquad (6)$$

$$d_{lp} \geq 0 \qquad \forall\, l \in L, p \in P \qquad (7)$$

The underlying rail network of the LPP is represented by an undirected graph $G = (V, E)$, where nodes $v \in V$ denote the stations and the edges $e \in E$ denote the tracks between the stations. The travel demand is defined by a symmetric origin-destination matrix. The set P denotes the pairs of stations with a positive demand. The pair is denoted by $p = (p_1, p_2) \in P$, where d_p is the number of passengers travelling between the stations p_1 and p_2. In addition, for each $p \in P$, E_p is the set of edges on the shortest path between the stations p_1 and p_2. The total number of passengers that travels along the edge e is denoted by $d_e = \sum_{p: e \in E_p} d_p$. Next, the set of potential lines L is assumed to be given a priori, where the set of edges of a line $l \in L$ is given by E_l. The objective is to choose a set of appropriate lines from the given set of potential lines L. Furthermore, certain capacities per train $c \in C$ and frequency of a line $f \in F$ have to be selected. The capacity of a line equals the capacity per train multiplied with the frequency of a line, i.e. $c_i f_i$. The index $i \in I$ denotes a feasible combination of a line $l \in L$, a frequency $f \in F$, and a capacity $c \in C$. The operational cost associated with $i \in I$ is defined by k_i. These costs are mainly determined by the variable rolling stock and crew cost. Decision variables are defined as x_i and d_{lp}, whereas $x_i = 1$, if line l_i is to be operated with frequency f_i and capacity c_i. The second decision variable d_{lp} denotes the number of direct passengers that travel on line l between the pair of station p_1 and p_2. Hence, the objective function (1) wants to obtain a balance between the two main conflicting objectives: (i) maximize the number of direct passengers while (ii) minimizing the operational costs. The parameters ω_1 and ω_2 are weights defining the importance of (i) and (ii). Constraint (2) denotes that at most one line $l \in L$ with a certain frequency and capacity per train has to be selected. Constraint (3) specifies that the provided capacity $f_i c_i$ on each track $e \in E$ has to be sufficient to meet passenger's travel demand d_e on track e. Next, constraint (4) indicates that for each line $l \in L$ and for each track $e \in E_l$, the total number of direct passengers that travel on line l should not exceed that line's provided capacity $f_i c_i$. Finally, constraint (5) describes that the total number of direct passengers between a pair of station p_1 and p_2 cannot exceed the total travel demand between these stations [6].

Early research on this topic was done by Bussieck et al. [32, 33], who formulated a linear MIP for the line optimization problem (LOP). The objective was to find an optimal line system with a maximum number of direct passengers. Whereas the frequency was variable for each line, the capacity was assumed to be the same for all trains. In order to reduce the size of the problem, they aggregated the number of decision variables. This required the capacity constraints to be relaxed. The underlying MIP was then solved by applying the CPLEX 3.0 LP solver. Adding suitable cutting planes, they succeeded to solve the MIP for all instances provided by the German and Dutch railway companies in less than 6 minutes. A solution of the LOP led to lower and upper bounds of the problem. For all instances the gap between those bounds was less than 3.2% [6, 32]. In contrast to Bussieck et al. [32], Claessens et al. [34] focused on the cost minimizing line planning problem (CLPP) for passenger trains and considered the allocation of passenger flows on tracks as given. They formulated a non-linear integer programming model with binary decision variables for the selection of lines and further decision variables for the frequencies and train lengths. As the nonlinearity of this problem results in computational difficulties, they switched to an integer linear programming (ILP) approach and solved it with a branch and bound procedure [6]. The ILP was solved by the CPLEX 3.0 MIP solver. The initial solution of the ILP had 5629 variables, 194 constraints, about 110.000 nonzero coefficients and a lower bound of about 6920. Before starting the branch and bound method several techniques such as reducing the number of constraints or decision variables were used to reduce the size of the problem. At the end, improvement was obtained by adjusting the coefficients of the ILP model and identifying superfluous constraints and variables. The problem was reduced to 1547 variables, 139 constraints, and about 18.000 nonzero coefficients. The lower bound, however, increased to 7577 [34]. Further research on the CLPP was done by Goossens et al. [31] who provided a similar approach compared to Claessens et al. [34]. Several preprocessing techniques with several classes of valid inequalities were used to improve the lower bounds. In addition, a branch and cut approach was used to solve the CLPP. Computational results were obtained by applying real life instances based on the Nederland's railway system. These results showed that the methods used, performed very well on practical instances and was significantly better than the solution obtained by the ILP solver CPLEX 6.6.1. Further research of the authors provided an IP model for solving the multi-type line planning problem (MLPP), simultaneously [35]. In order to reduce the decision variables, the origin-destination flows of passengers were combined and disaggregated [6]. Using three real life instances, they have compared the computational results for both multi-type and single-type line formulations. The latter one outperformed the first one in all chosen instances [35].

Finally, recent contributions to the LPP dealt with models where the objective was to minimize the number of transfers from one train to another. Scholl [36] developed a so called „Switch-and-Ride" network and solved it by using Lagrangian relaxation and several heuristic methods for generating feasible solutions. This problem is more complex than maximizing a number of direct passengers as for each origin-destination pair the associated path through the network has to be followed [6]. However, compared to a robust and cost-optimal line system where lines are short and passengers are forced to transfer often, this model tries to maximize the service towards passengers. Nevertheless, an overview about the models mentioned above is shown in table 2.

Line Planning					
Authors	**Problem type**	**Planning Horizon**	**Objective Function**	**Model Structure**	**Solution approach**
Bussieck et al. (1996)	Line planning	Strategic	max. number of direct passengers	Linear MIP	LP relaxation
Claessens et al. (1998)	Line planning	Strategic	min. cost line system	Nonlinear IP	Branch and Bound
Goossens et al. (2004)	Line planning	Strategic	min. cost line system	ILP	Branch and Cut
Goossens et al. (2006)	multi-type line planning	Strategic	min. cost line system	ILP	Branch and Cut
Scholl (2005)	Line planning	Strategic	min. the number of transfers	binary LP	Heuristics
					Dantzig-Wolf Decomposition
					Branch and Bound

Table 2. Line planning models

3.2. Train Timetabling Models

Train scheduling problems intend to obtain a timetable for a set of trains, e.g. intercity, local, and freight trains, without violating track capacities and satisfying some operational constraints [37]. Several variations of the problem can be considered and distinguished based on the complexity of the underlying rail network. As it was already mentioned in chapter 1 one may distinguish between non-cyclic and cyclic timetabling problems. Section 3.2.1. is referring to non-cyclic TTP, whereas section 3.2.2. is going to review cyclic TTP.

3.2.1. Non-cyclic timetabling

The non-cyclic timetabling problem is mainly relevant for heavy-traffic, long-distance corridors with one-way track linking two major stations and a number of intermediate stations in between. Oliveira and Smith [38] described the TTP as a job-shop scheduling problem for single-track railway systems, where trains were considered as jobs to be scheduled on lines. Caprara et al. [39] proposed a different ILP model based on a directed multi-graph representation of the TTP with line capacity and operational constraints. The basic ILP version of a non-cyclic TTP for a single line system can be formulated as follows [6, 39]:

$$\max \sum_{t \in T} \sum_{a \in A^t} p_a \, x_a \tag{8}$$

subject to

$$\sum_{a \in \delta_t^+(\sigma)} x_a \leq 1 \qquad \forall\, t \in T \tag{9}$$

$$\sum_{a \epsilon \delta_t^-(v)} x_a = \sum_{a \epsilon \delta_t^+(v)} x_a \qquad \forall\, t \in T, v \in V \setminus \{\sigma, \tau\} \tag{10}$$

$$\sum_{a \in C} x_a \leq 1 \qquad \forall c \in C \tag{11}$$

$$x_a \in \{0, 1\} \qquad \forall\, a \in A \tag{12}$$

Let S represent the set of station, ordered in a sequence in which they appear along the line for the running direction [6]. Times are discretized and expressed as integers from 1 to q. The length of the given period is denoted by q [39]. A timetable of a single, one-way line system consists of the departure time of its first station $f_t \in S$ and the arrival time of its last station $l_t \in S$, and the arrival and departure times for their intermediate stations $f_t + 1, \ldots l_t - 1$ for each train $t \in T$. Each train $t \in T$ is assigned to an ideal timetable with departure time d_{ts} for each station $s \in \{f_t, \ldots, l_t - 1\}$ and arrival time a_{ts} for each station $s \in \{f_t + 1, \ldots, l_t\}$. The ideal timetable is a desirable timetable which may be modified in order to satisfy the line capacity constraints. To be more precisely, a train operator is allowed to slow down and/or increase the stopping time interval of each train at the stations with respect to their ideal timetable. In addition, one can modify the departure time of each train from its first station or cancel the train. However, the final solution is called the actual timetable. The line capacity constraints denote that overtaking between trains is only allowed within the station. Therefore, a train is allowed to stop by at any intermediate station to overtake another train, although the ideal timetable does not include a stop in that station [6]. Furthermore, for each station $i \in S$, there are lower bounds a_i and d_i on the time interval between two consecutive arrivals and departures. As the speed of a train on a line segment is assumed to be constant, the lower bound on the departure time implicitly imposes a time interval of at least $max\{d_i, a_{i+1}\}$ between two consecutive trains in the line segment from station i to i+1. In addition to line capacity constraints, explicit time window constraints may be considered, requiring that train j arrives in a station not later than a given time, or departs from the station not earlier than a given time [39]. However, the objective is to maximize the sum of the profits of the scheduled trains. The profit for train $t \in T$ depends on the ideal profit π_t, shift v_t, and on stretch μ_t. The shift v_t is defined as the absolute difference between the departure times from station f_t in the actual and ideal timetables. The stretch μ_t denotes the difference between the total travel times in the actual and ideal timetables. Given the nonnegative parameter γ_t, the function penalizing the train stretch is assumed to be linear. The profit for each train and line type is defined as follows [6]:

$$\boldsymbol{\pi_t - \Phi(v_t) - \gamma_t \mu_t}, \quad (13)$$

where $\Phi(v_t)$ is a user defined non-decreasing function penalizing the train shift. In case of $v_t = 0$, the function $\Phi(v_t)$ equals 0. In case that the profit of train t is non-positive, it is better not to schedule the train [6, 39].

Caprara et al. [39, 40] introduced a maximum profit set paths in a directed acyclic multi-graph $G = (V, A)$, where nodes $v \epsilon V$ correspond to arrivals and departures from the stations along the line and arcs $a \in A$ correspond to train stops within the station as well to train trips from a station to the next one. The objective function (8) of the ILP formulation above is defined as the sum of profits p_a of the arcs associated with each path in the solution. For each train $t \in T$ and each arc $a \in A^t$, the binary variable x_a = 1, if the path in the solution associated with train t contains arc a. The set of arcs A is split into subsets A^t associated with each train $t \in T$. The terms $\delta_t^+(v)$ and $\delta_t^-(v)$ denote the sets of arcs A^t leaving and entering node v. To conclude the notations C indicates a subset of pairwise incompatible arcs. Constraint (9) describes that at most one arc associated with a train is selected among those leaving the starting node σ, while constraint (10) indicates equality on the number of selected arcs associated with a train entering and leaving each arrival and departure node. Finally, constraint (11) forbids the simultaneous selection of incompatible arcs [6]. However, the model was then solved by Caprara et al. [39, 40] using Lagrangian relaxation to derive bounds on the optimal solution as well as to

apply different heuristic procedures [6]. Furthermore, the algorithm was implemented in C and tested on a set of real-world instances [39].
A similar problem to that considered by Caprara et al. [39, 40] was proposed earlier by Brännlund et al. [37]. They discretized the time into one-minute time slots and divided the track line into blocks. They described an ILP model with track capacity constraints indicating that two trains cannot be in the same block in the same time slot. They proposed a binary decision variable x_{sbt} that equals 1, if train t occupies block b at time slot s, and 0 otherwise. However, this model was suited for larger instances such as those occurring for European corridors [39].

3.2.2. Cyclic timetabling

In many European countries, most passenger railway timetables are cyclic, which means that a subset of trains, also called lines, has the same routes and the same stop stations in a given manner. The only difference between these subsets is their arrival and departure times [6]. Once the line system has been designed, a timetable for its train lines can be constructed [10].
The first ones who developed a model for the cyclic TTP were Serafini and Ukovic [41], who presented the Periodic Event Scheduling Problem (PESP). A periodic event e is a countable infinite set of events E which have to be scheduled under cyclic time window constraints [42]. A timetable consists of a number of processes such as travelling between two stations or dwelling at a station. An event of a timetable is defined as the start and end times of these processes [6]. The PESP is defined as follows [6]: for each event $e \in E$, the decision variable v_e represents the time at which the event has to be scheduled. All constraints that have to be specified by these decision variables are denoted by a lower and upper bound (l_{ef}, u_{ef}) for the process time. For event e and f, the constraint can be formulated as follows: $l_{ef} \leq \left(v_e - v_f\right) mod\ \tau \leq u_{ef}$. Since the modulo operator which denotes the cyclicity of the timetable is hard to solve in optimization methods, a binary decision variable q_{ef} is introduced instead of the operator. This binary decision variable makes it difficult to solve the PESP

by the standard branch and bound method. Due to the large coefficient τ the LP relaxation on the PESP is quite weak.

Lindner [43], Kroon and Peeters [42], Lindner and Zimmermann [44] and Liebchen [45] proposed a cyclic train timetabling model formulated as a PESP based on Serafini and Ukovic [41]. To cope with the weak LP relaxation, they introduced an ILP model by removing the binary decision variables and introducing a larger and more complex set of constraints. By using branch and bound, the resulting LP relaxations are much stronger leading to faster computation times [46].

Furthermore, Kroon and Peeters [42] provided a PESP model including variable trip times. They were assuming three different timetable constraints: (i) trip time, (ii) safety, and (iii) commercial constraints. The trip time constraints relate the departure and arrival times of trains to their subsequent stations, whereas safety constraints ensure a certain time buffer to avoid conflicting train movements. Finally, the commercial constraints are used to satisfy customers or to be cost-effective [42].

Kroon et al. [47] provided a stochastic optimization model of the PESP. Real time railway operations are subject to stochastic disturbances resulting into train delays. As the underlying train timetable is a deterministic plan, it is important to consider disturbances in the train timetabling design as far as possible. To cope with such delays, buffer times can be included into travel and dwell times of trains on a number of consecutive trips along the same line. A trip is defined as a movement of a train from one station to another. In summary, Kroon et al. [47] considered at first a model which generated a timetable for a single train that operated under stochastic external disturbances and then created an extended model to improve the timetable with respect to the average delay by re-allocating buffer times and time supplements.

Cacchiani et al. [46] proposed heuristic and exact algorithms for the periodic and non-periodic TTP on a corridor. They formulated an ILP model that is a variation of the ILP model proposed by [39]. In contrast to previous approaches [39, 40], where variables were associated with departure and arrival times of a train at a specific station and time, Cacchiani et al. [46] proposed a model in which each variable corresponds to a train timetable. LP relaxation is used to solve both heuristic and exact branch and bound algorithm. The algorithm proposed were implemented in C and applied to real world instances. Compared to [39, 40], [46] showed that an equivalent LP relaxation in which the number of variables is exponentially large can be solved within a significantly smaller computing time, yielding notably better bounds.

As stated earlier real time railway operations are subject to stochastic disturbances. Thus, it is important to develop robust timetabling solutions in which a tradeoff between track capacity utilization and timetable robustness has to be provided. In contrast to Kroon et al. [47], who developed a stochastic programming approach for the cyclic TTP, Cacchiani et al. [48] provided a Lagrangian heuristic solution method for a non-periodic TTP on a corridor. Based on a time-space graph representation of the non-robust nominal timetabling problem, Cacchiani et al. [48] added two simple features to their solution approach. First, the model formulation was modified by introducing artificial parameters to control the timetable robustness. Second, the weight of the control parameters is changed dynamically during Lagrangian optimization to produce sub-problems with increased robustness. During this process a set of different heuristic solutions can be generated with different trade-offs between robustness and efficiency.

Fischetti et al. [49] studied four different methods to improve robustness of a given non-cyclic TTP solution by combining linear programming with stochastic programming and robust optimization techniques. The underlying nominal, non-robust timetable was formulated as a PESP modified for the non-periodic case.

For interested readers, further solution approaches about robust train timetabling problems are presented by Cacchinani and Toth [50] in 2012.

Finally, most recently Liu and Kozan [51], and Caimi et al. [52] proposed two different approaches to train scheduling problems. Whereas Caimi et al. [52] generated a conflict-free train schedule based on a graph, where the train path was represented by vertices and edges of pairwise conflicts Liu and Kozan [51] presented a no-wait blocking parallel-machine job-shop scheduling model for the train scheduling problem in a single-line rail network where prioritized and non-prioritized trains are traversed simultaneously. A modification of the no-wait condition is applied to non-prioritized trains, such as freight trains, which are allowed to enter the next section immediately if possible or to remain in a section until the next section becomes available [51].

3.3. Train Dispatching Models

For a given timetable, the train dispatching problem denotes the actual movements of trains providing real time information on train position and velocity [5]. In fact, there are extensive literature surveys on decision support tools for the timetable design problem. Cordeau et al. [5] proposed a classification of train dispatching support systems into fixed and variable velocity models. It is obvious, that velocity is an important feature of train dispatching models to minimize train delays or deviations from the planned schedule. However, models with fixed velocity often assume that trains operate at maximum speed whenever possible. To proof the feasibility of these models, a velocity profile for each train is then determined. In contrast, variable velocity models update speed profiles frequently during operations not only to minimize delays, but also to minimize fuel consumption [5].

In 1999, Sahin [53] developed a heuristic algorithm for rescheduling trains of a single-track railway system by modifying the existing train schedule and reducing the number of inter-train conflicting situations. The model itself was defined as a job shop scheduling problem where the objective was to minimize the sum of running times or delays from arrival times of trains.

In the same year, Adenso-Díaz et al. [54] proposed a MIP to maximize the number of passengers transported and developed a backtracking heuristic algorithm to solve train conflicts. A conflict resolution system of the underlying algorithm was then applied to help train dispatchers at the traffic control center of the Spanish national railway company.

The general railway traffic management problem is often formulated as a job shop scheduling problem with additional side constraints [10]. Recent contributions in the literature were proposed by Flamini and Pacciarelli [55]. They considered a real time scheduling problem for all circulating trains plus a given number of incoming trains of a metro rail terminus. The scheduling problem was formulated as a bi-criteria job shop scheduling problem with blocking constraints in which earliness/tardiness and time headways have to be optimized.

Törnquist and Persson [56] introduced a model for the dispatching problem of the n-tracked railway system with several merging and crossing points. The problem was formulated as a linear MIP model where the objective was to minimize the total final delay of the traffic and the total cost associated with delays when trains arrive at their final destination.

Most of the recent contributions about train dispatching problems were made by D'Ariano et al. [10, 57, 58, 59]. D'Ariano and Pranzo [58] studied short-term consequences of train delays and disturbances by applying a real time train dispatching system called ROMA (Railway traffic Optimization by Means of Alternative graphs) for minimizing delay and disturbance propagation. The railway traffic is usually regulated by traffic controllers by sequencing train movements and setting routes to limit train delays [57]. It is forecasted over a given time horizon usually defined in hours. Its objective is to minimize total train delays while satisfying some operational constraints. Total delay was defined as the difference between the calculated train arrival time and scheduled time of a train at a point in the network. First, primary delay is the result of failures and disturbances and cannot be recovered by train rescheduling but for train traveling at maximum speed. Second, consecutive delay may be caused by train interactions of a given time horizon. A conflict was defined as trains claim the same section of a track simultaneously and one of them has to change its speed profile. Hence, a solution is feasible if there are no conflicts between running trains exists [58]. D´Ariano et al. [57] developed a branch and bound algorithm for sequencing train movements, while a local search algorithm was applied for rerouting processes. Different types of disturbances were analyzed such as train delays and blocked tracks. The model was applied to real world instances and compared with common dispatching systems used in practice yielding good solutions to improve punctuality.

3.4. Locomotive Assignment Models

A related scheduling problem that considers the use of rail equipment is the basic LPP. Given a planned train schedule, the problem of assigning locomotives and cars to trains is a complex task for most railways [12]. For the LPP, a set of locomotives has to be assigned to preplanned scheduled trains by satisfying requirements expressed as a number of locomotives or as a measure of the power needed to pull the engines from its origin to its destination [5, 11]. The objective is usually to minimize the required fleet size at a strategic level; whereas one wants to minimize costs occurred by light travel or deadheading at the tactical and operational levels. Light travel or deadheading occurs when engines have to reposition themselves between two successive trips [5]. Deadheading plays an important role at the planning level, enabling locomotives to be moved by an active engine from a location with a surplus to locations with short supply. In contrast, light travel is different to deadheading as it is not limited by the train schedule and thus much faster. In that case, one locomotive from a set of engines pulls the others from one place to another. However, light travel is more costly than deadheading because an additional crew is required to be paid off and the moves are not generating any revenues as there are no cars assigned [60, 61].

However, in 1999, Ziarati et al. [62] formulated a time-space network approach for a locomotive scheduling problem with a heterogeneous fleet where engines were able to perform light travel and deadheading and where maintenance requirements were also considered. Train schedule was noncyclic with given fixed starting and ending times. The objective was to provide enough horsepower by multiple engines to pull a train, whereas the problem was presented as a MIP model and solved by problem specific cutting planes and via Dantzig-Wolfe decomposition [16].

Another publication of Ziarati et al. [63] proposed a model with a multi-commodity flow structure for a cyclic heterogeneous locomotive scheduling problem and it was solved by a heuristic genetic algorithm [16].

Recent research on the problem of assigning engines to trains was considered by Ahuja et al. [60]. They formulated the LPP as a MIP problem and solved it by using problem decomposition, integer programming, and very large-scale neighborhood search (VLSN) [11, 60]. An extended approach was provided by Vaidyanathan et al. [61] by adding new constraints and by developing additional formulations necessary to facilitate the application of the LPP models to practice.

Two kinds of locomotive planning models have been proposed in previous surveys: (i) Single locomotive models, where only one type of engine is available for assignment and (ii) multiple locomotive models which may require more than one engine for each train [5]. The problem of these underlying models has a multi-commodity network flow structure with linking constraints. Difficulties arise for the multiple locomotive problems when multiple engine types are available and each train may require more than one locomotive to satisfy its requirements [5]. Multiple locomotive problems were proposed by Ziarati et al. [62], Ahuja et al. [60] and Vaidyanathan et al. [61], recently. Ahuja et al. [60] considered consist busting and consistency to their proposed models. A set of locomotives of an inbound train, that are separated to reassign to two or more outbound trains, are called busted. In contrast, a solution is consistent if a train maintains the same locomotive assignment each day it runs.

Next, models with parallel assignment of locomotives and cars to passenger trains were taken into considerations in recent years. In comparison with freight transportation, where the problem of assigning cars and locomotives to trains is treated separately, in passenger transportation, however, both cars and locomotives can be assigned simultaneously. Because the same set of trains are used every week with a similar number of cars a cyclic solution is proposed to generate significant savings for most railways. In addition, the smaller size of the problem makes it possible to treat both, cars and locomotives assignment, simultaneously [12]. However, given a periodic train schedule and a fleet of several types of locomotives and cars the assignment problem consists of finding a set of minimum cost equipment cycles that cover a list of scheduled trains while satisfying a number of operational constraints such as those generated by maintenance requirements, car switching and substitution possibilities [64].

Cordeau et al. [12, 64, 65] proposed several models for the simultaneous locomotive and car assignment problem. Based on a multi-commodity network flow model with linking constraints the first approach was trying to optimize the model with a heuristic branch and bound method in which the linear relaxations are solved by column generation [12, 64]. The next approach proposed an exact algorithm with a solution method based on Benders decomposition [12, 65]. Further research recommended a model that facilitates some constraints such as maintenance, car switching penalties, and substitution possibilities due to the fact that computational experiments were applied to real-life data from a railway [12]. The large integer programming model was solved by a branch and bound method, followed by Benders decomposition in which the LP relaxations of the basic model were optimized either by a simple algorithm or by Dantzig-Wolfe decomposition. At last, some algorithms were proposed to improve the solution, such as the generation of Pareto-optimal cuts [12].

More recently, further research on this topic was done by Fügenschuh et al. [16]. They dealt with a strategic locomotive scheduling problem in freight transportation. The model was based on a multi-commodity minimum cost flow structure and was formulated as an ILP. Improvements and solutions were obtained by using a randomized greedy heuristic in combination with commercial ILP solvers [16].

In addition to the locomotive assignment problem, the locomotive routing problem (LRP) can be solved as an independent problem for each locomotive type [11]. This routing problem was considered by Vaidyanathan et al. [11] who formulated an integer programming problem on a space-time network where the objective was to route locomotives in cycles with some fueling and servicing constraints.

4. Passenger Railway Optimization

Passenger railway systems are rich of combinatorial optimization problems. Well-known operational planning problems are line planning, timetabling, traffic planning (route and platform assignment), rolling stock circulation, shunting and crew planning (Figure 3). To complete the survey, some areas of passenger railway optimization problems should be treated in this chapter. Line planning and train timetabling were already considered in previous sections. In the first part of this chapter, this work is going to give a short outlook of train platforming and rolling stock circulation including train unit shunting and maintenance routing, whereas the last part is going to give a short insight about crew planning problems.

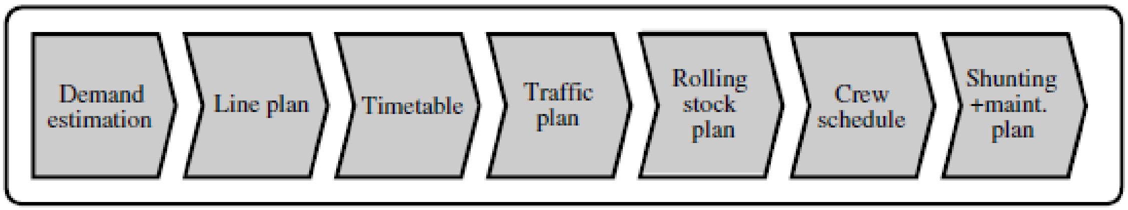

Figure 3. Different stages of the planning problem in passenger rail transportation **[35]**

4.1. Train platforming

Following the train timetabling problem discussed in section 3.2, the TPP is a routing problem which consists of assigning arriving trains to the available tracks in a railway station. The objective is to find a path from the point a train enters the station to the point where it leaves the station. The point at which a train may usually pass or stop to collect passengers and/or goods within a station is called a platform. In addition, these points correspond to directions of a travel. While this problem is easy to solve for small stations with a few platforms and alternative routes to path, it becomes extremely difficult of applying larger and thus complex railway station topologies [6, 66, 67].

First, the easiest versions of the TPP considered are those from De Luca Cardillo and Mione [68] and Billionnet [69] who formulated the TPP as a k l-list т coloring problem where the scheduled timetable for each train cannot be changed and the path used to route are determined by the choice of the platform. Because of the underlying vertex coloring graph problem the routes to be avoided was represented by a list of incompatible train platform pairs [6].

Another version of the problem, where arrival and departure times and routes were not fixed, was developed by Zwaneveld et al. [67]. They formulated an ILP model and a weighted node packing problem (WNPP) to solve the TPP.

In comparison to the two versions above, Carey and Carville [70] considered a train platforming and scheduling problem for busy and complex stations in that arrival and departure times can be changed, but routes are determined by the assignment of a train to a platform.

Finally, most recently Caprara et al. [66] formulated the TPP as a MIP model whose linear programming relaxation is used to derive a heuristic algorithm. A quadratic objective function was provided and linearized by introducing additional binary variables imposing linear constraints.

The general problem of the TPP was defined as follows: given a set of platforms and a set of trains to be routed there are a collection of possible patterns for each train which corresponds to a feasible route of a train within the station. A pattern has to be assigned for each train that will be repeated every day of the time horizon. In addition, operational constraints have to be considered for the train platforming problem. First, one may forbid the assignment of patterns to trains if this indicates an occupation of the same platform by two or more trains. In addition, it is also forbidden using arrival/departure paths that intersect at the same time which is represented by a pattern-incompatibility graph with one node for each train-pattern pair [66].

4.2. Rolling stock circulation

The RSCP has received considerable attention in the literature. Many surveys have been provided in recent years such as that of Caprara et al. [6] and Huisman et al. [7].

Railway rolling stock is the most significant operational cost component for passenger train operators since the acquisition of rolling stock has been expensive and a long-term investment which includes costs of maintenance and power supply such as electricity or diesel. Other important concerns about rolling stock management are passenger service and robustness of the circulation. Coupling and uncoupling operations arise by adding or removing rolling stock equipment to meet passengers' seat demand. These operations are usually penalized with switching costs. The removed equipment can be reassigned to later trains departing from the same station. However, two types of equipment can be distinguished: (i) locomotives and train carriages or (ii) train units. A train unit consists of a number of carriages in a fixed composition, and can move in both directions without being pulled by a locomotive. A scheduled train can be composed of several train units. In case where locomotives and carriages are considered, it is important to determine the number and types of locomotives and carriages in order to provide sufficient pulling capacity. Furthermore, two types of networks can be distinguished as well. A sparse network consists of long distances, thus longer travel times and lower frequencies of trains. In contrast, a dense network is characterized by short distances and thus higher frequencies of trains. Differences in network characteristics are important due to preventive maintenance and seat reservation. Seat reservation is not necessary for the dense network as the expected number of passengers is known. While rolling stock circulating in sparse networks need maintenance checks regularly provided by a maintenance center, those in sparse networks do not due to the fact that sufficient exchanging possibilities exist [6]. Two approaches for maintenance routing problems were provided by Maróti and Kroon [71, 72].

However, as mentioned above the main objective of the rolling stock circulating problem is to minimize the expected costs of the rolling stock and increases passenger service whereas the required capacities are influenced by requested service level and total demand. In addition to that one may distinguish between peak and off-peak demand whereas peak demands are usually not symmetric and thus require a balanced utilization rate of the rolling stock [6].

As section 3.4 described locomotive assignment problems, the remainder of this section is to discuss only a few examples of rolling stock management. Recent publications of rolling stock planning models were proposed by Abbink et al. [73] and Alfieri et al. [74]. Abbink et al. [73] proposed an integer programming model that allocates the available rolling stock capacity to different train lines in the morning rush hour.

In contrast, Alfieri et al. [74] presented an integer multi-commodity flow model to determine the optimal number of train units and their order in trains to be operated on a certain set of single lines. In addition to the tactical problem, the operational problem addressed the efficient circulation of a given set of train units along these lines. Three objective functions were defined: The first was to (i) minimize the shortages of seats, next (ii) the number of kilometers of train units or carriages and finally, (iii) the number of shunting movements which is a potential source for disturbances. In particular, the objectives were addressing to three different conflicting problems based on service, efficiency and robustness and were solved by using a solution approach based on column generation in which appropriate paths through the underlying transition graph was determined by using the shortest path algorithm.

Most recently, Cacchiani et al. [75] provided a two-stage optimization model that took robustness into account. Such disturbances include delays of trains or large disruptions where parts of a network are temporarily out of order. In this case the authors took recoverability measures into account that could deal with larger disruptions. The aim was to find a feasible recovered solution for the RSCP as soon as possible that fits with the recovered timetable. However, a tactical RSCP was considered and formulated as a MIP model where in the first stage a robust rolling stock circulation was generated and secondly, an optimal recovery plan was provided for a finite set of disturbances. The objective was to minimize the total nominal costs and to maximize the total recovery cost. The

problem was solved by the Benders decomposition method to obtain the optimal solutions for the linear programming relaxation. Then a heuristic method called Benders heuristic was used to obtain robust integer solutions [75].
To summarize, Cacchiani et al. [75] discussed the RSCP based on tactical planning to find the most effective allocation of train carriages and units, such that as many people can be transported as possible, in particular during peak times.
Besides the rolling stock circulating problem, there exist shunting processes for passenger railway transportation, the so called TUSP. This problem considers the assignment of arriving and departing train units as well as parking these units on a track of a shunting yard such that the total cost is minimized. A survey of shunting processes for freight transportation was provided by Cordeau et al. [5] and for passenger rail transportation by Caprara et al. [6].

4.3. Crew planning

The CPP is concerned with planning a work schedule for the crew needed to implement a given train timetable for train services. A train service includes both the actual passenger and freight travel and empty rolling stock movements. It has to be performed every day in a given time horizon and contains a sequence of trips which has to be serviced by the same crew. CPP usually consists of crew scheduling and crew rostering. Whereas crew scheduling considers short-term issues where a set of duties or pairings covers all the trips, crew rostering is showing a list of final duties to be attended. Moreover, a given crew depot, which is the starting and ending point of a work segment or duty, is located for each crew member. Besides the constraint that each crew member must return to its home depot within one day, an additional depot constraint indicates that the number of restricted duties is typically assigned to crew scheduling problems [6].
Although there are many papers concerning CPP in urban mass-transit systems, e.g. buses and airline, this work is referring to recent contributions of railway crew planning problems, especially under disturbances.

Whereas Abbink et al. [76] considered a crew scheduling problem at the Netherlands railroads with the objective to assign total workload among crew depots, Walker et al. [77] formulated an integer programming model that considered train timetabling and crew rostering under disturbances, simultaneously. As to be precise, the first part of the model suggested a timetable adjustment, followed by a set partitioning model for crew schedules.

A disruption recovery model was applied for real time problems with the objective function to minimize the deviation from the actual timetable and minimizing total cost occurred from the adjusted work schedule.

Most recently, another crew rescheduling problem that considers large disruptions of a rail network was proposed by Potthoff et al. [78]. They represented a column generation approach combined with a Lagrangian heuristic algorithm. As the number of duties was large, a core problem set of duties was defined. For the set of uncovered task neighborhood algorithm was applied to improve the solution of the core problem. However, the problem was defined as follows: for a given point in time of rescheduling, a replacement duty has to be determined for every unfinished point of duty. The proposed algorithm was then applied to real life data provided by the Netherlands railroad company and showed good solutions in a reasonable amount of time. In addition, it is worth mentioning, that the proposed approach was the cornerstone for the decision support system developed for train dispatching problems of the same company [78].

To summarize, in real life rail systems, disturbances result into recovery procedures according to timetabling, rolling stock scheduling, and crew scheduling (drivers and conductors) in a sequential way. Disruptions could be infrastructure malfunctioning, rolling stock breakdowns or accidents, which lead to delays or even cancellation of trains due to reduced capacity or complete blockage of a certain route [78].

Finally, a curfew planning problem for the maintenance of railway tracks was presented by Nemani et al. [79]. Curfew planning is a resource allocation problem to complete a given set of annual maintenance work on railway tracks. The working crew is called a subdivision. A model was formulated to develop a work schedule for each crew where the number of crew members under curfew was minimized. For these reasons a duty-generation model was developed and a column generation approach applied to improve the solution obtained. In addition, a decomposition-based heuristic was generated and implemented directly into real-world applications showing significant improvements in the number of disruptions [79].

5. Conclusion

The aim of this work was to provide a survey of recent contributions about freight and passenger transportation. Due to regulations on rail transportation the responsibilities on rail infrastructure and operating trains are separated. In many countries, the government is responsible for the rail infrastructure, but operating trains are carried out by independent companies. While an infrastructure manager is responsible for train planning and real time traffic control, a train operator is providing timetables, rolling stock and crew. Due to the complexity of railway systems, the planning process is often divided into sequential phases. Whereas passenger optimization models considered problems such as line planning, train timetabling, platforming, rolling stock circulation, shunting and crew scheduling, freight transportation dealt with issues concerning car blocking, train makeup, routing, and empty car distribution. The field of rail transportation has clearly received attention resulting in a diversity of literature contribution. One of the first surveys about rail transportation provided by Assad [3] suggests that rail optimization models were not widely used in practice and that problems were rather solved by simulation. In addition, the development of optimization models for train routing and scheduling was difficult to improve because of the large size and complexity of the underlying model. Due to the increase in more sophisticated mathematical techniques, constant refinements in development of the models were made that were able to deal with large rail optimization problems, both of practical and theoretical nature. In addition, a trend towards more efficient transportation support systems was observed taking robustness into account. Solution approaches, which can deal with larger disturbances of the rail environment in a considerable speed and time, have received attention. Thus, future research can be done to develop more integrated models of scheduling and routing problems of train and passenger transportation to provide robust solutions and problem solving methods that can handle disturbances of real time rail environment.

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