Simulation of Planning Strategies for Track Allocation at Marshalling Yards

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Abstract

Planning the operational procedures in a railway marshalling yard is a complex problem. When a train arrives at a marshalling yard, it is uncoupled on an arrival yard and then its cars are rolled to a classification yard. All cars should eventually be rolled to the classification track that has been assigned to the train they're supposed to depart with. However, there is normally not enough capacity to compound all trains at once. In Sweden, cars arriving before a track has been assigned to their train can be stored on separate tracks called mixing tracks. All cars on mixing tracks will be pulled back to the arrival yard, and then rolled to the classification yard again to allow for reclassification. Today all procedures are planned by experienced dispatchers, but there are no documented strategies or guidelines for efficient manual planning. The aim of this thesis is to examine operational planning strategies that could help dispatchers find a feasible marshalling schedule that minimizes unnecessary mixing. In order to achieve this goal, two different online planning strategies have been tested using deterministic and stochastic simulation. The Hallsberg marshalling yard was used as a case study, and was simulated for the time period between December 2010 and May 2011. The first tested strategy simply assigns tracks to trains on a first come-first served basis, while the second strategy uses time limits to determine when tracks should be assigned to departing trains. The online planning algorithms have been compared with an offline optimized track allocation. The results from both the deterministic and the stochastic simulation show that the optimized allocation is better than all online strategies and that the second strategy with a time limit of 32 hours is the best online method.

Keywords: Railways, Marshalling, Marshalling yards, Simulation.

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This dissertation is dedicated to my family especially my brother Saeid; this would not have been possible without his care and support. Finally I would like to express my gratitude to all my friends and classmates in Sweden for the two memorable years in Stockholm.

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The results of this thesis have also been presented in the 13th International Conference on Design and Operation in Railway Engineering, COMPRAIL in September 2012 and the corresponding paper will be published in the proceedings of the 16th International Conference on Computational Methods and Experimental Measurements in 2013.

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1 Introduction

Railway freight plays a key role in the transportation chain for many companies, and has benefits like, for instance, low cost and low environmental impact. To improve freight transportation services, minimizing delays in the railway network is absolutely necessary. Different factors can cause delays, however it is clear that marshalling is often a source of delay for freight in Sweden, Fakhraei Roudsari [1]. Therefore one effective and fruitful approach to decrease freight train delays would be to focus on optimizing marshalling yards procedures.

Planning the operational procedures in a railway marshalling yard is a complex problem. Currently all the classification procedures in Swedish marshalling yards are planned manually by highly experienced dispatchers. According to the author's investigations, there are no documented or systematic rules or guides to help operators with the planning tasks, and in this study it has therefore been investigated how different planning strategies would affect the marshalling.

The Hallsberg marshalling yard, which is the largest freight yard in the Nordic countries, and arguably the most important marshalling yard in Sweden, has heavy freight train traffic and therefore the potential power to impose delays to the railway network. Hence it is selected as a case study.

An optimization model to find the best operational solution for Hallsberg marshalling yard has already been developed at Swedish Institute of Computer Science (SICS). Although the model offers promising offline solutions to optimize the procedure, it is too complex to be used without a computer implementation. Further, the robustness of the model in case of any stochastic arrivals has not been evaluated yet; however this can be examined by the help of simulation methods. Moreover, due to the complexity of the model, chances to make it widely used by the operators are scarce. Another alternative would be developing some systematic online and straight forward rules for the operational procedures which are more user-friendly to be applied by dispatchers. This has been investigated in the current study.

In this study an *online solution* is defined as a simple and easy rule of thumb which can be applied for track allocations at the classification yard at the same instant a car arrives at the yard and it would not need initial analysis beforehand. On the contrary an *offline solution* for track allocation is the one which can offer a track allocation solution by applying some initial analysis and/or using mathematical models, before a car or train arrives at the yard; in this case some data regarding arrival and departure times of trains and their car assignments are required in advance before cars arrive at the yard.

1.1 Objective

The aim of this thesis is to apply discrete event simulation to evaluate different online planning strategies in marshalling yards with respect to efficiency and robustness, to increase the punctuality of freight transportation. Hallsberg marshalling yard is simulated in MATLAB as a case study. In this study, optimizing the operational procedures with respect to efficiency is defined as decreasing the number of unnecessary car movements. Further, a planning strategy is considered robust if it generates feasible allocations with no or few missed cars, both in the deterministic simulation and when stochastic delays are added to the arrival times.

1.2 Delimitations

The simulation is macroscopic and does not simulate the dynamic motion of cars or the interlocking system and switches, instead average times for tasks durations have been used. Moreover, in accordance with previous literature, it is assumed that any car arrangement within a train is acceptable, Bohlin *et al*. [2,3,4]. This thesis will cover a brief initial data analysis; however a deep focus on data analysis is not the aim of this thesis.

1.3 Thesis structure

The remainder of the thesis is organized as follows. First, a brief overview of the problem and previous works is outlined. Then the applied methods have been described in part 3. Part 3 also contains details about the deterministic and stochastic simulation models. Part 4 demonstrate an experimental evaluation and the analysis of the results. In conclusion, part 5, findings of this study have been summarized including suggestions for further research. Part 6 covers the list of useful and applied references.

The outputs of the models have been presented in more detail in Appendix A and Appendix B.

2 Background

2.1 What is marshalling

Marshalling /shunting is the process of combining certain cars from at least two different trains into a new departure train. This process can be performed in a marshalling /shunting yard, Gatto *et al.* [5].

In general, customers of rail freight transportation can be divided into two major categories. The first category contains customers that need to transport such large amounts of freight that they can buy or hire complete train sets for the transportation. These trains are called “unit trains”, and all the cars in such a train will have the same origin and destination, Fröidh *et al*. [6]. Unit trains do not require marshalling. The second category contains customers that have smaller amounts of freight to be delivered, and they are interested in the transportation of individual cars rather than complete trains. Trains transporting such freight will consist of cars from different origins and/or different destinations. These trains do require marshalling, and will travel to and/or from marshalling yards where the cars are sorted into new trains based on their destinations, Gatto *et al.* [5].

2.1.1 Marshalling process in brief

There are two types of marshalling yards: hump yards and flat yards. Most marshalling yards consist of three major sub-yards; an arrival yard, a classification yard and a departure yard. Each sub-yard has a set of tracks of different lengths. Further, hump yards have a hump between the arrival and the classification yard, and rely on gravity and switching systems to transport the cars from the top of the hump to the desired classification track (see Figure 1).

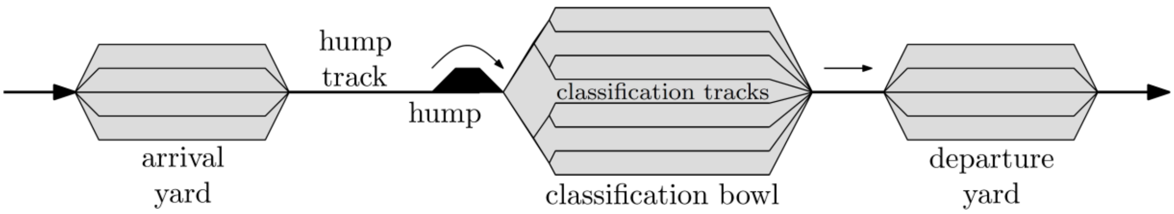

Figure 1: A typical layout of a marshalling yard with hump

When a train arrives to a hump yard it is parked on the arrival yard, and its cars are uncoupled and the brakes released. The cars are then pushed over the hump and rolled to the classification tracks. However, before pushing the cars over the hump, a decision has to be made about which classification track each car should be rolled to. In the Hallsberg marshalling yard, when a train is being compounded on a classification track, no cars belonging to other trains are allowed on that track. As a consequence, the classification yard needs at least one classification track for each departing train being compounded. Normally there is not enough capacity to compound all trains at the same time, and therefore special tracks, called *mixing tracks*, are used for cars whose trains have not yet been assigned to a classification track. For each departure train, a classification track should be booked for specific time duration; cars arriving before the start of this booking period should be rolled to a mixing track.

Cars on mixing tracks have to be reclassified. This is accomplished by pulling the mixed cars back to the arrival yard and then pushing them over the hump again so that they may be directed to their assigned classification tracks. Pulling a car back to the arrival yard and rolling it in again is an unnecessary car movement that wears on the car and yard, and causes extra work. Therefore, the number of cars being sent to mixing tracks should be kept low.

When all cars of a departing train have arrived to the assigned classification track, the cars are coupled and the train is pulled out to the departure yard where it waits for its departure time. In the Hallsberg marshalling yard, trains can also depart straight from the classification yard.

2.2 Developed models for marshalling yards in the world

According to Boysen *et al.* [7] and Assad [8] the history of research work to improve marshalling operational procedures began at 1955. In that first paper a Monte Carlo simulation was used to simulate a classification yard, according to Assad [8]. Many efforts have been made afterwards, mainly in US and China, to develop different algorithms and tools to help dispatchers at marshalling yards. Boysen *et al.* [7] have summarized the important academic works in this field and emphasizes robustness as a key subject for potential further research.

2.2.1 Europe

The simulation of marshalling yards in Europe started around 1996 in Czech Republic and Slovak Republic [9,10,11]. Kavicka, *et al.* [12] at the university of Zinila have developed a tool, named VirtuOS, for the railway simulation including marshalling yards. However, this tool cannot solve the shunting problem but it provides an environment to practice different policies and evaluate what would happen in case of any decision. This tool has been applied to simulate Zilina Teplicka marshalling yard [12]. Kavicka, *et al.* [13] have also worked on the simulation model of marshalling yard Linz VBF in Austria applying the same method.

In Italy, Stefano *et al.* [14] have applied a heuristic approach to find an optimal train order for parking the departure trains on the departure tracks at nights, to have a smooth departing in the morning. Although the corresponding problem is not similar to the one studied in this thesis, it does emphasize the feasibility of using mathematical approaches to obtain an optimal solution in a railway track allocation problem.

Later on in Switzerland, Marton *et al.* [15] have improved train classification procedure for the hump yard Lausanne Triage by applying multistage mathematical methods.

In Sweden SICS has developed an integer programming model for optimized classification track allocation, as well as a few heuristic methods [2,3,4]. This is further described in part2.3.3 .

2.2.2 United States

As mentioned previously US started working on marshalling yards development in 1955 at Massachusetts Institute of Technology [8]. In 1989, Keaton [16] at Michigan Technological University conducted a study for designing optimal railroad operating plans by applying Lagrangian relaxation and heuristic approaches.

Furthermore a tool named YARDSIM has been developed by Lin *et al.* [17] for marshalling yard simulation and it has been applied for a major yard at US. Lin *et al.* [18] have also applied this method to evaluate hump yards in North America. YARDSIM presents a visual tool for the simulation, although it cannot automatically solve the scheduling problem but it can be used for "what-if" analysis.

Dalal *et al.* [19] mentioned in 2001 that a new Computer Aided Dispatching system (CAD III) is under development in the US and that it will incorporate an automated movement planning component. They claim that this system will use an objective function based optimization and that it will be a major advance in railroad technology. However, the author could not find any more recent related documents.

Interestingly an innovative hump yard manager (IHYM) tool has been developed at Innovative Scheduling Company at Florida [20]. This tool has the power to simulate different parts at marshalling yard including arrival tracks, hump scheduling, classification track allocations, departure tracks, locomotive and crew assignments and schedules. This tool has 4 different options for track allocation at classification yards including [20]:

- Option 1: Use longest block to longest track rule
- Option 2: Blocks on same outbound train are on adjacent tracks
- Option 3: Pre-defined by user
- Option 4: Use optimization routines

However the power and evaluation of this tool and the algorithms behind the optimizations are not clear.

2.2.3 China

China is one of the countries that have been studying the problem of optimization and simulation of marshalling yards for several years. A study at Waterloo university in Canada was conducted for Chinese national railway in 1983 to develop a model for finding the optimal sequence of cars rolling over the hump, Yagar *et al.* [21]. Dahlhaus *et al.* [22] also conducted a study for China in

1999, working on the problem of rearranging cars in a train. Many different institutes in Germany, Kuwait and Australia cooperated in that study, Dahlhaus *et al.* [22].

He, *et al.* [23] have proposed and developed an integrated dispatching model for the optimal operation at marshalling yards and they have examined the results for 3 different yards in China applying a heuristic approach. Jing *et al.* [24] have worked on a model and algorithm for dynamic wagon-flow allocation under uncertainty conditions.

2.2.4 Summary of literature review

Developing the improved operational procedures has been investigated through the implementation of either optimization, heuristics or simulation models for many years and by various people and institutes. As has been presented, many of the track allocation studies focus on offline optimization solutions. Although different simulation models have been introduced, the only document which has mentioned few online track allocation policies is the IHYM [20]. However, the results of implementing those policies for track allocations are not known.

2.3 Marshalling in Sweden

Sweden has several marshalling yards. Hallsberg is the biggest and arguably the most important yard in Sweden. As mentioned previously some studies discussed that passing through a marshalling yard is one of the sources of freight train delay in Sweden, Fakhraei [1].. It should be noted that Sweden is one of the few countries that use a booking system for assigning cars to trains before a car starts its journey, which poses extra constraints on the marshalling procedures.

2.3.1 Booking system

A car booking system is used in Sweden, Heydenreich *et al*. [25]. This means that it has already been decided which departing train a car should join before it arrives at the marshalling yard. Booking systems give the freight operators better control over their fleet. However, booking systems also impose constraints on the planning and operational procedures at marshalling yards. If no booking system is used, operators can classify a car by simply assigning it to the earliest departing train that passes through the car destination. In contrast, when a booking system is used, operators have to send each car to its predetermined departing train even if there is another suitable train departing earlier. This drawback can be remedied by re-booking cars in situations where this makes sense, but this option has to be exercised with care since re-booking might violate agreements with the customers, and might also cause problems in other yards that are not expecting the car until later. In Europe, there are currently railway freight booking systems in Sweden, Belgium, the Netherlands and the Czech Republic.

2.3.2 Marshalling at Hallsberg marshalling yard

Hallsberg marshalling yard is arguably the biggest marshalling yard in the Nordic countries. It is located in the center of the Swedish transportation network where all the main tracks coming from Germany, Denmark, Norway and the northern parts of Sweden merge (see Figure 2). The strategic location of Hallsberg has made the yard one of the crowded yards in Sweden, and optimized use of capacity is therefore of interest.

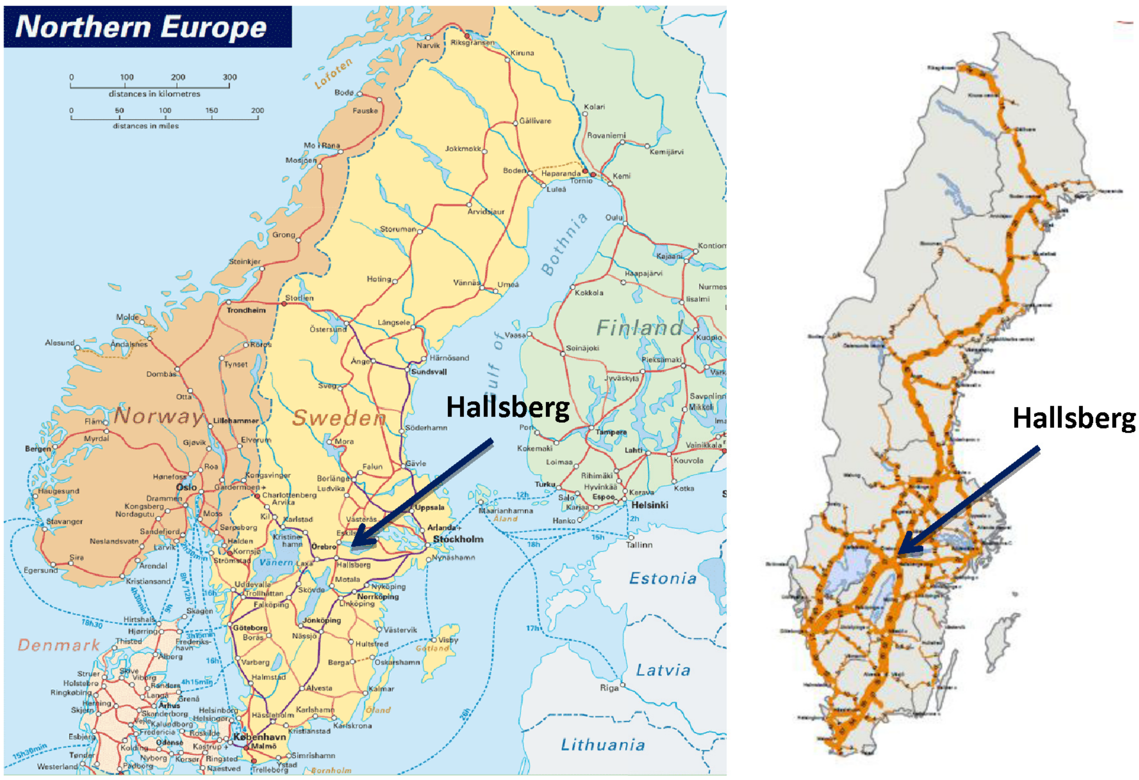

Figure 2: Location of Hallsberg in Swedish railway network [26]

The arrival yard in Hallsberg consists of 8 tracks with different lengths from 590 m to 690 m. The arrival yard is connected to the classification yard via a double hump (Figure 3), however only one hump is used at a time due to layout design and safety constraints. The classification yard has 32 tracks with different lengths from 374 m to 760 m (Figure 3). Finally, the departure yard consists of 12 tracks with lengths from 562 m to 886 m, Alzén [27]. A thorough description of the operations and timings of various marshalling tasks can be found in Bohlin *et al*. [2] and Alzén [27].

When a train arrives it should be prepared for rolling over the hump. The preparation process will take about 48 min for a set of 32 cars and it includes several tasks which are described in Table 1. Dedicated time to some operational tasks in more detail and also the preparation time before a train departure, are presented in Table 2 and Table 3, [27].

Figure 3: Hallsberg view from tower, *Left*: Hump, *Right*: Classification yard

As presented in Table 1, when a train arrives, it waits for the appropriate signal, when the signal is green then the train drives to an assigned track in the arrival yard. After parking in the arrival track, the line locomotive is uncoupled from the cars and the cars are coupled to a shunting locomotive. Then all the brakes are released and checked. When the time of rolling comes and the signals show the appropriate sign, cars are pushed over the hump and roll either to an assigned classification track or to the mixing tracks.

Table 1: Approximate time to prepare a train for shunting [27]

Tasks	Time (s)	Time (min)
Reserve time (based on braking before the signal)	14	0.23
Driving	157	2.63
Securing cars and uncoupling them from locomotive	30	0.50
Checking and preparation (1 min per car)	1920	32.00
Coupling to the shunting locomotive	5	0.08
Towing, releasing brakes, waiting for signals	60	1.00
Pushing cars over to the hump (230+40 m with 1.2 m/s)	225	3.75
Rolling over hump	465	7.75
Sum	2876	48.00

Several tasks should be performed on the cars before they can leave a track; this implies that when a track is occupied, a minimum certain amount of time should be passed before the track can become free again. Also some of the shunting tasks like releasing brakes consist of different detailed sub-tasks. More detailed information has been presented in Table 2.

.

Table 2: Dedicated time to different detailed operational tasks [27]

Tasks	Time (s)	Time (min)
Coupling cars and brakes (100 m/min + 10 s/car)	750	12.50
Time for filling the brake system with air	900	15.00
Testing the brake system	60	1.00
Refilling the brake systems after the test	20	0.33
Brake test, hitting the brakes, controlling each car	180	3.00
Releasing brakes	120	2.00
Controlling that all brakes have been released	180	3.00
Release buffer stops	15	0.25
Activate brakes	5	0.08
Time for driving the locomotive to the cars and coupling it	10	0.17
Releasing brakes	120	2.00
Simple brake test	60	1.00
Time for departure including path reservation	150	2.50
Time for activating buffer stops, relays, reaction time	60	1.00
Sum	2630	44.00

When a train is ready and all the cars are joined together, then the train leaves the classification yard and goes to an assigned track in the departure yard. In the departure yard several tasks are performed to prepare a train for departure. These tasks include for instance uncoupling from the shunting locomotive and coupling to the departure locomotive, checking and testing the brake systems, etc. More details including the minimum time for each task have been presented in Table 3.

Table 3: Dedicated time to different required tasks before the departure [27]

Tasks	Time (s)	Time (min)
Driving	96	1.6
Uncoupling from the shunting locomotive	60	1
Driving the shunting locomotive away	12	0.2
Driving the line locomotive to cars	12	0.2
Coupling to the line locomotive	10	0.17
Charging the brake pressure	300	5
Simple brake tests	60	1
Waiting for the signal	120	2
Departing	120	2
Sum	790	14.00

- **Planning**

Today's planning procedure at Hallsberg is as follows. Experience planners and dispatchers, sitting in the control tower; plan the arrangements of cars for the departure trains approximately one day ahead of the departure. The operational tasks are usually planned in the morning when the classification yard is not very crowded [28].

The composition of the trains changes as the operation date approaches. In fact, new orders from customers might cause the composition of trains to change as late as two hours before the departure time of a train [28]. This complicates planning as the preconditions are constantly changing.

- **Operational restrictions**

A car group is a set of cars which have the same origin and destination and are treated as one unit during the marshalling process. The maximum length of a car group which is going over the hump is 86 m. It should not have more than 10 axles and it should not be heavier than 450 tons; only the last car group in the train can be 125 m [28].

Although there are two humps in the yard, due to safety constraints and track layout, only one hump can be used at a time [28].

- **Fleet**

There are three shunting locomotives at the yard; two of them work in the arrival yard and the other one is assigned to the classification and departure yards. According to discussions with dispatchers, insufficient number of shunting locomotives has rarely been a bottleneck [28].

- **Brakes**

There are two different types of brakes in the classification yard. Brake beams which reduce the speed of rolling cars to 15 km/h and brake pistons which reduce the speed from 15 to 5 km/h [28]. After rolling over the hump, cars first pass over the brake beams and their speed is reduced to 15 km/h and then they pass over the brake pistons. These brakes help the cars stop smoothly in the classification track.

2.3.3 Optimization approach for Hallsberg marshalling yard conducted at SICS

Several mathematical programming models for finding an optimal classification track allocation have already been developed for the Hallsberg marshalling yard by SICS, Bohlin *et al.* [2,3,4]. SICS conducted the project in collaboration with RWTH Aachen and ETH Zürich universities. The goal of the optimization models is to minimize the number of cars being sent to mixing tracks to reduce the number of car pull-backs. Applying the model described in Bohlin *et al.* [4] a solution for an optimal track allocation, using train timetable data for five days ahead, is found within 13 minutes.

SICS has tried different approaches to find an optimal solution, for instance column generation approach, heuristics and mixed integer programming formulations [2,3,4]. However, the optimizing models are complex and require a computer implementation to be used in practice. It is therefore of interest to see if less powerful but simpler rules for classification track allocation could be found, since such rules would be more easy to apply in practice.

3 Method and model components

3.1 Applied method in brief

As explained in the previous parts, it is desirable to find online basic and simple rules for the track allocation at classification yards. Simulations run with MATLAB has been selected since it provides a flexible way for setting rules for track allocation, implementing stochastic arrival times and extracting the desired outputs for evaluations and validations.

Two simulation models have been developed: one deterministic and one stochastic model. The deterministic model uses the planned arrival and departure times, while the other one introduces stochastic delays in the arrival times. Apart from the arrival times, the two models are exactly the same. The different track allocation rules have been tested in both models.

The models are focused on the simulation of track allocation in the classification yard, therefore in addition to train arrival and departure times, other information such as the schedule of cars rolling over the hump, the time of pull-backs, the time when trains leave the classification yard and the information from the car booking system have also been provided as input data. Note that arrival and departure times have been provided from the planned arrival and departure time tables and car bookings are also provided by the booking systems. However the hump schedule, used for the simulation model, is the result from the heuristic pre-processing in [2,3,4].

Models were partially validated by checking that the sequence of events had followed the implemented rules using a visualization tool. This is explained further in part 3.6 and 3.7.

The stochastic model was executed 100 times for each period (total number of 2100 iterations for the whole 21 periods). A normal statistical test was applied to evaluate the difference between deterministic and stochastic results.

3.2 Input data

The case study was based on the planned arrival and departure times of trains which pass through the Hallsberg marshalling yard during the time period between December 11, 2010 and May 10, 2011, as well as car assignments for these trains. A planning horizon of seven days was used, and Saturday was chosen to be the first day of each planning period. The data was pre-processed as outlined in Bohlin *et al.* [3], and the heuristics approach (in Bohlin *et al.* [3]) were used to determine the hump schedule (including initial roll-in and pull-back times) as well as the times when the newly formed trains should be rolled out to the departure yard. Having all the mentioned information, only the simulation of the operations at the classification bowl had to be considered. Therefore the allocation problem is reduced to determining which classification track the departing trains should be assigned to, and when this booking period should start. In other words, for each car that is rolled over the hump, a decision has to be made whether to send it to a mixing track or to a normal classification track, and if it is decided to send it to a normal classification track then it also has to be decided which one.

The output from the heuristic pre-processing in Bohlin *et al.* [3] is an ordered list of time-stamped events. The events are the following:

1. *Roll-in*: A car group (i.e. cars that arrived with the same train, and that will also depart with the same train) is pushed over the hump from the arrival yard to the classification yard. The car group needs to be directed either to its train's classification track, or to a mixing track.
2. *Roll-out:* A train in the classification yard undergoes departure preparations and is rolled out to the departure yard. All car groups belonging to the train must be at the classification track by this time. If a car group has not arrived to the track by this time it is *missed*, i.e. it will not depart with its assigned train. When a car group was missed, its identity was recorded and it was removed from the simulation. That is, reassignment of cars to new trains was not part of the simulation.
3. *Pull-back:* All car groups on mixing tracks are pulled back to the arrival yard and rolled over the hump again to allow for reclassification.

The *mixing* tracks can be one or several tracks. In the experimental setup, two tracks with a total length of 1423 meters were reserved for this purpose. It was also assumed that the cars on both mixing tracks were pulled back at every pull-back event.

It must be noted that the original data contains only the arrival time, departure time and arrival and departure trains' compositions. However, Bohlin, *et al.* [4] have processed the data and determined the time points of roll-ins to the hump and pull-backs from mixed tracks. These time points have been given as input to the current simulation model.

3.2.1 Data pre-processing

Input data comprises the time period between December 11, 2010 and May 10, 2011, as well as car assignments for the included trains. This period covers both peak and off-peak traffic periods at the yard. In the data pre-processing, cars with a local source or destination were omitted from the data set. Further, cars being sent to maintenance tracks have not been considered.

In the data analysis it was revealed that there were some inconsistencies in the data such as for example some cars not being assigned to a departure train, several arrival and departure times for the same train ID in one day, repetition of the car ID, etc. Note that the initial data pre-processing have already been done for the development of the optimization model at SICS and more details can be found in Bohlin, *et al.* [3]. In total, 3594 arrivals, 3654 departures and 17684 car groups were handled. Arrival trains vary in length between 12.8 and 929 meters, departure trains between 12 and 1252 meters.

There are some cars which spend only few hours at the yard and the difference between their arrival and departure times is small. The histogram and probability density function of cars for the whole data according to various time differences between roll-in and roll-out time has been presented in Figure 4.

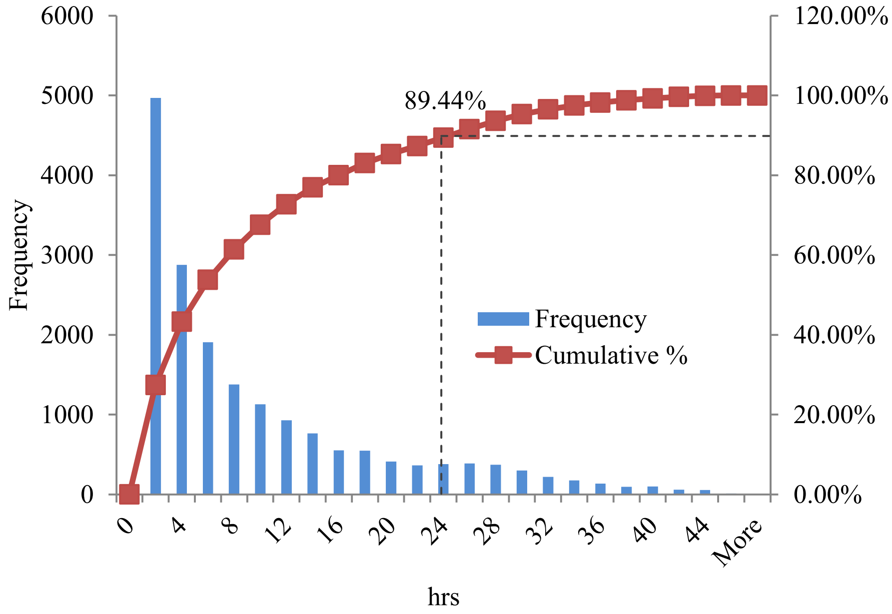

Figure 4: C.d.f of cars according to the difference between their arrival and departure times in hours.

Figure 4 shows that almost 40 % of all cars after rolling over the hump should leave the classification yard in only 4 hours. It also demonstrates that 90 % of all the cars leave the yard in 24 hours. The maximum stay at the classification yard for the input data is 46 hours and has the least frequency.

3.3 Time constraints

There are some operation constraints which should also be considered during the simulation. These constraints have been applied in the model as time limitations before starting some special tasks. For instance after a roll out event a new car cannot enter the track straight away and there should be a minimum time of 1.58 min before a roll in event. All these time limitations between different tasks are presented in Table 4.

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Table 4: Minimum time between different operations [2,3,4,28]

Events order	Seconds	Minutes
Roll out- pull back - roll out	4553.5	75.89
Roll out- roll in	95	1.58
Pull back - roll out	4458	74.30
Pull back - pull back	2730	45.50
Pull back- roll in	1832	30.53
Roll in - roll out	3093	51.55
Roll in - pull back	1365	22.75
Roll in- pull back - roll out	5823.5	97.06
Roll in - roll out	467	7.78

3.4 Planning strategies

This section outlines the two online planning strategies that were tested. The results of the online methods were compared with the results from an optimized allocation for 7 days which had been constructed using the method described in Bohlin *et al*. [4].

3.4.1 First come-first served strategy

The first strategy is a very simple first come-first served rule (FCFS). Every time a car group is rolled over the hump (a roll-in or a pull-back event) it is checked if that car group's train has been assigned to a track. If the train already has an assigned track, the car group is sent there; else an attempt is made to assign a track to the car group's train. If no feasible track is available for the train, the car group is rolled to a mixing track. If more than one feasible track is available, the shortest one is chosen. A track is considered available if it is not occupied.

3.4.2 Time limit strategy

The time limit strategy works in the same way as FCFS in many ways, but it also takes the trains' departure times into consideration. When a car group is rolled in, its designated train's departure time is checked. If the departure time is more than a certain number of hours away, the car group is sent to the mixing tracks. But if the departure time is within the time limit, it is tried to assign a track to the car group's train using the same rules as in FCFS. Once again, if a track has already been assigned to a car group's train, it will be sent to that track straight away.

3.5 Implementing stochastic arrival times

To evaluate how well the strategies cope with delays, random arrival times based on empirical data were generated. Although both early and late arrival times were sampled, only delays were propagated to the roll-in times used by the simulation.

3.5.1 Arrival time distributions

The variations in arrival times were sampled from an empirical distribution. The data consisted of measurements for two months, September and October 2008 and was taken from the Swedish train delay statistics database, TFÖR, Lindfeldt [29]. Extreme data points where trains had been more than 1000 minutes early or late were omitted. The cleaned data can be seen in Figure 5 where it has been mapped as a discrete cumulative probability density function. Positive values present delays while negative values show early arrivals. The variations were sampled from this density function.

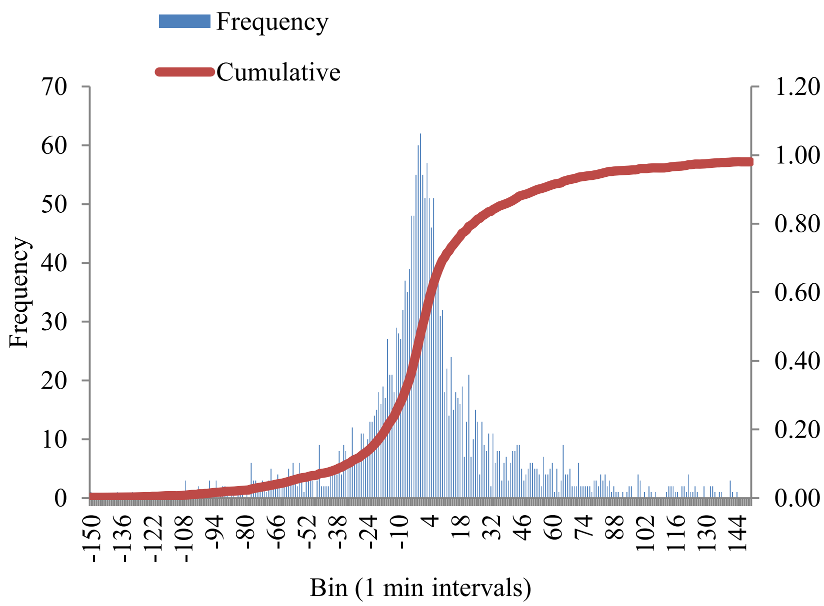


Figure 5: The number of trains and C.D.F for the variation in arrival times, Lindfeldt [29]. A negative value means the train was early and a positive value that it was late.

3.5.2 Random delay generation

In stochastic simulations, for each single arrival train a random number between 0 and 1 was generated. This random number represents the probability of the occurrence of a specific arrival delay; considering the cumulative density function (Figure 5) the corresponded delay was then extracted from the distribution. Note that delays from the empirical distribution are discrete data with 1 minute interval; therefore the interpolated delays have been rounded down to the nearest integer number. This implies that if a train suffered less than 1 minute delay, then no delays has been assigned to it.

3.5.3 Stochastic roll-in times

As the roll-in times are different from the arrival times further processing was needed to deduce the effect the delays had on the roll-in events. Most arriving trains had some buffer time on the arrival yard, i.e. they were parked on the arrival yard longer than what was needed for all necessary preparation work. If the sampled delay was shorter than this buffer time, no delay was added to the roll-in time. However, if the delay was longer than the buffer time, the excess delay was added to the roll-in time. Once all roll-in times had been updated to take the sampled delays into consideration, the event list was resorted such that the events were once again in time order. Finally, a sweep algorithm was used to make sure there was enough time between roll-in and pull-back events for all necessary engine movements. When there were events with too little time in-between, the later event was simply moved back to make space for the earlier event. If needed the delay was further propagated to even later events. Note that this method does not guarantee that there is enough capacity on the arrival yard for the trains to spend a prolonged period of time there, and that therefore the delays might cause capacity shortage on the arrival yard.

Early arrivals have not been considered. The simulation focuses on the track allocation in the classification yard, and therefore does not model the tracks in the arrival yard. Rather, it relies on the roll-in schedule to be given as an input. An early arrival will only affect the roll-in times if there is not enough capacity on the arrival yard for the early train to be parked there longer. As the simulation ignores the arrival yard it is not clear if there is a lack of capacity in the arrival yard, and hence it cannot tell how early arrivals affect the roll-in times.

3.5.4 Stochasticity implementation in the optimization model

The deterministic results from the optimization model include a specific reservation time for each classification track [2,3,4]. This means that a specific track is reserved for a specific train; and the times of the start and end of the reservation period have been determined.

To evaluate the solution of the optimization in case of stochastic arrivals, these reservation periods are given to the simulation model. When a car group rolls over the hump, if the time of the roll-in is within the reservation time for the assigned classification track then the car group is rolled to the assigned classification track; otherwise it is rolled to the mixing track. The former can happen in case of delays.

3.6 Outputs

Several output variables were selected to evaluate the different planning strategies. As mentioned before, cars can miss their assigned trains. This is a planning failure, and therefore the number of missed cars is a reasonable measure of a strategy’s aptness. A desired planning strategy should have no or few missed cars. A car that has missed its departure train can be considered as late, so the number of missed cars can also be used as a measure of transportation delay. Further, the mixing tracks have a predefined capacity, and planning strategies that use more mixing capacity than available are clearly not feasible. Finally, the number of cars being pulled back (car pull-backs) was counted as an efficiency measure. Lin *et al*. [18] also considered the percentage of missed cars and pull-back process time as typical performance measures.

The generated schedule will be visualized in a Gantt chart, by the help of an existing visualization code provided by SICS. A snapshot of the output is shown in Figure 6 . The x-axis represents time and the y-axis shows the tracks of the arrival, classification and departure yards. If the user clicks on a train, all events relevant to that train will be shown by lines. For example, in Figure 6, the blue train with number 17030 on track 12 has been chosen. The blue lines represent roll-ins of car groups going straight to train 17030, while red lines represent car groups that require mixing. The black line shows the roll-out of train 17030. The numbers written in the textboxes on the arrows show the number of cars.

Focusing on the mixing track in Figure 6, the x-axis represents time and the y-axis shows the length of the car groups. The dotted red line shows the maximum capacity of the mixing tracks. If the total length of the cars in mixing exceeds the red line then the marshalling solution is infeasible and more mixing track capacity is required.

3.7 Validation

The model has been validated by following the simulation, step by step and controlling whether the implemented rules have been followed. Further, the feasibility of the results and solutions has been considered. Track allocation has been demonstrated using a Gantt chart as described in the previous section.

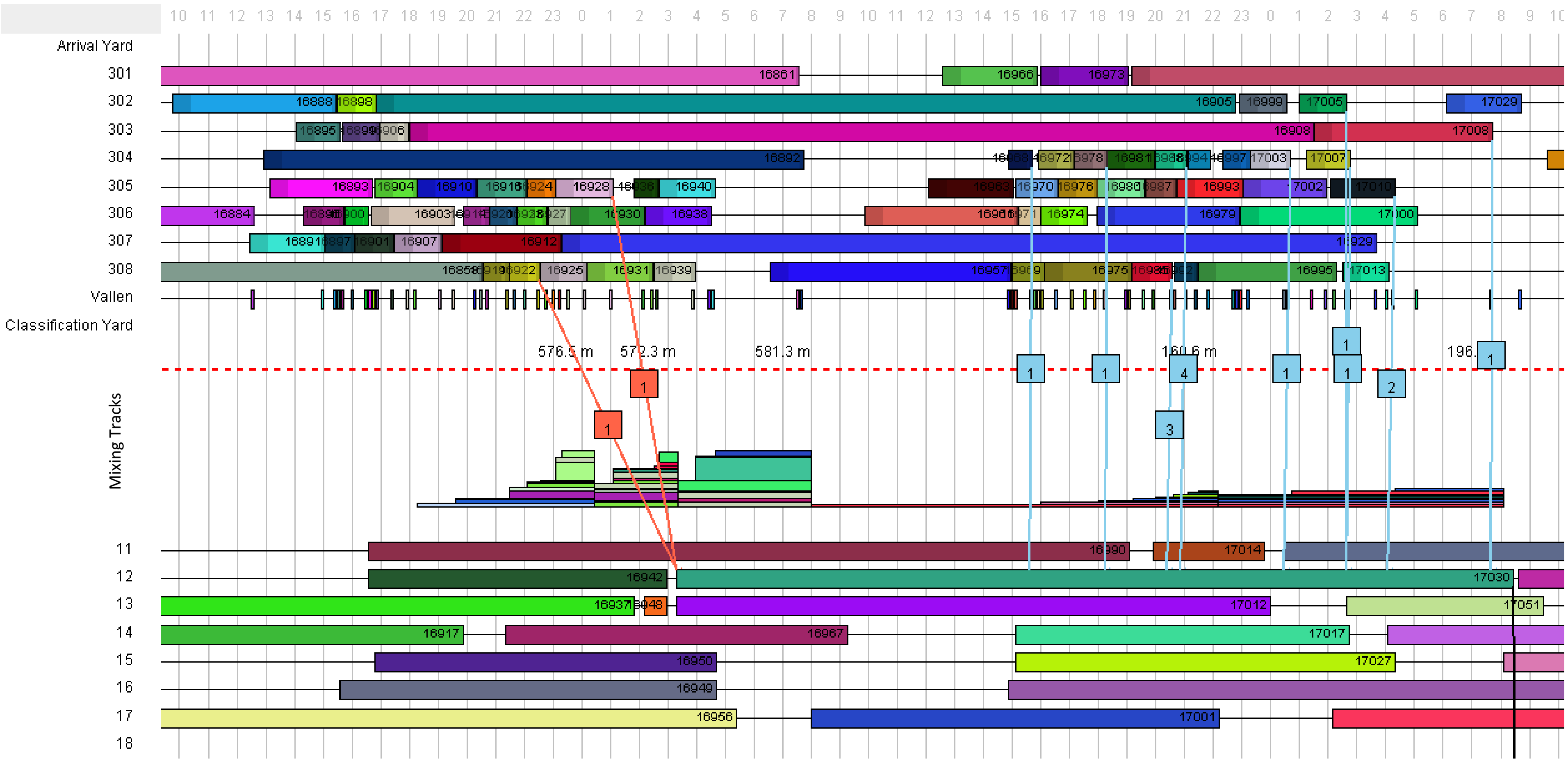


Figure 6: A snapshot of the visualized output of the model

4 Findings and discussions

4.1 Deterministic results

The allocation generated by the optimizing method in Bohlin *et al*. [4] will always be feasible and never miss any cars in the deterministic simulation. Therefore these results are omitted in this section.

First of all it is important to realize that car groups with a departure time that is earlier than the next pull-back time will miss their assigned trains if they are sent to mixing (as they will be stuck on the mixing track until the next pull-back event). Here such cars are called *urgent cars*. In the time limit strategy a time limit is introduced to prevent early arriving cars from occupying a classification track during the long wait for their trains' departure times. The aim was to free up space for trains that have prompt departure times, and thereby minimize the risk of sending urgent cars to mixing tracks. However, if the time limit is too restrictive urgent cars might be forced to the mixing tracks by the time limit. Therefore finding a suitable time limit is important. Further, as more and more of a train's cars ought to be rolled in as we get closer to its departure time, prioritizing trains with prompt departure times should limit the mixing track usage.

In Figure 7 the effects of the different time limits are clearly visible; a time limit of 28 hours is too restrictive while a time limit of 40 hours is not restrictive enough. 32 hours seems to be one of the best limits as it produces an infeasible allocation in only one period, and has a low percentage of missed cars. Due to the reasons stated above, it is not surprising that the first come-first served strategy misses a lot of car groups compared to the time limit strategies. However, it is worth noticing that for generating feasible allocations, i.e. schedules that use less than the available mixing capacity, a too restrictive time limit is worse than having no time limit at all.

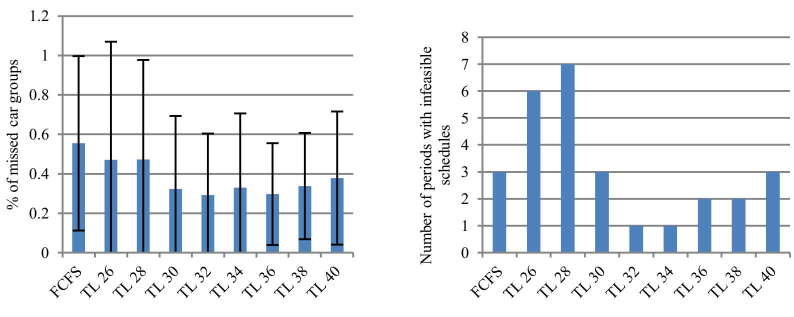


Figure 7: *Left:* The average percentage of missed car groups in the deterministic simulation for the FCFS strategy and the time limit strategy with time limits from 26 to 40 hours. Error bars show the standard deviation. *Right:* The number of periods (out of 21) for the deterministic simulation where the strategies generated infeasible allocations.

In Figure 8 the average number of car pull-backs in the deterministic simulation is presented for the different planning methods. As can be seen the optimized schedule out-performs the other strategies when it comes to minimizing the number of car pull-backs. Further, although the maximum mixing track usage seems to be limited by setting an appropriate time limit (see Figure 7), the average number of car pull-backs decreases as the time limit is increased. This is expected as the less restrictive time limits should send fewer cars to mixing on a general basis. The corresponding data in more detail is presented in Table 5.

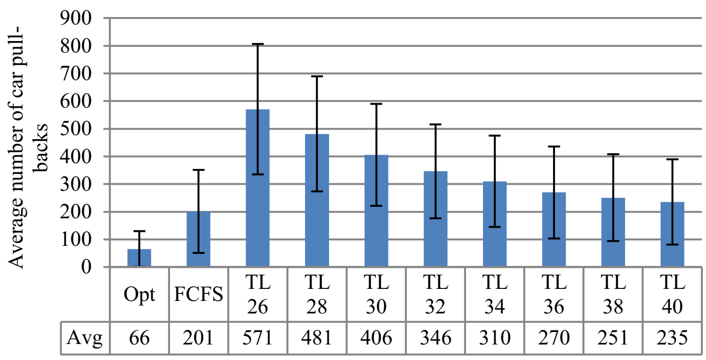


Figure 8: The average number of car pull-backs for the different planning methods in the deterministic simulation.

Table 5: Averages of deterministic results over all periods for all alternatives with the corresponding standard deviations

Strategies	% missed	Avg No. car pull-backs	Avg No. Infeasible schedules	No. infeasible periods	S.D %missed cars	S.D No. car pull backs
Opt	0.00	66	0.00	0	0.00	64.68
FCFS	0.55	201	0.14	3	0.44	150.00
TL 26	0.47	571	0.29	6	0.60	236.04
TL 28	0.47	481	0.33	7	0.50	207.77
TL 30	0.32	406	0.14	3	0.37	184.39
TL 32	0.29	346	0.05	1	0.31	169.49
TL 34	0.33	310	0.05	1	0.38	165.26
TL 36	0.30	270	0.10	2	0.26	166.00
TL 38	0.34	251	0.10	2	0.27	157.18
TL 40	0.38	235	0.14	3	0.34	154.16

Table 6 shows more detailed information of the results from each strategy. Deterministic results from FCFS strategy have been presented for instance; the similar output table for each of the other mentioned strategies has been generated presented in Appendix A.

Table 6: A typical output data from the deterministic model, the results belong to the FCFS strategy

Weeks	No. trains	No. car groups	No. Trains-missed few cars	No. Trains-missed all cars	No. missed cars	% Missed cars	No. Trains-departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterations	No. infeasible solutions	No. late missed cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull-backs	Infeasible period	S.D % missed cars	S.D No car pull-backs
1	188	928	1	1	11	1.1853	186	1207.70	0	1	0	0	11	1	394	0	-	-
2	121	444	0	0	0	0.0000	121	0.00	0	1	0	0	0	0	0	0	-	-
3	99	340	0	0	0	0.0000	99	0.00	0	1	0	0	0	0	0	0	-	-
4	137	487	0	0	0	0.0000	137	0.00	0	1	0	0	0	0	0	0	-	-
5	185	907	1	1	4	0.4410	183	1142.40	0	1	0	0	4	1	263	0	-	-
6	184	966	3	1	8	0.8282	180	1000.10	0	1	0	0	8	1	208	0	-	-
7	157	678	0	0	0	0.0000	157	0.00	0	1	0	0	0	0	0	0	-	-
8	177	824	0	1	3	0.3641	176	874.90	0	1	0	0	3	1	140	0	-	-
9	171	886	0	2	4	0.4515	169	732.80	0	1	0	0	4	1	134	0	-	-
10	185	936	3	3	10	1.0684	179	1380.70	0	1	0	0	10	1	382	0	-	-
11	185	899	0	1	5	0.5562	184	639.00	0	1	0	0	5	1	27	0	-	-
12	174	955	2	0	3	0.3141	172	609.50	0	1	0	0	3	1	142	0	-	-
13	190	972	1	4	13	1.3374	185	1627.80	0	1	1	0	13	1	249	1	-	-
14	200	1139	0	4	13	1.1414	196	1141.20	0	1	0	0	13	1	348	0	-	-
15	193	1084	2	1	3	0.2768	190	845.50	0	1	0	0	3	1	240	0	-	-
16	174	940	2	2	12	1.2766	170	1087.40	0	1	0	0	12	1	205	0	-	-
17	188	998	1	0	1	0.1002	187	828.70	0	1	0	0	1	1	162	0	-	-
18	199	1100	0	2	4	0.3636	197	1798.40	0	1	1	0	4	1	497	1	-	-
19	156	825	1	2	6	0.7273	153	1310.60	0	1	0	0	6	1	277	0	-	-
20	147	801	1	1	5	0.6242	145	675.40	0	1	0	0	5	1	136	0	-	-
21	186	1012	1	2	6	0.5929	183	1631.20	0	1	1	0	6	1	420	1	-	-
Avg.	171.24	863	0.90	1.33	5.29	0.55	169.00	882.54	0.00	1.00	0.14	0.00	5.29	0.81	201.14	-	0.4427	150.003

4.2 Stochastic results

When the arrival times are varied it is harder to produce a schedule with no missed cars. In fact, due to delays some cars were rolled in later than their departure times, making it impossible not to miss them. In Figure 9 these results are clearly visible. However, it is worth noticing that when it comes to cars that did not arrive after their departure time, all methods missed approximately the same percentage of cars in the deterministic and stochastic runs. Most notably, the optimized allocation does not miss any cars that arrive early enough to catch their assigned trains.

As can be seen in Figure 9 the stochastic simulations resulted in an increased number of periods where at least one infeasible allocation was generated for the online strategies, while the optimized allocations are still always feasible. Further, the stochastic arrival times seem to have decreased the average number of car pull-backs slightly (see Figure 8 and Figure 10). This might be due to the cars spending less time in the classification yard, but is probably also an effect of missed car groups being removed from the simulation. If we were to keep missed cars on the mixing tracks, the average number of car pull-backs would increase for the stochastic simulation.

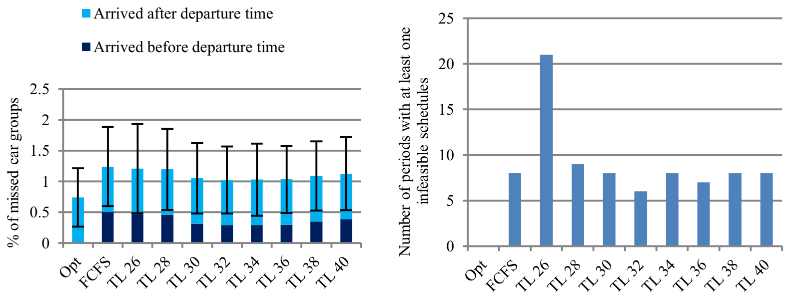
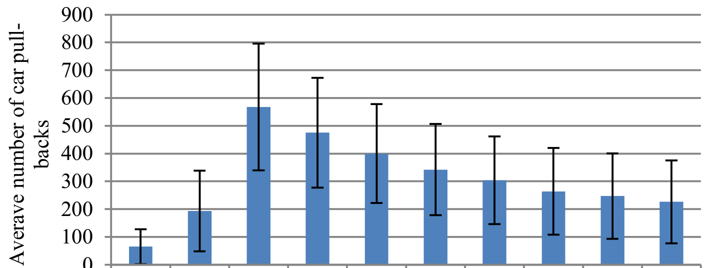


Figure 9: *Left:* The average percentage of missed cars for the stochastic simulation for all planning methods. Error bars show the standard deviation. *Right:* The number of periods (out of 21) for the stochastic simulation where at least one of the simulation runs resulted in an infeasible allocation being generated.



	Opt	FCFS	TL 26	TL 28	TL 30	TL 32	TL 34	TL 36	TL 38	TL 40
Avg	65	193	568	475	400	342	304	264	247	226

Figure 10: The average number of car pull-backs for the different planning methods in the stochastic simulation.

The corresponding data is presented in more detail in Table 7. As presented, the percentage of missed cars that arrived later than the departure time is the same for all the alternatives; this is due to applying the same random seed in the simulations of the different alternatives so that the results can easily be compared.

Table 7: Averages of stochastic results over all periods for all alternatives with the corresponding standard deviations

Strategies	% missed	% missed late	Avg No. car pull-backs	Infeasible schedules	No. infeasible periods	S.D % TOTAL missed cars	S.D No. car pull-backs
Opt	0.00	0.74	65	0.00	0	0.47	62.71
FCFS	0.50	0.74	193	15.00	8	0.64	145.28
TL 26	0.47	0.74	568	28.19	21	0.72	227.73
TL 28	0.46	0.74	475	28.52	9	0.66	197.69
TL 30	0.31	0.74	400	14.05	8	0.57	178.20
TL 32	0.28	0.74	342	6.14	6	0.54	163.88
TL 34	0.29	0.74	304	6.67	8	0.59	157.91
TL 36	0.30	0.74	264	10.10	7	0.55	156.50
TL 38	0.35	0.74	247	10.33	8	0.56	153.67
TL 40	0.39	0.74	226	12.71	8	0.59	148.85

Table 8 shows more detailed information of the results from each alternative. Stochastic results from FCFS strategy have been presented for instance; the similar output table for each of the other mentioned strategies has been generated and presented in Appendix B.

Table 8: A typical output data from the stochastic model, the results belong to the FCFS strategy

Weeks	No. trains	No. car group s	No. Trains- missed few cars	No. Trains- missed all cars	No. missed cars	% Missed cars	No. Trains- departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterat ions	No. infeasible solutions	No. late missed cars	% missed late cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull- backs	Infeasible period
1	188	928	8	1	10.4500	1.1261	179	1243.5300	3.9552	100	18	6.6300	0.7144	17.0800	100	374.2000	1
2	121	444	3	0	0.0000	0.0000	118	0.0000	0.0000	100	0	3.0800	0.6937	3.0800	87	0.0000	0
3	99	340	2	0	0.0000	0.0000	96	0.0000	0.0000	100	0	2.6800	0.7882	2.6800	85	0.0000	0
4	137	487	3	0	0.0000	0.0000	134	0.0000	0.0000	100	0	3.0300	0.6222	3.0300	82	0.0000	0
5	185	907	8	1	4.1400	0.4564	176	1108.9280	2.0696	100	1	6.9800	0.7696	11.1200	100	248.7000	1
6	184	966	8	1	7.5000	0.7764	175	899.9330	3.3227	100	0	6.1500	0.6366	13.6500	100	195.8400	0
7	157	678	4	0	0.0000	0.0000	153	0.0000	0.0000	100	0	4.0600	0.5988	4.0600	88	0.0000	0
8	177	824	5	1	3.1800	0.3859	171	867.8110	1.7488	100	0	5.4600	0.6626	8.6400	100	137.0200	0
9	171	886	6	2	3.6100	0.4074	163	722.1870	1.0140	100	0	6.1100	0.6896	9.7200	100	131.5700	0
10	185	936	9	3	11.1100	1.1870	172	1397.1950	3.7522	100	38	7.1900	0.7682	18.3000	100	366.0700	1
11	185	899	7	1	3.0200	0.3359	177	534.7480	2.2918	100	0	7.1000	0.7898	10.1200	100	30.3700	0
12	174	955	8	0	3.4800	0.3644	166	614.7650	2.0522	100	0	6.9800	0.7309	10.4600	100	141.3400	0
13	190	972	8	3	9.0300	0.9290	179	1485.4490	3.3256	100	74	8.1200	0.8354	17.1500	100	222.7200	1
14	200	1139	9	3	8.5500	0.7507	188	1187.5080	3.5201	100	7	9.0500	0.7946	17.6000	100	328.4600	1
15	193	1084	9	1	2.5800	0.2380	183	871.6040	1.0267	100	0	7.5800	0.6993	10.1600	100	245.4200	0
16	174	940	8	2	11.4200	1.2149	164	1065.4590	2.6215	100	0	6.6400	0.7064	18.0600	100	201.7000	0
17	188	998	10	1	1.9000	0.1904	177	929.4290	1.1237	100	0	9.3000	0.9319	11.2000	100	159.4600	0
18	199	1100	10	2	5.0400	0.4582	187	1673.4330	1.8582	100	74	9.6400	0.8764	14.6800	100	499.3600	1
19	156	825	6	2	5.5400	0.6715	148	1246.6040	1.7257	100	4	5.6300	0.6824	11.1700	100	247.5100	1
20	147	801	7	1	3.4900	0.4357	139	639.2320	1.5341	100	0	6.4600	0.8065	9.9500	100	109.9900	0
21	186	1012	8	2	6.5300	0.6453	176	1609.2900	1.8448	100	99	7.1900	0.7105	13.7200	100	419.3900	1
Avg.	171.23	863	6.95	1.28	4.78	0.50	162.90	861.76	1.84	100	15	6.43	0.73	11.22	97.23	193.29	-

4.3 Statistical evaluations

In a long run of stochastic simulation, the percentage of the number of missed cars would have a distribution. The parameters of this distributions are not known; hence for sufficiently large sample size (more than 30 samples is considered large), it is assumed that the distribution is normal and the standard deviation of the sample represents the standard deviation of the population. A sample from results also confirms that the distribution can be assumed as normal, Figure 11.

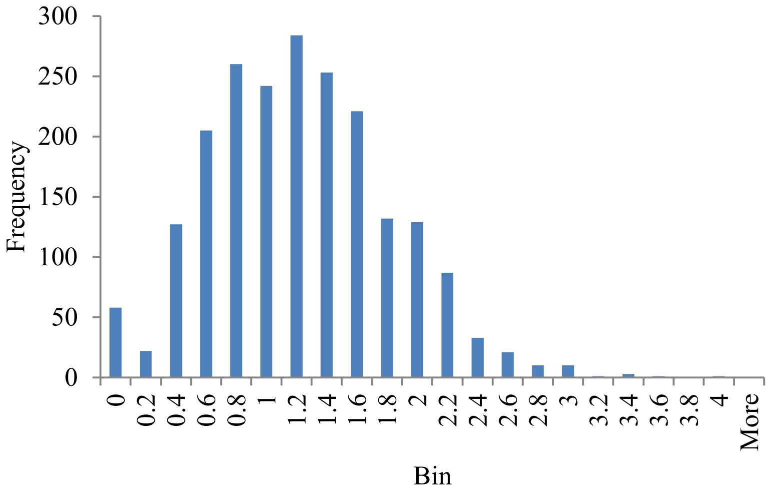


Figure 11: Distribution of the percentage of the missed cars, from the stochastic simulation for TL 40

Therefore normal statistical test (Z- test) can be applied to determine the confidence intervals. According to the Z-test the sample mean should be within the confidence interval.

$$\bar{X} - Z_{\frac{\alpha}{2}} * \frac{\sigma}{\sqrt{n}} \leq \mu \leq \bar{X} + Z_{\frac{\alpha}{2}} * \frac{\sigma}{\sqrt{n}}$$

Where:

μ: is the mean of the population

α : Error interval, here $\alpha = 0.05$

$Z_{\frac{\alpha}{2}}$: for 0.025 equals to 1.96

σ : Standard deviation of the population

$\bar{X}$: Point estimate of the population mean

n : Number of samples

The schematic confidence interval for 95 % has been illustrated in Figure 12. The upper and lower values for the confidence interval have been calculated for all strategies and as can be interpreted from Table 9, the averages of the percentage of missed cars over 2100 stochastic results (100 results for each period) are not significantly different from the deterministic results.

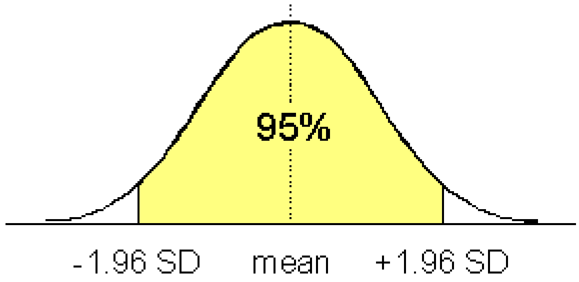


Figure 12: Illustration of confidence interval in normal distribution

Table 9: Normal statistical test for average percentage of missed cars

Strategies	Deterministic average % missed cars	Standard Deviation from stochastic	Acceptable lower range in 95% confidence interval	Acceptable upper range in 95% confidence interval	Stochastic average % missed cars
Opt	0.000	0.474	-0.093	0.093	0.000
FCFS	0.554	0.643	0.428	0.681	0.503
TL 26	0.471	0.723	0.329	0.612	0.468
TL 28	0.472	0.658	0.343	0.601	0.457
TL 30	0.323	0.573	0.210	0.435	0.314
TL 32	0.292	0.543	0.186	0.399	0.284
TL 34	0.329	0.585	0.214	0.443	0.290
TL 36	0.297	0.545	0.190	0.404	0.296
TL 38	0.338	0.562	0.228	0.448	0.349
TL 40	0.378	0.593	0.262	0.494	0.386

4.4 Final comments

More investigations of the input data and the results show that if the total number of arrival cars is higher than that in a normal week, it does not necessarily mean that the yard planning becomes harder. This can be clarified more by considering an example. In the deterministic results for FCFS strategy, week 18 with total 1100 cars has only 0.36% of missed cars while week 16 with fewer number of cars (940) has more percentage of missed cars 1.28%, see Table 6. This implies that there are other variables other than the total number of cars, for example the duration of cars stay at yard, which also can affect the capacity; Cars that their departure and arrival times are too close (less than two hours) and cars that their departure and arrival times are relatively far and they have to stay at yard for long hours will also affect the capacity at yard. In brief, the mixture of cars that need classification and the time table of arrivals and departures can define the hardness of the planning problem.

In the time limit strategy as the limit is more restrictive it keeps sending most of the cars to the mixing track which makes the capacity of the mixing tracks often insufficient. On the other hand if the time-limit is too free, more than 40 hours, there would be no or only few cars that their departure time is more than the time-limit and therefore only few cars will be sent to mixing tracks. In this situation the time-limit strategy will work as FCFS strategy and gives the priority to the cars which roll in first and in free time-limits the capacity of mixing tracks cannot be utilized optimally. Considering all the discussions here, it is expected that the optimal time-limit would be between 24 and 40 hours and further analysis also proved that. Considering the input data, a time limit of 32 hours is the best. More investigations of the input data could not reveal any systematic pattern or dependence between train's departure/arrival times and time-limit of 32 hours, also see Figure 4.

Simulation model in this study has been developed and evaluated specifically for Hallsberg marshalling yard but it can easily be applied on any other hump yard that uses booking systems. It should be noted that yard information and the duration of each task at each yard should be updated accordingly.

The model is highly sensitive to the number and time of the pull-back events. Therefore in the interpretations of the results, the number of pull backs should be considered. As explained in Method and model components section, in this study the time and the number of pull-backs have been given to the model as inputs from the heuristics described in [2,3,4].

5 Conclusion and further suggestions

In this study two simple online planning strategies were compared with an offline optimized classification track allocation. The Hallsberg marshalling yard in Sweden was used as a case study, and two simulations, one deterministic and one stochastic, were applied to compare different strategies. The deterministic simulation showed that the time limit strategy with 32 hours was the best online method with only one infeasible allocation and 0.29% missed cars on average. However, the optimized schedule never missed any cars nor produced infeasible allocations. Further, the optimized allocation minimized the number of extra car roll-ins, and used approximately $\frac{1}{5}$ of the car roll-ins needed by the 32 hour time limit strategy. During the stochastic simulation runs, all methods missed more cars compared to the deterministic results. However, the majority of these cars were so late that they were rolled into the classification yard after their assigned trains had departed. Notably, the optimized allocation missed no cars but from the ones that were rolled in later than their departure time. Further, the number of periods resulting in infeasible allocations increased for the online methods, while the optimized allocations remained feasible in all runs. The average number of car pull-backs was reduced when stochastic arrival times were used. However, this might change if the missed cars were to remain on the mixing tracks rather than being removed from the simulation when their trains depart.

This study presented some of the most basic planning strategies for allocating tracks in a classification yard. One of the draw-backs of the time limit strategy is that when short time limits are implemented cars are sometimes sent to mixing tracks even though there is no pull-back event before their departure time. Including pull-backs in the strategy would hence be an interesting further development. In addition, some initial offline analysis of train lengths and expected arrival times might further improve the strategies. Comparing the results with real planning data, and making more in-depth interviews with the planning staff, would also allow us to develop and adapt the online strategies.

Finally, looking at simple rules for planning the hump schedule and arrival and departure yards would be a good complement to this thesis.

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Appendix A:
Output results from deterministic model

Table A- 1: Results from the deterministic model applying optimization strategy

Weeks	No. trains	No. car groups	No. Trains-missed few cars	No. Trains-missed all cars	No. missed cars	% Missed cars	No. Trains-departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterations	No. infeasible solutions	No. late missed cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull-backs	Infeasible period	S.D % missed cars	S.D No car pull-backs
1	188	928	0	0	0	0	188	231	0	1	0	0	0	0	80	0	-	-
2	121	444	0	0	0	0	121	0	0	1	0	0	0	0	0	0	-	-
3	99	340	0	0	0	0	99	0	0	1	0	0	0	0	0	0	-	-
4	137	487	0	0	0	0	137	0	0	1	0	0	0	0	0	0	-	-
5	185	907	0	0	0	0	185	387	0	1	0	0	0	0	77	0	-	-
6	184	966	0	0	0	0	184	255	0	1	0	0	0	0	60	0	-	-
7	157	678	0	0	0	0	157	0	0	1	0	0	0	0	0	0	-	-
8	177	824	0	0	0	0	177	73	0	1	0	0	0	0	6	0	-	-
9	171	886	0	0	0	0	171	168	0	1	0	0	0	0	20	0	-	-
10	185	936	0	0	0	0	185	352	0	1	0	0	0	0	104	0	-	-
11	185	899	0	0	0	0	185	181	0	1	0	0	0	0	17	0	-	-
12	174	955	0	0	0	0	174	557	0	1	0	0	0	0	83	0	-	-
13	190	972	0	0	0	0	190	417	0	1	0	0	0	0	61	0	-	-
14	200	1139	0	0	0	0	200	607	0	1	0	0	0	0	117	0	-	-
15	193	1084	0	0	0	0	193	535	0	1	0	0	0	0	90	0	-	-
16	174	940	0	0	0	0	174	250	0	1	0	0	0	0	63	0	-	-
17	188	998	0	0	0	0	188	614	0	1	0	0	0	0	66	0	-	-
18	199	1100	0	0	0	0	199	544	0	1	0	0	0	0	238	0	-	-
19	156	825	0	0	0	0	156	420	0	1	0	0	0	0	63	0	-	-
20	147	801	0	0	0	0	147	261	0	1	0	0	0	0	22	0	-	-
21	186	1012	0	0	0	0	186	914	0	1	0	0	0	0	212	0	-	-
Avg.	171.24	863	0	0	0	0	171.24	322.19	0	1	0	0	0	0	65.67	0	0	64.68

Table A- 2: Results from the deterministic model applying FCFS strategy

Weeks	No. trains	No. car groups	No. Trains-missed few cars	No. Trains-missed all cars	No. missed cars	% Missed cars	No. Trains-departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterations	No. infeasible solutions	No. late missed cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull-backs	Infeasible period	S.D % missed cars	S.D No car pull-backs
1	188	928	1	1	11	1.1853	186	1207.70	0	1	0	0	11	1	394	0	-	-
2	121	444	0	0	0	0.0000	121	0.00	0	1	0	0	0	0	0	0	-	-
3	99	340	0	0	0	0.0000	99	0.00	0	1	0	0	0	0	0	0	-	-
4	137	487	0	0	0	0.0000	137	0.00	0	1	0	0	0	0	0	0	-	-
5	185	907	1	1	4	0.4410	183	1142.40	0	1	0	0	4	1	263	0	-	-
6	184	966	3	1	8	0.8282	180	1000.10	0	1	0	0	8	1	208	0	-	-
7	157	678	0	0	0	0.0000	157	0.00	0	1	0	0	0	0	0	0	-	-
8	177	824	0	1	3	0.3641	176	874.90	0	1	0	0	3	1	140	0	-	-
9	171	886	0	2	4	0.4515	169	732.80	0	1	0	0	4	1	134	0	-	-
10	185	936	3	3	10	1.0684	179	1380.70	0	1	0	0	10	1	382	0	-	-
11	185	899	0	1	5	0.5562	184	639.00	0	1	0	0	5	1	27	0	-	-
12	174	955	2	0	3	0.3141	172	609.50	0	1	0	0	3	1	142	0	-	-
13	190	972	1	4	13	1.3374	185	1627.80	0	1	1	0	13	1	249	1	-	-
14	200	1139	0	4	13	1.1414	196	1141.20	0	1	0	0	13	1	348	0	-	-
15	193	1084	2	1	3	0.2768	190	845.50	0	1	0	0	3	1	240	0	-	-
16	174	940	2	2	12	1.2766	170	1087.40	0	1	0	0	12	1	205	0	-	-
17	188	998	1	0	1	0.1002	187	828.70	0	1	0	0	1	1	162	0	-	-
18	199	1100	0	2	4	0.3636	197	1798.40	0	1	1	0	4	1	497	1	-	-
19	156	825	1	2	6	0.7273	153	1310.60	0	1	0	0	6	1	277	0	-	-
20	147	801	1	1	5	0.6242	145	675.40	0	1	0	0	5	1	136	0	-	-
21	186	1012	1	2	6	0.5929	183	1631.20	0	1	1	0	6	1	420	1	-	-
Avg.	171.24	863	0.90	1.33	5.29	0.55	169.00	882.54	0.00	1.00	0.14	0.00	5.29	0.81	201.14	-	0.4427	150.003

Table A- 3: Results from the deterministic model applying Time limit strategy with 26 hrs

Weeks	No. trains	No. car group s	No. Trains-missed few cars	No. Trains-missed all cars	No. missed cars	% Missed cars	No. Trains-departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterati ons	No. infeasible solutions	No. late missed cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull-backs	Infeasible period	S.D % missed cars	S.D No car pull-backs
1	188	928	0	3	4	0.43	185	1245.30	0	1	0	0	4	1	578	0	-	-
2	121	444	0	0	0	0.00	121	449.70	0	1	0	0	0	0	260	0	-	-
3	99	340	0	0	0	0.00	99	428.00	0	1	0	0	0	0	97	0	-	-
4	137	487	0	1	3	0.62	136	1213.00	0	1	0	0	3	1	259	0	-	-
5	185	907	1	0	6	0.66	184	942.50	0	1	0	0	6	1	568	0	-	-
6	184	966	0	0	0	0.00	184	1700.70	0	1	1	0	0	0	630	1	-	-
7	157	678	1	3	17	2.51	153	1446.60	0	1	1	0	17	1	326	1	-	-
8	177	824	1	1	6	0.73	175	951.90	0	1	0	0	6	1	438	0	-	-
9	171	886	1	2	9	1.02	168	1195.50	0	1	0	0	9	1	707	0	-	-
10	185	936	0	0	0	0.00	185	1522.50	0	1	1	0	0	0	695	1	-	-
11	185	899	0	2	12	1.33	183	1137.20	0	1	0	0	12	1	541	0	-	-
12	174	955	0	1	2	0.21	173	810.70	0	1	0	0	2	1	413	0	-	-
13	190	972	0	1	5	0.51	189	1287.90	0	1	0	0	5	1	499	0	-	-
14	200	1139	0	2	8	0.70	198	1224.90	0	1	0	0	8	1	748	0	-	-
15	193	1084	1	1	2	0.18	191	1758.20	0	1	1	0	2	1	733	1	-	-
16	174	940	1	1	4	0.43	172	1419.80	0	1	0	0	4	1	755	0	-	-
17	188	998	0	0	0	0.00	188	1900.30	0	1	1	0	0	0	793	1	-	-
18	199	1100	0	0	0	0.00	199	2106.40	0	1	1	0	0	0	1163	1	-	-
19	156	825	2	0	3	0.36	154	1279.50	0	1	0	0	3	1	586	0	-	-
20	147	801	0	0	0	0.00	147	1142.40	0	1	0	0	0	0	431	0	-	-
21	186	1012	0	1	2	0.20	185	1351.80	0	1	0	0	2	1	767	0	-	-
Avg.	171.24	863	0.38	0.90	3.95	0.47	169.95	1262.61	0.00	1.00	0.29	0.00	3.95	0.67	570.81	-	0.60	236.04

Table A- 4: Results from the deterministic model applying Time limit strategy with 28 hrs

Weeks	No. trains	No. car groups	No. Trains-missed few cars	No. Trains-missed all cars	No. missed cars	% Missed cars	No. Trains-departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterations	No. infeasible solutions	No. late missed cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull-backs	Infeasible period	S.D % missed cars	S.D No car pull-backs
1	188	928	0	2	3	0.32	186	1179.10	0	1	0	0	3	1	526	0	-	-
2	121	444	0	0	0	0.00	121	407.40	0	1	0	0	0	0	209	0	-	-
3	99	340	0	0	0	0.00	99	410.90	0	1	0	0	0	0	84	0	-	-
4	137	487	0	1	3	0.62	136	780.00	0	1	0	0	3	1	170	0	-	-
5	185	907	1	0	6	0.66	184	909.80	0	1	0	0	6	1	509	0	-	-
6	184	966	2	0	9	0.93	182	1805.10	0	1	1	0	9	1	540	1	-	-
7	157	678	2	1	14	2.06	154	1446.60	0	1	1	0	14	1	257	1	-	-
8	177	824	1	1	6	0.73	175	858.20	0	1	0	0	6	1	386	0	-	-
9	171	886	1	1	5	0.56	169	1024.10	0	1	0	0	5	1	581	0	-	-
10	185	936	0	1	4	0.43	184	1529.80	0	1	1	0	4	1	730	1	-	-
11	185	899	0	2	12	1.33	183	854.10	0	1	0	0	12	1	408	0	-	-
12	174	955	0	1	2	0.21	173	627.90	0	1	0	0	2	1	327	0	-	-
13	190	972	0	2	5	0.51	188	1287.90	0	1	0	0	5	1	451	0	-	-
14	200	1139	0	1	2	0.18	199	1129.90	0	1	0	0	2	1	659	0	-	-
15	193	1084	0	1	1	0.09	192	1461.50	0	1	1	0	1	1	607	1	-	-
16	174	940	1	1	4	0.43	172	1100.40	0	1	0	0	4	1	608	0	-	-
17	188	998	0	0	0	0.00	188	1504.10	0	1	1	0	0	0	662	1	-	-
18	199	1100	0	0	0	0.00	199	1949.60	0	1	1	0	0	0	939	1	-	-
19	156	825	2	0	3	0.36	154	1146.00	0	1	0	0	3	1	435	0	-	-
20	147	801	0	0	0	0.00	147	999.60	0	1	0	0	0	0	342	0	-	-
21	186	1012	0	2	5	0.49	184	1594.50	0	1	1	0	5	1	681	1	-	-
Avg.	171.24	863	0.48	0.81	4.00	0.47	169.95	1143.17	0.00	1.00	0.33	0.00	4.00	0.76	481.48	-	0.50	207.77

Table A- 5: Results from the deterministic model applying Time limit strategy with 30 hrs

Weeks	No. trains	No. car group s	No. Trains-missed few cars	No. Trains-missed all cars	No. missed cars	% Missed cars	No. Trains-departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterati ons	No. infeasible solutions	No. late missed cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull-backs	Infeasible period	S.D % missed cars	S.D No car pull-backs
1	188	928	0	1	2	0.22	187	1179	0	1	0	0	2	1	464	0	-	-
2	121	444	0	0	0	0.00	121	330	0	1	0	0	0	0	157	0	-	-
3	99	340	0	0	0	0.00	99	318	0	1	0	0	0	0	63	0	-	-
4	137	487	0	0	0	0.00	137	658	0	1	0	0	0	0	101	0	-	-
5	185	907	0	0	0	0.00	185	834	0	1	0	0	0	0	414	0	-	-
6	184	966	1	1	3	0.31	182	1090	0	1	0	0	3	1	472	0	-	-
7	157	678	1	1	10	1.47	155	1447	0	1	1	0	10	1	198	1	-	-
8	177	824	1	0	8	0.97	176	887	0	1	0	0	8	1	310	0	-	-
9	171	886	0	1	3	0.34	170	857	0	1	0	0	3	1	436	0	-	-
10	185	936	0	0	0	0.00	185	1380	0	1	0	0	0	0	558	0	-	-
11	185	899	0	1	5	0.56	184	765	0	1	0	0	5	1	346	0	-	-
12	174	955	2	1	5	0.52	171	730	0	1	0	0	5	1	280	0	-	-
13	190	972	0	1	1	0.10	189	1403	0	1	0	0	1	1	419	0	-	-
14	200	1139	0	1	2	0.18	199	1219	0	1	0	0	2	1	541	0	-	-
15	193	1084	0	1	5	0.46	192	1059	0	1	0	0	5	1	564	0	-	-
16	174	940	0	1	1	0.11	173	1088	0	1	0	0	1	1	510	0	-	-
17	188	998	1	1	2	0.20	186	1327	0	1	0	0	2	1	604	0	-	-
18	199	1100	0	0	0	0.00	199	1445	0	1	1	0	0	0	757	1	-	-
19	156	825	1	1	5	0.61	154	1125	0	1	0	0	5	1	468	0	-	-
20	147	801	1	0	2	0.25	146	979	0	1	0	0	2	1	232	0	-	-
21	186	1012	2	1	5	0.49	183	1870	0	1	1	0	5	1	636	1	-	-
Avg.	171.24	863	0.48	0.62	2.81	0.32	170.14	1047.08	0.00	1.00	0.14	0.00	2.81	0.71	406.19	-	0.37	184.39

Table A- 6: Results from the deterministic model applying Time limit strategy with 32 hrs

Weeks	No. trains	No. car groups	No. Trains-missed few cars	No. Trains-missed all cars	No. missed cars	% Missed cars	No. Trains-departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterations	No. infeasible solutions	No. late missed cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull-backs	Infeasible period	S.D % missed cars	S.D No car pull-backs
1	188	928	0	1	1	0.11	187	1003	0	1	0	0	1	1	467	0	-	-
2	121	444	0	0	0	0.00	121	286	0	1	0	0	0	0	111	0	-	-
3	99	340	0	0	0	0.00	99	200	0	1	0	0	0	0	51	0	-	-
4	137	487	0	0	0	0.00	137	402	0	1	0	0	0	0	77	0	-	-
5	185	907	0	1	1	0.11	184	979	0	1	0	0	1	1	386	0	-	-
6	184	966	1	1	3	0.31	182	868	0	1	0	0	3	1	343	0	-	-
7	157	678	1	0	7	1.03	156	1191	0	1	0	0	7	1	170	0	-	-
8	177	824	1	0	8	0.97	176	887	0	1	0	0	8	1	256	0	-	-
9	171	886	1	0	2	0.23	170	652	0	1	0	0	2	1	379	0	-	-
10	185	936	0	1	2	0.21	184	1418	0	1	0	0	2	1	508	0	-	-
11	185	899	0	0	0	0.00	185	416	0	1	0	0	0	0	272	0	-	-
12	174	955	2	0	3	0.31	172	610	0	1	0	0	3	1	244	0	-	-
13	190	972	0	3	8	0.82	187	1318	0	1	0	0	8	1	340	0	-	-
14	200	1139	0	2	3	0.26	198	1179	0	1	0	0	3	1	468	0	-	-
15	193	1084	0	1	5	0.46	192	986	0	1	0	0	5	1	503	0	-	-
16	174	940	0	1	1	0.11	173	1042	0	1	0	0	1	1	454	0	-	-
17	188	998	1	0	1	0.10	187	927	0	1	0	0	1	1	414	0	-	-
18	199	1100	0	0	0	0.00	199	1366	0	1	0	0	0	0	707	0	-	-
19	156	825	1	1	3	0.36	154	1371	0	1	0	0	3	1	327	0	-	-
20	147	801	1	0	2	0.25	146	882	0	1	0	0	2	1	211	0	-	-
21	186	1012	2	1	5	0.49	183	1870	0	1	1	0	5	1	584	1	-	-
Avg.	171.24	863	0.52	0.62	2.62	0.29	170.10	945.31	0.00	1.00	0.05	0.00	2.62	0.76	346.29	-	0.31	169.49

Table A- 7: Results from the deterministic model applying Time limit strategy with 34 hrs

Weeks	No. trains	No. car group s	No. Trains-missed few cars	No. Trains-missed all cars	No. missed cars	% Missed cars	No. Trains-departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterati ons	No. infeasible solutions	No. late missed cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull-backs	Infeasible period	S.D % missed cars	S.D No car pull-backs
1	188	928	0	1	1	0.11	187	1062.90	0	1	0	0	1	1	364	0	-	-
2	121	444	0	0	0	0.00	121	286.00	0	1	0	0	0	0	79	0	-	-
3	99	340	0	0	0	0.00	99	199.90	0	1	0	0	0	0	41	0	-	-
4	137	487	0	0	0	0.00	137	381.50	0	1	0	0	0	0	64	0	-	-
5	185	907	0	1	1	0.11	184	970.40	0	1	0	0	1	1	332	0	-	-
6	184	966	2	1	4	0.41	181	818.40	0	1	0	0	4	1	295	0	-	-
7	157	678	0	0	0	0.00	157	637.10	0	1	0	0	0	0	129	0	-	-
8	177	824	2	0	10	1.21	175	1156.70	0	1	0	0	10	1	317	0	-	-
9	171	886	0	0	0	0.00	171	484.60	0	1	0	0	0	0	290	0	-	-
10	185	936	2	0	2	0.21	183	1337.40	0	1	0	0	2	1	459	0	-	-
11	185	899	0	0	0	0.00	185	461.80	0	1	0	0	0	0	220	0	-	-
12	174	955	2	0	3	0.31	172	609.50	0	1	0	0	3	1	221	0	-	-
13	190	972	1	2	6	0.62	187	1066.00	0	1	0	0	6	1	275	0	-	-
14	200	1139	0	2	3	0.26	198	1179.20	0	1	0	0	3	1	398	0	-	-
15	193	1084	1	0	1	0.09	192	932.50	0	1	0	0	1	1	422	0	-	-
16	174	940	2	1	11	1.17	171	970.80	0	1	0	0	11	1	383	0	-	-
17	188	998	1	0	1	0.10	187	968.00	0	1	0	0	1	1	372	0	-	-
18	199	1100	0	1	8	0.73	198	1365.80	0	1	0	0	8	1	710	0	-	-
19	156	825	1	2	6	0.73	153	1370.50	0	1	0	0	6	1	374	0	-	-
20	147	801	1	0	2	0.25	146	799.90	0	1	0	0	2	1	183	0	-	-
21	186	1012	1	2	6	0.59	183	1909.80	0	1	1	0	6	1	582	1	-	-
Avg.	171.24	863	0.76	0.62	3.10	0.33	169.86	903.27	0.00	1.00	0.05	0.00	3.10	0.71	310.00	-	0.38	165.26

Table A- 8: Results from the deterministic model applying Time limit strategy with 36 hrs

Weeks	No. trains	No. car group s	No. Trains-missed few cars	No. Trains-missed all cars	No. missed cars	% Missed cars	No. Trains-departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterati ons	No. infeasible solutions	No. late missed cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull-backs	Infeasible period	S.D % missed cars	S.D No car pull-backs
1	188	928	1	1	2	0.22	186	1144.00	0	1	0	0	2	1	385	0	-	-
2	121	444	0	0	0	0.00	121	173.10	0	1	0	0	0	0	57	0	-	-
3	99	340	0	0	0	0.00	99	182.80	0	1	0	0	0	0	29	0	-	-
4	137	487	0	0	0	0.00	137	116.30	0	1	0	0	0	0	23	0	-	-
5	185	907	0	1	1	0.11	184	970.40	0	1	0	0	1	1	310	0	-	-
6	184	966	3	1	8	0.83	180	1111.30	0	1	0	0	8	1	257	0	-	-
7	157	678	0	0	0	0.00	157	463.00	0	1	0	0	0	0	64	0	-	-
8	177	824	0	1	3	0.36	176	897.20	0	1	0	0	3	1	255	0	-	-
9	171	886	0	2	4	0.45	169	906.00	0	1	0	0	4	1	276	0	-	-
10	185	936	4	1	5	0.53	180	1272.70	0	1	0	0	5	1	411	0	-	-
11	185	899	0	0	0	0.00	185	413.00	0	1	0	0	0	0	151	0	-	-
12	174	955	2	0	3	0.31	172	609.50	0	1	0	0	3	1	189	0	-	-
13	190	972	1	2	6	0.62	187	928.60	0	1	0	0	6	1	230	0	-	-
14	200	1139	0	2	3	0.26	198	1179.20	0	1	0	0	3	1	384	0	-	-
15	193	1084	1	0	1	0.09	192	932.50	0	1	0	0	1	1	384	0	-	-
16	174	940	1	2	4	0.43	171	1217.80	0	1	0	0	4	1	346	0	-	-
17	188	998	1	0	1	0.10	187	968.00	0	1	0	0	1	1	257	0	-	-
18	199	1100	0	1	8	0.73	198	1365.80	0	1	0	0	8	1	671	0	-	-
19	156	825	1	1	3	0.36	154	1456.80	0	1	1	0	3	1	271	1	-	-
20	147	801	1	0	2	0.25	146	569.70	0	1	0	0	2	1	162	0	-	-
21	186	1012	1	2	6	0.59	183	1897.50	0	1	1	0	6	1	557	1	-	-
Avg.	171.24	863	0.81	0.81	2.86	0.30	169.62	894.06	0.00	1.00	0.10	0.00	2.86	0.76	269.95	-	0.26	166.00

Table A- 9: Results from the deterministic model applying Time limit strategy with 38 hrs

Weeks	No. trains	No. car group s	No. Trains-missed few cars	No. Trains-missed all cars	No. missed cars	% Missed cars	No. Trains-departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterati ons	No. infeasible solutions	No. late missed cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull-backs	Infeasible period	S.D % missed cars	S.D No car pull-backs
1	188	928	0	2	3	0.32	186	1144.00	0	1	0	0	3	1	449	0	-	-
2	121	444	0	0	0	0.00	121	173.10	0	1	0	0	0	0	36	0	-	-
3	99	340	0	0	0	0.00	99	163.50	0	1	0	0	0	0	28	0	-	-
4	137	487	0	0	0	0.00	137	86.30	0	1	0	0	0	0	17	0	-	-
5	185	907	1	1	4	0.44	183	1142.40	0	1	0	0	4	1	312	0	-	-
6	184	966	3	1	8	0.83	180	1045.40	0	1	0	0	8	1	225	0	-	-
7	157	678	0	0	0	0.00	157	463.00	0	1	0	0	0	0	54	0	-	-
8	177	824	0	1	3	0.36	176	874.90	0	1	0	0	3	1	212	0	-	-
9	171	886	0	2	4	0.45	169	906.00	0	1	0	0	4	1	250	0	-	-
10	185	936	4	2	8	0.85	179	1406.00	0	1	0	0	8	1	514	0	-	-
11	185	899	0	0	0	0.00	185	389.70	0	1	0	0	0	0	115	0	-	-
12	174	955	2	0	3	0.31	172	609.50	0	1	0	0	3	1	189	0	-	-
13	190	972	2	2	7	0.72	186	1091.50	0	1	0	0	7	1	241	0	-	-
14	200	1139	0	3	6	0.53	197	1179.20	0	1	0	0	6	1	365	0	-	-
15	193	1084	2	0	2	0.18	191	858.10	0	1	0	0	2	1	316	0	-	-
16	174	940	1	2	4	0.43	171	1108.20	0	1	0	0	4	1	306	0	-	-
17	188	998	1	0	1	0.10	187	968.00	0	1	0	0	1	1	223	0	-	-
18	199	1100	1	1	4	0.36	197	1365.00	0	1	0	0	4	1	524	0	-	-
19	156	825	1	1	3	0.36	154	1490.50	0	1	1	0	3	1	249	1	-	-
20	147	801	1	0	2	0.25	146	569.70	0	1	0	0	2	1	147	0	-	-
21	186	1012	1	2	6	0.59	183	1767.20	0	1	1	0	6	1	499	1	-	-
Avg.	171.24	863	0.95	0.95	3.24	0.34	169.33	895.30	0.00	1.00	0.10	0.00	3.24	0.76	251.00	-	0.27	157.18

Table A- 10: Results from the deterministic model applying Time limit strategy with 40 hrs

Weeks	No. trains	No. car group s	No. Trains-missed few cars	No. Trains-missed all cars	No. missed cars	% Missed cars	No. Trains-departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterati ons	No. infeasible solutions	No. late missed cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull-backs	Infeasible period	S.D % missed cars	S.D No car pull-backs
1	188	928	0	1	2	0.22	187	1142.00	0.00	1.00	0.00	0.00	2.00	1.00	408.00	0.00	-	-
2	121	444	0	0	0	0.00	121	145.40	0.00	1.00	0.00	0.00	0.00	0.00	26.00	0.00	-	-
3	99	340	0	0	0	0.00	99	163.50	0.00	1.00	0.00	0.00	0.00	0.00	16.00	0.00	-	-
4	137	487	0	0	0	0.00	137	51.30	0.00	1.00	0.00	0.00	0.00	0.00	7.00	0.00	-	-
5	185	907	1	1	4	0.44	183	1142.40	0.00	1.00	0.00	0.00	4.00	1.00	295.00	0.00	-	-
6	184	966	3	1	8	0.83	180	1045.40	0.00	1.00	0.00	0.00	8.00	1.00	204.00	0.00	-	-
7	157	678	0	0	0	0.00	157	159.60	0.00	1.00	0.00	0.00	0.00	0.00	25.00	0.00	-	-
8	177	824	0	1	3	0.36	176	874.90	0.00	1.00	0.00	0.00	3.00	1.00	193.00	0.00	-	-
9	171	886	0	2	4	0.45	169	906.00	0.00	1.00	0.00	0.00	4.00	1.00	204.00	0.00	-	-
10	185	936	4	2	9	0.96	179	1380.70	0.00	1.00	0.00	0.00	9.00	1.00	437.00	0.00	-	-
11	185	899	0	0	0	0.00	185	389.70	0.00	1.00	0.00	0.00	0.00	0.00	103.00	0.00	-	-
12	174	955	2	0	3	0.31	172	609.50	0.00	1.00	0.00	0.00	3.00	1.00	184.00	0.00	-	-
13	190	972	1	3	9	0.93	186	1016.40	0.00	1.00	0.00	0.00	9.00	1.00	201.00	0.00	-	-
14	200	1139	0	3	6	0.53	197	1141.20	0.00	1.00	0.00	0.00	6.00	1.00	371.00	0.00	-	-
15	193	1084	2	0	2	0.18	191	858.10	0.00	1.00	0.00	0.00	2.00	1.00	310.00	0.00	-	-
16	174	940	2	2	10	1.06	170	1108.20	0.00	1.00	0.00	0.00	10.00	1.00	302.00	0.00	-	-
17	188	998	1	0	1	0.10	187	828.70	0.00	1.00	0.00	0.00	1.00	1.00	272.00	0.00	-	-
18	199	1100	0	2	4	0.36	197	1798.40	0.00	1.00	1.00	0.00	4.00	1.00	550.00	1.00	-	-
19	156	825	1	1	3	0.36	154	1456.80	0.00	1.00	1.00	0.00	3.00	1.00	249.00	1.00	-	-
20	147	801	1	0	2	0.25	146	569.70	0.00	1.00	0.00	0.00	2.00	1.00	130.00	0.00	-	-
21	186	1012	1	2	6	0.59	183	1731.20	0.00	1.00	1.00	0.00	6.00	1.00	454.00	1.00	-	-
Avg.	171.24	863	0.90	1.00	3.62	0.38	169.33	881.86	0.00	1.00	0.14	0.00	3.62	0.76	235.29	-	0.34	154.16

Appendix B:
Output results from stochastic model

Table B- 1: Results from the stochastic model applying optimization strategy

Weeks	No. trains	No. car group s	No. Trains- missed few cars	No. Trains- missed all cars	No. missed cars	% Missed cars	No. Trains- departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterat ions	No. infeasible solutions	No. late missed cars	% missed late cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull- backs	Infeasible period
1	188	928	6	0	0	0.00	182	230.54	0	100	0	7	0.71	7	98	80	0
2	121	444	3	0	0	0.00	118	0.00	0	100	0	3	0.69	3	87	0	0
3	99	340	2	0	0	0.00	96	0.00	0	100	0	3	0.79	3	85	0	0
4	137	487	3	0	0	0.00	134	0.00	0	100	0	3	0.62	3	82	0	0
5	185	907	7	0	0	0.00	178	385.55	0	100	0	7	0.77	7	98	76	0
6	184	966	6	0	0	0.00	178	253.45	0	100	0	6	0.64	6	99	60	0
7	157	678	4	0	0	0.00	153	0.00	0	100	0	4	0.60	4	88	0	0
8	177	824	5	0	0	0.00	172	72.90	0	100	0	5	0.66	5	93	6	0
9	171	886	6	0	0	0.00	165	167.17	0	100	0	6	0.69	6	97	20	0
10	185	936	7	0	0	0.00	178	351.18	0	100	0	7	0.77	7	99	102	0
11	185	899	7	0	0	0.00	178	179.63	0	100	0	7	0.79	7	100	17	0
12	174	955	7	0	0	0.00	167	556.51	0	100	0	7	0.73	7	98	82	0
13	190	972	8	0	0	0.00	182	413.54	0	100	0	8	0.84	8	99	60	0
14	200	1139	9	0	0	0.00	191	596.45	0	100	0	9	0.79	9	100	115	0
15	193	1084	7	0	0	0.00	185	529.77	0	100	0	8	0.70	8	100	89	0
16	174	940	6	0	0	0.00	168	247.90	0	100	0	7	0.71	7	99	63	0
17	188	998	9	0	0	0.00	179	607.06	0	100	0	9	0.93	9	100	65	0
18	199	1100	9	0	0	0.00	190	542.16	0	100	0	10	0.88	10	100	237	0
19	156	825	5	0	0	0.00	151	417.41	0	100	0	6	0.68	6	97	62	0
20	147	801	6	0	0	0.00	141	259.66	0	100	0	6	0.81	6	96	22	0
21	186	1012	7	0	0	0.00	179	902.94	0	100	0	7	0.71	7	99	211	0
Avg.	171.23	863	6.14	0.00	0.00	0.00	165.00	319.71	0.00	100	0.00	6.43	0.74	6.43	95.90	65.04	0.00

Table B- 2: Results from the stochastic model applying FCFS strategy

Weeks	No. trains	No. car groups	No. Trains-missed few cars	No. Trains-missed all cars	No. missed cars	% Missed cars	No. Trains-departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterations	No. infeasible solutions	No. late missed cars	% missed late cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull-backs	Infeasible period
1	188	928	8	1	10.4500	1.1261	179	1243.5300	3.9552	100	18	6.6300	0.7144	17.0800	100	374.2000	1
2	121	444	3	0	0.0000	0.0000	118	0.0000	0.0000	100	0	3.0800	0.6937	3.0800	87	0.0000	0
3	99	340	2	0	0.0000	0.0000	96	0.0000	0.0000	100	0	2.6800	0.7882	2.6800	85	0.0000	0
4	137	487	3	0	0.0000	0.0000	134	0.0000	0.0000	100	0	3.0300	0.6222	3.0300	82	0.0000	0
5	185	907	8	1	4.1400	0.4564	176	1108.9280	2.0696	100	1	6.9800	0.7696	11.1200	100	248.7000	1
6	184	966	8	1	7.5000	0.7764	175	899.9330	3.3227	100	0	6.1500	0.6366	13.6500	100	195.8400	0
7	157	678	4	0	0.0000	0.0000	153	0.0000	0.0000	100	0	4.0600	0.5988	4.0600	88	0.0000	0
8	177	824	5	1	3.1800	0.3859	171	867.8110	1.7488	100	0	5.4600	0.6626	8.6400	100	137.0200	0
9	171	886	6	2	3.6100	0.4074	163	722.1870	1.0140	100	0	6.1100	0.6896	9.7200	100	131.5700	0
10	185	936	9	3	11.1100	1.1870	172	1397.1950	3.7522	100	38	7.1900	0.7682	18.3000	100	366.0700	1
11	185	899	7	1	3.0200	0.3359	177	534.7480	2.2918	100	0	7.1000	0.7898	10.1200	100	30.3700	0
12	174	955	8	0	3.4800	0.3644	166	614.7650	2.0522	100	0	6.9800	0.7309	10.4600	100	141.3400	0
13	190	972	8	3	9.0300	0.9290	179	1485.4490	3.3256	100	74	8.1200	0.8354	17.1500	100	222.7200	1
14	200	1139	9	3	8.5500	0.7507	188	1187.5080	3.5201	100	7	9.0500	0.7946	17.6000	100	328.4600	1
15	193	1084	9	1	2.5800	0.2380	183	871.6040	1.0267	100	0	7.5800	0.6993	10.1600	100	245.4200	0
16	174	940	8	2	11.4200	1.2149	164	1065.4590	2.6215	100	0	6.6400	0.7064	18.0600	100	201.7000	0
17	188	998	10	1	1.9000	0.1904	177	929.4290	1.1237	100	0	9.3000	0.9319	11.2000	100	159.4600	0
18	199	1100	10	2	5.0400	0.4582	187	1673.4330	1.8582	100	74	9.6400	0.8764	14.6800	100	499.3600	1
19	156	825	6	2	5.5400	0.6715	148	1246.6040	1.7257	100	4	5.6300	0.6824	11.1700	100	247.5100	1
20	147	801	7	1	3.4900	0.4357	139	639.2320	1.5341	100	0	6.4600	0.8065	9.9500	100	109.9900	0
21	186	1012	8	2	6.5300	0.6453	176	1609.2900	1.8448	100	99	7.1900	0.7105	13.7200	100	419.3900	1
Avg.	171.23	863	6.95	1.28	4.78	0.50	162.90	861.76	1.84	100	15	6.43	0.73	11.22	97.23	193.29	-

Table B- 3: Results from the stochastic model applying Time limit strategy with 26 hrs

Weeks	No. trains	No. car groups	No. Trains-missed few cars	No. Trains-missed all cars	No. missed cars	% Missed cars	No. Trains-departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterations	No. infeasible solutions	No. late missed cars	% missed late cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull-backs	Infeasible period
1	188	928	6	3	3.78	0.41	179	1245.66	0.60	100	4	6.63	0.71	10.41	100	579.02	1
2	121	444	3	0	0.00	0.00	118	449.06	0.00	100	0	3.08	0.69	3.08	87	258.51	1
3	99	340	2	0	0.00	0.00	96	418.69	0.00	100	0	2.68	0.79	2.68	85	96.20	1
4	137	487	3	1	3.00	0.62	133	1213.00	0.00	100	0	3.03	0.62	6.03	100	257.79	1
5	185	907	8	0	6.08	0.67	177	944.14	0.27	100	0	6.98	0.77	13.06	100	565.43	1
6	184	966	6	0	0.00	0.00	178	1668.26	0.00	100	100	6.15	0.64	6.15	99	626.29	1
7	157	678	5	3	16.96	2.50	149	1444.49	0.20	100	99	4.06	0.60	21.02	100	323.79	1
8	177	824	6	1	6.00	0.73	170	951.90	0.00	100	0	5.46	0.66	11.46	100	435.88	1
9	171	886	7	2	8.99	1.01	162	1188.08	0.10	100	0	6.11	0.69	15.10	100	703.13	1
10	185	936	7	0	0.30	0.03	178	1486.15	0.90	100	83	7.19	0.77	7.49	99	705.16	1
11	185	899	7	2	11.97	1.33	176	1126.58	0.17	100	0	7.10	0.79	19.07	100	537.82	1
12	174	955	7	1	2.00	0.21	166	802.64	0.00	100	0	6.98	0.73	8.98	100	409.50	1
13	190	972	8	1	5.31	0.55	181	1288.10	0.46	100	0	8.12	0.84	13.43	100	507.26	1
14	200	1139	9	2	7.16	0.63	190	1222.93	0.87	100	0	9.05	0.79	16.21	100	753.77	1
15	193	1084	8	1	2.06	0.19	184	1750.45	0.24	100	100	7.58	0.70	9.64	100	727.75	1
16	174	940	7	1	3.76	0.40	166	1411.14	0.47	100	5	6.64	0.71	10.40	100	744.30	1
17	188	998	9	0	0.00	0.00	179	1868.05	0.00	100	100	9.30	0.93	9.30	100	794.13	1
18	199	1100	9	0	0.01	0.00	190	2067.14	0.10	100	100	9.64	0.88	9.65	100	1138.97	1
19	156	825	7	0	3.04	0.37	149	1268.60	0.78	100	0	5.63	0.68	8.67	100	578.32	1
20	147	801	6	0	0.00	0.00	141	1141.04	0.00	100	0	6.46	0.81	6.46	96	427.84	1
21	186	1012	7	1	2.02	0.20	178	1344.60	0.20	100	1	7.19	0.71	9.21	100	749.98	1
Avg.	171.23	863	6.52	0.90	3.93	0.47	163.81	1252.42	0.26	100	28.19	6.43	0.74	10.36	98.38	567.66	-

Table B- 4: Results from the stochastic model applying Time limit strategy with 28 hrs

Weeks	No. trains	No. car groups	No. Trains-missed few cars	No. Trains-missed all cars	No. missed cars	% Missed cars	No. Trains-departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterations	No. infeasible solutions	No. late missed cars	% missed late cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull-backs	Infeasible period
1	188	928	6	2	2.84	0.31	180	1188.61	1.61	100	3	6.63	0.71	9.47	100	518.93	1
2	121	444	3	0	0.00	0.00	118	407.40	0.00	100	0	3.08	0.69	3.08	87	207.73	0
3	99	340	2	0	0.00	0.00	96	401.59	0.00	100	0	2.68	0.79	2.68	85	83.07	0
4	137	487	3	1	3.00	0.62	133	761.78	0.00	100	0	3.03	0.62	6.03	100	168.58	0
5	185	907	8	0	6.11	0.67	177	915.51	0.31	100	0	6.98	0.77	13.09	100	502.74	0
6	184	966	8	0	7.45	0.77	176	1675.09	3.09	100	81	6.15	0.64	13.60	100	529.10	1
7	157	678	6	1	13.99	2.06	150	1444.36	0.10	100	99	4.06	0.60	18.05	100	254.34	1
8	177	824	6	1	6.00	0.73	170	856.61	0.00	100	0	5.46	0.66	11.46	100	383.88	0
9	171	886	7	1	4.99	0.56	163	1018.08	0.10	100	0	6.11	0.69	11.10	100	576.06	0
10	185	936	7	1	2.14	0.23	177	1437.60	1.94	100	55	7.19	0.77	9.33	99	701.82	1
11	185	899	7	2	11.97	1.33	176	853.90	0.17	100	0	7.10	0.79	19.07	100	401.22	0
12	174	955	7	1	2.16	0.23	166	638.55	0.55	100	0	6.98	0.73	9.14	100	324.27	0
13	190	972	8	2	3.63	0.37	181	1288.10	1.92	100	0	8.12	0.84	11.75	100	454.37	0
14	200	1139	9	1	1.51	0.13	191	1155.72	1.16	100	3	9.05	0.79	10.56	100	632.85	1
15	193	1084	7	1	1.10	0.10	184	1458.08	0.30	100	99	7.58	0.70	8.68	100	600.37	1
16	174	940	7	1	4.97	0.53	165	1146.77	2.46	100	0	6.64	0.71	11.61	100	612.11	0
17	188	998	9	0	0.17	0.02	179	1500.52	0.53	100	89	9.30	0.93	9.47	100	654.53	1
18	199	1100	9	0	0.08	0.01	190	1890.18	0.27	100	100	9.64	0.88	9.72	100	919.88	1
19	156	825	7	1	3.90	0.47	148	1161.36	1.28	100	0	5.63	0.68	9.53	100	450.29	0
20	147	801	6	0	0.00	0.00	141	1017.58	0.00	100	0	6.46	0.81	6.46	96	345.60	0
21	186	1012	7	2	4.70	0.46	177	1523.26	0.96	100	70	7.19	0.71	11.89	100	660.46	1
Avg.	171.23	863	6.62	0.86	3.84	0.46	163.71	1130.51	0.80	100	28.52	6.43	0.74	10.27	98.43	475.34	-

Table B- 5: Results from the stochastic model applying Time limit strategy with 30 hrs

Weeks	No. trains	No. car group s	No. Trains- missed few cars	No. Trains- missed all cars	No. missed cars	% Missed cars	No. Trains- departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterat ions	No. infeasible solutions	No. late missed cars	% missed late cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull- backs	Infeasible period
1	188	928	6	1	1.90	0.20	181	1192.10	0.33	100	1	6.63	0.71	8.53	100	470.84	1
2	121	444	3	0	0.00	0.00	118	330.12	0.00	100	0	3.08	0.69	3.08	87	155.75	0
3	99	340	2	0	0.00	0.00	96	317.80	0.00	100	0	2.68	0.79	2.68	85	62.89	0
4	137	487	3	0	0.00	0.00	134	648.32	0.00	100	0	3.03	0.62	3.03	82	100.16	0
5	185	907	7	0	0.16	0.02	178	841.53	0.37	100	0	6.98	0.77	7.14	98	407.82	0
6	184	966	7	1	2.87	0.30	176	1086.08	0.37	100	0	6.15	0.64	9.02	100	463.58	0
7	157	678	5	1	9.98	1.47	151	1442.74	0.14	100	98	4.06	0.60	14.04	100	195.92	1
8	177	824	6	0	6.90	0.84	171	868.04	2.69	100	0	5.46	0.66	12.36	100	303.25	0
9	171	886	6	1	2.99	0.34	164	851.20	0.10	100	0	6.11	0.69	9.10	100	431.04	0
10	185	936	7	0	0.31	0.03	178	1339.45	0.88	100	3	7.19	0.77	7.50	99	552.83	1
11	185	899	7	1	4.97	0.55	177	764.60	0.17	100	0	7.10	0.79	12.07	100	345.03	0
12	174	955	8	1	4.79	0.50	165	716.26	0.43	100	0	6.98	0.73	11.77	100	277.40	0
13	190	972	8	1	1.50	0.15	181	1375.41	1.47	100	4	8.12	0.84	9.62	100	404.87	1
14	200	1139	9	1	2.14	0.19	190	1206.30	2.27	100	3	9.05	0.79	11.19	100	536.81	1
15	193	1084	7	1	3.54	0.33	185	1026.12	2.36	100	0	7.58	0.70	11.12	100	543.03	0
16	174	940	6	1	1.19	0.13	166	1106.22	1.16	100	0	6.64	0.71	7.83	100	508.09	0
17	188	998	10	1	2.34	0.23	177	1376.33	1.28	100	33	9.30	0.93	11.64	100	591.63	1
18	199	1100	9	0	0.76	0.07	189	1409.51	1.74	100	60	9.64	0.88	10.40	100	759.93	1
19	156	825	6	2	4.60	0.56	148	1136.15	1.47	100	0	5.63	0.68	10.23	100	422.90	0
20	147	801	7	0	1.75	0.22	140	976.80	0.58	100	0	6.46	0.81	8.21	100	243.89	0
21	186	1012	9	1	4.75	0.47	176	1776.59	1.98	100	93	7.19	0.71	11.94	100	624.41	1
Avg.	171.23	863	6.57	0.67	2.74	0.31	163.86	1037.51	0.94	100	14.05	6.43	0.74	9.17	97.67	400.10	-

Table B- 6: Results from the stochastic model applying Time limit strategy with 32 hrs

Weeks	No. trains	No. car groups	No. Trains-missed few cars	No. Trains-missed all cars	No. missed cars	% Missed cars	No. Trains-departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterations	No. infeasible solutions	No. late missed cars	% missed late cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull-backs	Infeasible period
1	188	928	6	1	1.84	0.20	180	1105.32	1.99	100	0	6.63	0.71	8.47	100	461.68	0
2	121	444	3	0	0.00	0.00	118	286.00	0.00	100	0	3.08	0.69	3.08	87	110.16	0
3	99	340	2	0	0.00	0.00	96	199.73	0.00	100	0	2.68	0.79	2.68	85	50.90	0
4	137	487	3	0	0.00	0.00	134	402.20	0.00	100	0	3.03	0.62	3.03	82	76.79	0
5	185	907	7	1	0.99	0.11	177	967.16	0.61	100	0	6.98	0.77	7.97	100	372.04	0
6	184	966	7	1	2.86	0.30	176	859.16	0.38	100	0	6.15	0.64	9.01	100	339.45	0
7	157	678	5	0	6.75	1.00	152	1179.07	0.46	100	0	4.06	0.60	10.81	100	168.06	0
8	177	824	6	0	6.82	0.83	171	857.51	2.78	100	0	5.46	0.66	12.28	100	249.72	0
9	171	886	7	0	1.94	0.22	164	651.63	0.24	100	0	6.11	0.69	8.05	100	372.75	0
10	185	936	7	1	1.72	0.18	177	1363.49	1.11	100	14	7.19	0.77	8.91	100	498.65	1
11	185	899	7	0	0.00	0.00	178	420.65	0.00	100	0	7.10	0.79	7.10	100	270.89	0
12	174	955	8	0	2.65	0.28	166	603.38	0.58	100	0	6.98	0.73	9.63	100	242.36	0
13	190	972	8	2	5.70	0.59	180	1303.62	2.58	100	15	8.12	0.84	13.82	100	330.65	1
14	200	1139	9	2	2.23	0.20	190	1182.00	1.10	100	1	9.05	0.79	11.28	100	454.83	1
15	193	1084	8	1	2.61	0.24	185	984.05	2.48	100	0	7.58	0.70	10.19	100	464.62	0
16	174	940	6	1	3.48	0.37	166	1062.88	3.23	100	0	6.64	0.71	10.12	100	459.03	0
17	188	998	10	1	1.81	0.18	178	1019.25	1.09	100	0	9.30	0.93	11.11	100	444.63	0
18	199	1100	9	0	1.52	0.14	189	1345.71	3.05	100	4	9.64	0.88	11.16	100	704.68	1
19	156	825	6	1	3.59	0.44	149	1318.99	1.18	100	1	5.63	0.68	9.22	100	335.83	1
20	147	801	7	0	1.76	0.22	140	875.70	0.57	100	0	6.46	0.81	8.22	100	211.19	0
21	186	1012	8	1	5.09	0.50	176	1783.26	1.76	100	94	7.19	0.71	12.28	100	569.33	1
Avg.	171.23	863	6.62	0.62	2.54	0.28	163.90	941.46	1.20	100	6.14	6.43	0.74	8.97	97.81	342.30	-

Table B- 7: Results from the stochastic model applying Time limit strategy with 34 hrs

Weeks	No. trains	No. car groups	No. Trains-missed few cars	No. Trains-missed all cars	No. missed cars	% Missed cars	No. Trains-departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterations	No. infeasible solutions	No. late missed cars	% missed late cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull-backs	Infeasible period
1	188	928	6	1	0.96	0.10	181	1078.20	0.80	100	4	6.63	0.71	7.59	100	363.83	1
2	121	444	3	0	0.00	0.00	118	286.00	0.00	100	0	3.08	0.69	3.08	87	78.05	0
3	99	340	2	0	0.00	0.00	96	199.54	0.00	100	0	2.68	0.79	2.68	85	40.88	0
4	137	487	3	0	0.00	0.00	134	381.16	0.00	100	0	3.03	0.62	3.03	82	63.88	0
5	185	907	7	1	1.39	0.15	177	961.90	1.18	100	1	6.98	0.77	8.37	100	320.11	1
6	184	966	7	1	3.03	0.31	176	806.11	0.56	100	0	6.15	0.64	9.18	100	294.25	0
7	157	678	4	0	0.00	0.00	153	633.65	0.00	100	0	4.06	0.60	4.06	88	125.89	0
8	177	824	7	0	8.94	1.09	170	1109.83	2.58	100	0	5.46	0.66	14.40	100	305.73	0
9	171	886	6	0	0.00	0.00	165	485.57	0.00	100	0	6.11	0.69	6.11	97	281.75	0
10	185	936	8	1	2.58	0.28	176	1323.32	2.25	100	7	7.19	0.77	9.77	100	470.59	1
11	185	899	7	0	0.04	0.00	178	444.78	0.20	100	0	7.10	0.79	7.14	100	219.01	0
12	174	955	8	0	2.77	0.29	166	605.34	0.49	100	0	6.98	0.73	9.75	100	218.57	0
13	190	972	8	2	6.11	0.63	180	1103.16	1.83	100	2	8.12	0.84	14.23	100	279.33	1
14	200	1139	9	1	2.44	0.21	190	1185.98	1.74	100	1	9.05	0.79	11.49	100	399.45	1
15	193	1084	8	0	1.21	0.11	184	910.57	0.97	100	0	7.58	0.70	8.79	100	413.12	0
16	174	940	7	2	10.35	1.10	165	1066.84	3.43	100	0	6.64	0.71	16.99	100	382.78	0
17	188	998	10	1	1.81	0.18	178	1064.18	1.09	100	0	9.30	0.93	11.11	100	374.46	0
18	199	1100	9	1	2.86	0.26	189	1410.42	3.73	100	24	9.64	0.88	12.50	100	680.59	1
19	156	825	6	2	4.31	0.52	148	1308.38	1.44	100	1	5.63	0.68	9.94	100	316.43	1
20	147	801	7	0	1.76	0.22	140	796.73	0.57	100	0	6.46	0.81	8.22	100	187.21	0
21	186	1012	8	2	6.42	0.63	176	1868.89	1.71	100	100	7.19	0.71	13.61	100	569.88	1
Avg.	171.23	863	6.67	0.71	2.71	0.29	163.81	906.22	1.17	100	6.67	6.43	0.74	9.14	97.10	304.09	-

Table B- 8: Results from the stochastic model applying Time limit strategy with 36 hrs

Weeks	No. trains	No. car group s	No. Trains- missed few cars	No. Trains- missed all cars	No. missed cars	% Missed cars	No. Trains- departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterat ions	No. infeasible solutions	No. late missed cars	% missed late cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull- backs	Infeasible period
1	188	928	7	1	2.09	0.23	180	1167.72	1.85	100	15	6.63	0.71	8.72	100	374.83	1
2	121	444	3	0	0.00	0.00	118	173.07	0.00	100	0	3.08	0.69	3.08	87	56.20	0
3	99	340	2	0	0.00	0.00	96	182.61	0.00	100	0	2.68	0.79	2.68	85	28.79	0
4	137	487	3	0	0.00	0.00	134	115.33	0.00	100	0	3.03	0.62	3.03	82	22.93	0
5	185	907	7	1	1.51	0.17	177	953.86	1.24	100	1	6.98	0.77	8.49	100	296.05	1
6	184	966	8	1	6.09	0.63	175	895.49	2.01	100	0	6.15	0.64	12.24	100	254.93	0
7	157	678	4	0	0.00	0.00	153	461.84	0.00	100	0	4.06	0.60	4.06	88	63.00	0
8	177	824	5	1	3.09	0.38	171	888.59	1.83	100	0	5.46	0.66	8.55	100	250.88	0
9	171	886	6	2	3.94	0.44	163	896.46	0.42	100	0	6.11	0.69	10.05	100	270.22	0
10	185	936	10	2	5.74	0.61	174	1295.32	2.96	100	9	7.19	0.77	12.93	100	408.83	1
11	185	899	7	0	0.04	0.00	178	437.38	0.20	100	0	7.10	0.79	7.14	100	152.57	0
12	174	955	8	0	3.45	0.36	166	620.90	2.02	100	0	6.98	0.73	10.43	100	189.54	0
13	190	972	8	2	6.25	0.64	180	1019.19	1.99	100	3	8.12	0.84	14.37	100	226.14	1
14	200	1139	9	2	3.67	0.32	189	1176.84	1.94	100	0	9.05	0.79	12.72	100	376.09	0
15	193	1084	8	0	1.25	0.12	184	920.21	0.74	100	0	7.58	0.70	8.83	100	379.52	0
16	174	940	7	2	4.97	0.53	165	1005.70	2.45	100	0	6.64	0.71	11.61	100	333.31	0
17	188	998	10	1	1.92	0.19	177	1052.17	1.56	100	0	9.30	0.93	11.22	100	285.40	0
18	199	1100	10	1	2.94	0.27	189	1407.48	3.13	100	39	9.64	0.88	12.58	100	608.59	1
19	156	825	6	1	3.55	0.43	149	1362.08	1.24	100	45	5.63	0.68	9.18	100	270.39	1
20	147	801	7	0	1.86	0.23	140	603.24	0.57	100	0	6.46	0.81	8.32	100	142.39	0
21	186	1012	8	2	6.81	0.67	176	1850.04	1.97	100	100	7.19	0.71	14.00	100	556.03	1
Avg.	171.23	863	6.81	0.90	2.82	0.30	163.52	880.26	1.34	100	10.10	6.43	0.74	9.25	97.24	264.13	-

Table B- 9: Results from the stochastic model applying Time limit strategy with 38 hrs

Weeks	No. trains	No. car groups	No. Trains-missed few cars	No. Trains-missed all cars	No. missed cars	% Missed cars	No. Trains-departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterations	No. infeasible solutions	No. late missed cars	% missed late cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull-backs	Infeasible period
1	188	928	7	2	3.53	0.38	180	1183.56	1.62	100	15	6.63	0.71	10.16	100	418.98	1
2	121	444	3	0	0.00	0.00	118	172.38	0.00	100	0	3.08	0.69	3.08	87	35.27	0
3	99	340	2	0	0.00	0.00	96	163.32	0.00	100	0	2.68	0.79	2.68	85	27.79	0
4	137	487	3	0	0.00	0.00	134	86.30	0.00	100	0	3.03	0.62	3.03	82	16.74	0
5	185	907	8	1	3.93	0.43	176	1136.94	1.51	100	1	6.98	0.77	10.91	100	296.42	1
6	184	966	8	1	6.84	0.71	175	924.46	2.14	100	0	6.15	0.64	12.99	100	228.18	0
7	157	678	4	0	0.00	0.00	153	460.68	0.00	100	0	4.06	0.60	4.06	88	53.06	0
8	177	824	5	1	3.18	0.39	171	868.22	1.75	100	0	5.46	0.66	8.64	100	207.89	0
9	171	886	6	2	3.64	0.41	163	847.70	0.98	100	0	6.11	0.69	9.75	100	238.11	0
10	185	936	10	2	8.15	0.87	173	1383.71	3.56	100	30	7.19	0.77	15.34	100	479.55	1
11	185	899	7	0	0.04	0.00	178	419.97	0.20	100	0	7.10	0.79	7.14	100	116.65	0
12	174	955	8	0	3.35	0.35	166	620.05	2.08	100	0	6.98	0.73	10.33	100	187.52	0
13	190	972	9	2	6.84	0.70	179	1106.37	2.02	100	6	8.12	0.84	14.96	100	220.84	1
14	200	1139	9	3	5.91	0.52	189	1185.03	2.84	100	4	9.05	0.79	14.96	100	369.04	1
15	193	1084	9	0	2.06	0.19	184	889.93	0.74	100	0	7.58	0.70	9.64	100	312.75	0
16	174	940	7	2	4.23	0.45	165	1009.72	2.00	100	0	6.64	0.71	10.87	100	299.81	0
17	188	998	10	1	2.23	0.22	177	1057.87	2.42	100	0	9.30	0.93	11.53	100	268.83	0
18	199	1100	10	2	4.91	0.45	188	1374.39	2.70	100	10	9.64	0.88	14.55	100	546.44	1
19	156	825	6	1	3.65	0.44	149	1387.43	1.37	100	51	5.63	0.68	9.28	100	248.90	1
20	147	801	7	0	1.85	0.23	140	603.43	0.58	100	0	6.46	0.81	8.31	100	126.52	0
21	186	1012	8	2	5.90	0.58	176	1738.53	2.03	100	100	7.19	0.71	13.09	100	490.58	1
Avg.	171.23	863	6.95	1.05	3.34	0.35	163.33	886.67	1.45	100	10.33	6.43	0.74	9.78	97.24	247.14	-

Table B- 10: Results from the stochastic model applying Time limit strategy with 40 hrs

Weeks	No. trains	No. car group s	No. Trains- missed few cars	No. Trains- missed all cars	No. missed cars	% Missed cars	No. Trains- departed completely	Avg. of Max mixing length(m) for all iterations	S.D missed cars	No. iterat ions	No. infeasible solutions	No. late missed cars	% missed late cars	Total No. missed cars	No. schedules with missed cars	Avg. No. car pull- backs	Infeasible period
1	188	928	7	1	3.39	0.37	180	1178.54	2.23	100	15	6.63	0.71	10.02	100	384.06	1
2	121	444	3	0	0.00	0.00	118	143.62	0.00	100	0	3.08	0.69	3.08	87	25.46	0
3	99	340	2	0	0.00	0.00	96	162.49	0.00	100	0	2.68	0.79	2.68	85	15.25	0
4	137	487	3	0	0.00	0.00	134	51.30	0.00	100	0	3.03	0.62	3.03	82	6.90	0
5	185	907	8	1	4.13	0.46	176	1136.74	1.61	100	1	6.98	0.77	11.11	100	279.89	1
6	184	966	8	1	7.20	0.75	175	886.52	2.33	100	0	6.15	0.64	13.35	100	204.01	0
7	157	678	4	0	0.00	0.00	153	159.03	0.00	100	0	4.06	0.60	4.06	88	24.21	0
8	177	824	5	1	3.18	0.39	171	867.81	1.75	100	0	5.46	0.66	8.64	100	188.87	0
9	171	886	6	2	3.88	0.44	163	891.16	0.59	100	0	6.11	0.69	9.99	100	199.92	0
10	185	936	10	3	10.28	1.10	172	1408.50	3.76	100	40	7.19	0.77	17.47	100	436.88	1
11	185	899	7	0	0.04	0.00	178	419.54	0.20	100	0	7.10	0.79	7.14	100	102.83	0
12	174	955	8	0	3.37	0.35	166	614.64	2.08	100	0	6.98	0.73	10.35	100	181.20	0
13	190	972	9	2	6.96	0.72	179	1104.85	2.02	100	9	8.12	0.84	15.08	100	198.59	1
14	200	1139	9	2	5.33	0.47	189	1148.07	2.39	100	3	9.05	0.79	14.38	100	373.31	1
15	193	1084	9	0	2.17	0.20	184	888.53	0.91	100	0	7.58	0.70	9.75	100	303.02	0
16	174	940	8	2	9.17	0.98	164	1020.96	2.91	100	0	6.64	0.71	15.81	100	286.41	0
17	188	998	10	1	1.83	0.18	177	938.07	1.08	100	0	9.30	0.93	11.13	100	207.67	0
18	199	1100	10	2	5.05	0.46	187	1558.27	2.17	100	56	9.64	0.88	14.69	100	532.90	1
19	156	825	6	1	3.65	0.44	149	1359.76	1.41	100	44	5.63	0.68	9.28	100	245.67	1
20	147	801	7	0	1.86	0.23	140	567.50	0.57	100	0	6.46	0.81	8.32	100	110.41	0
21	186	1012	8	2	5.94	0.59	176	1688.76	2.25	100	99	7.19	0.71	13.13	100	442.23	1
Avg.	171.23	863	7.00	1.00	3.69	0.39	163.19	866.41	1.44	100	12.71	6.43	0.74	10.12	97.24	226.18	-

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