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Train Passes and Dwell Time Delays

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Abstract

Traffic on railways is increasing and this makes train traffic to be highly interconnected . This paper investigates how passing of train affects dwell time delays in Sweden. Three scenarios are considered by combining the scheduled and actual operations: passes that happened as scheduled, unscheduled passes that happened in operations, and scheduled passes that were cancelled. A logistic regression model is used to explore the effects of these spassing on delays. The results show that train passes rarely occur as scheduled, more frequently they are cancelled or unscheduled. When passes are cancelled, the probability of delay decreases, and when the passes are unscheduled, the delay probability increases. The approach used in this paper can be extended to other types of train movement, such as meeting of train , as well as other delay-influencing factors.

Keywords
train passes, train delay, dwell time, punctuality

1 Introduction

Traffic on the railways has been increasing steadily in recent years. High utilization combined with highly heterogeneous traffic has increased the complexity of railway traffic in Sweden. According to (Trafikanalys, 2018), the number of passenger trains increased by 19% from 852,000 to 1,016,000 between 2013 and 2018. Busy networks of railway traffic are constantly subjected to random disturbances. To minimize the impact of these disturbances, effective real-time dispatching measures are needed to reschedule train services into new conflict-free train path plans. However, dispatching actions can also lead to new conflicts between trains, and further propagation of delays.

Dwell Time Delays
Dwell times play an important role in ensuring the system performance, service reliability, and quality in public transportation, and are typically where most delays first occur (Palmqvist, 2019). Train dwell time can be defined as the time a train stops at the platform, often for the purpose of allowing passengers to board or alight. Andersson (2014) mentions that a delayed train can use its dwell time margin to recover in time. Realistic allocation of dwell time reduces the risk of a train from exceeding its track occupation time, thereby preventing deviations from the scheduled train paths. Nie (2005) statistically analyses train operations between two Dutch major railway stations in the Hague. She indicates that when

scheduled dwell times at stations and running times are exceeded due to hindrance by other trains, then the scheduled headway between arrival and departure of some pairs of trains at critical route nodes will be insufficient and this consequently causes route conflicts. Delays can propagate as secondary delays to other trains, and consequently, disturb the entire network, as was identified already by Carey & Kwieciński (1994). On the other hand, Goverde & Hansen (2013) find that a train will not hinder other trains as long as it is kept within its allocated train path envelope, as indicated by a high percentile of realized process times (for running, dwelling, and turning processes) and a sufficient buffer time in addition to minimum headway times between train paths.

Delay Management

Delays can be avoided through effective timetabling and dispatching decisions of traffic controllers. Goverde & Hansen (2013) defined timetable resilience as the flexibility of a timetable to prevent or reduce secondary delays using dispatching (retiming, reordering, rerouting). Management of unexpected delays depends on the ability of the train dispatchers to make accurate decisions in advance by taking into consideration the interdependency between trains. However, dispatching measures are often sub-optimal as train dispatchers have a limited view of the effects of conflict resolution methods and are unable to compare alternative solutions based on various performance indicators due to the limited time available for real-time decision making. D'Ariano & Pranzo (2009) mention that dispatchers are unable to precisely evaluate the consequences of timetable disturbances in complicated railway networks. Lindfeldt (2015) also finds that the dispatching algorithm is less efficient if it considers only one station ahead instead of two when calculating the best dispatching solution.

In order to effectively reschedule trains during operations, many efforts have been devoted to developing automatic decision support tools to forecast delays propagation in the rail network. D'Ariano & Pranzo (2009) use a dispatching system to proactively detect and globally solve conflicts on each time interval that decomposed from a long time horizon with the objective of improving punctuality. Spatiotemporal probabilities and analyses on delay increase and recovery by Huang et al. (2019) help dispatchers to improve their decision-making qualities through a better understanding of the trains' delay recovery abilities at each station and section. To help dispatchers in making more informed decisions when dealing with real-time traffic disturbances, Samà et al. (2015) present a multi-criteria decision support methodology that involved mixed-integer linear programming formulations, based on the alternative graph model and an iterative Data Envelopment Analysis based method to establish an efficient-inefficient classification of the formulations and to improve inefficient formulations. Goverde (2010) introduces an effective delay propagation algorithm based on a timed event graph representation of a scheduled railway system with its zutilization in real-time applications such as interactive timetable stability analysis and decision support systems to assist train dispatchers. Lee et al. (2016) propose a delay root cause discovery model which used a supervised decision tree method based on machine learning methodology to analyze the scheduled or unscheduled trains meetings and overtaking behaviors, and the subsequent delay propagations. Liang et al. (2017) develop a dispatching optimization algorithm based on greedy algorithm to achieve an optimal relationship between capacity and operation quality through the influence of dispatching.

This Paper

In order to improve the real-time decision-making abilities of train dispatchers, it is useful to first study the effects of their decisions. Dispatching decisions are closely related to the interaction between trains which can influence the train speed profiles and the orders of trains at conflict points, leading to complex problems if inaccurate decisions are made.

Thus, this paper focuses on passing of passenger train and explores its effects on dwell time delays, which are the most common type of delay for passenger trains in Sweden. With a better understanding of train passings and their impacts on delays, the use of dispatching measures can be improved, ensuring more punctual railway operations.

This paper is organized as follows: In Section 2, mathematical formulations and methodology used in this study are introduced. In Section 3, we analyze, and discuss the results generated, and measure of the effect of train passes. Finally, Section 4 makes a conclusion and recommendations for further research.

2 Train Passing and Delays

In this paper, we focus on the passing of train on double-track lines, because this is much more common than on single-track lines. The passing of trains occurs when a train passes another train moving in the same direction. Two assumptions are made in this study: 1) double tracks are treated as separate independent systems in each direction and 2) the separate systems are reserved for trains in one direction each. This implies that each track in the double track is subjected to one way traffic and the trains are assumed to not encountering oncoming trains or turns through oncoming trains since the trains can only move in one direction. Thus, trains conflicts in the opposite directions as well as in switching areas are not taken into consideration in this study. These assumptions are illustrated in Figure 1.

Figure 1: Double tracks as separate independent systems

Comparing the timetable to actual operations there are three possible outcomes with regards to the passing of trains. For instance, passing can be scheduled (1), cancelled (2), or unscheduled (3). The most common case (4) when there is no passing in the timetable, and none in the actual operations, is not considered here. Table 1 illustrates these different possibilities.

Table 1: Different types of train passing scenarios

Scheduled operations / Actual operations	No pass	Pass
No pass	No pass	Cancelled pass
Pass	Unscheduled pass	Scheduled pass

Figure 2 shows a scenario where train A is scheduled to enter the line after train B. At stations A and D, there is *no pass*, as the trains do not overlap. At station B, there is a *cancelled pass*, because train A was scheduled to pass train B, but did not do so. At station C, there is instead an *unscheduled pass*, where no pass was scheduled but one took place.

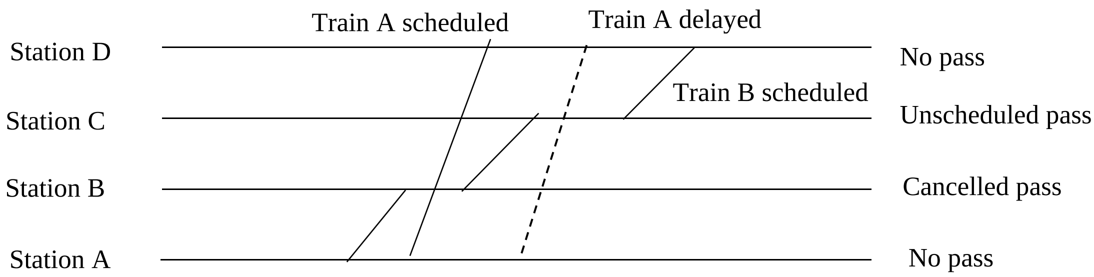

Figure 2: Scenario with different types of train passing

Data Studied

In this study, we used train operation data from the Swedish Transport Administration, which covers all train movements on double tracks in Sweden for the year 2014. Observations for Saturday and Sunday are omitted because there are differences in travel behavior between weekends and weekdays. There are also fewer trains on weekends, reducing the risk of delay propagation. As reported by Trafikanalys (2019), punctuality was measured to be 94-95% for Saturday and Sunday respectively but on weekdays, punctuality was in the range of between 90-91%.

Finally, the observations of train movements are reduced from 13,000,000 to 403,000 when all the trains with no passing are filtered out. Even though *no passing* constituted approximately 97% of the data, it is excluded from the analysis because inclusion trains without passing into the model reduce the representativeness of the model, causing a very large AIC and BIC and low R^2 and AUC. Instead, we focus on the 3% of train movements with scheduled and/or actual passes.

The whole data set is split into common split percentages, that is 80% training and 20% test data set. The 80% of training data is used for model training, while the remaining 20% is used for checking how well the model generalized on unseen data set by using performance measures.

Combined Dwell Time Delays

Yuan & Hansen (2007) and Harris et al. (2013) demonstrate that delays arise especially at stations since the crossing or merging of lines and platform tracks are in most cases the bottlenecks in highly used railway networks. Since delay is more common at stations, dwell time delay instead of delay in running time or arrival time is focussed in this study. Dwell time is the time that a train stops at a station. It is the difference between the arrival and departure times. If t_{dwell} is dwell time, t_{dep} departure time and t_{arr} arrival time, then

$$t_{dwell} = t_{dep} - t_{arr} \tag{1}$$

A dwell time delay is the difference between the realised and scheduled dwell time, given that the departure is delayed. It is also the difference between the arrival and departure delays at the given station.

$$d_{dwell} = t^{r}_{dwell} - t^{s}_{dwell} = (t^{r}_{dep} - t^{r}_{arr}) - (t^{s}_{dep} - t^{s}_{arr}) \tag{2}$$

where d_{dwell} = dwell time delay; t^{r}_{dwell} = realised dwell time delay; t^{s}_{dwell} = scheduled dwell time delay; t^{r}_{dep} = realised departure times; t^{r}_{arr}= realised arrival times; t^{s}_{dep}= scheduled departure times; t^{s}_{arr} = scheduled arrival times. The focus of this paper is on dwell time delays, here measured in terms of combined dwell delay for both trains:

$$C_{dwell}= d_{dwellA} + d_{dwellB} \tag{3}$$

where C_{dwell}= combined dwell delay of A and B at the same station; d_{dwellA} = dwell time delay of train A; dwell B = dwell time delay of train B. This study does not take into account the prioritization issues among trains, and a delay is said to occur when there is a net delay across both trains, without giving more weight to either train A or B. Since the data used in this study are in hours and minutes, we can only calculate a minimum delay of at least one minute. Thus, if C_{dwell} is greater than 0 mins it is considered as an increase in dwell time. In this paper, we focus on instances when this delay increases, not on the size of the delay increase.

3 Modelling with Odds Ratios and Logistic Regression

Odds is a way of using probabilities to estimate the chance that an event will occur.

$$Odds = \frac{\text{Probability of an event occurring}}{\text{Probability of an event not occurring}} = \frac{\pi_i}{1-\pi_i} \tag{4}$$

In this paper, we denote π_i as the probability of $C_{dwell} > 0$, that is:

$$\pi_i = \frac{\text{Number of instances with } C_{dwell} > 0}{\text{Total number of instances}} \tag{5}$$

In this study, the odds ratio (OR) is used as a comparison. Specifically, we compare the odds of delay for two cancelled and unscheduled passes with that when the pass was carried out as scheduled:

$$Odds\ ratio = OR = \frac{\text{Odds 1}}{\text{Odds 2}} = \frac{\frac{\pi_i}{1-\pi_i}}{\frac{\pi_j}{1-\pi_j}} \tag{6}$$

The logistic regression model is a statistical modelling technique that estimates the probability of a dichotomous outcome event being related to a set of explanatory variables. By convention, the dependent variable is designated as being positive when delays increase and negative when not with the scores of 1 versus 0 respectively for coding of the dependent variable in computerized data sets. The logistic regression model can also be written as

$$log\left(\frac{\pi_i}{1-\pi_i}\right) = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} \quad (7)$$

Notice that the left-hand side of the equation is the log odds of a delay increase occurring.

Logistic Regression Model

The model in this paper is a logistic regression model that is created to contain the main effects of different types of train passing and with the occurrence of increase in dwell time delay as the response. There is always a trade-off between the prediction performance and the underlying causal inference that must be taken into consideration when selecting suitable models for the topics to be studied (Tang et al., 2020). In this case, we opt for a statistical model, which can provide better understanding about the relationship between parameters, instead of more complex models. Other types of models might provide better predictive power, but be more difficult to interpret.

If x_1, x_2 are dummy variables representing cancelled and unscheduled passes, respectively, the model has the form:

$$log\left(\frac{\pi_i}{1-\pi_i}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \quad (8)$$

In this model, the independent variable in this study is the types of passing, a categorical variable with three categories. Thus, two dummy variables are created, with trains in the category for scheduled pass as reference group and baseline of operations running mostly as intended. This reference group was coded as zero in the dataset, and odds ratios for other group relative to the reference group were calculated. For the three scenarios we consider, the expressions for the logistic regressions are thus as follows:

$$\log \text{Odds (Scheduled pass)} = \log\left(\frac{\pi_0}{1-\pi_0}\right) = \beta_0 + 0 * \beta_1 + 0 * \beta_2 = \beta_0 \quad (9)$$

$$\log \text{Odds (Cancelled pass)} = \log\left(\frac{\pi_1}{1-\pi_1}\right) = \beta_0 + 1 * \beta_1 + 0 * \beta_2 \quad (10)$$

$$= \beta_0 + \beta_1$$

$$\log \text{Odds (Unscheduled pass)} = \log\left(\frac{\pi_2}{1-\pi_2}\right) = \beta_0 + 0 * \beta_1 + 1 * \beta_2 = \beta_0 + \beta_2 \quad (11)$$

Substituting and shifting these terms, we get the following:

$$\beta_1 = log\left(\frac{\pi_1}{1-\pi_1}\right) - log\left(\frac{\pi_0}{1-\pi_0}\right) = log\left(\frac{\pi_1/(1-\pi_1)}{\pi_0/(1-\pi_0)}\right) = log\left(\frac{\text{Odds (Cancelled pass)}}{\text{Odds (Scheduled pass)}}\right) \quad (12)$$

$$\beta_2 = log\left(\frac{\pi_2}{1-\pi_2}\right) - log\left(\frac{\pi_0}{1-\pi_0}\right) = log\left(\frac{\pi_2/(1-\pi_2)}{\pi_0/(1-\pi_0)}\right) = log\left(\frac{\text{Odds (Unscheduled pass)}}{\text{Odds (Scheduled pass)}}\right) \quad (13)$$

The odds ratios can thus be expressed as:

$$\text{Odds ratio}\left(\frac{\text{Cancelled pass}}{\text{Scheduled pass}}\right) = e^{\log\left(\frac{\text{Odds (Cancelled pass)}}{\text{Odds (Scheduled pass)}}\right)} = e^{\beta_1} \quad (14)$$

$$\text{Odds ratio}\left(\frac{\text{Unscheduled pass}}{\text{Scheduled pass}}\right) = e^{\log\left(\frac{\text{Odds (Unscheduled pass)}}{\text{Odds (Scheduled pass)}}\right)} = e^{\beta_2} \quad (15)$$

4 Results

Our first finding is that, in the data we study, passes rarely happen as scheduled. As we see in Figure 3, *cancelled passes* of trains are most common at 76%, followed by *unscheduled passes* at 21%. *Scheduled passes* are the least common, at 3%, and 97% of passes are thus *not* as scheduled. This indicates that the timetable is difficult to realize with a high level of accuracy, and it suggests a high degree of activity among dispatchers who cancel and reschedule train passes, often shifting them from one station to another.

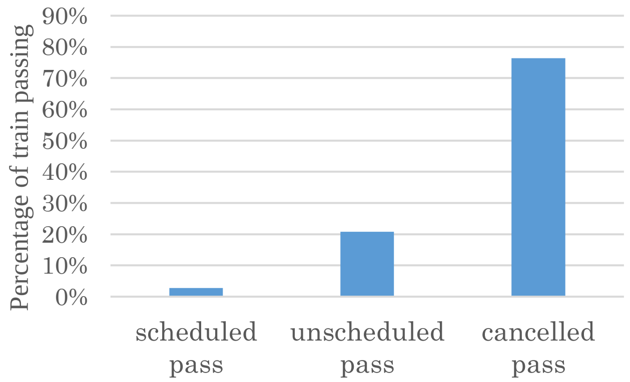

Figure 3: Distribution of different types of train passes

Our second finding is that these three types of train passes are associated with very different delay probabilities. As indicated in Figure 4, *unscheduled* passes are at most risk of leading to dwell time delays with a probability of 69%, while a *cancelled* passes is only associated with an 8% probability of delay. *Scheduled* passes are in between these two, with a 46% probability of dwell time delay. Cancelling a pass is thus a good way to reduce the risk of delay at one station, but it can bring with it a large increase in the delay probability at another station. For context, when there is *no pass*, which is the most common situation in operations, there is a 22% probability of a dwell time delay. Better than when there is a *scheduled pass*, but worse than if there is a *cancelled pass*.

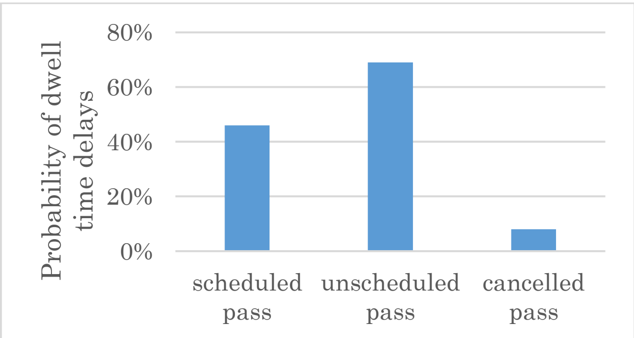

Figure 4: Probability of dwell time delays for each type of train passing

Regression Results

The results from the regression models are found in Table 2, and show essentially the same trend as Figure 4: delays are much less likely when passes are cancelled, and much more likely when they are unscheduled, compared to when they happen as scheduled. The odds ratios are about 0.1 and 2.6, respectively, in both models – where a value lower than 1 indicates a reduced risk and above 1 an increase. Cancelling train passes can thus be a useful way to reduce or avoid delays, and this is often done. In many cases, however, passes cannot simply be *cancelled*, but must be shifted from one station to another, where it instead appears as an *unscheduled* pass, and then have a greatly increased probability of delay.

Table 2: Summary of Logistic Regression Models

Predictor	Estimate	Odds Ratio (OR)	Confidence Interval	
			Lower	Upper
(Intercept)	-0.152***			
Train passes:				
Cancelled pass	-2.283***	0.102	0.098	0.107
Unscheduled pass	0.952***	2.592	2.479	2.710
R^2	0.310			

Model Evaluation

In this study, 80% of the data are used for training the model while 20% are used for testing the model that is built out of it. The performance from testing set data for the two logistic regression models set is measured with the receiver operating characteristic (ROC) curve. This plots the true positive rate (another name for recall) against the false positive rate (FPR) where:

$$\text{True positive rate} = \text{TPR} = \text{Recall} = \frac{\text{TP}}{\text{TP+FN}}. \tag{28}$$

where TP is the number of true positives and FN is the number of false negatives. The recall is intuitively the ability of the classifier to find all the positive samples. The FPR is the ratio of negative instances that are incorrectly classified as positive:

$$\text{False Positive Rate} = \text{FPR} = \frac{\text{FP}}{\text{TP+FN}}. \tag{29}$$

A perfect classifier will have area under the ROC curve (ROC AUC) equal to 1, whereas a purely random classifier will have a ROC AUC equal to 0.5. In Figure 5, the ROC AUC of the model used in this study is 0.79

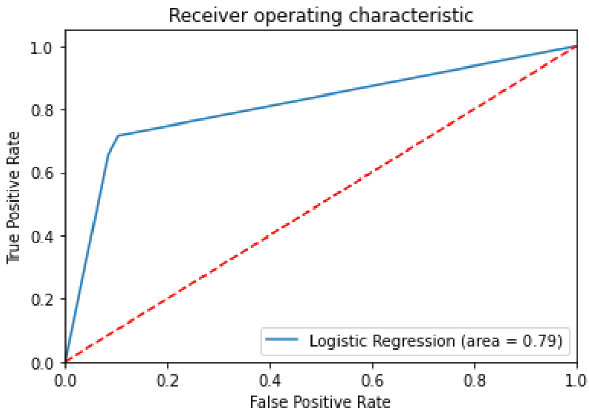

Figure 5: ROC curves for Logistic Regression Model

5 Conclusion

This analysis has shown two things:

1) Only a small percentage (3%) of train passes happen as scheduled, with a great many (76%) instead of being cancelled and a substantial percentage (21%) being unscheduled. This indicates there is significantly fewer train passes in actual operations than in timetables, and that dispatchers play a very active role in operations.

2) That train passes can significantly alter the probability of delays at stations. Compared to when they happen as scheduled, the odds of delays are reduced by about 90% when they are cancelled, and they increase by about 260% if they are unscheduled. Despite cancelling a pass can be used to mitigate the possibility of delay at one station, it will be registered as as an unscheduled pass at another station, greatly increasing the odds of delay at that station.

One of the main advantages of the applied logistic regression model is that is that it is simple, and not a ‘black box’ model, that it is easy to interpret. However, the model is associated with several limitations and simplifactions. For one, it only accounts for different types of passes, and omits many other variables (including other types of train interactions and conflicts). It is also based on macroscopic train operations data, on a station-by-station level, rather than signal-by-signal, which would be more precise. The R^2-value indicates that the model can only explain around 30% of the variance in dwell time delays, and that is only when considering the relatively small part of the data that includes some sort of (*scheduled*, *cancelled*, or *unscheduled*) pass. Including more variables, such as passenger data, other types of train movements, weather conditions, detailed timetable information, infrastructure failures, and so on, as well as using more complex models, would most likely improve the overall predictive power of the model. However, that would not necessarily teach us more about the importance of passing interactions.

In future work, we will continue to work on identifying the actions of dispatchers, and evaluate their consequences with empirical data. Previously, this has mostly been done theoretically or with manual observation, with relatively little work on large, real datasets. We will also consider other types of interactions and ways in which delays propagate between trains.

References

Andersson, E. V. (2014). Assessment of Robustness in Railway Traffic Timetables. In *Assessment of Robustness in Railway Traffic Timetables* (Issue 1636). https://doi.org/10.3384/lic.diva-103676

Carey, M., & Kwieciński, A. (1994). Stochastic approximation to the effects of headways on knock-on delays of trains. *Transportation Research Part B*, *28*(4), 251–267. https://doi.org/10.1016/0191-2615(94)90001-9

D'Ariano, A., & Pranzo, M. (2009). An advanced real-time train dispatching system for minimizing the propagation of delays in a dispatching area under severe disturbances. *Networks and Spatial Economics*, *9*(1), 63–84. https://doi.org/10.1007/s11067-008-9088-1

Goverde, R. M. P. (2010). A delay propagation algorithm for large-scale railway traffic networks. *Transportation Research Part C: Emerging Technologies*, *18*(3), 269–287. https://doi.org/10.1016/j.trc.2010.01.002

Goverde, R. M. P., & Hansen, I. A. (2013). Performance indicators for railway timetables. *IEEE ICIRT 2013 - Proceedings: IEEE International Conference on Intelligent Rail Transportation*, *August 2018*, 301–306. https://doi.org/10.1109/ICIRT.2013.6696312

Harris, N. G., Mjøsund, C. S., & Haugland, H. (2013). Improving railway performance in Norway. *Journal of Rail Transport Planning and Management*, *3*(4), 172–180. https://doi.org/10.1016/j.jrtpm.2014.02.002

Huang, P., Wen, C., Li, J., Peng, Q., Li, Z., & Fu, Z. (2019). Statistical Analysis of Train Delay and Delay Propagation Patterns in a High-Speed Railway System. *2019 5th International Conference on Transportation Information and Safety (ICTIS)*, 664–669. https://doi.org/10.1109/ICTIS.2019.8883805

Lee, W. H., Yen, L. H., & Chou, C. M. (2016). A delay root cause discovery and timetable adjustment model for enhancing the punctuality of railway services. *Transportation Research Part C: Emerging Technologies*, *73*, 49–64. https://doi.org/10.1016/j.trc.2016.10.009

Liang, J., Martin, U., & Cui, Y. (2017). Increasing performance of railway systems by exploitation of the relationship between capacity and operation quality. *Journal of Rail Transport Planning and Management*, *7*(3), 127–140. https://doi.org/10.1016/j.jrtpm.2017.08.002

Lindfeldt, A. (2015). *Railway capacity analysis - Methods for simulation and evaluation of timetables, delays and infrastructure*. https://www.diva-portal.org/smash/get/diva2:850511/FULLTEXT01.pdf

Nie, L., & Hansen, I. A. (2005). System analysis of train operations and track occupancy at railway stations. *European Journal of Transport and Infrastructure Research*, *EJTIR*, *5*(1), 31–54.

Palmqvist, C.W. (2019). Delays and Timetabling for Passenger Trains. Doctoral thesis. Lund: Lund University, Faculty of Engineering.

Tang, J., Zheng, L., Han, C., Yin, W., Zhang, Y., Zou, Y., & Huang, H. (2020). Statistical and machine-learning methods for clearance time prediction of road incidents: A methodology review. *Analytic Methods in Accident Research*, *27*, 100123. https://doi.org/10.1016/j.amar.2020.100123

Technology and Society, Transport and Roads, Lund, Sweden Samà, M., Meloni, C., D’Ariano, A., & Corman, F. (2015). A multi-criteria decision support methodology for real-time train scheduling. *Journal of Rail Transport Planning and Management*, *5*(3), 146–162. https://doi.org/10.1016/j.jrtpm.2015.08.001

Trafikanalys. (2018). *Transportarbete 2000–2017*.

Yuan, J., & Hansen, I. A. (2007). Optimizing capacity utilization of stations by estimating knock-on train delays. *Transportation Research Part B: Methodological*, *41*(2), 202–217. https://doi.org/10.1016/j.trb.2006.02.004