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Dwell Time Delays for Commuter Trains in Stockholm and Tokyo

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Abstract

The paper analyses dwell time delays for commuter trains in Stockholm and Tokyo. In both cities, small dwell time delays of at most five minutes make up around 90% of the total delays. Therefore, it is valuable to understand and deal with these disturbances. To this end, we use high resolution data on dwell times and passenger counts from both countries over the last several years. We find that these data alone can explain about 40% of the variation in dwell time delays and produce simple models which can be used in practice to assign more appropriate dwell times. A change of 15 passengers per car, in Tokyo translates to a delay of about one second. For every 10 remaining passengers per door in Stockholm, the delay increases by about one second, and one boarding or alighting passenger per door corresponds to about 0.4 seconds of delay. We also find that trains in Tokyo are much more congested than in Sweden, and that at most stations in the latter, the exchange of passengers is modest. In both cities, the range of dwell time delays is quite narrow, with between 40 and 50 seconds separating the 5th and 95th percentiles. This indicates further that most delays, by far, are very small, and that even small adjustments to dwell times can make a big difference in the overall picture. To facilitate such improvements, key stakeholders and practitioners are closely involved with the research.

Keywords

Commuter train, Dwell time, Delay, Timetable, Station, Passenger, Congestion, Urban transport, Public transport, Rail

1 Introduction

A problem across the world is that trains are often delayed. In major cities, where the flow of trains and passengers are large, even minor delays cause considerable inconvenience for both commuters and train operating companies. This paper studies commuter trains in Stockholm and Tokyo, two cities where minor delays are ubiquitous and larger ones are not uncommon.

In Stockholm, only 56 % of commuters report being satisfied with the punctuality of commuter trains, which is the lowest across all public transport options (Trafikförvaltningen Stockholms Läns Landsting, 2018). This is the single most important influencing factor for their overall satisfaction with the transportation mode. Thus, if the delays could be reduced, there is a clear potential for increasing the attractiveness and ridership of trains in Stockholm.

In the Tokyo-area, approximately 38 million train journeys are made every day (Tomii, 2013). During the rush hours, it is common for a single train to carry about 2 000 passengers and for trains to depart every two minutes on each line. Thus, even the slightest delay quickly spreads between trains and affects large numbers of passengers. Because of this, trains in Tokyo are very often delayed by several minutes during the rush hours, and this affects millions of people and causes considerable costs to society.

In Stockholm and Tokyo, minor delays of at most five minutes make up 96 and 97 % of delay hours respectively. In both cities, the delays mostly occur at stations in the form of dwell time delays. In Stockholm, 91 % of the total delay time is generated at stations, while the corresponding figure in Tokyo is 88 %. Thus, small dwell time delays make up a clear majority of all delays.

The objective of this paper is to study the dwell time delays that occur in both railway systems. Different timetabling policies are discussed, and detailed passenger count data is used to help explain the delays in both cities. The ambition is that the study will lead to better timetable planning, which will in turn lead to a decrease in delays and improved punctuality in both cities. This will improve the daily commutes of millions of people and make public transportation more attractive.

2 Background

In an overview of timetabling research, Hansen (2009) concludes that one of the key issues for high quality timetables is using realistic dwell times, and that this is often not the case, neither in practice nor in modelling.

Bender, Büttner & Krumke (2013) also state that the time required for passenger boarding and alighting at stations is a critical element of overall train service performance. There is considerable empirical evidence for this across the world, of which we can only cite a few pieces here.

In New Zealand, Ceder & Hassold (2015) found that one of the main causes for delays was heavy passenger load, which increased dwell times.

In Norway, Olsson & Haugland (2004) studied punctuality and found that the boarding and alighting of passengers was the single most important influencing factor in congested areas. Considering stations in the Oslo area, Harris, Mjøsund & Haugland (2013) found that the delays were often small in nature, poorly recorded and not well understood.

In the Netherlands, Wiggeraad (2001) studied seven stations in detail, finding that dwell times are longer than scheduled, that the scheduled dwell times were the same at peak and off-peak, and that passengers concentrated around platform access points. Focusing on the station area of the Hague, Nie & Hansen (2005) also concluded that dwell times at platforms are systematically extended, partially due to the behaviour of the train personnel. Studying punctuality and delays at stations, Yuan & Hansen (2002) found that the mean excess dwell time was around 30 seconds, and that this sometimes depended on the train having arrived early and not being permitted to depart before the schedule, but also due to a lack of discipline with train drivers and conductors.

In Sweden, previous research (Palmqvist, Olsson & Hiselius, 2017) shows that most delays happen during scheduled stops. Analyses of such stops reveal a wide variation in dwell times (Heinz, 2000), while interviews with timetable planners (Palmqvist, Olsson & Winslott Hiselius 2018) indicate that dwell times in Sweden are not scheduled to account for the number of passengers, rush hour traffic, and the like.

In Japan, Kunimatsu, Hirai & Tomii (2009) describe the mechanism of how a dwell time is exceeded because there are many passengers. This delay increases the distance between trains and allows more people to accumulate at the next platform, so that both the congestion and delay increase further and continue to be amplified, in what they call a “snowball effect” – similar to bus bunching. They then create a simulation model to evaluate timetables, with input from smart card data, which takes these interactions into account.

There is also a literature focusing more explicitly on the boarding and alighting of passengers, as well as their behaviour on platforms and in stations. Seriani, Fujiyama & Holloway (2017) have done detailed observations at metro stations in the United Kingdom to examine how queues and lanes form when boarding trains, the densities of passengers and distances between them, in the semi-circular area outside the doors. Several

publications (such as Kamizuru, Noguchi & Tomii 2015; Qi, Baoming & Dewei 2008; Seriani & Fernandez 2015; Bae et al. 2012) deal with simulations of passengers moving between the train and platform to study various kinds of passenger management strategies. Fujiyama & Cao (2016) instead used smart-card data to study how long passengers spend at railway terminals, beyond simply walking from the access point to the train, a factor which influences and increases the level of congestion at stations.

Finally, there is a literature on modelling dwell times. Buechmuller, Weidmann & Nash (2008) modelled dwell times in Switzerland, breaking them down into five components, and used over three million observations for calibration. D’Acierno et al. (2017) modelled how they depend on the congestion and flows of passengers. Most use track occupancy data, like Pedersen, Nygreen & Lindfeldt (2019) who studied how dwell times vary over time and running direction in Norway, Longo & Medeossi (2008) who applied their dwell time models in micro-simulation, Li, Daamen & Goverde (2015) who focused on short intermediate stops in the Netherlands, and Kecman & Goverde (2015) who were interested in real time prediction. Others, like Li, Yin & He (2018) use a combination of track occupancy data and manual observations, and this is what we do in this paper.

3 Method

3.1 Data

Four datasets are used and combined in this paper, as outlined below.

(1) Train movements in Stockholm. This data is derived from the signalling system and specifies the arrival, departure and passage times at stations. The times are truncated as to only contain minutes and hours, not seconds. Data from seven years, 2011-2017, is used, for a total of 16.6 million train movements.

(2) Automatic passenger counts in Stockholm. About one eighth of commuter train cars in Stockholm are equipped with automatic passenger counters, which detect the boarding and alighting of passengers at stations. These cars are circulated among the different branches of the network, to provide data on most trains and stations from time to time. Along with the counts of passengers, the equipment also provides both run and dwell times with a precision of one second. We have 5.5 million such observations spanning the years of 2013-2017.

(3) Train movements in Tokyo. These are also generated from the signalling system from a railway company and specifies times at stations, but with a precision of seconds. The data spans six years, from 2013 to 2018,

and contains 63.7 million train movements.

(4) Manual passenger counts in Tokyo. At least twice every year manual passenger counts are conducted for trains at stations, to estimate the level of on-train congestion. While this is only a spot check, it is the result of considerable effort and provides valuable insights into how the number of passengers varies between trains and stations. From about 6:30 to 9:00 in the morning, staff at a handful of stations observe all trains that stop or pass by, making note of exact arrival and departure times, the train number and the number of cars, as well as the estimated congestion rate on the train. Approximately 50 trains are observed in this manner, per station, and over the years 2013-2018, over 4000 observations were made.

3.2 Combining the Data

As the data from the two countries varied slightly in structure, different methods had to be used to combine them.

In the Japanese case, we mainly make use of the manual observations, as these are generally of a higher quality and the more relevant ones to use, and the number of observations is sufficient for our purposes. In the timetable dwell times are set intended to correspond to the times that are measured using the manual methods: from the train stopping to starting its movement at the platform. The automatic system instead uses the occupation of track circuits, which are located further out on the respective sides, and on average registers times that are about 20 seconds longer. However, a problem with manual observations is that mistakes can sometimes be made, and we have used the larger dataset of automatic registrations to be able to detect these errors. Because of how the measurements are made, the manual ones should never be longer than the automatic ones. In such cases, we have simply excluded the observation as faulty. The connection between the two datasets was quite straightforward, as they both contain station names, dates and train numbers that match up very well and, in the end, we produced 2 684 good matches. In the future, it may be possible to do some extrapolation from these onto other train numbers or dates, but for now we have stuck with the observations themselves.

For the Swedish case, the process was not so straightforward. The on-board system did not contain train numbers matching those used in the dataset from the signalling system. As a first step, however, observations were merged from being door by door, to a train level, with averages across the different doors. The number of doors per train with the measuring equipment varied from one to eight, with four being the most common. Then, these trains were matched to train numbers in the larger dataset, following some assumptions: that the dates and stations were the same, that

the origins and destinations match up, and that the total deviation between the arrival and departure times between the two sets was less than two minutes. We know that the coding of station names, as well as origins and destinations, sometimes differs between the two sets, but because both datasets were quite large the number of matches is quite good, even without considering such cases. Finally, we excluded any cases where there was more than one possible match, focusing on the clear and unambiguous ones.

For the Swedish data, we primarily used the connection between the two datasets to filter out any observations with unusually long scheduled dwell times. The on-board system does not state the scheduled times, only the observed ones, while the infrastructure-based system only retains the minutes, not the seconds. However, we know from timetable planners that the scheduled dwell time for commuter trains in Sweden is, in most cases, 42 seconds, with a few exceptions. Some peripheral stations instead have 30 seconds, Stockholm Central Station around two minutes, and a few other cases where trainsets turn around or are either combined or separated also have longer dwell times. To get rid of the shorter times, we asked planners which stations had shorter times, and excluded observations from these. In order to get rid of the stops with longer scheduled times, we used a threshold of one minute in the larger off-board dataset. Finally, to harmonize with the Japanese data which was only collected between six and ten in the morning, on Mondays and Tuesdays in April, May and November, we filtered out any observations outside of these time intervals. This greatly reduced the amount of observations, from about 180 000 to around 3 300, but this later number is more comparable to the number of Japanese observations. The regression results vary slightly between how this filtering is done, with coefficient estimates and the R^2 both shifting by a few tenths of a percentage point, but not in any major ways.

3.3 Analysing the Data

In the analysis we are primarily concerned with using the information on passenger volumes to explain the variation in dwell time delays. In the Japanese data, this exists in the form of an estimated congestion rate, which is the ratio between the number of people on board a train, to the number of seats and handles for standing passengers to hold. The train cars in Tokyo have four doors and are 20 meters long, each with about 58 seats and 92 handles, and are usually combined in sets of eight or ten cars. In Stockholm, the commuter trains are composed of either six or twelve cars, each of which is about 18 m long with two doors and room for 62 sitting and 71 standing passengers. For these trains we have explicit counts of the number of boarding, alighting, and passing passengers from sensors at between one and

eight doors per train. The total capacity for a full-length train is 1600 people, averaging 66.7 per door, compared to 37.5 in Tokyo. In both cities, we also have information of the incoming arrival delay, as well as dummy variables for the different stations, hours, months, and weekdays.

The effects are studied using regression analysis with the software R. A number of regressions have been performed, using different combinations of the variables, their squares and interactions, and both with and without intercepts. With the regressions we essentially have two purposes: (1) to estimate the degree to which we can explain the variation in the dwell time delays, using passenger data, and (2) to estimate the impact of passenger volumes on the dwell time delays, in a comprehensible way. The first point relates to the coefficient of determination, the R^2 or adjusted R^2 , while the second has to do with coefficient estimates. To fulfil the first purpose, it is relevant to include both squared variables, as well as variable interactions, as these may well, in fact, have impacts on the delays and add to the share which we can explain. The second purpose, however, is better served by keeping the models simple and straightforward, sacrificing explanatory power for interpretability. In this paper, we will only present the coefficient estimates for the second set of models, but also mention the degree to which more complicated models can add to the picture.

4 Results and Analysis

The following sections describe the two cases and presents the results of some regression analyses on the data. The first sections describe how dwell times are scheduled in both cities, what the delays are like, and how the passenger volumes differ. The fourth and fifth section describe how much of the delays can be explained by the passenger volumes and estimates that can be relevant for timetable planning.

Table 1. Percentiles describing the arrival and dwell time delay distributions across the two cities.

Percentile	5%	25%	50%	75%	95%
Arrival Delay (s)					
Stockholm	-300	0	60	60	120
Tokyo	-20	3	25	63	158
Dwell Time Delay (s)					
Stockholm	-8	-1	6	14	34
Tokyo	-21	-4	5	15	30

4.1 Scheduled Dwell Times

The railway companies in the two cities have different policies on scheduling dwell times. The default in Stockholm is to use 42 seconds regardless of day, time or station, with a few exceptions. Stockholm Central Station is one such exception, when the dwell times are extended, as are stops where trains are coupled, separated or turned around. At a few small stations in the periphery times are either lowered to 30 seconds or extended to handle meetings on single track sections. In most cases, however, the scheduled dwell time is 42 seconds, and these are the ones that we use in this study. In Tokyo, the dwell times are adjusted to a much greater extent. The range is quite similar to that found in Stockholm, but the variation is greater: the 5th, 25th, 50th, 75th and 95th percentile values are 40, 45, 50, 60 and 115 seconds, respectively. Almost across the board, the dwell times in Tokyo also longer than the 42 seconds used in Stockholm, and adjustments are made in five-second intervals, across different train numbers, stations, and hours.

4.2 Arrival and Dwell Time Delays

The delay scenarios are quite similar in both cities. Arrival delays are not measured as precisely in Stockholm as in Tokyo, which makes it difficult to compare them in detail. Overall, however, in both scenarios a small share of trains arrives early, while the median is for delays of 60 seconds in Stockholm and 25 seconds in Tokyo. Arrivals are rarely delayed by more than two or three minutes, with the 95th percentile in Stockholm being 120 seconds, and in Tokyo 158 seconds. In both cases, the signalling data contains a larger share of trains arriving early than the count and combined data.

Dwell time delays are remarkably similar across the two combined datasets. In Stockholm the median delay is 6 seconds, compared to 5 in Tokyo, and the 95th percentile values are 34 and 30 seconds respectively. About the same share of trains make up time during the stops, in the two cities, but in Tokyo the ones that do make up slightly more time, with the fifth percentile being 21 seconds early there, compared to 8 seconds in Stockholm. The range of dwell time delays, from the 5th to the 95th percentiles, are quite small and comparable: 42 seconds in Stockholm and 51 seconds in Tokyo. As these are commuter trains, however, stops are frequent, and the seconds add up.

4.3 Passenger Volumes

Perhaps the biggest difference between the two cases is the number of passengers. In Tokyo, the trains that we study are often very congested, as

seen in Table 2. The congestion rate is defined so that 100 represents all 58 seats being taken, as well as all of the 92 standing positions with handles. In the data we study, the 25th percentile has a congestion rate of 105, the median is 130, and the 95th percentile 180. The lowest we see, in the 5th percentile, is 60, corresponding to 90 passengers and a case where all seats are taken, and about an equal amount of people are standing.

In Stockholm the number of passengers is less extreme. Despite the observations also being made during the morning rush hours, the figures suggest that the median scenario is two people alighting, four boarding, and 25 remaining, per door, corresponding to a congestion rate of 43. When the 95th percentile values are added together, there are 104 passengers on board per door, or 208 per car, compared to 270 in Tokyo. The peak congestion rate of 156 in Stockholm is also lower, but comparable to, the peak of 180 in Tokyo. The relatively low numbers of boarding and alighting passengers depend in part on the fact that we excluded stations with longer dwell times, for reasons described in section 3.2, and thus omit both the central station and the origins of many trains, where the number of passengers is larger. Stockholm also has a more monocentric structure than Tokyo, and generally lower levels of population density and congestion.

As the measurements are made automatically in Stockholm, and manually in Tokyo, there may be issues of calibration or measurement error. The engineers and planners responsible in Stockholm say that the measurements are not very accurate for high flows, and systematically gives too low values in such cases. This implies that the figures from that city are

Table 2. Percentiles describing the passenger volumes in either city. The figures from Stockholm are passengers per door, with either 12 or 24 doors per train. Congestion rate in Stockholm is defined per door, so that a value of 100 entails 67 passengers (31 sitting, 36 standing). In Tokyo it is normalized per car so that 100 entails 150 passengers (48 sitting, 92 standing), split across four doors.

	5%	25%	50%	75%	95%
Stockholm					
Alightings/door	0	0	2	7	21
Boardings/door	0	1	4	9	22
Passing Travellers/door	3	12	25	43	82
Congestion Rate	4	19	43	78	156
Tokyo					
Congestion Rate	60	105	130	150	180

underestimated, rather than overestimated, although it is unclear to what degree. As we see in Table 2, the flows are not large at most of the stops we include in this analysis, so this is unlikely to be an issue here, and more likely to cause problems in Stockholm Central Station, which we have omitted from the analysis.

4.4 The Contribution of Passengers to Delays

To estimate how much of the dwell time delays can be explained by passenger data, we use linear regression models including both squared and interaction terms. These models are impractical to use and interpret, but their adjusted R^2 values provide a convenient estimate of how much information is contained in the data. We also include terms for the arrival delay and, in the case of Tokyo, scheduled dwell time, as these can be expected to interact somewhat with the passenger flows. Dummy variables for stations, weekdays, months, etc. are not used, because they do not help us estimate the influence of the passengers. Summaries of the two respective models are presented in Table 3. The data in Stockholm could explain slightly more of the variation than that in Tokyo, which is to be expected as it also contained the number of people getting on and off, rather than only counting those on-board.

In both cases, about 40% of the variation is explained using the full models, and about half as much by the simple models. While the models are in no way complete, and the residuals are not normally distributed, these levels are reasonable. There are many other factors which affect delays, such as weather, train interactions like meetings and overtakes, driver behaviour, technical errors in the train or infrastructure, etc. Thus, there is no reason to

Table 3. Summary statistics from linear regressions in Tokyo and Stockholm. The full models include squared and interaction terms, the simple ones do not.

	Full models		Simple models	
	Tokyo	Stockholm	Tokyo	Stockholm
Residual standard error	16.87	16.13	19.53	19.02
Degrees of freedom	2621	3046	2681	3297
Multiple R^2	0.3951	0.4687	0.1712	0.2004
Adjusted R^2	0.3806	0.4242	0.1703	0.1995
F-statistic	27.18	10.54	184.7	206.6
Coefficient estimates	63	255	3	4
p-value	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16

believe that the exchange of passengers, alone, would explain all of the variation in delays, even though it may be one of the more important causes. In this light, levels between 20 and 40% are reasonable.

4.5 Relevance to Timetable Planning

To make timetables in practice, simpler models are required. We have thus also performed linear regressions without considering squared terms or interactions. The summary statistics are presented in Table 4, and they had about half as much explanatory power as the full models, with adjusted R^2 values of about 0.17 in Tokyo and 0.20 in Stockholm. The coefficient estimates are found in Table 4 and can be used as a reference when allocating dwell times in the timetable planning process.

In Tokyo, we find that a rise in the congestion rate of 10% corresponds to an increased dwell time delay of about one second. Discussing this result with timetable planners at the relevant company, they say that this figure is close to their intuitive sense, even though they do not have a formal model. For arrival delay and scheduled dwell time, we find small negative effects. This implies that trains that arrive late have slightly shorter dwell times than otherwise, and that the influence of the staff and driver are somewhat successful in reducing delays. Longer scheduled dwell times see slightly less delays, indicating that they include some margins, not just the minimum required time for the increased congestion rates.

In Stockholm, we see a rather large effect from both alighting and boarding passengers. The estimates are about 0.4 seconds per person and door, in either direction, and these are additive. We also see an effect from congestion, as the number of passing travellers further increases the delays.

Table 4. Coefficient estimates on the impacts on dwell time delay, from the simple linear regression models in Tokyo and Stockholm.

	Estimate	Std. Error	t-value	Pr(> t)
Tokyo				
Arrival Delay	-0.0479	0.0057	-8.35	<2e-16
Congestion Rate	0.1051	0.0047	22.30	<2e-16
Scheduled Dwell Time	-0.0707	0.0068	-10.40	<2e-16
Stockholm				
Arrival Delay	0.0001	0.0000	3.970	7.33e-05
Alightings/door	0.3889	0.0438	8.881	< 2e-16
Boardings/door	0.4103	0.0453	9.060	< 2e-16
Passing Travellers/door	0.0968	0.0128	7.573	4.70e-14

Arrival delays essentially have no impact on the delays in Stockholm, partly because of limitations when combining the data in section 3.3, and the scheduled dwell times in the sample are all the same, so it is not possible to estimate any further impact from them.

5 Conclusions

In conclusion, the data we use in this study can explain approximately 40% of the variation in dwell time delays in rush hours. While by no means perfect, this is high compared to other studies attempting to explain delays or punctuality with empirical data. It is also a reasonable number, considering the range of other factors which can cause delays.

The number of passengers differs greatly between the two cities, with trains in Tokyo being on average much more congested, and trains in Stockholm often having empty seats even during the morning rush hours. The median values are 58 passengers per car in Stockholm compared to 195 in Tokyo, and the difference in capacity is not nearly so large. The dwell time delay distributions are quite similar across the cities: ranging from -8 to +34 seconds in Stockholm, and -20 to +30 seconds in Tokyo, as we compare the 5th and 95th percentiles. The ranges are narrow, suggesting further that seemingly small delays add up to large numbers, and underlining the importance of well-calibrated high-precision data. Arrival delays are also similar across cases, although the data from Stockholm is less precise in this regard. The early arrivals there are also more extreme, with the 5th percentile being at -300 seconds compared to -20 in Tokyo.

Estimates from our simpler models, which can be used in practice, suggest that a rise in the congestion rate of 10% leads to about one additional second of dwell time delay in Tokyo. This value is close to the intuitive sense of the planners there. In Stockholm, we have measurements on the number of boarding and alighting passengers per door and find that every one of these causes about 0.4 seconds of delay, which is a relatively large number. There is also an influence from the number of passengers remaining on-board, due to crowding, and for every ten such people per door, delays increase by about one second.

The results we have presented can be used in practice to help assign better dwell times. If planners know roughly how many passengers get on and off at a station, or the level of congestion, these figures can be converted to seconds, with which the dwell times can be extended or shortened. In Tokyo such modifications are common, but they are based on the planners' experience, informed by the measured congestion rates. A model such as

this can help make this implicit knowledge more explicit, and to help planners who do not yet have so much experience. In Stockholm, and many other cities where dwell times are not usually adapted to the passenger flows, our results can help to start and inform such a process.

By extension, this work will help to reduce the delays plaguing train operations both in the two cities of Stockholm and Tokyo, and further afield. In Stockholm, 91 % of all delays are small dwell time delays, five minutes or less, and on average they cause about 29 500 train delay hours per year. For the railway company we study in Tokyo, one of many in that city, the corresponding figures are 88 % and 69 000 train delay hours. While it is somewhat difficult to go from train delay hours to person delay hours or punctuality, clearly, the potential for improvement is considerable. Even a small decrease in these delays would have considerable benefits for both the railway operators and the passengers. Adjusting the dwell times to the actual flows of passengers is one way to achieve this.

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