Proceedings of the 2020 Winter Simulation Conference
K.-H. Bae, B. Feng, S. Kim, S. Lazarova-Molnar, Z. Zheng, T. Roeder, and R. Thiesing, eds.

MICROSIMULATION OF BUS TERMINALS: A CASE STUDY FROM STOCKHOLM

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ABSTRACT

When new bus terminals are being planned or existing ones redesigned, suitable tools that are able to describe the complex situation at a terminal are needed. Using microsimulation, vehicle movements and interactions can be simulated and the congestion and capacity of a terminal can be evaluated. In this study, a discrete event simulation model is used in a case study of the Slussen bus terminal in Stockholm, Sweden. The model is calibrated and validated with empirical data that are automatically collected at the terminal. Already with this limited amount of data, the parameter time per boarding passenger can be calibrated with a relative error less than 1 % and the validation gives further insights into the data needed for calibration of a terminal simulation model.

1 INTRODUCTION

Bus terminals are important parts of public transport systems. They serve a large number of bus lines and are often connected to other modes of public transport. Transfers are common and a great number of passengers often pass through a terminal each day. If the terminal is not properly dimensioned for its amount of traffic and has too low capacity, buses risk delays and large variations in departure times. This will increase waiting times and lead to uncertainty among the passengers. Even so, terminals with too low capacity are not uncommon. In the region of Stockholm, it has been reported that 45 % of the bus terminals are experiencing capacity-related issues (Al-Mudhaffar et al. 2016). The risk of planning a terminal with insufficient capacity increases when there is a conflicting requirement of reducing the size of the terminal so that the valuable land can be exploited for other purposes. Suitable tools are needed in order to ensure that the terminal is planned with sufficient capacity. In previous research, a discrete event simulation model of bus terminals was developed (Lindberg et al. 2017; Lindberg et al. 2018). No other such models, to our knowledge, capture the length of the vehicles, their movements, and their interactions in space where queues and blockages can form at any place throughout the terminal.

A simulation model needs to have a reasonably accurate representation of reality. This can be assured by calibrating and validating the model with empirical data. The access to data is of great importance as this puts boundaries on the complexity of the model and its calibration and validation. At bus terminals, the operators often collect bus data automatically for quality control and monitoring purposes. It is of

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interest to evaluate the extent to which this already collected, limited amount of data can also be used for model calibration and validation. In a first validation approach, the predictive power of the model using data already available for the Slussen bus terminal in Stockholm is tested. The purpose of this study is to analyze the application of discrete event simulation to a real bus terminal and to examine the extent to which available empirical data can be used to predict future conditions. In a case study of the Slussen bus terminal, the previously developed simulation model has first been calibrated using four weeks of empirical data and then validated using another two weeks. The contribution of the study consists of application of the simulation model to a real world terminal and insights into how existing data can be used for this task.

In the following sections of this paper, previous research and approaches to validation of terminal simulation models are presented in Section 2, followed by a description of the case study in Section 3. Section 4 gives a short presentation of the simulation model, Section 5 presents the calibration and validation and Section 6 the conclusions of the paper and future research.

2 VALIDATION OF STOP AND TERMINAL SIMULATION MODELS

In this section, previous validation studies of stop and terminal simulation models will be reviewed. In the literature, only few reports on simulation models of bus terminals can be found. They are often used to evaluate design alternatives, such as in Adhvaryu (2006), or the performance of a system, such as in Figueras Jové and Casanovas-García (2018). To our knowledge, there are no papers presenting validation of a terminal simulation model. There are, however, a few examples of validation of smaller systems consisting only of a single bus stop.

A simpler version of validation is included in van der Spek et al. (2017), who validate their simulation model for high frequency bus lines by comparing simulated and measured punctuality. Several studies use t-tests to validate their simulation models. The stop simulation model in Fernández (2010) is first calibrated and then validated using separate data sets. In the validation, simulation outputs, including bus delay and queue length, are compared directly to measured values presented with the percentage difference. This is followed by a t-test at 95 % confidence level on several of the outputs. A similar approach is taken by Zhao et al. (2018a), as they validate their model of stop loading area effectiveness. First, simulated and empirically measured number of effective loading areas are compared and the percentage difference calculated. Then, a paired t-test of the same quantity is performed. Zhao et al. (2018b) present a tram simulation model that is validated by both comparing the difference between simulated and measured average passenger waiting time and number of waiting passengers and by using a t-test with 95 % confidence level on the same quantities. Another approach is taken by Tan et al. (2013) and Ye et al. (2017), who both use the Kolmogorov-Smirnov test for validation. Tan et al. (2013) validate their bus stop model by using the test with 95 % confidence level on simulated and empirically measured bus delays. The same confidence level is used by Ye et al. (2017) as they validate their bus stop model by using the test on simulated and measured service times. Among those of these studies reporting values of the relative error, this can be both very small (0 %) or quite large (over 20 %).

In summary, most of the presented stop simulation studies validate their models without a preceding calibration step and use common statistical tests in the validation. Simulation model studies of larger terminals are uncommon, however, and those models are rarely validated.

3 THE SLUSSEN BUS TERMINAL IN STOCKHOLM

In the case study, the Slussen bus terminal is simulated and the simulation output is validated against empirical data. This is a temporary terminal located in central parts of the city of Stockholm that is mainly used by commuters. Bus lines start or end at the terminal and many passengers transfer to or from the metro network. The terminal has about 39,200 boarding passengers each day (SL 2016). It is a busy terminal that operates close to its capacity limits. Ever since its opening during 2018, the terminal has had capacity related problems.

3.1 Physical Layout

The terminal has separate stops for boarding, alighting, and layover time. Figure 1 shows a drawing of the terminal with its entrance, exit, stops, and driving directions. The terminal has 18 angle stops with drive-in, back-out operations located at the bottom of the figure and three linear stops with unfixed berths, at the top and in the middle, where vehicles either enter from the back of the stop or directly into any empty space of sufficient size. All angle stops are used for boarding operations except one which is used for layover time (the one furthest to the right in Figure 1). When driving next to these stops, vehicles may need to wait on other vehicles backing out from stops further ahead. Backing out from a stop is done in two steps. First, the vehicle backs out a small stretch of the stop to get a better view of the surroundings. Then, it waits for any passing vehicles before backing the rest of the way. The linear stop at the top in Figure 1 is used for alighting processes. Here, vehicles enter at the back of the stop and drive to the front or to the back of the last vehicle. After having dropped off passengers, the vehicle directly leaves for the adjacent driving lane. The two linear stops in the middle are used for layover time and vehicles simply enter these where there is enough space. The lengths and scale of various parts of the terminal has been determined by measurements of a technical drawing. No pedestrians are allowed in the driving areas and there are no pedestrian crossings. Vehicles leave the terminal directly into a bus lane without any waiting time.

3.2 Traffic on the Terminal

The timetable for autumn 2018 has been used in this case study. 28 bus lines have at least one arrival or departure during the afternoon peak period between 3 and 6 p.m, with the number of departures ranging from 0 (only arrivals) to 36. There are three operators responsible for the lines at the terminal. Most lines stop at their single dedicated stop. The only exception is a line that uses two neighboring stops, where a vehicle will use whichever of these is free. This has been simplified by letting half of the arrivals use one of the stops and the other half the other. Most vehicles arrive to the terminal as a particular line number carrying alighting passengers, then pick up new passengers and leave as either the same line number or a different one. Some vehicles are deadheading empty into the terminal, while others arrive with passengers but leave empty directly after. It has been assumed that no vehicle that deadheads into the terminal will arrive earlier than 4 minutes before departure. This assumption relies on the vehicles having the possibility to adjust their arrival time outside of the terminal. For vehicles having to wait between alighting and boarding, the layover stops are used. The vehicles have no dedicated stop, but will use whichever has enough space. There are four types of buses at the terminal, with lengths of 12 m, 15 m, 18 m, or 19 m. All types have three doors. Only the front door is used for boarding, but all three are used for alighting.

3.3 Terminal Rules and Simplifications

The traffic on the terminal follows a set of traffic rules. These control priority, driving behavior, and time limits for when a vehicle should drive to various positions. Not all of these situations are governed by official rules, and drivers instead act according to unofficial ones or their own judgement. Due to a

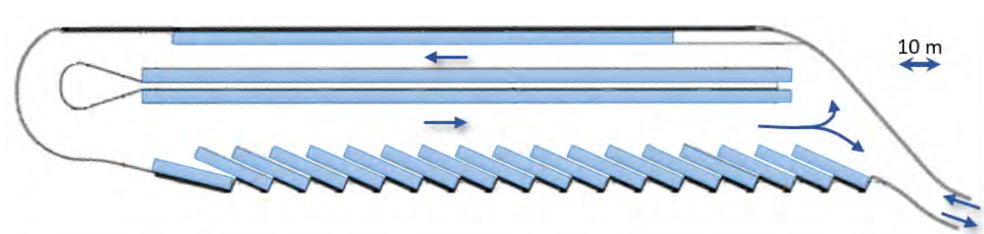


Figure 1: The Slussen bus terminal (Source: SLL, adopted).

Table 1: The lognormal parameter values used in the case study.

	Calibration		Validation	
Lateness at arrival (min)	$\mu = 2.22$	$\sigma = 0.485$	$\mu = 2.06$	$\sigma = 0.565$
Number of boarding passengers	$\mu = 4.43$	$\sigma = 0.219$	$\mu = 4.45$	$\sigma = 0.212$
Number of alighting passengers	$\mu = 4.31$	$\sigma = 0.168$	$\mu = 4.32$	$\sigma = 0.174$

limited number of empirical data sources, there is a need to keep the terminal rules simple with few model parameters.

There are a number of situations where priority between vehicles needs to be considered. First, when two vehicles are reversing out from neighboring angle stops at the same time, the front vehicle is assumed to have priority. Second, there is also a priority situation between a vehicle wanting to back out from a stop and another wanting to drive past. We have assumed that there is a fixed position in the driving lane in relation to the stop where any vehicle having passed this will drive before the backing vehicle and any vehicle before this point has to wait. Third, another similar situation arises when a vehicle wants to leave a linear stop. Here we assume that a vehicle in the stop drives before a vehicle in the driving lane if the driving lane bus has its front after the back of the stopped bus. Fourth, when vehicles coming from the entrance and the driving lane next to the angle stops meet at the right side, priority again needs to be established. We assume that the vehicles drive in the order they arrive.

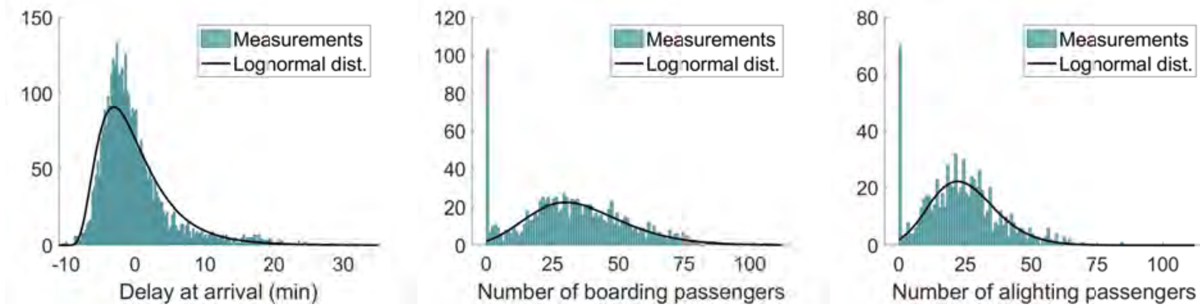
Any vehicle arriving at the terminal will at most drive to three positions at the terminal, the stop for alighting passengers, a layover stop, and a boarding stop. Layover will only be considered if the time until departure is long enough. To simplify the rules for all arrivals of all operators and make the results more robust, all vehicles are assumed to use the layover stops if the time until departure is more than 4 minutes, and go from layover to their departure stop when the time until departure is 4 minutes. This is based on the rules of the largest operator at the terminal, where buses that use the layover area should leave 4 minutes before the departure time.

3.4 Data and Parameters

The afternoon peak period between 3 and 6 p.m has been chosen for this case study. The first half hour, which still has a rather low demand, is used as a warm-up period. Empirical data, gathered during 6 weeks in autumn 2018, have been received from the operator responsible for all lines except two. For the other two operators, the data have been unavailable or incomplete. The data are separated into two data sets, one consisting of the first four weeks and one of the last two. The first set is used during the calibration and the second during the validation. Estimation of probability distribution parameters is based on the maximum likelihood method using MATLAB functions.

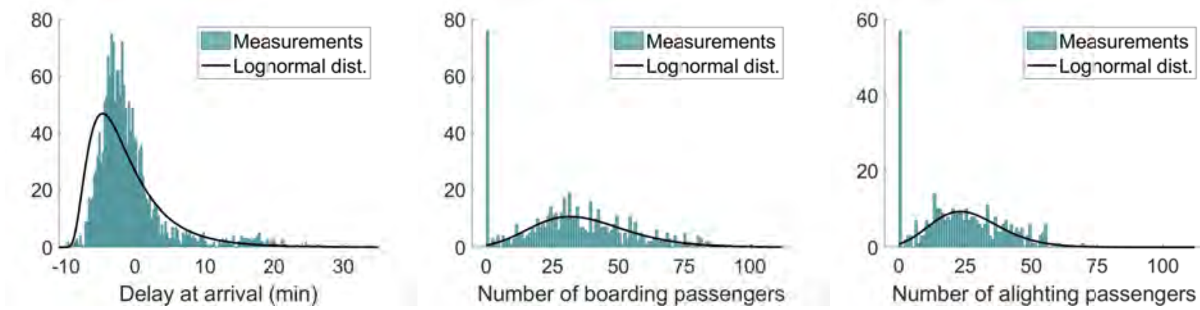
Vehicle arrivals to the terminal, set in relation to their planned arrival times (lateness at arrival), are represented by a lognormal probability distribution. This distribution has previously been used, e.g., by Rietveld et al. (2001). Estimations of distribution parameters are based on automatically measured arrivals with a planned arrival time between 3 and 6 pm. Since the lognormal distribution is only defined for positive values, all data points were shifted to positive values in the estimation. A shift of 10.37 minutes was used for the calibration data and one of 9.65 minutes for the validation data. This corresponds to the absolute value of the most negative measurement in each data set. The parameters of the lognormal distribution, both for calibration and validation, are given in Table 1 and histograms of the calibration and validation data together with the fitted probability distributions are shown in Figure 2a and Figure 3a (the shift is not shown in the figures).

The numbers of boarding and alighting passengers are also represented by probability distributions. The data used for parameter estimation are based on automatic passenger counting, available at about 20 % of the operator's buses, and show the number of boarding and alighting passengers for each arrival and



(a) (b) (c)

Figure 2: Vehicle delay at arrival and number of boarding and alighting passengers in the calibration.



(a) (b) (c)

Figure 3: Vehicle delay at arrival and number of boarding and alighting passengers in the validation.

departure between 3 and 6 pm. The data sets have a large number of zeros, where there are no boarding or alighting passengers. The rest of the data have a right-tailed form, for which the lognormal distribution is a good candidate (see the histograms in Figure 2b, 2c, 3b and 3c). For this reason, the data sets have been divided a second time, separating the zeros from the rest of the data. The number of boarding or alighting passengers can then be described with a probability of 0 passengers (based on the fraction of zero-valued measurements) and, if there are passengers, a lognormal distribution controlling the number of passengers (estimated from the non-zero measurements). In the parameter estimation, the non-zero sets include measurements of just a few passengers. Since these values close to zero can give a bad fit to the data, all values are shifted during the estimation. A positive shift of 50 passengers was used. The distribution parameters for both alighting and boarding and for calibration and validation can be seen in Table 1 and the distributions fitted to the nonzero values are shown in Figure 2b, 2c, 3b and 3c (the shift is not shown in the figures). The probability of 0 boarding passengers were 9.3 % in the calibration and 13.7 % in the validation and the probability of 0 alighting passengers were 9.3 % in the calibration and 15.7 % in the validation. When using the distributions, all resulting numbers are rounded up to integers.

Since a terminal simulation model needs more parameters than what can be estimated from the data listed in this section, the number of model parameters is kept to a minimum. Parameters included have been estimated or set based on values from the literature or rules at the terminal. The vehicles are assumed to drive at a fixed speed of 10 km/h, based on the speed limit of the terminal. The minimum space gap between vehicles is set to 2 m, which is a typical value of the minimum gap for city traffic in several car-following models according to Treiber and Kesting (2013). The minimum time gap is also based on values from road traffic and set to 1.8 s. This is based on stop-and-go traffic in Neubert et al. (1999). For the total time a vehicle spends at a stop, it is not enough to know only the number of boarding or alighting passengers, but also the time per boarding or alighting and the dead time, the constant time needed to open and close doors and other processes not dependent on the number of passengers. For the time per alighting and for the dead time, the values from Tirachini (2013) of 1.3 s and 5.2 s are used, respectively. These are based on a low-floor bus and payment with a magnetic strip prepaid card, a situation similar to the one at Slussenterminalen. Time per boarding passenger is used as a calibration parameter.

4 THE SIMULATION MODEL

The Slussen terminal is simulated using a discrete event simulation model previously presented in Lindberg et al. (2018). In this section, a brief description of the model structure will be given together with more detailed descriptions of new parts of the model, including angle stops and two types of linear stops.

4.1 Model Structure

The basic idea of the model is to describe the movements of each vehicle as it drives through the various parts and interacts with other vehicles at the terminal. Both time and space are discretized, time by using a discrete event approach and space by dividing driving areas into cells. The system is described by defining a set of events, for instance arrival to the terminal, starting to drive to a stop, or initiating dwell time. Using a network description, nodes represent one or more events, and arcs represent activities taking place between events (e.g., driving or dwelling). Events are instantaneous, while activities have an extension in time. A small example of a network describing a part of a terminal with a stop can be seen in Figure 4.

The size of the cells of the model is a tunable parameter. Here, a value of 1 m has been used and in general, the value will be small enough for one vehicle to occupy several cells at the same time. In order to capture blockages and interactions between vehicles, the model keeps track of the state of each cell. Whenever a vehicle drives through a cell, both arrival time of the front and departure time of the back of the vehicle are stored. This allows the model to account for other vehicles when calculating the time of a driving activity. In general, a driving activity will include several cells at once. Since the future state of cells further ahead is not known, a preliminary driving time and preliminary cell occupations are calculated. These are updated as needed if the future state of these cells is changed.

The durations of the various activities in the model are calculated based on probability distributions and formulas. The dwell times for boarding and alighting passengers are calculated by using simple, linear equations. These assume that passengers board only in the front door, but use all doors when alighting. The dwell time equations for alighting, $T^{DT,alight}$, and for boarding passengers, $T^{DT,board}$, are

$$T^{DT,alight} = t_0 + t^{alight} \left\lceil \frac{n^{alight}}{n^{doors}} \right\rceil \qquad \text{and} \qquad T^{DT,board} = \max(t^{to\_dep},\ t_0 + t^{board} n^{board}), \tag{1}$$

where t_0 is the dead time, t^{alight} and t^{board} are the time per alighting or boarding passenger, n^{alight} and n^{board} are the number of alighting and boarding passengers, n^{doors} is the number of doors and t^{to_dep} is the time until the planned departure time.

In order to model the Slussen terminal, the simulation model needed to be adapted and additional sub-models added. Three new types of stops have been added to the model, angle stop and linear stop with many unfixed berths and entry either at the back or in a gap.

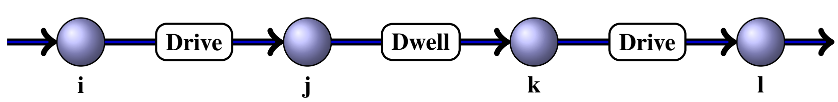


Figure 4: A small example network representing a part of a terminal. The arcs represent activities, either driving or dwelling, and the nodes events corresponding to the start and end of activities.

4.2 Linear Stop with Unfixed Berths and Entry at Back

A linear stop with unfixed berths and entry at the back is used for alighting processes at the Slussen terminal and can be seen at the top of Figure 1. Figure 5 shows a network description of the events and activities of the modeling of the stop. When arriving at node *i*, a vehicle either starts to drive past or to the stop. If driving past (*il* in Figure 5), arrival and departure times through each cell of the driving lane are calculated. If the road is blocked somewhere along the stretch, the arrival and departure time to cells after the blockage gets a later arrival that accounts for the blockage. The departure times from previous cells in which the vehicle will be waiting also get later departure times. If the vehicle is instead entering the stop (*ij* in Figure 5), the first activity is an iterative driving activity through the stop (the stop is not divided into cells). In each of these iterations, the vehicle drives to the position of the back of the last vehicle currently in the stop. When the vehicle arrives, the leading vehicle may have left and another iteration is initiated. This is iterated until the vehicle has reached the back of a vehicle or the front of the stop. The next activity is a dwell time activity where on-board passengers are dropped off. After dwelling, a second driving activity is initiated where the vehicle drives out from the stop to the driving lane and through the rest of the section. Just like when driving past the stop, arrival and departure times are calculated for the cells in the driving lane that the vehicle will drive through. For both vehicles having passed or been to the stop, the last activity of the stop model is an iterative extra driving activity between node *l* and *m*. This is used if the initially calculated driving times between node *i* and *l* or node *k* and *l* were too short.

4.3 Linear Stop with Unfixed Berths and Entry in Gap

Linear stops with unfixed berths and entry in a gap are used for the layover process and can be seen in the middle of Figure 1. The modeling of the stop is simplified in such a way that vehicles enter directly into the stop without driving in the adjacent lane looking for a gap. After having dwelled, the vehicle returns to the same position it entered from. A network description can be seen in Figure 6. At node *i*, a dwelling activity is initiated and at *j*, an iterative waiting activity holds the vehicle until the road ahead is clear, i.e. until there is enough space for the vehicle to fit into the driving lane. Any following vehicle that has not yet arrived to the driving lane where the vehicle wishes to enter, will have to wait. Both stops of this kind at the Slussen terminal are modeled with a capacity of seven vehicles using the stops at the same time, independent of the length of the vehicles.

4.4 Angle Stop

Angle stops are used for boarding processes at the Slussen terminal and can be seen at the bottom of Figure 1. Figure 7 shows a network representation of the modeling of the stop. At node *i*, vehicles either initiate an activity to drive past or to the front of the stop. In both cases, there are certain positions where the vehicle may need to stop and wait. These are set in relation to stops further ahead, and represent the positions where a vehicle will wait if another vehicle is backing out from a stop ahead. The activity is iterated until there is no longer any need to wait. The driving lane is divided into cells and as a vehicle

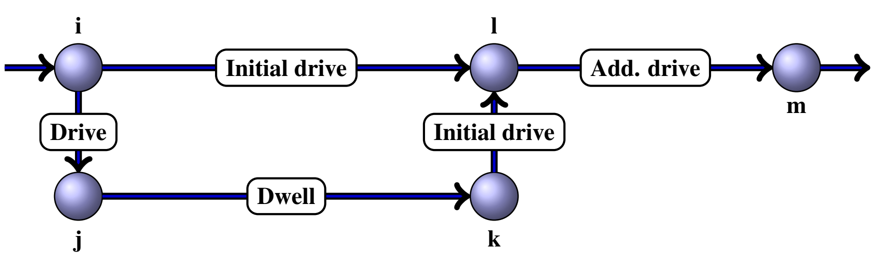


Figure 5: Network representations of a linear stop with unfixed berths and entry at the back.

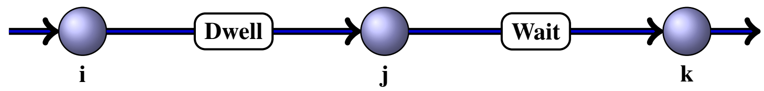


Figure 6: Network representations of a linear stop with unfixed berths and entry in gap.

drives through, these are given arrival and departure times. When entering the stop, the vehicle continues to its front. At node j, the initial driving time can be iteratively adjusted if the initial time was too short. This is followed by dwell time at node k and by two backing activities, where the first is initiated directly. The second backing activity, initiated at node m, will include waiting time if there is another vehicle blocking the way. The activity is iterated until the vehicle has been able to completely back out. The last activity, at node n, is a second additional driving time activity that is iterated until the driving time is correct.

Vehicles reversing out from a stop first back out a distance of 3 m, which has been estimated from videos of the terminal. The point where vehicles in the driving lane will wait on a reversing vehicle is located 20 m from the position the front of the reversing vehicle will reach after having finished reversing.

4.5 Other Model Adaptations

Since a vehicle will drive for another lap if their stop is occupied, there is a possibility of a whole lap becoming congested and each vehicle being hindered from moving by the one in front. A technical way to avoid this deadlock has been implemented. An extra queue is added between the upper and lower parts of the terminal were vehicles return for another lap. This queue only lets vehicles pass if the road is clear ahead and since it has no extension in space, it acts as a storage of vehicles.

5 CALIBRATION, SENSITIVITY ANALYSIS, AND VALIDATION

Due to the limited number of empirical data sources available for the case terminal, only the parameter time per boarding passenger is used for calibration and the simulated average lateness at departure for comparisons with empirical measurements (gathered during the same six weeks as the input data). Other alternative calibration parameters are not expected to have such a big effect as the boarding time. The minimum time and space gaps go into details of the driving behavior, and while the speed decreases the time through the terminal, it is not the origin of queuing. The dead time is a small fraction of the total dwell time, unless there are very few boarding or alighting passengers. The time per alighting passenger occurs earlier in the progression through the terminal, often before planned lay-over time. This parameter is still tested in a sensitivity analysis (see the following sections).

5.1 Method

The data set is divided into two parts, so that the first four weeks are used for calibration and the last two for validation. The same separation is done on the input data to the model (see Section 3.4). The analyses are based on 100 repetitions in order to get average values.

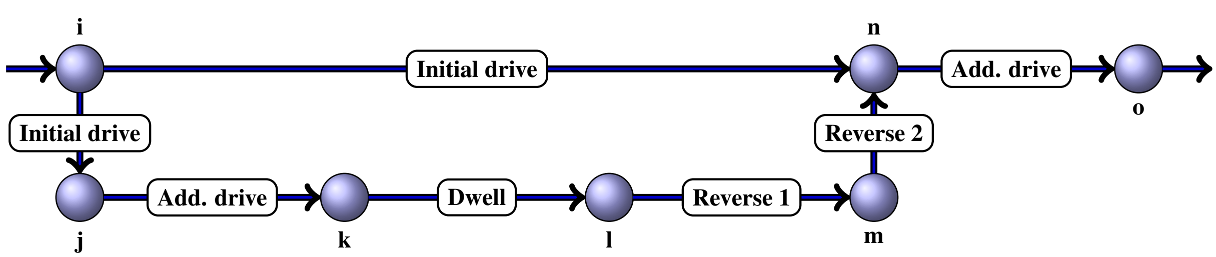


Figure 7: Network representation of the angle stop.

In the calibration, the time per boarding passenger, (t^{board} in Equation (1)), is adjusted until there is a sufficiently small error between simulation output and empirical measurements and it passes a two-sided independent t-test for two samples with 95 % confidence interval (see, e.g., Moore and McCabe 1999). Validation is carried out using the calibrated model and comparing simulation output based on the second set of input data with the second set of empirical measurements of the average lateness at departure during one afternoon peak period. A sensitivity analysis is also carried out on the parameter time per alighting passenger, t^{alight} in Equation (1). This parameter is varied in order to see how much it affects the average lateness at departure using the calibration data set.

5.2 Results

The calibration resulted in a value of the time per boarding passenger of $t^{board} = 2.4$ s. With this parameter, the simulation gave an average lateness at departure of 1.28 minutes (Table 2). The corresponding value of the empirical measurements was 1.27 minutes, which gives a difference between measured and simulated lateness, set in relation to the measured lateness, of 0.86 %. With a p-value of 0.87, the null hypothesis of the sets of measured and simulated lateness having equal means could not be rejected. The calibrated value of time per boarding passenger, 2.4 s, is lower than the value 4.6 s reported by Tirachini (2013) for similar buses. Brief inspections of the terminal have suggested that this reported value is too high, however, and the calibrated value is reasonable.

The results of the sensitivity analysis of the time per alighting passenger can be seen in Table 3. Large changes of 1 s give changes to the relative error of up to 1.35 percentage points. This is a much smaller change than that observed when the time per boarding passenger is varied. A change of the same magnitude from the calibrated value gave rise to changes to the percentage error of up to 36 percentage points. The big difference in the effect of the parameters on the results can be explained by the fact that the time per boarding passenger is closely related to the lateness at departure, while the time per alighting passenger affects an earlier stage of the way through the terminal and delays occurring during this stage can often be absorbed by the layover time.

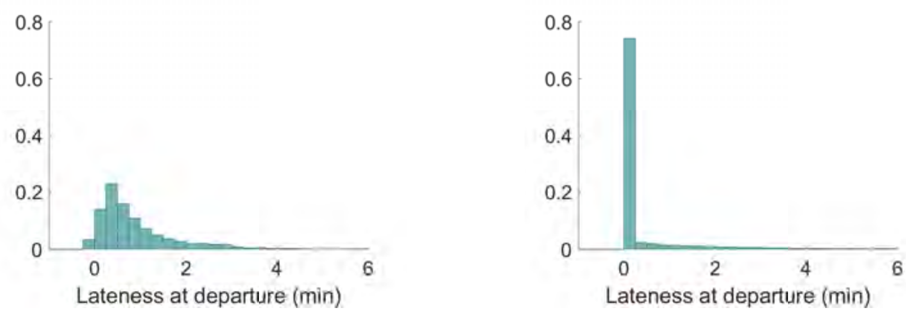
In the validation, the simulation output gave an average lateness at departure of 1.29 minutes and the empirical data had an average lateness of 1.02 minutes. This gives a relative error of 26 %, a somewhat large difference. In order to compare the simulation output to the measurements further, Figure 8 shows histograms of the lateness at departure for each departing vehicle, normalized so that all vehicles sum up to one, for both the simulation output and the empirical data. This shows that a large fraction of the simulated lateness output is equal to 0. This means that many vehicles need to wait for the timetable after having finished boarding all passengers. This can partly be explained by the fact that the empirical measurements of the lateness also include negative values (early departures). This is not allowed in the simulation model, since allowing some vehicles to leave early would result in more parameters and a need for more empirical data than available. In the calibration, this results in shorter boarding times and more departures with zero-valued lateness. The simulated lateness also goes to higher values (not shown in Figure 8) than the measured ones. The zero-valued lateness output thus also compensates for the output with high values. This shows that while the model can be calibrated solely based on the boarding time per passenger, this

Table 2: The resulting lateness at departure in the calibration and validation for both simulation output and measurements and the relative error of the simulation output.

	Calibration	Validation
Average simulated lateness at departure	1.28 min	1.29 min
Average measured lateness at departure	1.27 min	1.02 min
Relative error	0.86 %	26 %

Table 3: The lateness at departure and the relative error of the simulation output for different values of the time per alighting passenger.

Time per alighting passenger	0.3 s	1.3 s	2.3 s
Average lateness at departure	1.26 min	1.28 min	1.28 min
Relative error	-0.49 %	0.86 %	0.96 %



(a) (b)

Figure 8: Empirical measurements (a) and simulated output (b) of the lateness at departure.

calibration can compensate for other parts of the model, including the values of other parameters, and may become incorrect when the data set is changed. Using more calibration parameters and output metrics for comparison may improve upon the result, for instance the parameter vehicle speed and the metric average driving delay. Empirical measurements of the driving delay are not readily available, however.

It can be noted that while there is a notable change in the average lateness of the empirical measurements between the two data sets, the same can not be said about the simulated average lateness. This implies that the differences between these time periods are not represented in the model. The input data differing between the time periods consist of number of boarding and alighting passengers and lateness at arrival to the terminal. Since such a large fraction of the simulated lateness at departure is equal to zero, more boarding passengers do not have a big effect since the vehicles already need to wait for the timetable. Differences in lateness at arrival and alighting times are handled by layover time and the wait time margins at boarding. With a calibrated model based on more parameters and output metrics, there may be less wait time margin at the boarding and a larger difference between the lateness at departure for the two data sets. An interesting parameter to investigate further is the time limit for when vehicles leave the layover area for the boarding stop. Now the four minutes used is based on regulations, which may not be a correct representation of the behavior of the drivers in reality. Four minutes is a long time period and if the vehicle arrives shortly after leaving the layover area, the number of passengers required for the vehicle to become late is large. This indicates that drivers indeed may leave later than this limit. It can also be noted that even if a vehicle arrives very early, passengers may still arrive close to the departure time. If many arrive simultaneously, the vehicle may become late. This is not captured in the model.

It is also possible that there are indeed factors of the terminal differing between the two time periods that are not represented in the model. The first period starts August 20$^{\text{th}}$ and passengers may still have followed a different travel pattern associated with the summer months. Another quite likely explanation is that since this was still a rather new terminal during this period (it was gradually put into use during the spring), the behavior and informal and formal driving rules were not yet fixed. The terminal was experiencing congestion and various ways to relieve this were likely tested during the period. Another possible reason for the difference between simulated and measured average lateness is the somewhat small size of the empirical data sets. Two weeks give a set of only ten averages of the lateness at departure. It can also be noted that the lognormal distribution describing the delay at arrival for the validation data set seems to have a worse fit to the data (see Figure 3a). This could have effects on the results and can be investigated further.

6 CONCLUSIONS AND FUTURE RESEARCH

In this research, a discrete event simulation model is adapted to the Slussen bus terminal in Stockholm, Sweden. The adaptation includes modeling of three new types of stops. Using four weeks of empirical data, the model has been calibrated by adjusting the parameter time per boarding passenger and comparing simulated and measured average lateness at departure. The same quantity was then used to validate the model against a separate empirical data set of two weeks. The resulting difference between simulated and empirically measured average lateness at departure shows a need for a more advanced calibration approach using more empirical data than readily available, or possibly a more advanced model. A sensitivity analysis of the time per alighting passenger was also carried out, which showed that the parameter had only a marginal effect on the simulation results.

In future research, this promising new area of bus terminal simulation will be further explored and the first approach to model validation expanded. This includes investigations on new data sources, and with this, more calibration parameters and output metrics for comparisons. It is also of interest to investigate the effects of terminal rules and related simplifications of the model. In a later stage, the model can be used to test various bus terminal designs and solutions in order to give general advice and guidelines. It could also be used to optimize the stop allocation planning at a bus terminal.

ACKNOWLEDGMENTS

This research was done in collaboration with K2 – The Swedish Knowledge Centre for Public Transport. We would also like to thank the Transport Administration, Stockholm County Council, as well as Keolis, Nobina, and Arriva for access to empirical data and helpful ideas.

REFERENCES

Adhvaryu, B. 2006. "Design of Bus Station: A Case Study in Brighton". *Traffic Engineering and Control* 47(5):182–186.

Al-Mudhaffar, A., A. Nissan, and K.-L. Bång. 2016. "Bus Stop and Bus Terminal Capacity". *Transportation Research Procedia* 14:1762–1771.

Fernández, R. 2010. "Modelling Public Transport Stops by Microscopic Simulation.". *Transportation Research Part C* 18:856–868 (Special Issue on Transportation Simulation).

Figueras Jové, J., and J. Casanovas-García. 2018. "Modelling and Analysis of Intermodal Passenger Operations in a Cruise Terminal". In *Proceedings of the 2018 Winter Simulation conference*, edited by M. Rabe, A. Juan, N. Mustafee, A. Skoogh, S. Jain, and B. Johansson, 1515–1526. Piscataway, New Jersey: IEEE.

Lindberg, T., A. Peterson, and A. Tapani. 2017. "A Simulation Model of Local Public Transport Access at a Railway Station". In *7^{th} International Conference on Railway Operations Modelling and Analysis (RailLille2017)*. April 4^{th}–7^{th}, Lille, France.

Lindberg, T., A. Peterson, and A. Tapani. 2018. "A Simulation Model for Assessment and Evaluation of Bus Terminal Design". In *the Conference on Advanced Systems in Public Transport and TransitData*. July 23^{rd}–25^{th}, Brisbane, Australia.

Moore, D. S., and G. P. McCabe. 1999. *Introduction to the Practice of Statistics*. 3rd ed. New York: W. H. Freeman and Company.

Neubert, L., L. Santen, A. Schadschneider, and M. Schreckenberg. 1999. "Single-Vehicle Data of Highway Traffic: A Statistical Analysis.". *Physical Review E* 60(6):6480–90.

Rietveld, P., F. Bruinsma, and D. Van Vuuren. 2001. "Coping with Unreliability in Public Transport Chains: A Case Study for Netherlands". *Transportation Research Part A: Policy and Practice* 35(6):539–559.

SL 2016. "Fakta om SL och Länet 2016". AB Storstockholms Lokaltrafik. https://sl.se/contentassets/9314f2e3ea1a4890b5e25d8fa5092c9a/sl_och_lanet_2016.compressed.pdf, accessed June 4^{th} 2020.

Tan, J., Z. Li, L. Li, Y. Zhang, and L. Lu. 2013. "Berth Assignment Planning for Multi-Line Bus Stops". *Journal of Advanced Transportation* 48(7):750–765.

Tirachini, A. 2013. “Bus Dwell Time: The Effect of Different Fare Collection Systems, Bus Floor Level and Age of Passengers”. *Transportmetrica A: Transport Science* 9(1):28–49.

Treiber, M., and A. Kesting. 2013. *Traffic Flow Dynamics*. Berlin, Heidelberg: Springer.

van der Spek, T., B. van Stein, M. van der Holst, and T. Bäck. 2017. “A Multi-Method Simulation of a High-Frequency Bus Line”. In *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*. October 1st–6th, Yokohama, Japan.

Ye, P., Z. Chen, and H. Yang. 2017. “Modeling Bus Service Time for a Curbside Stop”. *Transportation Research Record* 2647(1):71–79.

Zhao, J., K. Chen, T. Wang, and J. O. Malenje. 2018a. “Modeling Loading Area Effectiveness at Off-Line Bus Stops with no Clear-Cut Separation of Berths”. *Transportmetrica A: Transport Science*:1–21.

Zhao, X., Y. Li, S. Xu, and H. Zhai. 2018b. “Modeling a Modern Tram System Integrated with a Road Traffic Simulation”. *Simulation: Transactions of the Society for Modeling and Simulation International* 94(1):77–90.

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