Mesoscopic Modeling of Bus Public Transportation

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Analysis of public transport system performance and level of service in urban areas is essential. Dynamic modeling of traffic conditions, passenger demand, and transit operations is important to represent adequately the complexity of and the interactions between these components in modern public transportation systems. This paper presents a transit simulation model designed to support evaluation of operations planning and control, especially in the context of advanced public transportation systems. Unlike most previous efforts in this area, the simulation model is built on a platform of a mesoscopic traffic simulation model, which allows modeling of the operation dynamics of large-scale transit systems, taking into account the main sources of service uncertainty and stochasticity. The capabilities of Mezzo as an evaluation tool of transit operations are demonstrated with an application to a real-world, high-demand bus line in metropolitan Tel Aviv, Israel, under various scenarios. The application shows that important phenomena such as bus bunching are reproduced realistically. A comparison of simulated running times and headway distributions with field data shows the model is capable of replicating observed data.

Public transportation systems are increasingly complex, incorporating diverse travel modes and services. As a result, various advanced public transportation systems (APTS) designed to assist operators have been developed and implemented (*1*). The need to integrate and efficiently operate these systems poses a challenge to planners and operators. As new technologies and applications are proposed, tools to assist in their development and evaluation before field implementation are needed.

Simulation models have been established as the primary tool for evaluation at the operational level for general traffic operations. Most of the advances in these models related to transit systems have focused on implementation of transit signal priority (*2–7*), operation of bus stops (*3, 5, 7–9*), and bus lanes (*7, 10*).

Transit simulations provide a dynamic perspective on transit operations by enabling comparison of various scenarios and representation of complex interactions between the network components: general traffic, transit vehicles, and passengers. Algers et al. report that the majority of simulation model users they interviewed were interested in large-scale applications at the urban or regional context and that these users ranked modeling of public transportation the second most important capability in traffic simulation models (*11*). Boxill and Yu report that the capability of existing simulation models to effectively simulate APTS applications in large networks is limited (*12*). While they found that few microscopic models simulate well the local impacts of APTS, none of the mesoscopic models they reviewed had any transit simulation component at all.

Most efforts in modeling public transportation and APTS have focused on microscopic simulations. However, these models are inefficient when applied to large-scale applications because of the unnecessary level of detail and extensive computational effort they require. In contrast, mesoscopic simulation models, which represent individual vehicles but avoid detailed modeling of their second-by-second movement, may be as useful for systemwide evaluation of transit operations and APTS as they are for general traffic.

This paper reports on the development of a mesoscopic transit simulation model designed to support evaluation of operations planning and control, especially in the context of APTS. Examples of potential applications include frequency determination, evaluation of real-time control strategies for schedule maintenance, restoration from major disruptions, and assessing the effects of vehicle scheduling on the level of service.

The rest of the paper is organized as follows: first, the overall framework and implementation details of the transit simulation model are presented. The application of the transit simulator is demonstrated with an application to a high-demand bus line in metropolitan Tel-Aviv, Israel. The case study includes a validation, study of travel time variability and demand levels, and a sensitivity analysis showing the impact of the recovery time policy on performance. Finally, a discussion and concluding remarks are presented.

TRANSIT SIMULATION

Mezzo

The transit simulation model is built within the platform of Mezzo, a mesoscopic traffic-simulation model. Mezzo is an object-oriented, event-based simulator that models vehicles individually but does not represent lanes explicitly. Links in Mezzo are divided into two parts: a running part, which contains vehicles that are not delayed by the downstream capacity limit, and a queuing part, which extends upstream from the end of the link when capacity is exceeded. The boundaries between the running and queuing parts are dynamic and depend on the extent of the queue. Vehicles enter the exit queue in the order that they complete their travel in the running part. The earliest exit time is calculated as a function of the density in the running part

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only. Separate queue servers with their corresponding capacities are used for each turning movement in order to capture link connectivity and lane channeling. A complete description of the structure of Mezzo and its implementation details is available elsewhere (*13, 14*).

Transit Object Framework

Mezzo was extended to simulate transit operations with six transit-oriented classes: bus type, bus vehicle, bus line, bus route, bus trip, and bus stop. The bus type objects define the characteristics of the different types of vehicles, such as length, number of seats, and passenger capacity. Each bus vehicle object inherits the attributes of the specific bus type and general attributes and functions that are relevant for each vehicle in the simulation. In addition, bus vehicles maintain a list of their scheduled trips, which allows explicit modeling of trip chaining, including layover and recovery times in the trip sequence. During the simulation, the bus vehicle object maintains updated passenger loads and determines crowding levels and the maximum number of passengers that may board at each stop.

A bus line is defined by its origin and destination terminals and the sequence of stops that it serves in between. The bus line object holds information on scheduled departure times from the origin and keeps track of the list of active trips, as it may have several simultaneously. Each bus line indicates the vehicle type that should be assigned for this service. It may also store a subset of the stops that serve as possible time-point stops and the appropriate holding strategy. The unique route, in terms of a sequence of links travelled, is stored by a bus route object. The bus line service is performed through individual bus trips. The bus trip object maintains the schedule of expected arrival times at each stop for the specific trip.

The bus stop object is characterized by the link on which it is located and its position on that link. It also contains information on physical characteristics, such as length and type of stop (in-lane or bay stop), and holds a list of bus lines that serve this stop.

Simulation Flow

As this is an event-based simulation model, the time clock of the simulation progresses from one event to the next according to a chronological list of events that refers to the relevant objects. At the start of the simulation, all objects are initialized, and some of them register an event. The execution of most events triggers the generation of new, subsequent events. The transit simulation introduces several new event types. Figure 1 shows a flowchart of the transit simulation process. On initialization of the simulation run, a list of the bus lines that are modeled is read, and the corresponding bus line, bus route, and bus type objects are created. At this stage, events are registered in the event list for the next scheduled departure for each line. When a scheduled trip departure event is activated, the bus trip object is generated. A bus vehicle is assigned to this trip. If the assigned vehicle is not yet in service (i.e., in the case that this trip is the first on its trip chain), then a bus vehicle object is generated and assigned the properties of the required bus type. It then enters the first link on its route. This is also the case if the bus vehicle object already exists and is available to depart. If the bus vehicle is not yet available to depart (i.e., has not completed the recovery time from its previous trip), the trip departure is deferred until the vehicle becomes available.

A bus vehicle that enters a link on its route checks whether there are bus stops to be serviced on this link. If there are no stops on the link, the link exit time is calculated, and an event to enter the next link is added to the event list. Link travel times are calculated on the basis of traffic conditions, as for all vehicles in Mezzo. If there is a stop on the link, the travel time to the stop is calculated, and an event to enter the stop is generated with the appropriate arrival time. The driving time to the stop is calculated as a proportion of the link travel time, depending on the location of the stop. Once the bus enters a stop, the dwell time is calculated. On the basis of the dwell time and taking into account any control strategies that may be implemented, the timing for a new event to exit the bus stop is determined. The event in which the bus exits the stop is similar to the event of entering a link. Mezzo checks if there are any more stops on the link and calculates the driving time to the next stop or to the end of the link on the basis of the current traffic conditions and the distance to the next stop or the end of the link. An event to enter the next stop or to exit the link is then generated. The simulation model is able to process multiple bus trips and bus lines simultaneously.

Finally, when the bus arrives at the end of its route and the trip ends, Mezzo checks whether there is an additional trip for this bus vehicle. If so, and the next trip has already been activated (i.e., the trip's scheduled departure time has already passed), the bus vehicle is assigned to the next trip and enters its first link. If the next trip has not been activated, then the bus vehicle waits until the scheduled departure time. The bus vehicle is deleted if there are no more trips on the vehicle scheduling of this vehicle.

The main simulation loop is designed to support the implementation of control strategies, which requires additional steps. Each object that is a potential subject for a control strategy is indicated by a flag. Every time an event is executed, the model checks whether a control strategy is defined for this type of event, and if so, executes the control logic to determine the appropriate action.

Outputs from the simulation include stop-level statistics, such as early and late arrivals; dwell times; numbers boarding and alighting; bus loads; and travel times between stops. Aggregations at the level of the trip, the vehicle, or the line, such as schedule adherence, headway and passenger wait-time distributions, load profiles, and other level of service measures, are also computed.

Implemented Transit Models

The additional transit simulation components were designed to include a detailed representation of the operations of public transportation. This subsection describes the main transit simulation submodels: passenger arrival and alighting processes, dwell time functions, and trip chaining.

Passenger Arrival and Alighting Processes

Passenger demand is represented by two components: the arrival rates at stops of passengers for each line and the demand to get off the bus at each stop. This level of representation is detailed enough to support study of the impacts of demand on service times and crowding levels, while relying on aggregate modeling of transit users and avoiding explicit generation of individual passengers.

Thus, the inputs to the model are time-dependent matrices of passenger arrival rates and alighting fractions for each bus stop and each bus line. They are used as mean values in stochastic arrival and alighting processes. It is assumed, as in most studies of these processes, that passenger arrivals follow a Poisson distribution (*15, 16*):

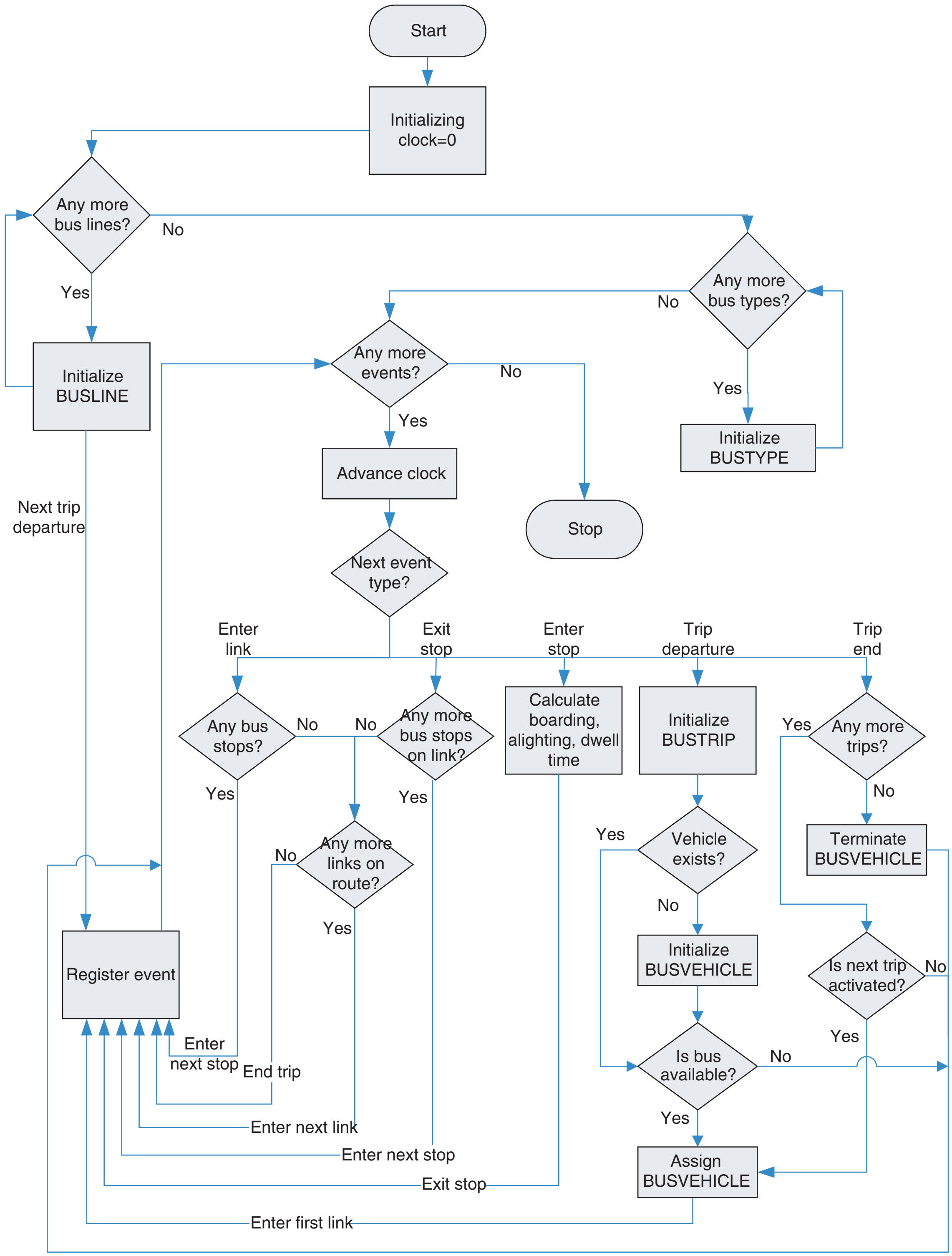


FIGURE 1 Flowchart of transit simulation process.

$$B_{ijk} \sim \text{Poisson}\left(\lambda_{ijt_k}, h_{ijk}\right) \tag{1}$$

where

B_{ijk} = number of passengers wishing to board line i at stop j on trip k,

λ_{ijt_k} = arrival rate for line i at stop j during relevant time period t_k, and

h_{ijk} = time headway on line i at stop j between preceding bus (on trip $k - 1$) and bus on trip k.

The passenger arrival process depends on service frequency (*17*). The Poisson distribution is an appropriate assumption for high-frequency services in which passengers' arrival at stops is a random process. In the case of low-frequency service or an intensive transfer stop (e.g., a train station), passenger arrivals cannot be regarded as a

Poisson process, and an alternative distribution (e.g., lognormal) should be used.

The passenger alighting process is assumed to follow a binomial distribution (*18, 19*):

$$A_{ijk} \sim \text{binomial}\left(L_{ijk}, P_{ijt_k}\right) \tag{2}$$

where

A_{ijk} = number of alighting passengers from line *i* at stop *j* on trip *k*,
L_{ijk} = load on arrival at stop *j* on bus on trip *k* of line *i*, and
P_{ijt_k} = probability, during relevant time period t_k, that a passenger on line *i* will get off the bus at stop *j*.

Dwell Times

Dwell times include the time needed for the doors to open, boarding and alighting of passengers, closing the doors, and the bus to get off the stop. The default dwell time function implemented in the model is based on the one adopted in the *Transit Capacity and Quality of Service Manual* (*20*). Dwell times in the simulation model are determined as a function of the door that has the longest passenger service time, type of stop (bay or in-lane), and physical space availability. For standard buses, the resulting dwell time function is given by

$$\text{DT}_{ijk} = \beta_1 + \max\left(\text{PT}_{ijk}^{\text{front}}, \text{PT}_{ijk}^{\text{rear}}\right) + \beta_2 \cdot \delta_j^{\text{bay}} + \beta_3 \cdot \delta_{ijk}^{\text{full}} + \upsilon_{ijk} \tag{3}$$

where

DT_{ijk} = dwell time for line *i* at stop *j* on trip *k*;
PT_{ijk}^{d} = total passenger service time on door $d \in$ {front, rear}, which depends on numbers of boarding and alighting passengers and crowding level on the bus;
δ_j^{bay} = bay stop indicator (= 1 if bus stop is in a bay and 0 otherwise);
$\delta_{ijk}^{\text{full}}$ = indicator for available physical space at stop (= 1 if all the stop is completely occupied and 0 otherwise);
β_1, β_2, and β_3 = parameters; and
υ_{ijk} = error term.

Passenger service time is the main component of the dwell time function. In the case that boarding is allowed only at the front door and alighting is possible from both doors, the following functions are used:

$$\text{PT}_{ijk}^{\text{front}} = \alpha_1 \cdot p_{\text{front}} \cdot A_{ijk} + \alpha_2 \cdot B_{ijk} + \alpha_3 \cdot \delta_{ijk}^{\text{crowded}} \cdot B_{ijk} \tag{4}$$

$$\text{PT}_{ijk}^{\text{rear}} = \alpha_4 \cdot \left(1 - p_{\text{front}}\right) \cdot A_{ijk} \tag{5}$$

where

p_{front} = fraction of passengers that alight from the front door,
α_1, α_2, α_3, and α_4 = parameters, and
$\delta_{ijk}^{\text{crowded}}$ = crowding indicator (= 1 if number of passengers on the bus exceeds the number of seats, and 0 otherwise).

Trip Chaining

Transit vehicles follow a schedule that includes a sequence of trips. The ability to model the chain of the trip the vehicle undertakes allows the simulation to model the accumulated impact of the planned schedule on the level of service. Thus, the actual departure time of a chained trip is calculated as the scheduled departure time and the time the bus vehicle is available to depart after it completes its previous trip plus some recovery time:

$$\text{DPT}_{bk} = \max\left(\text{ST}_{bk}, \text{AT}_{b,k-1} + \text{RT}_{\min} + \epsilon_{bk}\right) \tag{6}$$

where

DPT_{bk} and ST_{bk} = actual and scheduled departure times for trip *k* by bus vehicle *b*, respectively;
$\text{AT}_{b,k-1}$ = arrival time of bus *b* from previous trip at origin terminal of current trip;
$\text{RT}_{\min}$ = minimum recovery time required between trips; and
ϵ_{bk} = error term.

The error term is aimed to represent the possible delay for the first trip of the vehicle as it comes from the garage or depot. In addition, it captures departure supervision for the intermediate trip chain. The explicit representation of trip chaining enables fleet-size constraints through the respective recovery time policy.

CASE STUDY

Bus Line Description

To demonstrate its capabilities, the transit simulator is applied to a case study to evaluate the operations of Line 51 in the Tel Aviv metropolitan area. The line route and demand profiles in the peak hour for the inbound and outbound directions are shown in Figure 2. This high-demand urban line connects a dense satellite residential city to the central business district. Its 14-km route follows a heavily congested urban arterial. The line includes 30 stops in the inbound direction and 33 in the outbound direction, and the average running time is 49 and 41 min, respectively.

Replications

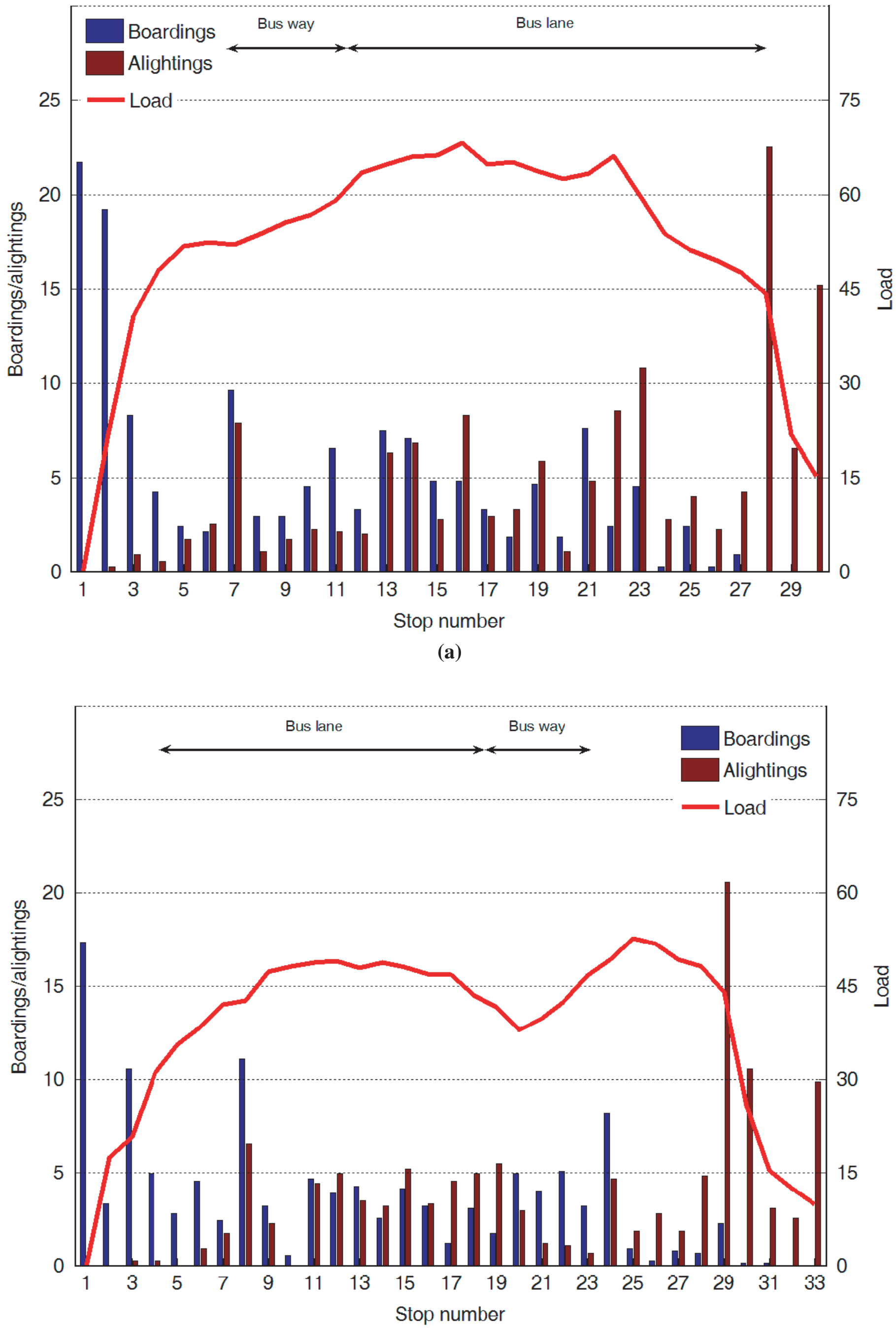
Since the simulation model includes several interrelated stochastic components—passenger arrival and alighting processes, dwell time, departure time from origin terminal, travel time, and recovery time—it is essential to conduct multiple runs (replications) for output analysis.

The standard deviation (SD) of the headway is an important service measure that is the outcome of a complex interaction between all random processes in the system. Given this output measure, the number of required repetitions can be calculated by using Equation 7 (*21, 22*):

$$N(m) = \left(\frac{S(m) \cdot t_{m-1, \frac{(1-\alpha)}{2}}}{\bar{X}(m) \cdot \epsilon} \right)^2 \tag{7}$$

where

$N(m)$ = number of replications required given *m* initial simulation runs;
$\bar{X}(m)$ and $S(m)$ = estimated mean and standard deviation from a sample of *m* simulation runs, respectively;



(b)

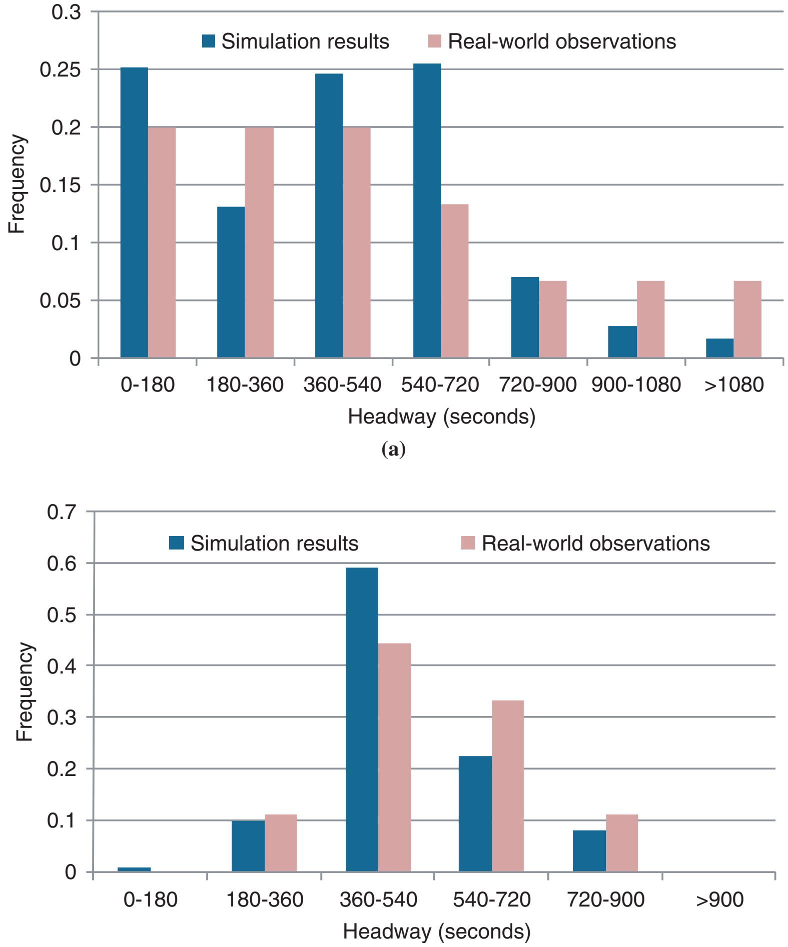
FIGURE 2 Schematic route and load profile during peak hour for (a) inbound and (b) outbound directions of Line 51.

ϵ = allowable percentage error of estimate $\bar{X}(m)$ of μ; and
α = level of significance.

Given $\epsilon = 0.05$ and $\alpha = 0.05$, then $N(60) = 47.22$ at the worst case, indicating that the initial 60 replications are sufficient for the validation. Different applications or output measures may require a different number of repetitions depending on the desired level of accuracy.

Validation Results

The outputs of the simulation were tested against two sets of real-world data. First, video traffic records were available from two bus stops: Stop 28 in the inbound direction and Stop 4 in the outbound direction for the period from 6:30 to 8:30 a.m. Figure 3 shows the observed and simulated headway distributions for these two stops. Two-sample Kolmogorov–Smirnov tests were conducted in order to



(a)

(b)

FIGURE 3 Headway distribution at (*a*) Stop 28 on inbound route and (*b*) Stop 4 on outbound route.

compare the distributions of the observed and simulated headways at these two stops. The test results are that the hypothesis that the observed and simulated headways are derived from the same distribution cannot be rejected ($D = 0.204$ and $D = 0.253$ compared with $D_{8,0.05} = 0.457$ and $D_{15,0.05} = 0.338$, respectively).

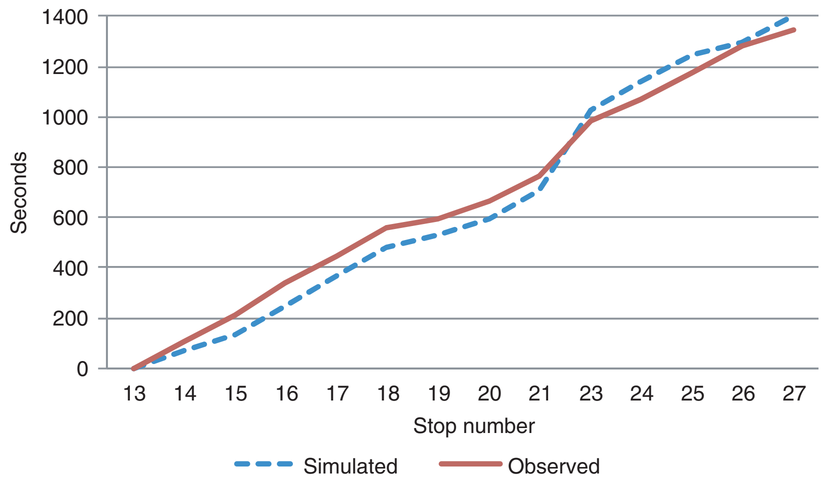
For the second part of the validation, a data set of observed running times between intermediate stops along the bus line during the morning peak period was compared with simulated running times. The observed data set contains bus arrival times for Stops 13 through 27 on the inbound route. Figure 4*a* presents the expected trajectories according to observed and simulated data in the section covered by the data. It is evident that the simulated trajectory replicates the observed trajectory closely. Both simulated and observed running times incorporate dwell times at stops.

Figure 4*b* shows the upper and lower bounds of the 95% confidence interval of the means of simulated and observed running times. The simulated and observed intervals overlap continuously along the presented trajectory. The hypothesis that the simulated and observed running times are drawn from the same distribution cannot be rejected at the 95% level for any of the stops. In addition, the simulated and observed overall running times between Stop 13 and Stop 27 were compared. The hypothesis that the observed and simulated running times are derived from the same distribution cannot be rejected based on the Kolmogorov–Smirnov test ($D = 0.384$ compared with $D_{9,0.05} = 0.432$).

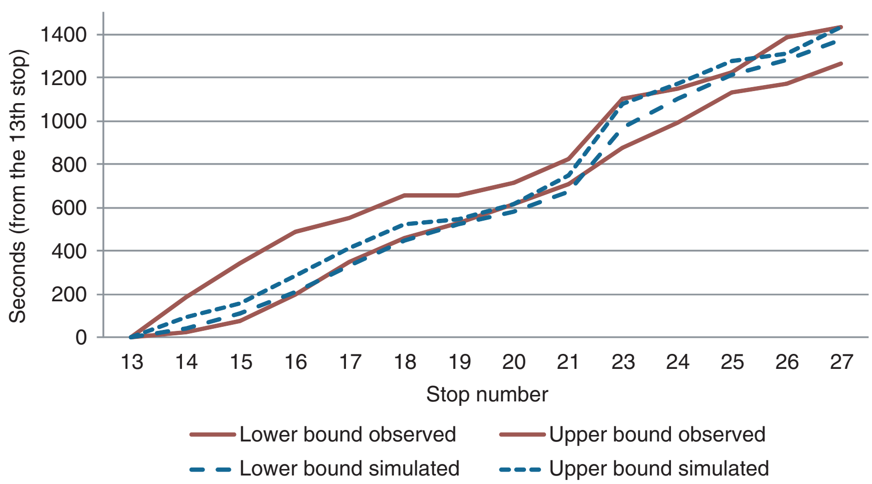
In addition, the assumption that passenger arrival processes follow the Poisson distribution was tested by using boarding counts from Stops 13 through 27 on the inbound route and Stops 4 through 19 on the outbound route. Based on the Kolmogorov–Smirnov test, the hypothesis that passenger arrivals at stops follows the Poisson distribution cannot be rejected for all stops with the exception of Stop 21 on the inbound direction. This stop is characterized by low-frequency events of large numbers of boarding passengers, which seems to be caused by passengers transferring from the nearby train station.

Experiment

The demonstration experiment studied the impact of two factors on the line performance: passenger demand and travel time variability. Passenger demand varied from 50%, 100%, and 150% of its observed values, and travel time variability varied from 50%, 100%, and 150% of the mean travel time based on values found in the literature (*15–17, 23*). Nine scenarios were simulated, one for each possible combination of these factors.



(a)



(b)

FIGURE 4 Partial trajectory of inbound route: (*a*) mean and (*b*) upper and lower bounds of 95% confidence interval of mean.

For each scenario, 60 simulation runs were conducted for a 4-h period (6:30 to 10:30 a.m.) with time-dependent passenger demand and headways in the range of 6 to 10 min. The total execution time for the 60 runs was about 10 s using a personal computer with a Pentium 4 3.01 GHz processor and 512 MB RAM running Windows XP. Using Equation 8, ten replications were found to be sufficient for all of the scenarios with an allowable error of 5%. The reported results are the average of the 60 replications for each scenario.

In the case study, running times between stops were assumed to follow lognormal distributions, with means equal to the scheduled times. At both trip ends, recovery times were calculated on the basis of the 85th percentile of the trip travel times, calculated according to the lognormal distribution (*24*). These recovery times were then used as minimum requirements in determining the trip assignment for each bus vehicle; the layover times were already integrated into the scheduled times. In addition, a sensitivity analysis on the layover policy was conducted. The trip chain was designed with two additional recovery policies that used the 55th and the 70th percentile of total travel times. These policies were implemented with the intermediate demand and variability levels.

Results

The detailed representation of the bus operations in the simulation allows evaluation of its performance ranging from the level of a single run to the overall system performance. Figure 5 presents a time– space diagram showing the trajectories of two buses (Buses 12 and 13 out of the 17 assigned bus vehicles). The simulated and scheduled trajectories are displayed with continuous and broken lines, respectively. Both buses make three trips. Bus 12 is ahead of schedule on its first trip, is increasingly late on the second, and on time on the third. The well-known bunching phenomenon (*25*) is reproduced by the simulation as is evident in the second and third trips, when Buses 12 and 13 arrive simultaneously as they progress along their routes. Recovery times between trips at both terminals are also apparent in the figure, as both buses conducted three sequential trips.

A phenomenon in transit systems that may have significant impact on levels of service is the accumulation of variability in travel times as buses progress through their schedules. Figure 6 demonstrates the evolution of headway variability at the various stops along the inbound route. As the standard deviation of the headway increases

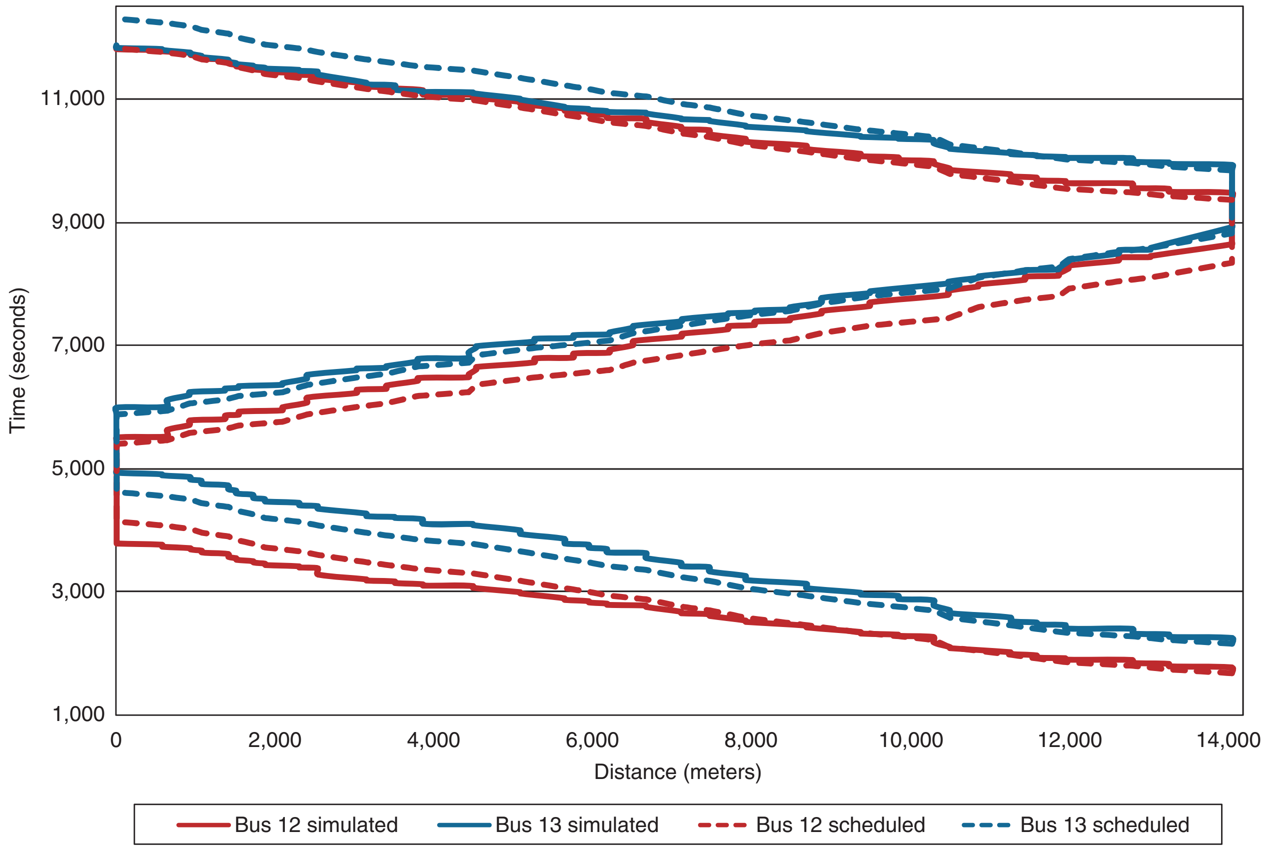


FIGURE 5 Time–space diagram of buses in service on Line 51.

along the route, the on-time performance statistic decreases from 100% to 73%. Following Ceder, a bus is considered to adhere to schedule at a specific stop if it arrives between 1 min early and 4 min late compared with its scheduled arrival (*17*).

Figure 7 shows an example of the load profiles of the outbound route for two successive buses. The leading bus had a long headway followed by a bus with a short headway. For comparison the expected load profile for the planned headway, which was tested by a simulation run with deterministic conditions (constant running times and dwell times) is presented as well. It can be seen that the actual load profile varied significantly from the one expected under deterministic conditions: the first bus with high headway had to pick up all the passengers that had accumulated, which resulted in longer dwell times, causing the following bus that had fewer passengers and therefore

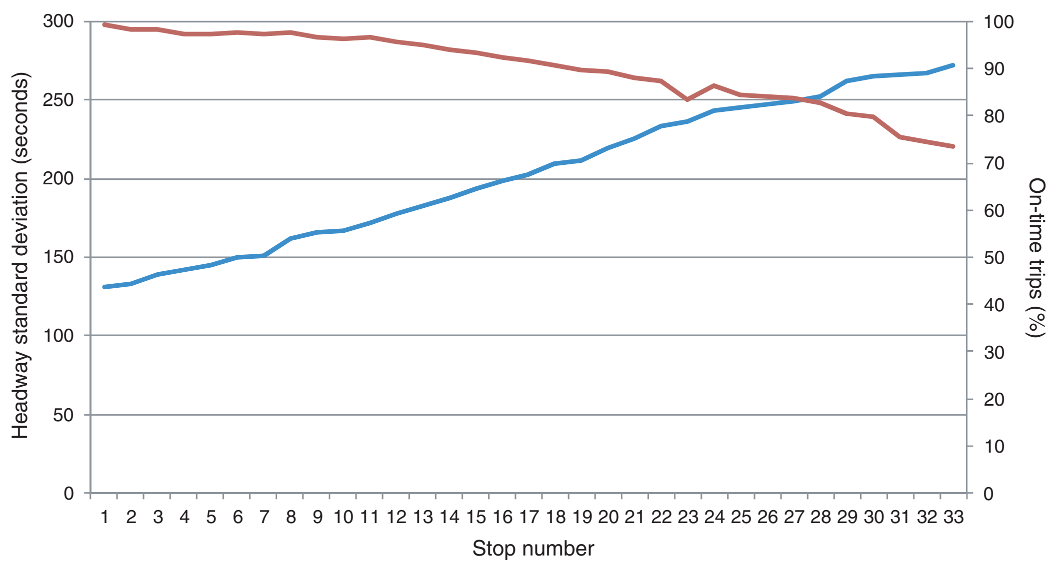


FIGURE 6 Standard deviation of headway and on-time performance on inbound route.

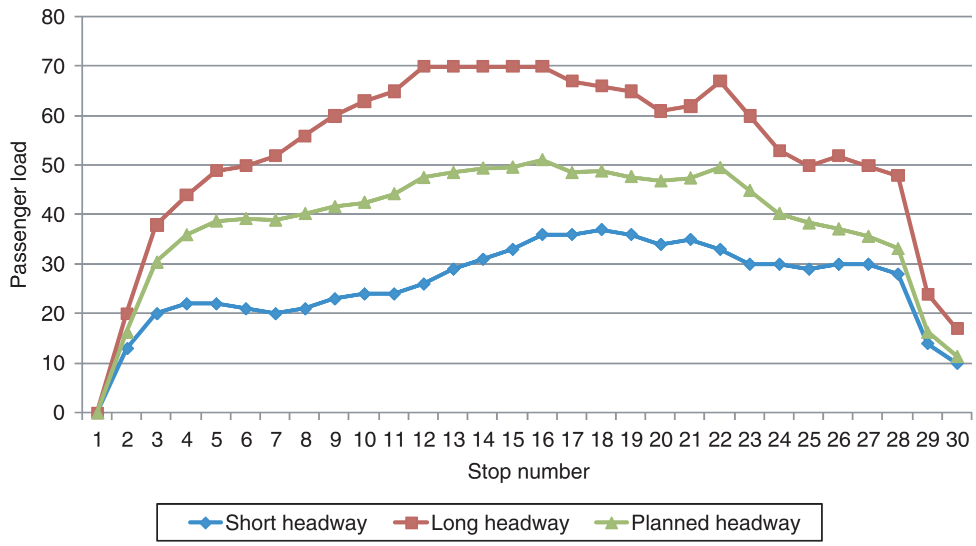


FIGURE 7 Planned and experienced load profiles for bunched buses on inbound route.

shorter dwell times to catch up with it. This trend was restrained in the intermediate stops, as the first bus with the long headway reached its capacity (70 passengers) and left waiting passengers behind. As a result, the second bus with the short headway had to serve more passengers than expected according to its headway. Finally, the headway at the destination terminal was only 2.5 min, instead of 10 min, as planned. From the passenger point of view, being unable to board overcrowded buses is a source of unreliable and inconvenient service.

At the system level, several measures of performance were calculated for each scenario. Table 1 summarizes these measures for the various scenarios. Headway variability is the main measure for evaluating transit reliability, in particular for short-headway services, when bus bunching occurs. Headway variability was calculated for each stop along the route. The reported statistics are the mean values across all stops in each direction.

Headway variability increases with the level of variability of running times between stops. It is evident that higher travel-time variability results in less regular service, with fewer stop arrivals that adhere to the planned headway. Higher travel-time variability causes higher frequency of extreme values, which represents bunching. Interestingly, an hour-by-hour analysis reveals that the short headway service in the peak hour results in a much higher headway variability, not only in relative terms but also in absolute terms. The irregularity effect caused by the short headway continues into the next hour, even though the average headway returned to its previous level.

Another important measure of service reliability is on-time performance. On-time performance was measured for all trips and all stops. The relatively high share of early arrivals from the total number of buses that did not arrive on time calls for the implementation of schedule-based holding. The last system-level measure in Table 1 is the average number of passengers per stop that are unable to board because the bus is overcrowded. As expected, this statistic increases with the level of passenger demand.

Sensitivity Analysis of Recovery Time Policy

The objective of fleet assignment procedures is to generate trip chains with the minimal number of vehicles required to fulfill the schedule. This objective is better served by shorter layover and recovery times. However, the operator has to balance between the economic criteria and the level of service criteria, since shorter layover and recovery

TABLE 1 Service Measures of Performance Under Various Scenarios

Scenario		Measure of Performance					
Demand (%)	Travel Time Variability (%)	Inbound Headway, SD (s)	Outbound Headway, SD (s)	Early Arrivals (%)	Late Arrivals (%)	On-Time Trips (%)	Passengers Unable to Board per Stop
50	50	154.8	141.5	19.3	1.2	79.4	0.00
50	100	155.1	141.5	19.4	0.7	80.0	0.00
50	150	159.0	146.3	18.8	0.8	80.5	0.00
100	50	187.2	188.7	3.7	5.3	91.0	0.09
100	100	190.8	202.0	4.3	7.4	88.3	0.10
100	150	192.6	201.0	4.3	8.1	87.5	0.10
150	50	188.1	256.5	0.3	40.7	59.0	2.71
150	100	188.3	260.5	0.4	42.0	57.7	2.70
150	150	190.0	261.6	0.6	42.6	56.8	2.56

TABLE 2 Sensitivity Analysis of Recovery Time Policy

Recovery Time (percentile of travel time)	Fleet Size	On-Time Performance (%)	Schedule Deviation (s)	Late Departures (%)
55	15	75.7	211	21.5
70	16	83.1	175	13.4
85	17	88.3	146	7.4

times will result in late departures, missed trips, and poor on-time performance. Table 2 summarizes the results of a sensitivity analysis for the outbound direction aimed at elaborating the impact of different recovery time policies on bus performance. The results demonstrate that as the recovery times decrease, the number of late departures increases. For example, a reduction of 12% in the number of buses used (from 17 to 15) results in an 18% decrease in the on-time performance, a 69% increase in the average schedule deviation, and almost three times more late departures from the origin terminal. The transit simulation supports evaluation of this trade-off in order to identify optimal strategies.

CONCLUSIONS

This paper presents a transit simulation model based on the platform of an event-based mesoscopic traffic-simulation model, Mezzo. The developed simulation represents schedules, trip chains, boarding and alighting processes, passengers left behind, dwell time, layover and recovery times, and trip chaining. The model also captures the propagation of delays through the system and from trip to trip.

The capabilities of Mezzo as an evaluation tool of transit operations planning and control have been demonstrated with an application to a real-world, high-demand line in the Tel Aviv metropolitan area. The case study results validate the performance of the simulation model and demonstrate the value of the implementation of bus operations and the kind of outputs that are generated by the simulation. Moreover, the model reproduces important phenomena such as propagation of headway variability along the route and bus bunching, which were validated with field data. The simulation model has yet to be tested on realistic systemwide networks. Further developments of Mezzo focus on modeling of various control strategies, such as holding and expressing, with application to real-time control. A detailed representation of passenger demand draws an additional interesting direction for future research as it would enable the capture of the interaction between transit operation strategies and scheduled-based passenger route choice.

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