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Modeling Passenger Boarding Times Using Sumonity's Sub-Microscopic Pedestrian Simulation

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Abstract. Short dwell times at bus stops are crucial for efficient public transport operations, yet existing traffic simulation tools commonly simplify passenger boarding. In this paper, we extend the SUMO-based co-simulation framework, Sumonity, to incorporate a sub-microscopic pedestrian model for city bus boarding. Our approach simulates real-time passenger flow, pathfinding, and door congestion in a Unity-based environment. We conduct a full-factorial simulation experiment with four bus door configurations, ranging from fully open double doors to partially closed options. We also consider different passenger loads between 1 and 50, yielding 200 unique scenarios. Detailed spatiotemporal data on passenger movements and boarding times are generated for each scenario. Analysis of crowding behaviors and door usage reveals significant sensitivity of boarding times to both passenger volume and door availability. These findings demonstrate the importance of accurately modeling pedestrian interactions for reliable dwell-time forecasts and underscore the potential of sub-microscopic pedestrian simulations.

Keywords: Sub-Microscopic Traffic Simulation, Pedestrian Modelling, Dwell Time, Microscopic Traffic Simulation

1. Introduction

Public transport efficiency plays a pivotal role in urban mobility, where growing ridership and sustainability goals emphasize the need to optimize bus operations [1]. Among the critical factors affecting bus service reliability and overall passenger experience is the *dwell time*—the interval a bus spends at stops to accommodate boarding and alighting passengers. Longer dwell times can accumulate in a transit network, reducing schedule adherence and passenger satisfaction.

Existing traffic simulation tools, such as SUMO, provide robust frameworks for modeling vehicular movement at a microscopic level. However, passenger processes are often simplified: individuals are typically lined up in fixed positions at bus stops and are *teleported* onto the bus. This approach disregards the dynamic interactions among passengers, variations in bus interior layouts, and real-world phenomena such as queue formation and congestion at doors. To address these limitations, we extend the capabilities of the SUMO-based co-simulation framework, Sumonity [2], by integrating sub-microscopic, three-dimensional pedestrian models for passenger boarding. Our approach aims to capture realistic movement behaviors at the doors, enabling more accurate dwell-time estimations. In this paper however, we focus on boarding time and exclude the alighting process. Specifically, we investigate how different door configurations (e.g., fully open or partially closed double doors) and varying passenger loads (from 1 to 50) influence boarding times.

The remainder of this paper is structured as follows. Section 2 provides a literature review that summarizes key findings on dwell times and related passenger-flow models. Section 3 details our methodology, including the simulation scenario setup and the enhancements made to the pedestrian simulation model. Sections 4 and 5 present and discuss the results, with a focus on how door configurations and passenger volumes influence boarding times and movement patterns. Finally, Section 6 concludes the paper by highlighting our key contributions, addressing limitations, and outlining directions for future research.

2. Literature Review

Bus dwell time is commonly defined as the interval between a vehicle's arrival at a station and its departure, encompassing passenger boarding, alighting, and related door operations [1], [3], [4]. While numerous variables affect dwell time, the *volume of boardings and alightings* is frequently highlighted as a principal factor: larger passenger counts often lead to congestion at vehicle entrances and increased friction among riders, thereby prolonging service intervals [5], [6], [7]. Beyond passenger loads, bus design characteristics, including door width, the number of doors, and low-floor configurations, also streamline boarding and alighting [8], [9]. Notably, low-floor buses improve boarding speeds for older adults and individuals with mobility impairments, further enhancing operational efficiency [10]. Fare collection methods likewise shape dwell time dynamics; for instance, cash payments at a front door slow boarding processes, whereas electronic payment systems and pre-paid fares can reduce passenger queues [11], [12].

In addition to vehicle and passenger attributes, contextual and route-related variables are equally important. Locating bus stops directly after intersections can minimize delays from congested turning lanes and crossing pedestrians [13], whereas stops placed before intersections or in areas with limited visibility risk increased dwell durations due to pedestrian conflicts and blocked exit paths [14]. Peak-hour conditions exacerbate these challenges because limited interior space constrains passenger flow and intensifies crowding [15]. Methodologically, linear or multiple regression models have traditionally been employed to estimate and predict dwell time [11], [16]. However, advanced approaches such as hazard-based models [17] and machine learning techniques [18], [19] are gaining traction, offering more detailed insights by capturing nonlinearities and complex variable interactions. Despite extensive research on conventional bus operations, gaps remain around automated shuttle services, where the absence of a human driver, novel sensor configurations, and distinct interior layouts could alter boarding and alighting patterns [20]. As public transit systems increasingly adopt automation, future studies must examine how sensor-based infrastructure, remote supervision, and user-interface innovations influence dwell times and overall service effectiveness.

3. Methodology

3.1 Study Design

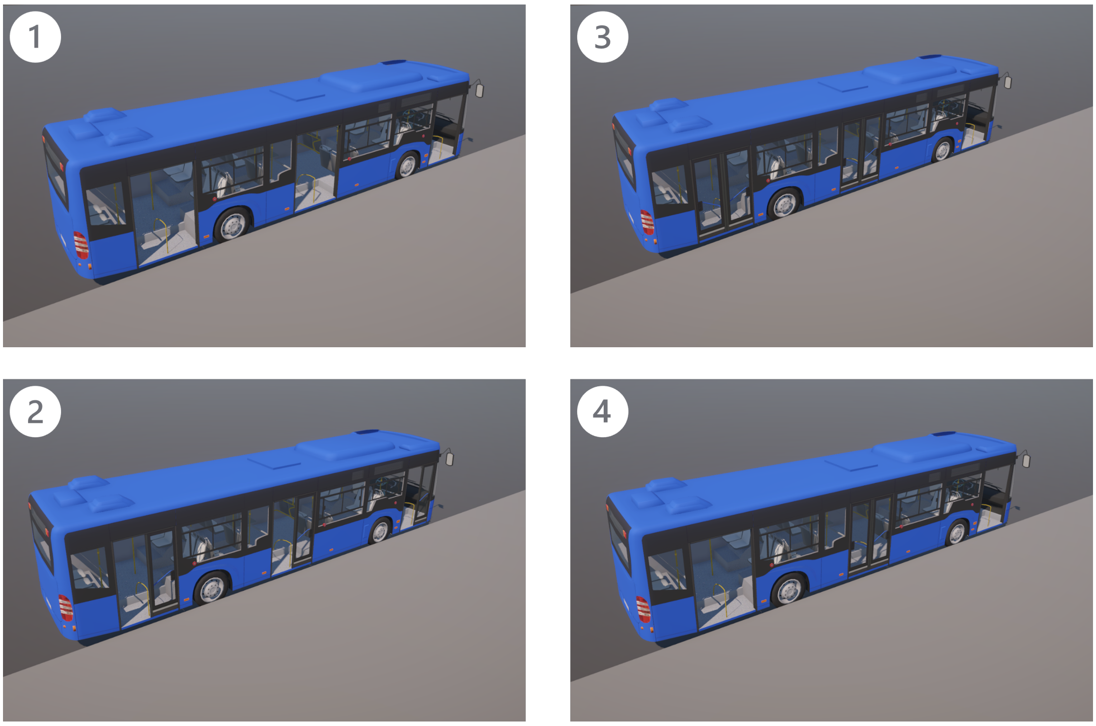


Figure 1. *Simulation Scenarios: (1) all double doors opened, (2) all doors opened but only one side, (3) only front double door open, (4) front and rear double door opened.*

In this study, we model the boarding process of a city bus, aiming to address limitations in standard SUMO simulations that assume fixed passenger positions and teleportation onto the vehicle. By contrast, our approach enables passengers to queue, navigate, and interact realistically.

Multiple bus configurations (see Figure 1) are examined to explore how door access—such as fully open or partially closed double doors—impacts boarding efficiency. In each scenario, the bus is empty, and passengers range from 1 to 50, allowing us to assess the effect of passenger load on boarding time. The door configuration, together with the passenger volume, constitute the independent variables, while the principal dependent variable is boarding time, measured from the moment passengers arrive at the bus stop area to the time the last individual finishes boarding.

To reduce complexity, we do not simulate seat selection or movement within the vehicle beyond a certain point. Each passenger starts from a randomly assigned position in the bus stop area and proceeds to their nearest available door. The scenario ends once the passenger reaches a designated area inside the bus, ensuring minimal obstruction for subsequent boarders.

3.2 SUMO Integration

Our simulations build on the Sumonity framework [2], an open-source solution that combines SUMO with the Unity game engine for sub-microscopic traffic simulation. The Sumonity codebase is publicly available on GitHub[1].

[1] https://github.com/TUM-VT/Sumonity

Using SUMO's TraCI API, we retrieve real-time pedestrian states—positions at each timestep (see Figure 2). Traditional SUMO workflows teleport passengers onto the bus, but in Sumonity, passengers continuously walk from the platform into the vehicle. As soon as a pedestrian enters the defined bus stop area, a waiting position is assigned; once the bus arrives, the system attaches a bus identifier to the passenger, signaling the start of the boarding process and defines a goal point near the closest door. Detailed position data are then recorded for subsequent dwell-time analysis or human-in-the-loop research.

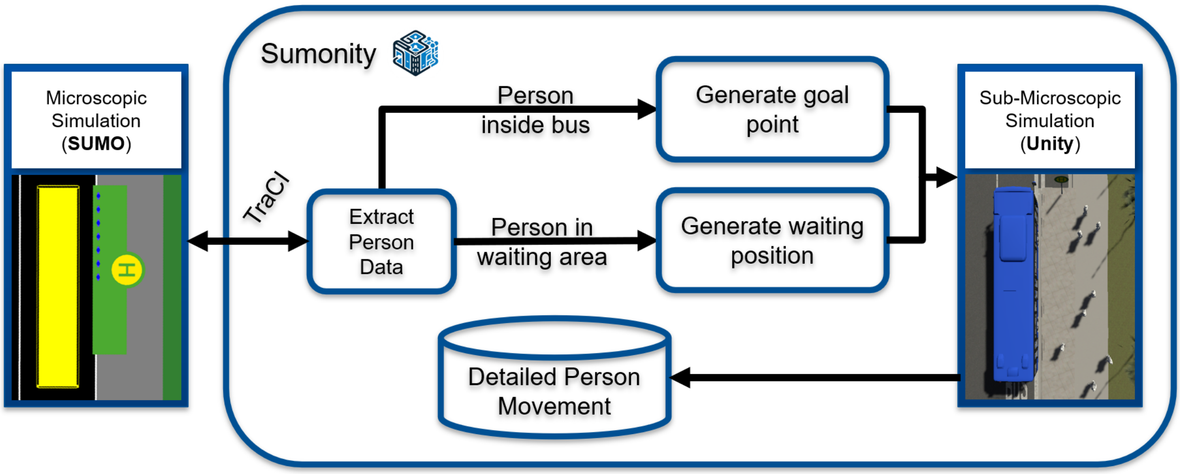


Figure 2. *Data flow of the Sumonity pedestrian simulation system used in this study.*

3.3 Simulation Model

3.3.1 Pedestrian Simulation Model

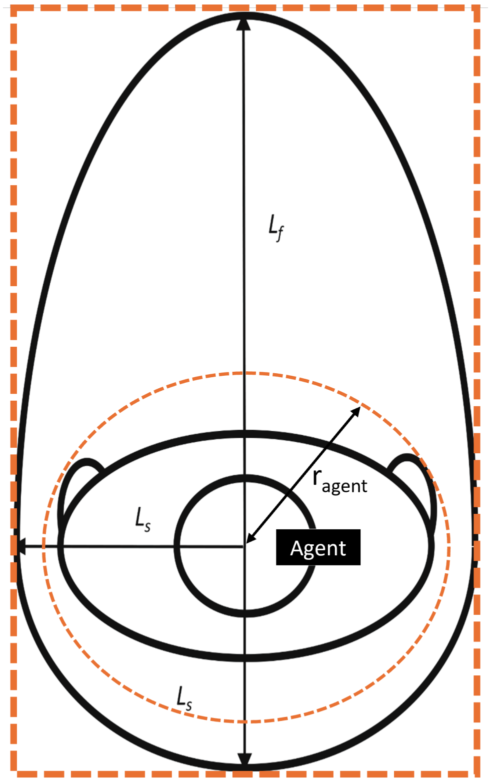
The simulation model encompasses four key areas: **Physical Agent Space**, **Path Search**, **Speed Choice**, and **Animation**. We further describe thresholds and model assumptions.

Physical Agent Space

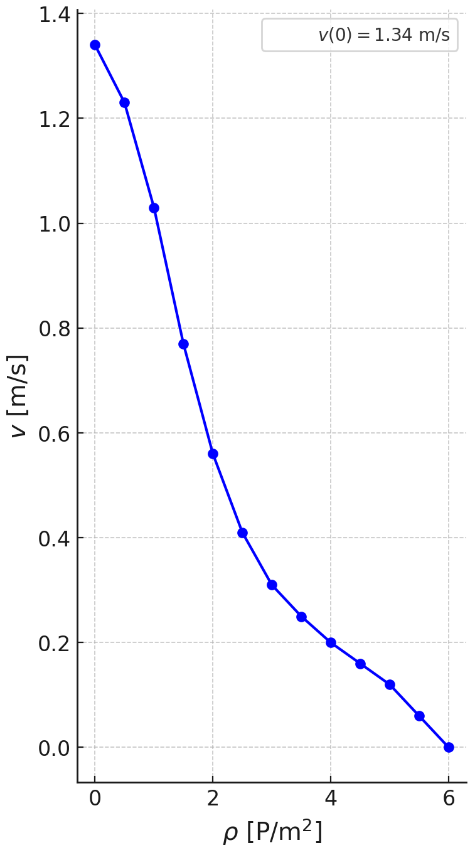
Each passenger is represented by a circular agent with a radius of $0.45\,\mathrm{m}$, based on standard pedestrian-flow and transportation literature [22], [23]. This simplified model omits individual variability in body size but provides a baseline for crowd interactions; future extensions could incorporate heterogeneous agent sizes.

Path Search

The environment is preprocessed into a navigation mesh (navmesh), which partitions the walkable area into convex polygons. We employ an A* pathfinding algorithm within Unity to guide passengers around obstacles, including bus doors, walls, and other agents. The input geometry specifies the 3D layout, while real-time collision checks ensure agents avoid overlap.



(a) *Physical Agent Space and Interaction Space based on [21].*



(b) *Speed-density correlation [22].*

Figure 3. *Key concepts in the pedestrian simulation model.*

Speed Choice

Agent speed adapts to crowd density in a predefined interaction space. We approximate this space with a rectangular bounding box, inspired by the agent space model and the NOMAD model [21], [24]. At each timestep, the local density is computed, and speeds are updated according to the empirical relationship from Weidmann [22]. This allows agents to slow down in dense areas, capturing typical pedestrian-congestion behavior.

Animation

Although root-motion animations can enhance realism, especially for human-in-the-loop applications, we use only visual (non-root-motion) animation. The agent's motion is determined by explicit velocity and heading updates, while the animation layer serves mainly for visual plausibility.

Door-Balancing and Deadlock Avoidance

Passengers may reroute to a less crowded door if their velocity remains under $0.75\,\mathrm{m/s}$ for 2 seconds (see Figure 4). Should any agent's average speed drop below $0.1\,\mathrm{m/s}$ for 1.5 seconds, the system interprets this as a deadlock and repositions one agent slightly to clear the blockage. If a deadlock persists beyond 180 seconds, the run is terminated and the data excluded from the final dataset.

Summary of Model Parameters:

- **Physical Agent Space:** $r_{\text{agent}} = 0.45\,\text{m}$
- **Path Search:** Navigation mesh, A* algorithm
- **Speed Choice:** Density-based according to Weidmann [22]
- **Agent Interaction Space:** $L_s = 0.84\,\text{m}$, $L_f = 5.95\,\text{m}$ (adapted from [21])
- **Animation:** Non-root-motion humanoid avatar

3.3.2 Simulation Runs

We adopt a full factorial design featuring four door configurations (Fig. 1) and passenger counts ranging from 1 to 50, leading to 200 unique scenarios. Each scenario is repeated 100 times to capture variability and ensure reliable statistics, totaling 20,000 runs. Key outputs include boarding times, agent trajectories, and crowd density heatmaps, which are aggregated and analyzed in subsequent sections to evaluate boarding efficiency and crowding behaviors.

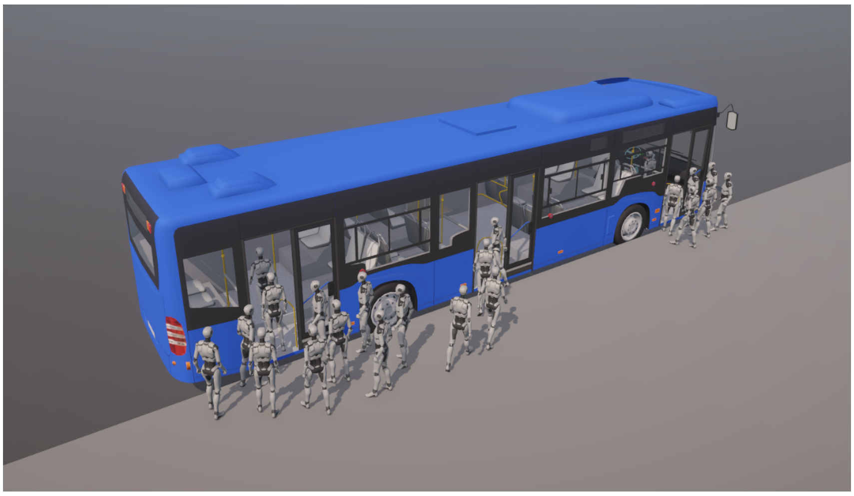


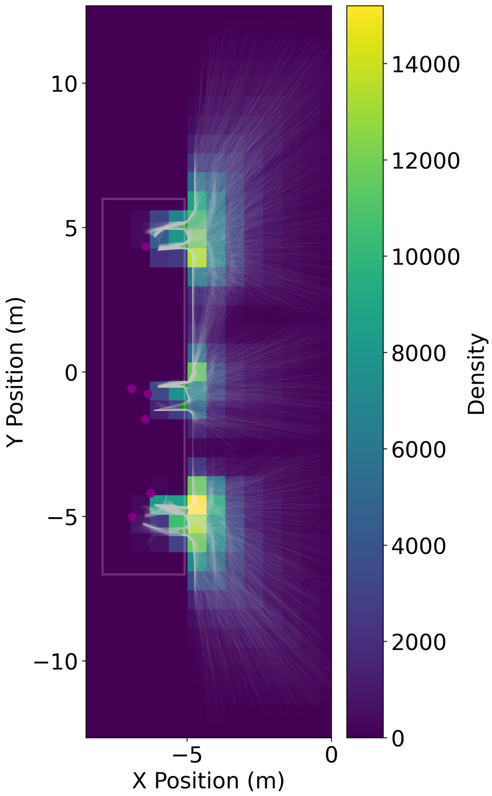
Figure 4. *Pedestrian agents boarding the bus.*

4. Results

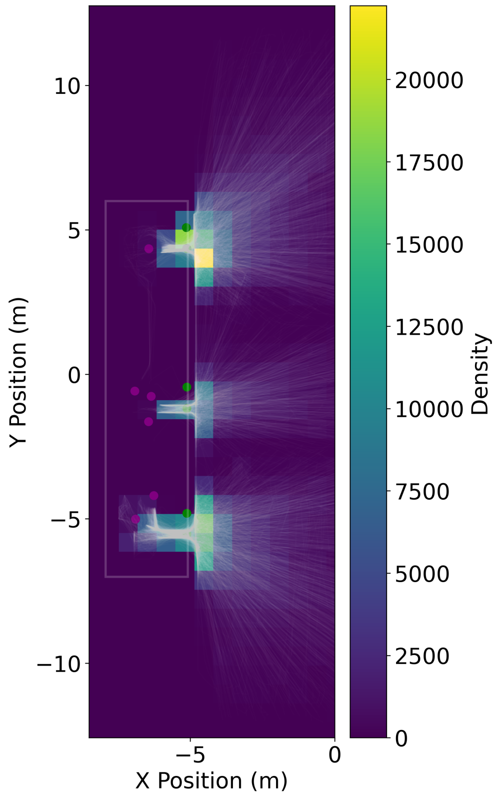
4.1 Passenger Occupation Analysis

Figure 5 shows the spatial distribution of passenger positions represented as a heatmap generated from a 2D histogram. In this figure, green points indicate door centers while purple points mark the goal locations inside the bus. A black rectangle outlines the bus, with its position and dimensions based on predefined parameters.

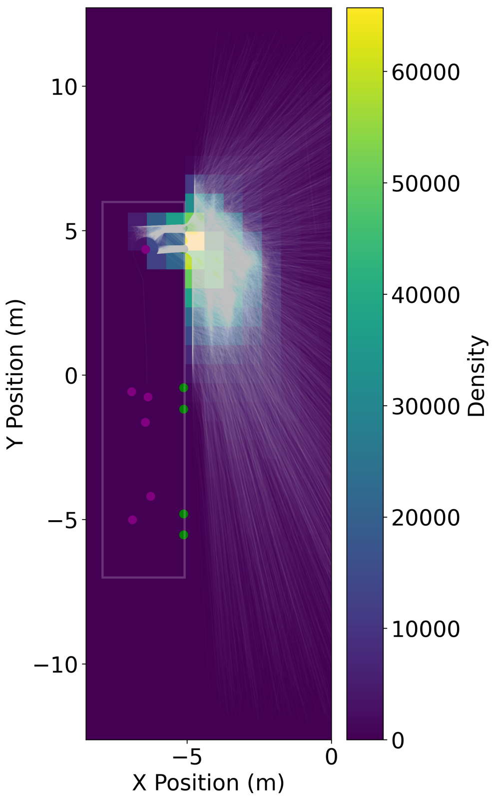
To analyze pedestrian occupation in the 2D space, we use a bin size that corresponds to the physical agent space (radius $0.45\,\text{m}$), resulting in grid cells of size $64 \times 64\,\text{cm}$. The heatmap clearly reveals the trajectories taken by passengers from their randomly assigned starting positions in the bus stop area. Depending on the scenario, one or two distinct streams of boarding are observed as passengers converge toward the open door(s). Notably, in scenario 3—where only the front door is open—a significant backlog of passengers is apparent, indicating congestion at that door.



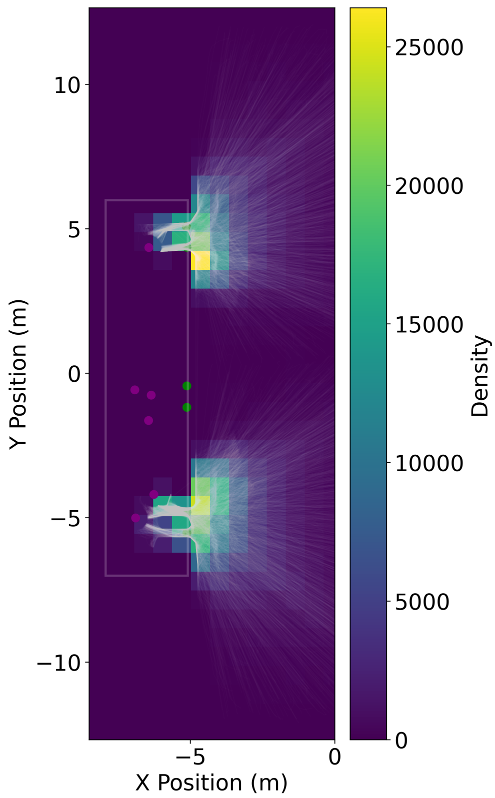
***(a)** Scenario 1: all doors open*



***(b)** Scenario 2: all doors half open*



***(c)** Scenario 3: only front door open*



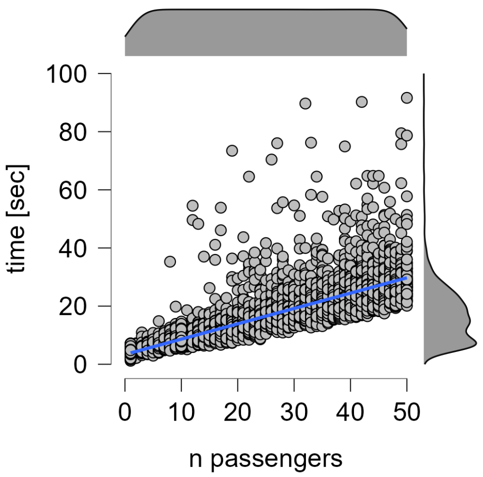
***(d)** Scenario 4: front & rear door open*

***Figure 5.** Heatmap for passenger occupancy analysis for 40 agents. The points green points highlight the door positions. The purple points the goal points in the bus.*

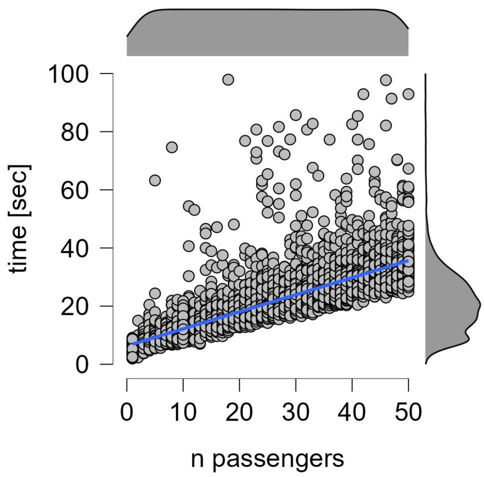
4.2 Boarding Times

We apply a linear regression model to estimate boarding times, with boarding time as the dependent variable and the number of boarding passengers as the independent variable. Each scenario is evaluated separately. Figure 6 displays the scatter plots, density plots, and corresponding linear regression lines for all scenarios, while Table 1 provides detailed statistics and regression model parameters. For the analysis, we removed outliers exceeding the 75th percentile by more than 1.5 times the interquartile distance.

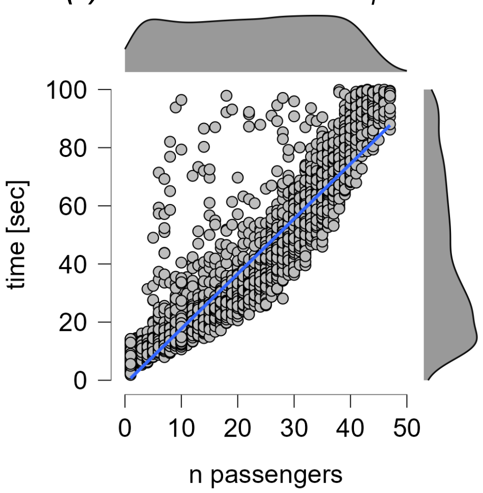
The key parameters in our regression analysis are the intercept and the β coefficient. The intercept varies across scenarios, which is plausible since it depends heavily on the starting positions and also serves as an indicator of the average agent backlog at the doors. Notably, scenario 3 (only the front door open) exhibits a negative intercept. The β coefficient represents the boarding time change per additional passenger. Among the scenarios, scenario 1 (all doors open) has the smallest change rate ($\beta = 0.500$), followed by scenario 2 (all doors half open, $\beta = 0.557$) and scenario 4 (front and rear door open, $\beta = 0.790$). In contrast, scenario 3 (only the front door open) shows by far the highest change rate with $\beta = 2.275$.



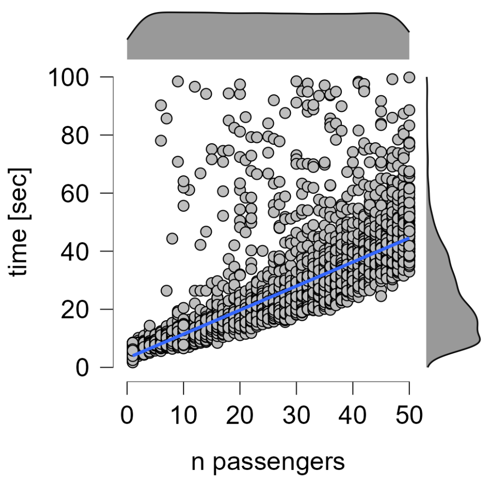
(a) *Scenario 1: all doors open*



(b) *Scenario 2: all doors half open*



(c) *Scenario 3: only front door open*



(d) *Scenario 4: front & rear door open*

Figure 6. *Scatter plots including density plots and linear regression line for all scenarios.*

Table 1. *Descriptive statistics and regression model parameters for each scenario.*

Scenario	**N**	**Mean**	**SD**	**SE**	$\mathbf{R^2}$	**Intercept**	β
1	4925	16.243	8.158	0.116	0.779	3.587***	0.500***
2	4898	20.484	9.083	0.130	0.781	6.406***	0.557***
3	4793	52.582	36.215	0.523	0.830	-6.430***	2.275***
4	4750	22.761	12.907	0.187	0.784	2.896***	0.790***

Included Data: $n_{\text{pass}} = [1, 50], time <$ *75-Quartile* $+1.5\times$ *Inter-Quartile-Distance*
Note: N = Number of included simulation runs; SD = Standard deviation; SE = Standard error;
***p-value < 0.001;

5. Discussion

The regression model parameters yield several insights. Analysis of the β coefficient shows that scenarios with all doors open (scenarios 1 and 2) exhibit the lowest boarding time change rates—even when the doors in scenario 2 are only half open. In contrast, scenario 4 (front and rear doors open) shows a change rate approximately 40% higher than that of scenario 2, despite having a larger combined door width (four single-door widths versus three single-door widths). This finding suggests that increasing the number of accessible doors helps distribute passengers more evenly, thereby reducing boarding times at higher passenger volumes.

Notably, the regression model for scenario 3 (only the front door open) stands out. Its negative intercept, which lacks a meaningful real-world interpretation, may indicate that an alternative modeling approach could better capture the underlying dynamics. Nonetheless, the significantly higher boarding time change rate in this scenario—approximately three times or more than that of the other scenarios—reflects the severe congestion caused by having a single open door.

Since real-world validation of our simulation scenarios is not feasible, we compare our results with findings from the literature. For example, [8] analyzed the influence of door width (double versus single), bus-door distance, and payment method on boarding times. Their study reported values of 1.50 seconds for double doors and 1.67 seconds for single doors, which are about one second higher than our simulated values of 0.500 and 0.557 seconds, respectively. This discrepancy is plausible, as their analysis includes the time required for passenger movement inside the vehicle, which our simulation deliberately omits. Importantly, the ratio between single-door and double-door scenarios remains consistent, with the double-door configuration requiring roughly 90% of the duration of the single-door scenario. Furthermore, comparison with the Highway Capacity Manual (HCM) [3] reveals similar per-passenger boarding times; for instance, the HCM estimates approximately 0.5 seconds per passenger for a scenario featuring three double doors and a prepaid fare system.

6. Conclusion and Outlook

In this paper, we presented a sub-microscopic traffic simulation framework for modeling bus boarding processes. Our novel approach integrates microscopic traffic simulation with a pedestrian model based on navigation meshes and 3D simulation techniques. By simulating boarding scenarios with passenger counts ranging from 1 to 50 and various door configurations, we developed linear regression models to estimate boarding times. Our results indicate that both the number of doors and their configuration (double versus single) significantly affect boarding times due to congestion at the doors. In particular, the scenario with only one open door led to congestion, resulting in much higher boarding time change rates per additional passenger.

Future work should include a sensitivity analysis of key model parameters. For example, the speed adjustments based on local pedestrian density may differ in these specific boarding scenarios compared to previous model settings. Similarly, refining the agent interaction space and incorporating variability in physical agent dimensions, reflecting differences in passenger body sizes, could further enhance model realism. Moreover, while this study focused solely on the boarding process, future simulation models should also address the alighting process and the interactions between boarding and alighting passengers.

Data availability statement

The data can be obtained by contacting the corresponding author or the Chair of Traffic Engineering and Control (https://www.mos.ed.tum.de/vt/startseite/) at Technical University of Munich via info.vtk@ed.tum.de.

Underlying and related material

The implementation of the given framework is published on the GitHub page of the Chair of Traffic Engineering and Control of the Technical University of Munich: https://github.com/TUM-VT/Sumonity

Author contributions

Johannes Lindner: Conceptualization, Data Curation, Formal Analysis, Funding Acquisition, Investigation, Methodology, Resources, Supervision, Validation, Visualization, Writing – Original Draft, Writing – Review & Editing.

Mathias Pechinger: Conceptualization, Data Curation, Project Administration, Resources, Software, Validation, Visualization, Writing – Original Draft, Writing – Review & Editing.

Klaus Bogenberger: Conceptualization, Funding Acquisition, Supervision, Writing – Review & Editing.

Competing interests

The authors declare that they have no competing interests

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