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DISCRETE EVENT SIMULATION FOR ASSESSING THE IMPACT OF BUS FLEET ELECTRIFICATION ON SERVICE RELIABILITY

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ABSTRACT

This paper aims to derive a simulation model to evaluate the impact of bus fleet electrification on service reliability. At its core, the model features a micro discrete event simulation (DES) of an urban bus network, integrating a route-level bus operation module and a stop-level passenger travel behavior module. Key reliability indicators—bus headway deviation ratio, excess passenger waiting time, and abandonment rate—are computed to assess how varying levels of electrification influence service reliability. A case study of route 35 operated by DASH in Alexandria, VA, USA is conducted to demonstrate the applicability and interpretability of the developed DES model. The results reveal trade-offs between bus fleet electrification and service reliability, highlighting the role of operational constraints and characteristics of electric buses (EBs). This research provides transit agencies with a data-driven tool for evaluating electrification strategies while maintaining reliable and passenger-centered service.

1 INTRODUCTION

Buses account for more than 80% of public transportation trips (UITP, 2023). As a critical component of urban mobility infrastructure (Cascajo & Monzon, 2014), the electrification of bus systems is therefore required to support sustainable urban development. Although electric buses (EBs) offer zero-emission benefits compared to diesel-powered buses, they face technological limitations such as limited driving range and extended charging times (Perumal et al., 2022). These constraints introduce significant challenges when electrifying complex public transit networks, including issues related to fleet replacement, charging infrastructure placement, and vehicle scheduling (Alamatsaz et al., 2022; Häll et al., 2019). In particular, as governments continue to invest in EBs, strategic planning for bus fleet replacement becomes vital for transit agencies to effectively procure EBs and meet electrification goals (Islam & Lownes, 2019).

Progressively determining a bus fleet electrification plan is challenging. Researchers have identified three key issues around bus fleet electrification: the timing of EB purchases, the selection of EB types and the number of EB to purchase (Li, 2016; Zhou et al., 2023). To answer these three questions, prior studies have primarily focused on cost-effectiveness, optimizing factors such as purchase costs, charging infrastructure investments, and total cost of ownership (TCO) (Jefferies & Göhlich, 2020; Pelletier et al., 2019). In addition to cost-driven approaches, environmental considerations, such as life cycle emissions of carbon dioxide (CO_2), also play a role in informing the selection of EB types (Cooney et al., 2013). While these economic and environmental aspects are essential from the perspective of public authorities and transit agencies, they have largely overlooked the interests of other key stakeholders, particularly passengers. The fundamental objective of public transportation is to deliver high-quality service to its users (Ibarra-Rojas et al., 2015). When the transport infrastructure fails to meet the passenger demands, it often result in unreliable service that is the major deterrent to existing and potential passengers (Lodovici & Torchio, 2015). Therefore, the potential impacts of electrification on service quality must be carefully considered when transitioning bus fleets. Existing studies have shown that the operational challenges introduced by bus fleet electrification can negatively affect existing bus operations and passenger travel behavior (Guo et al., 2018; Manzolli et al., 2022). For instance, the range anxiety and increased charging demands of EBs may lead to inconsistent headways and longer waiting times, ultimately diminishing the overall service reliability of bus systems. Therefore, to enhance the understanding of the impacts of bus fleet electrification in the perspective of passenger interest, a quantitative model that is capable of incorporating bus operations and passenger travel behavior to analyze service reliability (e.g., bus headway and passenger waiting time) is needed.

To address the research gap, this study aims to propose a discrete event simulation model to evaluate the impacts of bus fleet electrification on service reliability. Specifically, a micro simulation model of an bus system is developed, integrating route-level bus operation and stop-level passenger travel behavior to represent the interaction between supply and demand within the bus system. Within the simulation framework, three attributes, namely bus headway deviation ratio, excess passenger waiting time, and abandonment rate, are computed to measure bus service reliability. To prove the feasibility and applicability of the proposed approach, a bus fleet electrification problem for route 35 of DASH in Alexandria, VA, USA is studied. The remainder of this paper is organized as follows. First, a brief literature review on bus fleet electrification planning is presented. Second, details of the research methodology are presented. Third, building upon the simulation model, service reliability is evaluated through a case study. Finally, research contributions, limitations, and potential future work are concluded.

2 LITERATURE REVIEW

Previous research on bus fleet electrification planning has primarily focused on optimizing economic costs and environmental benefits. This section reviews the literature on these two dimensions and highlights the rational for incorporating service reliability as well as the associated methodological challenges.

Regarding economic considerations, a major focus has been the total cost of ownership (TCO), which includes vehicle acquisition, operation, and charging infrastructure costs. Some studies have incorporated fleet replacement planning alongside electric bus scheduling and infrastructure investment to evaluate the full cost implications of electrification. These approaches often seek to optimize depot planning and bus scheduling based on TCO calculations and charging constraints (Rogge et al., 2018). Other research has extended this analysis by minimizing life cycle costs through deterministic mixed-integer programming, simultaneously addressing the need for charging infrastructure and the goal of reducing greenhouse gas emissions (Islam & Lownes, 2019). A broader cost-based framework has also been proposed, incorporating purchase costs, salvage revenues, operational expenses, infrastructure investment, and demand charges. This framework is typically formulated as an integer linear program and tested across different scenarios to determine cost-effective electrification strategies (Pelletier et al., 2019). More recent work has introduced heuristic approaches to compare cost structures between battery electric buses (BEBs) and fuel cell electric buses (FCEBs), highlighting the potential benefits of a mixed fleet under specific operating conditions (Wagner & Walther, 2024).

In addition to economic concerns, environmental benefits—particularly the reduction of greenhouse gas (GHG) emissions—have also been a major driver in urban bus fleet electrification planning. Numerous studies have employed life cycle assessment (LCA) methods to evaluate the long-term environmental impacts of various types of electric buses compared to conventional diesel fleets. These assessments typically account for emissions generated throughout the vehicle's life cycle, including production, operation, and end-of-life disposal (Cooney et al., 2013). A recent LCA conducted across several African countries further emphasized the environmental value of electrification, demonstrating that replacing internal combustion engine buses with electric buses could reduce emissions by up to 99.9% in regions powered primarily by renewable energy sources (Ayetor et al., 2021). By comparing diesel, electric, and hybrid-electric buses, the study underscores the importance of strategic planning in aligning fleet electrification with climate mitigation goals. Similarly, a study in an intermediate city in Ecuador proposed a multi-criteria prioritization approach that incorporates GHG emission reduction potential alongside operational and passenger-related factors, offering a practical framework for guiding route-level electrification decisions (Wenz et al., 2021).

Although prior studies have advanced the understanding of the economic and environmental impacts of bus fleet electrification, they predominantly reflect the perspectives of public authorities and transit agencies. In reality, urban transit systems involve multiple stakeholders, and among them, passengers represent the a critical and directly impacted group. As the primary users of public transportation infrastructure, passengers ultimately determine the success and sustainability of any transit initiative through their satisfaction, usage patterns, and behavioral responses. Despite the significance, their perspectives have been largely overlooked in the planning of electrifying bus fleet. This gap underscores the need to integrate passenger-centered metrics (i.e., service reliability) into the bus fleet electrification strategies. (Ceder, 2016). However, analyzing service reliability in complex urban settings is challenging due to the stochastic interactions of vehicles and passengers. As a result, researchers have increasingly adopted simulation modeling, particularly micro-level simulation, which can capture the complex interactions between vehicle operations and passenger demand (Khorasani, 2023; Liang et al., 2023; Xie et al., 2024). Therefore, to address the identified gap, this study proposes a simulation-based approach to evaluate the impacts of bus fleet electrification on service reliability.

3 METHODOLOGY

This section presents the micro discrete event simulation model to evaluate the impact of bus fleet electrification on service reliability. The model consists of two core modules: the route-level bus operation module and the stop-level passenger travel behavior module. An overview of the model structure is illustrated in Figure 1.

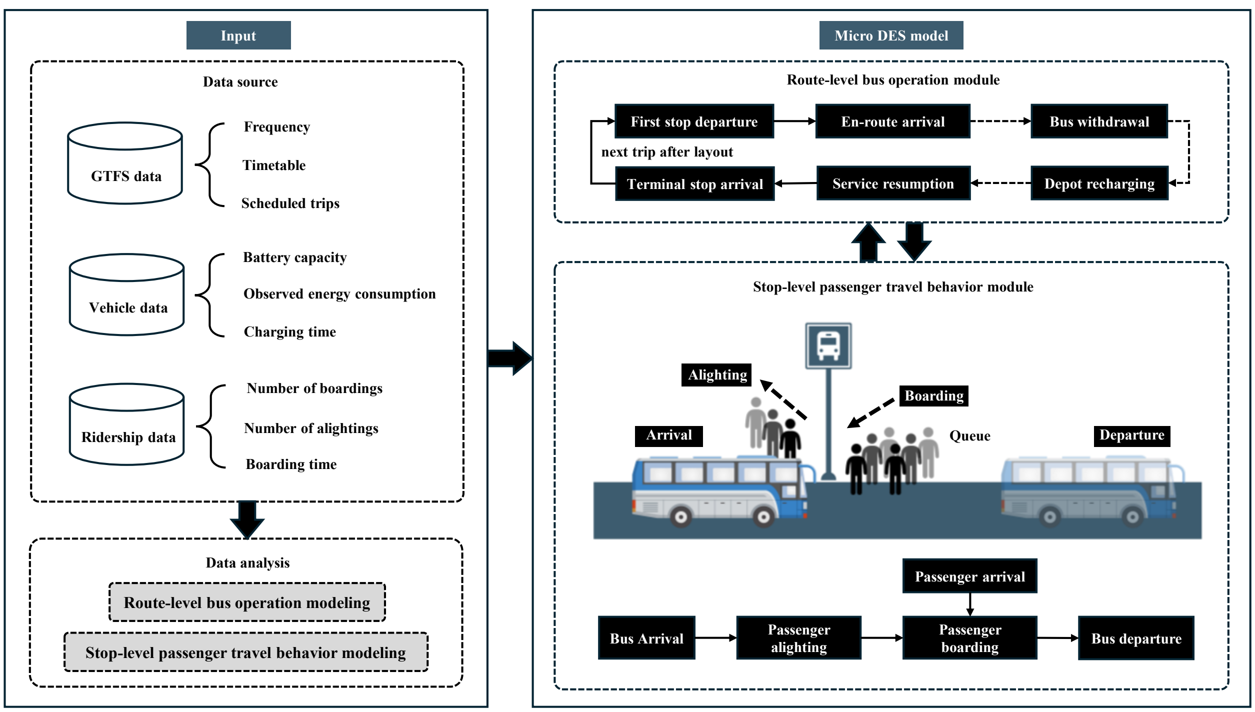

Figure 1: Micro discrete event simulation model.

3.1 Route-level Bus Operation Simulation Module

The route-level simulation module consists of two core components: the bus network and route-level bus operations.

3.1.1 Urban bus network modeling

A bus network is formally defined as a directed and weighted graph $G = (N, E)$, where N is a set of nodes representing bus stops, and $(n_i, n_j) \in E$ denotes a directed edge representing the travel paths between stops in a specific direction. Each directed edge is assigned a weight w_{ij}, corresponding to the scheduled travel time from stop n_i to n_j. For each route, we define it as an ordered sequence of stops $R_d = \{s_{1d}, s_{2d}, \dots, s_{nd}\}$ where $d \in \{0,1\}$ denotes the direction (e.g., 0 for southbound, 1 for eastbound), s_{id} is the ith stop along direction d. This directional distinction allows the simulation to model bidirectional services explicitly.

3.1.2 Route-level bus operation modeling

Building upon the bus network structure, the simulation adopts a DES framework to replicate the dynamics of daily bus operations. Buses are core entities in modeling bus operations. We define a bus fleet for each route as a set of buses $B = \{b_1, b_2, \dots, b_n\}$. Each bus is represented as an entity characterized by static attributes (e.g., vehicle specifications and scheduled timetable) and dynamic state variables (e.g., actual arrival/departure time and battery level). These states evolve over time in response to events, including departures, arrivals, exits, reentries, and passenger interactions. To reflect real-world variability, travel times between consecutive stops are modeled using a lognormal distribution (Strathman & Hopper, 1993).

This simulation module incorporates a set of operational assumptions to reflect real-world service dynamics. A fixed dwell time is applied at all intermediate stops, while no dwell is assigned at trip origins and terminals. Upon arriving at the final stop of a trip, each bus takes a scheduled layover before initiating the return trip in the opposite direction. For electric buses, energy consumption of electric buses is primarily modeled based on a baseline deterministic energy consumption rate, derived from average operational data under typical urban driving conditions. When a bus's battery level drops below a capacity threshold, it exits service and enters a charging cycle. After charging, the bus is eligible to reenter service if it can catch up with any remaining scheduled trips; otherwise, it remains out of service for the rest of the day. An illustrative example of the key definitions and operational logic is provided in Figure 2.

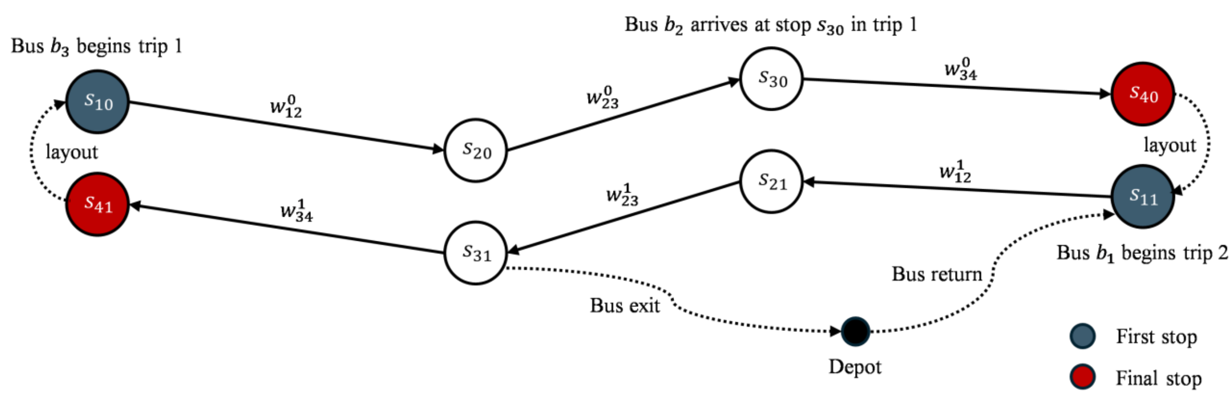

Figure 2: Illustrative example of route-level bus operation.

3.2 Stop-level Passenger Travel Behavior Simulation Module

The stop-level passenger behavior simulation module models three core processes: arrival, queueing and boarding, and alighting. In this simulation environment, passenger entities are modeled as temporally distributed arrivals at bus stops. Each passenger is characterized by key static attributes (i.e., arrival time) and state variables (i.e., boarding time and boarding status).

3.2.1 Passenger arrival

Let $T = \{t_1, t_2, \dots, t_k\}$ denote the set of discrete time intervals (e.g., 60-minute periods) in a simulation day. Building upon the previously defined route $R_d = \{s_{1d}, s_{2d}, \dots, s_{nd}\}$, we assume passenger arrivals follow a time-dependent Poisson process at stop $s_{id} \in S$ during time interval $t_k \in T$, as shown in Equation (1) (Fu & Yang, 2002; Toledo et al., 2010).

$$A_{ik} \sim Poisson\ (\lambda_{ik}, h_{ik}) \tag{1}$$

Where A_{ik} denotes the number of passengers arriving at stop s_{id} during time interval t_k. λ_{ik} is the average arrival rate at stop s_{id} during time interval t_k estimated from empirical ridership data. h_{ik} is the scheduled headway at stop s_{id} during time interval t_k. This formulation allows temporal heterogeneity in passenger demand. Each passenger entity is defined as $P_{idk}^{(a)}$ and assigned an arrival timestamp $a_{idk}^{(a)} \in [t_k, t_{k+1})$ drawn uniformly over the interval.

3.2.2 Passenger queueing and boarding

Passengers are assigned to queues at each stop based on their arrival time. Waiting passengers at each stop are managed via a First-In-First-Out (FIFO) queue. Let $Q_{id}(t)$ denote the passenger queue at stop s_{id} at simulation time t. Each bus arriving at stop s_{id} at simulation time t serves the waiting queue $Q_{id}(t)$ up to its remaining available capacity C_t. Passengers that are unable to board due to capacity limits remain in the queue or may abandon the system if their waiting time exceeds a predefined threshold θ. Each passenger's boarding outcome is recorded: those who successfully board are marked as "boarded"; those who are still in the queue and have waited less than the threshold are considered "waiting"; and those who exceed the threshold without boarding are labeled as "abandoned".

3.2.3 Passenger alighting

The passenger alighting process is assumed to follow a Binomial distribution, as presented in Equation (2) (Liu & Wirasinghe, 2001; Morgan, 2002).

$$B_{jidk} \sim Binomial\ (L_{jidk}, P_{idk}) \tag{2}$$

Where B_{jidk} is the number of passengers alight from bus b_j at stop s_{id} during time interval t_k. L_{jidk} is the onboard load of bus b_j just before arriving at stop s_i during time interval t_k. P_{idk} is the empirically derived probability that a passenger alights at stop s_{id} during time interval t_k.

3.3 Bus Service Reliability Evaluation

To evaluate urban bus service reliability under fleet electrification, we propose metrics that reflect both bus operation and passenger travel behavior.

3.3.1 Bus operation metrics

Bus service reliability is evaluated by the headway deviation ratio (HDR), which measures how much the actual time between buses differs from the scheduled time, helping to show how regularly buses are arriving. Following (Chen et al., 2009), headway deviation ratio is computed as shown in Equation (3).

$$HDR_{idk} = \frac{H_{idk} - H_{0id}}{H_{0id}} \tag{3}$$

Where HDR_{idk} is the headway deviation ratio at stop s_{id} during time interval t_k. H_{idk} represents the simulated headway at stop s_{id} during time interval t_k. H_{0id} is the scheduled headway at stop s_{jd} during time interval t_k.

3.3.2 Passenger travel behavior metrics

In perspectives of passengers , we include excess waiting time (EWT) and abandonment rate (AR) as key indicators of service reliability. These metrics capture how service irregularities caused by EBs translate into passenger dissatisfaction.

Excess waiting time is simply the difference between the actual waiting time and the scheduled waiting time as shown in the equation (4).

$$EWT_{idk} = AWT_{idk} - SWT_{idk} \tag{4}$$

Where EWT_{idk} represents the excess waiting time of passengers at stop s_{id} during time interval t_k. AWT_{idk} is the actual average waiting time of passengers at stop s_{id} during time interval t_k. SWT_{idk} is the scheduled average waiting time of passengers at stop s_{id} during time interval t_k.

In order to identify potential service shortages or supply-demand imbalances, this research also records the number of passengers who fail to board due to long waits to calculate the AR, as shown in Equation (5).

$$AR_{idk} = \frac{LW_{idk}}{A_{ik}} \tag{5}$$

Where AR_{idk} is the passenger abandonment rate at stop s_{id} during time interval t_k. LW_{idk} represents the total number of passengers who fail to board due to long waits at stop s_{id} during time interval t_k.

4 CASE STUDY

In this section, a case study is conducted on Route 35 of DASH in Alexandria, VA, USA to demonstrate the feasibility and applicability of the proposed simulation-based approach. DASH is a public transit agency which has committed to operating a 100% zero-emissions fleet by 2030. Among DASH's routes, route 35 has the highest weekday ridership, with an average of 3,397 daily boardings. It also features the longest route—approximately 20 km southbound and 21 km northbound. To accommodate its high ridership, route 35 operates at a high frequency, with buses arriving every 10 minutes between 6:00 a.m. and 7:00 p.m. on weekdays. Given its heavy passenger demand, frequent service, and long-distance travel requirement, electrifying the bus fleet for this route poses substantial operational challenges. As such, route 35 serves as a representative case for assessing the impacts of fleet electrification on both bus operations and passenger travel behavior. The geographic layout of route 35 is illustrated in Figure 3.

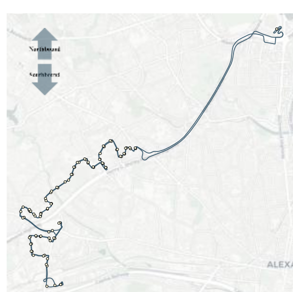

Figure 3: Route 35 of DASH in Alexandria, Virginia, USA.

4.1 Data Preparation

4.1.1 Bus operational inputs

We first collected General Transit Feed Specification (GTFS) data to model the structure and operations of route 35. Based on the shapes.txt and stops.txt files, we reconstruct the spatial network of route 35, including the sequence of stops in each direction and the distances between adjacent stops. To reflect the most typical and stable service pattern for Route 35, we focus on weekday service data. Using the frequencies.txt and stop_times.txt files in GTFS, along with DASH's official route information and estimated travel times from Google Maps, we generate a base schedule for each bus in service. This includes scheduled departures, trip assignments, and estimated travel durations and distance between stops. Route 35's fleet size and daily trips are used to ensure consistency with actual operations.

To incorporate electrification factors, we introduce electric bus (EB) parameters into the simulation. Two EB models are considered in this study, each with specified battery capacity, energy consumption rate (kWh/km), and estimated charging time. These parameters allow us to simulate EB behavior under different levels of fleet electrification. Specific parameter details are shown in Table 1.

Table 1: Parameters of EB

Model	Seat	Battery capacity	Energy consumption rate	Estimated charging time
Proterra ZX5	40	220 kWh	1.2 kWh/km	108 minutes
BYD K9	38	324 kWh	1.3 kWh/km	180 minutes

4.1.2 Passenger ridership inputs

Passenger ridership data were collected from archived boarding and alighting records covering three consecutive weeks from October 13 to November 1, 2024. The dataset includes, for each stop and time interval, the number of boardings, alightings, and onboard load. Only weekday data were extracted to align with the operational assumptions in the simulation. For each stop and time period, we calculated the average boarding and alighting volumes, which were then used to estimate time-dependent passenger arrival rates (assumed to follow a Poisson process) and alighting probabilities (used in the Binomial distribution for modeling passenger alightings). These values serve as key inputs to the passenger behavior module in the simulation.

4.2 Simulation Design and Scenarios

This section outlines the simulation design, including key operational assumptions and the electrification scenarios used to evaluate service reliability under different fleet configurations.

The simulation is built on a micro-level discrete event framework that replicates individual vehicle movements and passenger interactions throughout the operating day. To realistically capture the operational dynamics of route 35, several assumptions are made. Each bus stops for 0.5 minutes at intermediate stops to simulate dwell time associated with boarding and alighting. No dwell time is applied at the first and last stop of each trip. At the end of each trip, a layover period of 3 minutes is scheduled to simulate the required recovery and transition time before the bus begins its next trip in the opposite direction. Buses follow a fixed round-trip pattern, alternating directions throughout the day in accordance with the base schedule.

To evaluate the effects of fleet electrification, we design a series of scenarios with varying levels of electric bus deployment. Specifically, the electrification ratio ranges from 0% to 100% in 5% increments, resulting in 21 distinct scenarios. In each case, electric buses are evenly distributed across the available fleet, ensuring balanced utilization throughout the schedule and across both directions. Each electric bus operates under the same schedule as conventional buses but is constrained by battery capacity. Once a vehicle's remaining battery falls below 30% of its total capacity, it is removed from service for recharging. Reentry into operation is only permitted if the bus is fully recharged and can complete at least one remaining scheduled trip within the service window. Each scenario is simulated 100 times to account for the stochastic nature of urban transit operations. The performance indicators for service reliability are averaged across runs to ensure statistical robustness and reduce the effect of random fluctuations.

4.3 Results and Analysis

This section presents and analyzes the simulation results under different electrification scenarios for two electric bus models: Proterra ZX5 and BYD K9. Three key indicators of service reliability are evaluated: HDR, EWT and AR. All indicators are computed at the stop level across hourly intervals throughout the day, as described in the methodology. To illustrate representative results, we focus on stop 6000930, which records the highest average daily boardings along route 35. This stop also exemplifies a broader trend observed across the network. For HDR, we also compute a route-level metric by aggregating stop-level values using a weighted average. The weights are based on the proportion of boardings at each stop during each time interval relative to the total boardings on the route (Chen et al., 2009).

4.3.1 Bus Operation Reliability: HDR

Figure 4 presents the stop-level HDR at stop 6000930 under different electrification ratios for the two electric bus models. The results show that HDR remains relatively low and stable across all time intervals when the electrification ratio is below 70%. However, when electrification exceeds this threshold, particularly beyond 85%, HDR values begin to rise sharply. Interestingly, the BYD K9 model shows its highest deviation later in the day (17:00–18:00), while the Proterra ZX5 peaks earlier (around 13:00–15:00). This shift in peak time reflects the larger battery capacity of the BYD K9, which allows it to remain in service longer before needing to recharge. These patterns suggest that service regularity deteriorates at this high-demand stop when electric buses are heavily utilized, and that the timing and severity of this degradation are strongly linked to vehicle-specific technical characteristics.

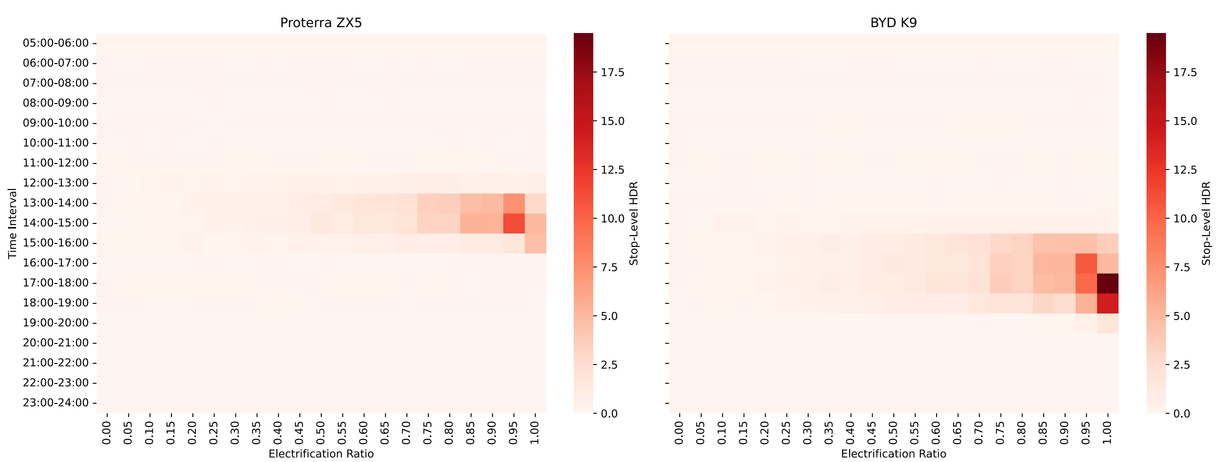

Figure 4: Stop-level HDR at stop 6000930 under different electrification ratios.

As shown in Figure 5, the route-level results mirror the trends observed at stop 6000930, confirming that service reliability remains largely unaffected under low-to-moderate electrification levels, but begins to degrade significantly beyond the 70–80% threshold. The Proterra ZX5 model exhibits a more abrupt increase in HDR around 90–100% electrification, especially between 13:00 and 15:00, while the BYD K9 model shows a more gradual yet still noticeable rise during the same period. These findings reinforce the conclusion that high levels of electrification can introduce systemic service instability, and that the degree of disruption is influenced by the operational characteristics of specific EB models.

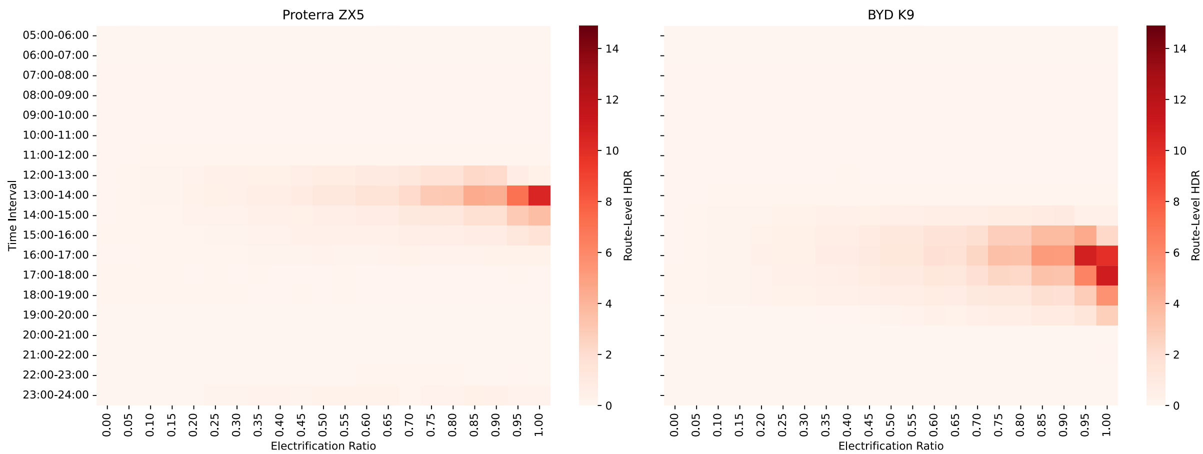

Figure 5: Route-level HDR of route 35 under different electrification ratios.

4.3.2 Passenger Waiting Time

Figure 6 displays the stop-level Excess Waiting Time (EWT) at stop 6000930 across different electrification ratios. A clear upward trend is observed for both electric bus models. For the Proterra ZX5, EWT remains relatively low up to an electrification ratio of around 40%, beyond which it increases sharply—peaking during the 13:00–15:00 window and exceeding 20 minutes at full electrification. The BYD K9 follows a similar trend but with a more gradual rise in EWT. While overall EWT values remain lower than those of the Proterra ZX5, the duration of elevated waiting times is notably longer, often extending into the late afternoon. This pattern reflects the effect of BYD K9's larger battery capacity, which allows buses to stay in service longer and delays the onset of supply shortages. However, once BYD K9 vehicles begin to withdraw for charging, the impact becomes more prolonged and sustained. As a result, while BYD K9 offers better reliability earlier in the day, it also leads to longer recovery periods, highlighting a trade-off between delaying service disruption and extending the duration of passenger delays.

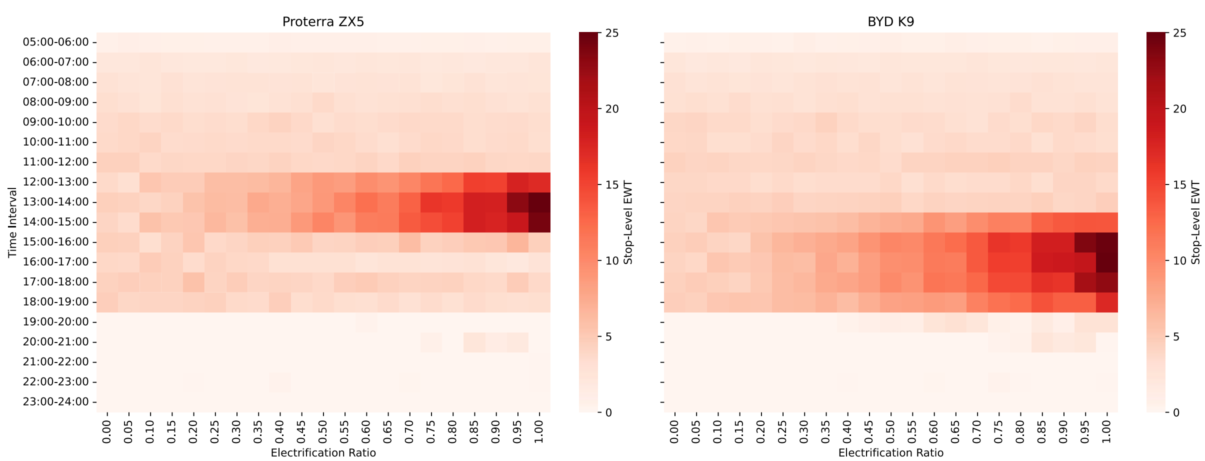

Figure 6: Stop-level EWT at stop 6000930 under different electrification ratios.

Passenger dissatisfaction is further assessed through the AR, which captures the share of passengers who abandon their wait due to excessive delays. Figure 7 illustrates the stop-level AR. Both electric bus models exhibit very low AR values at low electrification levels, but the Proterra ZX5 sees a rapid increase in AR beginning around the 75% electrification mark, peaking at 1.0 (i.e., all waiting passengers abandon their trip) during the 13:00–14:00 period. In contrast, the BYD K9 demonstrates better performance, with AR values rising more gradually and peaking later in the day. These findings reinforce the trade-off observed in the EWT analysis.

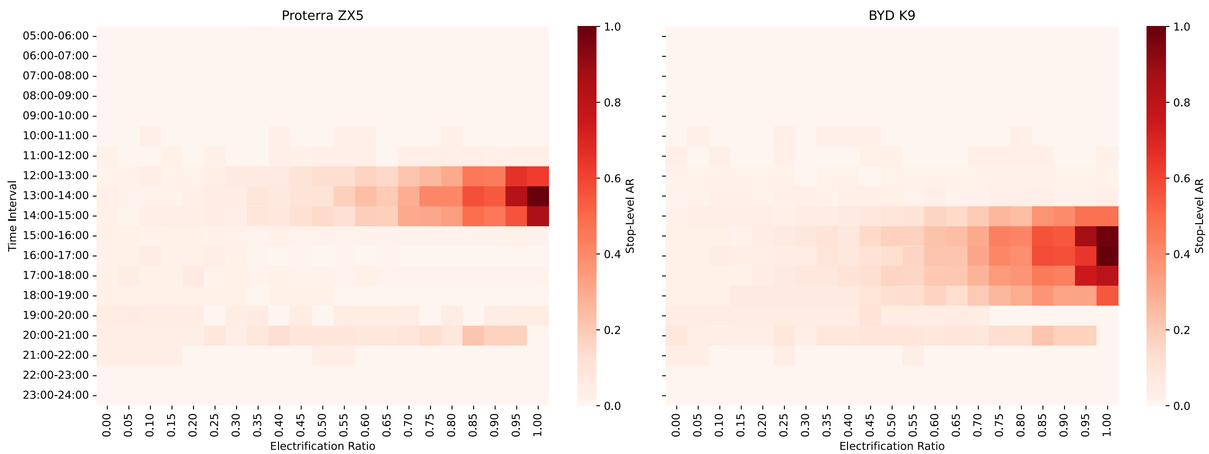

Figure 7: Stop-level AR at stop 6000930 under different electrification ratios.

5 CONCLUSION

This study developed a micro-level discrete event simulation model to evaluate the impact of urban bus fleet electrification on service reliability. By integrating a route-level bus operation module with a stop-level passenger travel behavior module, the model captures the complex interactions between bus service, passenger demand, and operational constraints of EBs. A case study on route 35 of DASH in Alexandria demonstrated the feasibility and applicability of the proposed approach under real-world conditions. Results show that while moderate levels of electrification (below 70%) have limited impact on service reliability, higher electrification ratios introduce significant operational disruptions. These are reflected in increased headway deviations, excess waiting time, and higher passenger abandonment rates. Comparative analysis of two electric bus models—Proterra ZX5 and BYD K9—further underscores the importance of vehicle-specific characteristics, particularly battery capacity and charging requirements, in shaping the timing and severity of service disruptions. This research contributes a passenger-centered simulation framework for supporting electrification planning that goes beyond transit agency's perspectives. By quantifying service reliability impacts, the model offers a novel data-driven tool to evaluate fleet electrification strategies with respect to both operational efficiency and passenger experience.

Still, the current model has several limitations. First, the simulation is based on a single route case study and assumes fixed operating conditions across all vehicles and time periods. This simplification may not fully reflect the variability found in larger, more dynamic transit networks. Second, while the model considers two representative electric bus types, it does not incorporate real-time battery degradation, charging station availability, or adaptive vehicle dispatching strategies. In the future, the model could be extended to cover multi-route systems and incorporate stochastic elements such as traffic congestion, energy price fluctuations, and charging infrastructure constraints. In addition, empirical validation using operational data from transit agencies would enhance the model's robustness and practical applicability.

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