DEPARTMENT OF FINANCE AND BUSINESS ECONOMICS

UNIVERSITY OF DELHI

Simulation-Based Analysis of Electric Bus Charging Operations: A Case Study of a DTDC Bus Depot in New Delhi

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Research Paper

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Abstract

The rapid adoption of electric buses necessitates robust infrastructure planning to ensure reliable operations within urban transport systems. This study develops a discrete-event simulation model to evaluate the performance of a bus depot under varying infrastructure and fleet configurations. Using real-world operational data from a fleet of 110 electric buses and 21 chargers, a baseline simulation is constructed to replicate actual charging and scheduling conditions. Key operational metrics—such as wait times before charging, charger utilization, energy delivered, and final state of charge—are analyzed and validated against observed data to ensure model reliability.

Two strategic what-if scenarios are then tested. In the first scenario, the number of chargers is increased from 21 to 25 to assess whether infrastructure augmentation improves performance under current fleet size. The second scenario evaluates the impact of expanding the fleet to 130 buses without altering the existing charger infrastructure. Results indicate that adding chargers leads to a notable reduction in R2 wait times and improved overnight charging completion, while fleet expansion without infrastructure scaling results in increased congestion and delayed charging. Energy delivery and SOC outcomes further highlight the operational strain under overloaded conditions.

The simulation outcomes provide actionable insights for policymakers and transit authorities planning for the transition to electric mobility. The model offers a flexible decision-support tool to test future scenarios, optimize infrastructure investments, and ensure sustainable depot-level operations as fleet sizes evolve.

Keywords: Electric buses, depot charging, Monte Carlo simulation, operational efficiency, managed charging, time-of-use interventions

1. Introduction

The transition to electric mobility is no longer a future goal—it is a present imperative, especially for public transportation systems striving toward sustainability. Electric buses offer the promise of reduced carbon emissions, lower operating costs, and quieter urban environments. However, their integration into existing transport networks brings operational complexities that cannot be overlooked. Unlike traditional diesel fleets, electric buses require systematic and carefully scheduled charging. Constraints such as battery capacity, limited charging infrastructure, and variability in route schedules demand precise planning to ensure depot efficiency and service reliability.

Figure 1: A wide-angle view of the electric bus depot in Delhi where the study was conducted

This research focuses on simulating the charging operations of an electric bus depot using discrete-event modelling. The motivation for this study stems from the increasing urgency to support data-driven infrastructure planning as cities scale their electric vehicle (EV) fleets. We used actual operational data from a fleet of 110 electric buses operating over multiple days, with the third day (Day 3) selected as the focal point for modelling. The simulation replicates real-world route patterns, charging durations, and vehicle availability windows, making it both representative and realistic.

The core objective of the simulation is to evaluate whether the existing infrastructure—specifically 21 chargers—is sufficient to meet operational demands, and what happens when this setup is stressed or improved. To answer these questions, we build a baseline model using the real data, and then develop two additional scenarios for analysis:

- **Scenario 1** tests the impact of increasing the number of chargers from 21 to 25, keeping the bus fleet constant at 110.

- **Scenario 2** examines the operational impact of scaling the fleet to 130 buses while maintaining the original 21-charger infrastructure.

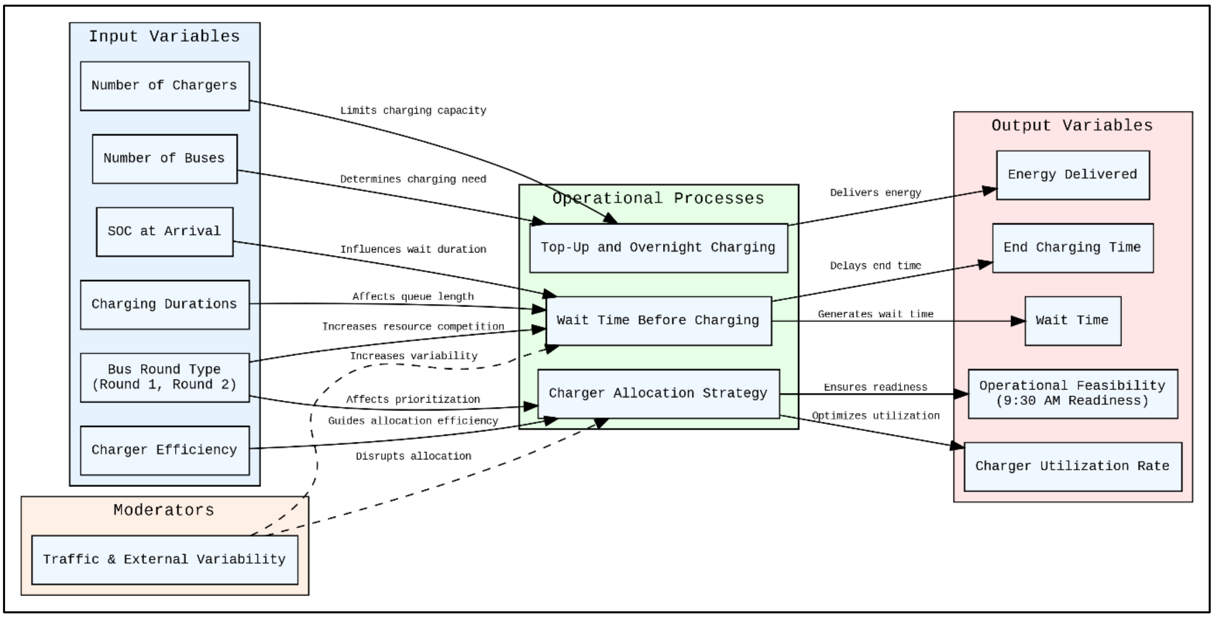
Through these scenarios, the simulation provides insights into charger utilization, waiting times before charging, energy delivery, and state of charge (SOC) outcomes—metrics that directly influence depot performance and bus availability. By comparing simulated results with actual observed data, we validate the effectiveness of the model and identify how each scenario affects performance.

1.1 Theoretical and Conceptual Framework

The study draws upon queuing theory to model and explain bus wait times in a constrained depot environment, where charger capacity versus demand, including the impact of bus round types (Round 1 and Round 2), plays a critical role in delays. Discrete-event simulation, using SimPy, and Monte Carlo methods provide the computational backbone for modelling uncertain arrival times, state-of-charge (SOC) variations, charger allocation, and the prioritization influenced by round types, reflecting real-world stochasticity. These are grounded in theories of stochastic operations management and resource optimization, commonly applied in electric fleet planning and urban logistics. Additionally, fleet management and scheduling theory guides the analysis of time-of-use patterns, operational windows, and resource competition driven by round-specific scheduling needs.

To structure this analysis, we developed a conceptual framework that outlines the relationships between key variables (see Figure 1). This framework identifies input variables—number of buses, number of chargers, SOC at arrival, charging durations, charger efficiency, and bus round type (Round 1, Round 2)—that drive operational processes such as top-up and overnight charging, wait time before charging, and charger allocation strategy. These processes influence output variables: wait time, end charging time, energy delivered, charger utilization rate, and operational feasibility (measured via 9:30 AM readiness). Traffic and external variability act as moderators, affecting wait times and allocation efficiency.

Figure 2: Conceptual Framework for Electric Bus Charging Optimization



2. Literature Review

The adoption of electric buses (e-buses) in urban transit systems has spurred research into their operational and environmental impacts, yet depot charging efficiency remains a critical area needing deeper exploration. Studies on electric vehicle (EV) charging provide a starting point. Deb et al. (2017) reviewed the effects of EV charging stations on power grids, noting that concentrated charging demands can strain infrastructure. While their findings highlight energy management challenges, they focus on passenger vehicles rather than the scheduled, high-volume operations of bus depots. Similarly, Hove and Sandalow (2019) analyzed charging infrastructure policies, emphasizing the importance of managing peak loads. Their work, however, lacks specificity to depot contexts where buses follow fixed routes and recharge in tight windows.

Research targeting e-bus depots is limited but growing. Kaur and Sharma (2022) examined charging schedules, identifying variable arrival times and limited charger availability as key factors in operational delays. Their static analysis suggested scheduling improvements but did not test dynamic solutions. Singh and Chauhan (2023) conducted a case study on urban depot operations, observing high energy demands during overnight charging. Their descriptive approach, while useful, offered no strategies to mitigate inefficiencies, leaving a gap in actionable insights.

Simulation modelling offers a robust method to address these challenges. Liu et al. (2015) applied discrete-event simulation to EV charging, demonstrating its ability to model time-dependent processes like arrivals and departures—relevant to depot dynamics. Kamel and Badr (2020) used Monte Carlo simulation to forecast energy demand in EV charging scenarios, capturing variability in usage patterns. Both studies underscore simulation's potential, yet their application to e-bus depots is rare, limiting their relevance to this context.

Optimization strategies also inform this research. Fachrizal et al. (2020) explored managed charging for EVs, showing that prioritizing low-state-of-charge (SOC) vehicles reduces congestion. Gupta et al. (2021) simulated load-shifting for e-bus depots, suggesting that adjusting charging times could balance energy use. While promising, these studies lack integration with real-world depot data, reducing their practical applicability.

Research Gap

In the face of increased interest in electric bus (e-bus) uptake and charging infrastructure, a vast India-specific, depot-level empirical research gap exists. Most of the current research has taken into consideration higher-level EV charging strategies (Deb et al., 2017; Hove & Sandalow, 2019) or top-down system planning, unconnected from reality. Where simulation modeling has been utilized, it is often theoretical or static, lacking variability and complexity of real-life depot dynamics (Fachrizal et al., 2020; Gupta et al., 2021). Furthermore, studies that look at e-bus operations seldom use Indian operational realities such as route scheduling, charging windows, and fleet-specific energy requests (Kaur & Sharma, 2022). This work closes the gap by creating a Monte Carlo simulation out of empirical data for a large Indian e-bus depot over 330 charging sessions over three days. In merging real operations with the scenario-based interventions, we provide a practical contribution to optimizing depot efficiency, especially in the Indian context, where data-driven, scalable solutions are underrepresented.

3. Research Objectives

This study seeks to enhance the operational efficiency of electric bus (e-bus) depot charging using simulation modelling and actual data. Based on the literature, there is a gap in the use of dynamic simulation methods to address depot-specific inefficiencies such as lagged waiting times and biased charger usage. In order to bridge this gap and provide recommendations that can be used by transit operators, the study employs the following objectives:

1. To evaluate current charging operations of an electric bus depot and identify bottlenecks in wait time and energy delivery.
2. To develop and validate a simulation model that replicates real-world depot operations.
3. To assess the impact of alternative charging strategies and infrastructure changes on depot performance.

These objectives work together to improve our understanding of e-bus depot operations and enable the scalability of sustainable transportation systems. By integrating empirical analysis with simulation-based evaluation, the study tackles the limitations of previous research and provides a framework for optimizing charging procedures.

4. Methodology

This study explores and maximizes the charging efficiency of electric bus (e-bus) depots using a simulation-based method from empirical data. The empirical analysis and Monte Carlo simulation modeling are designed to replicate the randomness of charging activities, assess performance in three important scenarios, and provide valuable information for depot-level decision-making.

4.1 Research Design and Approach

The nature of the simulation model is realized in SimPy, a Python library for discrete-event simulation, through Monte Carlo techniques to introduce randomness to inputs to the simulation. This is highly suitable to simulate dynamic and stochastic systems such as bus depot operations, where traffic congestion, battery state-of-charge (SOC), and charger capacity vary from day to day.

Monte Carlo simulation enables us to simulate depot operation iteratively using random samples of empirical distributions of operating variables. It provides a reasonable analysis of charging habits and infrastructure use. The model simulates 110 e-buses for three consecutive days (March 29–31, 2025). The dates cover a Friday (weekday), Saturday (weekend), and Sunday (weekend) and enable us to examine differences between operation days and workload variability during the week.

Three scenarios were simulated:

- **Baseline Scenario**: Reflects actual observed depot operations with 21 chargers and 110 buses.
- **Scenario 1**: Expands charger infrastructure from 21 to 25 while maintaining the same fleet.
- **Scenario 2**: Expands the fleet to 130 buses while keeping chargers fixed at 21.

Each simulation run spans 3 full days, divided into 4,860 minutes, and was repeated 1,000 times to ensure convergence and statistical reliability.

4.2 Data Sources

The primary dataset was compiled from internal operational records of the depot, capturing data for 330 individual bus charging operations (110 buses × 3 days). This includes:

- Timestamps of Round 1 (R1) and Round 2 (R2) departures and arrivals
- Top-Up and Overnight charging start and end times
- Charging durations (in minutes)
- Initial and post-charging SOC levels
- Wait times before charging sessions
- Charger allocation and usage patterns

In addition to primary data, secondary sources were used to collect route and schedule information, such as departure times, route distances, and expected runtimes from public domain platforms, including the Delhi Transport Corporation (DTC) website and the Moovit application.

The structured dataset used for simulations includes detailed records of each bus's operation per day—such as departure and arrival times for R1 and R2, SOC levels, and charging durations. **Appendix A.**

4.3 Field Visits and Stakeholder Consultations

To supplement quantitative insights, field visits were conducted to the e-bus depot in March 2025, where direct observations and informal interviews were carried out with depot staff, service engineers, and charging operators. These interactions provided critical qualitative understanding of ground realities, including:

- **Reasons for fleet limitations**: Expansion of the e-bus fleet is constrained due to the existing **energy supply ceiling**. Approvals are required from multiple utility stakeholders to upgrade supply capacity.
- **Charging window constraints**: Charging is typically restricted to two primary windows—Top-Up charging (midday) and Overnight charging—due to scheduling limitations and SOC thresholds.
- **External factors**: **Traffic conditions** were consistently mentioned as a significant contributor to arrival variability. While weather conditions like rain or winter had minimal impact on operations, summer months saw higher energy consumption due to air conditioning, which consumes approximately 10–12% of the battery over an 8-hour shift.

Figure 3: A charging operator initiating a charging session for an electric bus, highlighting the manual aspects of charger deployment

Photographic documentation of the depot and infrastructure was also collected during the visits. This includes images of the depot layout, chargers, and operational activities, which have been included in the report to visually ground the study in its applied context.

4.4 Population and Operational Parameters

The study models a closed fleet of 110 electric buses, all operating under a centralized depot charging setup. Each bus has a battery capacity of 400 kWh, and charging operations are governed by an efficiency rate of 85%, consistent with contemporary lithium-ion charger performance.

Charging takes place in two primary phases:

- **Top-Up Charging (Midday)**: Between 12:00 PM to 6:00 PM, buses arriving post R1 may undergo a quick top-up charge depending on availability.
- **Overnight Charging (Post R2)**: Begins at approximately 8:00 PM and must conclude by 9:30 AM the next day, ensuring full SOC by morning departures.

Figure 4: A dedicated e-bus charging booth at the depot featuring standard fast-charging equipment

4.5 Tools and Implementation

The entire data pipeline was built and executed using Python and the following libraries:

- **Pandas**: For data cleaning, transformation, and preprocessing
- **Matplotlib & Seaborn**: For generating data visualizations
- **SimPy**: To implement the discrete-event simulation logic, model queues, charging sessions, wait times, and bus transitions

- **NumPy**: To apply random sampling and statistical distributions for Monte Carlo iterations

The simulation logs every charging event, SOC transition, and wait time, and then compiles daily and scenario-specific performance metrics for validation against actual operational data.

4a. Exploratory Data Analysis

The exploratory data analysis (EDA) targets three consecutive operating days—March 29 to 31, 2025—at an electric bus depot with 110 buses and 21 chargers. The objective of the EDA is to examine patterns and inefficiencies in charging processes, i.e., wait times, charger saturation, and energy consumption. Through a careful analysis of key variables like wait times, state of charge (SOC), charging times, and hourly distributions, the analysis helps identify operational bottlenecks that hinder the efficiency of the depot. 330 records (110 buses over three days) were analyzed after stringent data cleaning for accuracy and consistency, including missing value handling and time format standardization. The findings developed in this section form the foundation of the simulation model developed later, and are presented through wait time variation visualizations, SOC behaviors, and charger utilization trends.

Descriptive Statistics

Before visual exploration, descriptive statistics were used to summarize the data. The dataset includes more than 220 observations of electric buses operating over two full days. The fields record bus IDs, trip days, arrival and departure times, SOC levels, waiting times before charging, and charging durations.

The descriptive statistics suggest a high degree of operational consistency. SOC levels post-Round 1 generally ranged between 48% and 55%, while after Round 2, the SOC dropped to 35%–45% for most buses. Charging durations followed two distinct patterns:

- **Top-Up Charging**: Typically ranged between 45 to 60 minutes, in line with depot practices aimed at partial recharging post-R1.
- **Overnight Charging**: Generally ranged between 130 to 145 minutes, consistent with full SOC recovery to 100%.

Waiting times, however, exhibited significant variance, with some buses waiting over 60 minutes for charging, signalling periods of congestion, especially during post-morning peaks.

Table 1: Summary statistics of charging and scheduling parameters across 220 bus entries (110 each day)

Variables	count	mean	min	25%	50%	75%	max	std
Bus ID	330	55.50	1	28	55.5	83	110	31.80
Day	330	2.00	1	1	2	3	3	0.82
Duration_R1_N	330	404.15	260	399	406	422	468	33.15
SOC R1	330	42.52	33	38	41.5	47	54	5.66
Before Charging WT R1	330	25.81	0	9.25	26	37	81	20.02
Top-Up Dur	330	74.64	45	71	76	80	117	7.32
SOC Top-Up	330	75.08	70	73	75	78	80	3.05

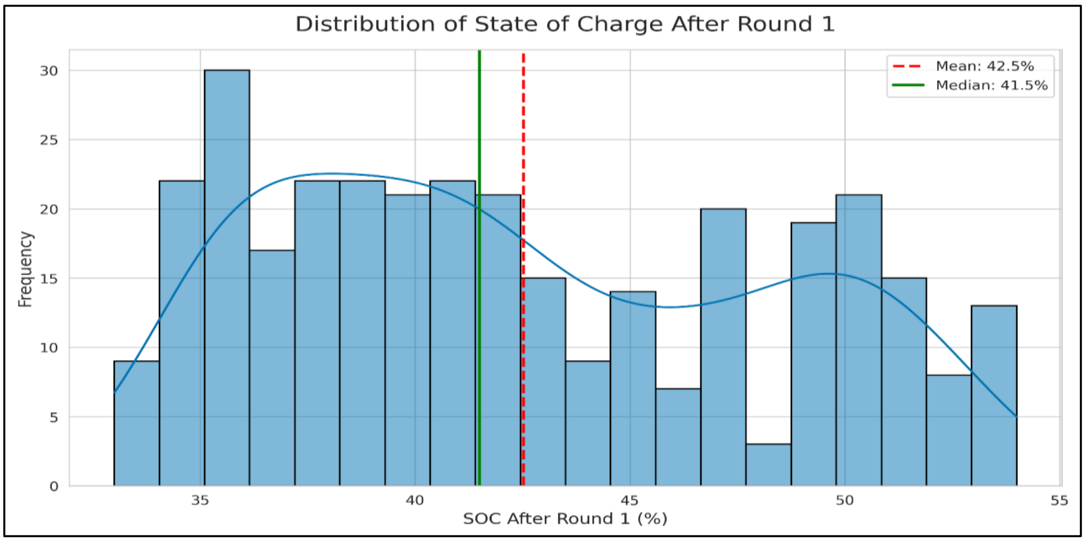
Duration_R2_N	330	386.24	306	356	374	405	522	47.18
SOC R2	330	21.41	11	16	20	27	37	6.40
Before Charging WT R2	330	138.26	0	49.25	102.5	200.8	414	111.01
Overnight Dur	330	132.52	74	121	136	144	180	17.42
Arrival Hour	330	13.24	11	12	13	14	16	1.31
SOC Top-Up Diff	330	32.56	26	30	33	34	39	2.83
Top-Up kWh	330	105.49	84.24	97.2	106.9	110.2	126.4	9.16
Overnight kWh	330	254.64	204.1	236.5	259.2	272.2	288.4	20.75

The table confirms that most buses operate between 5 to 7 hours per route, with SOC levels dropping to the 35–55 range before top-up, and further down to 14–45 before overnight charging. Waiting times before charging range from 0 to 45 minutes in the case of Top-Up and are often longer during peak evening hours.

State-of-Charge (SOC) Analysis

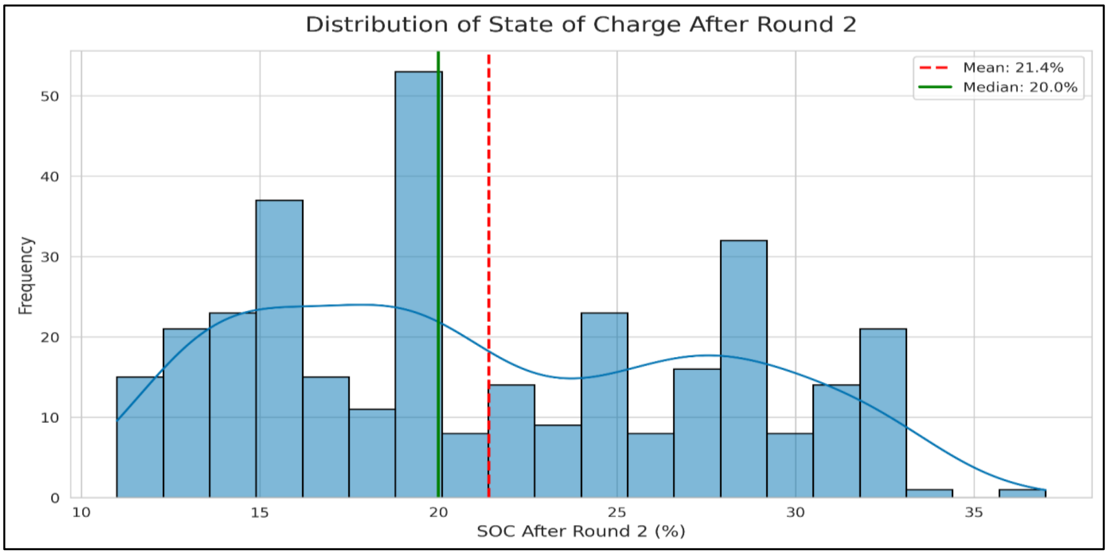
This figure highlights how most buses return from their first round with an SOC between 30% and 55%, confirming that the energy consumption across routes is fairly predictable. This aligns with field observations where drivers target a mid-day SOC recharge up to 70%–80% before proceeding for their second round.

Figure 5: Distribution of State-of-Charge (SOC) Post Round 1



After completing the second operational round, SOC typically drops to 14%–35%, triggering the need for Overnight charging to bring the battery back to 100% for the next day. This consistency demonstrates disciplined adherence to charging schedules, minimizing the risk of undercharging across shifts. These plots reveal depot policy: Top-Up charging is partial, based on time constraints and SOC thresholds, while Overnight charging is standardized to full capacity.

Figure 6: Distribution of State-of-Charge (SOC) Post Round 2

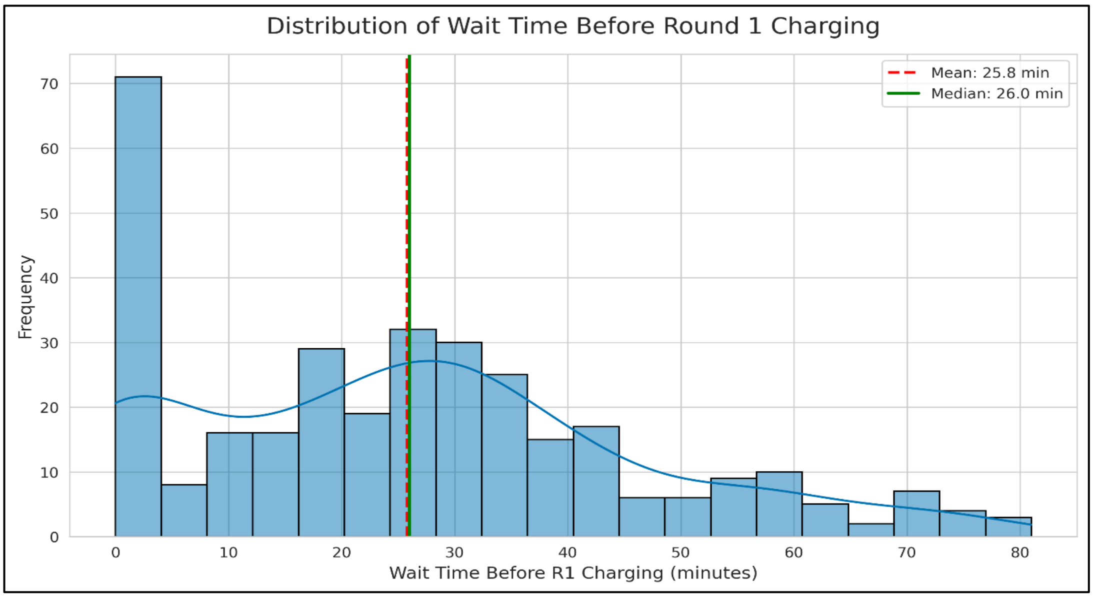


The daily and stage-wise distribution of SOC across the depot fleet was analyzed to understand typical battery depletion and recovery patterns. The detailed visualization is provided in **Appendix Figure A1**, which highlights the variability and central tendencies of SOC values across multiple days and operational stages (R1, R2, Top-Up). This supporting analysis serves as the baseline reference for identifying outlier events and refining battery management strategies.

Waiting Time Patterns Before Charging

Figure 6 shows the waiting time distribution shows a noticeable right-skew, particularly for Top-Up charging.

Figure 7: Distribution of Waiting Times for Top-Up Charging



A large number of buses experience wait times under 25 minutes, but several outliers extend beyond 40 to 80 minutes. This suggests that while the majority of the fleet faces manageable wait times, during peak return hours charger availability becomes a bottleneck.

The figure highlights the waiting time pattern for buses returning after completing Round 2. The average waiting time hovers around 140 minutes, but the distribution shows considerable variability, with some buses waiting as long as 400 minutes before accessing a charger. This wide spread can be attributed to the flexible nature of the overnight charging window, which typically spans 13 hours. Since buses are not scheduled for immediate redeployment during this period, drivers and depot staff prioritize orderly queuing rather than speed. The primary operational focus remains ensuring that all buses achieve full charge well before the next day's early morning dispatch.

Figure 8: Distribution of Waiting Times for Overnight Charging

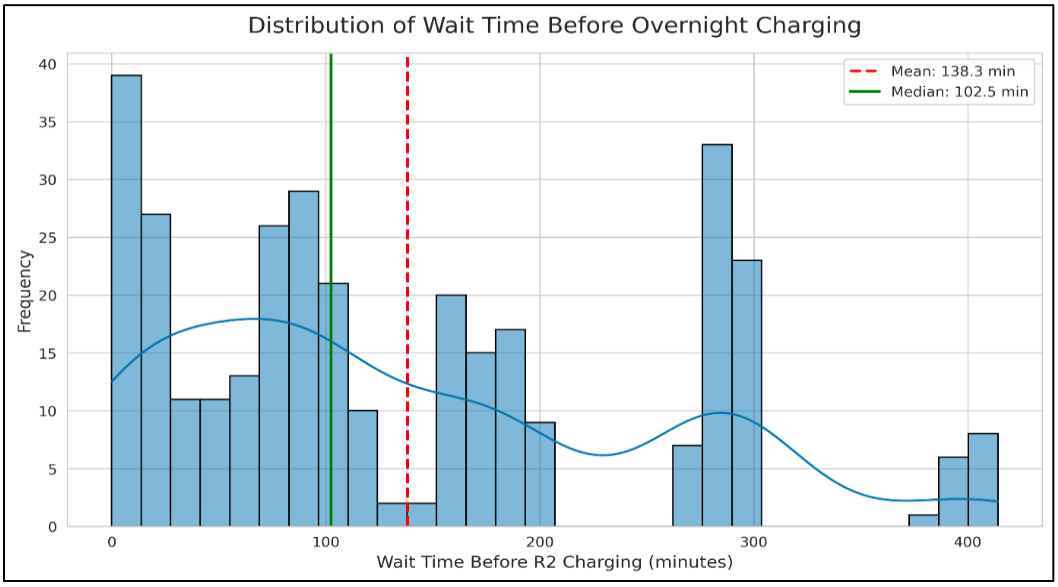
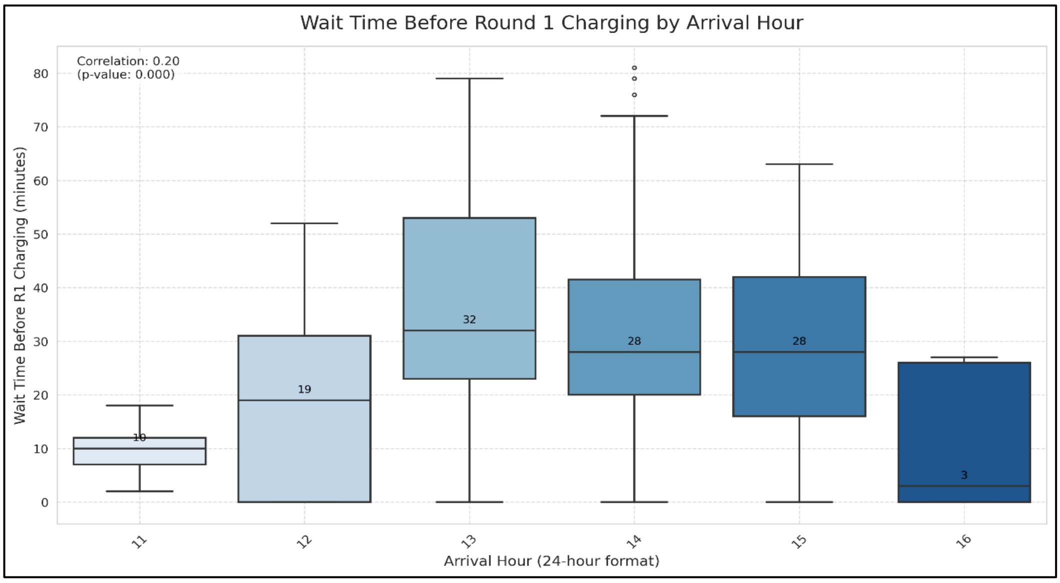


Figure 8 highlights operational congestion at the depot during specific hours. Buses arriving between 1:00 PM and 3:30 PM face the longest waiting times, often exceeding 30 minutes. This surge is closely tied to post-Round 1 returns, where multiple buses compete for limited charger availability at the same time. After 4:00 PM, waiting times significantly decline, reflecting a more balanced distribution of top-up charging. This insight suggests that minor scheduling adjustments or staggered arrival policies during the early afternoon could reduce wait times and improve charger turnover.

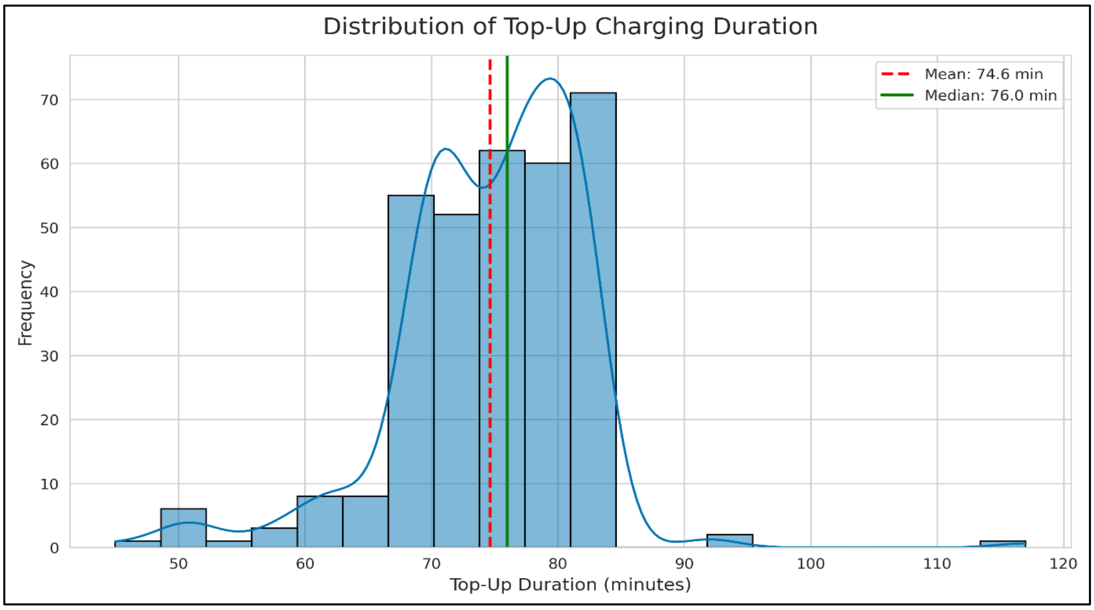
Figure 9: Relationship Between Arrival Hour and Waiting Time



Charging Duration Comparison

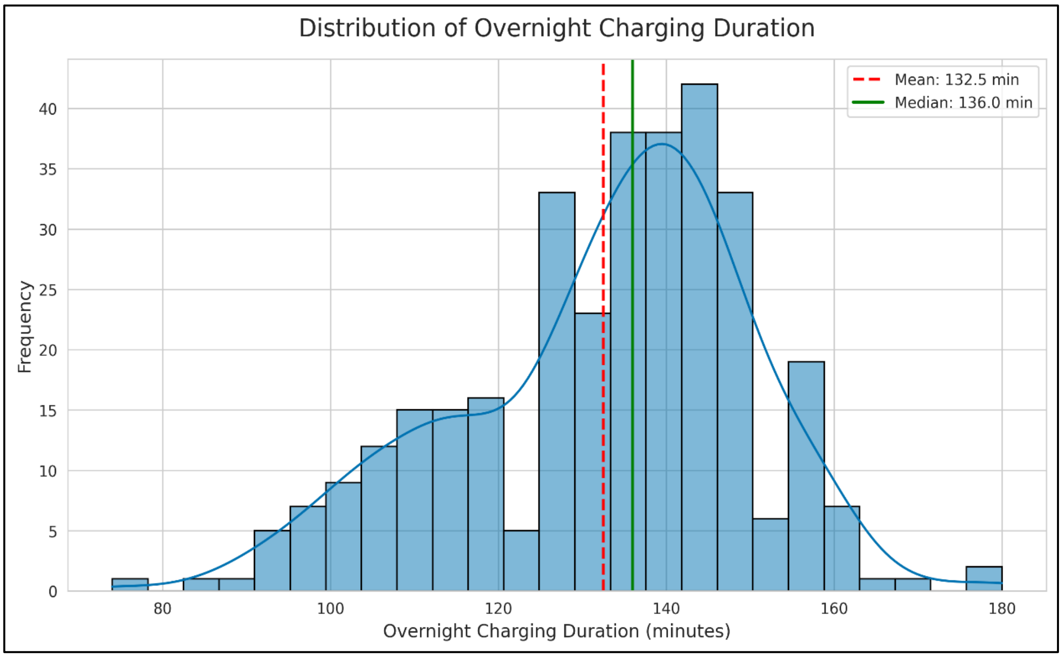
Figure 9 shows that Top-Up charging typically stays within the 45–60-minute window, while Overnight charging centres around 130–145 minutes. This separation is expected, as Top-Up sessions are designed for partial SOC replenishment, whereas Overnight sessions restore SOC to 100%, regardless of arrival SOC. This distinct difference reinforces operational discipline at the depot and validates the structured nature of the charging schedule.

Figure 10: Charging Duration Distribution for Top-Up



Overnight charging durations range between 80–180 minutes, reflecting the time required for full recharge from mid to low SOC to 100% — closely matching the depot's observed practice of full overnight charging.

Figure 11: Charging Duration Distribution for Overnight



Route-Level Charging Behavior

This figure focuses on buses operating on high-frequency routes such as 891, 721, 108, 569, and 73. Notably, Route 891 and 569 consistently experience higher waiting times compared to others. This suggests either a higher volume of buses per route or longer completion times for these routes, which in turn delay their arrival at the depot, pushing them into high-traffic charger queues. Understanding this relationship could help prioritize these buses for early charging slots to prevent delays on high-demand routes.

Figure 12: Wait Time Patterns Across High-Frequency Routes

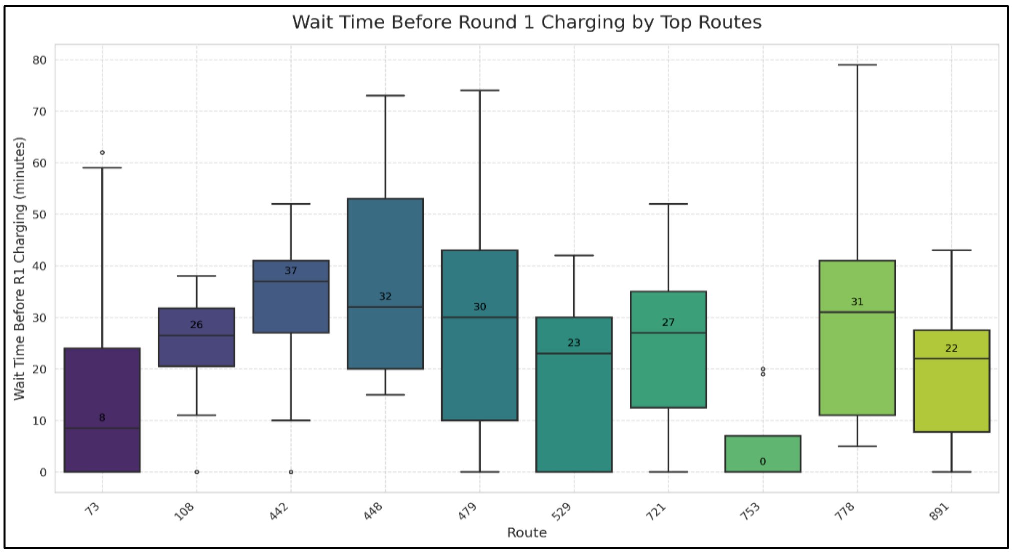
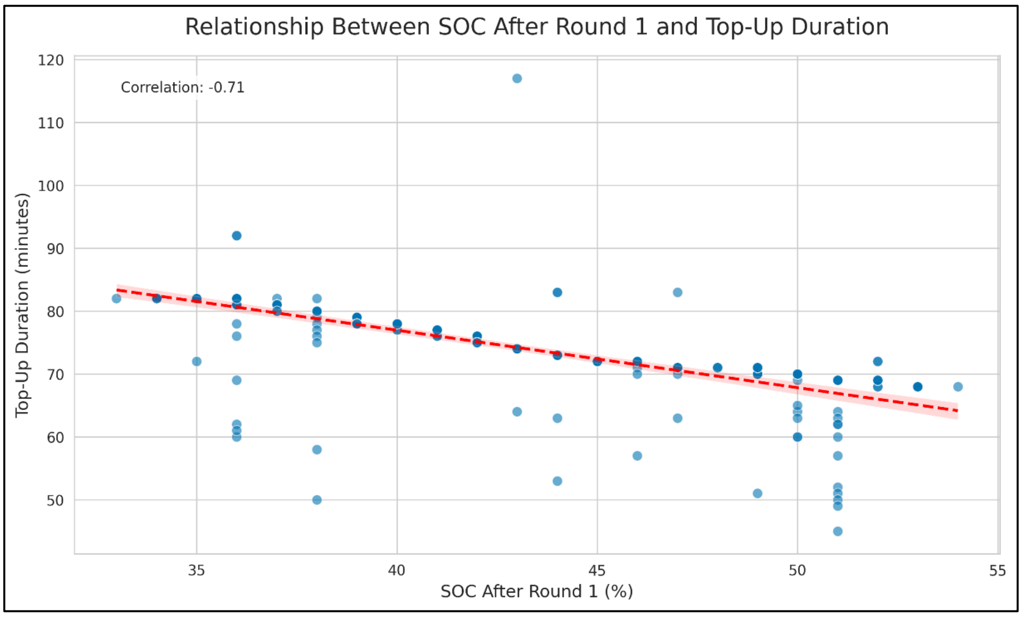


Figure 12 illustrates the relationship between the State of Charge (SOC) measured at the end of Round 1 and the corresponding Top-Up duration required to meet the operational threshold. A clear negative correlation is observed, indicating that vehicles returning with a higher SOC after the initial round require significantly less time for subsequent top-up charging.

Figure 13: Relationship between State of Charge (SOC) after Round 1 and the Required Top-Up Duration



This insight underlines the importance of route planning and charging strategy alignment, as optimizing for higher post-Round 1 SOC can lead to considerable reductions in idle time and energy overheads in the depot environment.

4b. Evaluating Operational Efficiency

This section fulfils Objective 1 of the study: to assess the day-to-day effectiveness of the e-bus depot's current charging operations. The evaluation centres on key performance indicators (KPIs) including charger utilization, wait times, charging durations, and energy efficiency. These indicators offer insights into how well the existing infrastructure—comprising 110 electric buses and 21 chargers—is equipped to meet the operational needs of the depot.

The analysis draws on empirical data from three continuous days of depot activity (March 29–31, 2025), comprising 330 recorded charging sessions. Each bus in the fleet is powered by a 400-kWh battery, and energy delivery is adjusted for real-world efficiency losses using an industry-standard conversion rate of 85%. This foundational assessment provides both a diagnostic overview of current performance and a baseline for evaluating future improvements through simulation.

Charging Duration Patterns

Depot charging follows a two-stage pattern—midday top-up charging and evening charging following service. Both these stages represent normal habits with regard to usage duration and usage behavior.

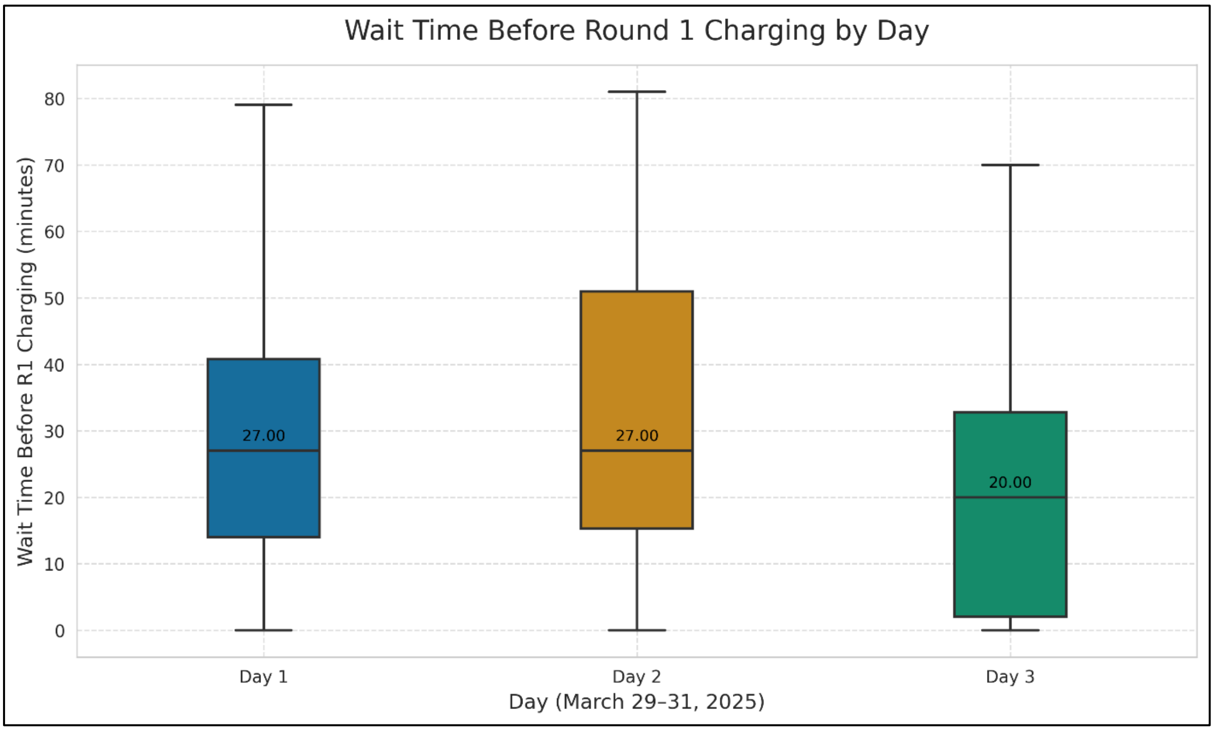
Top-up charging, typically between 12:00–6:00 PM, is intended to provide partial recharge following the completion of the first route (Round 1). These charging sessions take approximately 74.64 minutes (SD = 7.32) and vary between 45 and 117 minutes. The variability is primarily due to variations in state-of-charge (SOC) at arrival. Buses arrive following Round 1, on average, with an SOC of 42.52% (SD = 5.66%). The variability is due to external influences such as route mileage, traffic, and energy draw through air conditioning—particularly in summer months when AC can provide 10–12% of the total charge.

Waiting Time Patterns

Wait time before charging is probably the most direct indicator of depot operational stress and infrastructure efficiency. It shows how well the existing configuration—21 chargers—is performing in terms of managing incoming buses during peak demand hours. After Round 1 (R1), when buses return at midday to reload, the waiting time averages 25.81 minutes (SD = 20.02). Waiting time is not consistent across the three-day period.

Following Round 1 (R1), when buses return midday for top-up charging, the average waiting time is recorded at 25.81 minutes (SD = 20.02). This delay is not uniform across the three-day period. On Day 1 (Friday), average wait time peaked at 27.37 minutes, while on Day 3 (Sunday), it dropped to 19.11 minutes. This day-wise variation suggests that external operational factors, particularly traffic conditions, play a substantial role in depot timing dynamics. Conversations with depot staff confirmed that weekends typically experience lighter traffic, allowing buses to return earlier and in a more staggered manner, thereby reducing mid-day queuing at the chargers.

Figure 14: Day-wise Wait Time for charging after completing Round 1 trip



In contrast, waiting times after Round 2 (R2)—the second service route typically concluding in the evening—are significantly longer. The average overnight waiting time stands at 138.26 minutes (SD = 111.01), with a notable number of instances exceeding 400 minutes. These delays are primarily observed between 10:00 PM and 3:00 AM, a peak congestion window during which most of the fleet arrives and queues simultaneously. Since all buses are required to begin service the next morning with a full charge, charger contention during this period is especially critical. This raises operational challenges in managing staggered arrival times and enforcing optimal scheduling to avoid overlap.

4c. Energy Consumption and Charging Efficiency

This section provides an in-depth analysis of energy usage and charging performance across the three-day observation period. Drawing on real-world data and validated simulation outputs, we assess how effectively energy is delivered to buses, evaluate per-session and per-bus energy patterns, and analyse energy efficiency in the depot's operations. All metrics were calculated using the assumptions and formulas described in **Appendix 9.1**.

Total Energy Consumption

Across the 330 observed operations over three days, the depot consumed a total of 118,843.2 kWh of energy. This comprises two distinct charging windows:

- Top-Up Sessions: These occurred in the afternoon between the two service rounds. A total of 34,811 kWh was delivered during these sessions, with an average of 105.49 kWh per session.
- Overnight Sessions: These took place in the late evening to early morning hours. A total of 84,032.64 kWh was consumed during these sessions, averaging 254.64 kWh per charging event.

Theoretically, based on average State of Charge (SOC) values and the depot's battery and efficiency assumptions (400 kWh battery, 85% efficiency), top-up and overnight sessions are expected to deliver 110.70 kWh and 267.21 kWh per session, respectively. The slight deviations observed in actual energy delivery stem from variability in SOC at the time of charging, occasional partial charging, and operational constraints.

Per-Bus Energy Metrics

When the total energy consumption is averaged across all buses and days, each bus receives approximately 360.13 kWh per day, indicating a high degree of utilization. Assuming an average consumption rate of 1.45 kWh/km—based on estimates from the depot and comparable electric fleets—each bus covers nearly 248 kilometers per day. This aligns well with the expected route lengths and real-world usage patterns.

Table 2: Per-Bus Charging Efficiency Metrics Over Three Days (March 29–31, 2025)

Metric	Value
Energy Per Bus Per Day (kWh)	360.13
Consumption Per km (kWh/km)	1.45
Battery Capacity (kWh)	400
Number of Batteries	110
Total Battery Capacity (kWh)	44,000

Furthermore, the total available battery capacity across the fleet of 110 buses amounts to 44,000 kWh, highlighting the scale of energy management required in depot operations.

Charging Efficiency

The amount of energy delivered per unit of time is a measure of charging efficiency. While nighttime sessions, which are longer and more reliable, produced a greater efficiency of 2.02 kWh/min, top-up sessions delivered an average of 1.48 kWh/min. These figures show how SOC gaps and session durations affect throughput as a whole.

Table 3: Energy Consumption Metrics for Charging Sessions Over Three Days

Metric	Top-Up Charging	Overnight Charging
Mean Energy (kWh)*	110.70 (SD = 9.61)	267.21 (SD = 21.78)
Total Energy (kWh)	34,810.56	84,032.64
Number of Sessions	330	330
Average Charging Time (min)	74.64 (SD = 7.32)	132.52 (SD = 17.42)
Charger Utilization (%)	47–71%	100%
Wait Time (min)	25.81 (SD = 20.02)	138.26 (SD = 111.01)
Energy Efficiency (kWh/min)	1.48	2.02

5. Simulation Results and Analysis

This section provides the simulation-based outcome for the three scenarios: baseline model (as-is infrastructure), Scenario 1 (upgraded charger capacity), and Scenario 2 (expanded fleet size). The analysis is centered on operational performance metrics like wait times, charging times, State of Charge (SOC) differences, and energy supplied. All models are illustrated with accompanying tables and figures, offering quantitative and visual evidence of system behavior under different levels of demand and resources. The analysis is organized along two dimensions:

- **Objective 2:** Validate the Baseline model against real-world depot data.
- **Objective 3:** Assess the effect of smart infrastructure scaling through scenario-based analysis.

5.1 Baseline Model (110 Buses, 21 Chargers)

The baseline simulation was conducted to reflect the actual operational setup at the depot, where 110 electric buses are served by 21 available chargers across a single day (Day 3). The model captures both top-up and overnight charging patterns and compares simulated outputs with observed field data across multiple metrics.

5.1.1 Charging Behavior Metrics

The following table summarizes the key comparative performance metrics between simulated results and actual observed data.

Table 4: Baseline Model: Simulated vs Actual Metrics

Metric	Description	Simulated Mean	Observed Mean	Difference (Sim - Obs)	Interpretation
R1 Wait Time (min)	Time spent waiting before first route charging	18.78	19.11	-0.33	Slight improvement in morning wait time
R2 Wait Time (min)	Time spent waiting before overnight charging	141.88	137.44	4.45	Slight delay observed in return wait time
Top-Up End Time (min)	End time of mid-day charging session	3834.56	3802.35	32.21	Top-up ends slightly later than actual
SOC After Top-Up (%)	State of charge at end of top-up session	74.08	74.21	-0.13	SOC slightly lower after top-up
Overnight End Time (min)	End time of overnight charging session	4489.2	4487.3	1.9	Almost similar overnight charging end time
SOC After Overnight (%)	State of charge at end of overnight charging	100	100	0	Same as observed

The simulated R1 and overnight SOC values closely match observed data, indicating a high degree of model accuracy. The R2 wait time shows a slight overestimation (~4.5 minutes), potentially due to modeled queueing effects. Similarly, the simulation projects a marginal delay in top-up and overnight charging end times, suggesting moderate charger congestion under the current configuration.

5.1.2 Energy Delivery Metrics

To understand the energy requirement and operational load on the grid, we analyze the cumulative energy delivered through both charging windows.

Table 5: Baseline Model: Energy Summary (Day 3)

Energy Metric	Value (kWh)
Top-Up Charging Energy	16,742.03
Overnight Charging Energy	41,162.35
Total Energy Delivered	**57,904.38**

The majority of energy delivery occurs during the overnight window, as expected in a depot-based charging system. Top-up energy usage remains substantial but significantly lower than overnight totals. The energy requirements simulated align well with realistic depot consumption patterns, validating the modeled charging durations and SOC dynamics.

5.1.3 Visualization Insights – Baseline Model

To complement the tabular findings and gain a more intuitive understanding of system behavior, a series of visualizations were developed based on the 1,000 simulation runs of the baseline configuration.

Figure 15: Average Hourly Charger Utilization (Baseline)

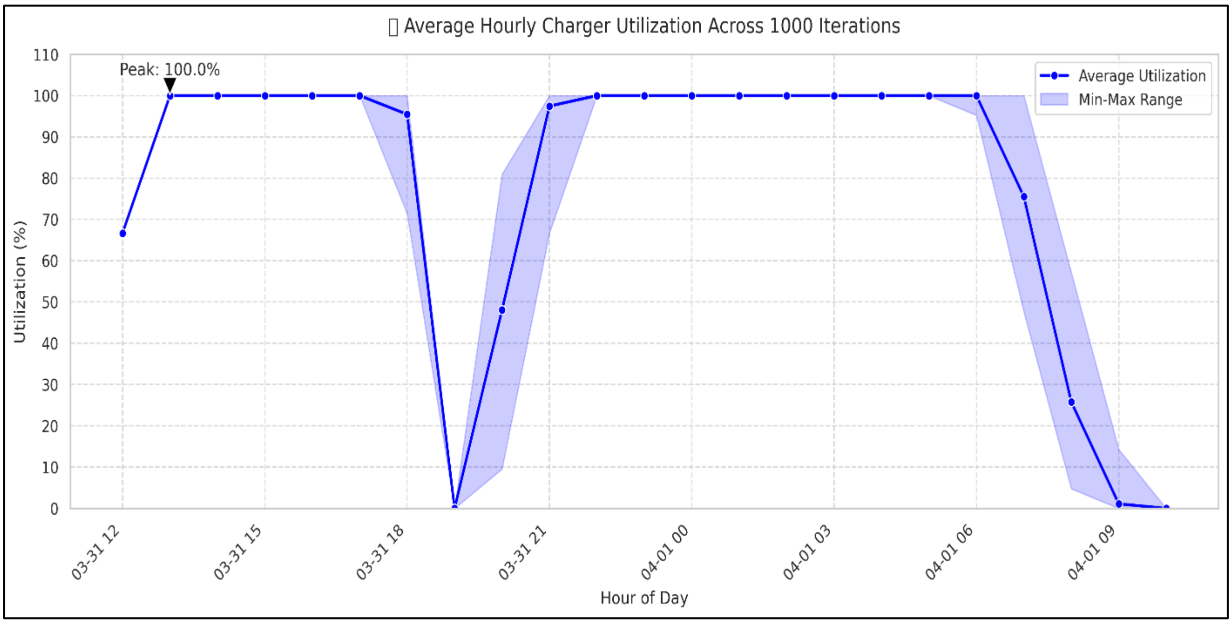


Figure 14, presents the average hourly charger utilization across the day. The plot reveals two distinct peaks in charger activity. The first peak occurs during the mid-day window between 12:00 PM and 6:00 PM, coinciding with the scheduled top-up charging period. The second, more sustained peak extends through the night hours, starting after 9:00 PM and continuing until early morning, which aligns with the overnight charging schedule. This bimodal

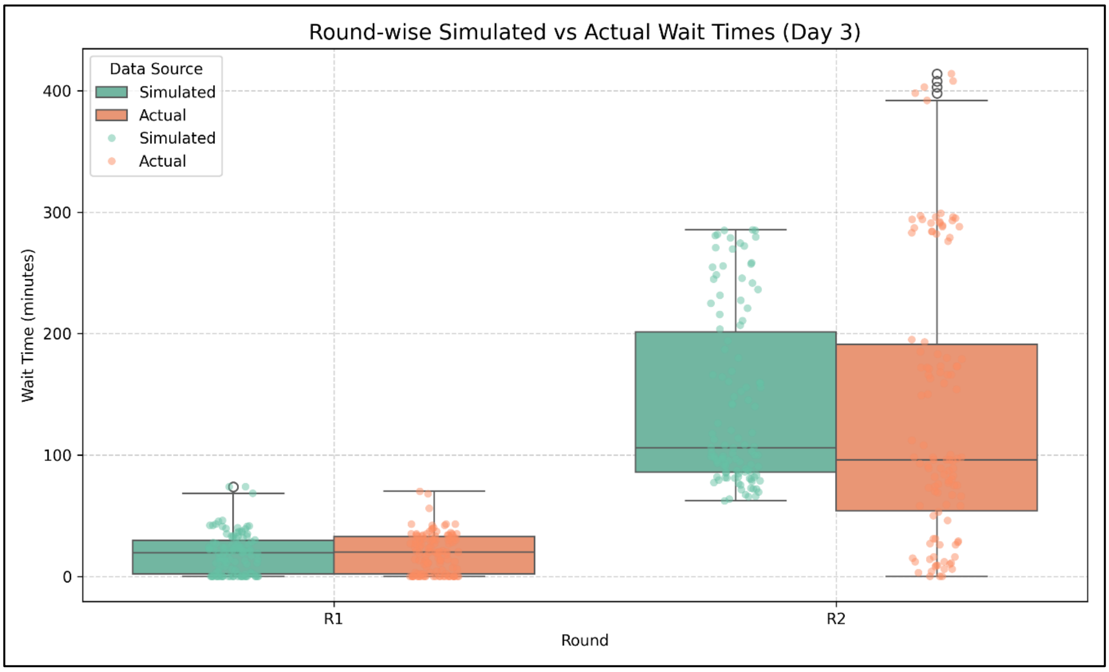
utilization pattern highlights the temporal clustering of demand and confirms that the simulation appropriately captures both operational windows. The relative smoothness of the curve across iterations also reflects the stochastic robustness of the simulation model.

Table 6: Summary of Average Charger Utilization

Hour	Mean	Min	Max	Utilization (%
31-03-2025 12:00	14	14	14	66.67
31-03-2025 13:00	21	21	21	100
31-03-2025 14:00	21	21	21	100
31-03-2025 15:00	21	21	21	100
31-03-2025 16:00	21	21	21	100
31-03-2025 17:00	21	21	21	100
31-03-2025 18:00	20.05	15	21	95.47
31-03-2025 19:00	0	0	0	0
31-03-2025 20:00	10.1	2	17	48.08
31-03-2025 21:00	20.47	14	21	97.46
31-03-2025 22:00	21	21	21	100
31-03-2025 23:00	21	21	21	100
01-04-2025 00:00	21	21	21	100
01-04-2025 01:00	21	21	21	100
01-04-2025 02:00	21	21	21	100
01-04-2025 03:00	21	21	21	100
01-04-2025 04:00	21	21	21	100
01-04-2025 05:00	21	21	21	100
01-04-2025 06:00	21	20	21	100
01-04-2025 07:00	15.86	10	21	75.51
01-04-2025 08:00	5.41	1	12	25.77
01-04-2025 09:00	0.23	0	3	1.09
01-04-2025 10:00	0	0	0	0

Figure 15 provides a **route-wise comparison of simulated and actual wait times** for both R1 and R2 rounds. The side-by-side bar visualization captures wait times per bus, enabling a direct assessment of how closely the model replicates real-world performance. A clear alignment is observed between actual and simulated values, particularly for R1, where discrepancies are minor and symmetrically distributed. This indicates high model fidelity in simulating post-R1 top-up behavior. For R2, while broader variance is visible in simulated values, the model still reflects realistic trends.

Figure 16: route-wise comparison of simulated and actual wait times for both R1 and R2 rounds



Supporting this visualization, Table 7 presents the descriptive statistics for both actual and simulated wait times in R1 and R2:

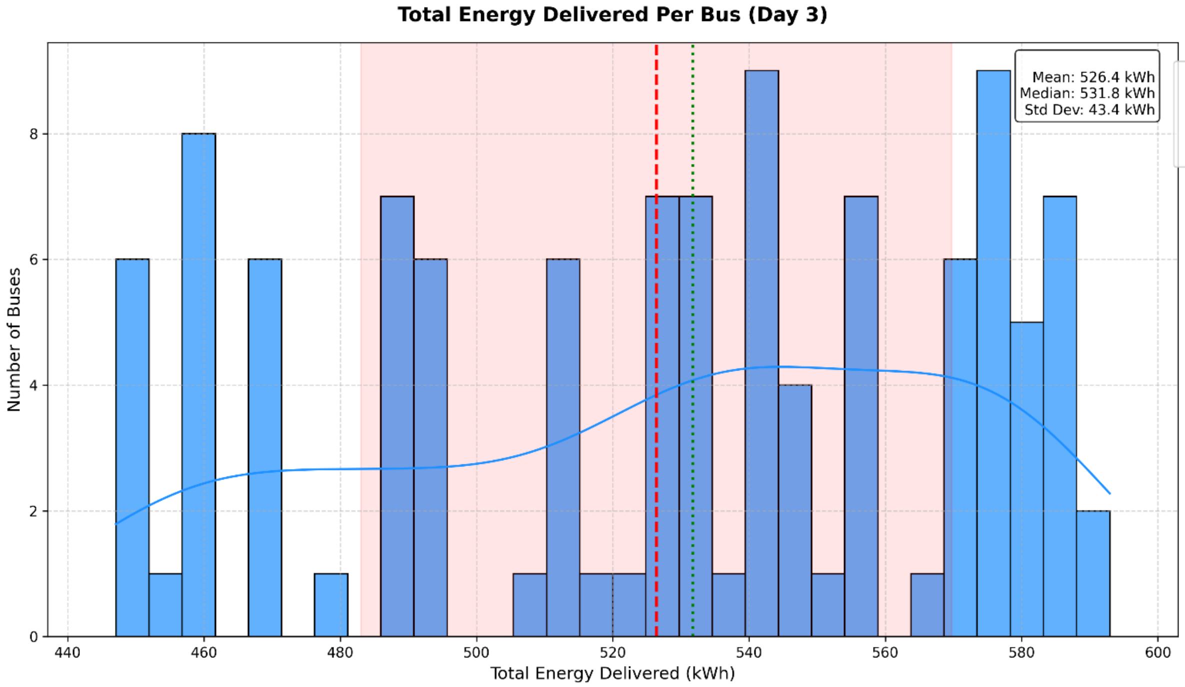
Table 7: Descriptive statistics for both actual and simulated wait times in R1 and R2

Round Type	Count	Mean	Std	Min	25%	50%	75%	Max
R1 Actual	110	19.1	16.3	0.0	2.0	20.0	32.8	70.0
R1 Simulated	110	18.8	16.8	0.0	2.0	19.5	29.6	73.8
R2 Actual	110	137.4	112.5	0.0	54.3	96.0	191.0	414.0
R2 Simulated	110	141.9	71.4	62.1	85.9	106.1	201.2	285.4

From this summary, it is evident that the simulation approximates actual values quite well. For R1, the mean wait time differs by only **0.33 minutes**, with near-identical medians and interquartile ranges. The slightly higher variance in simulated R2 wait times is expected, given the added randomness and potential queuing effects during overnight charging. However, the simulation's lower maximum value compared to the observed data indicates a more stable system under modeled conditions, possibly due to the controlled queuing assumptions in SimPy.

Lastly, **Figure 16** illustrates the *distribution of total energy delivered per bus* (aggregating top-up and overnight sessions) via a histogram. The distribution is slightly right-skewed, with the majority of buses clustered between 400 and 500 kWh in total energy consumption. This shape reflects the heterogeneity in bus duty cycles, travel lengths, and SOC requirements. The absence of extreme outliers or unrealistic values further supports the soundness of the simulation assumptions. Additionally, the alignment of this distribution with expected depot behavior underscores the model's effectiveness in capturing the nuances of energy demand across a varied fleet.

Figure 17: Distribution of total energy delivered per bus



Collectively, these visualizations offer strong support for the numerical insights drawn from the tabulated results. They confirm that the baseline simulation not only reproduces observed depot dynamics but does so in a statistically consistent and interpretable manner.

5.2 Scenario 1: Increasing Chargers from 21 to 25

To assess the effect of increasing charger availability, Scenario 1 simulated the baseline system with 25 chargers instead of 21, while keeping the fleet size constant at 110 buses. Table 8 summarize the results.

Table 8: Key operational performance metrics for Scenario 1

Metric	Observed Mean	Simulated Mean	Difference (Sim - Obs)	Interpretation
R1 Wait Time (min)	19.11	25.89	6.78	Unexpected increase in wait time (possible queue timing shifts)
R2 Wait Time (min)	137.44	114.34	-23.1	Significant reduction — better overnight access
Top-Up End Time (min)	3802.35	3809.07	6.72	Nearly aligned

SOC Top-Up (%)	74.21	74.21	0	Same as actual
Overnight End Time (min)	4487.3	4444.33	-42.97	Earlier finish — reflects improved efficiency
SOC Overnight (%)	100	100	0	Fully charged overnight

Table 8 reports key operational performance metrics. Notably, the Mean R2 Wait Time reduced by over 23 minutes, highlighting that greater charger availability significantly alleviates overnight congestion. Additionally, the Overnight End Time improved by nearly 43 minutes, reflecting faster turnaround. However, R1 Wait Time increased slightly by 6.78 minutes, suggesting that a few early-arriving buses might still experience some queuing due to overlapping demand. Importantly, both SOC Top-Up and SOC Overnight metrics remained identical to actual values, indicating reliable charge completion.

The total energy delivered (57,971.76 kWh) was almost unchanged from the baseline, suggesting that energy requirements remain consistent across different charger configurations for the same fleet size. However, efficiency in timing improved — energy was delivered earlier, especially during overnight sessions.

5.3 Scenario 2: Increasing Fleet Size from 110 to 130 Buses

Scenario 2 tested system scalability by expanding the fleet to 130 buses while maintaining the original 21 chargers. As summarized in Table 9, this led to a substantial increase in wait times and charging delays, especially for overnight charging.

Table 9: Key operational performance metrics for Scenario 2

Metric	Observed Mean	Simulated Mean	Difference (Sim - Obs)	Interpretation
R1 Wait Time (min)	19.11	19.07	-0.04	Nearly identical to observed
R2 Wait Time (min)	137.44	175.35	37.91	Significant congestion — overloaded overnight
Top-Up End Time (min)	3802.35	3861.6	59.25	Delays in top-up completion
SOC Top-Up (%)	74.21	71.13	-3.08	Lower SOC after top-up due to charger limits
Overnight End Time (min)	4487.3	4544.19	56.89	Extended overnight charging — queue overflow
SOC Overnight (%)	100	98.41	-1.59	Fewer buses fully charged

The R2 Wait Time increased by 37.91 minutes, and the Overnight End Time was delayed by almost 57 minutes. The SOC after overnight charging also dropped by 1.59%, indicating that not all buses could be fully charged before the required departure time. These changes confirm that the system became overloaded under this scenario. While the R1 Wait Time and Top-Up SOC experienced only minor changes, the cumulative pressure from 20 additional buses is clearly visible in the output metrics.

5.4 Comparative Analysis of Baseline and Scenarios

To compare the impact of different charger and fleet configurations, we created three insightful figures based on simulation outputs from the Baseline model, Scenario 1, and Scenario 2.

Figure 17 presents the *Average Hourly Charger Utilization* across all three scenarios. This visualization highlights how charger demand varies over the course of the day. In the baseline case (110 buses, 21 chargers), utilization rises during typical top-up and overnight windows. Scenario 1 (25 chargers) leads to a noticeable smoothing of peak usage, indicating more availability and reduced contention. In contrast, Scenario 2 (130 buses with 21 chargers) shows sharp peaks, pointing to system strain and limited charging slots during busy periods.

Figure 18: Average Hourly Charger Utilization across all three scenarios

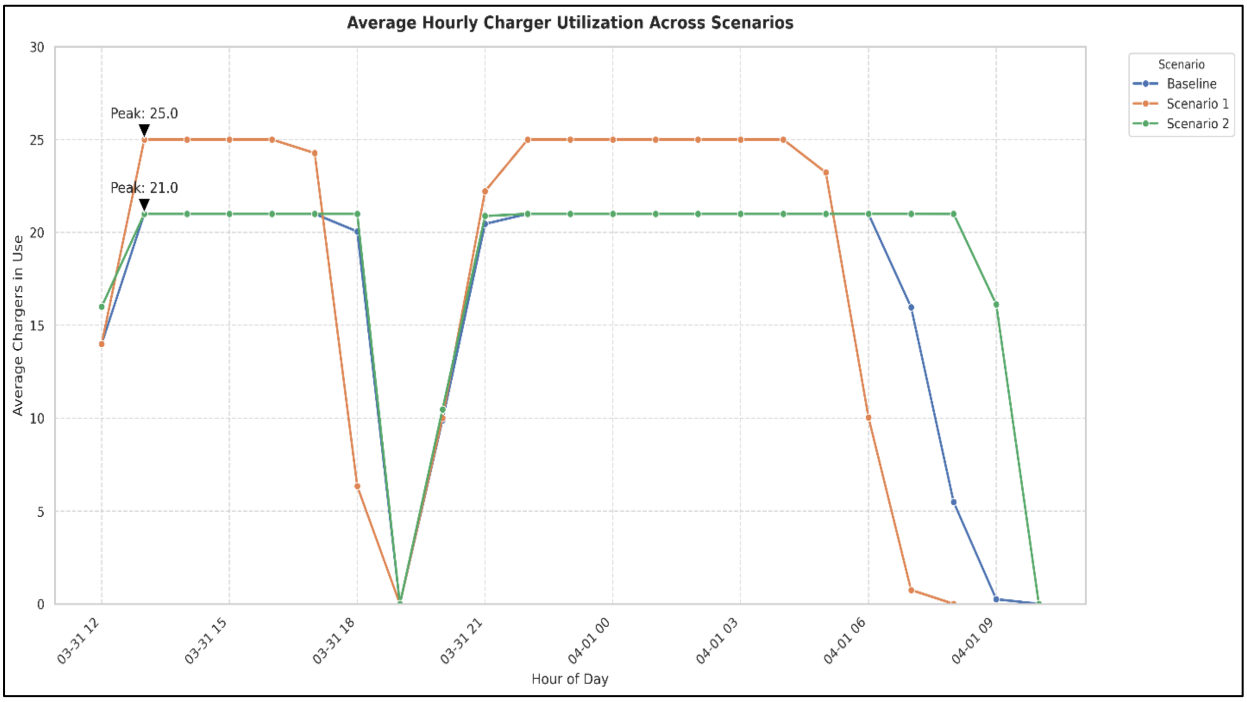


Figure 19: Compares Round 1 (R1) Wait Times across scenarios

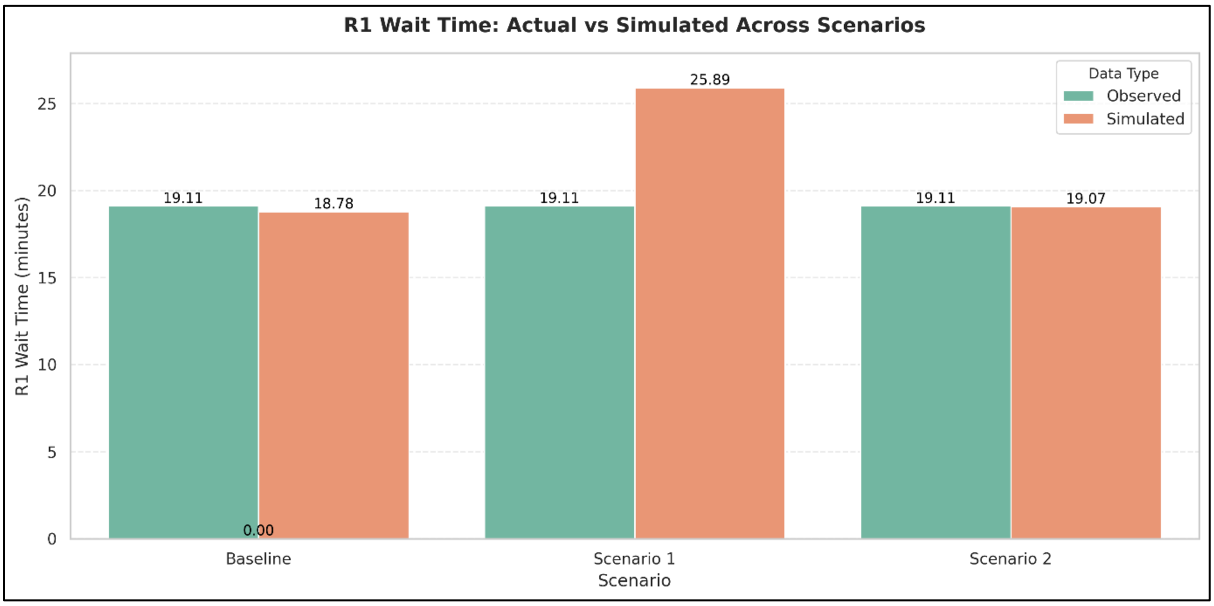


Figure 18 presents Round 1 (R1) Wait Times by scenario. Baseline and Scenario 2 are similar, but Scenario 1 has higher simulated wait times—an unusual anomaly which we can explain by redistribution of charging windows and early arrivals. It suggests a trade-off between added infrastructure and coordination of schedules.

Figure 20: Compares Round 2 (R2) Wait Times across scenarios

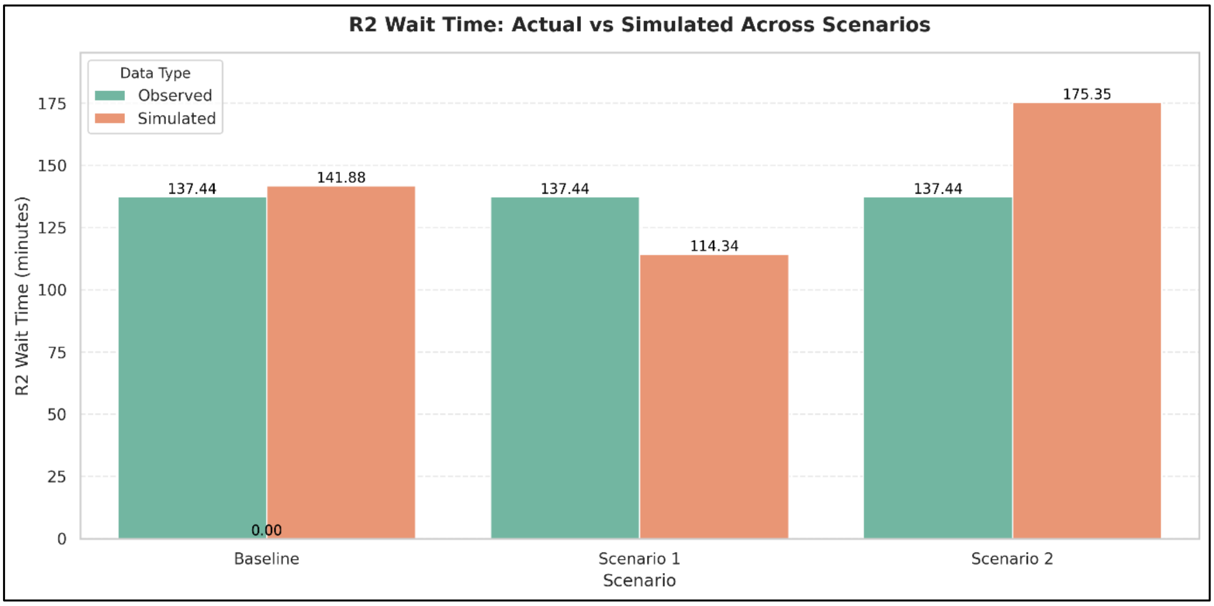


Figure 19 illustrates Round 2 (R2) Waiting Times. Scenario 1 is much better than baseline and Scenario 2, with lower mean waiting times and demonstrating overnight charging with additional chargers significantly minimizes delays. Scenario 2, with more buses but without additional infrastructure, generates massive queuing and rising waiting time, indicating a scalability limitation.

This comparative analysis confirms the observation that charger availability has a more positive impact on system performance than being able to serve a larger fleet size with available resources. The analysis establishes the importance of strategic scaling of infrastructure in electric bus depot planning.

6. Discussion

This study intended to investigate the operation of an electric bus depot with varying infrastructure conditions using simulation analysis. The reference case model at 110 buses and 21 chargers was initially tuned using actual operating data. The subsequent scenarios simulated the effect of scaling up charger capacity (Scenario 1) and fleet size (Scenario 2) on selected key performance metrics.

Baseline simulation output was highly correlated with true results. Wait times, end times, and SOC levels simulated and observed differed only slightly, validating model assumptions and design. For instance, Round 1 and Round 2 wait times deviated from observed quantities by -0.33 minutes and +4.45 minutes, respectively. This indicates that the baseline system is effectively at capacity, and any additional demand or inefficiency would perturb equilibrium.

In Scenario 1, a doubling of the chargers to 25, with the same fleet size, significantly improved overnight charging efficiency. Round 2 wait time came down by over 23 minutes from the observed data. This shows that ramping up infrastructure can unlock substantial efficiencies, especially in the overnight time window when demand is bunched up. Round 1 wait times did increase marginally in this scenario, likely because buses come a little early or charger contention shifts into the top-up window. Still, the ability to complete overnight charging well before the 9:30 AM deadline is a remarkable outcome of this configuration.

In Scenario 2, we applied a 20% fleet size increase without changing chargers in quantity. This caused system overload as anticipated. Round 2 wait times went up by nearly 38 minutes on average, and SOC levels after overnight charging dropped by 1.6%. The chargers became increasingly bottlenecked in peak windows, and a number of sessions operated precariously close to cut-off times. This further drives home the point that infrastructure growth must walk in step with any growth in fleet size to provide reliability and performance.

The comparative visualizations confirm these impressions. Charger use plots prominently display the strain on infrastructure in Scenario 2 with substantially higher peak loads than the baseline. Likewise, the R1 and R2 wait time comparisons between scenarios display the sensitivity of these metrics with respect to charger availability and scheduling logic.

Operationally, these findings offer hands-on guidance. Depot managers, for instance, can use this framework to plan infrastructure renewal or bus timing more efficiently. The marginal gains in energy supply and SOC levels also offer further incentive to the case for forward-looking planning in fleet electrification projects.

7. Conclusion

The simulation model created in this research offers a robust tool to test and validate electric bus depot operations under various conditions. With real data, random modelling, and sensitivity analysis conducted in parallel, we obtained valuable insights towards the interrelation between charger infrastructure, scheduling rules, and fleet performance.

The baseline model acted as a good starting point, showing the efficiency of the system at the moment and areas of possible improvement. Scenario 1 uncovered the real advantages of introducing chargers — a comparatively inexpensive intervention that cut wait times considerably and enhanced overnight readiness. Scenario 2, on the contrary, uncovered the limitation of the current configuration when tested with an expanded fleet size, highlighting the necessity of coordinated expansion of hardware and scheduling flexibility.

As electric transportation grows in urban transport, simulation tools such as ours can assist data-driven decision-making. This allows stakeholders to analyse infrastructure investment, calculate operational risk, and plan capacity growth in an intelligent manner. Subsequent studies could further develop this model to include real-time charging power curves, heterogeneous arrival patterns, and energy price models to make it even more realistic and usable.

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9. Appendix

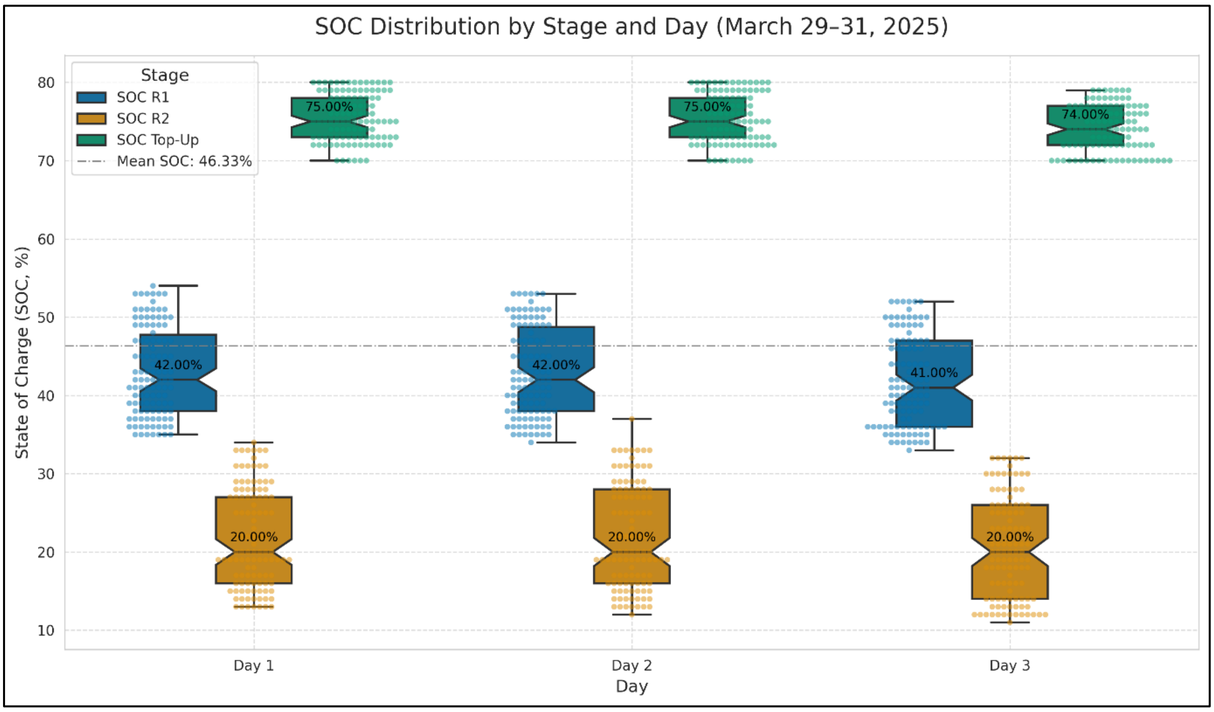
Appendix A: Dataset Access

The dataset used for simulation modelling was compiled from real-world operational logs collected between March 29–31, 2025, covering 330 electric bus movements across three days. It includes fields such as timestamps, state of charge (SOC), energy usage, and wait times.

A cleaned and pre-processed version of this dataset (used for simulation) is available via the following link: [Google Drive Dataset – View Only Access]

This dataset is referenced in the Methodology section and was used to generate all simulation results.

Appendix Figure A1. Boxplot illustrating the distribution of State of Charge (SOC) across different operational stages and days.



9.1 Assumptions and Formulas

This appendix outlines the assumptions and equations used to calculate key energy and efficiency metrics across the simulation and empirical data.

9.1.1 Assumptions

The following assumptions form the foundation of the calculations:

Assumption	Value / Description
Battery Capacity	400 kWh per bus (confirmed by depot)
Charging Efficiency	85% (industry standard; accounts for losses during energy transfer)

Energy Consumption per km	1.45 kWh/km (estimated based on operational interviews and literature)
Number of Charging Sessions	330 top-up and 330 overnight sessions (110 buses × 3 days)
Target SOC for Overnight	100% (depot operational goal)
Uniform Daily Energy Use	Assumes consistent energy need across fleet

9.1.2 Formulas

The following formulas were used to derive the results, each accompanied by an explanation and, where applicable, an example:

Energy Consumption Calculation

Formula: Energy (kWh)=(SOC Final−SOC Initial)*100×Battery Capacity×Efficiency

Explanation: This calculates the energy delivered during a charging session. The SOC difference (as a percentage) is converted to a decimal (divided by 100), multiplied by the battery capacity (400 kWh), and adjusted for charging efficiency (85%) to account for losses.

Example: For a top-up session with SOC Initial = 42.52% and SOC Final = 75.08%: Energy= (75.08−42.52100)×400×0.85=0.3256×400×0.85=110.70 kWh

Energy Efficiency

Formula:
Energy Efficiency (kWh/min) = Energy Consumed (kWh)Charging Time (min)

Explanation: This measures the rate of energy delivery during charging, useful for comparing the effectiveness of different session types (e.g., top-up vs. overnight). A higher value indicates faster charging.

Example: For a top-up session with 110.70 kWh consumed over 74.64 minutes: Energy Efficiency=110.7074.64=1.48 kWh/min

Consumption per Kilometer

Formula:
Consumption per km (kWh/km)=Total Daily Energy (kWh)Total Daily Distance (km)

Explanation: This estimates the energy efficiency of the buses in terms of distance traveled. Since exact distances were unavailable, daily distance was derived by dividing daily energy use by the assumed consumption rate (1.45 kWh/km).

Example: For a bus using 360.13 kWh/day: Daily Distance=360.131.45≈248 km/day

The assumed 1.45 kWh/km aligns with the depot's range and is validated by this calculation.