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AGENT-BASED MODELING AND SIMULATION OF BATTERY DYNAMICS IN ELECTRIC DELIVERY VEHICLES UNDER REALISTIC URBAN SCENARIOS

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ABSTRACT

Electric delivery vehicles are becoming increasingly common in last-mile logistics. Thus, the shift to electric transport introduces new challenges to urban transportation management, as these vehicles are range-constrained under heavy loads and require charging infrastructures on a daily basis. Battery systems constitute the most critical component of these vehicles and understanding their energy consumption is essential. This paper presents a simulation-based framework to evaluate battery performance under realistic delivery scenarios, focusing on how operational variables, such as speed, payload, and travel distance affect power consumption. Hence, an integrated agent-based simulation model is proposed, incorporating an equivalent electric circuit model of the battery, and a mechanical model of the vehicle energy requirements. Moreover, ground-based vehicles are considered for experiments. Two battery configurations are used in the simulated scenarios, representing small and medium-sized battery systems. Similarly, short and long delivery times are considered to evaluate the impact of battery size on distribution.

1 INTRODUCTION

Environmental awareness has expanded the adoption of electric mobility in recent years, emerging as a pivotal factor of sustainable transportation. The global fleet of electric vehicles (EV) is rapidly increasing and attracting the interest of the researchers driven by the advances in technology. EVs accounted for around 18% of all cars sold in 2023 worldwide, up from 14% in 2022 and surpassing the value of 4% in 2020, reflecting the momentum behind electrification (IEA 2024). However, private EVs alone are not able to provide a definitive solution to sustainable urban mobility. In this context, electric delivery vehicles will play a key role in the transition to greener transportation systems. Governments and industries are increasingly shifting towards electrification not only for private cars but also for public transportation and last-mile delivery fleets to improve sustainability and efficiency in logistics. Delivery companies are likely to invest in technology that improves delivery productivity as customer expectations of delivery times continue to rise and e-commerce sales continue to accelerate. In this context, electrified means to carry parcels and demands have gained importance. Electric delivery vehicles can be broadly classified into ground-based vehicles such as autonomous delivery robots (ADRs), electric vans and trucks, and aerial vehicles such as drones or unmanned aerial vehicles (UAVs). All these vehicles offer option for range and payload to navigate sidewalks, roads and the sky for urban freight and parcel distribution.

According to Kaiser et al. (2024) study, ADRs are positioned as a key solution to reduce the environmental effects of last-mile logistics, as their emissions account for only 2% of those produced by vans with internal combustion diesel engines. ADRs are expected to significantly improve the efficiency of last-mile distribution operations in the coming years and the COVID-19 pandemic has certainly had a positive impact on the acceptance of ADRs by end users, as they increase the social distance between individuals (Lemardele et al. 2024). In the aerial category, delivery drones have emerged as a promising solution for fast and energy efficient last-mile deliveries of packages. Delivery Companies such as Amazon and UPS have invested in drone delivery, as researchers the flexibility of these services and their advantage in offering higher delivery speeds by avoiding traffic congestion issues Zou et al. (2023). However, EV face some limitations. Both ADRs and UAVs are typically restricted to certain areas and regulations, such as sidewalks or ruled airspace, and they must handle obstacles and safety concerns. Moreover, as it happens with larger electric vans and trucks, all this vehicles are constrained with range limitations under heavy loads and require charging infrastructure or stations to support daily operations. Therefore, the shift to electric means introduces new challenges to urban transportation management and operations and these issues are particularly related to battery performance and reliability.

Furthermore, lithium-ion batteries are the most used in electric vehicles due to their high energy efficiency, small size, long lifespan, and low self-discharge rate. Batteries are the energy source that power EV and the its performance depends on the battery voltage (V) and current (I) dynamics. EV require advance monitoring and management to have smart energy storage systems and thus, all EV are equipped with Battery Management Systems (BMS). These monitor key parameters of batteries such as the state of charge (SoC), the state of health (SoH), the state of power (SoP), and the remaining useful life (RUL). Despite the growing interest in EVs in logistics, there is a gap in the modeling found in the Operations Research literature regarding battery energy consumption. Most studies neglect dynamic electrical behavior of batteries, when factors such as speed and payload influence battery performance, as high current demands lead to voltage drop and reduced battery efficiency. Likewise, this paper presents an agent-based simulation model to evaluate the power consumption of electric delivery vehicle batteries under operating conditions. A simulation framework that captures the voltage–current operating characteristics of batteries, combined with key determinants of energy consumption (vehicle speed, travel distance, and payload), is developed to evaluate battery performance in delivery vehicles. Thus, this model considers the electrical dynamics of the battery with the physical parameters ruling vehicle operation, providing a comprehensive analysis of battery-powered mobility systems.

Therefore, the main contributions of this work are: (*i*) the development of a simulation approach for modeling electric vehicle energy consumption, reducing the dependency on large empirical datasets; (*ii*) the integration of a mechanical force-based power model with an electrical battery model, enabling consistent estimation of current and voltage profiles under load; (*iii*) the analysis of the impact of operational variables such as speed, distance, and payload on power consumption through realistic delivery scenarios; and (*iv*) the provision of a flexible agent-based modeling structure that allows for comparison across different electric delivery platforms, including ground robots and aerial drones.

The rest of the paper is structured as follows. Section 2 reviews the relevant literature and methodologies addressing EV battery simulation. Section 3 explains the proposed approach, and Section 4 outlines the computational experiments. In Section 5, the research findings are discussed, and Section 6 draws the main conclusions.

2 LITERATURE REVIEW

Unlike fuel-powered vehicles, EV depend on advanced BMS to mantain safety, efficiency and longevity of their energy storage systems (Demirci and Aydin 2024). As battery technologies have evolved, different battery models have also been developed. Comparative reviews classify battery modeling approaches into three main types (Adaikkappan and Sathiyamoorthy 2022): electrochemical models, equivalent circuit models (ECMs), and data-driven models. Although recent reviews of BMS technologies highlight the shift towards data-driven and artificial intelligence methods (Kurucan and Yilmaz 2024; Nyamathulla and Dhanamjayulu 2024; Thelen and Smith 2024), as Demirci and Aydin (2024) conclude in their review, traditional approaches are still the most popular despite their limitations in handling complex real-time scenarios. Even if electrochemical models are very accurate, for simulation purposes ECMs provide a simpler and though less accurate alternative.

Simulation-based studies have applied these models to assess real-world BMS performance. For instance, Jafari et al. (2015) validated an ECM for EV batteries with experimental data and real-world driving scenarios through battery simulations. Similarly, Jeong et al. (2018) explored the impact of battery degradation on e-bus operations through the simulation of bus operation driving cycles. By incorporating an ageing model, they demonstrated the quantitative relationship between the installation of the charging infrastructure and battery life extension, highlighting the importance of considering ageing effects in long-term planning and fleet management strategies. These aging effects are critical for battery characteristics and can be tackled through experimental analysis and modeling approaches to evaluate battery performance under different operational conditions. In fact, recent studies (Stroe et al. 2017; Irujo et al. 2025) propose experimental procedures, aging models and parameter fitting strategies that allow comprehensive analysis of aging behavior for real-world applications.

As Izco et al. (2024) highlight in their research, agent-based modeling has proven to be an alternative way to model complex problems. In recent years work includes studies on ABM simulating the logistic operations of electric vehicles, such as drones (Wang et al. 2022; Chour et al. 2023), autonomous delivery robots (Bachi et al. 2024; Cepolina et al. 2024), and multi-agent collaboration. As such, Hedayati et al. (2024) analyzed cost saving opportunities in ADR-UAV collaborative delivery models, and Ropero et al. (2019) developed a coordinated ADR-UAV routing strategy to overcome energy constraints. Besides, Figliozzi and Jennings (2020) and Figliozzi et al. (2020) investigated the energy consumption and emissions reduction potential of ADRs using simulation-based models. The previous studies generally accounted for the energy consumed by the vehicle as a constant number, such as the maximum range of the vehicle or the average energy consumption per distance (or time). However, in reality, energy consumption is not a linear function of traveled distance or time, but also it is influenced by speed, gradients, and payload.

3 METHODOLOGY

This section presents the battery simulation model that is used to study battery performance under controlled operational scenarios. For this aim, an agent-based modeling (ABM) simulation model is developed, where the battery operation modes are represented within a statechart. This approach represents a realistic operation cycle typical of electric vehicles and the statechart captures the transitions between charging, resting, and discharging states of the battery.

3.1 Electric Model of the Battery

In order to simulate electrical dynamics of an EV battery, an Equivalent RC Circuit model (ECM), also known as Thevenin Battery Model, consisting of resistive (R) and capacitive (C) elements is implemented (see Figure 1 for details). Here, V_{oc} represents the open circuit voltage, R_p and C_p model the electrochemical polarization resistance and capacitance and R_s is the input ohmic resistance. The state variable of the circuit is the V_{bat}, that represents the battery voltage and its state space equation is derived from equations (1) - (3).

The electrical behavior of the Thevenin model shown in Figure 1 considering the RC branch, is expressed as the following differential equation:

$$C\frac{dV_{RC}}{dt}+\frac{V_{RC}}{R_p}=I_{cc} \tag{1}$$

The solution to this differential equation, where the time constant is defined as $\tau = R_p \cdot C$ is given by:

$$V_{RC}(t)=I_{cc}\cdot R_p-(I_{cc}\cdot R_p-V_{RC_0})\cdot e^{-\frac{t}{\tau}} \tag{2}$$

Considering boundary conditions and initial values and discretizing the formulation to implement it in the simulation framework:

$$V_{bat(t)}=V_{bat(t-1)}-\left(V_{bat}^{max}-V_{bat(t-1)}\right)\cdot(1-e^{-\frac{t}{\tau}}) \tag{3}$$

Following the same procedure, the battery current function is obtained:

$$I_{bat(t)}=I_{bat(t-1)}\cdot e^{-\frac{t}{\tau}} \tag{4}$$

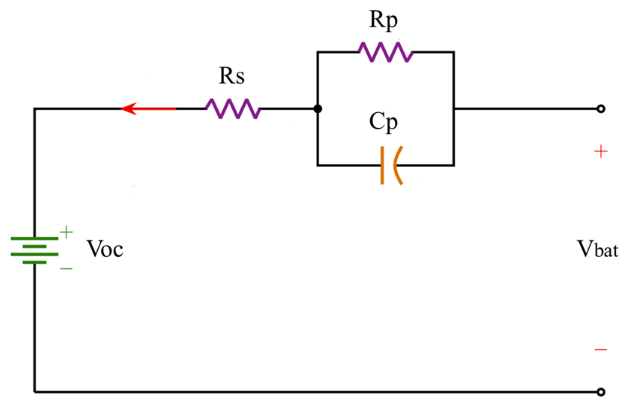

Figure 1: The equivalent Thevenin circuit model for the battery cell.

This RC equivalent circuit is an effective way to capture how the battery voltage (V) and current (I) evolve in each operational mode.

3.2 Agent-Based Battery Operation Modeling

In this study, the battery is modeled as an agent in the simulation framework whose variables change following the statechart shown in Figure 2. Agent-based modeling was chosen for its flexibility in simulating individual battery cycles, offering the potential to integrate more complex behaviors in future experiments. This model combines electrochemical battery dynamics with logistic operations for parcel delivery and the statechart is composed of three main states: charging, resting, and discharging. The state transitions are triggered by time-based events or by thresholds, such as cut off current, minimum state of charge or cut off voltage.

The charging state consists of two sub-states: constant current (CC) and constant voltage charging. The cycle starts at the charging state and the agent transitions from CC to CV once the voltage approaches V_{max}. After entering CV mode, the battery continues charging at a constant voltage V_{max}, while the current gradually decreases. The SoC increases proportionally to the charging current and time elapsed. The battery transitions from CV mode to the resting state when the charging current drops below the cutoff current threshold I_{cutoff} which indicates the battery is fully charged, that is $SoC = 100\%$.

After charging, the battery transitions into the resting phase. From an electrical point of view, this is a rest period as no current is drawn and thus, the simulation sets the battery current to zero ($I = 0$). However, operationally, the vehicle is considered to be in the load state, as this is the time when the vehicle is being loaded with parcels to be delivered. During this state, new demand is created, by storing new orders in the parcel agent population. Each parcel is assigned a weight from $\mathscr{U}[a,b]$ kg, that should not exceed the maximum payload of the delivery vehicle. The resting state is time-triggered and the resting time is defined as a uniform distribution $\mathscr{U}[c,d]$.

After loading, the discharging process begins in the delivery state, where the agent simulates the vehicle traveling to deliver parcels. During the discharging state, the agent delivers parcels sequentially, one per loop, until all parcels have been delivered or the battery reaches minimum voltage threshold V_{cutoff} or a minimum SoC threshold. In the back state, the agent simulates the return back to the loading and charging station, which is modeled as a fixed speed and a time that follows a uniform distribution $\mathscr{U}[e,f]$. After this state, two conditions are evaluated: whether the battery requires recharging, and whether the vehicle still has parcels left to deliver. If all parcels were delivered, the parcel agents are reset removing old parcels and a new batch of parcels is generated for the next delivery cycle. If undelivered parcels remain but but battery SoC is low or battery has reached voltage threshold, the agent transitions back to the charging state to restore energy before completing the deliveries.

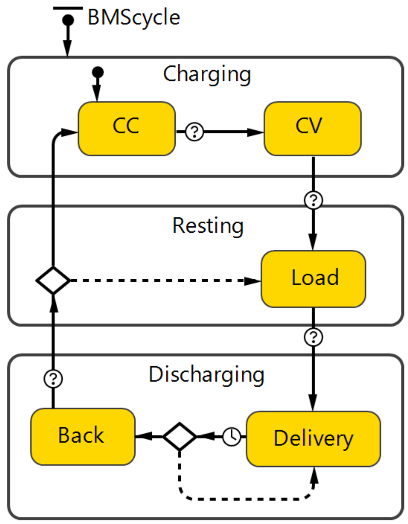

Figure 2: Battery simulation model statechart in Anylogic.

3.3 Electric Vehicle Mechanical Model

The mechanical model represents the battery consumption rate as the power demand required to the battery as the result of the vehicle motion. It is the amount of charge consumption per minute, that is, the rate at which battery charge decreases measured in Watts (W). Focusing on ground vehicles, this model is derived from physical principles and accounts for the forces the vehicle must overcome during operation as proposed in Ko et al. (2019). These include rolling resistance F_{rr}, aerodynamic drag F_{ad}, hill climbing F_{hc}, and linear acceleration F_{la}, thus $F_{te} = F_{rr} + F_{ad} + F_{hc} + F_{la}$. Assuming constant speed and neglecting the slope of the road, the power needed to move a delivery vehicle is estimated with statistical methods as described in Equation (5):

$$P_{mec} = F_{te} \cdot s = \mu_r \cdot m \cdot g + \frac{1}{2} \cdot \rho \cdot C_d \cdot A \cdot s^2 \tag{5}$$

The electrical power consumed by a EV in a delivery action is estimated with statistical methods as described in Equation (6), adapted from Wu et al. (2015) energy consumption estimation model for electric vehicles:

$$P_{elec} = \frac{1}{\eta} \cdot P_{mec} = \frac{1}{\eta} \cdot (g \cdot \mu_r \cdot (m_t + w) \cdot s + \frac{1}{2} \cdot \rho \cdot C_d \cdot A \cdot s^2) \tag{6}$$

Where η is the drivetrain efficiency that accounts for losses between mechanical and electrical energy and the mass considered accounts for the vehicle mass m_t and the carried payload w. Using the relationship between power, current, and voltage, we can directly link both electrical and mechanical models developed. The current $I(t)$ calculated from the mechanical model is inputted to the electrical battery model, specifically in the discharging state of the statechart in Figure 2 and it is computed as:

$$I(t) = \frac{P_{elec}(t)}{V_{bat}(t)} \tag{7}$$

This integration ensures that changes in vehicle load and speed are integrated in the electrical behavior, enabling a comprehensive simulation of energy consumption and battery performance in electric delivery vehicles. The main parameters considered in the electrical and mechanical models are displayed in the Tables 1 and 2.

4 COMPUTATIONAL EXPERIMENTS

This section presents the experimental setup and parameter values used in the agent-based battery simulation model described. The aim of these experiments is to evaluate the energy consumption of electric delivery vehicles under realistic last-mile delivery scenarios with varying operational factors such as payload and travel distance. To do so, multiple delivery scenarios are simulated using two different battery configurations, representing small and medium-sized battery systems.

In this study, the parameters used are set according to the empirical protocols described in the XJTU Battery Dataset reported in Wang et al. (2024). This benchmark dataset provides data for lithium-ion battery cells, which are characterized by a nominal capacity of 2,000 mAh and a nominal voltage of 3.6 V, with charge and discharge cut-off voltages of 4.2 V and 2.5 V, respectively. In our simulation scenarios, we replicate the charging and discharging strategy described in the XJTU battery experiments (batch 5): Specifically, all cells are charged to V_{max} at a rate of 1C using a constant current–constant voltage (CC–CV) mode, followed by a rest period, and then discharged to V_{cutoff}.

Two battery configurations are considered for the simulation scenarios. On the one hand, the 1-cell battery scenario corresponds to a single lithium-ion cell with a nominal capacity of 2000 mAh, a nominal voltage of 3.6 V and the battery is charged at 1C (2A). On the other hand, the 2-cell battery scenario represents a battery pack composed of two cells in series (2S), with a nominal voltage to 7.2 V and capacity to 5000 mAh and the battery is charged at 1C (5A). In all scenarios discharge cycles are simulated with variable current drops based on the vehicle dynamics. Tables 1 and 2 gather all the parameters considered in the computational experiments. In addition to the battery parameters, a set of physical characteristics related to the delivery vehicle are included to calculate the mechanical power requirements during each delivery cycle and to derive the corresponding electrical current draw from the battery.

Four simulation scenarios are considered. Firstly, two scenarios per battery configuration, in order to evaluate the impact of battery size on delivery operations. Secondly, for a given battery configuration, two additional scenarios are considered: short and long travel times. Travel times between delivery points are drawn from a uniform distribution between of 1 to 5 minutes in the short delivery scenarios and between 5 and 10 minutes in the long delivery scenarios to reflect the variability in urban routing conditions. These values assume that the delivery vehicle operates within a relatively small area, such as a urban area, a university campus or last-mile delivery zone, where the distance between consecutive deliveries remains limited. Each scenario is run for a total duration of 8 hours, simulating a full working day of delivery. This duration is sufficient to observe multiple charge–discharge cycles, enabling the analysis of long-term operational performance. During the simulation, the following performance indicators are recorded: total energy consumption, number of delivery cycles completed, total distance traveled, time spent delivering parcels, and the evolution of the battery SoC. These metrics allow for a comparative evaluation of delivery efficiency and battery usage across both small and medium battery configurations and short and long distance delivery areas.

Table 1: Simulation model parameters and their values for proposed the scenarios.

Parameter	Description	1-cell scenario	2-cell scenario
V_{nom}	Nominal voltage	3.6 V	7.2 V
V_{max}	Maximum voltage	4.2 V	8.4 V
V_{cutoff}	Cut-off voltage	2.7 V	2.7 V
I_{cc}	Constant charge current	1 C (2 A)	1 C (5 A)
I_{cutoff}	Cut-off current	0.04 A	0.2 A
C_{nom}	Nominal capacity	2000 mAh	5000 mAh
τ_{CC}	CC time constant	2500 s	2500 s
τ_{CV}	CV time constant	800 s	800 s
k	Degradation rate constant	1.67×10^{-3}	1.67×10^{-3}

Table 2: Robot parameters considered for experiments.

Parameter	Description	Value
η	Power transfer efficency	0.95
m_t	Tare weight of a robot without load in kg	22.7 kg
p_{max}	Maximum payload	15 kg
A	Frontal area of the robot	0.4 m2
C_d	Drag coefficient	0.8
μ_r	Rolling resistance coefficient	0.006
s_{max}	Maximum speed of the robot	10 km/h
ρ	Air density at sea level	in 1.2 kg/m3

In each delivery cycle, a batch of parcels is generated and assigned to the delivery vehicle. Parcels are created one by one, each assigned a weight drawn from a continuous uniform distribution between a=0.5 and b=3 kg. The maximum payload is limited to 15 kg per delivery batch, in accordance with the constraints defined in Table 2. As a result, the number of parcels per batch is not fixed and depends on the weight values sampled during that cycle. During delivery, robot speed is sampled from a triangular distribution with a mode of 6 km/h and a maximum speed s_{max} of 15 km/h, whereas the return trip to the loading station is performed at a fixed speed of 6 km/h. These values are consistent with typical operational speeds of autonomous delivery robots reported in recent literature (Plank et al. 2022; De Maio et al. 2024). Similarly, the parcel loading time at the depot is modeled using a uniform distribution between c=5 and d=20 minutes and the return back time to the loading station is considered to follow a uniform distribution between e=5 and f=10 minutes. We consider those parameter to be realistic for our experiments and it must be noted that these values are configurable and can be adjusted to reflect alternative delivery scenarios or to evaluate the model sensitivity to operational changes.

5 RESULTS AND DISCUSSION

This section presents the results obtained from running the simulation model under the proposed scenarios. All experiments were conducted on a Windows 11 desktop with Intel Core i7-10750H CPU 2.60GHz, and 16 GB of RAM and are solved using IBM®ILOG CPLEX 12.6.2 API for the Java Environment solver in the Anylogic simulation software.

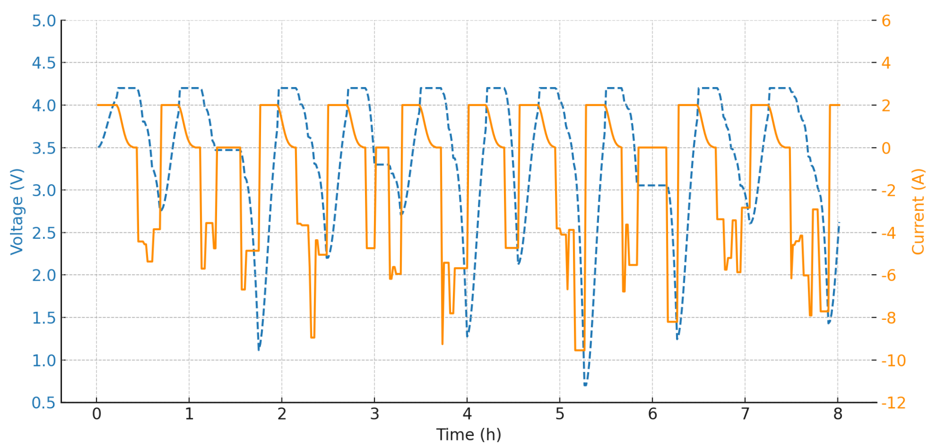

Figure 3: Battery current (solid yellow line) and voltage (dashed blue line) curves for an eight hour delivery simulation with charging and discharging cycles for 1-cell and short delivery time (1C-S) scenario.

Figures 3, 4, 5 and 6 depict the V–I profiles of the battery corresponding to the four simulated scenarios. These curves reflect the dynamics analyzed in the methodology section and thus, the battery follows the sequence of operational cycle defined in the agent-based statechart: constant current charging phase with increasing voltage that transitions into a constant voltage phase where current gradually decreases as the battery approaches full charge, until reaching the cutoff current threshold I_{cutoff}. Once charged, the battery enters the resting state where there is no current, that coincides with the loading of parcels into the vehicle. After some minutes resting, the battery enters the discharging phase, with load-dependent, randomly generated current steps that reflect realistic variations in payload and vehicle performance, which show the stepwise pattern depicted in the figure. The larger capacity battery scenarios (2C-S and 2C-L) reach higher voltage levels, and show faster transitions, consistent with a higher charging current and charging capacity. Additionally, the number of full charge cycles differs across scenarios and as expected, in short-duration simulations, fewer charge cycles are completed with 10 charges in 1C-S compared to 13 charges in 1C-L and 5 charges in 2C-S compared to 9 charges in 2C-L during the 8 hour simulated time. Moreover, batteries with smaller capacity (1C-S and 1C-L) require more frequent charging than the larger capacity batteries (2C-S and 2C-L), which is consistent with their lower nominal energy storage capacity.

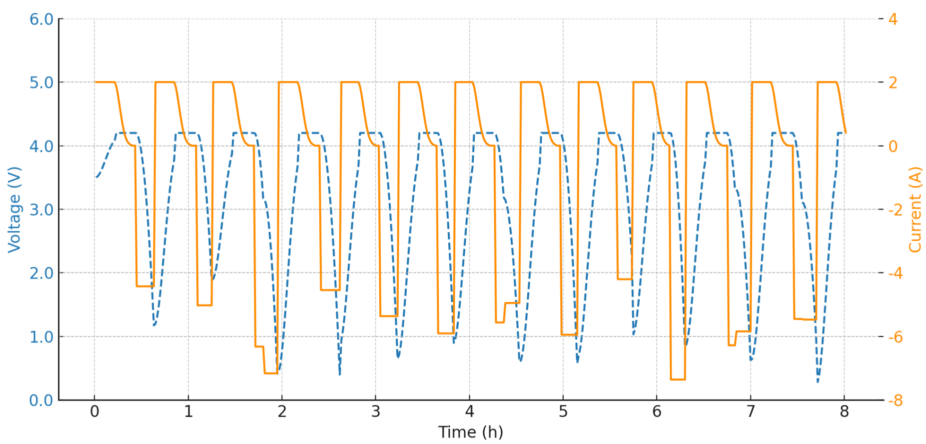

Figure 4: Battery current (solid yellow line) and voltage (dashed blue line) curves for an eight hour delivery simulation with charging and discharging cycles for 1-cell and long delivery time (1C-L) scenario.

Boxplots in Figure 7 summarize the distance traveled by the delivery vehicle in each simulation scenario for a given delivery, providing insights of how the battery capacity, speed and load conditions influence in the vehicle range. As expected, the scenarios where travel times were set to be larger (1C-L and 2C-L) present larger average delivery distances (around 750 meters), while shorter time scenarios (1C-S and 2C-S) have average distance of 300 meters. The dispersion of the obtained traveled distance comes from the random generation of payload and speed parameters, demonstrating the capacity of the simulation to reproduce realistic delivery behavior in urban logistics operations. However, it is important to note that these figures refer to the distance per individual delivery done and therefore, they do not account for the total number of deliveries performed during the simulation. Scenarios with greater battery capacity (2C-S and 2C-L) enable the vehicle to complete more delivery cycles before needing to stop for a recharge, leading to greater overall energy consumption despite similar average distances per trip. For instance, if we compare the simulation outputs in Figures 3 and 5, we observe that in the first charge–discharge cycle of the short-distance 1C-S scenario only three steps of negative current appear, indicating that just two deliveries and a return trip were completed before charging was needed. In contrast, the larger battery in the 2C-S scenario allows the vehicle to carry out seventeen deliveries, including two return trips to the

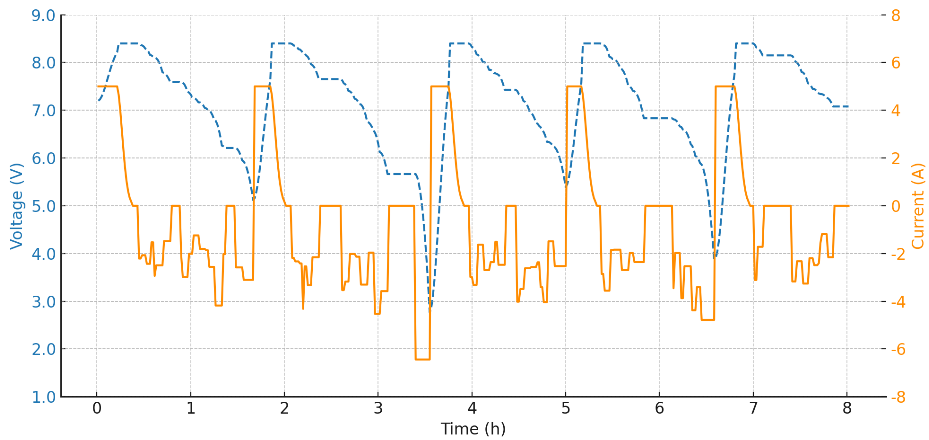

Figure 5: Battery current (solid yellow line) and voltage (dashed blue line) curves for an eight hour delivery simulation with charging and discharging cycles for 2-cell and short delivery time (2C-S) scenario.

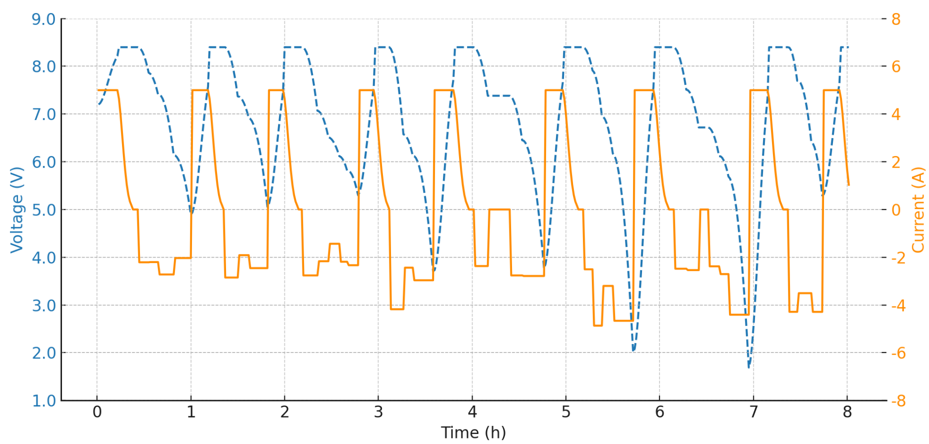

Figure 6: Battery current (solid yellow line) and voltage (dashed blue line) curves for an eight hour delivery simulation with charging and discharging cycles for 2-cell and long delivery time (2C-l) scenario.

station, first to reload the vehicle with more deliveries and second to recharge the battery. This is reflected by eighteen distinct discharging steps in the current profile in Figure 5.

Lastly, the evolution of the battery power profile and its corresponding to the SoC over time were analyzed. Figure 8 presents a representative charge–discharge cycle selected from the 2C-S scenario to illustrate an example of the relationship between power and SoC within the simulation. Positive power values represent energy input during charging and negative power values represent the energy consumption discharging the battery by the delivery vehicle. These negative and positive values are directly linked to the energy balance concept, as the integral of the integral of the power curve (the area under the curve) indicates the total energy stored or released by the battery throughout the charging and discharging cycle. In Figure 8, it can be seen how the areas under the positive and negative phases are approximately the same, suggesting that most of the energy stored in the charging state is later consumed in the discharging state, validating the the energy conservation and logic of the simulation model. Besides, the SoC line matches the power profile, as it increases fast in the CC and steadily in the CV charging and decreases stepeddly during the discharging state.

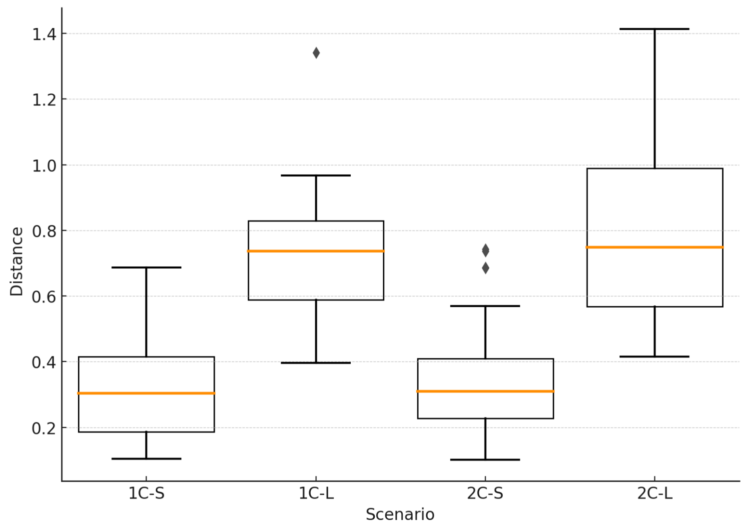

Figure 7: Distance traveled by the vehicle in each delivery for all the simulation scenarios.

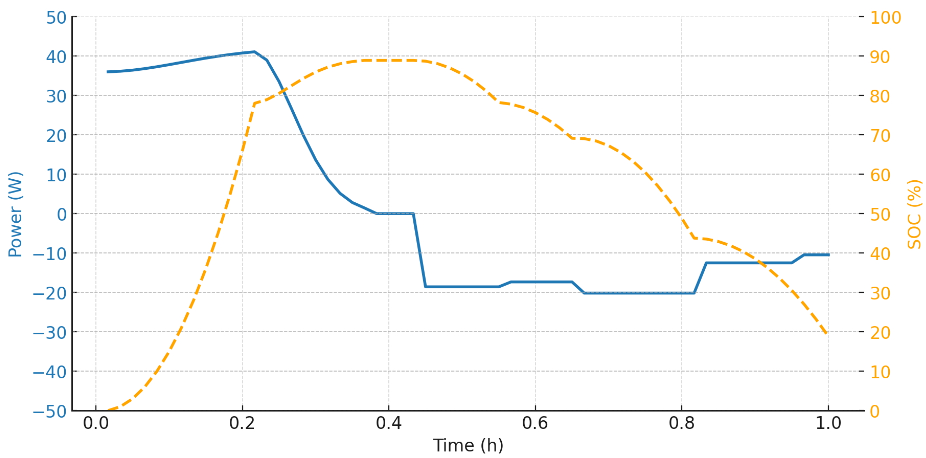

Figure 8: Power (solid blue line) and SoC (dashed yellow line) of a single charge–discharge cycle selected from the 2C-S scenario.

6 CONCLUSIONS

This work studies the performance of electric vehicle batteries operating under realistic delivery scenarios on an urban area. A simulation framework based on agent-based modeling is used to assess electric vehicle battery parameters, such as voltage, current, power consumption profiles, and state of charge (SoC), for a range of delivery scenarios. The simulation framework integrates a battery model that that includes an electrical and mechanical model. This includes capturing the voltage–current dynamics during discharge and charge states, that provide an accurate description of energy consumption during the delivery operations. The electric battery behavior is simulated using an equivalent circuit model, while the mechanical power is computed from the forces applied to the vehicle dynamics. There are two major conclusions derived from this work. On the one hand, the impact of battery capacity, payload, and distance on battery performance has been proven, as we evaluated how varying these factors influences the vehicle energy efficiency and the charging frequency of electric delivery vehicles batteries. The experimental results obtained through different battery configurations and operational parameters demonstrate how battery size influences not only the maximum travel range per delivery but also the frequency of recharging and the delivery performance over time. Specifically, higher capacity batteries demonstrate notable advantages in terms of operational continuity, allowing more deliveries to be completed with charging cycles. These findings provide insights into the operational limits of this vehicles, as well as battery management strategies and understanding energy consumption patterns. On the other hand, we explored the integration of electrical and mechanical models and demonstrated the advantages of using agent-based modeling to tackle battery powered delivery vehicles, a novel approach in logistics literature. This modeling framework offers an accurate representation of the energy flows in electric vehicles, providing a decision-making tool for route planning and optimization, vehicle operation strategies, and charging infrastructure planning, and ultimately improve the sustainability and reliability of last-mile delivery systems.

Future work should explore the extension of this simulation model to a fleet of vehicles rather than a single battery analysis, simulating the interaction between multiple delivery agents and customer agents in urban logistics scenarios. Additionally, the model could be extended to a multi-modal delivery framework that incorporates various types of electric delivery vehicles, both ground and aerial, for urban logistics solutions. Besides, using simulation power consumption patterns could be evaluated to compare delivery performance, energy efficiency, range limitations, and operational constraints between ground-based EV such as autonomous delivery robots, e-trucks or e-vans, and aerial drones. Furthermore, from a methodological point of view, the simulation model could be extended by incorporating methodologies such as optimization techniques and AI-driven algorithms. Such extension would support the development of integrated multi-modal delivery systems. In particular, incorporating advanced BMS functions such as machine learning based state of health (SoH) estimation would enhance the simulation model. These extensions would provide a more robust framework for decision-making related to battery management, infrastructure planning, and operational strategies under real-world uncertainty.

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