

Article

Reproducible State-of-Charge and Range Evaluation of a 350 W Electric Scooter Under an Urban NEDC Driving Cycle

Juan C. Castro-Galeano ¹, Edgar E. Tibaduiza-Rincon ¹ and Freddy F. Valderrama ^{2,*}

¹ School of Electromechanical Engineering, Duitama Branch Faculty, Pedagogical and Technological University of Colombia (UPTC), Carrera 18 with Calle 22, Duitama 150461, Colombia ;

juan.castrogaleano@uptc.edu.co (J.C.C.-G.); edgar.tibaduiza@uptc.edu.co (E.E.T.-R.)

² School of Industrial Education, Duitama Branch Faculty, Pedagogical and Technological University of Colombia (UPTC), Carrera 18 with Calle 22, Duitama 150461, Colombia; freddy.valderrama@uptc.edu.co (F.F.V.)

* Correspondence: freddy.valderrama@uptc.edu.co

Abstract

This article presents an experimental–computational methodology for evaluating the state of charge (SoC), energy consumption, terminal-voltage behavior, and driving range of a 350 W electric scooter powered by a 36 V, 7.8 Ah lithium-ion battery. The test was carried out using a 117 s elementary urban driving cycle derived from the low-speed section of the New European Driving Cycle (NEDC) and limited to the 32 km/h operating speed of the scooter. Laboratory measurements were performed on rollers under controlled conditions. Battery current and terminal voltage were recorded during the discharge test. The experimental SoC was reconstructed from the measured current by trapezoidal Coulomb counting. The voltage-derived SoC values included in the original laboratory file were kept only for traceability, since they did not correspond to current integration. A MATLAB/Simulink model was developed to reproduce the driving cycle, longitudinal vehicle dynamics, DC motor demand, battery current, and SoC evolution. The valid experimental endpoint occurred at 5233 s, when the terminal voltage reached 31.50 V. At this point, the tested distance was 16.49 km, the discharged capacity was 5.817 Ah, and the final experimental SoC was 25.42%. The simulation produced a discharged capacity of 5.147 Ah and a final SoC of 34.01%, with a charge deviation of 11.51%. Energy consumption was also evaluated from the measured and simulated electrical power. The experimentally integrated discharged energy was 208.10 Wh, equivalent to 12.62 Wh/km. The simulated electrical demand was 184.41 Wh, equivalent to 11.18 Wh/km. A semiempirical terminal-voltage reconstruction, based on the simulated SoC, current demand, an open-circuit-voltage curve, and a fixed internal resistance, reproduced the global voltage-decay trend observed in the experiment. The simplified model captured the general discharge behavior, although it underestimated the measured charge and energy demand. The proposed workflow provides a reproducible basis for comparing manufacturer-declared range, laboratory measurements, current-based SoC reconstruction, energy consumption, and simplified simulation results in light electric vehicles.



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Keywords: Coulomb counting; driving range; electric scooter; lithium-ion battery; light electric vehicles; MATLAB/Simulink; NEDC; state of charge

1. Introduction

Electric mobility has gained increasing relevance as part of the transition toward lower-emission transportation systems and more sustainable urban mobility strategies. The evolution of electric and hybrid electric vehicles has been widely discussed from technological, historical, and system-level perspectives, highlighting advances in powertrains, energy storage systems, power electronics, control strategies, and vehicle integration [1,2]. In this context, light electric vehicles and electric micromobility platforms have become increasingly relevant for short-distance urban trips, particularly because they require lower energy per trip, occupy less road space, and can complement conventional public and private transportation systems.

In Colombia, the institutional framework for electric mobility has progressively expanded. Law 1964 of 2019 promoted the adoption of electric vehicles through incentives such as tax benefits, reductions in vehicle taxes, discounts on Mandatory Traffic Accident Insurance (SOAT), and exemptions from license plate-based traffic restrictions [3]. More recently, the regulatory discussion has moved toward light electric vehicles intended for personal urban mobility. Law 2486 of 2025 defines these vehicles as electrically assisted or electrically propelled urban mobility devices with nominal powers below 1000 W, including electric scooters and similar micromobility platforms [4]. At the same time, the Colombian Ministry of Transport has advanced regulatory proposals aimed at establishing operational and safety conditions for electric scooters, electric bicycles, monocycles, and related micromobility systems [5]. These regulatory developments show that electric micromobility is no longer only a technological trend, but also an emerging component of national mobility policy.

The growth of the Colombian electric mobility sector is also reflected in recent transportation statistics. According to the National Traffic Registry (RUNT), motorcycles represented the largest share of the Colombian vehicle fleet in 2024, with 12,417,740 registered units, while electric vehicles reached 42,615 initial registrations, corresponding to a growth of 53.8% [6]. In parallel, FENALCO and ANDI reported 7294

electric vehicles registered during the first semester of 2025, with a 204% increase compared with the same period of the previous year [7]. Although a significant fraction of these registrations corresponds to passenger vehicles, these figures illustrate the accelerated expansion of electric mobility technologies in the country and reinforce the relevance of evaluating low-power electric transportation systems under realistic operating conditions.

The deployment of electric mobility also depends on incentives, charging infrastructure, and interoperability mechanisms. UPME has documented incentives and certification procedures for electric and hybrid vehicles [8], as well as technical guidelines for the implementation of the System for the Interoperability of Electromobility (SIEM) [9]. In addition, the Ministry of Mines and Energy of Colombia and the World Bank have analyzed business models for electric vehicle charging infrastructure in Colombia [10]. These aspects are relevant because the adoption of electric vehicles depends not only on vehicle performance, but also on the availability of supporting infrastructure, regulatory clarity, charging services, and economic feasibility.

Battery electric vehicles (BEVs) depend directly on electrochemical energy storage systems, making battery performance a central aspect of vehicle operation. In the case of light electric vehicles, the reduced battery capacity and low-power drivetrain configuration make the effective driving range especially sensitive to operating conditions, user weight, driving profile, terrain, rolling losses, and energy management. Charge and discharge cycles also influence battery lifetime and total cost of ownership, especially when battery sizing and charging strategies are considered in commercial electric vehicle applications [11]. Although battery testing and maintenance practices have been standardized for station-

ary applications, including vented lead–acid and nickel–cadmium batteries [12,13], the experimental evaluation of small lithium-ion battery packs in light electric vehicles requires procedures adapted to dynamic operating conditions and vehicle-level energy demand.

State-of-charge (SoC) estimation is therefore essential for evaluating vehicle autonomy, battery utilization, and discharge behavior. Research on lithium-ion batteries has addressed SoC estimation, battery degradation, energy management, and battery modeling from different perspectives [14–16]. Xiong et al. [17] reviewed several SoC estimation approaches, including lookup tables, ampere-hour integral methods, electrochemical models, equivalent circuit models, electrochemical impedance models, and data-driven techniques. Other studies have explored combined strategies, such as Coulomb counting and fuzzy logic methods, for lithium-ion battery SoC estimation [18]. These approaches demonstrate the importance of accurate SoC estimation; however, in low-power electric scooters, experimental current integration remains particularly useful because it provides a transparent and reproducible basis for reconstructing discharge behavior from measured data.

Vehicle simulation environments have also played an important role in the analysis of electric mobility systems. MATLAB/Simulink and related computational platforms have been used to represent vehicle dynamics, power demand, battery discharge, and energy management strategies. Yuniarto et al. [19] modeled, simulated, and validated the energy consumption of an electric scooter, while Jorge et al. [20] studied an electric scooter using a dynamic modeling approach. Wu et al. [21] presented rapid-prototyping designs for a hybrid electric scooter with fuzzy-control energy management, and the MathWorks Formula Student demo files provide a reference simulation environment for vehicle modeling and energy analysis [22]. These works support the use of computational models as tools for understanding vehicle energy behavior, provided that simulation results are compared with experimental evidence.

Driving-cycle-based simulation has been widely used to evaluate vehicle energy consumption under controlled and repeatable operating conditions. Teoh et al. [23] analyzed electric vehicle performance under the Worldwide Harmonized Light Vehicles Test Procedure using vehicle simulation models in ADVISOR. Software-based approaches for simulating the energetic behavior of electric vehicles have also been reported in academic work [24]. From a vehicle dynamics perspective, longitudinal motion, rolling resistance, tire behavior, and traction demand must be represented with sufficient consistency to relate a prescribed speed profile to power consumption and battery discharge [25]. These elements are particularly important for light electric vehicles, where small variations in load, speed, or resistance forces can significantly affect the estimated driving range.

Recent studies on electric micromobility have expanded the discussion toward energy consumption modeling, operational planning, charging infrastructure, and shared mobility systems. Ding et al. [26] proposed data-driven models for energy consumption estimation in electric micromobility systems using open datasets, while Liu and Ouyang [27] analyzed charging station planning and service operations for dockless electric micromobility systems. In the Colombian context, Carrillo Pallares [28] discussed the contribution of electric scooters to sustainable urban mobility, and Cuéllar analyzed emissions and ownership-cost aspects of conventional and electric vehicles under Colombian operating conditions [29]. These studies confirm the relevance of electric scooters and similar vehicles within the broader discussion on sustainable urban mobility, but they also reveal the need for reproducible experimental procedures focused on vehicle-level energy behavior.

Despite these advances, reproducible experimental procedures for evaluating the driving range and discharge behavior of light electric vehicles remain limited. Manufacturer-reported range values are frequently obtained under proprietary or simplified conditions, making direct comparison difficult. Experimental datasets are often unavailable, and the

relationship between driving-cycle implementation, vehicle dynamics, laboratory measurements, and SoC reconstruction is not always explicitly documented. This becomes particularly relevant in low-power electric scooters, where relatively small variations in load, rolling resistance, or speed profile can produce noticeable differences in energy consumption and effective range.

The present work addresses this problem through a reproducible experimental–computational framework for evaluating the discharge behavior and operating range of a 350 W electric scooter powered by a 36 V, 7.8 Ah lithium-ion battery. The urban segment of the New European Driving Cycle (NEDC), defined in Directive 91/441/EEC [30], was selected because its velocity profile is compatible with the speed limitations of the tested scooter and can be reproduced under controlled roller-based laboratory conditions.

The proposed methodology combines laboratory testing with a MATLAB/Simulink implementation that includes the driving cycle, longitudinal vehicle dynamics, motor demand, and battery discharge behavior. Experimental SoC reconstruction was performed through trapezoidal integration of the measured battery current, while voltage-derived SoC indicators were retained only for traceability purposes because terminal voltage is affected by load-dependent recovery effects and transient polarization phenomena.

The contribution of this work lies in the development of a reproducible framework that allows the comparison between manufacturer-declared range, experimentally measured discharge behavior, and simulation-based energy estimation under controlled operating conditions. The results provide quantitative evidence regarding the gap between simplified simulation models and laboratory behavior in light electric vehicles, while also contributing to the discussion on reproducible testing methodologies for electric micromobility systems.

The remainder of this paper is organized as follows. Section 2 presents the experimental and computational framework, including the driving cycle implementation, laboratory setup, vehicle model, and SoC reconstruction procedure. Section 3 describes the simulation and experimental results, together with the comparison between measured and simulated battery discharge behavior. Finally, Section 4 summarizes the main conclusions and discusses possible directions for future work.

2. Experimental and Computational Framework

2.1. Case Study and Driving Cycle

The case study corresponds to a commercial 350 W electric scooter powered by a 36 V, 7.8 Ah lithium-ion battery pack. According to the manufacturer specifications, the scooter reaches a maximum speed of 32 km/h and provides an estimated driving range of approximately 25 km under unspecified operating conditions. The scooter mass is 12.5 kg and the maximum recommended rider mass is 80 kg. In the experimental tests, a rider mass of 70 kg was considered, resulting in a total moving mass of 82.5 kg.

The scooter includes two operating modes. The first mode, referred to as Normal Drive, limits the speed to approximately 20 km/h. The second mode, Super Sport, enables a maximum speed of 32 km/h. Because of these speed limitations, only the low-speed urban component of the New European Driving Cycle (NEDC) was implemented.

Figure 1 compares the complete NEDC profile with the 117 s elementary urban cycle implemented in this work. The extra-urban portion of the NEDC was not considered because its speed levels exceed the physical operating limit of the tested scooter. The implemented profile therefore preserves the low-speed urban structure of the standard while remaining compatible with the available driving modes of the vehicle.

The adopted driving profile was constructed from two elementary urban segments. The first segment includes an acceleration phase up to 15 km/h, consistent with the Normal Drive operating mode. The second segment reaches 32 km/h, corresponding to

the maximum speed available in Super Sport mode. The complete elementary cycle has a duration of 117 s and was repeated 45 times during the discharge test, resulting in a programmed duration of 5265 s.

The implemented profile should therefore be interpreted as an urban NEDC-derived cycle adapted to the physical speed limit of the scooter, rather than as a full representation of the complete NEDC statistical structure.

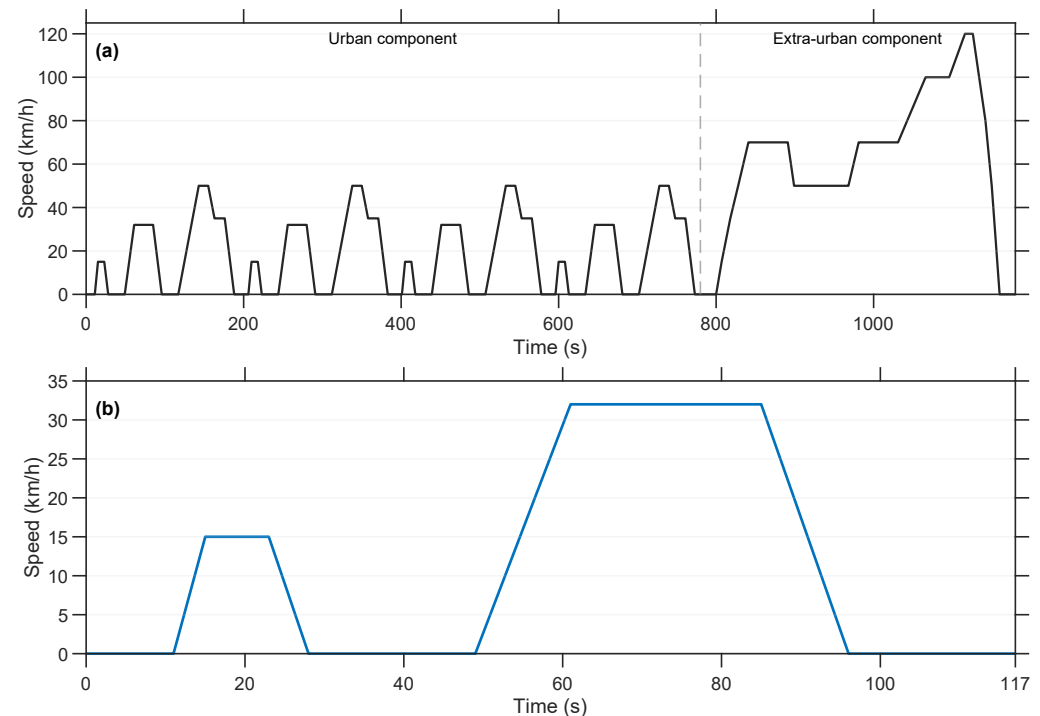


Figure 1. Comparison between the original New European Driving Cycle (NEDC) and the 117 s elementary urban driving cycle implemented for the tested scooter. (a) Complete NEDC profile. (b) Implemented urban profile constrained to the 32 km/h operating limit of the vehicle.

2.2. Experimental Setup and Data Acquisition

Experimental validation was conducted at the Electromechanical Testing Laboratory (LEM) [31] of the Pedagogical and Technological University of Colombia under controlled indoor conditions. Ambient temperature was maintained at approximately $(20 \pm 0.5)^\circ\text{C}$ with relative humidity close to 60%.

The scooter was mounted on a roller dynamometer system to reproduce the prescribed urban driving cycle while keeping the vehicle stationary. This configuration allowed repeatable traction conditions and controlled execution of the speed profile.

Battery current was measured using a calibrated Fluke 374 FC DC clamp meter (Fluke Corporation, Everett, WA, USA; purchased by the Electromechanical Testing Laboratory in Bogotá, Colombia) with an accuracy of $\pm 2\%$ of the reading. Terminal voltage was measured using a Fluke 287 digital multimeter (Fluke Corporation, Everett, WA, USA; purchased by the Electromechanical Testing Laboratory in Bogotá, Colombia) with an accuracy of $\pm 0.025\%$.

Prior to the discharge test, the battery was fully charged using the charger recommended by the manufacturer. After charging, the battery remained in open circuit for approximately 30 min to reach a quasi-equilibrium condition. The measured open-circuit voltage after the resting period was 39.34 V and was associated with the fully charged initial condition.

For the experimental reconstruction, the initial state of charge was defined as

$$\text{SoC}_0 = 1.0. \quad (1)$$

Because the battery was fully charged with the manufacturer-recommended charger and allowed to rest before the discharge test. This initial condition refers to the fully charged state relative to the nominal capacity used in the analysis, and should not be interpreted as an independent verification of 100% battery state of health.

The discharge process continued until the terminal voltage approached the manufacturer cut-off voltage of 31.47 V. The last valid experimental record occurred at 5233 s with a measured voltage of 31.50 V. Two subsequent records were labeled as failure in the archived laboratory dataset and were excluded from the official analysis.

2.3. Experimental SoC Reconstruction

The laboratory dataset contained time, measured current, terminal voltage, and an auxiliary SoC column. Before validation, the dataset was audited to verify the physical consistency of the recorded variables. The original experimental timestamps were retained without interpolation or smoothing. The archived file contained 406 records, of which 404 were valid for the official analysis after excluding the two final records labeled as failure.

The SoC column included in the laboratory spreadsheet was found to correspond to a linear transformation of terminal voltage rather than to Coulomb counting. Since terminal voltage is affected by load recovery and polarization effects, this variable was retained only for traceability purposes and was not used as the primary experimental SoC reference.

Instead, the experimental SoC was reconstructed directly from the measured battery current using trapezoidal integration of the discharge current:

$$Q_{\text{exp}}(t_k) = \frac{1}{3600} \int_{t_0}^{t_k} I_{\text{exp}}(t) dt, \quad (2)$$

$$\text{SoC}_{\text{exp}}(t_k) = 1 - \frac{Q_{\text{exp}}(t_k)}{C_n}, \quad (3)$$

where $I_{\text{exp}}(t)$ is the measured battery current and $C_n = 7.8$ Ah is the manufacturer-rated nominal battery capacity. Therefore, the reconstructed SoC is expressed with respect to the nominal capacity of the battery pack. No independent capacity or state-of-health test was performed to determine the effective available capacity at the time of the experiment.

The use of trapezoidal integration was motivated by the nonuniform sampling intervals associated with operating-mode transitions during the laboratory test. Since all valid current samples were nonnegative, no regenerative correction was applied.

At the valid experimental endpoint, the reconstructed discharge capacity was 5.8170 Ah, corresponding to a final experimental SoC of 25.42%.

The ampere-hour integration method was selected because the objective of this work was not to design a high-fidelity BMS estimator, but to reconstruct the experimentally discharged capacity from directly measured current under a reproducible laboratory procedure. Model-based or data-driven estimators, such as Kalman-filter, ECM-based, or neural-network approaches, require additional parameter identification, training data, or electrochemical characterization that were outside the scope of this study.

2.4. MATLAB/Simulink Vehicle Model

A MATLAB/Simulink model was developed to reproduce the implemented driving cycle and estimate the battery discharge behavior of the scooter. The computational

framework integrates four main subsystems: driving cycle generation, longitudinal vehicle dynamics, DC motor representation, and battery response.

The driving-cycle subsystem generates the reference speed and acceleration associated with the implemented urban NEDC profile. Based on these variables, the longitudinal dynamics subsystem computes the traction force required to reproduce the prescribed motion while accounting for inertial, aerodynamic, rolling-resistance, and grade-related effects.

The traction force is expressed as

$$F_t = ma + mg \sin(\alpha) + \frac{1}{2}\rho C_x S v^2 + C_r mg \cos(\alpha), \quad (4)$$

where m is the total moving mass, a is acceleration, g is gravitational acceleration, α is the road slope angle, ρ is air density, C_x is the aerodynamic drag coefficient, S is the frontal area, v is vehicle speed, and C_r is the rolling resistance coefficient.

The wheel torque and required mechanical power are calculated as

$$T_w = F_t r, \quad (5)$$

$$P_m = F_t v, \quad (6)$$

where r is the wheel radius.

Figure 2 presents the implemented 117 s urban driving cycle together with the corresponding traction mechanical power demand obtained from the longitudinal vehicle dynamics model. The highest power demand occurs during the acceleration intervals, particularly during the transition toward the 32 km/h operating condition.

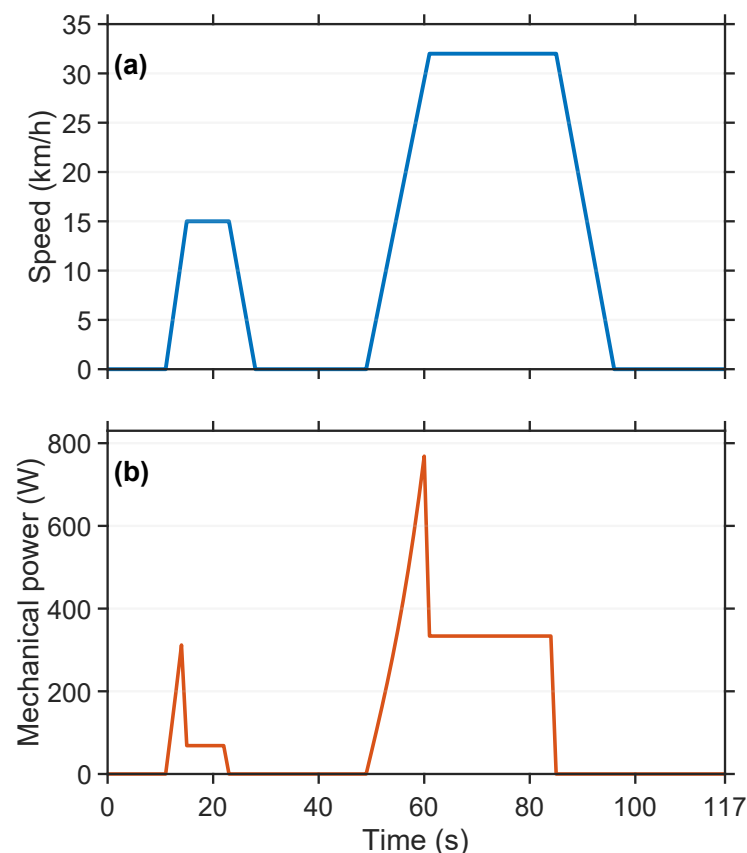


Figure 2. Implemented 117 s urban driving cycle and corresponding traction mechanical power demand. (a) Implemented 117 s urban driving cycle. (b) Corresponding traction mechanical power demand obtained from the longitudinal vehicle dynamics model.

The battery subsystem was implemented using the Battery block from the Specialized Power Systems library in MATLAB/Simulink. The battery was parameterized as a 36 V, 7.8 Ah lithium-ion pack with an initial SoC of 100%, a cut-off voltage of 31.47 V, and a constant internal resistance of 0.015 Ω .

Temperature effects, aging, hysteresis, polarization dynamics, and SoC-dependent internal resistance were not explicitly modeled. These simplifications were adopted to preserve transparency and reproducibility of the computational framework while maintaining consistency with the available experimental information.

Figure 3 summarizes the complete experimental–computational validation workflow adopted in this study. The framework connects the urban NEDC driving cycle, the roller-based laboratory measurements, the reconstruction of the experimental SoC through Coulomb counting, the MATLAB/Simulink vehicle model, and the validation metrics used to compare measured and simulated battery discharge behavior.

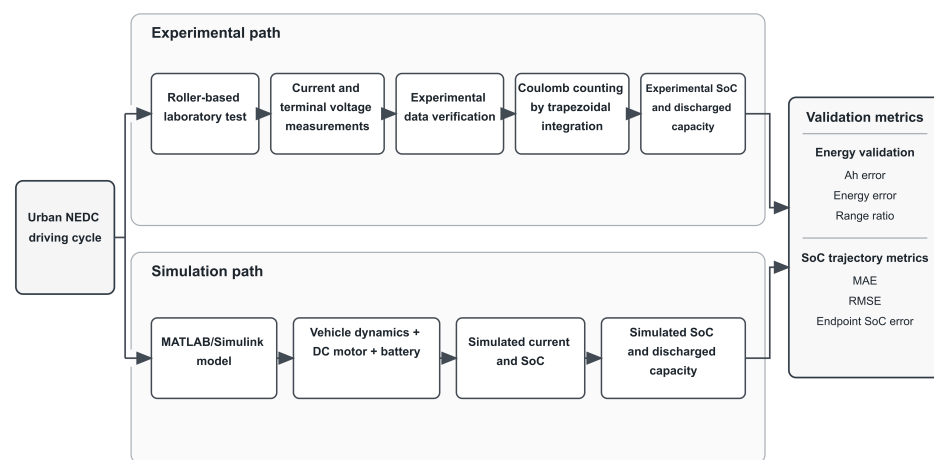


Figure 3. Experimental–computational validation workflow used to evaluate the battery discharge, state of charge, and driving range of the electric scooter under the implemented urban NEDC profile.

Figure 4 presents the computational architecture of the MATLAB/Simulink model used to reproduce the driving cycle, vehicle dynamics, DC motor demand, battery response, and SoC estimation process.

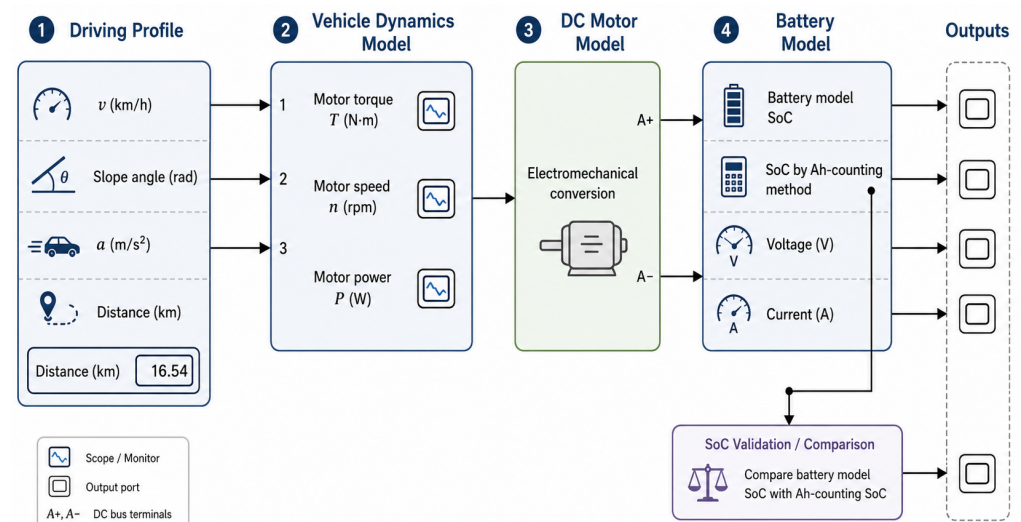


Figure 4. Computational architecture of the MATLAB/Simulink model used to reproduce the electric scooter driving cycle, motor demand, battery response, and SoC estimation.

2.5. Model Parameters

Table 1 summarizes the main parameters used to configure the experimental scooter model in MATLAB/Simulink. The electrical parameters were defined from the battery nameplate information and the available laboratory measurements. The nominal voltage and rated capacity correspond to the 36 V, 7.8 Ah lithium-ion battery pack used in the scooter, while the cut-off voltage was taken from the final valid discharge condition observed during the laboratory test. The initial SoC was set to 1.0 p.u. because the battery was fully charged before each test and allowed to rest before the discharge process.

The mechanical parameters were selected to represent the tested operating condition. The total moving mass includes the scooter mass and the rider mass used during the laboratory test. The aerodynamic and rolling-resistance parameters were kept constant during the simulation, which is consistent with the simplified longitudinal vehicle model adopted in this work. Since the objective was to obtain a reproducible first-order representation of the discharge behavior, temperature-dependent battery parameters, aging effects, and speed-dependent rolling losses were not included.

Table 1. Main parameters used in the MATLAB/Simulink scooter model.

Parameter	Symbol	Value	Unit
Nominal battery voltage	V_{nom}	36	V
Rated battery capacity	C_n	7.8	Ah
Initial state of charge	SoC_0	1.0	p.u.
Coulombic efficiency	η	1.0	–
Internal resistance	R_{int}	0.015	Ω
Cut-off voltage	V_{cut}	31.47	V
Scooter mass	m_s	12.5	kg
Rider mass	m_r	70	kg
Total moving mass	m	82.5	kg
Air density	ρ	1.225	kg/m^3
Drag coefficient	C_x	0.9	–
Frontal area	S	0.62	m^2
Rolling resistance coefficient	C_r	0.013	–
Wheel radius	r	0.108	m
Sampling time	T_s	1	s
Maximum speed	v_{max}	32	km/h

2.6. Canonical Reproducible Workflow

To guarantee reproducibility and avoid dependence on implicit MATLAB workspace variables, the final analysis was organized into a canonical execution pipeline.

The workflow automatically reads the archived laboratory Excel file, identifies the relevant columns from their headers, excludes the records labeled as failure, reconstructs the experimental SoC using trapezoidal current integration, executes the MATLAB/Simulink model, and computes the charge, energy, range, and SoC comparison metrics.

The experimental SoC reconstruction was performed exclusively from the measured battery current through Coulomb counting. During the audit of the archived laboratory spreadsheet, it was verified that the stored spreadsheet SoC values corresponded to a voltage-derived indicator rather than to direct ampere-hour integration. For this reason, those voltage-derived values were retained only for traceability and were not used as the primary validation reference.

The complete programmed distance associated with the 45-cycle profile was 16.5438 km. Since the valid experimental endpoint occurred before the final programmed record, the effective tested distance was computed using only the valid experimental interval.

The canonical pipeline also performs automatic consistency checks, including deterministic re-execution tests, validation of the laboratory file structure, and comparison between MATLAB numerical integration and Simulink outputs. These procedures were incorporated to ensure that the reported results can be reproduced without manual intervention or hidden preprocessing steps.

3. Results and Discussion

3.1. Experimental Data Audit and SoC Reconstruction

Before comparing the experimental measurements with the simulation results, the laboratory dataset was audited to verify the consistency of the recorded variables. The implemented 117 s elementary urban cycle, shown in Figure 2a, was repeated 45 times during the discharge test. The programmed duration was 5265 s, whereas the last valid laboratory record occurred at 5233 s, when the terminal voltage reached 31.50 V, close to the manufacturer cut-off voltage of 31.47 V. Two subsequent records were labeled as failure in the archived dataset and were excluded from the official analysis. Consequently, the valid tested distance was 16.4949 km.

The dataset included time, measured current, terminal voltage, and an auxiliary SoC column. The current measurements were verified against the acquisition setup and confirmed to correspond to the real battery current after applying the scaling associated with the clamp measurement configuration. All valid current samples remained nonnegative during the test, indicating the absence of regenerative current under roller-based operation.

Figure 5 presents the measured terminal-voltage evolution during the repeated execution of the implemented urban driving cycle. The voltage exhibits the expected progressive decrease associated with the increase in depth of discharge. Periodic oscillations are also observed because of the transient traction demand imposed by the acceleration and deceleration intervals of the driving cycle.

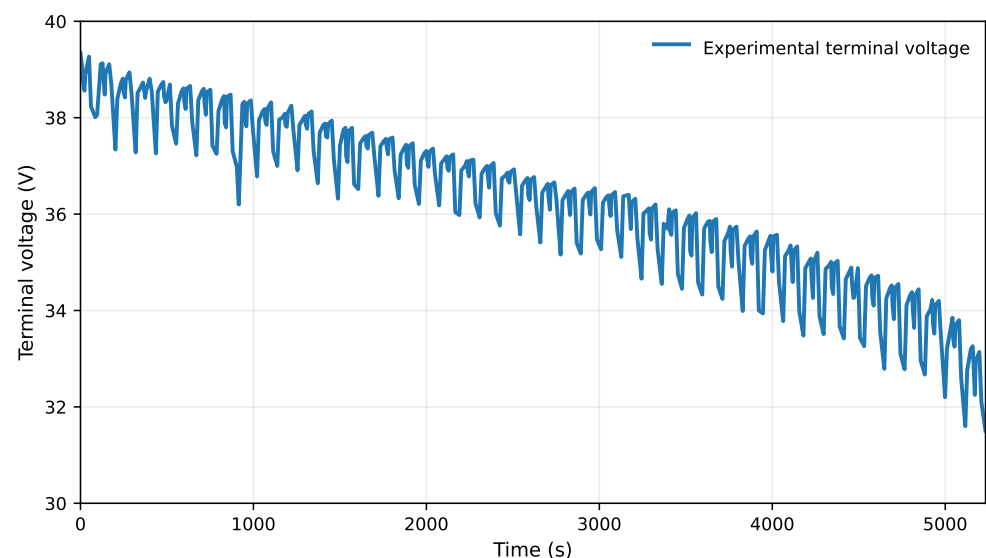


Figure 5. Measured terminal-voltage evolution during the repeated execution of the implemented urban driving cycle.

A relevant observation obtained during the audit was that the SoC column contained in the laboratory spreadsheet did not correspond to Coulomb counting. Instead, it was found to be a linear transformation of terminal voltage between the fully charged condition and the cut-off voltage. Since terminal voltage is affected by load recovery and polarization

effects, this variable was retained only for traceability purposes and was not used as the experimental SoC reference.

The experimental SoC was therefore reconstructed directly from the measured battery current using trapezoidal integration. At the valid experimental endpoint, the reconstructed discharge capacity was

$$Ah_{\text{exp}} = 5.8170 \text{ Ah}, \quad (7)$$

which corresponds to a final experimental state of charge of

$$SoC_{\text{exp,final}} = 1 - \frac{5.8170}{7.8} = 0.2542, \quad (8)$$

equivalent to 25.42%.

Table 2 summarizes the measured variables for one representative elementary urban cycle.

Table 2. Laboratory measurements obtained during one elementary urban cycle.

Mode	Time (s)	Real Current (A)	Terminal Voltage (V)
Stop	0	0.000	39.34
Stop	11	0.000	39.01
Accelerate	15	4.207	38.73
Constant 15 km/h	23	5.478	38.56
Brake	28	3.769	38.90
Stop	49	0.061	39.27
Accelerate	61	7.413	38.23
Constant 30 km/h	85	8.504	38.01
Brake	96	6.593	38.06
Stop	117	0.063	39.11

3.2. Simulation Results

The MATLAB/Simulink model was executed using the canonical scooter parameters summarized in Table 1. The simulation reproduced the implemented driving cycle and estimated the corresponding battery discharge behavior throughout the complete test horizon.

At the valid experimental endpoint of 5233 s, the simulated discharged capacity was

$$Ah_{\text{sim}} = 5.1474 \text{ Ah}, \quad (9)$$

which corresponds to a final simulated state of charge of

$$SoC_{\text{sim,final}} = 1 - \frac{5.1474}{7.8} = 0.3401, \quad (10)$$

equivalent to 34.01%.

The simulated discharge capacity is lower than the experimentally reconstructed value. This difference is analyzed in the following subsection through the comparison between the experimental and simulated SoC trajectories and the accumulated discharge metrics.

3.3. Comparison Between Experimental and Simulated Discharge

Figure 6 compares the experimentally reconstructed SoC obtained from trapezoidal integration of the measured current and the simulated SoC trajectory produced by the MATLAB/Simulink model.

Both trajectories exhibit the same global discharge tendency throughout the test. The simulated SoC decreases monotonically and follows the general behavior observed experimentally. However, the simulated trajectory remains above the experimental reconstruction

for most of the discharge process, indicating that the model underestimates the accumulated battery discharge under the implemented laboratory conditions.

The absolute charge difference between the experiment and the simulation was

$$\Delta Ah = 5.8170 - 5.1474 = 0.6696 \text{ Ah}, \quad (11)$$

which corresponds to a relative charge deviation of 11.51%.

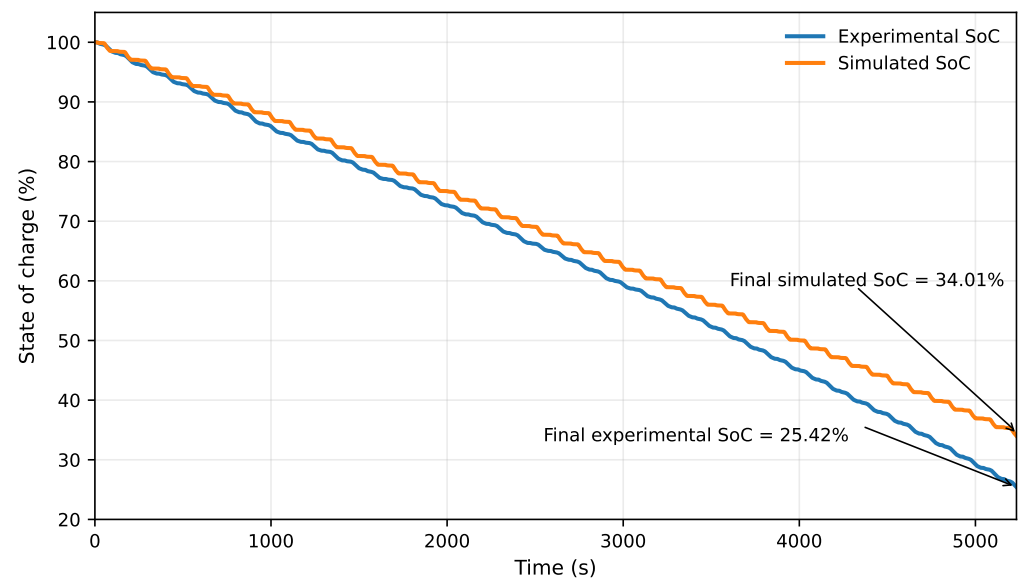


Figure 6. Comparison between experimentally reconstructed SoC and simulated SoC under the implemented urban driving cycle.

Similarly, the final SoC difference between experiment and simulation was approximately 8.58 percentage points.

The observed deviation is attributed to the simplified battery and drivetrain representations adopted in the MATLAB/Simulink model. In particular, the model assumes constant internal resistance, unity Coulombic efficiency, idealized traction conditions, and does not explicitly represent thermal effects, hysteresis, aging, controller-efficiency variations, roller-bench losses, or load-dependent electrochemical dynamics. Experimental uncertainties associated with current measurements and roller-based operation may also contribute to the cumulative discrepancy. Table 3 summarizes the main comparison metrics obtained at the valid endpoint.

Table 3. Comparison between experimental and simulated discharge results.

Quantity	Experimental	Simulation	Difference
Valid time (s)	5233	5233	–
Valid distance (km)	16.4949	16.4949	–
Discharge capacity (Ah)	5.8170	5.1474	0.6696 Ah
Final SoC (%)	25.42	34.01	8.58 p.p.
Relative charge error (%)	–	–	11.51

3.4. Energy Consumption and Specific Mobility Metrics

In addition to the discharged capacity and SoC trajectories, energy-based mobility metrics were computed to provide a more direct interpretation of the scooter performance under the implemented urban driving cycle. For the experimental test, the discharged

energy was obtained by trapezoidal integration of the instantaneous electrical power calculated from the measured terminal voltage and battery current:

$$E_{\text{exp}} = \frac{1}{3600} \int_{t_0}^{t_f} V_{\text{exp}}(t) I_{\text{exp}}(t) dt, \quad (12)$$

where $V_{\text{exp}}(t)$ is the measured terminal voltage, $I_{\text{exp}}(t)$ is the measured battery current, and t_f corresponds to the last valid experimental record. The same endpoint used in the SoC analysis was retained for the energy calculation. Therefore, the two final records labeled as failure in the original laboratory dataset were excluded, and the official comparison horizon ended at $t_f = 5233$ s, corresponding to a valid tested distance of 16.4949 km.

For the simulation, the integrated energy was computed from the electrical power exported by the canonical model:

$$E_{\text{sim}} = \frac{1}{3600} \int_{t_0}^{t_f} P_{\text{sim}}(t) dt. \quad (13)$$

The exported simulated electrical power was numerically equivalent to the product between the simulated current and the model terminal-voltage signal. However, the simulated terminal voltage corresponds to an algebraic fixed-source/internal-resistance representation and should not be interpreted as a validated electrochemical terminal-voltage response. Consequently, the simulated integrated energy is used here as a model-based electrical demand estimate.

Specific energy and charge consumption were calculated as

$$e_{\text{Wh/km}} = \frac{E}{d}, \quad (14)$$

$$q_{\text{Ah/km}} = \frac{Q}{d}, \quad (15)$$

where E is the discharged energy in Wh, Q is the discharged capacity in Ah, and d is the valid tested distance in km. Nominal energy values based on $36V \times Ah$ were also computed for traceability, but the integrated energy obtained from $V(t)I(t)$ was used as the primary experimental energy metric.

Table 4 summarizes the resulting energy and mobility indicators. The experimentally integrated discharged energy was 208.10 Wh, while the simulated model-based energy demand was 184.41 Wh. This represents a difference of 23.69 Wh, equivalent to a relative deviation of 11.38%. The corresponding specific integrated energy consumption was 12.62 Wh/km for the experimental test and 11.18 Wh/km for the simulation.

These results are consistent with the discharged-capacity comparison and confirm that the simplified model underestimates the electrical demand required to reproduce the laboratory driving-cycle test. The nominal energy values were close to the integrated-energy results because the equivalent average voltage during the valid interval remained near the nominal battery voltage. Nevertheless, the integrated energy obtained from $V(t)I(t)$ provides the most appropriate basis for reporting experimental energy consumption in the tested scooter.

Table 4. Energy consumption and mobility metrics obtained at the common valid endpoint of 5233 s. Experimental energy was computed by trapezoidal integration of measured terminal voltage and battery current. Simulated energy corresponds to the integrated electrical demand exported by the canonical model. Nominal energy values based on $36V \times Ah$ are included only for traceability.

Quantity	Experimental	Simulation	Difference	Relative Difference (%)
Valid endpoint time (s)	5233.0000	5233.0000	0.0000	0.0000
Valid distance (km)	16.4949	16.4949	0.0000	0.0000
Discharged capacity (Ah)	5.8170	5.1474	0.6696	11.5110
Integrated discharged energy (Wh)	208.1006	184.4148	23.6858	11.3819
Nominal discharged energy, $36V \times Ah$ (Wh)	209.4133	185.3078	24.1055	11.5110
Specific charge consumption (Ah/km)	0.3527	0.3121	0.0406	11.5110
Specific integrated energy consumption (Wh/km)	12.6161	11.1801	1.4359	11.3819
Specific nominal energy consumption (Wh/km)	12.6957	11.2343	1.4614	11.5110
Average electrical power (W)	143.1611	126.8667	16.2944	11.3819
Equivalent average voltage, Wh / Ah (V)	35.7743	35.8265	0.0522	0.1459
Range achieved with respect to manufacturer claim (%)	65.9794	65.9794	0.0000	0.0000

3.5. Semiempirical Terminal-Voltage Reconstruction

The original canonical MATLAB/Simulink implementation employed a simplified algebraic voltage representation based on a constant nominal voltage source and fixed internal resistance. Although this approach preserved consistency between current, power, and Coulomb-counting calculations, it did not reproduce the progressive terminal-voltage decay experimentally observed during the discharge process.

To obtain a voltage trajectory more consistent with the measured battery behavior, a semiempirical terminal-voltage reconstruction was performed using the simulated current and state-of-charge signals. The reconstructed voltage was computed as

$$V_t(t) = V_{OC}(SoC(t)) - I(t)R_{int}. \quad (16)$$

where $V_t(t)$ is the reconstructed terminal voltage, V_{OC} is the open-circuit voltage associated with the simulated state of charge, $I(t)$ is the simulated battery current, and R_{int} is the constant internal resistance of the battery pack.

The open-circuit voltage was approximated through a piecewise-linear Li-ion open-circuit-voltage curve representative of a 36 V battery pack. The reconstruction used the simulated SoC trajectory obtained from Coulomb counting together with the simulated current demand generated by the vehicle model.

Figure 7 compares the experimentally measured terminal voltage and the reconstructed semiempirical voltage trajectory.

The reconstructed voltage reproduces the global decreasing tendency observed experimentally and captures the influence of the transient current demand imposed by the repeated urban driving cycles. Nevertheless, differences remain at low state-of-charge conditions because the adopted model does not include polarization effects, hysteresis, thermal behavior, or electrochemical aging mechanisms.

The comparison indicates that the simplified energetic model adopted in this work is sufficient to reproduce the global discharge tendency and energy consumption of the scooter under the implemented driving cycle, while still preserving transparency and reproducibility of the computational framework.

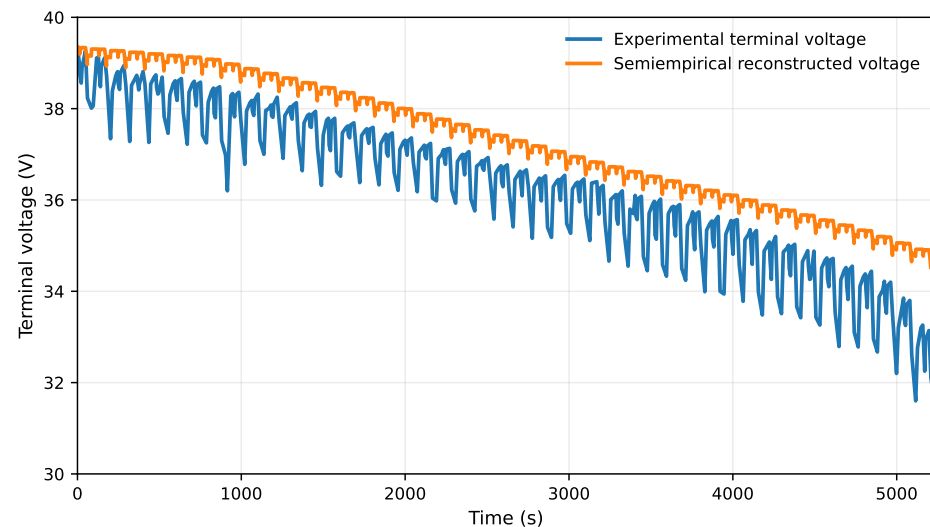


Figure 7. Comparison between experimentally measured terminal voltage and semiempirical reconstructed voltage obtained from the simulated SoC and current signals.

3.6. SoC Error Metrics

To quantify the agreement between the experimental and simulated trajectories, several error indicators were calculated, including mean absolute error (MAE), root mean square error (RMSE), maximum absolute error, and endpoint error. The obtained values are summarized in Table 5.

Table 5. Error metrics obtained from the comparison between experimental and simulated SoC trajectories.

Metric	Value (p.u.)	Percentage
MAE	0.033847	3.3847%
RMSE	0.040298	4.0298%
Maximum absolute error	0.089854	8.9854%
Endpoint error	0.085846	8.5846%

The results indicate that the simplified model reproduces the global discharge tendency but does not provide an exact prediction of the experimental battery behavior. The discrepancy increases progressively during the test because the simulated current remains systematically lower than the measured current.

3.7. Discussion of Model Deviations

The observed discrepancy cannot be explained exclusively by instrumentation uncertainty. The measurement uncertainties associated with the clamp meter and the digital multimeter are significantly smaller than the 11.51% charge deviation obtained during the comparison.

The deviation is mainly associated with the simplified assumptions adopted in the model. The computational framework uses an ideal prescribed speed profile rather than the measured roller speed, constant internal resistance, unity Coulombic efficiency, and simplified drivetrain representation. The model also neglects several physical effects that increase real energy consumption, including tire deformation on rollers, controller-efficiency variations, auxiliary consumption, thermal effects, and SoC-dependent internal resistance.

Under these conditions, the proposed framework should not be interpreted as a high-fidelity battery-management-system estimator. Instead, it provides a transparent and

reproducible first-order approximation of battery discharge behavior under controlled driving-cycle conditions.

From this perspective, the quantified deviation is itself an informative result because it reveals the magnitude of the difference between simplified simulation assumptions and experimentally observed operation.

3.8. Sensitivity Analysis

A sensitivity analysis was carried out to evaluate the influence of the initial SoC and the Coulombic efficiency on the reconstructed discharge behavior.

The initial state of charge was varied between 1.00, 0.98, and 0.95 p.u., while the Coulombic efficiency was varied between 1.00, 0.995, and 0.99.

Table 6 summarizes the obtained final SoC values.

The results show that variations in Coulombic efficiency produce relatively small changes in the final SoC when compared with the direct influence of the assumed initial state of charge. This indicates that the experimental reconstruction remains numerically stable provided that the fully charged initial condition is properly established.

Table 6. Sensitivity of final SoC to variations in initial SoC and Coulombic efficiency.

SoC ₀	η	Final SoC
1.00	1.000	0.25423
1.00	0.995	0.25796
1.00	0.990	0.26169
0.98	1.000	0.23423
0.98	0.995	0.23796
0.98	0.990	0.24169
0.95	1.000	0.20423
0.95	0.995	0.20796
0.95	0.990	0.21169

3.9. Range Assessment and Reproducibility

The effective tested distance obtained under the implemented urban driving cycle was 16.4949 km. This value is considerably lower than the approximately 25 km range declared by the manufacturer.

The obtained ratio between experimental and declared range is

$$\frac{16.4949}{25} = 0.6598, \quad (17)$$

which indicates that the scooter achieved approximately 66% of the declared range under the controlled test conditions implemented in this work.

All simulations were executed in MATLAB R2024a using Simulink and the Specialized Power Systems toolbox. The complete workflow, including the laboratory dataset audit, trapezoidal SoC reconstruction, simulation execution, and metric computation, was organized into a canonical reproducible pipeline. Under these conditions, the proposed methodology can be independently reproduced using equivalent laboratory instrumentation and MATLAB/Simulink configurations.

4. Conclusions

This work presented an experimental–computational framework for evaluating the state of charge, energy consumption, and effective driving range of a 350 W electric scooter powered by a 36 V, 7.8 Ah lithium-ion battery. The scooter was tested under a repeated 117 s urban driving cycle derived from the low-speed component of the NEDC and constrained

to the 32 km/h operating limit of the vehicle. The proposed workflow combined roller-based laboratory testing, current and terminal-voltage measurements, trapezoidal Coulomb counting, MATLAB/Simulink simulation, and reproducible post-processing of discharge, energy, and range metrics.

The experimental analysis showed that the valid test ended at 5233 s, when the terminal voltage reached 31.50 V, close to the manufacturer cut-off voltage of 31.47 V. The corresponding effective tested distance was 16.49 km, which represents approximately 66% of the 25 km range declared by the manufacturer. This result highlights the need for transparent and reproducible range-evaluation procedures for light electric vehicles, particularly because manufacturer-reported autonomy values are often obtained under undocumented or simplified operating conditions.

A key methodological result was the audit of the laboratory dataset. The SoC values originally stored in the experimental spreadsheet were found to correspond to a voltage-derived indicator rather than to Coulomb counting. Therefore, they were retained only for traceability and were not used as the experimental validation reference. The official experimental SoC trajectory was reconstructed directly from the measured battery current using trapezoidal integration. At the valid endpoint, the reconstructed discharged capacity was 5.8170 Ah, corresponding to a final experimental SoC of 25.42%.

The MATLAB/Simulink model reproduced the overall discharge tendency but underestimated the accumulated battery demand. At the common endpoint, the simulated discharged capacity was 5.1474 Ah, corresponding to a final simulated SoC of 34.01%. This produced a charge difference of 0.6696 Ah and a relative deviation of 11.51%. The SoC trajectory metrics confirmed the same behavior, with an MAE of 3.38%, an RMSE of 4.03%, and an endpoint error of 8.58 percentage points.

Energy-based mobility metrics provided a complementary interpretation of the results. The experimentally integrated discharged energy, computed from the measured terminal voltage and current, was 208.10 Wh, corresponding to a specific energy consumption of 12.62 Wh/km. The simulated model-based electrical demand was 184.41 Wh, equivalent to 11.18 Wh/km. Thus, the simplified model underestimated the integrated electrical energy by 23.69 Wh, or 11.38%. These values are consistent with the discharged-capacity comparison and provide a practical basis for evaluating the scooter performance in terms of energy consumption rather than SoC alone.

The semiempirical terminal-voltage reconstruction improved the physical interpretation of the simulated discharge behavior by combining the simulated current and SoC trajectories with an open-circuit-voltage representation and a fixed internal resistance. The reconstructed voltage reproduced the global decreasing tendency observed experimentally, although it did not represent polarization, hysteresis, thermal effects, or electrochemical aging. Consequently, the voltage reconstruction should be interpreted as a transparent first-order approximation rather than as a high-fidelity battery model.

Overall, the proposed framework contributes a reproducible procedure for comparing manufacturer-declared range, laboratory discharge measurements, simplified simulation results, and energy-based mobility indicators in light electric vehicles. The results also show that voltage-derived SoC indicators may lead to misleading interpretations under dynamic load conditions and should not be used as primary validation references without independent current-based reconstruction.

Future work should incorporate repeated experimental trials, measured wheel-speed trajectories, drivetrain efficiency maps, roller-bench loss characterization, thermal coupling, and battery models with SoC-dependent internal resistance, polarization, and hysteresis. Additional studies could also evaluate alternative urban driving cycles, different

rider masses, real-road operation, regenerative braking strategies, and battery-swapping scenarios for electric micromobility systems.

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Abbreviations

The following abbreviations are used in this manuscript:

SoC	State of charge
EM	Electrochemical model
ECM	Equivalent circuit model
EIM	Electrochemical impedance model
BMS	Battery management system
BEV	Battery electric vehicle
NEDC	New European Driving Cycle
ECE	Economic Commission for Europe
EEC	European Economic Community
WLTP	Worldwide Harmonized Light Vehicles Test Procedure
LEV	Light electric vehicle
SPS	Specialized Power Systems
FENALCO	Federación Nacional de Comerciantes
ANDI	Asociación Nacional De Empresarios de Colombia
UPME	Unidad de Planeación Minero Energética
INM	Instituto Nacional de Metrología

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