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Validation of a MATLAB/Simulink State-of-Charge Model for a Micro Electric Vehicle

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Abstract. This paper presents the development and validation of a compact computational model to estimate battery state of charge (SoC) and energy consumption of a Quantum One micro electric vehicle under urban operation. The drivetrain is modelled in MATLAB/Simulink using Virtual Vehicle Composer, with a mapped 16s Li-ion battery, motor, transmission and auxiliary loads. Fifteen repeatable drive cycles were recorded inside a university campus with GPS, while battery voltage and recharge time were measured to reconstruct field SoC and specific energy consumption. These routes were processed into drive-cycle inputs for the model. Agreement between simulation and field data was quantified using pointwise error, RMSE and MAPE. The validated model achieved MAPEs of 1.03 % (SoC), 0.28 % (voltage) and 5.29 % (Wh/km), supporting its use for autonomy estimation and route analysis.

1 Introduction

Electric vehicles (EVs) are increasingly deployed in urban transport as a means to reduce local emissions and dependence on fossil fuels. Their effective use, however, depends on how accurately the available battery energy can be monitored and managed along typical routes. For light and micro electric vehicles, small changes in speed profile, auxiliary loads or road grade can produce noticeable variations in autonomy and user confidence. In this context, accurate estimation of battery state of charge (SoC) and specific energy consumption under real driving conditions is essential for trip planning and charging strategies [1], [2].

Previous works have applied equivalent-circuit models and observers in MATLAB/Simulink to estimate SoC and predict energy use in EVs, often using standardized driving cycles and detailed measurement hardware [3]. Other studies have shown that real-world urban drive cycles built from GPS data better capture the variability of traffic and road topology, improving the representativeness of energy assessments [4], [5]. Nevertheless, most contributions focus on passenger cars or larger light-duty EVs in temperate climates, with limited attention to micro-EVs operating in Latin American cities with warm weather and “stop-and-go” traffic.

In the case of the Quantum One micro-EV used at a university campus in San Pedro Sula, Honduras, on-board instrumentation is restricted to a basic charge indicator and total

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charging time. There is no direct access to SoC or current, which prevents a quantitative assessment of how different routes and traffic conditions affect battery usage. On the contrast, various articles explore the energy matrix in Honduras [6], [7] that can help increase the use of electric vehicles since renewable energies are a perfect match for this technology.

This paper develops and validates a compact MATLAB/Simulink model of the Quantum One, driven by real campus drive cycles, and compares its SoC, terminal voltage and Wh/km against field-based references using error metrics. The validated model is then used to explore the expected performance of the micro-EV on representative urban routes in San Pedro Sula.

2 Context

San Pedro Sula is one of the main industrial and commercial hubs of Honduras and concentrates a significant share of the national vehicle fleet. Recent statistics show a sustained growth in the number of registered vehicles in the country, with road transport dominating final energy consumption and greenhouse-gas emissions from the sector [6]. In this setting, even small fleets of electric and micro electric vehicles can contribute to local emission reductions and fuel savings, provided that their operation is well understood and integrated into daily mobility patterns.

The local climate further constrains electric vehicle performance. San Pedro Sula experiences high ambient temperatures and humidity for most of the year, which tend to increase auxiliary loads such as air conditioning and can affect both energy consumption and lithium-ion battery efficiency [5], [7], this can be seen in Figure 1. At the same time, urban trips combine short distances, frequent stops and moderate gradients, creating highly variable speed profiles. These characteristics make the city a relevant case study for assessing micro-EV operation under realistic Latin American conditions.

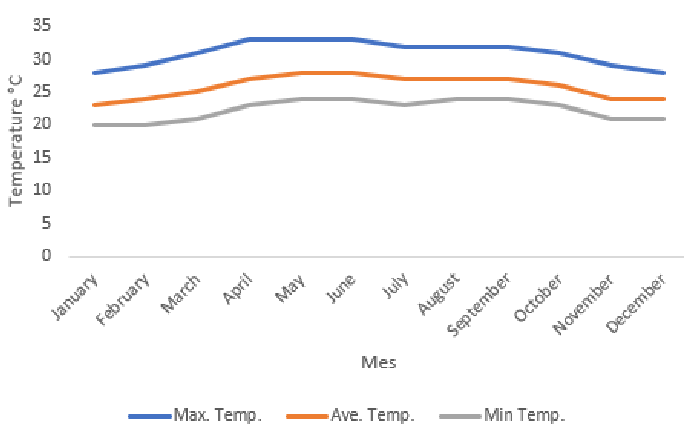

Fig. 1. Minimum, Average, and Maximum Temperature per Month in SPS (2024)

Within this context, the Quantum One micro electric vehicle is used as an internal shuttle in the campus of Universidad Tecnológica Centroamericana (UNITEC) in San Pedro Sula. The vehicle is equipped with a Li-ion battery pack of about 6.38 kWh and is operated on short, repetitive routes with low to medium traffic [8]. However, it lacks advanced instrumentation: the only practical indicators of battery status are a basic charge display and the total charging time reported by the off-board charger. This combination of local traffic patterns, climatic conditions and limited on-board data makes the Quantum One (see Figure 2) a representative platform for developing and validating a computational model capable of estimating SoC and energy consumption under real urban drive cycles.

Fig. 2. Electric Vehicle Quantum One

3 Methodology

3.1 Vehicle and Battery Model

The Quantum One micro electric vehicle is modelled in MATLAB/Simulink using the Virtual Vehicle Composer (VVC) toolbox [9]. An electric-vehicle-with-one-motor (EV 1EM) architecture is selected, which includes a longitudinal vehicle body, a traction motor and inverter, a fixed-ratio transmission, wheels, brakes and a DC-link connected to a high-voltage battery as shown in Figure 3. The vehicle mass, motor power, wheel radius and basic aerodynamic and rolling parameters are configured from the manufacturer's data and on-site measurements.

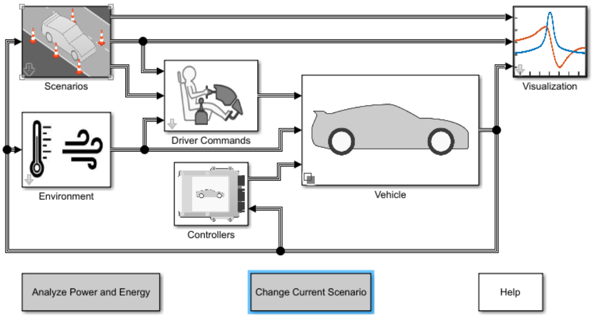

Fig. 3. Simulink Blockset Model for an EV

The high-voltage source is represented as a 16-series-cell lithium-ion pack with nominal voltage of 60.8 V and capacity of 105 Ah. In VVC, the battery is modelled as an equivalent circuit with open-circuit-voltage (OCV) and internal resistance mapped as a function of SoC and temperature [2], [5], [9]. The OCV–SoC curve is tuned so that the simulated terminal voltage in load and the relaxation behaviour at the end of the drive cycles match the values observed in the field.

3.2 Drive Cycle acquisition and processing

Real-world drive cycles are obtained from the Quantum One operating on a fixed internal route in the UNITEC San Pedro Sula campus. Fifteen runs of this route are recorded using the Open GPX Tracker application, which generates GPX files with time-stamped latitude, longitude and altitude samples [10], [11] . These files are processed in MATLAB to compute distance, instantaneous speed and road grade for each run. The position data are transformed into incremental distances, and speed is obtained as the distance derivative with respect to time. Altitude is used to calculating grade as the height change over horizontal distance.

All signals are resampled to a constant time step (1 s) for numerical stability. For each run, a drive-cycle file is created, containing time, speed and grade, in the format expected by the Drive Cycle Source and scenario blocks in the VVC-based model. These files are then used as inputs to the Simulink model to reproduce the measured speed and road-grade profiles.

3.3 Field SoC and Energy Consumption estimation

Because the Quantum One does not provide direct SoC or current measurements, a field-based estimate of SoC and specific energy consumption is reconstructed from the charging time after each run. Let t_{full} denote the time (hours) required for a full charge (from empty to 100 %), and $t_{rec,i}$ the recharge time measured after drive cycle i. Assuming a quasi-linear relation between charge time and energy restored in the shallow-discharge regime, the percentage of SoC consumed in cycle i is approximated by

$$\Delta SoC_{i,field} = \frac{t_{rec,i}}{t_{full}} \tag{1}$$

The field estimate of SoC for cycle i is then

$$SoC_{i,field} = 100 - \Delta SoC_{i,field} \tag{2}$$

If E_{nom} is the nominal energy capacity of the pack in Wh, the energy drawn from the battery during cycle i estimated as

$$E_{i,field} = \frac{SoC_{i,field}}{100} \times E_{nom} \tag{3}$$

The corresponding field specific energy consumption is obtained by normalizing this value by the travelled distance d_i (in km):

$$C_{i,field} = \frac{E_{i,field}}{d_i} \tag{4}$$

On the simulation side, the VVC *Analyze Power and Energy* report directly provides the net battery energy delivered during each cycle, $E_{i,sim}$ from which the simulated specific energy consumption is computed as

$$C_{i,sim} = \frac{E_{i,sim}}{d_i} \tag{5}$$

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3.4 Validation Metrics

For each cycle i the pointwise error between simulation and field for a given variable y (final SoC, terminal voltage or energy consumption) is defined as

$$e_i = y_{i,sim} - y_{i,field} \tag{6}$$

The root-mean-square error (RMSE) is used to quantify the typical magnitude of this error in absolute units [12]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \tag{7}$$

Where n is the number of cycles (here n = 15). To express the error in relative terms, the mean absolute percentage error (MAPE) is also computed [13]:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_{i,sim} - y_{i,field}}{y_{i,field}}\right| \tag{8}$$

These metrics are calculated separately for SoC, terminal voltage and energy consumption, and are later used to evaluate the overall agreement between the computational model and the field-based reference.

4 Results

4.1 Campus validation cycles

Table 1 summarizes the aggregate results for the fifteen validation cycles. Field estimates of final SoC lie between 87 % and 91 %, with an average shallow depth-of-discharge of about 11 %, while the simulated SoC closely matches these values on average. Final terminal voltage also shows a narrow spread (around 60–62 V), and the model reproduces this band without systematic bias. Specific energy consumption from field data ranges between approximately 118 and 155 Wh/km; the simulated values fall within the same range, reflecting traffic and auxiliary-load variability rather than structural model errors.

Table 1. Summary statistics for campus validation.

Variable	Field Mean	Simulation Mean	Pointwise error mean
Final SoC [%]	88.39	89.22	0.83
Final Voltage [V]	61.51	61.52	0.17
Energy consumption [Wh/km]	136.19	131.69	4.49

As shown in Table 1, the mean differences are small: about 0.8 percentage points in SoC, 0.17 V in terminal voltage and 4.49 Wh/km in specific energy. This indicates that, on average, the model reproduces the shallow discharges and energy use of the campus cycles with limited bias.

4.2 Error Statistics

Table 2 reports the error statistics computed over the fifteen cycles. For final SoC, the model achieves an RMSE of 0.099 percentage points and a MAPE of 1.03 %, confirming that the end-of-cycle state of charge is reproduced with very small relative error [14], [15]. For terminal voltage, the RMSE is 0.19 V and the MAPE is 0.28 %, which is negligible within the 60–62 V operating range. Regarding specific energy consumption, the RMSE is 7.86 Wh/km and the MAPE is 5.29 %, indicating that the model tends to underestimate the Wh/km observed in the field by about 4–5 Wh/km on average. This bias remains within acceptable bounds for autonomy estimation and reflects mainly simplifications in the representation of low-speed losses rather than a structural mismatch of the model.

Table 2. Validation Metrics.

Metric	SoC [%]	Final Voltage [V]	Energy Consumption [Wh/km]
RMSE	0.099	0.193	7.861
MAPE [%]	1.03	0.28	5.29

Overall, these error levels indicate that the proposed model can reliably reproduce the battery SoC, terminal voltage and specific energy consumption of the Quantum One under the studied operating conditions, and is therefore suitable for autonomy estimation and comparative route analysis.

4.3 External Urban Routes in San Pedro Sula

Table 3 summarizes the average behaviour of the two external urban routes simulated with the validated model. Both routes lead to shallow discharges, with final SoC values above 93 %, confirming that they are relatively mild from the battery standpoint. Urban Route #1 is slightly more demanding, with a lower mean SoC and a higher specific energy consumption (68.65 Wh/km versus 65.85 Wh/km), while mean terminal voltage remains close to 61 V in both cases. These results indicate that, under representative urban conditions in San Pedro Sula, the Quantum One would operate with moderate energy use and ample remaining SoC margin after each trip.

Table 3. Summary statistics for urban cycles.

Variable	Urban Route #1	Urban Route #3
Final SoC mean [%]	93.33	94.98
Final Voltage mean [V]	61.79	61.07
Energy consumption mean [Wh/km]	68.65	65.85

These urban-route simulations illustrate how the validated model can be used to project the expected SoC evolution and energy consumption of the micro-EV on real city trips, providing a practical basis for planning daily operation in San Pedro Sula. This lays the foundations for the development of upcoming works that can validate external routes in the field.

5 Conclusion

This work developed and validated a compact MATLAB/Simulink model for estimating the battery state of charge and specific energy consumption of a Quantum One micro electric vehicle operating in San Pedro Sula, Honduras. The drivetrain was implemented using Virtual Vehicle Composer with a mapped Li-ion battery, basic representations of auxiliaries and drivetrain losses, and real drive cycles obtained from repeated campus runs. Because the vehicle lacks direct SoC and current measurements, field references for final SoC and Wh/km were reconstructed from recharge time and pack voltage, allowing a consistent comparison between simulation and operation.

The validation over fifteen campus cycles showed close agreement between simulated and field quantities. Mean differences were 0.83 percentage points in final SoC, 0.17 V in terminal voltage and 4.49 Wh/km in specific energy. The corresponding RMSE and MAPE values (0.099 and 1.03 % for SoC, 0.19 V and 0.28 % for voltage, and 7.86 Wh/km and 5.29 % for Wh/km) indicate that the model reproduces shallow discharges and energy use with small absolute and relative errors, despite the limited on-board instrumentation of the micro-EV. These results support the use of the model as a reliable tool for autonomy estimation and sensitivity analysis under the studied conditions.

The validated model was then applied to two representative urban routes in San Pedro Sula, yielding modest SoC drops (around 5–7 % per route) and mean specific energy consumptions between 65 and 69 Wh/km. This suggests that the Quantum One could cover roughly 90–100 km from a full charge while maintaining a comfortable SoC margin, and demonstrates that a model calibrated only with campus data can be reused to explore micro-EV performance on external routes. Future work will refine the representation of auxiliary loads and temperature effects and extend the methodology to deeper discharge levels and other micro-EV platforms, enabling broader studies of efficient operation in Latin American urban contexts.

References

1. C. S. y. J. X. J. Zhang, «A simulation-driven prediction model for state of charge estimation of electric vehicle lithium battery»,» p. 10.1016/j.heliyon.2024.e30988., 2024.
2. S. M. y. H. R. A. S. Abdelaal, « «Battery Energy Management Techniques for an Electric Vehicle Traction System»,» *IEEE,* nº 10.1109/ACCESS.2022.3195940., 2022.
3. Z. Z. Y. L. Z. X. y. X. Q. X. Zhang, ««A review of machine learning approaches for electric vehicle energy consumption modelling in urban transportation», Renewable Energy,» vol. 234, nº 10.1016/j.renene.2024.121243., 2024.
4. I. N. C. F. y. V. P. M. Montanino, « «A traffic-flow-dependent macroscopic model of electric vehicle energy consumption», Transportation Research Part C: Emerging Technologies,» vol. 178, nº 10.1016/j.trc.2025.105220., 2025.
5. I. K. y. A. M. S. Harasis, ««Operation of EVs in hot climates: Modeling of temperature-driven energy consumption including Li-ion battery energy loss», Energy ReportS,» vol. 13, nº 10.1016/j.egyr.2025.03.008, 2025.
6. J. L. O. Fernandez, J. L. O. Avila y R. A. Ordoñez, «Potential effect on the energetic matrix of Honduras with the installation of residential photovoltaic generators for self-consumption,» *IEE ,* 2019.

7. I. O. H. V. Maria Parada, «Green hydrogen assessment of generation and storage potential from solar and wind energy shedding in Honduras,» *E3S Web of Conferences,* nº https://doi.org/10.1051/e3sconf/202337903003, 2023.

8. Instituto Nacional de Estadística, ««Boletín Parque Vehicular 2017 - 2021»,» *INE Honduras - Estadísticas Oficiales,* nº https://ine.gob.hn/2022/12/09/boletin-parque-vehicular-2017-2021/, 2025.

9. S. L. P. y. A. Gudipalli, ««Optimal Energy Consumption Control Strategy for Electric Vehicle»,» *IEEE,* vol. 12, nº 10.1109/ACCESS.2024.3512188, 2024.

10. QUANTUM, «Tu Quantum SV, «ONE - QUANTUM».,» nº https://tuquantum.com.sv/producto/one/, 2025.

11. MathWorks,, « «Explore Virtual Vehicle Composer - MATLAB & Simulink»,» nº https://la.mathworks.com/help/vdynblks/ug/explore-virtual-vehicle-composer.html, 2025.

12. TopoGrafix, «TopoGrafix, «GPX: the GPS Exchange Format».,» nº https://www.topografix.com/gpx.asp, 2025.

13. Open GPX Tracker, , ««GPS Tracker for iOS: Open GPX Tracker,» nº https://www.merlos.org/iOS-Open-GPX-Tracker/, 2025.

14. K. Gülem, « «¿Qué es el error cuadrado de raíz (RMSE)? - Dataconomy ES»,» nº https://es.dataconomy.com/2025/04/03/que-es-el-error-cuadrado-de-raiz-rmse/, 2025.

15. Academia Lab, ««Error porcentual absoluto medio _ AcademiaLab»,» nº https://academia-lab.com/enciclopedia/error-porcentual-absoluto-medio/, 2025.