An Electric Vehicle Simulator for Realistic Battery Signals Generation from Data-Sheet and Real-World Data

Raimondo Gallo, Alessandro Aliberti, Edoardo Patti,
Gianluca Bussolo, Paolo Tosco, Marco Zampolli and Rémi Jaboeuf

May 9, 2023

An Electric Vehicle Simulator for Realistic Battery Signals Generation from Data-sheet and Real-world Data

Omitted for Double Blind Review

***Abstract*—Electric vehicles (EVs) have been globally recognized as a reliable alternative to fossil fuel vehicles. The core component of an electric vehicle is its rechargeable battery pack, and Lithium-ion battery (LIB) cells are currently the dominating technology in battery pack design. This game-changing technology pushes toward the investigation of new ideas to improve the offered services. However, there still needs to be large-scale publicly available EV data to investigate and distribute effective solutions to monitor the conditions of the EV's battery pack. Hence, we propose an EV simulator that generates EV battery pack internal signals starting from the input driving cycle. The simulated data resemble the behavior of a multi-cell EV battery pack undergoing the user's utilization of the EV. The simulated data include vehicle speed, voltage, current, State of Charge (SOC), and internal temperature of the battery pack. The virtual-EV model simulator, including the battery pack subsystem, has been tuned using real-world EV data sheet information. The battery pack embeds thermal and aging models for further realism, influencing the output signals given the environmental temperature and the battery's State of Health (SOH). The data generated by the virtual-EV simulator have been validated with real EV data signals sampled by an equivalent real-world EV. The data comparison yields a minimum R^2 value of 0.94 and an Root Mean Squared Error not higher than 2.74 V for the battery pack's voltage and SOC, respectively.**

***Index Terms*—EV, simulation, Battery, SOH**

I. Introduction

Climate change is gaining more concern as one of the critical worldwide challenges. It is estimated that the road transport sector accounts for three-quarters of transport CO_2 emissions [1]. Electric vehicles (EVs) are considered a cleaner and more sustainable technology than fossil fuel vehicles, reducing air pollution, especially in urban settings. Therefore, as EVs become the leading road transportation means, improving their technologies becomes paramount to offer a better driving experience to the users.

The core component of an EV is its rechargeable battery pack which is hierarchically structured into three levels: cell, module, and pack. Multiple battery cells are connected in series and parallel to form a battery module, and then a certain number of modules are assembled to form a battery pack. Lithium-ion battery (LIB) cells are the dominating technology for the battery pack design, thanks to a broad set of properties [2]. LIB cells experience degradation due to time and usage, leading to decreased capacity and increased internal resistance. Therefore, monitoring the EV battery pack conditions is essential to determine the efficiency of the EV and, consequently, the driver's safety. For instance, an indicator of capacity loss due to degradation is the State of Health (SOH), expressed as the ratio of the battery's actual capacity to its nominal capacity. The SOH's supervision is critical since it identifies when an EV must retire. A brand new EV battery pack will have a SOH equal to 100%, but with the vehicle's utilization, the SOH will eventually decrease to 80%, reaching the battery's end-of-life [3].

The discovery of a new and reliable solution to monitor the EV battery conditions will require vast datasets, especially for machine learning data-driven approaches. But, unfortunately, only a few open datasets, including internal battery signals, are nowadays available [4] [5], which are not representative of an EV battery pack. Private EV fleet management companies could provide such data at a very high price, inaccessible to many researchers. Therefore, the necessity of richer and more valuable datasets pushes towards alternative and affordable solutions to gather such data.

Hence, in this work, we propose an EV model simulator defined using MATLAB and Simulink programming environments. The simulator is built as an assembly of several constituents and mutually dependent EV subsystems, modeling the main operational mechanisms of a general EV. For instance, the electric motor, wheels, braking system, and battery pack. The definition of a full EV simulator allows the generation of battery pack signals that embed complex interactions among all subsystems. The simulator receives an input speed time series, resembling the user's driving cycle, which induces a change in the building blocks accordingly. Moreover, we configured thermal and aging models of the battery pack subsystem to adequately describe its conditions at the beginning of the simulation. For the sake of our study, we solely monitor the simulated output signals of the battery pack, including current, voltage, State of Charge (SOC), and internal temperature. Finally, we employed real driving session monitoring data for a real-world EV acquired from a private EV fleet management company to assess the performances of the simulator.

The paper is organized as follows. Section II presents an overview of the available EVs simulators and their limitations; Section III describes in detail the structure of the simulator, its inputs and outputs, and the chosen aging and thermal models of the battery pack. In Section IV, we thoroughly discuss the performances of the simulator. Finally, in Section V, we make our final considerations over the developed simulator and provide an overview of the possible future works.

II. Related works

In the literature, different simulation approaches are available. In terms of load exchange, it is possible to encounter simulators that model the impact of EVs over the power grid. Conversely, other simulators model the inner dynamics of an EV, monitoring its performance. The availability of EV simulators enables the development of data-driven methodologies, i.e., machine learning, to improve EV technologies under both the manufacturing and use perspectives.

For instance, Canizes et al. [6] developed a travel simulation tool to simulate a real environment, enabling the creation of personalized profiles, schedules, and destinations. The tool allows the inclusion of trips and charging stations, taking into account the behavior of real users. The presented tool highlights the variable-rate electricity prices that are more advantageous to the users, considering the impact of electricity price variation on the behavior of EV drivers. Rigas et al. [7] proposed EVLibSim, a Java event-based simulator to model EV activities at a charging station level inside the power grid. Considering the user's demands, the simulator allows the configuration of a charging station, enabling an accurate simulation of charges, discharges, and queues.

Gaete-Morales et al. [8] developed an open-source Python tool, Emobpy, that generates EV time series ranging from the vehicle's mobility and energy consumption to the grid's availability and demand information. The tool exploits empirical mobility statistical and physical properties data from 200 input vehicle profiles from Germany to extensively personalize and characterize the simulation scenarios. Emobpy allows the customization of the length and temporal granularity of the output time series enabling the monitoring of large EV fleets.

Ciabattoni et al. [9] proposed an event-based web simulator called ePopSimulator, which allows the creation of customizable individual and aggregated charge, discharge, and plugin/out events for an EV fleet. Moreover, the tool includes a Matlab/Simulink block to extend its possibilities, enabling integration into different applications. The simulator is well suited for investigating vehicle-to-grid technologies by customizing the simulation scenarios. Successively, Ciabattoni et al. [10] extended the capabilities of ePopSimulator, including an aging model to include degradation mechanisms on battery performances. The aging behavior expresses the degradation in terms of residual capacity that allows the estimation of the battery's SOH.

Simic and Bäuml [11] exploited Modelica packages to develop a hybrid EV model which includes an idealized battery pack. They parameterized the EV model employing available measurements and data sheets information, selecting real measured current as a reference signal. The model achieves good performances for the battery voltage yielding a deviation of 5% between the measured and simulated signals. Finally, Baker et al. [12] defined FASTSim, as an open-source vehicle simulation tool that analyzes and designs EVs and conventional vehicles. The tool models car components at the highest level while maintaining accuracy, ensured through the validation of the results employing data from hundreds of cars. The potentialities offered by the tool allow researchers to explore numerous solutions to improve EV technologies, such as estimating energy consumption.

This work proposes a virtual-EV model simulator developed with Simulink and MATLAB. Concerning the solutions available in the literature, we wanted to create an EV simulator focused on generating internal battery pack signals, given a few inputs fully customizable by the user. Hence, we concentrate on the EV rather than its impact on the power grid. However, the proposed EV simulator could be integrated into broader co-simulation contexts.

The proposed EV simulator is equipped with a multi-cell battery model that generates the battery pack's current, voltage, State of Charge (SOC), and internal temperature time series given the input driving cycle (i.e., a time series of speeds). The selection of a multi-cell structure for the battery pack allows us to mimic the actual inner structure of an EV battery pack, with the cells organized in modules and connected in series and parallel. The realistic battery pack generates the output current, voltage, SOC, and internal temperature considering the contribution of all and each cell. In this way, we can generate precise and realistic internal battery pack signals. Furthermore, the battery pack embeds aging and thermal models; the former permits the customization of the initial degradation conditions of the battery pack at the beginning of the simulation; the latter manages the heat exchanges between the battery pack and the external environment to keep the internal temperature between 30 °C and 40 °C.

We parameterized the EV simulator solely using data-sheet information publicly accessible online to replicate the target real-world EV model, the Volkswagen e-Golf. Each building block of the EV simulator can be extensively modified to match a target real-world EV model, changing the inner parameters. Hence, the user might define an EV simulator representing any real-world EV model whenever technical data-sheet information is available. Using the proposed EV simulator, we can generate a synthetic and realistic dataset including internal battery pack signals, which might be only accessible through either costly and time-consuming laboratory experiments or devices directly connected to the EV's battery management system. The generation of realistic internal battery data enables thorough research exploiting data-driven methodologies to improve EV technologies, overcoming the issue of data unavailability.

III. Data and methodology

This section describes the employed dataset and how we defined the EV simulator. We thoroughly discuss the design choices of the simulator's subsystems, the required inputs, and generated outputs.

A. Dataset

The utilized dataset, acquired from a private company, consists of actual EV battery pack measurements relative to an individual real-world EV model, a Volkswagen e-Golf. The dataset comprises five driving session data from the same vehicle but characterized by a different mileage, hence with other battery pack conditions, i.e., SOH. The data were collected through a device connected to the battery management system of the EV, which gathered environmental and internal information concerning the monitored EV. The dataset includes measurements of environmental temperature [°C], EV speed [Km/h], current [A], voltage [V], SOC [%], and internal temperature [°C] of the whole battery pack. Each of the observed properties is sampled with a different frequency. Indeed, the device sampled current and voltage with a higher frequency since these physical quantities tend to vary more rapidly over time with respect to the listed others. We report the employed frequencies to sample the data for the real-world EV in Table I. We used the available real EV data to validate the simulated signals generated by the EV simulator. We report in Table II an overview of the available driving sessions belonging to the dataset.

TABLE I
THE SAMPLING FREQUENCIES OF THE ACQUIRED REAL SIGNALS.

Input signal	Sampling frequency [s]
Speed	19
Current	0.1
Voltage	0.1
SOC	11
Battery internal temperature	41
Outside temperature	110

TABLE II
GENERAL INFORMATION OF THE AVAILABLE DRIVING CYCLES (DC).

Driving cycles	Duration [s]	Avg. speed [Km/h]	Avg. Environmental temperature [°C]	Avg. SOC [%]	Battery pack's SOH [%]
DC1	7777	38.50	21.32	78,20	99
DC2	3749	81.85	30.08	50.74	98
DC3	3039	58.04	17.60	84.19	95
DC4	4584	60.59	19.74	78.11	94
DC5	6089	67.02	20.04	73.71	93

B. The EV simulator

The EV simulator has been developed using Simulink [13], a simulation environment allowing the definition of complex systems using modular components. Indeed, we defined the proposed EV simulator as an assembly of individual blocks, each modeling a specific EV subsystem. To correctly represent a fully operational EV, we included the following blocks: driver, motor, braking system, drivetrain, wheels, vehicle body, vehicle dynamics, and battery pack. We thoroughly describe the building blocks of the simulator later in the manuscript, while Figure 1 shows the schematic diagram of the simulator's inner structure. For the sake of this study, we tuned the simulator's parameters to match a specific real-world EV, a Volkswagen e-Golf, for which we own real battery pack measurements. In this way, we can correctly assess the performances of the simulator. The main parameters of the simulator's blocks have been retrieved from online sources and technical data sheets. Hence, with this approach, numerous real-world EV models can be simulated by changing the parameters following the technical specifications of the target EV model.

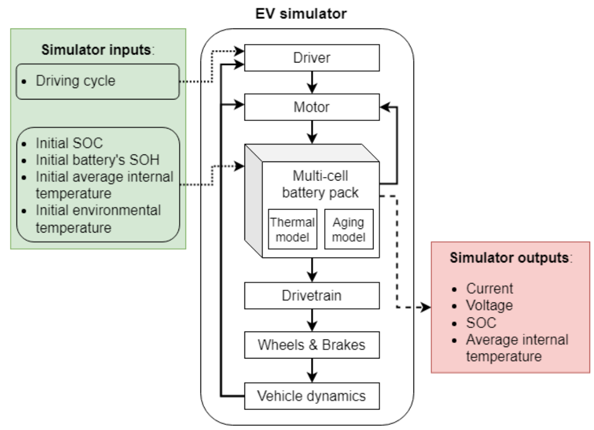

Fig. 1. The inner structure of the EV simulator with the subsystem interactions and relative inputs and outputs.

The EV simulator receives a driving cycle as input, expressed as a time series of speeds representing the user's driving routine. Hence, according to the driving cycle, the EV simulator generates accurate internal battery pack signals, including current, voltage, internal temperature, and SOC. We added thermal and aging models to the battery pack to further improve the quality of the synthetic output signals. Therefore, besides the input driving cycle, the user can specify the environmental temperature and battery pack's degradation status in terms of SOH. In such a way, it becomes possible to customize the conditions of the simulated EV model to match the researcher's needs. As previously mentioned, the EV simulator comprises mutually dependent subsystems, *Driver*, *Motor*, *Wheels & Brakes*, *Drivetrain*,*Vehicle dynamics*, and *Multi-cell battery pack*. The modules are connected through the signals generated during the simulation. Referring to Figure 1, the *Driver* block implements a discrete-time proportional-integral controller that mimics the vehicle's human driver. At each time step, the controller tracks the given input driving cycle and the simulated vehicle speed, attempting to line them up by acting on the brake and accelerator pedals. The *Motor* block, taken from the Simscape library [14], implements a mathematical model of an electric motor operated in torque-control mode.

The *Drivetrain* in Figure 1 is the set of rotating shafts and gears that distributes the mechanical power generated by the electric motor to the wheels. The vehicle body implements a three-degree-of-freedom rigid vehicle body with constant mass. The three degrees of freedom are the pitch, yaw, and roll, allowing the correct suspension system implementation. The *Wheels and Brakes* are modeled using the Longitudinal wheel with disc brake Simulink block. The braking system is based on two contributions: friction and regenerative braking. The former is the conventional braking mechanism activated by pressing a brake pedal, generating a friction force opposing the direction of the wheel; the latter recharge the EV battery pack while slowing down the vehicle. Regenerative braking was not implemented in the baseline block; hence, we added it to mimic the dynamics of a real EV. The *Vehicle dynamics* block handles the forces acting on the vehicle body, and it enables the definition of the wind resistance and slope of the road. Finally, as shown in Figure 1, the *Multi-cell battery pack* subsystem, taken from the Simscape library, is modeled as a multi-cell battery pack. The cells are individually organized in modules and connected in series and parallel, mimicking the actual inner structure of an EV battery pack. The chosen multi-cell battery pack module provides data on each cell's current, voltage, SOC, and internal temperature. But, for the sake of our study, we consider their aggregate outputs computed as average values for current, SOC, and internal temperature. At the same time, for the voltage, we calculate the sum of the individual cell voltages. We consider the aggregate values of the battery pack's signals to properly compare them with the real available Volkswagen e-Golf's battery signals. The number of cells, their configuration data, and all the other subsystems' main parameters have been chosen based on publicly available technical data sheets. In this way, we configure the EV simulator to represent the target real EV model we intend to replicate as much as possible.

The EV simulator does not consider the impact of auxiliary devices within the vehicle, such as air-conditioning units, headlights, radio, power steering, etc. Therefore, to contemplate the effect of such devices over the battery's SOC, we include an offset to be added to the generated current equal to 5.5 A. Moreover, we added a minimal wind resistance component of 4 m/s to the opposing forces acting against the vehicle during the driving. In this way, we define an EV simulator that emulates more realistic driving conditions the vehicle experiences. Unfortunately, we cannot assess the goodness of such values since the available dataset does not include environmental information, beside external temperature, prone to their validation.

C. Thermal and aging models

As introduced in the previous Section III-B, we added thermal and aging models to the battery pack to further improve the quality of the synthetic output signals. We defined the thermal model as a state flow chart, depicted in Figure 2, that receives each battery pack cell's variation of temperature, voltage, and current to compute the percentage of generated power to be exchanged as heat between the battery pack and the external environment. The state flow chart ensures that the overall battery pack temperature stays between 30 °C and 40 °C to guarantee the correct battery pack functioning. Referring to Figure 2, each block identifies a state. At the same time, *heat* is the heat to be exchanged, *i*, *volt*, and *Temp* are the aggregated current, voltage, and internal temperature of the battery pack, respectively.

On the other hand, through the aging model, we can modify the initial health conditions of the battery pack. The input to

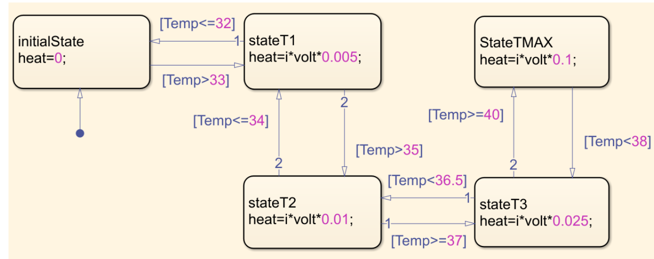

Fig. 2. The inner structure of the thermal model state flow chart.

the aging model is the desired SOH, expressed as a percentage, which is generally defined through the following relation,

$$SOH = \frac{C_{actual}}{C_{nominal}} \tag{1}$$

where C_{actual} and $C_{nominal}$ are the current and nominal capacities of the battery pack, respectively. Given the battery pack's desired initial SOH and its nominal capacity (retrieved from technical data sheets of the EV model), we can compute the C_{actual}. Indeed, using Equation (1), a 1% decrease of SOH corresponds to a 1% reduction of the battery pack's nominal capacity. Through such a relation, we compute the actual capacity, which is then assigned to the battery pack subsystem of the EV simulator at the beginning of the simulation, affecting the initial battery's aging conditions.

IV. Experimental results

In this section, we present the performances of the EV simulator, comparing the simulated battery pack signals with the real ones, given the same input driving cycle, environmental conditions and battery pack's initial state. We use the Volkswagen e-Golf's real battery pack signals as our benchmark. The performance metrics used to quantify the error between actual and simulated output signals are the *Root Mean Square Error* (RMSE) and *Coefficient of determination* (R^2). The RMSE quantifies the standard deviation of the residuals and prediction errors, while the R^2 measures the variability in the observed values that can be explained using the predicted values. The mathematical formulation of the selected metrics is the following,

$$RMSE = \sqrt{\frac{\sum_{n=1}^{N}(y_{sim,n} - y_{real,n})^2}{N}} \tag{2}$$

$$R^2 = 1 - \frac{\sum_{n=1}^{N}(y_{real,n} - y_{sim,n})^2}{\sum_{n=1}^{N}(y_{real,n} - \overline{y}_{real})^2} \tag{3}$$

where y_{sim} is the simulated value, y_{real} is the observed value, $\overline{y}_{real}$ is the mean value of the observed values, and N is the total number of simulated values. As mentioned, the EV simulator generates internal battery signals according to the input driving cycle, the desired battery pack's aging status, and environmental conditions. We individually measure the performances of the generated synthetic data for each input driving cycle and output signal using the performance indicators introduced above. The simulator generates all output battery signals with a sampling frequency of 0.1 s to correctly capture the sub-second evolution of signals, especially for current and voltage. Therefore, for correct results validation, the real signals are down-sampled with the same frequency using linear interpolation. The simulation duration is proportional to the input driving cycle length.

We provide a complete overview of the simulator's performances in Table III, for all the individual input driving cycles. We report the RMSE and R^2 assessed by comparing each output simulated battery signal with its corresponding real signal. The chosen input driving cycles are characterized by different environmental conditions and, most importantly, distinct battery aging statuses. Nevertheless, observing Table III, the errors between actual and simulated battery signals are all approximately of the same magnitude over the different driving cycles. Indeed, for the voltage, the RMSE ranges between 2.14 V and 2.74 V for DC 3 and DC 1, in that order. Or, for the SOC, the R^2 lies between 0.94 and 1.00 for DC 3 and DC 5, respectively. Such performances prove the thermal and aging model's capability to describe the battery pack's degradation correctly. Indeed, for all tested driving cycles, and their relative scenarios, the R^2 for the SOC is well above 0.90, reaching 1.0 for DC 5. In contrast, the RMSE for the internal temperature is approximately 1 °C except for DC 1. Also, for the simulated voltage, the RMSE does not exceed 3 V and the minimum R^2 equals 0.89 for DC 2 and DC 3.

However, the real driving cycle included in the dataset, utilized as the primary input to the simulator, has been collected by the device on board the monitored EV with a much higher sampling frequency than the current or voltage. We have no information about the driver's velocity between two speed sampled measurements. This inevitably leads to an approximation of the input driving cycle, which results in less detailed simulated output signals, especially of current, compared to the real ones. This limitation explains the performances drop for the simulated current, which is highly correlated to the pilot's driving behavior. Indeed, for the current, the minimum RMSE is 29.92 A for DC 5, while the maximum R^2 is 0.40 for DC 4. Still, considering this limitation, the simulator provides accurate battery pack signals.

Moreover, we do not have any information related to the road traits traveled by the driver but the speed, e.g., slope and wind resistance, which highly influence the behavior of the EV. All these contributions are embedded into the real dataset signals and unknown to us, making perfect alignment between simulated and actual battery pack signals impossible. Despite this limit for the performances assessment validation, the EV simulator demonstrates surprising accuracy in simulating battery pack data, given the heterogeneous driving cycle and battery degradation condition.

In Figure 4 and Figure 3, we show the simulator's output signals for two distinct driving cycles, DC 2 and DC 5, compared to the real ones, providing to the reader a clearer insight of the results. The EV simulator catches the correct evolution of the signals, proving its accuracy. Indeed, looking at the simulation results in the mentioned images, we can observe

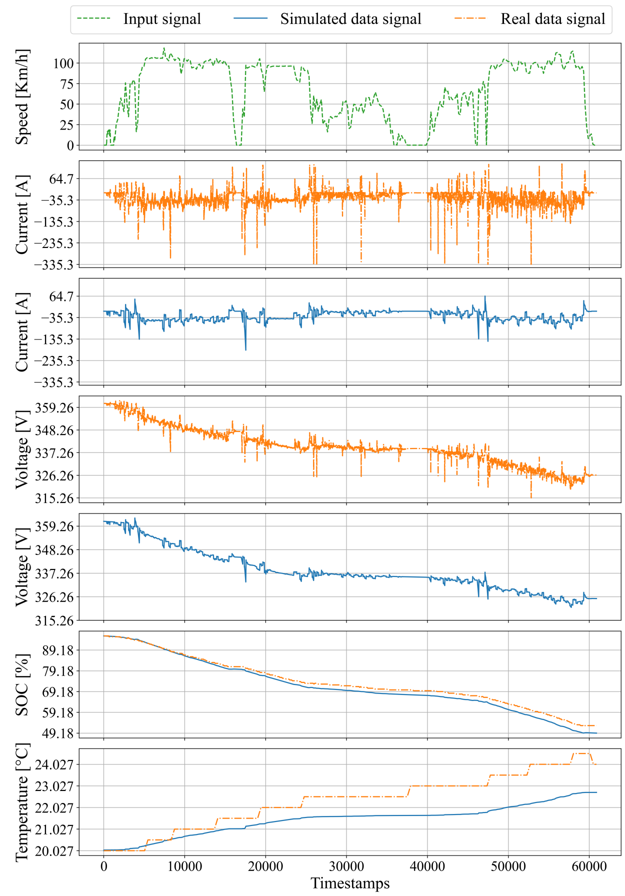

Fig. 3. The comparison between real and simulated battery pack signals generated that uses the input DC 5.

a decrease of SOC and the rising of internal temperature as the vehicle's mileage and utilization increase. Moreover, with the reduction of SOC, we can observe a gradual decline of the battery pack's voltage, consequence of the electrical potential reduction, as expected. We can also notice negative current spikes in conformity of the vehicle's accelerations; and, conversely, positive current spikes in correspondence of sudden braking. In addition, observing Figure 4 and Figure 3, it is possible to demonstrate the relatively low R^2 for the internal temperature. Indeed, the actual internal temperature signal is sampled once every 41s (see Table I), resulting in a stepped curve over time. In comparison, its simulated version changes smoothly with the other outputs making the real and simulated temperature signals quite different. The different curve shapes produce a low R^2, although the RMSE remains small.

V. Conclusions

In this work, we proposed an EV simulator developed in MATLAB and Simulink environments that, starting from an input driving cycle, generates internal battery pack signals, namely, current, voltage, SOC, and internal temperature. The simulator includes the multi-cell battery pack subsystem equipped with an aging model that allows us to specify its

TABLE III

THE PERFORMANCES OF THE EV SIMULATOR IN TERMS OF RMSE AND R^2 FOR EACH OUTPUT BATTERY PACK SIGNAL AND INPUT DRIVING CYCLE.

	DC 1		DC 2		DC 3		DC 4		DC 5	
Battery signal	**RMSE**	**R^2**	**RMSE**	**R^2**	**RMSE**	**R^2**	**RMSE**	**R^2**	**RMSE**	**R^2**
Current	51.65 A	0.19	38.09 A	0.27	33.77 A	0.39	40.0 A	0.40	29.92 A	0.35
Voltage	2.74 V	0.92	2.42 V	0.89	2.14 V	0.89	2.33 V	0.94	2.26 V	0.94
SOC	1.95 %	0.97	2.54 %	0.96	1.56 %	0.94	1.06 %	0.99	0.62 %	1.00
Internal temp.	5.04 °C	-0.74	0.59 °C	0.76	1.07 °C	-0.27	1.31 °C	0.48	1.14 °C	0.15

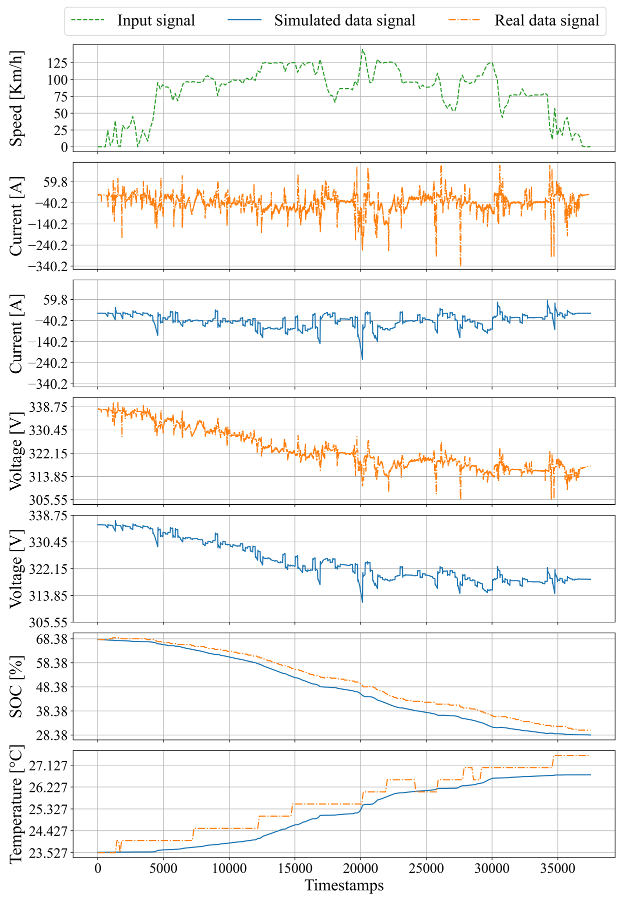

Fig. 4. The comparison between real and simulated battery pack signals generated that uses the input DC 2.

degradation conditions at the beginning of the simulation. Moreover, we defined the thermal model, which accurately describes the heat exchanges between the battery subsystem and the external environment. The simulator proves accuracy in generating output signals given different driving cycles and battery aging statuses.

The user could generate a vast and realistic dataset of internal battery pack signals of current, defining any custom driving cycle and operating scenario. Moreover, we selected the parameters for the EV simulator's subsystems exclusively from freely accessible technical data sheets related to the target real-world EV model. In this way, the user can define an EV simulator mimicking any EV model of interest whenever its data sheet information is available.

For future works, we plan to include a detailed contribution of all the auxiliary devices onboard the EV, affecting the outcome of the simulation, into the EV simulator. Finally, we will generate a synthetic and realistic dataset allowing the development of applications to improve the monitoring of the battery pack.

REFERENCES

[1] IEA, Transport sector CO2 emissions by mode in the Sustainable Development Scenario, 2000-2030, IEA, Paris https://www.iea.org/data-and-statistics/charts/transport-sector-co2-emissions-by-mode-in-the-sustainable-development-scenario-2000-2030, IEA. Licence: CC BY 4.0

[2] G. dos Reis, C. Strange, M. Yadav, and S. Li, "Lithium-ion battery data and where to find it," Energy and AI, vol. 5, p. 100081, 2021.

[3] S. Saxena, C. Le Floch, J. MacDonald, and S. Moura, "Quantifying EV battery end-of-life through analysis of travel needs with vehicle powertrain models," Journal of Power Sources, vol. 282, pp. 265–276, 2015.

[4] Birkl, C. Oxford Battery Degradation Dataset 1. University of Oxford. 2017.

[5] Saha B, Goebel K. Battery data set. NASA Ames Progn Res Center. 2007.

[6] B. Canizes, J. Soares, A. Costa, T. Pinto, F. Lezama, P. Novais, and Z. Vale, "Electric vehicles' user charging behaviour simulator for a smart city," Energies, vol. 12, no. 8, p. 1470, 2019.

[7] E. S. Rigas, S. Karapostolakis, N. Bassiliades, and S. D. Ramchurn, "EVLibSim: A tool for the simulation of electric vehicles' charging stations using the EVLib Library," Simulation Modelling Practice and Theory, vol. 87, pp. 99–119, 2018.

[8] C. Gaete-Morales, H. Kramer, W.-P. Schill, and A. Zerrahn, "An open tool for creating battery-electric vehicle time series from empirical data, emobpy," Scientific Data, vol. 8, no. 1, 2021.

[9] L. Ciabattoni, S. Cardarelli, M. D. Somma, G. Graditi, and G. Comodi, "A novel open-source simulator of electric vehicles in a demand-side management scenario," Energies, vol. 14, no. 6, p. 1558, 2021.

[10] L. Ciabattoni, F. Ferracuti, E. Marchegiani, and A. Monteriù, "An Open Source Electric Vehicle Simulator with Battery Aging Modeling." 2021 IEEE 11th International Conference on Consumer Electronics (ICCE-Berlin), 2021.

[11] Simic, Dragan and Bäuml, Thomas. Implementation of Hybrid Electric Vehicles using the VehicleInterfaces and the SmartElectricDrives Libraries, 2008.

[12] C. Baker, M. Moniot, A. Brooker, L. Wang, E. Wood, and J. Gonder, "Future Automotive Systems Technology Simulator (fastsim) validation report - 2021," 2021.

[13] Documentation, S., 2023. Simulation and Model-Based Design, MathWorks. Available at: https://www.mathworks.com/products/simulink.html.

[14] Documentation, S., 2023. Simscape, MathWorks. Available at: https://it.mathworks.com/products/simscape.html.