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Modelling battery packs of real-world electric vehicles from data sheet information

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***Abstract*—Lithium-ion batteries have emerged as the leading enabling technology in developing Electric Vehicles (EVs). But, large-scale publicly available EV data are extremely difficult to find. Hence, investigating and distributing new techniques to check the conditions of the EV's battery pack becomes challenging. In this work, we propose a Simulink-based approach to define a virtual-EV model that simulates EV battery pack signals starting from input driving sessions. The virtual-EV model simulator includes the battery pack subsystem, which has been tuned using data gathered from EV real-world data sheet information. Moreover, the simulator's battery pack subsystem embeds thermal and aging models, impacting on the output signals, considering the temperature of the surrounding environment and the battery's State of Health (SOH). The simulator generates data of vehicle's speed, and battery pack's voltage, current, State of Charge (SOC), and average internal temperature measured throughout the input driving cycle. We defined two Simulink EV models emulating two distinct real-world-EVs. Then, we assessed the performances of the simulators comparing the simulated data and real EV data signals collected by the same real-world-EV models. The comparison yields, for both simulated EV models, R^2 values higher than 0.70 and an RMSE of at most 7V and 8% for the battery pack's voltage and SOC, respectively.**

***Index Terms*—Electric vehicle, Battery pack, Simulation, Matlab, Simulink**

I. Introduction

Mitigating climate change is considered one of the critical challenges of our century. It is estimated that the transport sector accounts for 27% of the global emissions of greenhouse gases [1] and, more specifically, road travel accounts for three-quarters of transport CO_2 emissions [2]. EVs have been widely accepted as a clean and reliable alternative to fossil fuel vehicles, both in private and public transportation sectors, and are expected to take over the market in the upcoming years quickly [3]. It is, therefore, essential to investigate the leading technologies that can enhance EV performances.

The battery pack is the core component of an EV, and it is typically made up of many battery cells connected in parallel and series. Nowadays, lithium-ion battery (LIB) cells are the most important technology in battery pack design, due to many beneficial properties [4]–[6]. LIB cells, like all batteries, are subject to degradation phenomena with time and usage due to various chemical and mechanical changes to the electrodes. Monitoring the EV battery pack is essential to gain preliminary knowledge of its conditions and longevity. In many disciplines, data-driven methodologies, such as machine learning (ML) approaches, can achieve state-of-the- art results, given the capabilities of such models at solving non-linear problems. Indeed, in recent years, academia and industry have shown a growing interest in discovering new techniques to monitor EVs' performances by integrating ML algorithms, such as LIB performances forecasting [7] or detecting symptoms of battery failure [8]. Nonetheless, large volumes of measurements are necessary to implement data-driven methods, and, unfortunately, the available data are either scarce or difficult to access.

Few open battery datasets are accessible to users [9] [10]. Still, they include monitoring data obtained through laboratory experiments conducted over a single cell or small group of cells, which cannot represent the battery pack as a whole. A few private EV fleet management companies provide onboard diagnostic devices collecting direct measurements from the battery pack. However, the availability of large-scale, freely accessible datasets of real EV monitoring data is minimal [11], making the investigation and development of innovative solutions challenging. Therefore, the definition of EV simulators would allow synthetic data generation for the entire battery pack, filling the data unavailability gap. In this way, we would provide researchers with enough data to develop new data-driven techniques for monitoring the EV's battery pack, allowing them to train the proposed ML models with EV-simulated data.

In this work, we developed an EV model simulator created using MATLAB and Simulink programming environments. The EV model simulator is composed of several mutually dependent subsystems, e.g., electric motor, wheels, braking system, and battery pack, to emulate the main operational mechanisms of a real EV. The modeling of a full EV allows the generation of battery pack signals that integrate complex interactions among all subsystems. The proposed methodology foresees the employment of actual driving session monitoring data for two distinct real-world-EV models to parameterize and validate the battery's simulated data. With driving session, we refer to the user's driving experience that will impact the vehicle's dynamics, including the battery pack. Hence, the driving session data include measurements collected from the selected real-world-EVs reflecting the driving experience of the user.

Firstly, given the unavailability of technical specifications, we discover the optimal parameters of the battery pack through an iterative tool that minimizes the error between simulated and real signals. Subsequently, the simulated output of the parameterized battery pack is validated using real signals. Finally, we consider the full EV simulator, embedding all subsystems along with the tuned battery pack, and assess the battery pack's performances in a vehicular environment. We repeated such a methodology for two independent Simulink EV model simulators, emulating two distinct real-world-EVs, given the availability of real data collected from the two different real-world-EVs. In this way, we can demonstrate the efficacy of the methodology generalizing over different EV models. To avoid misunderstandings throughout the document, from now on we refer to the developed Simulink simulators as virtual-EVs, while everything concerning the reference data sheet EVs as real-world-EVs.

The rest of this paper is organized as follows. Section II provides a general outlook of the available EV simulators in the literature and their limitations; Section III describes in detail the structure of the proposed virtual-EV and the required inputs and outputs. Section IV discusses the experimental results. Finally, Section V provides our concluding remarks and future works.

II. Related works

In the literature, many studies aim at improving EV performances monitoring through ML. However, large and descriptive datasets are necessary to fulfill the data-driven methodologies. Therefore, through the definition of EV simulators, we might obtain enough data to be fed as input to ML algorithms. Much effort has been put into modeling and simulating EVs on a large scale to monitor the load exchanged between EVs and the power grid. Canizes et al. [12] created a travel simulation tool to simulate a real environment, including trips and charging stations, that considers the behavior of real users, allowing the creation of personalized profiles, destinations, and schedules. The presented tool focuses on the impact of the variation of electricity prices on the behavior of EV users, highlighting that variable-rate electricity prices are more advantageous to the users. Rigas et al. [13] suggested a Java-based tool, named EVLibSim, that allows to simulate EV activities at a charging station level in a smart grid context. EVLibSim is an event-based simulation framework that enables the design of a charging station depending on the user's demands. In this way, it is possible to precisely simulate charges, discharges, and queues of EVs.

Gaete-Morales et al. [14] created Emobpy, an open-source Python tool that produces EV time-series sourcing from 200 input vehicle profiles in Germany. Providing empirical mobility statistical and physical properties of vehicles, Emobpy generates four output time series with a customizable length and resolution. The output time series include vehicle mobility, driving electricity consumption, grid availability, and grid demand information. The simulation tool allows the monitoring of large EV fleets, offering core inputs to energy, environmental, and economic applications.

A fully customizable event-based simulator was created by Ciabattoni et al. [15] that generates plug-in/out, charge, and discharge events for a group of EVs or a single EV. The tool is designed as a web simulator called ePopSimulator, as well as a Matlab/Simulink block to expand the tool's capabilities and allow it to be integrated into various applications. The simulator is ideal for investigating vehicle-to-grid solutions, since it lets users alter the simulation scenario and receive both aggregated and individual EV statistics. Brooker et al. [16] created an open-source vehicle simulation tool, named FASTSim, that designs conventional vehicles and EVs. It models vehicle components maintaining high accuracy, ensured through the validation of the results utilizing data from hundreds of cars. The tool enables researchers to explore solutions to improve EV technologies, including the estimation of energy consumption.

Using Modelica packages, Simic and Bäuml [17] constructed a hybrid electric vehicle model. The suggested model has an ideal battery set. Using accessible measurements and data sheets, they parameterized the EV model and used actual observed current as a reference signal. The observed and simulated signals differ by 5% according to the battery voltage validation.

In this work, we present a virtual-EV model simulator that, given an input driving cycle, generates the current, voltage, SOC, and average internal temperature signals for the EV's battery pack. In particular, we designed two virtual-EVs, parameterized with data from actual data sheets, for two different real-world-EVs. Bypassing the need for time-consuming laboratory tests or expensive devices gathering data from the EV's battery management system, we are able to create a synthetic and realistic dataset made up of internal battery pack signals. By gathering such precise battery data, data-driven ML techniques may be used to conduct in-depth study on the battery performances and solve the problem of data scarcity.

III. Materials and methodology

The complete pipeline of the proposed methodology is shown in Fig. 1 (a), which describes the three phases necessary to develop each of the two virtual-EVs. In the following, we report a detailed description of each phase along with the input and output data.

A. Dataset

The employed dataset includes real time series of vehicular speed [Km/h], battery's current [A], voltage [V], SOC [%], environmental and internal average temperatures [°C] relative to four driving sessions for two distinct real-world-EVs, for a total of eight driving sessions. The data have been used as input to the three phases depicted in Fig. 1 (a) and validation data for the performances' assessment steps. At the time of the data collection, the two real-world-EVs, here in after referred to as real-world-EV-A and real-world-EV-B, were equipped with a battery pack characterized by a SOH of 88% and 94%, respectively. Therefore, given the limited availability of

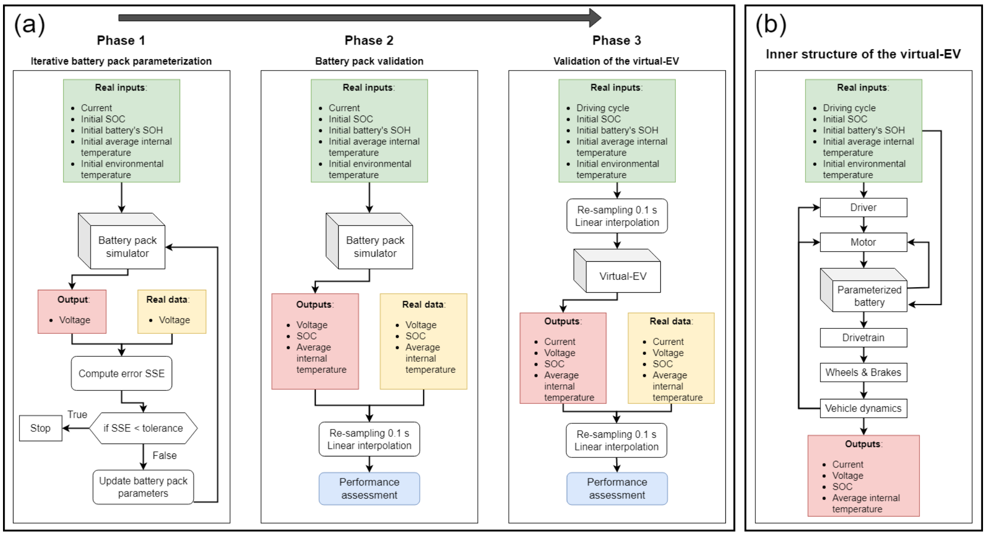

Fig. 1. (a) The complete pipeline of the proposed methodology, which starts with the battery pack parameterization (phase 1), followed by the validation of the tuned battery alone (phase 2), and, lastly, the validation of the full virtual-EV (phase 3). (b) The inner structure of the virtual-EV.

real data, we cannot assess the performances of the proposed methodology for different input SOH values. Nevertheless, the available data are enough to fulfill all steps of the methodology and evaluate the performances of both the battery pack and virtual-EV, relative to both real-world-EVs A and B.

Moreover, the onboard device collecting the real signals samples the data with different sampling frequencies. Table I reports the original sampling frequency for all signals gathered from the real-world-EVs A and B. The discrepancy among sampling frequencies forces us to re-sample the data with a common frequency of 0.1 s through linear interpolation to ensure consistency among all signals and to validate the simulation results. The choice of the sampling rate is a trade-off between computation time and signal fidelity; a fast sampling rate may capture high-frequency changes in the signals more accurately, at the cost of a higher simulation time.

B. The virtual-EV

The main focus of our work is to develop a virtual-EV model simulator to generate accurate battery pack's current, voltage, average internal temperature, and SOC signals, allowing the monitoring of battery conditions throughout the EV's operational time. Therefore, the battery pack becomes the most critical component of the virtual-EV. Indeed, modeling an EV battery pack is challenging due to the literature's unavailability of internal design specifications. Furthermore, the definition of the battery pack as a group of interconnected cells would significantly increase the complexity of the simulation. Hence, the solution we propose to overcome such issues is to represent the battery pack as if it consisted of only one high-voltage cell. In Section IV, we demonstrate that such proposed approximation yields acceptable performances for the battery pack's output signals.

The battery pack has been modeled using the Generic Battery Model block from the Simscape electrical Simulink library [18], which implements thermal and aging models. The former describes the battery-to-ambient thermal interactions, specifying the environmental and average internal temperatures at the beginning of the simulation; the latter affects the discharge characteristics based on the battery pack's SOH. Nevertheless, the Simulink generic battery block implements a very low-complexity thermal model, which cannot precisely capture heat transfer phenomena at the cell and module level. The implemented aging model allows users to specify the starting battery age in terms of SOH, which characterizes the battery pack throughout the simulation. The battery's lifetime has to be defined in Equivalent Full Cycles (EFC) rather than a SOH percentage. An EFC is defined as a virtual cycle of the battery's charge and discharge at a specified depth of discharge (typically Depth of Discharge = 100%, i.e., a full charge and a full discharge).

We set up a battery pack model simulation imposing a constant 1 C discharge current, starting with a SOC of 100% until its complete discharge, i.e., SOC of 0%. Then, we computed the actual battery's capacity by multiplying the magnitude of the imposed discharge current and the ending time of the simulation in hours. Finally, we calculated the SOH by dividing the multiplication result by the theoretical nominal battery capacity. We repeated this experiment for EFC values ranging from 0 to 3000 with a step of 100. We discovered a linear relationship between EFC and SOH for Simulink's generic battery model, shown in Fig. 2. In this way, at the beginning of the simulation, the user can easily specify the

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

initial battery SOH, which is then converted into EFC. Since the battery pack aging model is parameterized similarly for both virtual EVs, the EFC-to-SOH mapping is unique for the two models.

Referring to Fig. 1 (a), phase 1 of our procedure is the *iterative battery pack parameterization*. Due to the unavailability of battery data sheet specifications, we employ the Simulink Parameter Estimator app [19] to discover the best parameters. Such an application implements an iterative procedure that, for each iteration, executes a simulation, tuning the battery's parameters so that the target simulated, and real signals match as much as possible. As shown in Fig. 1 (a), during the battery pack parameterization, the Parameter Estimator receives the battery pack current signal as input, extracted from an actual driving session covering an entire discharge cycle of the battery. In this way, we ensure the discovery of parameters well-fitted for almost any section of the discharge curve of the battery pack. The initial values of the battery's SOC, SOH, environmental and average internal temperatures are initialized accordingly to the selected driving session. The parameters are tuned so that the simulated voltage signal matches the experimental one as much as possible, see next Section IV. The iterative procedure uses the Nelder-Mead method [20] to solve the optimization problem, minimizing the Sum of Squared Errors (SSE) between simulated and real voltage time series. The SSE quantifies the difference between the true and the synthetic values, and its mathematical formulation is the following,

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

where y_{sim} is the simulated value, y_{real} is the observed value, and N is the total number of simulated values. The iterative procedure continues until the SSE gets below a tolerance threshold. As soon as such a condition is satisfied, the battery pack parameterization stops, and the selected combination of parameters is assigned to the battery pack. The iterative battery pack parameterization is independently accomplished for the battery pack of both real-world-EV-A and real-world-EV-B, selecting the relative inputs and outputs.

Once the battery packs relative to both real-world-EV-A and real-world-EV-B have been parameterized, referring to Fig. 1 (a), we proceed to phase 2, the *battery pack validation*, in which we assess the performances of the battery pack alone. Therefore, we utilize the real driving session current time series, initial battery SOC, SOH, environmental and average internal temperatures, as inputs to the simulation. But, in this case, we are also interested in monitoring the simulated output time series of SOC and average internal temperature, along with voltage. Therefore, after a linear interpolation with a common time step of 0.1 seconds, the simulated output signals of the battery pack are compared with the real ones belonging to the same driving session. Phase 2 is repeated for both battery packs, peculiar to both real-world-EV-A and real-world-EV-B, and the achieved results are discussed in Section IV.

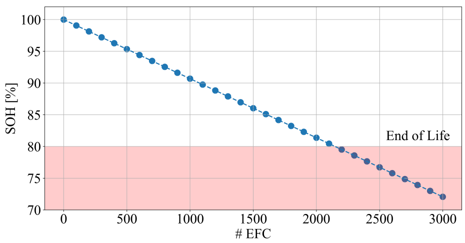

Fig. 2. The assessed linear relationship between EFC and SOH [%].

The last phase 3 of the proposed methodology is the *virtual-EV validation*. In this phase, we embed the parameterized and validated battery pack into a full virtual-EV model simulator, which includes additional subsystems that will mimic the complex dynamics of an EV. The developed Simulink EV model is based on the existing model [21]. Still, we improved and added several components to better suit our experimental needs, most notably the battery pack and the regenerative braking subsystem. The virtual-EV comprises many mutually dependent subsystems connected through the signals generated during the simulation. The subsystems are the driver, motor, braking system, drivetrain, wheels, vehicle body, and battery pack. A graphical representation of the inner structure of the virtual-EV, along with inputs and outputs, is depicted in Fig. 1 (b).

The *driver* block implements a discrete-time proportional-integral controller to mimic a human driver for the vehicle. At each time step, the controller tracks the input reference driving cycle speed signal and the simulated vehicle speed, trying to match them by acting on the brake and accelerator pedals. The *motor* is implemented in our EV model through the Mapped Motor block in Simulink, a mathematical model of an electric motor operated in torque-control mode. The *braking system* is based on two different contributions: friction braking and regenerative braking. The former is the conventional braking mechanism activated by pressing a brake pad, generating a friction force opposing the direction of the wheel; the latter, while slowing down the vehicle, recharges the EV battery pack. Regenerative braking has been added to the baseline Simulink model to mimic the dynamics of a real EV. The *drivetrain* is the set of rotating shafts and gears that distributes the mechanical power generated by the electric motor to the wheels, and it has been modeled through proper Simulink blocks. The *wheels* are modeled using the Longitudinal wheel with disc brake Simulink block, which also models disc brakes. The *vehicle body* implements a one-degree-of-freedom rigid vehicle body with constant mass undergoing longitudinal motion; and the previously parameterized *battery pack*.

The virtual-EV receives the input driving cycle as a time series of speed measurements, the initial battery's SOC, SOH, environmental temperature (as a constant or time series), and average internal temperature. In contrast, the generated output time series for the battery pack include current, voltage, SOC, and internal average temperature, which are calculated and updated at each simulation time step according to the provided inputs. Also, in this case, we re-sample through linear interpolation the simulated and real battery's signals with a time step of 0.1 seconds to ensure a common time base and fairly compare the simulated time series with the real ones. The simulation duration is proportional to the length of the input speed signal. During this validation phase of the virtual-EV, we execute four simulations for both virtual-EV-A and virtual-EV-B, matching the available real driving session data to assess the performances of the virtual-EV as a whole.

IV. Experimental results

In this section, we discuss the results achieved during the validation phase of the parameterized battery pack alone and the virtual-EV as a whole. We utilize the *Root Mean Square Error* (RMSE) and *Coefficient of determination* (R^2) to measure the deviation between actual and synthetic output signals. The RMSE measures the average difference between simulated values and the actual values, whilst the R^2 appraises the proportion of variance in the observed values that can be explained using the predicted values. The performance metrics are defined as follows,

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

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

where y_{sim} is the simulated value, y_{real} is the actual value, $\overline{y}_{real}$ is the mean value of the actual values, and N is the total number of samples. Due to page limitations, we solely depict through Fig. 3 and Fig. 4 the performances peculiar to the battery pack of the real-world-EV-A and the virtual-EV-A, respectively. But, Table II and Table III provide a thorough description of the simulation results for both battery packs and both virtual-EVs, separately.

We assess the performances of the tuned battery pack, for both real-world-EV-A and real-world-EV-B independently, providing input real current signals belonging to the relative available driving sessions. Fig. 3 shows the input current signal and output signals along with real ones for the battery packs of the real-world-EV-A. Observing the curves in Fig. 3, all simulated signals follow the measured ones, and a precise matching can be observed. The simulated voltage, SOC, and battery temperature signals are compared with the real ones using the RMSE and R^2 performance metrics. The overall simulation performances of the battery packs for both models, across all input currents, are reported in Table II in terms of RMSE and R^2. All battery pack's simulated signals achieve an R^2 well above 0.90, and an RMSE relatively low, proving the accuracy of the proposed battery pack.

TABLE II
Overall performances of the battery pack for both real-world-EV A and B, and for all output signals.

	Battery pack real-world-EV-A		Battery pack real-world-EV-B	
Output signal	**RMSE**	**R^2**	**RMSE**	**R^2**
Voltage	3.18 V	0.96	2.73 V	0.96
SOC	0.31%	0.99	1.16%	0.99
Internal average temperature	0.71 °C	0.99	0.29 °C	0.98

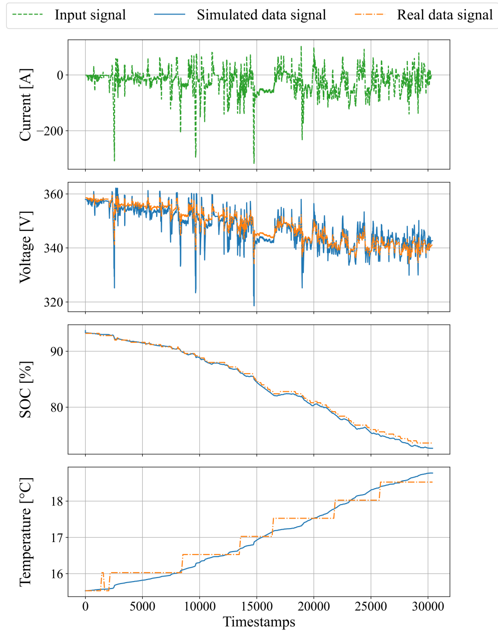

Fig. 3. Comparison between real and simulated signals generated by the real-world-EV-A battery pack simulator for one of the four input currents.

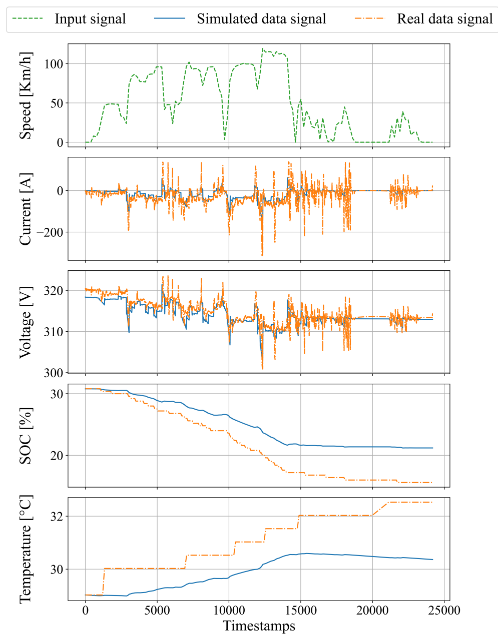

Fig. 4. Comparison between real and simulated signals generated by the virtual-EV-A for one of the four selected input driving cycles.

Once we tuned the battery pack and assessed its accuracy, we tested the performances of the virtual-EV as a whole, which includes all other subsystems as shown in Fig. 1 (b). In this case, the input signal is a time series of speeds representing the user's driving cycle. However, we also monitor the output current besides the battery's voltage, SOC, and average internal temperature. As we did for the battery pack, we assess the performances of the whole virtual-EV-A and virtual-EV-B, relative to the real-world-EV-A real-world-EV-B respectively,

TABLE III
OVERALL PERFORMANCES OF BOTH VIRTUAL-EVS, RELATIVE TO THE REAL-WORLD-EV-A AND REAL-WORLD-EV-B, RESPECTIVELY.

	Virtual-EV-A		**Virtual-EV-B**	
Output signal	**RMSE**	$\mathbf{R^2}$	**RMSE**	$\mathbf{R^2}$
Current	40.22 A	0.18	17.13 A	-0.01
Voltage	3.43 V	0.95	7.05 V	0.75
SOC	4.66%	0.97	8.01%	0.78
Internal temperature	0.95 °C	0.99	0.55 °C	0.94

providing four different input driving cycles specific to the analyzed real-world-EV. In this way, we can test the virtual-EV's capability at generalizing over different inputs.

Fig. 4 shows one input driving cycle and the obtained battery's output signals, along with real ones, for the virtual-EV-A. While, Table III reports the overall simulation performances for all battery's output signals generated by the two developed virtual-EV-A and virtual-EV-B relative to the real-world-EV-A real-world-EV-B, respectively, in terms of RMSE and R^2. Observing the simulation results, the virtual-EV as a whole is not as accurate as the battery pack alone since we include all other subsystems that, inevitably, add complexity to the simulation. Indeed, considering real-world-EV-B, and comparing Table II and Table III, the RMSE over the SOC jumps from 1.04% to 8.01% for the battery pack alone and for the whole virtual-EV-B, respectively. Nonetheless, the RMSE over the voltage remains relatively low compared to the other outputs, which is a direct consequence of having tuned the battery pack, during phase 1, to minimize the error between simulated and real voltages.

Also, observing Table III, for the virtual-EV-B, the RMSE between simulated and real SOCs reaches 8.01%, while for the virtual-EV-A, it reaches 4.66%. For both virtual-EVs, the RMSE over the internal battery temperature does not exceed 1 °C, and the R^2 is equal to 0.99 and 0.94 for the real-world-EV-A and real-world-EV-B, respectively. Hence, the virtual-EVs can capture the evolution of the monitored signals given the input driving cycle. Therefore, after the analysis of virtual-EVs performances, we can state that the proposed methodology achieves promising results and allows the generation of a synthetic and realistic battery pack dataset starting from the input driving cycle, easily customizable by the user.

V. CONCLUSION

In this work, we proposed a virtual-EV that generates battery signals given the input driving cycle. The embedded aging model allows the specification of the initial battery's SOH that will affect the output signals. The results for both distinct virtual-EV-A and virtual-EV-B are promising. They prove the efficiency of the proposed methodology generalizing over different real-world-EV models, allowing the extension of the analysis to, potentially, any EV of interest. Nonetheless, the virtual-EV can be improved by considering the introduction of several enhancements. In fact, in our future works, we will extend the virtual-EV by including: i) the effects of auxiliary devices, e.g., air-conditioners and car lights, that might influence the battery's behavior; ii) external driving conditions, e.g., changing road slope and wind direction; and iii) the rolling resistance. We believe that the inclusion of such internal and external factors in the virtual-EV would further enhance its performances.

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