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## Modeling of smart batteries for the realization of a digital twin prototype

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**Abstract**—Digital Twin (DT) is one of the major technology trends that has attracted many industries lately. The safety and reliability of lithium-ion batteries is a critical issue for both their design and operation to qualify their degradation due to aging. The digital twin offers new paradigms that can provide an effective solution to evaluate the degradation of the lithium-ion battery as it provides an efficient solution to physical and digital systems integration. It reflects the behavior of the equipment by building a virtual representation of the latter, providing supports for real time control, reliability, and stability. In this paper, the steps towards battery digitization are studied through a real case study, aiming at providing a generic solution for battery digital twins development and integration.

**Index Terms**—Digital Twins, Battery, State Estimation, SoC and SoH Estimation, Digital Transformation

### I. INTRODUCTION

Since the beginning of the 21st century and the advent of Industry 4.0, the world is experiencing a fundamental change in the design and use of products and means of production. This paradigm shifting does not only concern the industrial sector, but also many other fields, such as energy, logistics, construction, health, and this within the framework of what is commonly called the digital revolution. The key technologies that are driving this revolution are those that allow to capture data, process it, extract information from it, establish models, as well as provide services adapted to needs and uses such as: Internet of Things, Data mining, Artificial Intelligence, and especially the Digital Twin.

In addition to the industrial sector, which is certainly experiencing the most rapid digitalization, thanks in particular to Smart Manufacturing, the energy sector is not left behind, mainly due to the development of Smart Grids. These smart grids allow the collection and management of data between suppliers and consumers in order to adjust the flow of electricity in real time [1]. These new smart systems now allow for better management of a power grid powered by intermittent energy sources (wind, solar, tidal). However, even if this technology can overcome the constraints related to the control and management of this type of energy in

the network, the need to have storage resources for this energy within the network remains paramount. This is one of the reasons why manufacturers are developing increasingly sophisticated batteries, both in terms of storage capacity and functionality [2] [3] [4] [5]. In order to be integrated into smart structures, batteries must therefore also have smart modules, or at least be able to interface with such systems.

If there were to be a technology that is essential for the integration of any physical object (in this case the battery) into a global digitalization process, it would be the "Digital Twin". This technology allows not only to keep a digital flow throughout the process of design and validation of the product (or physical object) upstream of its production, but also during the operation phase. Having a digital twin for the design, development, and use of a new generation of batteries can only provide a considerable competitive advantage. This offers the possibility to validate and improve the different versions of the product before it is manufactured and put on the market, but also to improve its performance and optimize its running in operation, in addition to providing feedback and having a digital continuity allowing the improvement of the product for future versions. It is also with the objective of investigating the feasibility of such an approach that we conducted the study that is the subject of this paper.

### II. STATE OF THE ART

#### A. The Digital Twin:

The digital twin has become a popular research topic in recent years due to its potential to improve decision making in many sectors, such as industrial production, construction, maintenance, and urban planning. The digital twin is used in industry to simulate production processes and improve efficiency, including real-time monitoring; production control; part performance prediction; human-robot collaboration and interaction; process evaluation and optimization; asset management; production planning [6]. It is also found in the field of smart city construction and development [7] [8] [9] [10]. Moreover, applications related to logistics and

transportation [11], energy [12], and even healthcare [13] are increasingly seeing the emergence of tools based on digital twin technologies.

Other works have focused on issues related to the definition of concepts and the proposal of formalism that allow this technology to be better understood given its growing use and the diversity of application domains. [14] proposed one of the most robust models in the literature, allowing to define a digital twin as an entity composed of 5 distinct dimensions (Physical Element, Virtual Element, Data, Services, Connections). [15] proposed a typology composed of 11 elements, allowing to draw up the profile of the digital twin to be developed in the first stages of this process, this was validated thereafter by [16] on maintenance applications. As for the interactions that this technology could have with its environment, [17] looked at the different surroundings with which the DT would come to interact, as well as the effects that this could have on its evolution in operation. While [18] focused on the human aspects of this interaction.

For their part, [19] were more interested in the modes of use of this technology from the point of view of the precision and complexity of the models as well as the rate of synchronization, according to the needs and uses. Although the digital twin is seen as a powerful tool for improving decision making, there are still challenges to overcome in order to get the most out of it. A key challenge is reconciling the accuracy of the data used to create the digital twin with the amount of data available [20]. In addition, there is a need to develop methods to manage the data in real time and ensure its quality. Finally, it is important to develop solutions to integrate the digital twins into existing systems seamlessly and efficiently [21].

### B. Lithium Battery:

The state of the art in the design and development of new lithium batteries has been the subject of a large amount of research in recent years, due to the rapid growth of the portable and electric technology industry. Lithium batteries are considered the most promising for mobile and electric vehicle applications due to their high energy density and low cost.

The first step in designing new lithium batteries is to optimize the anode material. Conventional anode materials used for lithium batteries include graphite and graphite composites, but these materials have limitations in terms of energy density and stability [22]. New anode materials under development include metals such as lithium metal, silicon, and silicon alloys [23].

The second step in the design of new lithium batteries is to optimize the cathode material. Conventional cathode materials used for lithium batteries include lithium oxides, such as  $\text{LiCoO}_2$  and  $\text{LiMn}_2\text{O}_4$ , but these materials also have

limitations in terms of energy density and durability [24]. New cathode materials in development include lithium sulfides and lithium phosphates [25]. Finally, it is important to develop new electrolytes to improve the stability and durability of lithium batteries. Conventional electrolytes used for lithium batteries include organic solvents such as acetonitrile and propylene carbonate, but these solvents have safety and stability limitations [26]. New electrolytes in development include solid electrolytes and protective membranes [27].

However, our partner in this study (the Otonohm company), aims to develop a new generation battery, which is innovative not from the point of view of the materials used, but rather from the internal architecture itself. Therefore, the possession of a Prototype Digital Twin would allow to have models offering the possibility of apprehending the conduct of the physical object, to simulate its behavior, as well as to evaluate its future performances according to various scenarios and modes of operation. Moreover, this prototype twin can be made to evolve into an Instance Digital Twin, which can be used during the operation of the battery at the customer's site in order to provide even more advanced services.

In this paper we present the main part of the conducted work in this perspective. In what follows, we will present the battery under development by our partner, the various tests carried out on it, as well as the various models developed to support the digital twin.

## III. CASE STUDY:

### A. Otonohm's technology

Otonohm is an engineering company that develops innovative solutions for lithium batteries. It has a breakthrough technology, the switched BMS, which aims to minimize losses in the power supply chain. Traditional batteries use a serial/parallel architecture where all the cells of the battery are already connected in the circuit, whereas in the switched BMS technology, the cells are not connected in a serial/parallel configuration, but are individually isolated and are put in series/parallel by means of switches according to the control commands provided by the micro-controllers. Currently, this technology allows batteries to deliver any type of signals and voltages by adding or removing cells in series without using a converter or inverter. In this study we chose one of Otonohm's prototypes to deploy the digital twin.

### B. Battery pack 48V

A 48V battery pack was developed with a slave board divided into 4 slave blocks each consisting of 4 Sony VTC6 cells (Figure 1). There is also a power supply block and a master block. The pack is capable of charging and discharging at 48V. The cell voltage varies between 4.1V and 2.8V. To have the possibility of intelligent management of the battery and to optimize its functionality, we studied the deployment of a digital twin of the pack.



Fig. 1. The 48V pack with 16 cells.

### C. Battery modeling

One of the main steps for a digital twin is to have a model that matches its physical object well. The strategy adopted here is to first model the cell and then build a model of the pack using MATLAB/Simulink. There are a wide variety of cell models, which have been developed with different complexities that can be used in various application areas. An important factor in modeling a cell is parameter estimation. Different modeling strategies for extracting battery parameters are electrochemical, mathematical, circuit-oriented, and data-driven. In real-world applications, battery models are used to predict operating voltage, power and energy capacity to ensure reliable performance and safety. Battery models are critical to the development of accurate algorithms for estimating battery condition, such as state of health (SOH) and state of charge (SOC). Considering the research objective and application, the Equivalent Circuit Model (ECM) was chosen.

#### 1) The ECM model:

Currently, the equivalent circuit model (ECM) is widely used due to its simplicity. When modeling the dynamic behavior of a cell, accuracy and complexity are two important factors. The ECM effectively satisfies both of these factors. ECM uses different combinations of electrical components such as resistance, capacitance, voltage source to simulate the charging and discharging characteristics of lithium-ion cells. The model is simple but represents the non linearity of the cell very accurately. The model is composed of a resistor  $R_0$  and resistors  $R_n$  each in parallel with a capacitor  $C_n$ . The accuracy of the n-RC model increases with the number of resistors and capacitors in parallel [28][29]. However, the accuracy of the model with 2 resistors-capacitors in parallel is sufficient considering the accuracy and complexity of the model which increases very greatly when the number of resistors-capacitors in parallel increases [28] (Figure 2). In this paper, the 2-RC model is finally chosen as the equivalent battery circuit model.

In the circuit model,  $U_{oc}$  represents the open circuit voltage;  $R_0$  is the internal resistance of the cell; circuits  $R_1$  and  $C_1$  are used to simulate the rapid voltage rise process of the cell; circuits  $R_2$  and  $C_2$  are used to simulate the slow voltage stabilization process;  $R_1$  and  $R_2$  are the internal biased resistances of the cell, and  $C_1$  and  $C_2$  are the biased capacitances of the cell. In this model, the steady state and

transient Characteristics of the cell can be best simulated by the two RC circuits [30].

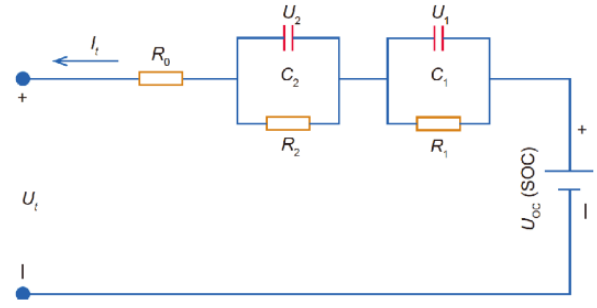


Fig. 2. Equivalent circuit model 2-RC

### D. Experimental protocol

In order to capture the dynamic characteristics of the cell accurately, a test was performed (Figure 3). The test is divided into three steps: (1) Capacitance test, (2) SOC-OCV test and (3) Hybrid Pulse Power Characterization (HPPC) test (Figure 4).



Fig. 3. The tests on the 4 cells of Sony VTC6

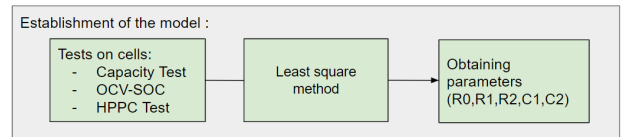


Fig. 4. The least squares experimental protocol

#### 1) Capacity test:

This test measures the cell capacity in ampere-hours using a constant current equal to  $1C$ . The discharge ends at a discharge voltage limit specified by the manufacturer. The one-hour rate ( $1C$ ) is used as a reference for the static capacitance measurement and as a "standard" for the subsequent stages of the test. The capacitance measurement is performed to confirm the rated capacity of the cell and to ensure that the  $1C$  current is accurate. To perform these tests, the cells were placed in

an environmental chamber at 25°C for 2h, and then they were charged with constant current (CC) at 1C up to 4.2V and then the voltage is kept constant (CV) until a current equal to C/10. Then they were discharged in CC at 1C to 2.5V. Between each step a 30 minute pause was performed (Figure 5).

2) *The OCV-SOC Test:*

The characterization of the open circuit voltage (OCV) is to determine experimentally its correlation with the state of charge. To measure the OCV, one method consists in discharging the cell initially charged with a very low current compared to its capacity until 0%. Since the cell can be considered in a quasi-steady state during the solicitation at a low current, its voltage during the solicitation can therefore be considered as the OCV. In this study the test was performed at 25°C. For this purpose a discharge was made in DC at C/25 up to 2.5V and after a charge was made in DC at C/25 up to 4.2V then CV up to a current equal to C/250. Between each step a 30 minutes break was performed (Figure 6)

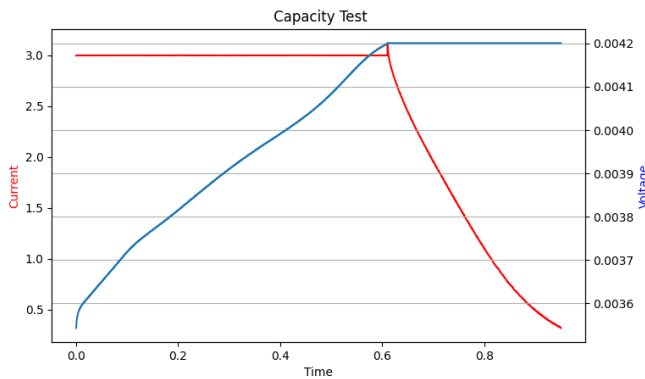


Fig. 5. The Capacity Test

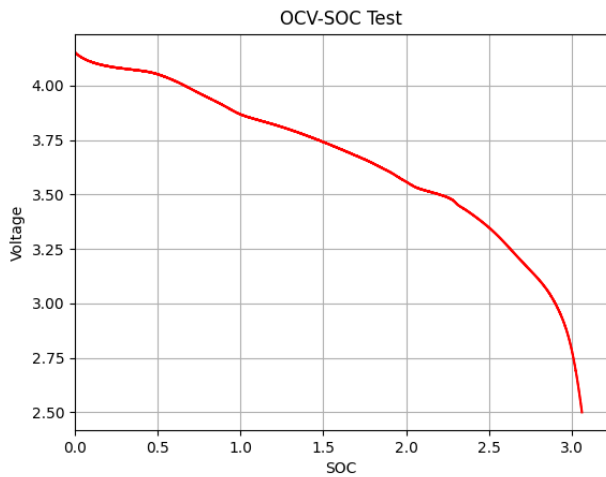


Fig. 6. The OCV-SOC Test

3) *The HPPC Test:*

The HPPC test protocol has been proposed in international standards. It consists of applying a train of current pulses in charge and discharge and then measuring the voltage response to each pulse. From the analysis of this voltage response, the model parameters can be extracted. In order to establish the parameters of the equivalent electrical circuit, the entire range of the SOC must be scanned. Pulses should be applied in charge and discharge to study the effect of the current direction on the evolution of the parameters. And finally, the whole test is to be repeated at different temperatures in order to integrate its effect on the battery behavior. In this study we have done the test at 25°C (Figure 7).

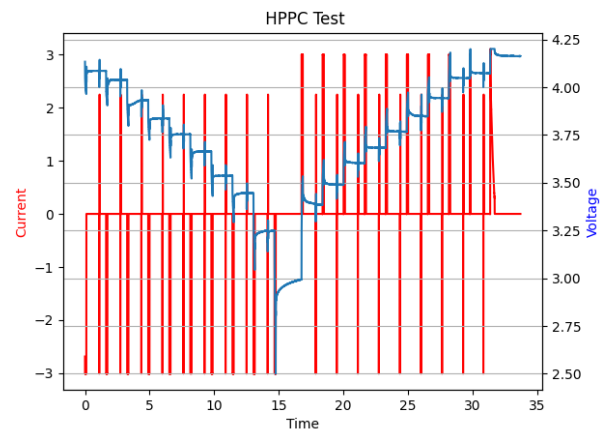


Fig. 7. The HPPC Test

E. *The cell model*

The tests performed allow us to find the parameters of the cell as well as to model the cell. Figure 8 shows the cell model on Simulink. In this equivalent circuit model, the voltage is the output, and the current is the input, while OCV, R0, R1, C1, R2 and C2 are the parameters of the model and are a function of the SOC of the cell.

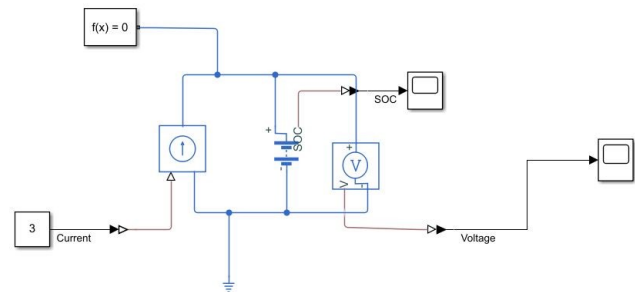


Fig. 8. The Cell Model

### F. The Pack model

Thanks to the cell model, the block composed of 4 cells has been built (Figure 9). Once the block model is complete, the pack model with the 4 connected blocks is built.

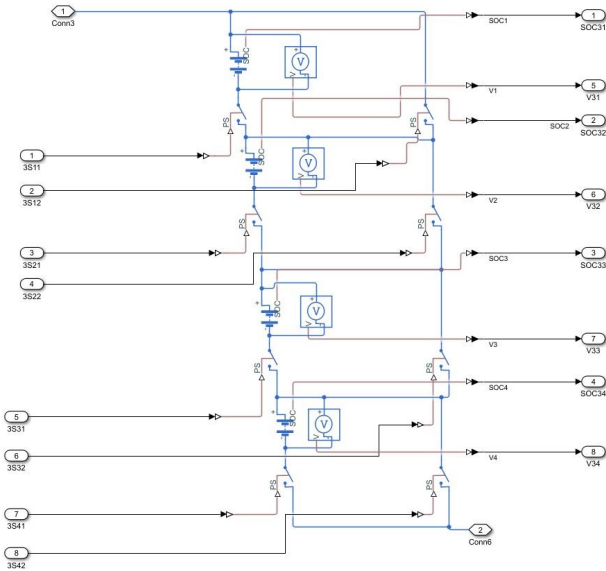


Fig. 9. The block model

## IV. RESULTS

In an attempt to validate the models, two comparisons were made. First, the cell model was compared to the validation test results. Second, the pack model was compared to the 48V pack cycling result.

### A. Cell model validation experiments

In order to validate the models, fully charged cells were discharged to 1C for 5 minutes and then allowed to rest for 30 minutes. This step was repeated 3 times. Then they were discharged with a current equal to 1C up to 2.5V. The experimental current data was used as the input for the cell model, and the model voltage was then calculated as the output using MATLAB/Simulink. The predicted voltage from model was then compared to the experimental voltage to evaluate the model performance (Figure 10).

It is possible to say that the cell model performed relatively well in predicting the voltage, given that the root mean square error (RMSE) is relatively small, at 0.0252V. However, it is important to note that even a small error can have a significant impact on system performance. This cell model was used to build the 48V pack model.

### B. Pack model validation experiments

Concerning the architecture of the battery pack, the model of the pack has been developed on Simulink. To verify the pack model a validation test was performed using the 48V pack (Figure 11). The test consisted of a cycling of the pack. The cells were switched every 30 ms. This means that

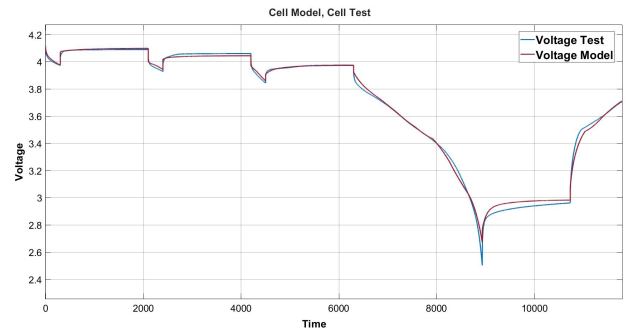


Fig. 10. Validation test of the cell model

every 30 ms, the software sorts the cells by voltage. If the pack is charged, the software disconnects the three cells with the highest voltage, if the pack is discharging, the software disconnects the three cells with the lowest voltage. Thus, at any given time, only 13 cells are connected, and 3 cells are set aside. The test was performed in a test chamber with a controlled ambient temperature of 25°C. To charge the pack, a constant current of 3A (equivalent to a 1C load) was applied and to discharge the pack, a constant current of 10A was applied. To compare with the model made on MATLAB, only the first three cycles were used because the model does not take into account cell aging.

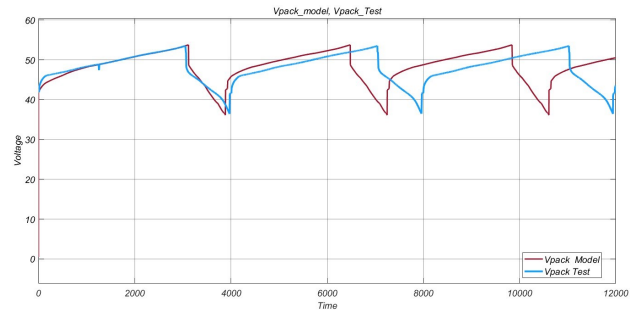


Fig. 11. Validation test of the pack model

The result shows that there is a difference between the voltage output of the real pack and the voltage output of the model. There are reasons that can explain this difference.

- Our model does not take into account the internal temperature of the cells which can vary due to their internal resistance and cause changes in the cell voltage.
- The components used in the real pack such as MOSFET (metal-oxide-semiconductor field-effect transistor) or operational amplifiers have not been modeled in Simulink due to the complexity required to simulate these components.
- The voltage of the modeled cell is not a perfect representation and the cumulative error of the 16 cells in the model make the error more pronounced in the pack model.

## V. CONCLUSION

In this paper, we have dealt with a topical issue, which is the development of new generation lithium-ion batteries, an important technology of the ecological transition. This, by using a technology just as topical, which is the Digital Twin (DT). By means of a digital twin of the "prototype" type, we were able to model our physical object of interest (the battery), in order to carry out various simulations, allowing us to better understand the behavior of this technology before moving on to its physical manufacture. Moreover, although this model is relatively accurate, it does not fully represent the operation of the real pack, it is therefore necessary to continue to improve its accuracy and reliability. To do so, we aim to act jointly on the models and on the data, on the one hand by using more accurate models or other modeling approaches (as physical-chemical models), and on the other hand by feeding the digital twin with new tests, and new data sets. These new data will also allow the development of new types of models, such as data-driven models (as machine learning models for example). Finally, once the first physical versions of the battery have been manufactured, it will be a question of evolving this "prototype" digital twin into an "instance" digital twin, by setting up bidirectional communication mechanisms between the digital twin and its physical counterpart (the battery) in order to ensure a certain level of synchronisation. This will allow the DT to offer various services depending on the use that will be made of the battery in operation.

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