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A Long Short-Term Memory-Based Deep Learning Digital Twin of a Li-Ion Cell for Battery SOC Estimation †

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Abstract: This study aims to implement the digital twin of a Li-ion battery by using real measurement data and to create a deep learning-based SOC (state of charge) estimation solution. In the case of the SOC estimator, a special type of deep learning, so-called long short-term memory (LSTM), was used to increase the capabilities of the estimator. The digital twin and the SOC estimator were created by using MATLAB and MATLAB/Simulink. As a result, the implemented system can accurately simulate the non-linearities of the Li-ion battery and provide a satisfactory estimation of the SOC of the battery.

Keywords: Li-ion battery; deep learning; digital twin; SOC estimation; LSTM; MATLAB/Simulink

1. Introduction

Nowadays, Li-ion batteries play a crucial role in our lives. This role is due to the everyday use of portable, rechargeable devices like mobile phones and laptops and the increasing demand for electric cars. However, the everyday use of electric cars faces multiple challenges, mainly related to Li-ion batteries [1].

First of all, the energy density of Li-ion batteries is much lower than the energy density of fossil fuels used in internal combustion engine cars, which makes it challenging to reach a similar range. The electric vehicle range can be increased by increasing the number of cells within the battery pack or by developing battery cells with a higher energy density [2,3]. Both of these solutions demand a longer development process where accurate simulations are essential, leading to the creation of digital twins. To reach the most effective range of a given electric car, it is crucial to estimate the actual SOC of the electric vehicle as accurately as possible [4]. Of course, this can be performed with multiple different solutions [5], like using Coulomb Counting [6], a Kalman Filter [7], or creating an AI-based solution [8]. With the widespread use of more and more effective AIs, their use has become more common in the case of SOC estimation. Still, it must be mentioned that there is no universal best solution to estimate the SOC of the system because the use of different methods demands a different depth of knowledge about the given system and a different amount of available measurement data [9]. This is another crucial reason for using digital twins: they can be used to find the best estimation method before they are used in a real car.

Furthermore, Li-ion batteries are sensitive, especially to temperature, meaning that a proper monitor and control system must be created to secure the operating conditions of the Li-ion battery [10]. The task of the so-called battery management system (BMS) is to ensure these conditions, which means that the malfunction of this system can lead to damage or a reduced lifespan of the battery [11].

Finally, the battery's aging must be mentioned, which is normal if the battery is kept in its normal working conditions [12]. However, aging can also be caused by multiple factors, such as too high a temperature or too deep discharging of the battery. Naturally, modern

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electric cars try to reduce the possibility of aging as much as possible, but aging cannot be eliminated.

Fortunately, most of these challenges can be eliminated or at least reduced by using proper simulations and running as many virtual tests as possible. By doing so, an extremely high number of tests can be conducted on the Li-ion battery, and the measurement data provided by these tests can be used to train and finetune an AI-based SOC estimator [8,9].

This study aimed to create a reusable digital twin for Li-ion batteries and a deep learning-based SOC estimator that can accurately estimate the SOC of the simulated battery.

2. Materials and Methods

As previously mentioned, the digital twin of the Li-ion battery was created in MATLAB/Simulink. For its implementation, the Simscape battery was crucial, simplifying the modeling of the battery and its cooling system. Due to the non-linear nature of the Li-ion batteries, the so-called 1RC or Thevenin equivalent circuit model (ECM) was used, as shown in Figure 1 [13,14].

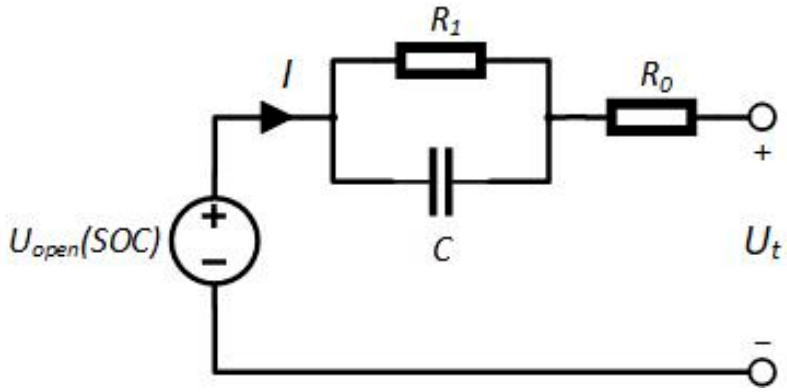


Figure 1. The 1RC (Thevenin) model.

The main equations of the 1RC model are the following:

$$U_t = U_{open}(SoC) - i \cdot R_0 - U_1 \tag{1}$$

$$\dot{U}_1 = -\frac{U_1}{C_1 \cdot R_1} + \frac{i}{C_1} \tag{2}$$

$$C_1 = \frac{\tau_1}{R_1} \tag{3}$$

After implementing the digital twin, the parameters of the Thevenin model were estimated using the MATLAB Parameter Estimator app and open-source real measurement data [15]. For creating the artificial intelligence-based (AI-based) SOC estimator, a special type of deep learning, the LSTM, was chosen for multiple reasons [16]. On one hand, using LSTM allows the recognition of long-term connections within the measurement data, making the results more accurate. On the other hand, using LSTM eliminates the main drawback of recurrent neural networks, the problem of vanishing gradients, making the training process smoother and better. For the design of the layers of the neural network, the Deep Network Designer app was used, and the training of the network was performed by using an Adaptive Moment Estimation (ADAM) solver with continuous validation to train the best possible neural network by using as few epochs as possible. After the successful training of the neural network, it was tested using different scenarios, which will be discussed in the following chapter. The neural network design in Deep Network Designer can be seen on Figure 2.

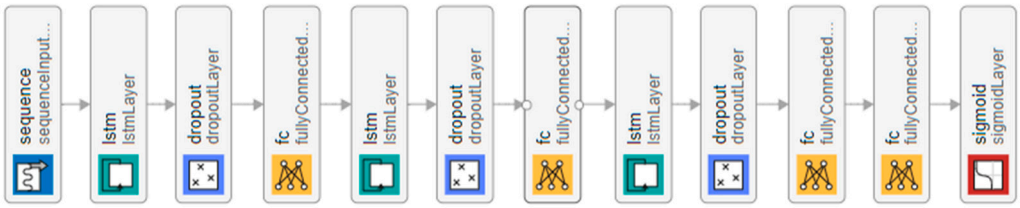


Figure 2. A screenshot of the neural network being designed for this experiment in MATLAB's Deep Network Designer.

3. Results and Discussion

As was previously pointed out, the Simscape battery was used to create the basis of the digital twin. This library provides predefined parameters for the simulation of different types of batteries, but these parameters are only sometimes as accurate as they should be, and using different ECM models can further improve the digital twin. This is why the so-called MATLAB Parameter Estimator app was used to estimate more accurate ECM parameters for the digital twin. By using this method, the accuracy of the battery model was significantly improved, leading to better mimicking of the real-life Li-ion battery. The following figure shows the difference between the simulated voltage and the measured voltage in the case of using predefined parameters and estimated parameters. This example was selected because it highlights the significant improvement that can be reached using estimated parameters. As shown in Figure 3, using measurement-based estimated parameters significantly increases the accuracy of the digital twin, meaning that it is worth estimating the critical parameters of the given system if the necessary amount of measurement data is available.

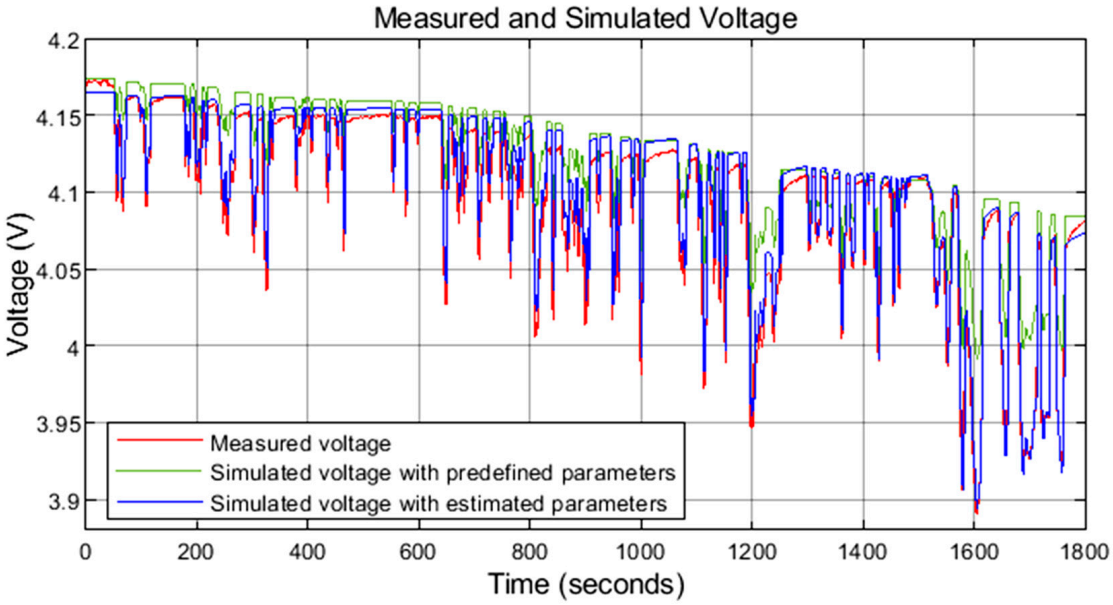


Figure 3. The reaction of the Li-ion battery digital twin on the WLTP load current in the case of predefined parameters and estimated parameters compared to the real response of the system.

After implementing the digital twin, the neural network for SOC estimation was designed using the Deep Network Designer app. During the design process, it was pointed out that after a given number of hidden layers, the further increase in the number of layers does not lead to a rise in the quality of the neural network, but it even decreases the accuracy of the given neural network. In the case of the layer and training parameters, a very similar tendency was observable because the finetuning of these parameters led to the increase of quality only until a given point. After this point, changes in these parameters in the given direction either started to decrease the system's quality or increase the neural

network's training time significantly. After finding the proper parameters, a good quality neural network was trained to estimate the SOC of the Li-ion battery, which can estimate the SOC of the battery with good accuracy, as seen in Figure 4.

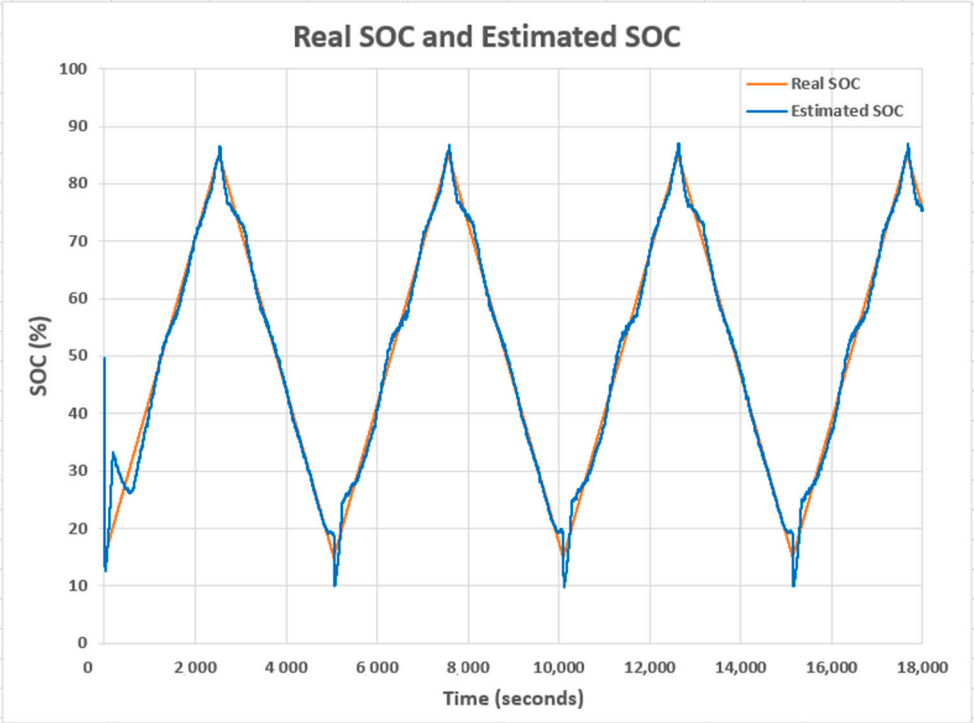


Figure 4. Comparison of the deep learning-based estimation of the SOC with the real SOC of the Li-ion battery.

As the figure shows, the created neural network gives a good estimation result and estimations close to the real SOC values provided by the previously mentioned digital twin. However, the developed simulation system also faces some challenges because it has some problems when the simulation switches between charging and discharging. The main reason for this is that during the testing of the neural network with the digital twin, a simplified charging–discharging logic was implemented, which caused some challenges for artificial intelligence. This is why the next step of this research will be implementing a more realistic charging-discharging logic, allowing better tests of the digital twin and the LSTM-based neural network.

4. Conclusions

Based on the results, a digital twin was created that is suitable for adequately reproducing the behavior of the real Li-ion battery. What is more, the parametrization method being used for the creation of this digital twin makes it possible to use the battery model as a digital twin of a different type of Li-ion battery if the necessary amount of measurement data is available for the parametrizing of the model.

In the case of the LSTM-based SOC estimator, it was shown that the proper structure of the neural network and its parametrization plays a crucial role in reaching attaining good results. However, the importance of the training parameters and settings must be mentioned as well because they can influence the training time of the neural network and its accuracy. As a result of the training, a neural network was created, which is suitable for estimating the current state of charge of the simulated Li-ion battery, meaning that it could be greatly used for multiple purposes.

In conclusion, the research reached its aim and created a reusable simulation. The digital twin of the Li-ion battery can be reparametrized, and the LTSM-based neural

network can be retrained at any time if the necessary amount of proper measurement data is available. Thanks to this flexibility, both the digital twin and the estimator can be used in further research and refined to reach even better results.

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Abbreviations

U_{open}	Open-circuit voltage (V)
U_1	Polarization voltage over the first RC network (V)
R_0	Terminal resistance (Ω)
R_1	Polarization resistance
C_1	Polarization capacitance of the first RC network (F)
τ_1	Time constant (s)

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