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Simulation and Experimental Validation for Takagi-Sugeno Fuzzy-Based Li-ion Battery Model

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Abstract- The significant growth in electric vehicles use has increased the demand for lithium-ion batteries. Battery modeling is vital for optimal and safe usage of batteries. In this paper, a novel battery model based on the Takagi-Sugeno fuzzy has been proposed. It has been demonstrated that the battery behavior is strongly dependent on its state of charge (SoC). As a result, the developed model takes into account the SoC effect, which can significantly improve the model accuracy. Simulation and experimental tests validated the pertinence of the proposed model. It has been also shown that the estimated battery internal voltage is identical to the experimental ones with a low root-mean-square error (around 11mV) and high variance accounted for function of around 98% for different operating conditions. Overall, a model with high accuracy and reasonable computational time of a lithium-ion battery is created.

Keywords Lithium-ion battery; Battery modeling; Takagi-Sugeno Fuzzy; State of charge; Equivalent circuit model.

1. Introduction

Nowadays, energy storage technology is considered one of the most critical technology for facilitating the integration of electric mobility and all sustainable power applications [1, 28-31, 36-38]. Over the years, various storage technologies have been developed to meet different specifications of different industrial sectors. Lithium-ion (Li-ion) battery is among the most widely used storage technology due to its fast development. It has many performance characteristics such as the long cycle life, safety, lightweight, high-temperature resistance and great energy density.

Battery modeling is an important task for ensuring safe charging and discharging and hence, optimal battery utilization. Moreover, accurate estimation of batteries' parameters like state of charge, state of health, state of energy, remaining useful life, state of function, state of power and remaining discharge time requires appropriate battery modeling. A good example is the development of an advanced Li-ion battery management system (BMS) for electric vehicles, which is a trending research topic. Battery modeling is one of the key functions of a BMS; hence, accurate modeling ensures safe management and reliable operation.

The complex internal mechanism and electrochemical reactions make the Li-ion battery system highly nonlinear [2]. Numerous models for Li-ion batteries have been examined in the literature and mainly fall under two main categories: the physics-based electrochemical model [3] and the equivalent circuit model [4]. Electrochemical models provide full information about the internal battery states as they could identify the behavior of Li-ion batteries based on the chemical characteristics of the composites and the design parameters. Although the high accuracy of the physics-based electrochemical models, they are complex to be applied in real-time applications and require a large number of unknown parameters to be identified [2]. This has been led researchers to investigate another type of modeling called equivalent circuit (EC) models, empirical models or Thevenin models. The EC models have a simplified structure and are adequately accurate and easy to be identified. In addition, many applications need to achieve the balance between the model accuracy and complexity so that models can be adequate for embedded microprocessors and ensure precise results in real-time [5]. Therefore, the EC modeling has gained increasing interest for a wide range of applications especially the electric vehicles application [6].

The EC model uses electrical components to describe the battery behavior. It mostly consists of an ideal voltage source (the open circuit voltage OCV), a serial resistance (Rs) and an RC network (parallel resistor-capacitor). According to the level of detail, one [7], two [8], or even more [9] RC networks can be employed. In [1], an overview of the different EC-type battery models is addressed. By adding more RC networks, the model accuracy increases, however, the complexity increases too. The model with one RC network (See Fig.1) can simulate the charge and discharge behavior of Li-ion batteries with high fidelity as shown in ref [10]. This model is often chosen for a reasonable compromise regarding computational effort and computing cost [2].

The EC battery model parameterization is a significant task in the modeling procedure based on two main parts (i) Experimental tests, and (ii) parameters identification. Imagine we applied a current impulse to a battery where the resulted response is as presented in Fig. 2. Then, each part of this response must be taken into consideration for an appropriate modeling process. The charge-discharge current impulse tests are the most common types of experimental tests. Then, a system identification technique is used to calculate the battery model parameters. Several techniques have been proposed in the literature enabling the estimation of the EC model parameters. They can be classified to four principal techniques according to Ref. [11] (i) analytical equations-based [12, 13] (ii) least square-based [14, 15] (iii) metaheuristic algorithm- based [16, 17] and (iv) Kalman filter-based [18]. Each technique has its own merits and demerits, nevertheless, guaranteeing a high-fidelity parameterization technique is still considered an important issue.

The Takagi-Sugeno (TS) fuzzy- based modeling tool has been widely employed to represent nonlinear and complex systems [25, 32-33]. The fuzzy model is generally described by a collection of fuzzy IF-THEN rules where each rule represents a local linear relationship between the input and output of the system. The global fuzzy model is obtained by blending together the local models using the fuzzy membership functions. As far as we know, the TS fuzzy approach has never been explored for battery modeling. In [34], a Mamdani fuzzy- based model has been proposed for Li-ion battery. However, the Mamdani fuzzy type is less flexible and less effective and accurate in computational terms than the TS one [35]. In addition, the authors in [34], have not deeply investigated the parameterization part.

In this work, the TS fuzzy has been adopted as a method of modeling enabling the accurate prediction of the Li-ion battery behavior under its different states of charge.

First, a characterization test has been conducted to extract the experimental characteristic of the battery and determine its EC model parameters at different SoC values. Second, local models ensuring the minimum estimation error have been defined according to each SoC range. Then, the global behavior of the battery has been represented using the multi-model representation, which is developed by combining the adopted local models through the TS fuzzy approach. Finally, the developed battery model has been validated and its accuracy has been evaluated.

Hence, the purpose of this research is to analyze the Li-ion battery behavior, cope with the problems of parameters extraction, and propose a novel well-performed battery model. The main contributions of the present paper can be summarized as follow:

- Develop an advanced EC battery model based on Takagi-Sugeno fuzzy logic, which is an intelligent approach known for its accuracy, its flexibility and its practical feasibility in managing the nonlinearities of the system and dealing with uncertainties.
- Investigate the effect of SoC on the model parameters, which can hugely improve the reliability as well as accuracy.
- Validate the proposed modeling technique through simulations using Matlab/Simulink as well as experimental tests.
- An average root mean square error of around 11mV and an average variance accounted for function of around 98% have been achieved, which evaluate quantitatively the proposed model accuracy.

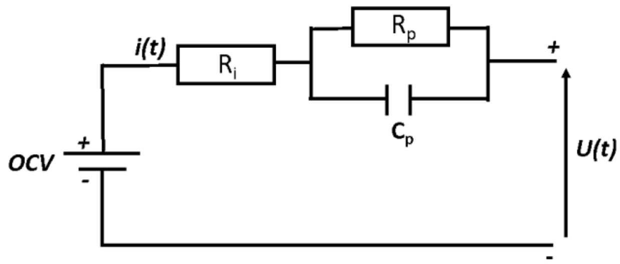


Fig. 1. Li-ion battery's equivalent circuit model.

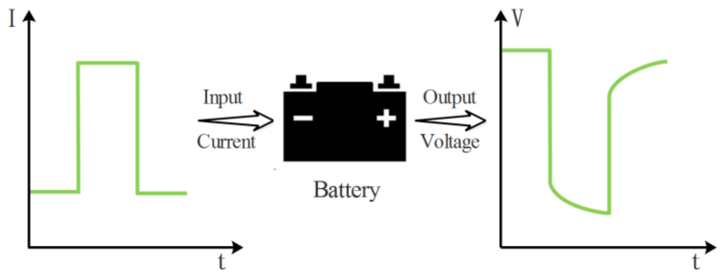


Fig. 2. Battery response to a current impulse.

2. The Proposed Li-Ion Battery Modelling

As aforementioned, the EC model structure presented in Fig.1 is selected in this study to ensure both accuracy and simplicity.

2.1. Experimental Setup and Test Procedures

The complete experimental setup is depicted in Fig.3. It is principally made up of:

- A Lithium-ion battery with a nominal voltage of 12.8V and a nominal capacity of 27.5Ah;

- An automatic battery discharger BDX, which can be programmed to discharge the battery with a precisely controlled constant current, adjustable from zero to the maximum rated value;
- Voltage and current sensors;
- High-speed NI USB-6259 data acquisition board, connected to a PC.

The experimental measurements have been performed in the laboratory at an ambient temperature of 25°C.

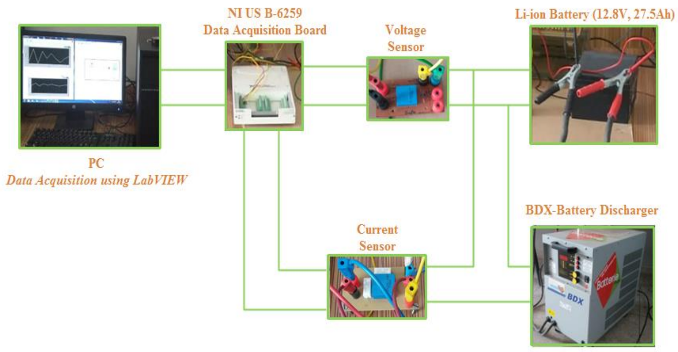


Fig. 3. The complete experimental setup.

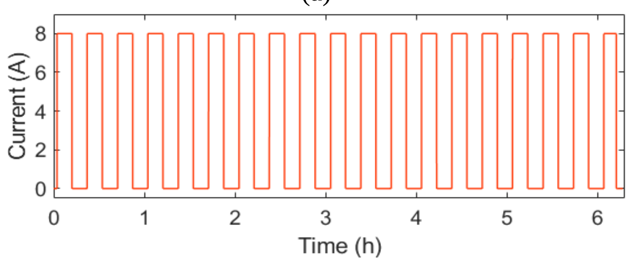
To determine the EC model parameters (OCV, Rs, Rp and Cp) of the utilized battery at different SoC values, a characterization test was conducted.

First, the battery is fully charged. Afterward, the discharge current pulse test starts, where the current profile used to excite the battery is shown in Fig.4 (a). We applied a constant current pulse with an amplitude of 8A and 50% duty cycle, hence, the pulse period and relaxation period are the same 10min. The test was ended when the discharge voltage limit was met. The resulted battery voltage curve is shown in Fig.4 (b). For the SoC calculation, the Coulomb counting method defined by Eq.1 is used in this study due to its simplicity and good accuracy [19].

$$SOC(t) = SOC_{init} - \frac{1}{C_n} \cdot \int_0^t i(t).dt \qquad (1)$$

where Cn is the nominal capacity of the battery.

(a)



(b)

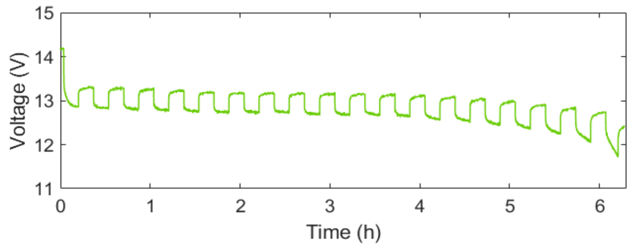


Fig. 4. Characterization test. (a) Current profile (b) Battery voltage response.

The EC model parameters were estimated with the aid of the Optimization Toolbox of Matlab [20], which can use an optimization technique as Nonlinear Least Squares to minimize the error between the measured and the estimated battery voltage curve. Specifically, this tool can be effectively utilized if the following steps are respected [21]:

- Build the EC model in Simulink or Simscape as shown in Fig.5, where the current profile is the input signal and the voltage and SoC are the output signals. To represent the battery nonlinearity, use the nonlinear capacitors and resistors.
- For parameters estimation, import the measured data into the tool Parameter Estimation of Simulink as shown in Fig.6, then select the parameters to estimate that are OCV, Ri, Rp and Cp and set the optimization options.
- After getting the estimation results, compare the simulated and experimental data to be sure that the error is small enough. If not the case, then either the model or the identification technique or the current profile should be changed.

A block diagram of the general parameter identification is depicted in Fig.7. As previously stated, the optimization is performed based on the least-squares criterion defined by Eq.2, which minimizes the sum of the squared errors between the experimental battery voltage *Uexp (t)* and the simulated one *Usim (t).*

$$\varepsilon(t) = \sum_{k=0}^{N}\left(U_{exp}(tk) - U_{sim}(tk,\Theta)\right)^2 \qquad (2)$$

where N is the number of samples and Θ is the model parameters estimator.

By using the described identification procedure above, the obtained values of the different model parameters within the entire SoC range are shown in Fig.8.

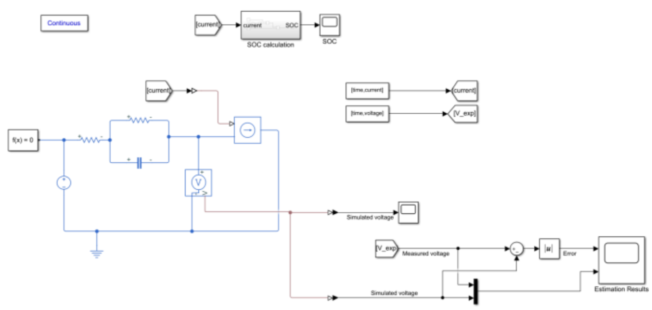


Fig. 5. The EC model in Simulink.

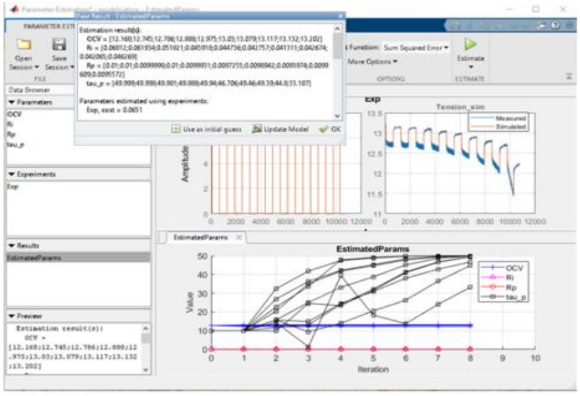


Fig. 6. Parameter estimation using Optimization Toolbox of Matlab.

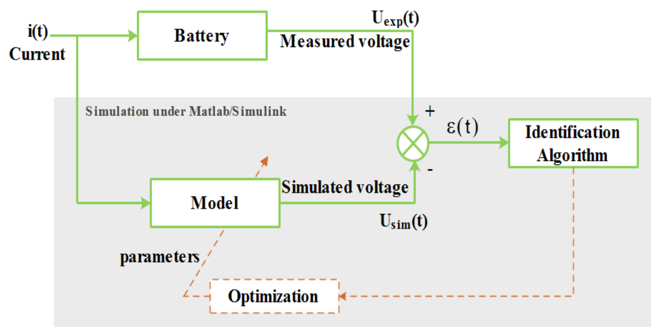
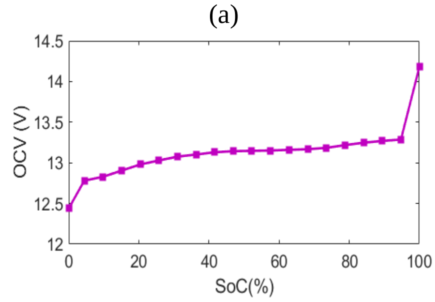


Fig. 7. Block diagram of the general parameter identification.

(a)



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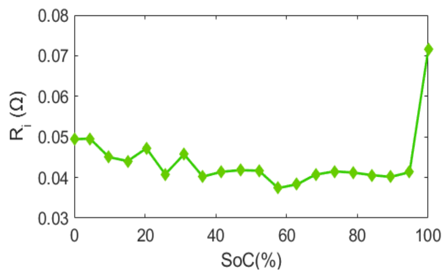
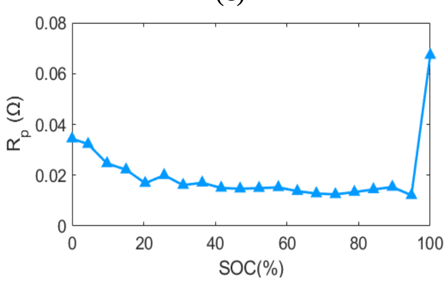


(c)



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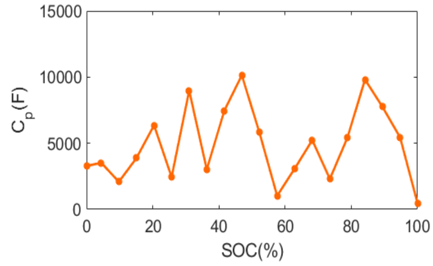
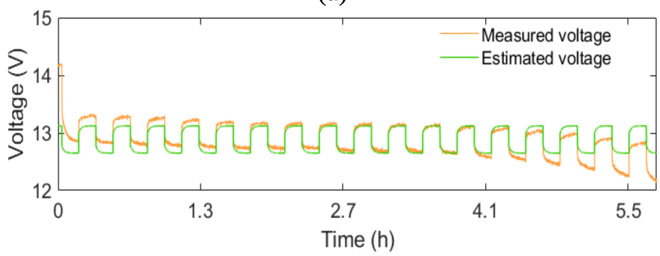


Fig. 8. Evolution of the EC model parameters as a function of SOC (a) OCV (b) R_i (c) R_p (d) C_p.

As it can be observed, the model parameters vary depending on the state of charge SoC. From the results, the average values of each parameter can be obtained as: OCVmoy=13.122V, Rimoy= 0.043 Ω, Rpmoy= 0.01635 Ω, Cpmoy= 4876.83 F. Assuming the model is identified using these values, then the estimated battery voltage profile compared to the experimental one will be as illustrated in Fig.9 (a) and the resulted error between both curves is shown in Fig.9 (b). To report the error quantitatively, we calculated the Root Mean Square Error (RMSE) and the Variance Accounted For (VAF) function.

(a)



(b)

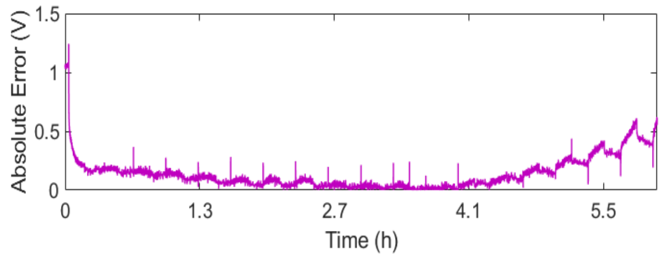


Fig. 9. Time response of the studied battery. (a) Simulated and measured voltage (b) The error between them.

The RMSE defined by Eq.3 is one of the most commonly used measures of accuracy as it is considered an excellent general-purpose error metric for numerical predictions.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(yk - \widehat{yk})^2} \tag{3}$$

where y is the measured output, $\hat{y}$ is the predicted output and $1 \le k \le N$ is the number of samples available for analysis.

The VAF is often calculated to verify the correctness of a model, by comparing the experimental output with the predicted output of the model. If both signals are the same then the VAF is 100%, otherwise, the VAF will be lower. The VAF between y and $\hat{y}$ for the i^{th} component can be defined as

$$\mathrm{VAF} = 100\%\left[1 - \frac{var(y-\hat{y})}{var(y)}\right] \quad (4)$$

By using Eq.3 and Eq.4, an RMSE value of 0.23V and a VAF of 70.81% were obtained. These resulting measures demonstrated that the model fitting was not sufficient. Hence, the model accuracy cannot be achieved by using the average parameter values. As noted earlier, this is due to the model's parameters that are not fixed-value constants and strongly change with the battery SoC. Therefore, an adaptive fuzzy logic-based EC model taking into consideration the SoC effect on the parameters has been proposed in this paper.

2.2. Introduction to the Proposed TS Fuzzy-Based EC Model

Since Zadeh's works [22], fuzzy logic has been very successful in the modeling and control of complex nonlinear systems [24]. In the literature, two main classes of fuzzy approaches can be distinguished: The Mamdani approach and the Takagi-Sugeno approach [23, 24]. The main difference between these two approaches lies in the consequence part. The Mamdani fuzzy approach uses fuzzy subsets in the consequence part while the TS fuzzy approach uses (linear or nonlinear) functions of the input variables. The TS fuzzy systems can be generally described by a set of IF-THEN fuzzy rules and they are based on three main stages [25]: Fuzzification of crisp inputs, Fuzzy Inference using knowledge base and Defuzzification.

To cope with the problem of parameters variation with the SoC described in the above section, a new TS fuzzy-based model has been introduced in this study. The proposed model would be able to generate the appropriate value of the parameters (OCV, Ri, Rp and Cp) depending on the state of charge of the battery.

Specifically, an EC model with the parameters' valu ensuring the minimum error will be selected according to tl SoC range. This can be met by adopting the so-called mul model representation illustrated in Fig.10, which developed by combining local models through the TS fuz approach. The SoC of the battery has been identified as input of the fuzzy inference system that processes employing pre-specified fuzzy rules to produce the outpu that are the four battery parameters as shown in Fig.11.

For typical values of SoC, the fuzzy inference rules have the form in Eq.5,

$$R^i: \quad \text{IF } SoC_i \text{ is } \sigma_i \quad \text{THEN } OCV_i \text{ and } R_{i_i} \text{ and } R_{p_i} \text{ and } C_{p_i} \quad (5)$$

where *i=1, 2…n*; *n* is the number of inference rules, σ_i is the i^{th} fuzzy set. The premise variable SoC is a measurable variable of the system (Eq.1). Crisp input data is converted into fuzzy values using membership functions. In this study, the number and value of each membership function were properly selected as follow

Based on the presented finding in Fig.8, we have considered six EC battery models (named M1, M2…M6) with different parameters values over SoC range of 10-90% which is the widest operating range for real-world applications. The EC model parameters values corresponding to the different SoC are provided in Table I.

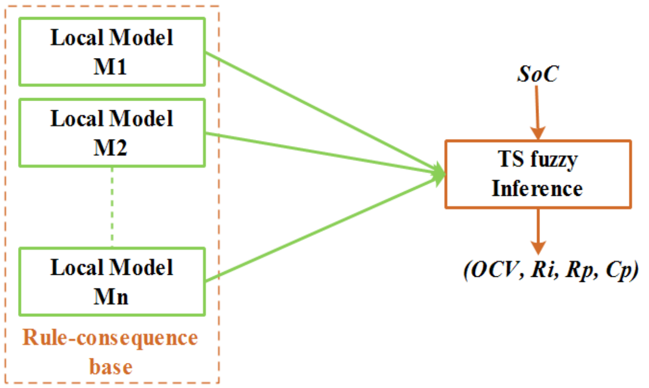


Fig. 10. The multi-model representation using TS fuzzy logic.

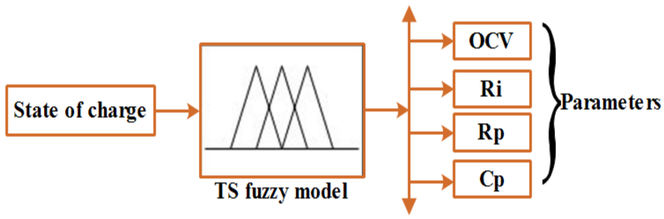


Fig. 11. The studied TS fuzzy system

Table I. The EC model parameters for different state of charge SoC

	SOC (%)	***OCV (V)***	***R_i (Ω)***	***R_p (Ω)***	***C_p (F)***
M1	9.77	12.8278	0.0450	0.0246	2.9124e+3
M2	15.07	12.9041	0.0440	0.0222	3.2646e+3
M3	20.41	12.9798	0.0465	0.0125	6.3588e+3
M4	31.01	13.0759	0.0457	0.0161	5.8348e+3
M5	52.19	13.1474	0.0417	0.0149	4.1505e+3
M6	89.41	13.2691	0.0401	0.0153	4.2672e+3

For each model, the error between the experimental battery voltage and the model's prediction has been drawn as illustrated in Fig.12. As it can be seen from this figure, there are intervals (named I1, I2…I6) on which at least one model presents the best agreement with the experimental data and shows the minimal estimation error. As an illustrative example, let us consider interval I6 which corresponds to a SOC range [76, 100%], the black curve corresponding to the

EC model M6 gives the minimal error over this interval. The remaining curves show likewise the minima of the estimation error in a specific interval. These observations lead us to properly define the universe of discourse and the membership functions associated with the fuzzy rules.

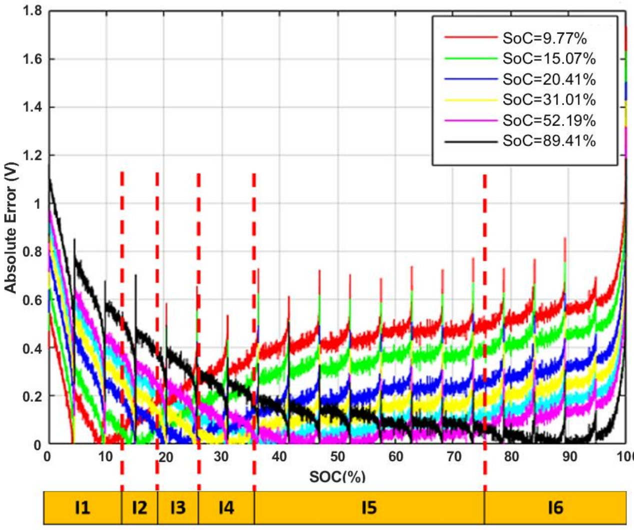


Fig. 12. The error between the measured and estimated battery voltage for six different EC models

The TS fuzzy system parameters have been set according to the above findings, the number of inference rules n=6, the chosen membership functions corresponding to the SoC are portrayed in Fig.13. The shape of membership functions has been decided using the trial-and-error method.

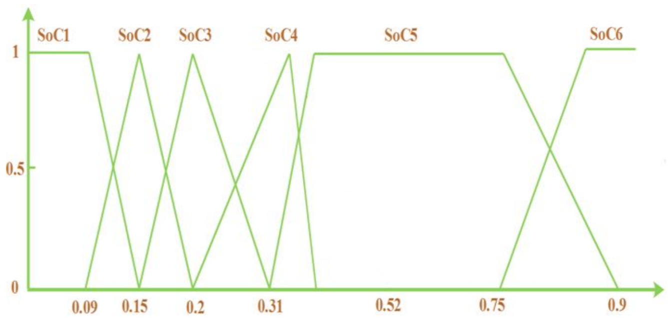


Fig. 13. Membership functions for the battery SoC

Using a standard fuzzy inference method that uses singleton fuzzifier, product inferred, and weighted average defuzzifier, the fuzzy system inferred outputs are

$$OCV = \frac{\sum_{i=1}^{n} \mu_i(SoC_i)OCV_i}{\sum_{i=1}^{n} \mu_i(SoC_i)} \qquad (6)$$

$$R_i = \frac{\sum_{i=1}^{n} \mu_i(SoC_i)R_{i_i}}{\sum_{i=1}^{n} \mu_i(SoC_i)} \qquad (7)$$

$$R_p = \frac{\sum_{i=1}^{n} \mu_i(SoC_i)R_{p_i}}{\sum_{i=1}^{n} \mu_i(SoC_i)} \qquad (8)$$

$$C_p = \frac{\sum_{i=1}^{n} \mu_i(SoC_i)C_{p_i}}{\sum_{i=1}^{n} \mu_i(SoC_i)} \qquad (9)$$

where μ is the normalized membership function and $\mu_i(I_{pv_i}) \Big/ \sum_{i=1}^{n} \mu_i(I_{pv_i}) \geq 0$ are the normalized weights.

3. Validation of The Proposed Battery Model

Simulations have been conducted into the Matlab/Simulink environment in order to validate the proposed TS fuzzy-based EC battery model. Simulink block diagram of the developed model is depicted in Fig.14. The TS Fuzzy system was created using the fuzzy logic controller (FLC) block from the Simulink library. This block enables flexible configuration and convenient implementation of the fuzzy interference system.

In order to verify how accurately the proposed parameterization procedure and the developed performance model are, the battery voltage was simulated for the same current profile shown in Fig.4 used in the practical tests. Comparing the obtained results in Fig.15, excellent accordance between the experimental and estimated battery's voltage curves can be observed over the studied SoC range [10-90%]. This confirms that the proposed model can accurately estimate the battery parameters and hence, represent its real behavior. This good agreement of the simulation and the measured data has been also evaluated by plotting the estimation error as illustrated in Fig.16. As expected, the proposed TS fuzzy model was able to accurately predict the Li-ion battery voltage with a mean error of 45mV only.

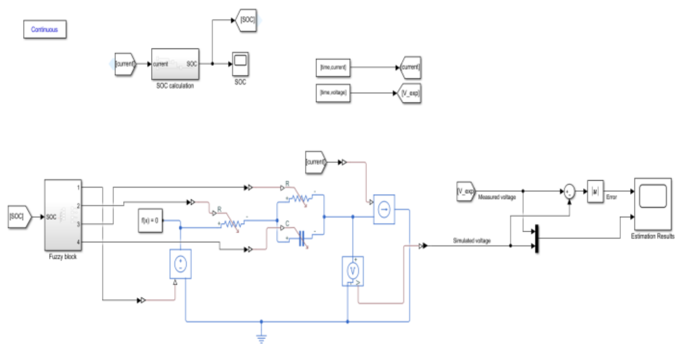


Fig. 14. Simulink block diagram of the proposed TS fuzzy-based EC battery model.

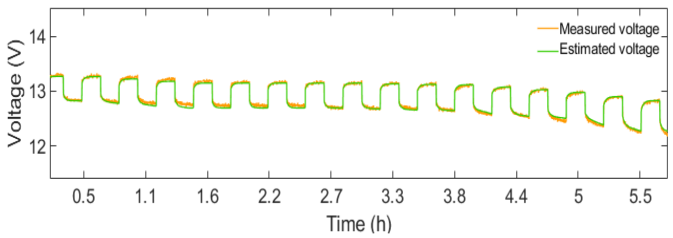


Fig. 15. Experimental and estimated battery's voltage profiles using the proposed modeling.

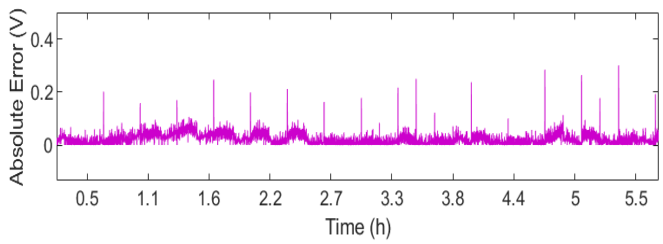


Fig. 16. The error between the simulation and experiment

To evaluate the model performance, the RMSE and VAF function were computed based on Eq.3 and Eq.4. A low RMSE value of 11mV and a high VAF of 98.85% have been achieved. Accordingly, the proposed consistent EC model using the TS fuzzy approach can significantly reduce the estimation error and improve the model accuracy. This is owing to the fact that the developed model managed correctly the variation of the parameters with the SoC and thus, the battery is properly characterized. It is worth mentioning that generally the battery cannot be ideally modeled as different factors contribute to errors apart from the model imprecision, such as the equipment error and the experimental data noise.

The resulting RMSE value using the proposed model is comparable to the RMSE values obtained in the literature. For the same EC model (Fig.1), the RMSE calculated in [26] was around 12mV, whilst in [28] results showed an average RMSE of around 12.35mV, which indicates the accuracy of the developed battery modeling technique.

To further analyze the proposed battery modeling, a series of pulse tests with different current profiles have been carried out. We present the results of three of them in this paper.

As illustrated in Fig.17, the Li-ion battery is subjected to three pulse discharge tests with different constant currents (4A, 12A and 16A). The considered current profiles are shown in Fig.18. More details about the experimental pulse tests are documented in Table II. The proposed battery model was simulated for the same current profiles, and then the obtained voltage response is compared to the measured one.

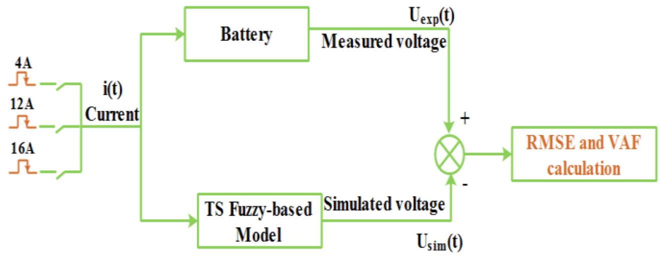
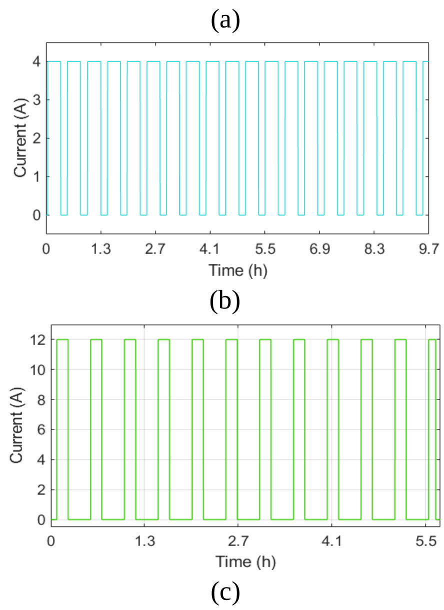


Fig. 17. Diagram of the proposed model validation for different current profiles

The model estimation is accurately matched to the actual test data for the three current profiles. This has been numerically evaluated by calculating the mean estimation error, the RMSE and the VAF as given in Table III. As it can be noticed, the proposed model remains valid and was not affected wherever the applied current level (4, 8, 12 and 16A). From the findings, the interval of RMSE, VAF and mean estimation error can be defined as [8-13mV], [97-99%] and [1-7mV], respectively. Thus, the proposed model is able to correctly identify the battery parameters, shows good accuracy and preserves its performance whatever the applied current profile.



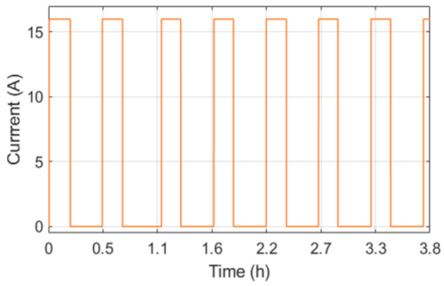


Fig. 18. The three considered current profiles (a) 4A (b) 12A (c) 16A

Table II. Information about the experimental pulse tests

	Amplitude (A)	*Pulse-discharging period (min)*	*Rest period (min)*	*Test period (h)*
I=4A	4	20	10	10
I=12A	12	10	20	7
I=16A	16	12	20	4

Table III. Comparison of errors for different applied current profiles

	RMSE (V)	*VAF (%)*	*Mean estimation error (V)*
I=4A	0.00808	97.3459	0.00210
I=12A	0.01246	97.3661	0.00083
I=16A	0.01174	98.1740	0.00681

4. Conclusion

This paper presents the development and validation of an advanced Thevenin EC model based on TS fuzzy approach for Li-ion batteries. The adopted process to extract the battery model parameters has been described in detail. It has been noted that the model parameters are highly dependent on the battery SoC. Hence, we investigated the effect of the SoC on the model parameters in order to achieve higher accuracy. The TS fuzzy-based model was developed to estimate the parameters' values precisely according to the SoC.

The current pulse test has been carried out to extract the experimental voltage response of an actual battery and then, the verification with the simulated voltage under Matlab/Simulink was demonstrated that the proposed model is able to appropriately identify the parameters. It has been concluded from the obtained results that the proposed TS fuzzy battery model reveals a high prediction ability to describe the battery bank behaviour. The RMSE values calculated when validating the model were low, while the achieved VAF value was high (around 98%), which evaluate quantitatively the proposed model accuracy.

Furthermore, the influence of the applied discharging current pulse profile was analyzed. It has been proven that the proposed model remains valid with the same precision of estimation.

The proposed TS fuzzy-based model contributes towards the future development of more accurate and advanced battery models to be utilized in real-world applications. Future works include incorporating the effect of the temperature and the state of health on the battery internal voltage and the EC model parameters.

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