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State of charge estimation of lithium-ion batteries using adaptive neuro fuzzy inference system

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ABSTRACT

A battery's state of charge (SOC) is used to assess its residual capacity. It is a very important parameter for the control of the electric vehicle (EV). The objective of this paper is to estimate the SOC of a lithium-ion battery (LIB) using an adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN) because SOC of a battery must be estimated from measurable battery parameters such as current, voltage or temperature. Two intelligent SOC estimation methods are compared according to their suitability and accuracy. ANN estimation is more precise and perfectly represents the experimental data.

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1. INTRODUCTION

In order to reduce carbon dioxide (CO_2) emissions, the road transport industry is turning to electric vehicles, which are considered environmentally friendly, highly efficient and reliable. Electric vehicles (EVs) include hybrid electric vehicles, Plug-in hybrid electric vehicles, depending on the electrification level of the vehicle. To meet the growing demand for EVs, considerable investment from governmental sectors, research institutions, industry have been focused into research and development, production of EVs. They have a wide range of caracteristics. Each application places different demands on the motor and hence many different technologies are appropriate [1]. Energy storage systems (ESS) are categorized to different methods. They are mechanical and others techniques to stock the electrical energy produced by all sources. Each technique has its own merits and disadvantages, all of them have benefits for electric utilities, end users, equipment vendors, energy service providers, regulators and independent system operators and environments. Optimal forecast of ESS requires two important informations to be identified. First is a precise prediction of the load over a period where the ESS will work. While, the second available energy in the system at the time of forcasting that is determined through state-of-charge (SOC) assessment which is the aim of our contribution using adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN) techniques.

2. LITHIUM-ION BATTERY (LIB) MODELING

There are many battery models with different characteristics. They have been published in the literature in recent years [2]–[8]. The equivalent circuit of the battery is shown in Figure 1 [9].

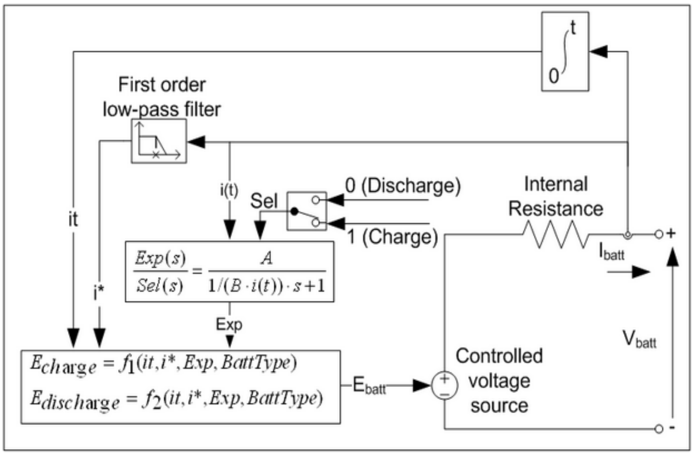

Figure 1. Equivalent circuit of LIB

2.1. Discharge model (i*>0)

$$f_1(it, i^*, i) = E_0 - k\frac{Q}{Q-it}i^* - K\frac{Q}{Q-it}it + A\,exp(-B\text{ it}) \quad (1)$$

2.2. Charge model(i*<0)

$$f_2(it, i^*, i) = E_0 - k\frac{Q}{it+0.1Q}i^* - K\frac{Q}{Q-it}it + A\,exp(-B\text{ it}) \quad (2)$$

Where, E_{Batt} is nonlinear voltage (V), E_0 is constant voltage (V), Exp(s) is exponential zone dynamics (V), Sel(s) is represents the battery mode. Sel(s) is 0 during battery discharge, Sel(s) is 1 during battery charging. K is polarization constant (Ah^{-1}) or polarization resistance (Ω), i* is low frequency current dynamics (A), i is battery current (A), it is extracted capacity (Ah), Q is maximum battery capacity (Ah), A is exponential voltage (V), B is exponential capacity $(Ah)^{-1}$.

3. SOC ESTIMATION IN LITHIUM-ION BATTERY USING ANFIS

ANFIS technique is used to implement the SOC estimation of LIBs. Lately, fuzzy logic has gained widespread attention from researchers due to its ability to model nonlinear systems using if-then rules. Fuzzy logic is inspired by human reasoning of a descriptive nature. The reinforcement of fuzzy logic by ANNs has made fuzzy logic more adaptive. Jang in 1993 proposed ANFIS as a function composed by ANN and a fuzzy logic. To solve nonlinear problems, it can be cited that the ANFIS offers better results than a fuzzy logic. According to the ANFIS technique, a fuzzy logic is employed for training in a multilayer feed-forward network. By using least-squares methods and back propagation gradient descent, membership function (MF) parameters can be trained through training the input data by the ANFIS. In Figure 2 the layers are organized as [10]–[18]:

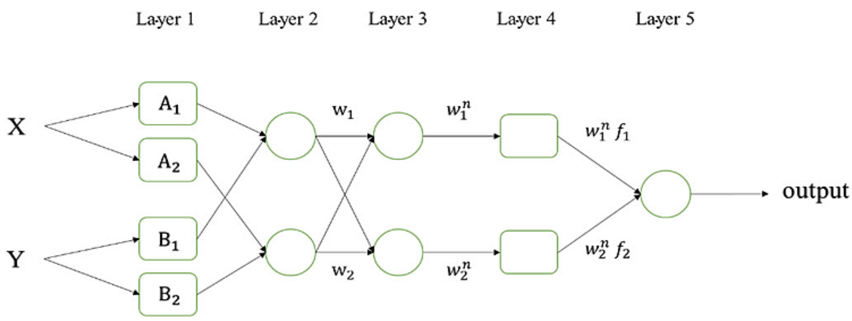

Figure 2. Typical ANFIS structure

4. SOC ESTIMATION IN LITHIUM-ION BATTERY USING ANN

ANN uses the functioning of the brain as a basis to develop algorithms. They can model complex patterns and predict problems. The simple neuron is modeled according to basic principle as shown in Figure 3. The input p is multiplied by the weight w and added to the bias to form the argument of the transfer function *f* [9]. An ANN has some advantages but one of the most known of these is the fact that it can learn from data sets. The artificial network is tuned, based on a comparison of the output and the target, until the ANN output hits the target as is seen in the Figure 4.

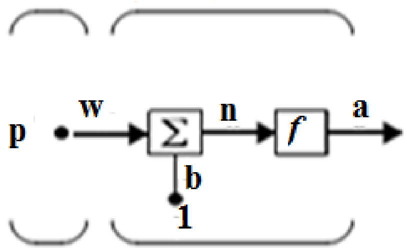

Figure 3. Basic principles of an artificial neuron

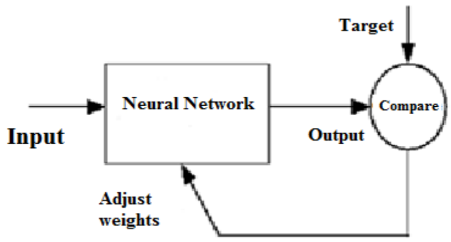

Figure 4. Basic principles of ANN design

In this paper, the ANN and ANFIS are implemented for the accurate estimation of SOC in LIBs. The results obtained are compared to determine the best technique. This simulation is managed by a graphical user interface neural net fitting tool (nftool) under MATLAB. This intelligent estimate is made possible by data from the battery manufacturer. This technical data is non-linear relation between open circuit voltage (OCV) and SOC for different temperatures from -30-55°C. By the curve fitting technique, approximate 5th order polynomial equations of the curves are extracted as in (3) [19] and related coefficients are shown in Table 1. The manufacturer's data given according to Table 1 are presented in the following Figure 5.

$$y = a_5x^5 + a_4x^4 + a_5x^5 + a_3x^3 + a_2x^2 + a_1x + a_0 \quad (3)$$

Table 1. Coefficients of the polynomial

Temperature	a_5	a_4	a_3	a_2	a_1	a_0
55°C	-4.1599	8.3420	-4.6414	0.5083	0.6186	3.4710
40°C	-2.1649	3.2388	-0.0489	-1.1715	0.8145	3.4770
25°C	-2.6941	4.2599	-0.5109	-1.2740	0.8955	3.4613
0°C	-0.2981	0.5460	1.1475	-1.6024	1.0298	3.3935
-20°C	-0.5971	0.6231	0.8659	-0.5327	0.3995	3.4431
-30°C	25.5020	-78.174	92.857	-52.030	14.117	2.0284

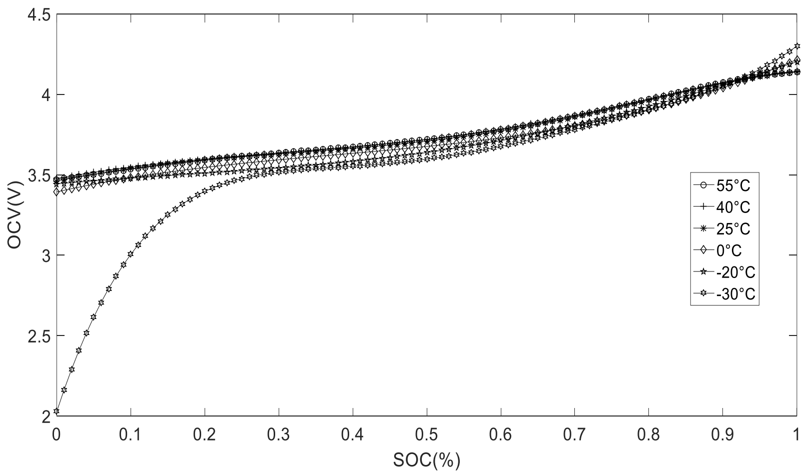

Figure 5. Technical specifications SOC and OCV provided by manufacturer for different temperatures

In this paper, we have modeled SOC by ANFIS. As a second approach, we have estimed SOC by ANN. The obtained results are then compared according to (4):

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(\hat{y}_t - y_t)^2}{T}} \quad (4)$$

where, $\hat{y}_t$ is the predicted values by ANFIS and yt is the observed values.

5. SIMULATION AND DISCUSSION

The simulation has three parts. The first one, which is done in Figure 6, concerns the effect of the temperature in the LIB under the parameters. The second one, concerns the estimation of SOC using ANFIS. The last simulation presents the estimation of SOC using ANN [20]–[25].

- Preset battery: 7.4 V; 5.4 Ah; ($LiCoO_2$)
- Initial state of charge (SOC)=100%;
- Battery response time=30 s

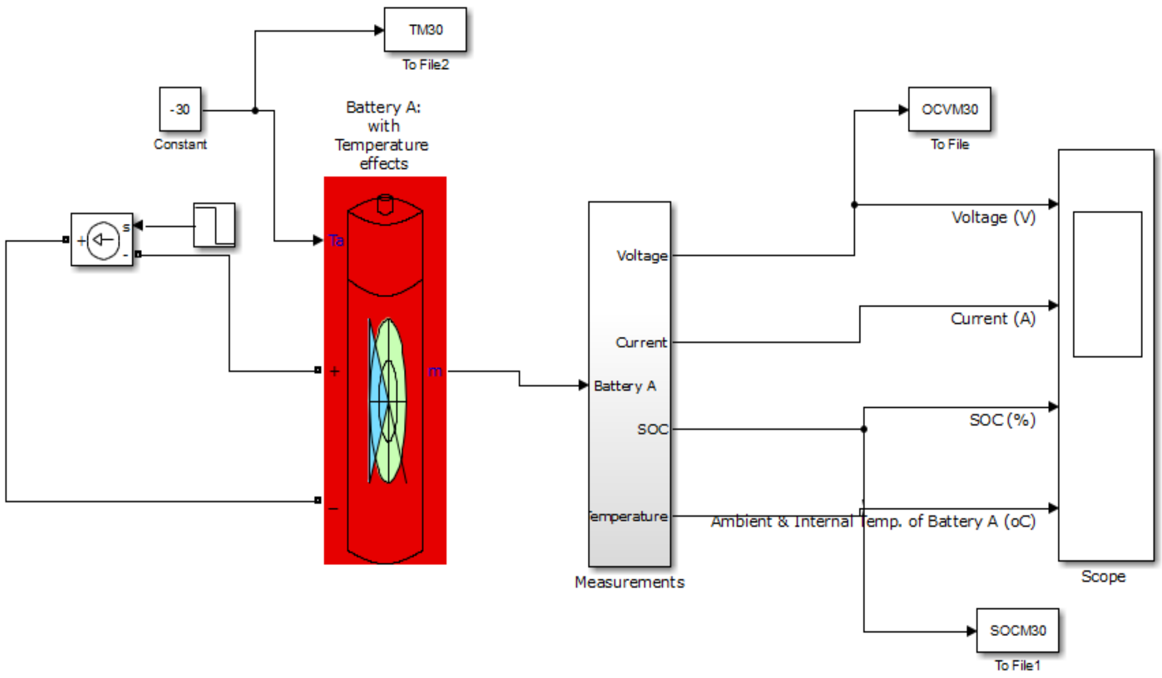

Figure 6. Simulation of temperature's effect on LIB

The impact of temperature on OCV and SOC of LIBs is presented respectively in Figure 7 and Figure 8. The effect is significant and the variation of both OCV and SOC are proportional to the increase of the temperature. These results demonstrate the role of the temperature on LIB's accuracy.

5.1. Simulation of SOC estimation in lithium-ion battery using ANFIS

The second part concerns the estimate of the SOC using an ANFIS because SOC must be estimated from measurable battery parameters such as current, voltage or temperature. The figures below explain the different steps to follow for implementing an intelligent model which can estimate SOC using the anfisedit GUI and the simulink/Matlab. Figure 9 shows ANFIS designer. ANFIS output is presented in Figure 10. The structure of ANFIS with ten membership function for each input is shown in Figure 11. Figure 12 shows SOC fuzzy inference system with two input DataOCV and DataTemp based on Sugeno inference system. Figure 13 presents rule viewer with a numerical exemple: DataOCV=2.5 V; DataTemp=-10 °C; DataSOC=7.71 10-5. Figure 14 shows the simulation of the ANFIS model under Matlab/Simulink.

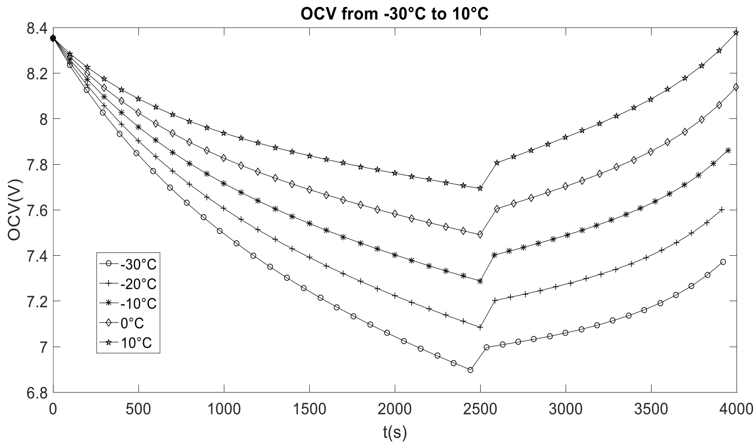

Figure 7. OCV with different temperatures

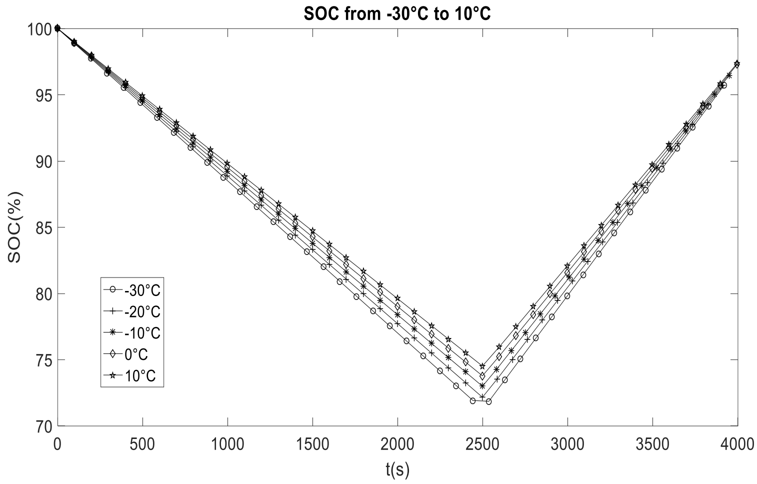

Figure 8. SOC with different temperatures

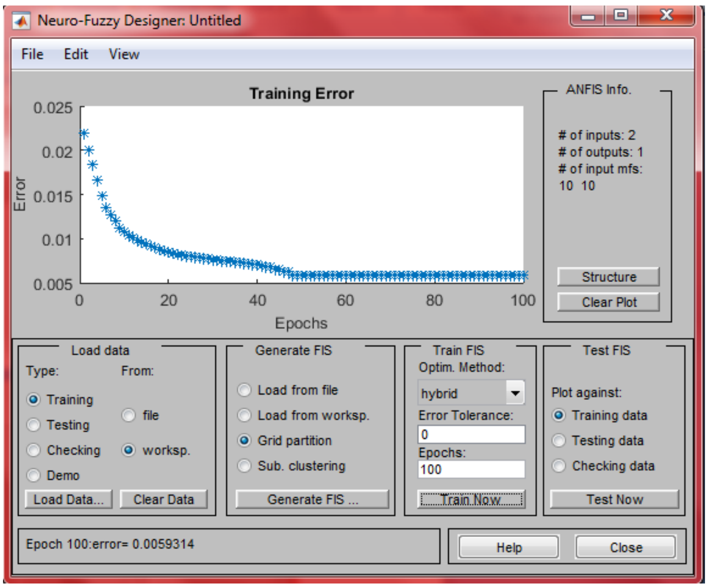

Figure 9. ANFIS designer (Traning error)

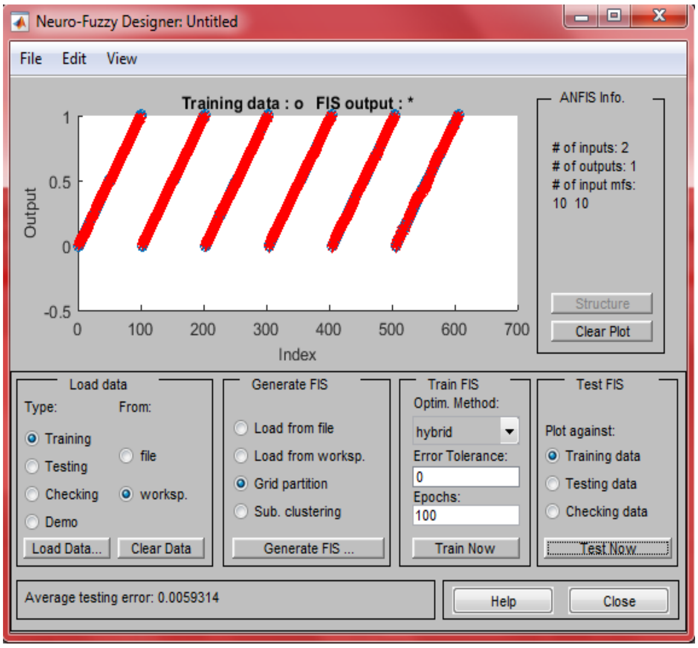

Figure 10. ANFIS designer (traning test)

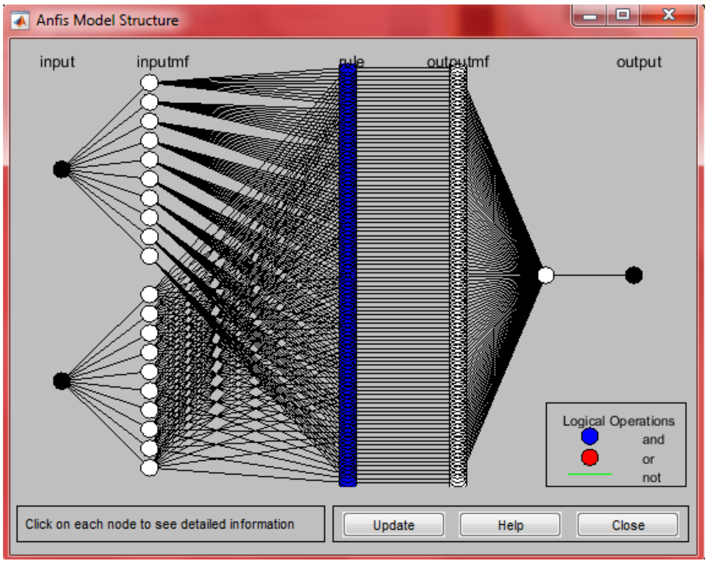

Figure 11. ANFIS model structure

For set the ANFIS we used 606 datasets and choose 10 generalized bell curve membership functions (gbellmf) type for membership functions. The value for Epochs is set as 100 to train the ANFIS 100 epochs for each number of member functions. The other parameters are: number of nodes: 245; number of linear parameters: 100; number of nonlinear parameters: 60; total number of parameters: 160; number of training data: 606; number of checking data: 0; number of fuzzy rules: 100.

The obtained results shown in Figure 15 and Figure 16 show the accuracy of the ANFIS model to estimate SOC under different temperature knowing the OCV. For this intelligent technique, we have presented the impact of the epoch number on the accuracy of the ANFIS comparing the RMSE value as shown in Table 2. We can notice that the ANFIS with 100 epochs is more suitable than ANFIS with 10 epochs which is presented in Figure 15 and especially at -30°C where the prediction is difficult for both ANFIS at the beginning. So, the ANFIS on 100 epochs shown in Figure 16 will be compared to that of the ANN.

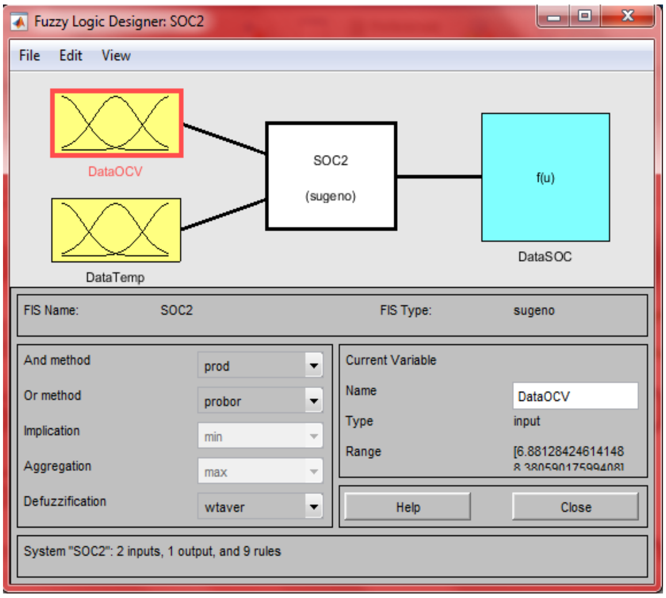

Figure 12. Fuzzy logic designer SOC.fis

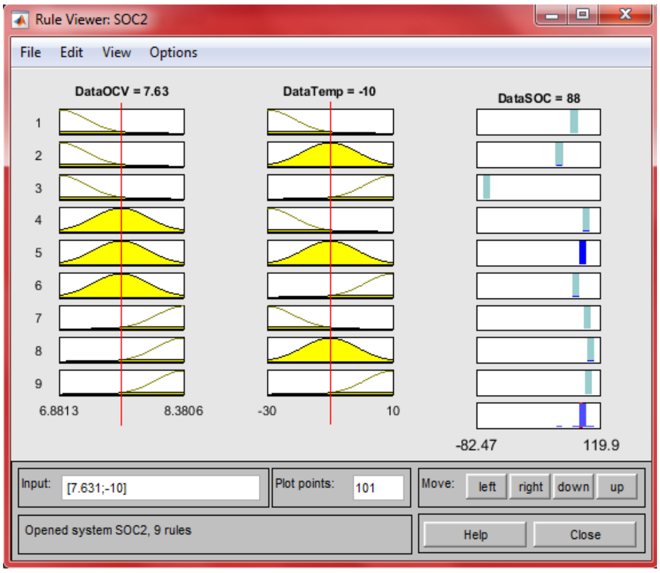

Figure 13. Rule viewer DataOCV=2.5 V; DataTemp=-10 °C; DataSOC=7.71 10^{-5}

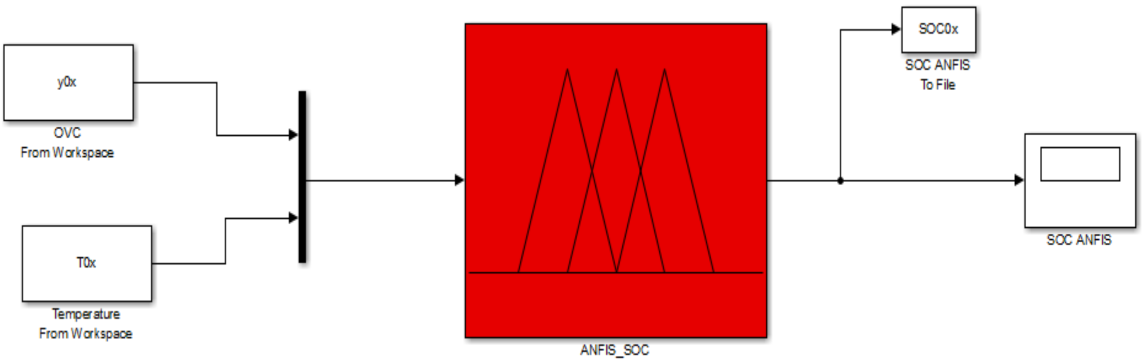

Figure 14. Simulation of the ANFIS model

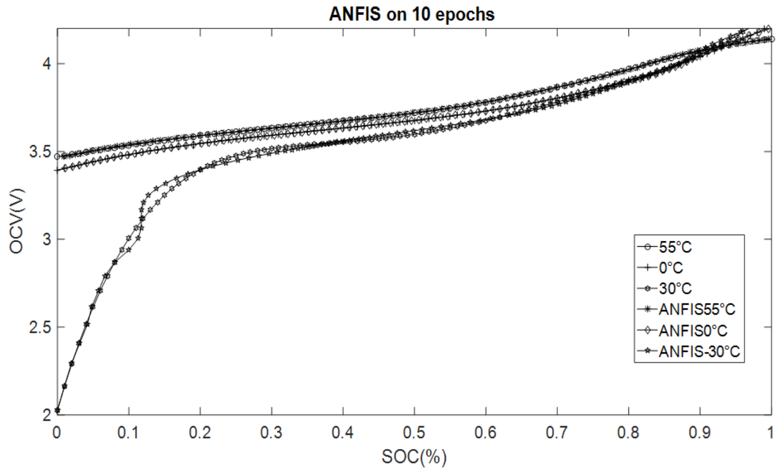

Figure 15. Comparison between manufacturer model and ANFIS model on 10 epochs

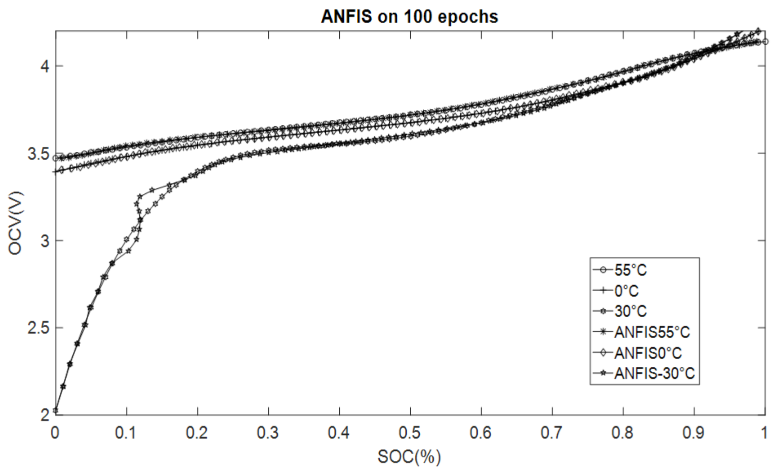

Figure 16. Comparison between manufacturer model and ANFIS model on 100 epochs

Table 2. RMSE for each ANFIS

T°C	ANFIS/10 Epochs	ANFIS 100 Epochs	Difference
55	**0.0037**	0.0056	-0.0019
0	0.0035	**0.0032**	0.0003
-30	0.0181	**0.0113**	0.0069

5.2. Simulation of SOC estimation in lithium-ion battery using ANN

ANN type is used for this purpose is a 2 layer "Feed-forward backprop" with 10 neurons. "TRAINLM" is considered as training function and "LEARNFGM" is set for adaption learning function. Figure 17 shows the neural network training and Figure 18 presents its performances. While, Figure 18 and Figure 19 show respectively the values of learning and validation. Figure 20 shows performances of ANN which estimates SOC of LIB.

Figure 21 shows the prediction of the ANN model compared to manufacturer model. Figure 22 presents the predictions of the two intelligent methods ANFIS and ANN which are compared to the manufacturer's model. We can see that the prediction of ANN at -30°C is much more perfect than that of ANFIS. Figure 22 presents the predictions of the two intelligent methods ANFIS and ANN which are compared to the manufacturer's model and the zoom of this comparison is presented in Figure 23. We can see that the prediction of ANN at -30°C is much more perfect than that of ANFIS. The zoom in Figure 23 and the value of RMSE=at -30°C from Table 2 confirm this advantage where the ANN model is much more precise than that of ANFIS. Table 3 presents RMSE for both techniques ANFIS and ANN.

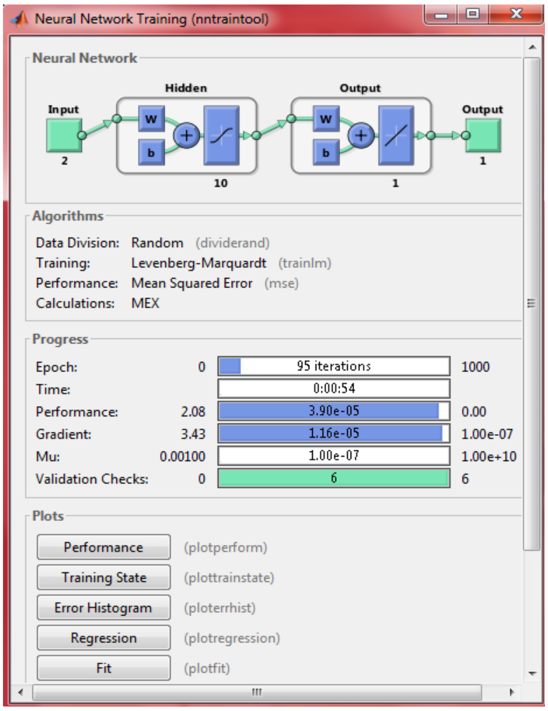

Figure 17. Neural network training-input=OCV and temperature, output=SOC

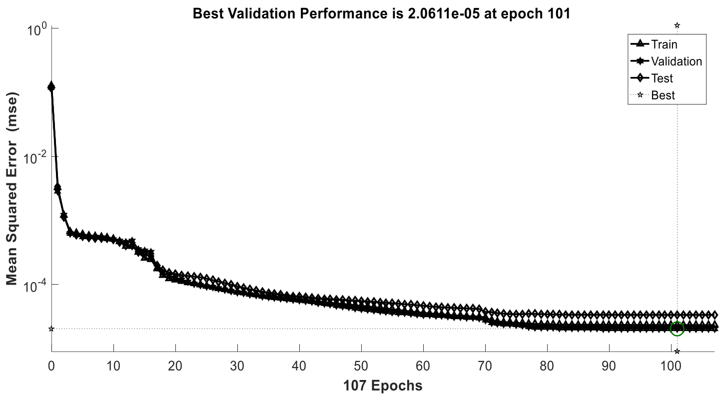

Figure 18. Neural network training-best validation performance of SOC estimation

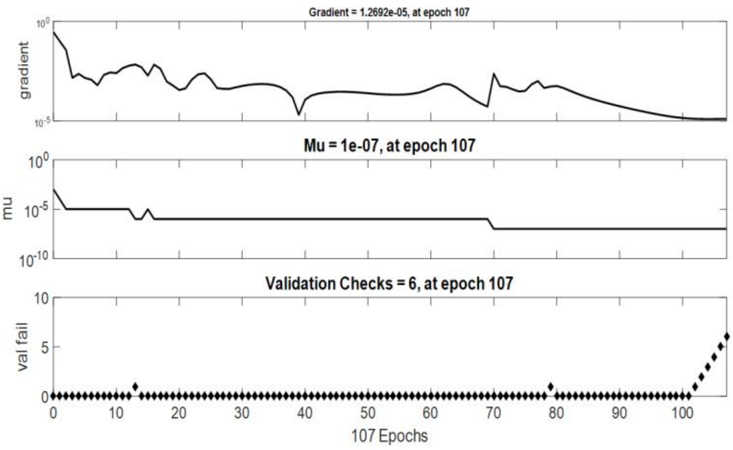

Figure 19. Neural network training state for SOC estimation

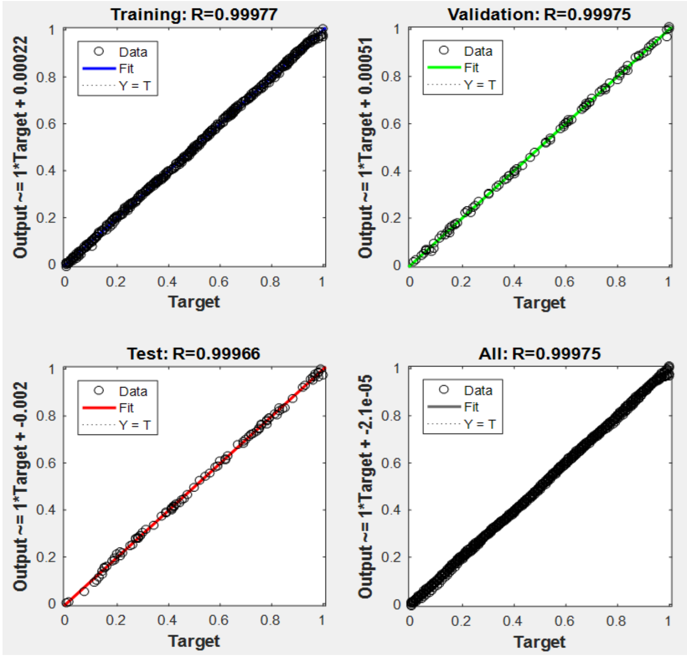

Figure 20. Neural network training-regression and validation performance of SOC estimation

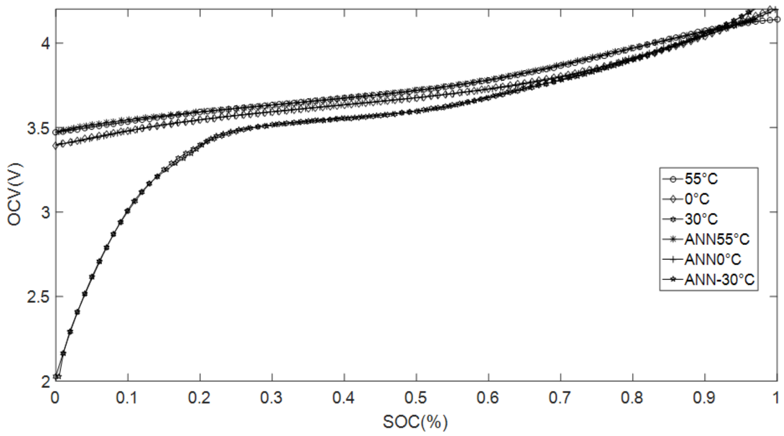

Figure 21. Comparison between manufacturer and ANN model

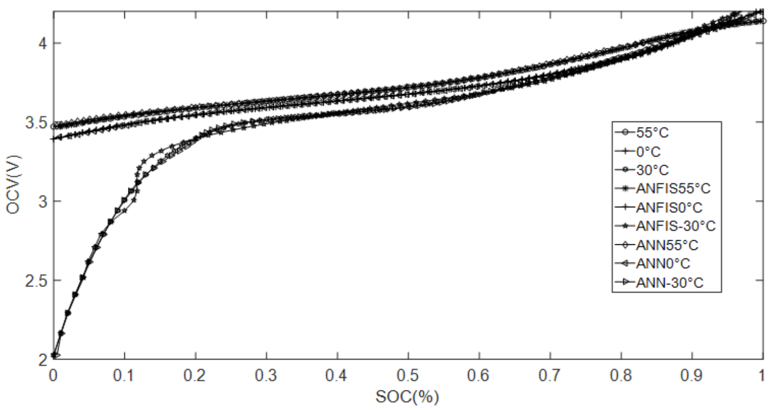

Figure 22. Comparison between manufacturer, ANFIS and ANN model

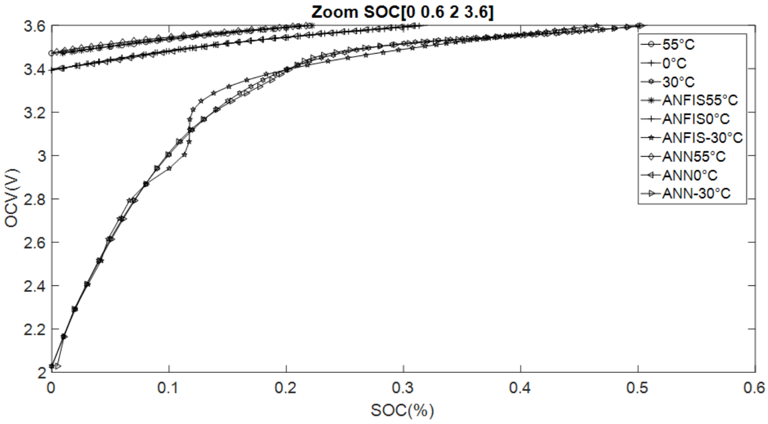

Figure 23. Zoom of the comparison between manufacturer, ANFIS and ANN model

Table 3. RMSE for each model ANFIS and ANN

T°C	ANFIS	ANN	Difference
55	0.0056	0.0086	-0.003
0	0.0032	0.0046	-0.0014
-30	0.0113	**0.0038**	0.0075

6. CONCLUSION

The effect of the temperature is significant on LIB's behavior and it must be modeled. The exactness of SOC estimation is a decisive part of using lithium-ion batteries pack in the storage of energy to make a contribution with battery management system to keep the storage system in a safe and efficient condition. This, to increase the cycle of the batteries. According to the root mean square error (RMSE) values, increasing the number of epochs has increased the accuracy of the ANFIS method. The obtained results are satisfactory and the ANN model is very close to the data provided by the manufacturer. The ANN method has predicted an accurate SOC indication which is thus important for the user convenience and to ensure the battery's efficiency, safety, and longevity.

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