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The wavelet-based artificial neural network for state of charge estimation in lithium ion battery

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Abstract. State of charge (SOC) is described as the percentage of the amount of energy available in a battery to the maximum battery energy. It is one of battery parameters that play an important role in providing remaining driving range in electric vehicles with a long term benefit of preventing battery performance deterioration and accelerated ageing. Consequently, models with various approaches have been developed for SOC estimation. However, SOC estimation is very difficult to implement due to complex characteristics of a battery functioning by electrochemical reactions. Accurate SOC estimation requires detailed physical knowledge so that capacitive effects of a battery can be captured. To overcome those parametric uncertainties, a data-driven approach such as an artificial neural network is one strategy used. Therefore, it is the objective of this work to propose a technique that delivers a reliable SOC estimation. The back-propagation neural network was employed with the help of wavelet transformation. Battery current, battery voltage, temperature, and SOC at the previous time steps were considered as inputs to the network. Cylindrical Lithium-Ion batteries with a capacity of 2.6 Ah were used to obtain the experimental data. The results showed that the proposed method was numerically efficient and the obtained SOC estimation was consistent with the associated battery experiments.

1. Introduction

As the issue of global warming attracts public awareness, electric vehicles (EVs) gain much interest as clean-power transportation. Battery is one of the main source that EVs have to rely on. In electric vehicles, different battery chemistries—lead acid, lithium ion, nickel cadmium, nickel metal hydride—are used. Among those, lithium ion batteries are mostly prominent due to their high energy density and long cycle life [1]. Lithium ion batteries are applied in various type of EVs such as Hybrid Electric Vehicle, Plug-in Hybrid Electric Vehicle, and Battery Electric Vehicle.

For mobile applications, Lithium-ion battery has been used in portable electronic devices, e.g. cell phones, laptops, etc. for many years. Battery status, which is an important parameter providing available energy for user, should be more accurate and reliable in electric vehicles than in portable devices. Consequently, improving reliable estimation of remaining battery capacity has been the focus of battery and EV manufacturers.

The remaining usable energy can be defined from state of charge (SOC) which is one of battery parameters. SOC is described as the percentage of the amount of energy available in a battery to the nominal battery capacity. It can be implied to a remaining driving range and a warning to recharge battery. Many approaches have been proposed for SOC models. This ranges from the direct methods [2-

4] to the indirect methods [5-8]. Coulomb counting is an example of a direct method that directly measures the battery current in order to calculate SOC by integrating the measured values through time [4]. Even though this method is online and simple, errors are accumulated over time from the integration. As a result, less accurate SOC estimation is obtained. Moreover, employing the Coulomb counting requires the high speed current sensor because fluctuated current signal is produced in EVs. This makes the method more expensive and less practical. Other estimation techniques are also proposed through an understanding of a relationship between SOC and some physical battery properties such as the terminal voltage, open circuit voltage (OCV), and impedance [2,3]. However, using these battery parameters in an SOC estimation comes with consequences. The method cooperating with OCV is not practical to estimate SOC during operation in EVs as OCV needs to be measured offline. Even though the terminal voltage can be measured online and is widely applied to relate with SOC in portable devices and EVs, SOC accuracy depends on applied model as the battery is a nonlinear time-variant dynamic system.

To obtain more robust SOC estimation subjected to parametric uncertainties, an indirect approach, such as fuzzy logic [8], neural network [1,9-11], Kalman filters [6,7,12], are presented in order to simulate a nonlinear SOC behaviour. These methods are adaptive systems for SOC estimation developed from artificial intelligence. They require no knowledge of physical battery properties and show good estimation. Among these indirect methods, artificial neural network (ANN), which is a data-driven approach, shows less computational time [12] and offered better SOC estimation [7,9]. Although ANN shows much superiority, it also comes with problems such as under- and over-fitting causing poor performance in actual applications. The occurrence of noise presented in the SOC estimation obtained from NN is another issue as shown in the study of [2,8]. Consequently, the hybrid methods, whose objective is to benefit from the advantages of various methods, are introduced to help in yielding a better ANN model. Kalman filters, such as extended Kalman filter (EKF) [6,12], unscented Kalman filter (UKF) [7] , adaptive extended Kalman filter (AEKF), and wavelet transform [5] are taken into account with NNs to avoid noises created in the NN estimation. It has been shown in many literatures that superior SOC estimating results are obtained from the hybrid methods [5,8]. Further literature surveys on the categories and mathematical methods of SOC estimation can be found from [2].

In this work, the objective is to propose a technique that delivers a reliable SOC estimation by using the back-propagation neural network and the wavelet transformation and to visualise this technique limitations. The used techniques is detailed in Section 2. The proposed SOC estimation method and detailed experiments are presented in Section 3. The obtained experimental data are compared with the estimated SOC which is shown in Section 4. Discussion is elaborated in Section 5. The last section draws conclusions of this work.

2. Methodology

2.1. Back-propagation neural network

Artificial neural network (ANN) is a mathematical tool which is capable of representing arbitrarily complex non-linear processes. It is inspired by the way the human brain processes information. ANN consists of three main parts; input layer, hidden layer and output layer. Each layer consists of nodes, analogous to neurons in the brain. The nodes or artificial neurons communicate with others in the next layer by multiplying each of the inputs by a weight. Then the multiplications are combined and passed to an activation function as shown in Figure 1. Typically, the network can have one or more hidden layers in which Figure 1 illustrates a neural network with one hidden layer used in this work.

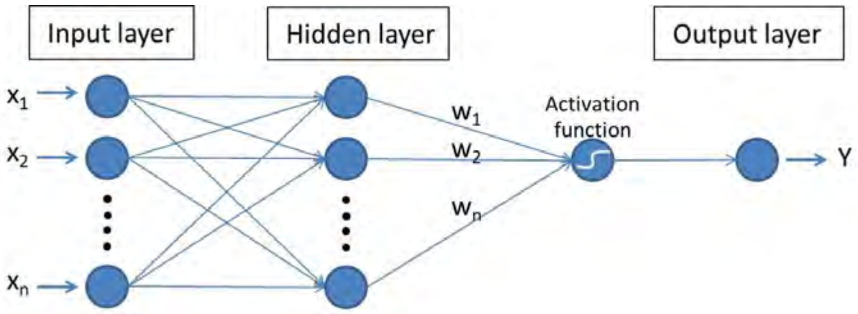

Figure 1. Graphical sketch of a neural network with one hidden layer.

A back-propagation neural network is one of algorithms defining how weights are adjusted in order to achieve the desired outputs of the network. It is the most popular type in artificial neural networks due to their good ability of nonlinear mapping [10,11]. The weights of a back-propagation network are determined from the difference between the targeted and actual output values of all output and hidden neurons. This is done by a backward propagation of errors during the training phase in order to minimise the output error.

2.2. *Discrete wavelet transformation*

Discrete wavelet transformation (DWT) is a mathematical tool that can decompose a time-domain signal into different frequency groups. It can provide the localisation property in both the time and frequency domain [5]. The output of DWT on a given set of discrete signal provides the corresponding approximation coefficients and detail coefficients of the input signal. By applying a signal with the low-pass filter and the high-pass filter, the approximation and the detail information are obtained, respectively. Typically, the length of each scaling coefficients is generally decreased by half.

In this work, À-trous wavelet transform is employed. It is a non-decimated wavelet transformation which decomposes signal into coefficient series with the same length as the input signal. As presented in Figure 2, given a time signal *x(k)*, the À-trous wavelet transform gives the approximation, $A_j(k)$, and detail coefficients, $D_j(k)$, at resolution level *j* at position *k* as:

$$A_j(k) = \sum_{l=0}^{n} h(l) A_{j-1}(k + 2^j l), \tag{1}$$

$$D_j(k) = A_{j-1}(k) - A_j(k). \tag{2}$$

This is done by passing the signal *x(k)* through a series of low pass filters *h* analysed at each resolution level *j* at position *k*. Finally, the signal can be reconstructed using the mathematical expression as follows:

$$x(k) = A_n(k) + \sum_{j=1}^{n} D_j(k), \tag{3}$$

where *n* is a number of resolution levels.

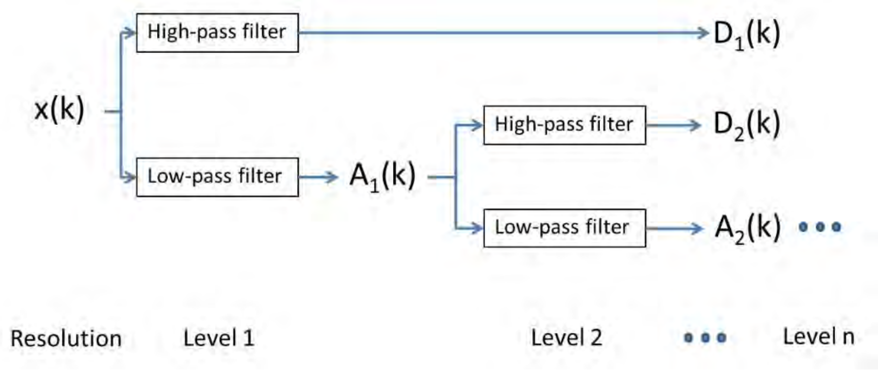

Figure 2. Wavelet transformation filtering process with resolution level equals to 2.

3. Estimation of Lithium Ion Battery SOC

3.1. The proposed technique

In this work, the combining SOC model of the back-propagation NN and wavelet decomposition is proposed. Figure 3 describes the underlying idea of our technique which comprises 3 main steps; wavelet decomposition, NN training, and wavelet recombination. Prior to the network learning, wavelet decomposition is applied on each battery input data. Two sets of wavelet coefficients, for which one pattern represents detail information of each data and the other acts as a smoothing filter, are extracted for the ANN. The number of resolution levels chosen in this work is 2 and the choice of the mother wavelet is the Daubechies 2 wavelet (Figure 2).

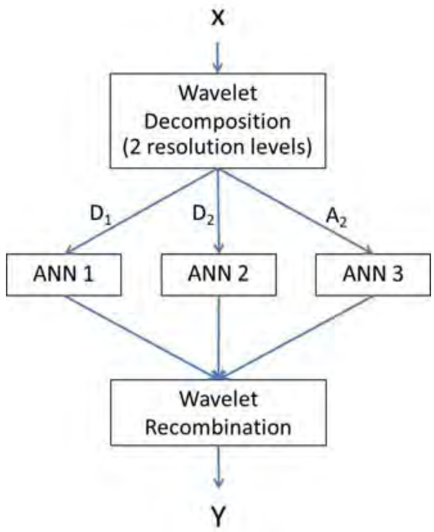

Figure 3. Wavelet-based ANN.

Next, the decompositions are fed to the neural networks in order to predict the SOC data at the current time. As can be seen in Figure 3, three networks are trained for each set of wavelet coefficients. In the learning process, a conjugate gradient back-propagation neural network is used. The Fletcher-Reeves update is utilised to perform weight adjustment, due to its fast and efficient computation.

Finally, the obtained wavelet SOC estimation at different resolution levels obtained from the neural network are combined to reconstruct the original SOC data. This can be done by performing the calculation in equation (3).

3.2 Experimental data for the neural network

It is a known practice that accuracy of an artificial neural network model is dependent on an input variable selection. Battery factors influencing on the battery SOC are therefore determined as inputs to ANN models. Commonly, the battery terminal voltage, and discharge current are considered [6,8-11]. As environmental conditions and ambient temperature also affect battery SOC, many researchers proposed a model incorporating temperature as an additional input in order to improve accuracy [7,11].

In addition, training data are also crucial in establishing an NN model. In order to obtain accurate NN model for SOC estimation, all possible real-life loading conditions should be considered in the training process. However, this is very difficult as the real-life loading conditions of EVs are complex and uncertain. This is due to road conditions, speeds used, and driving styles. Even though training data collected during the field test of EVs can improve the NN performance, at this stage we scope ourselves for data obtained in a laboratory.

In this work, cylindrical lithium-ion batteries with a capacity of 2.6 Ah were used in order to obtain the training and testing data for the neural network. Different 5 charge and discharge currents (C/5, C/4, C/3, C/2, and 1C) and two thermal environments (25°C and 45°C) for battery testing were considered in order to construct the NN. The past values of battery voltage, current, temperature, and SOC were considered as input factors to the neural network since they are related to the battery SOC at the current time step. For each charge/discharge cycle, the battery's terminal voltage, SOC, and current were measured. All test cycles for each battery data are illustrated in Figures 4 – 5.

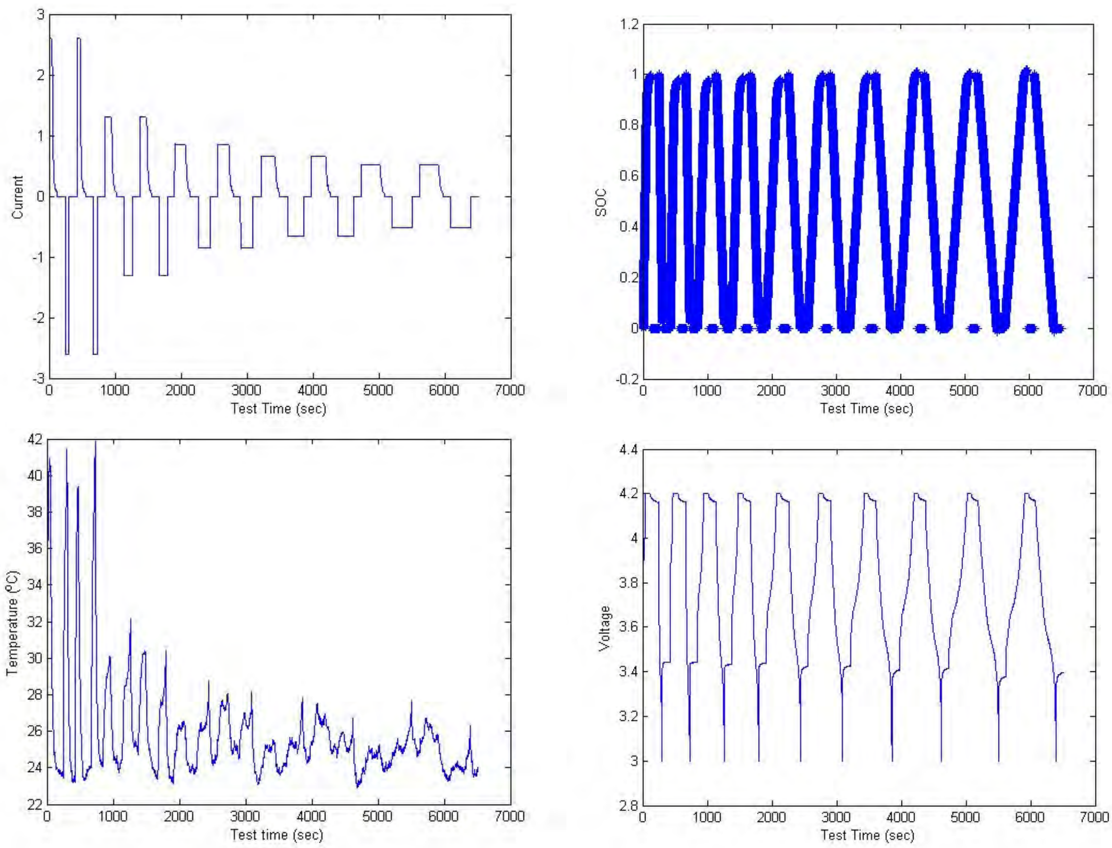

Figure 4. Battery profiles for NN training and testing, which were measured at 25°C.

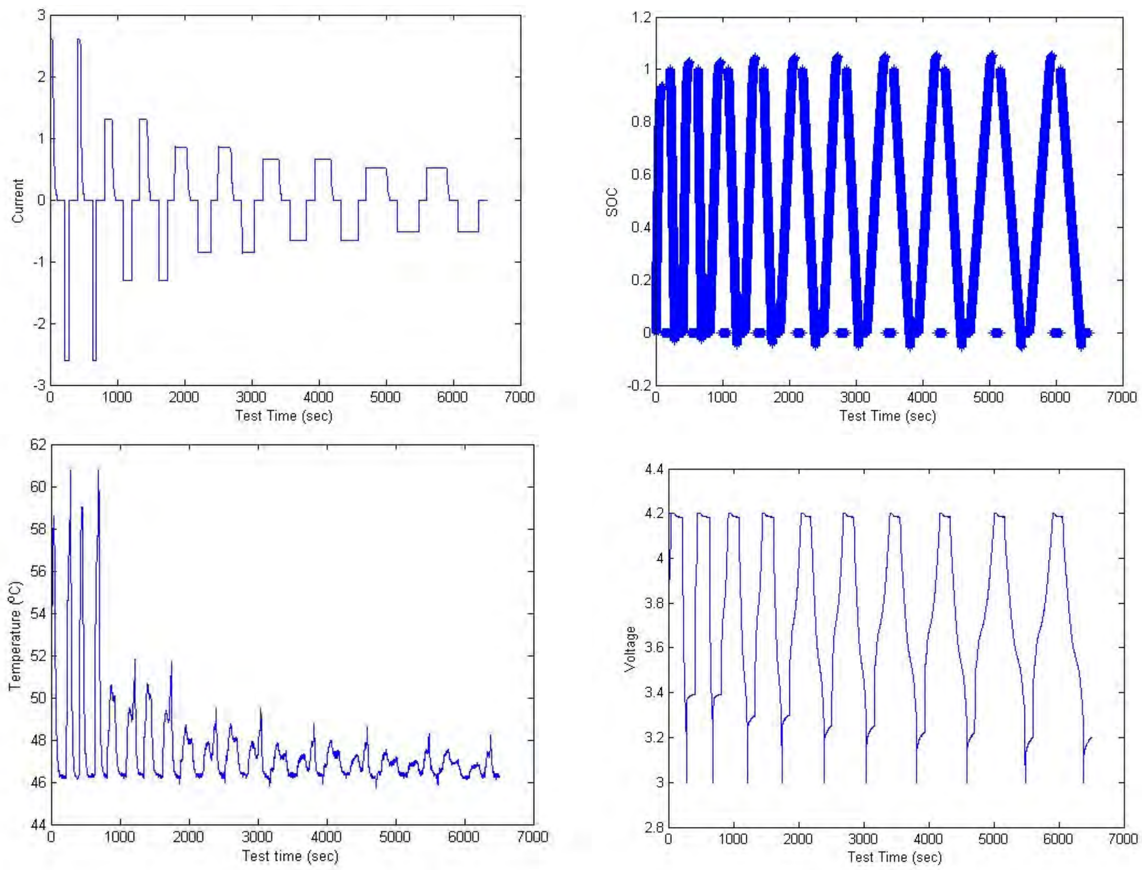

Figure 5. Battery profiles for NN training and testing, which were measured at 45°C

The validation of the NN models should be different from the training and testing data. In this study, pulse discharge tests which represent the Economic Commission for Europe (ECE) standard driving cycle were used as a validation of the trained ANNs. The battery profile are shown in Figures 6-7. It was our purpose to employ these battery data to test the robustness and generalization of the obtained ANNs.

3.3 Design of the neural network architecture

For the SOC estimation using ANN in this work, the input vector **X** = (**S, I, V, T**) composed of four input battery parameters representing SOC, current, voltage, and temperature at the previous time steps. The output **Y**(**X**) of the network was designed to be the SOC estimation at the current time step.

In general, the accuracy of the NN result can be improved from increasing number of nodes used in the hidden layer. As a result, the network can be more complex and the computational time can be more expensive. Therefore, numbers of nodes were experimentally varied for both the input and hidden layers. The battery data from the battery cells collecting in laboratory, shown in Figures 4-5, were used to train and design the NNs. No differentiation between current classifications; charging and discharging, was considered in the training process. And the resting stage was not included in the SOC estimation study. However, to avoid over-training of an NN, the second cycle of each testing current (C rate) was selected for the network training and testing.

To evaluate the performance of the obtained SOC model, the collected experimental SOC was compared against the estimated SOC. The network performance was evaluated by the Root mean squared error (RMSE) and the coefficient of determination (R^2).

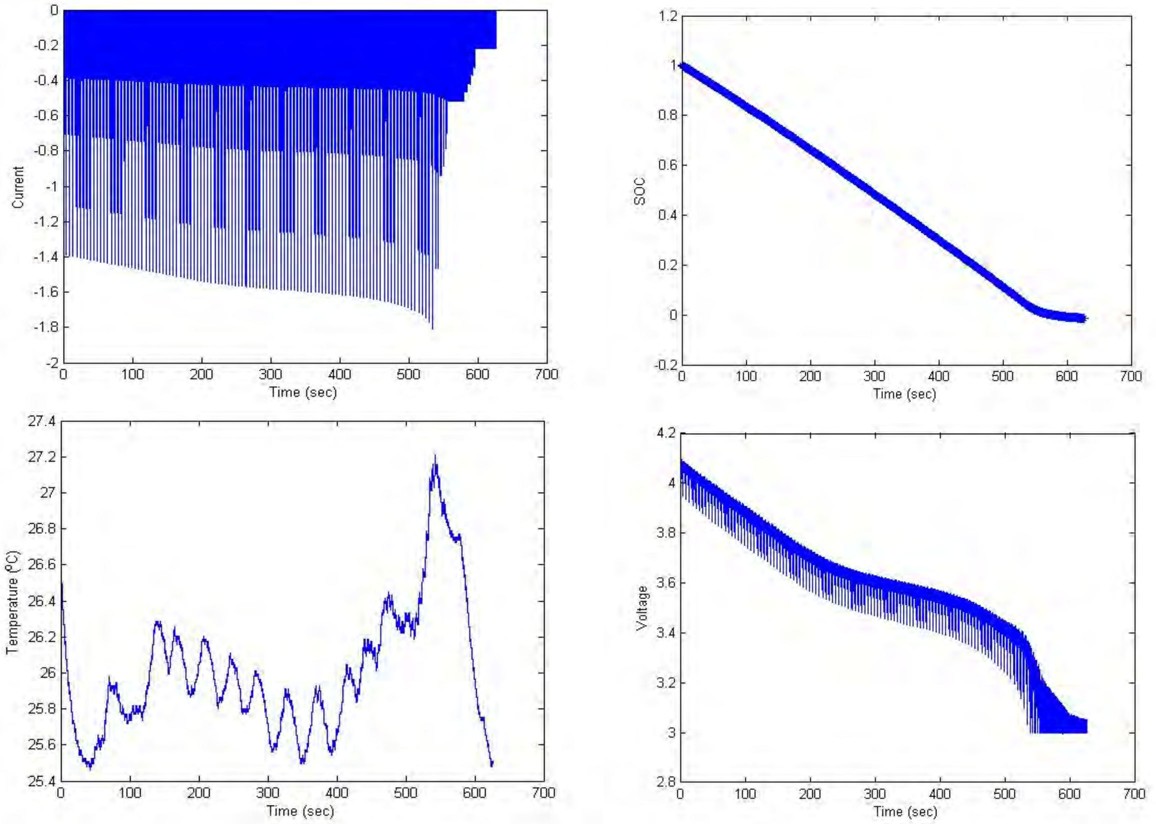

Figure 6. Pulse test for NN model validation, which was measured at 25°C.

4. Results

The constant charging and discharging battery profiles illustrated in Figures 4-5 were employed to establish NN models for SOC estimation. The total dataset of approximately 25,000 was divided into two sets for the network training and testing. The training set was used to train the network whereas the testing set was used to test the network during the model development and also to continuously correct it by adjusting the weights of network links. Detailed descriptions of how battery data are divided for the training and testing set are elaborated in Table 1.

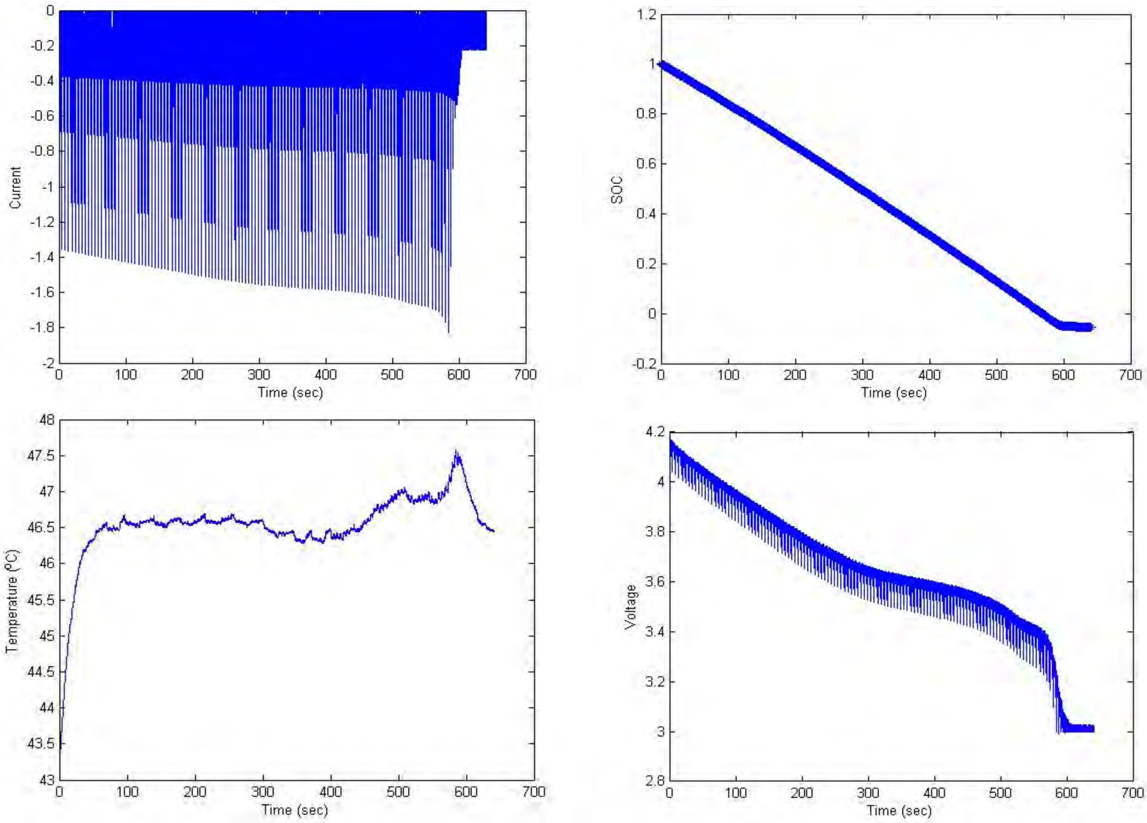

Figure 7. Pulse test for NN model validation, which was measured at 45°C.

Table 1. Model description used in establishing an NN for SOC estimation.

Model	Detailed description Training set	 Testing set
1	75% of all data obtained from both temperature	25% of all data obtained from both temperature
2	All data obtained from both temperature and charge/discharge by the 1C,C/2, and C/3 rates	All data obtained from both temperature and charge/discharge by the C/4, and C/5 rates
3	All data obtained from both temperature and charge/discharge by the 1C,C/3, and C/4 rates	All data obtained from both temperature and charge/discharge by the C/2, and C/5 rates
4	All data obtained from 25°C and charge/discharge by the 1C,C/2,C/3, C/4, and C/5 rates and data from 45°C charge/discharge by the C/5 rate	All data obtained from 45°C and charge/discharge by the 1C,C/2,C/3, and C/4 rates
5	All data obtained from 25°C and charge/discharge by the 1C,C/2,C/3, C/4, and C/5 rates	All data obtained from 45°C and charge/discharge by the 1C,C/2,C/3, C/4, and C/5 rates

4.1. Training and testing results

After performing experiments on the ANN architecture, the designed NNs used for each SOC model were obtained as shown in Table 2. Detailed estimation performance about SOC during the training and testing schemes, obtained from comparison between the measured and estimated values at charging and discharging with constant currents, are presented in Table 2 for each NN model. The RMS errors for all model are within 3% except for Model 5 which gives error of 20%. Figure 8 shows SOC estimations obtained from NN models during the network testing. The results exhibit great consistency between the estimation and the actual SOC for most models. However, Model 5 gave relatively poor performance. The error was mainly presented when SOC approached a fully-charged state. It can be seen in Figure 8e that this behaviour could not be accurately captured.

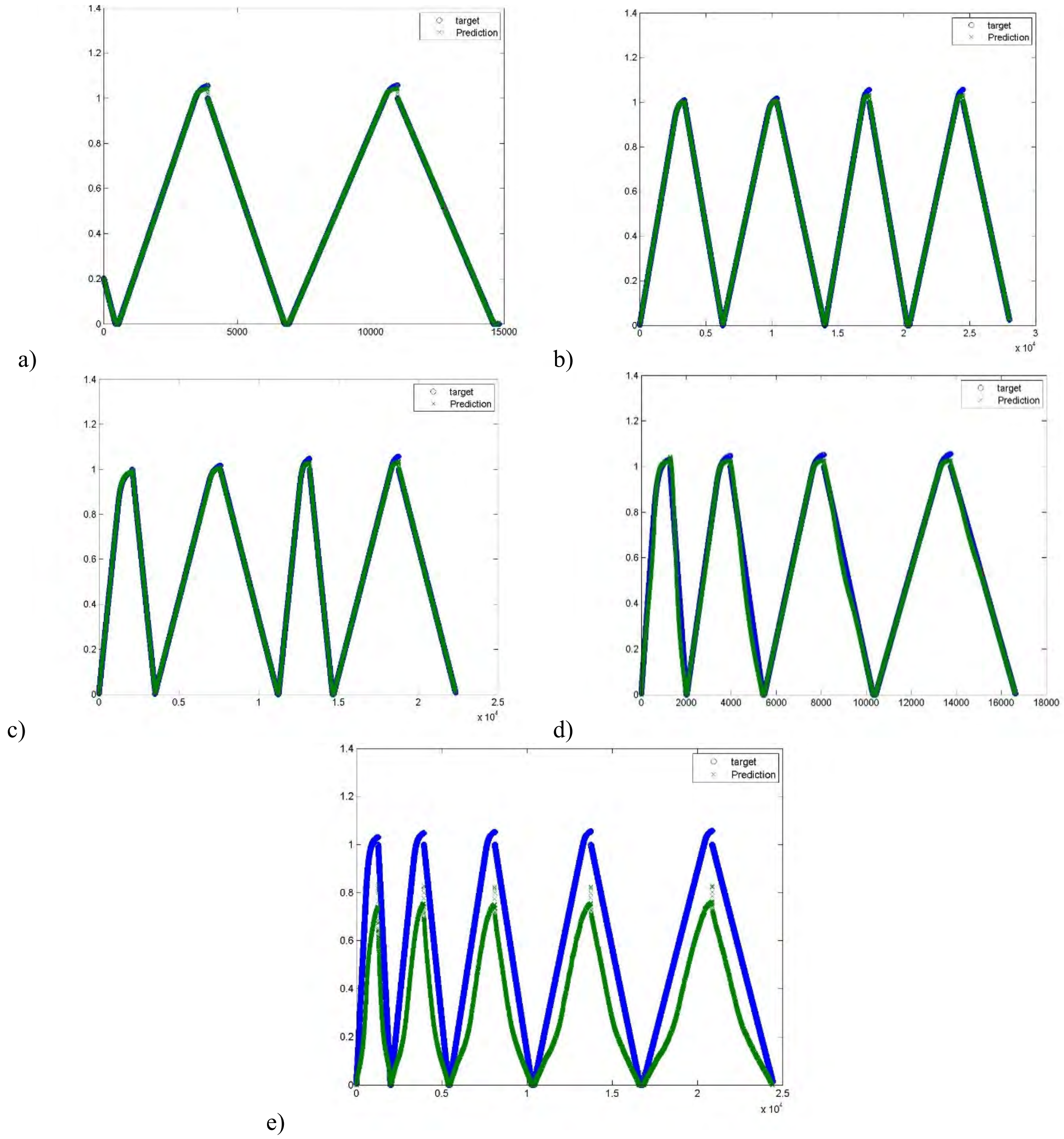

Figure 8. SOC estimations obtained from different NN models during the network testing: a) Model 1, b) Model 2, c) Model 3, d) Model 4, e) Model 5.

Table 2. SOC estimation performances compared among different NN models during the network training and testing.

NN Model	Architecture	Training set		Testing set	
		RMSE	R^2	RMSE	R^2
1	4-3-1	0.0036	0.9998	0.0063	0.9998
2	4-16-1	0.0041	0.9998	0.0011	0.9996
3	4-15-1	0.0042	0.9998	0.0044	0.9997
4	4-19-1	0.0052	0.9998	0.0328	0.9897
5	8-14-1	0.0049	0.9997	0.2017	0.5929

4.2. Validation results

In this section, the validation data set, which is not presented to the network during the network training, was used to validate the established NN models described in Section 4.1. The pulse discharging test profile (Figures 6-7) were considered in order to determine the robustness and generalisation of the obtained NN models. Figures 9 and 10 show the comparison between the estimated and the actual SOC measured at 25°C and 45°C, respectively. It can be seen that the estimated SOC for the pulse test obtained from Model 1-5 are consistent with the associated actual SOC. Its estimation error of each NN model is shown in Table 3. The average error is less than 2% for Model 1-4. Errors are presented in the middle of the discharging cycle as illustrated in Figures 9-10. Only Model 5 provides errors more than 2% for both temperature. However, the estimated SOC at 45°C obtained from Model 5 provides relatively higher RMS error of 20%. It can be seen in Figure 10e that pulse discharging behaviour at the battery fully charged state cannot be simulated.

Table 3. SOC estimation performances compared among different NN models.

NN Model	25°C		45°C	
	RMSE	R^2	RMSE	R^2
1	0.0071	0.9994	0.0063	0.9995
2	0.0112	0.9988	0.0039	0.9998
3	0.0118	0.9985	0.0037	0.9998
4	0.0165	0.9972	0.0128	0.9984
5	0.0226	0.9948	0.2017	0.5929

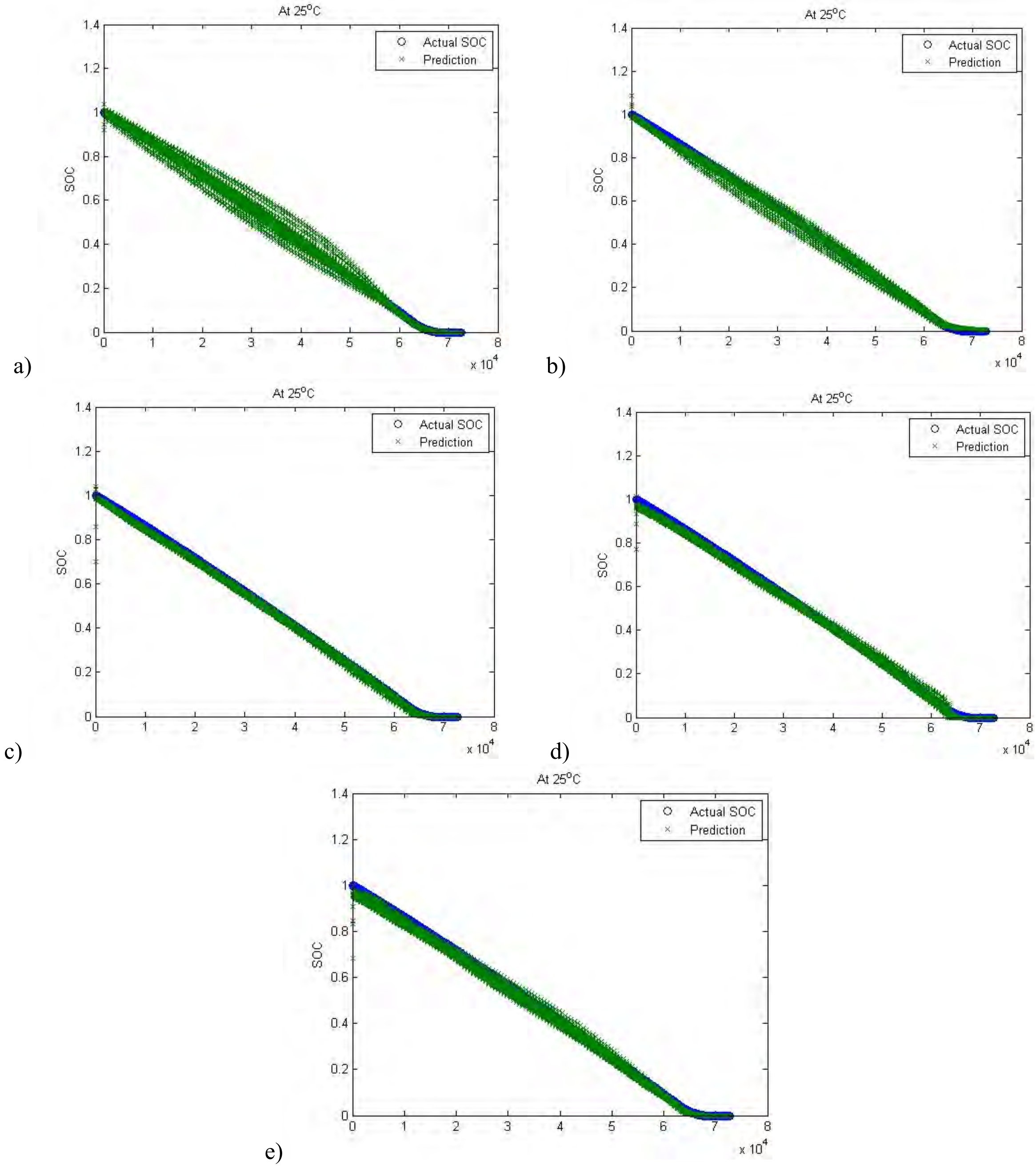

Figure 9. SOC comparison for the pulse test, measured at 25°C, obtained from: a) Model 1, b) Model 2, c) Model 3, d) Model 4, e) Model 5.

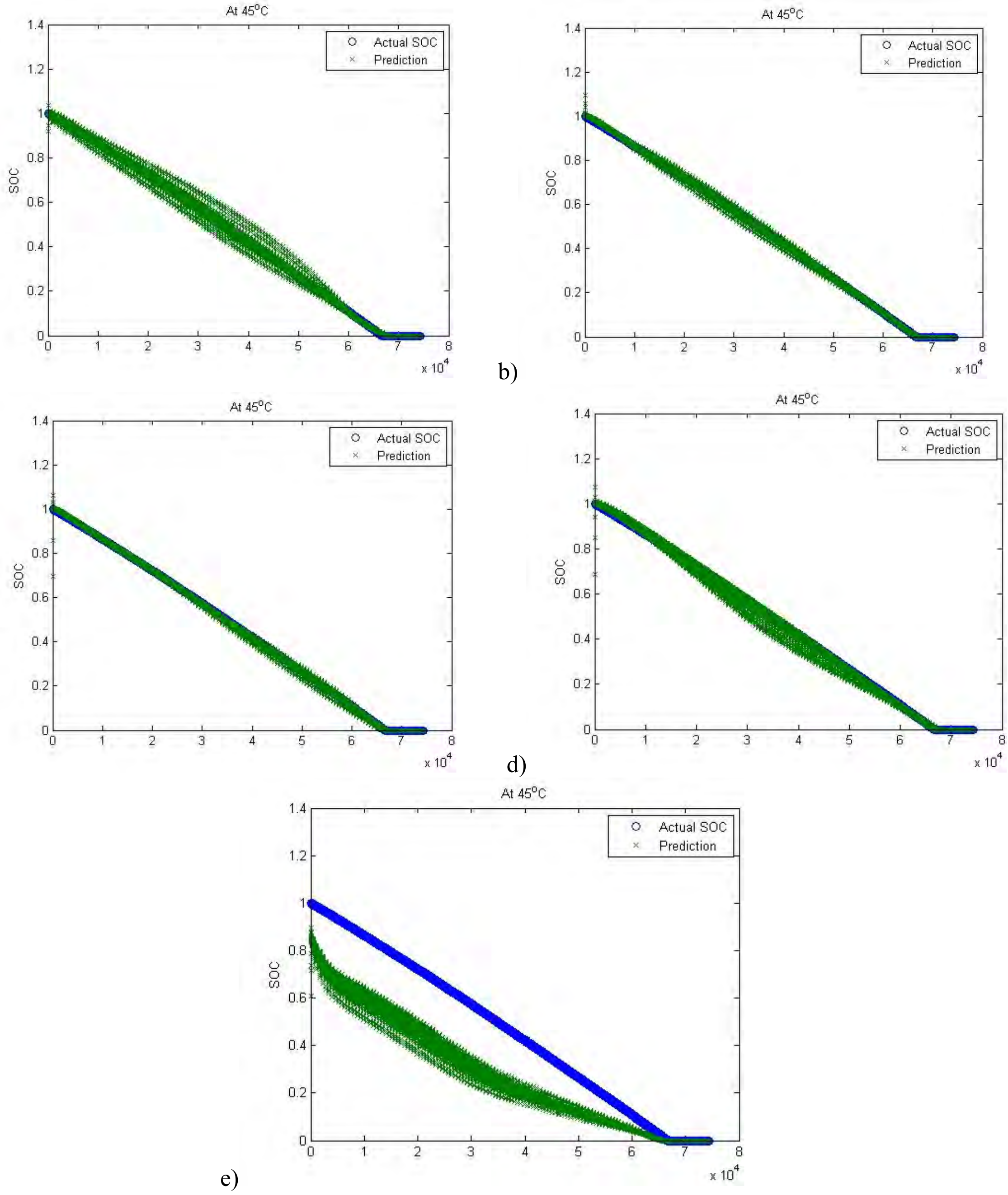

Figure 10. SOC comparison for the pulse test, measured at 45°C, obtained from: a) Model 1, b) Model 2, c) Model 3, d) Model 4, e) Model 5.

5. Discussion

In this work, the NNs for SOC estimation were first designed from the network training and testing processes by employing battery data consisting of a variety of current steps with different amplitudes and lengths. As the used data is a simplification from the real-life loading conditions of battery, the established models obtained from the network training and testing were validated further with more realistic conditions. Validation results showed that the neural network based on wavelet decomposition was preferable for lithium-ion battery SOC estimation as the obtained SOC estimation and the experiments were consistent. Furthermore, Validation results demonstrated that the established models simulated the battery SOC behaviour with great accuracy and robustness. Accuracy of SOC estimation gave satisfactory with a RMS error less than 2% for Model 1 to 4, as can be seen in Table 3. Moreover, Figures 9-10 shows that there was no presence of noise in the SOC estimation for both temperatures. Unlike our SOC estimation, using solely ANN methods gave noise, which is commonly appeared in ANN estimation, and lower accuracy as presented in [8] and [12]. This signified the pre-processing step as an important step in the construction of ANN model for SOC estimation. The wavelet transform was able to extract the chaotic components from the original data for the trained neural network.

Nevertheless, it can be seen in Figures 8e and 10e that SOC behaviour could not be accurately simulated. This makes estimation error for Model 5 relatively large with RMS error more than 20% for 45°C. This was a result of not including the 45°C data in the training process and the proposed NN models were constructed through a normalisation of the data into the range [0,1]. This suggested that possible extreme battery conditions should be exposed to the network training. Unexpected extreme events like 45°C battery environment, in which the network did not experience, caused error and wrong estimation as shown in Figure 10e. Unlike Model 1-4, in which the trained network experienced possible scenarios of the testing and validating sets, the obtained SOC was accurately estimated as seen in Figures 10a-10d. Hence, exposing all possible real-life loading conditions is crucial for data-driven approach like ANNs in order to obtain an accurate and robust model.

For future work, the merits of this method will be testified further by different temperature and field collected data in order to ensure the reliability of the purposed method. Other types of batteries can also be considered to investigate its adaptability.

6. Conclusion

In this work, the combining technique of ANN and wavelet decomposition was proposed for SOC estimation. The technique was tested on cylindrical lithium ion battery SOC data obtained from the experiments. In theory, it has been known that battery SOC is influenced by many factors. However, in this work, the experimental results showed that introducing four important factors such as the battery voltage, temperature, current and SOC at the previous time steps was sufficient for SOC estimation at the current time. Our training and testing results showed good agreement between the obtained SOC estimation from the wavelet-based ANN technique and the associated battery experiments. Likewise, no occurrence of unrealistic spikes in the output was noticed. This signifies the important role of wavelet transformation in the data pre-processing step of our technique. Furthermore, validation results showed that the established models simulated pulse discharging battery profile with great accuracy and robustness.

Acknowledgement

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