UNIVERSITY OF CALIFORNIA
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Feed-forward Neural Network Model Based on Back-propagation Algorithm for Voltage Prediction in Electric-Vehicle Batteries

A thesis submitted in partial satisfaction of the
requirements for the degree of Master of Science
in Chemical Engineering

by

Shuang-Yuan Chang

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ABSTRACT OF THE THESIS

Feed-forward Neural Network Model Based on Back-propagation Algorithm for Voltage Prediction in Electric-Vehicle Batteries

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Professor Panagiotis D. Christofides, Chair

This work focuses on developing electric-vehicle battery models that can precisely predict voltage from measurable properties with limited errors using feed-forward neural network models of the backpropagation algorithm. Recently, the neural network has been utilized in a variety of different predictions such as the state of charge prediction or the state of health prediction. Also, electric vehicles like the model X, model 3, and model Y from Tesla have been widespread from 2015 until today. Our model for electric-vehicle battery voltage prediction achieves 25 times reduction in the maximum voltage error and 273 times reduction in the average voltage error comparing to the existing models from Contemporary Amperex Technology (CATL). This is accomplished by using the neural network models in comparison to the equivalent circuit model, which is a way to describe working conditions in a circuit by using the mathematical method, for the lithium-ion battery. Advantages of using a battery model to run the test instead of installing a pack in a vehicle are that our model can reach the tolerant error range. This allows automakers

to use our model to design cars at an initial stage and provide guidance to choose the particular specification of battery packs to run the vehicle performance test without much cost.

The thesis of Shuang-Yuan Chang is approved.

Junyoung O. Park
Dante A. Simonetti
Panagiotis D. Christofides, Committee Chair

University of California, Los Angeles

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Chapter 1: Introduction

To date, our civilization has become more and more advanced like introducing the great number of transporting vehicles using fuel. However, these vehicles contaminate our environment, especially the fresh air in the cities. Many countries around the world have been promoting electric vehicles instead of using fuel transportation to reduce environmental damage such as air pollution in their cities. Electric vehicles sales are gradually increasing around the world, but the lack of a credible battery model slows their spread. If several problems with electric vehicles can be solved, then electric vehicles will rapidly spread.[1]

At the early design phase of a vehicle, automakers would benefit from a simulation model without a battery pack before the vehicle performance test on the production phase, which involves:

1. selecting automobile types, automobile calibrations, initial design,
2. managing heat (temperature change),
3. maintaining the voltage (V), current (I), and power (P) between the maximum and minimum values.

Thus, we try to simulate the battery model that can control voltage error in the acceptable range, and the appropriate voltage can be the input for driving an electric motor.

To date, because there is no article discussing the voltage prediction using equivalent circuit models, we need to refer the article discussing the equivalent circuit models applied to the state of charge (SOC) prediction. The following **Table 1.1** shows that the present equivalent circuit models cannot be acceptable in the battery simulation by automakers. This SOC prediction, which has also been applied to voltage prediction, is having high errors.

Table 1.1 The list shows that lowering the Relative SOC Error of Output by different equivalent circuit models.

Battery System	**Capacity (Ah)**	**Inputs**	**Simulation Model**	**Relative SOC Error of Output**	**Reference**
Li-ion	2.15	N/A	Continuous-Discrete Extended Kalman Filter	<0.01	[2]
	4.4	SOC	An Improved Coulomb-Counting Algorithm Based on a Piecewise SOC-OCV Relationship	<0.02	[3]
	6	Current	An Electrochemical Model-driven Extended Kalman Filter	~0.1	[4]

Chapter 2: Preliminary Background Information

2.1 Definition of Nomenclatures

2.1.1 Open Circuit Voltage (V_{oc})

Open circuit voltage (or potential) is the potential difference between two terminals under the open loop, which is unconnected to any load in the circuit.[5]

2.1.2 Terminal Voltage (V)

Terminal voltage is the potential difference of the battery. If a battery does not connect to the circuit, the voltage of the terminal is equal to battery voltage.[6]

2.1.3 Current (I)

Current, which is equal to flow, is the rate of electrons flowing past a certain point in the overall circuit. One ampere means electrons in one coulomb (which is equal to 6.24×10^{18} electrons) go through a certain point in the overall circuit within one second. [7]

2.1.4 State of Charge (SOC)

State of Charge (SOC) is used to indicate how much distance people can drive and prevent overcharging and over-discharging from shortening the battery lifetime. SOC can be obtained by the integration of the C/D battery current over time when driving, and by OCV when a vehicle is parking. Therefore, in the context of parking, SOC is proportional to OCV for different batteries.

SOC describes the remaining charge in the battery equal to the ratio of current capacity to nominal capacity, which demonstrates the maximum amount of charge[11], is given by the following equation:

$$SOC = 1 - \frac{1}{C_n} \int \eta i(t) dt \tag{2.1}$$

where i is current, t is time, C_n is nominal capacity, and η is coulomb efficiency (the ratio of the total output charge to the total input charge).[1]

2.1.5 Errors

In the Results and Discussion, we show our performance diagrams in absolute error versus time, which is widely used in industries while relative error versus time is used in the other publication. Also, we mark the mean error and the maximum error to check if they are in the tolerant range. The equations of the voltage errors are as shown in Eq. (1.2), Eq.(1.3), Eq.(1.4), and Eq.(1.5).

$$Absolute\ Error = V_{model(i)} - V_{real(i)} \tag{2.2}$$

$$Relative\ Error = \frac{V_{model(i)} - V_{real(i)}}{V_{real(i)}} \times 100 \tag{2.3}$$

$$Mean\ Error = \frac{1}{n} \times \sum_{i=1}^{n} \left| V_{real(i)} - V_{model(i)} \right| \tag{2.4}$$

$$Max\ Error = max(\left| V_{real(i)} - V_{model(i)} \right|) \tag{2.5}$$

where $V_{model(i)}$ is predicted by the simulation model, $V_{real(i)}$ is known from datasets, and n is the number of voltage samples.

2.2 The Mechanism of the Feed-forward Neural Network Model of the Backpropagation Algorithm

Neural network (**Figure 2.1**) is a popular method in machine learning. The neural network builds nonlinear functions from input to output variables. The basic feedforward structure has hidden layers with multiple inputs and a single output, where $X_{uj}, j = 1, 2, \dots, n$ represents input variables in the input layer, $y_{1i}, i = 1, 2, \dots, m$ performs the neurons in the hidden layers and Y are as shown in the following equations:

$$y_{1i} = f_1\left(\sum_{j=1}^{n} W_{ij}^{(1)} X_{uj} + B_{i0}^{(1)}\right) \tag{2.6}$$

$$Y = f_2\left(\sum_{j=1}^{m} W_j^{(2)} y_{1i} + B_0^{(2)}\right) \tag{2.7}$$

where f_1, f_2 are nonlinear activation function, $W_{ij}^{(1)}$ and $W_j^{(2)}$ are the weights, and $B_{i0}^{(1)}$ and $B_0^{(2)}$ are biases. To simplify, all inputs X_{uj} are represented by X_u, and all weights and biases are denoted by W.

In the training data points, the input vectors $X_u^i = 1, 2, \ldots X_T$ and target vectors X_t^i are given to minimize the errors to train neural network models, and this can be expressed by loss function:

$$E(W) = \frac{1}{2}\sum_{i=1}^{X_T} |X_y^i(X_u^i, W) - X_t^i|^2 \tag{2.8}$$

where $X_y^i(X_u^i, W)$ belongs to X_u^i prediction category under W. By using the stochastic gradient descent (SGD), the nonlinear optimization problem can be solved, which applies the backpropagation to calculate the gradient of $E(W)$ and update W simultaneously:

$$W = W - \eta\nabla E(W) \tag{2.9}$$

where learning rate η is assigned to determine the rate of convergence. Also, k-fold cross validation is applied to a random partition on a dataset, which is transferred into k-1 training subsets and one validation subset to avoid overfitting in the training process.

In brief, because the validation subset is independent of training subsets, the accuracy of the validation subset can prove the ability of neural networks, and the accuracy of training neural network model is shown:

$$N_{acc} = \frac{n_c}{n_{val}} \tag{2.10}$$

where n_c represents the number of data points of correct prediction, n_{val} shows the total number of data points in the validation subset. The ability of neural networks usually depends on several factors; for example, the size of a dataset, the number of hidden layers and neurons, and the degree of disturbance. [8]

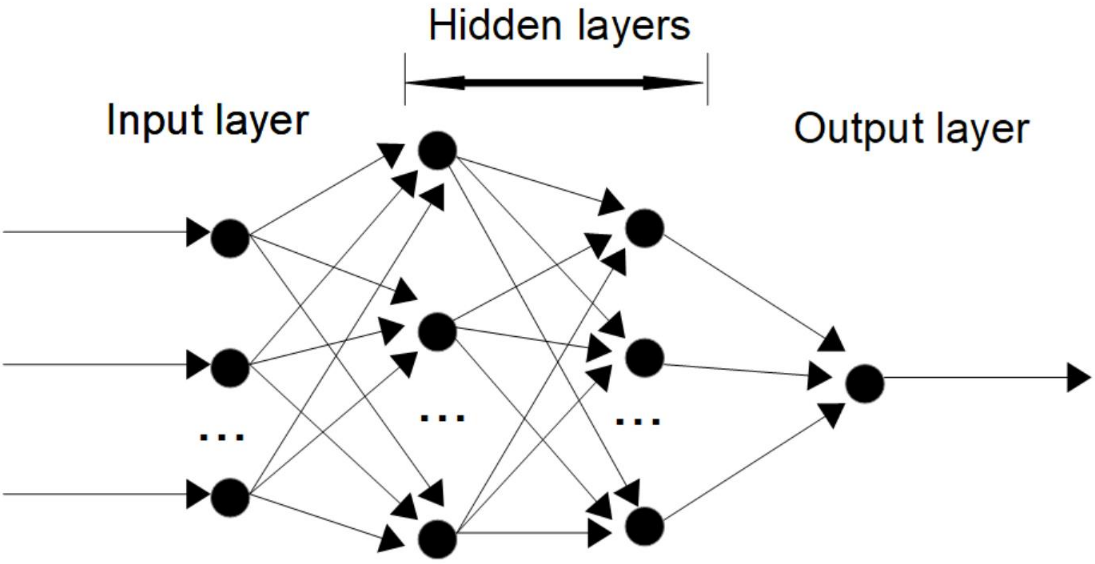


Figure 2.1 The structure of the feed-forward neural network

2.2.1 Weights and Bias

Weight represents the strength of the connection between units. The output is as shown in Eq.(2.11)

$$Y = f(\sum_{i=1}^{n} W_i X_i) \quad (2.11)$$

where i is one to the number of inputs $(= n)$, W_i represents the weights, X_i represents inputs, and Y is the output. Weights in ANN are the most important factor in outputs.[8]

Bias is applied to adjusting outputs Y and the summation of inputs at neurons. The procedure is done by neurons described as Eq.(2.12):

$$output = sum(weights \times inputs) + bias \quad (2.12)$$

2.2.2 Activation Function

A function applied to the output is called the activation function (**Figure 2.2**)[8]. The standard choices of activation function are sigmoid function [Eq.(2.13)] and hyperbolic tangent function [Eq. (2.14)]. It has been reported that hyperbolic tangent function is equipped with nonlinear amplifying gain, which can manage weak signal among high gain in [-1, 1]. Also, when the difference in characteristics is apparent, *tanh* performs well. Furthermore, the effects of characteristics would continuously expand under the subsequent cycles. Last, *tanh* is similar to the *y*=*x* function and passes over the origin. The matrix operation can be directly performed under low activation value, so the training is relatively easy. Based on the above advantages, *tanh* is better than sigmoid, so *tanh* is applied as an activation function in our work.[10]

Activation Function

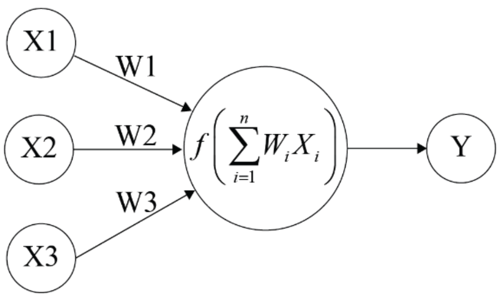


Figure 2.2 The next layer input is the output of the neurons in previous layers through the activation function.

$$\sigma(x) = \frac{1}{1+e^{-x}} \quad (2.13)$$

$$tanh(x) = \frac{e^{2x}-1}{e^{2x}+1} \quad (2.14)$$

where *x* represents the input data.

2.3 The SOC Prediction Performance of Neural Network Models of the Backpropagation Algorithm

There are many methods for lowering the voltage error, such as the integration of the charging/discharging battery current over time model, the open-circuit voltage model, the internal resistance method, the electrochemical model, and neural network models. Among these models, neural network models of the backpropagation algorithm, which is the traditional training method, achieve the best performance (**Table 1.2**). Therefore, we choose neural network models to predict the voltage.

Table 1.2 The list shows that lowering the Relative SOC Error of Output by different neural network model of the backpropagation (BP) algorithm.

Battery System	Capacity (Ah)	Inputs	Simulation Model	Relative SOC Error of Output	Reference
$LiFePO_4$	60	Voltage, current, highest & lowest cell temperature, maximum & minimum cell voltage, cell voltage time, discharge power	BP	< 0.018 0.0020 (Average)	[12]
Li-ion	83	Voltage, current and four different battery pack temperatures	Recurrent Neural Network with BP Algorithm based on a Nonlinear Autoregressive with External Input	< 0.0025	[1]
$LiFePO_4$	N/A	N/A	Modified Elman + BP	0.005	[16]

The neural network models perform precisely with a large amount of training data compared to other models. The accuracy of the models is determined by the performance of the training data.[10] Because there is a lack of reference for lowering the voltage error, we refer to [12] by discussing how to reduce SOC error instead. In the article, excellent SOC performance has been reported. The output relative error and the average error of the SOC are respectively under 0.018 and 0.0020 based on the feed-forward neural network with backpropagation algorithm, which is used in correcting weights (with inputs including voltage current, highest and lowest cell temperature, maximum and minimum cell voltage, time, discharge power).[15] (This excellent performance makes us choose the backpropagation algorithm as our primary method.)

After determining our model structure, we have to select which is that features from the battery would be the proper input. D. Jiménez-Bermejo et al. have proposed a way to improve the SOC prediction that applies real data from daily voyages of a vehicle. A nonlinear Autoregressive with External Input (NARX) artificial neural network (ANN) is built to evaluate the SOC of EV. The relative error of the SOC [k + 1] is smaller than 0.0025 by applying inputs of the previous and the present SOC, voltage (V), current (I), and four temperatures. [1] (This method was also introduced to our models.)

Except for applying the above techniques to our system, electrode polarization usually has to be considered in a battery system. It is a mechanism when the potential of the anode is unexpectedly higher than the cathode. It causes the effects of lowering output voltage and increasing the voltage or decreasing current in the electrolytic cell.[12]

2.4 The Current Voltage Prediction Performance of Equivalent Circuit Model at CATL

The current voltage error performance (**Table 1.3**) is based on Resistor-capacitor (RC) Circuit with Kalman Filter, which is equivalent to circuit model, under current pulse profiles provided by the BMS department at CATL. To date, the maximum error is equal to 194.04 mV under the SOC varying between 65% and 30%, and the mean error is equal to 60.01mV under the SOC varying between 15% and 0%. These values are not in the tolerant range for automakers. Thus, we need to seek another model that can satisfy the requirement of acceptable error range, and the appropriate voltage can be the input for driving an electric motor.

Table 1.3 The errors perform under current pulse profiles.

SOC Range	**100%-65%**		**65%-30%**		**30%-15%**		**15%-0%**	
Temp. (℃)	**Mean Error (mV)**	**Max Error (mV)**	**Mean Error (mV)**	**Max Error (mV)**	**Mean Error (mV)**	**Max Error (mV)**	**Mean Error (mV)**	**Max Error (mV)**
25℃	16.95	118.31	22.52	194.04	28.84	162.84	60.01	192.66

Equivalent circuit model with Kalman Filter originated as the prototype model called the rint models as following:

$$V_k = V_{OC,k} - i_k R_s \tag{2.15}$$

where V_k is the battery's terminal voltage and i_k is the throughput current. An ideal voltage source V_{OC} to represent the battery's OCV as a function of SOC and an internal series resistance R_s, which describes the internal ohmic losses, is a function of temperature and SOC.[13] The internal resistance usually represents inside resistance in a battery, and it can limit the potential of external loading.[14]

2.5 Goal

Automakers need a more accurate voltage simulation to be the input in the electrical motor. The simulation test can lower the developing costs in the initial stage by replacing the process of the real battery pack test.

By introducing the feed-forward neural network model of the backpropagation algorithm mentioned above (**Figure 2.3**), we set our goal on the output to lower the voltage error under 30 mV between 20% and 80% SOC and decrease the voltage error under 50 mV for the rest.

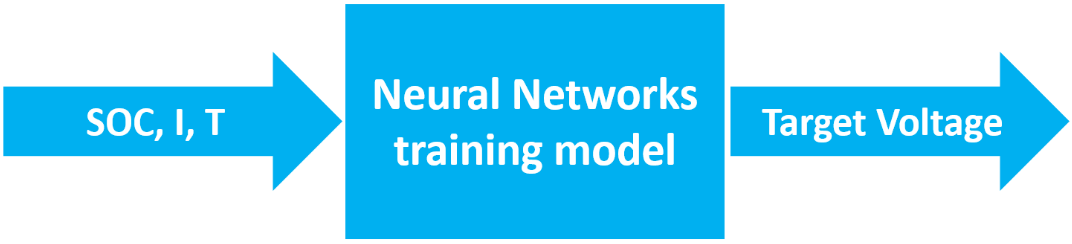


Figure 2.3 The procedures of how we reach the outcome

Chapter 3: Approach

3.1 Datasets

Figure 3.4, **Figure 3.5**, and **Figure 3.6** are three current and voltage profiles based on the experimental test data of $LiNiMnCoO_2$ (NCM) battery pack from the research institute at CATL. The pack offered by CATL contains around ten cells in a module, and there are six modules in a pack. The current is constant in the series circuit, and the current and the voltage were measured by the current and the voltage sensors. The reason why voltage changes with current are because that ion transfer causes the potential difference when charging and discharging. The minimum and maximum values of voltage are between 2.8 V and 4.2 V.

Figure 3.4 is the A1 working condition test report (Cell #: 061740204009, test #: 80509, Nominal capacity: 67Ah) obtained under 80% SOC-OCV at 25℃, and the battery is charged under constant current.

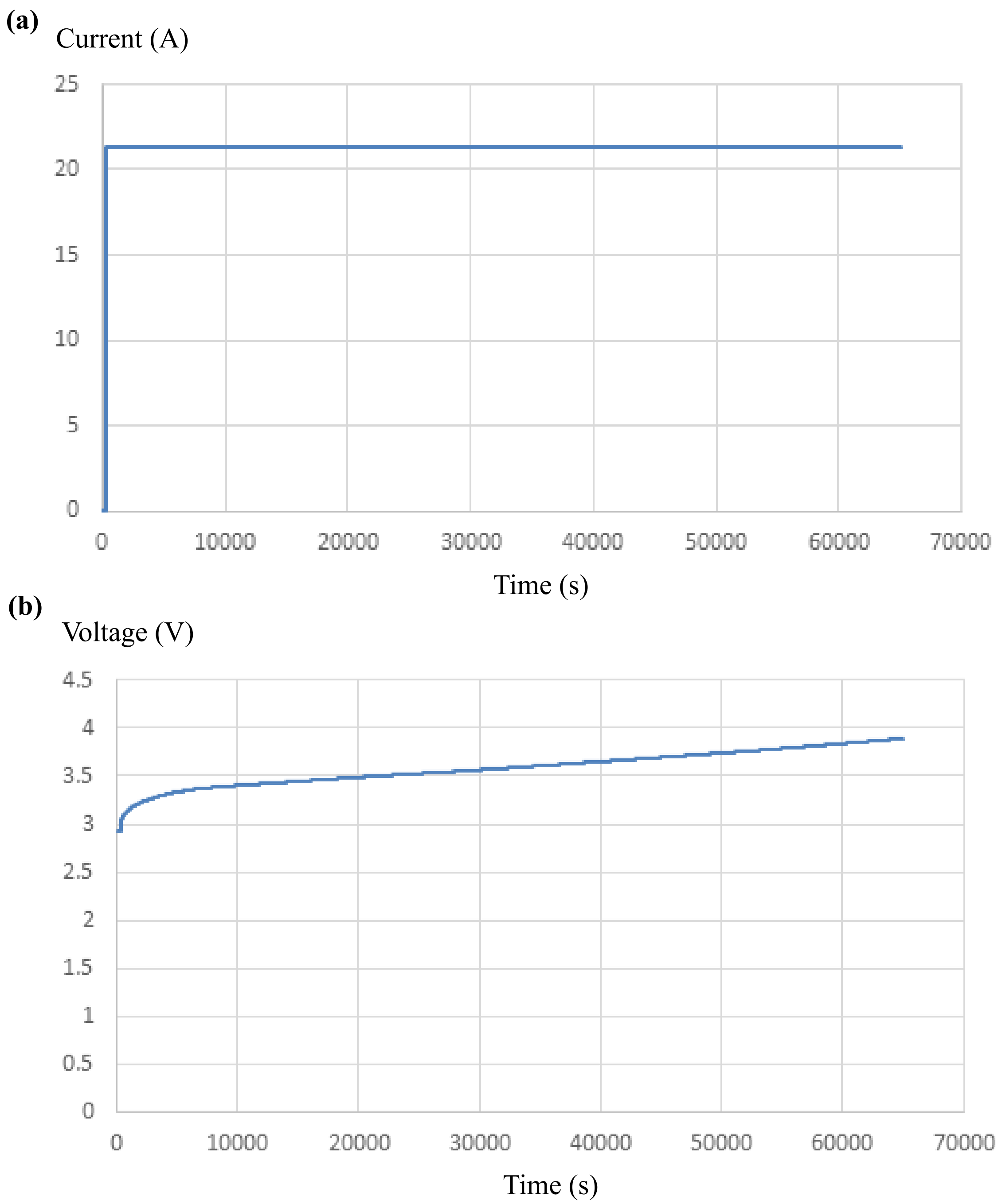
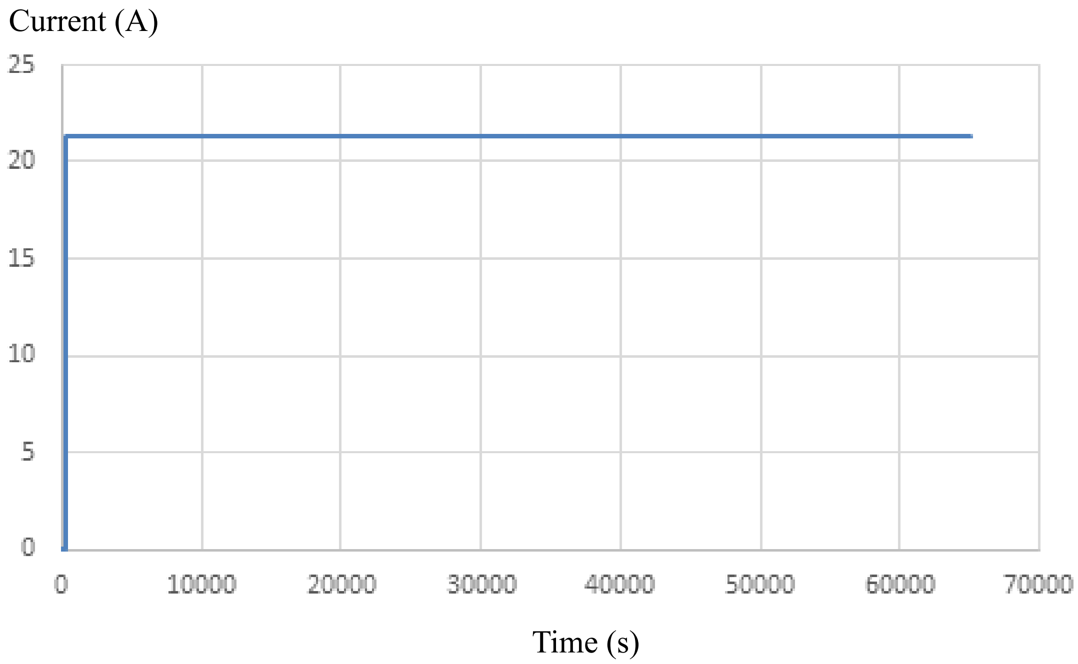


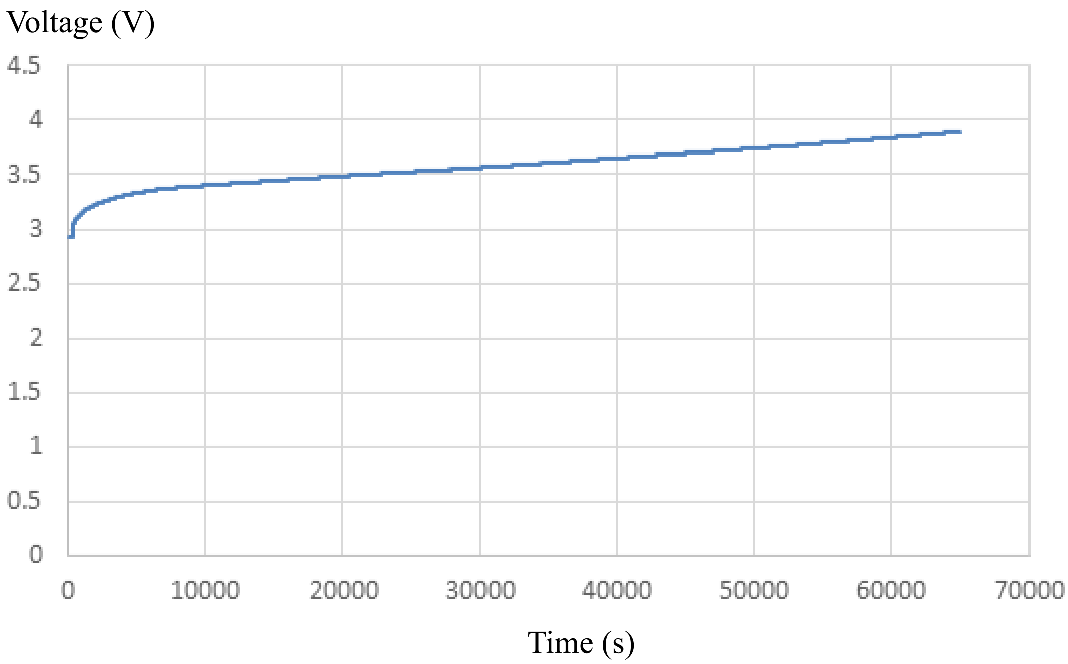
Figure 3.4 A1 working condition test report

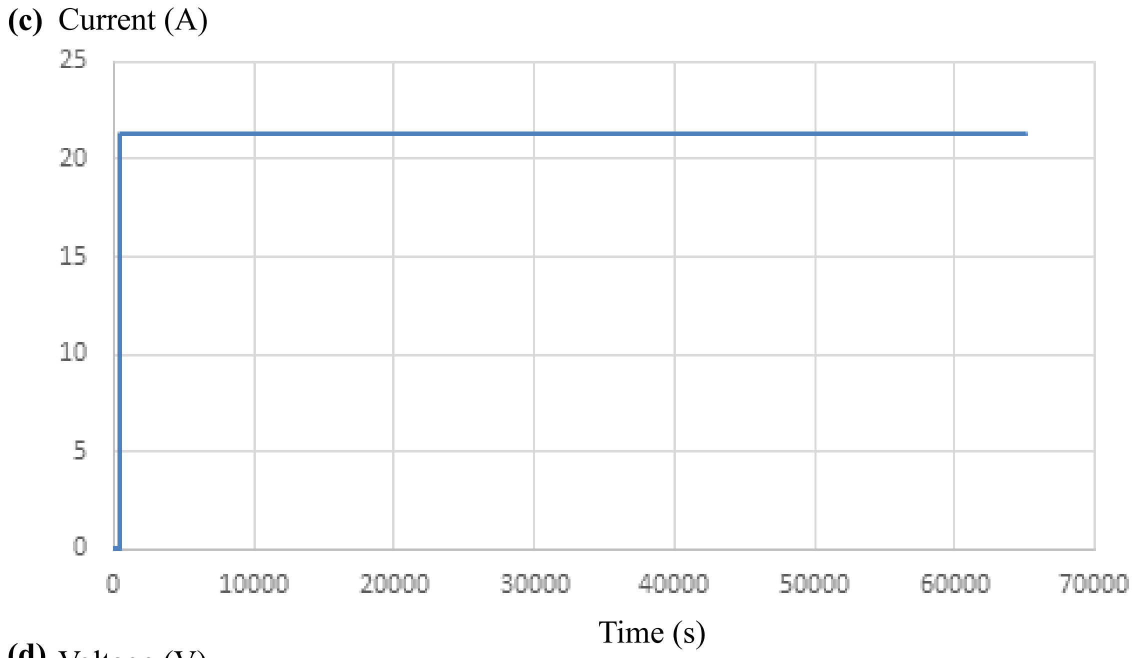
The A2 working condition test report (Cell #: 061740204009, test #: 80509, Nominal capacity: 67Ah) in **Figure 3.5** is obtained under 80% SOC-OCV at 25℃, and the battery is charged under constant current.

(a)


Current (A)
25
20
15
10
5
0
0
10000
20000
30000
40000
50000
60000
70000
Time (s)

(b)


Voltage (V)
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
0
10000
20000
30000
40000
50000
60000
70000
Time (s)



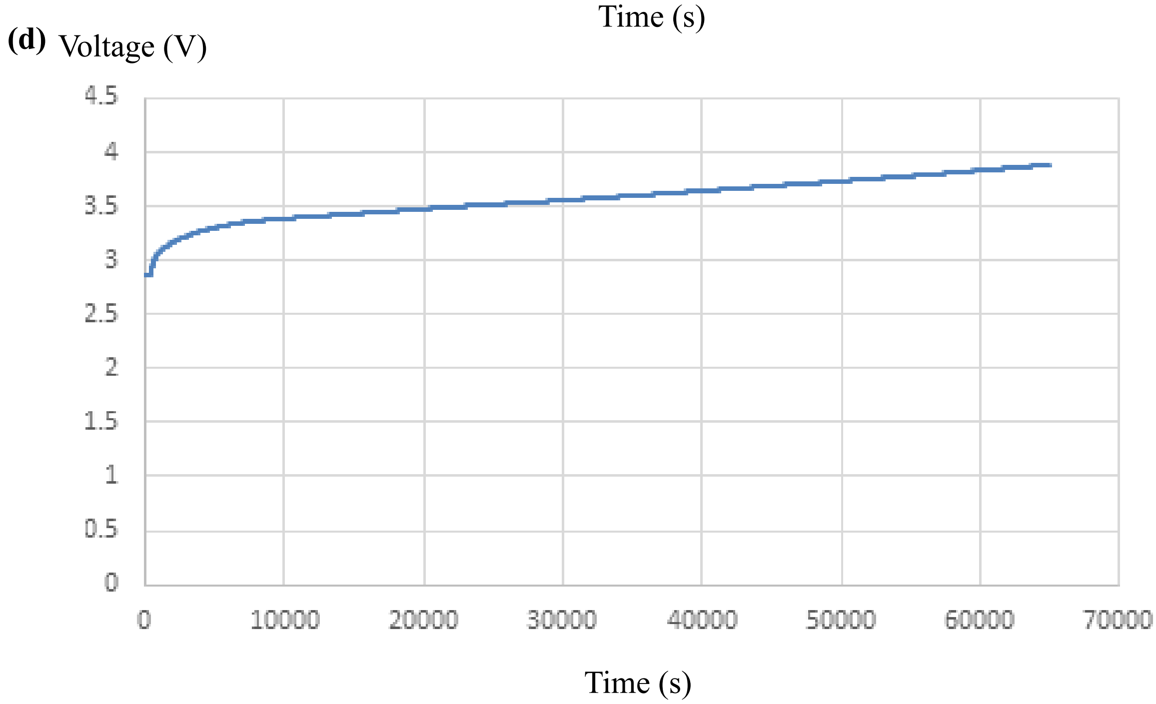


Figure 3.5 A2 working condition test report with more data points

The A3 working condition test report (Cell #: 061740204002, test #: 80508, Nominal capacity: 67Ah) in **Figure 3.6** is obtained at 25℃, and the battery is cyclically charged, rested and discharged under changing current size.

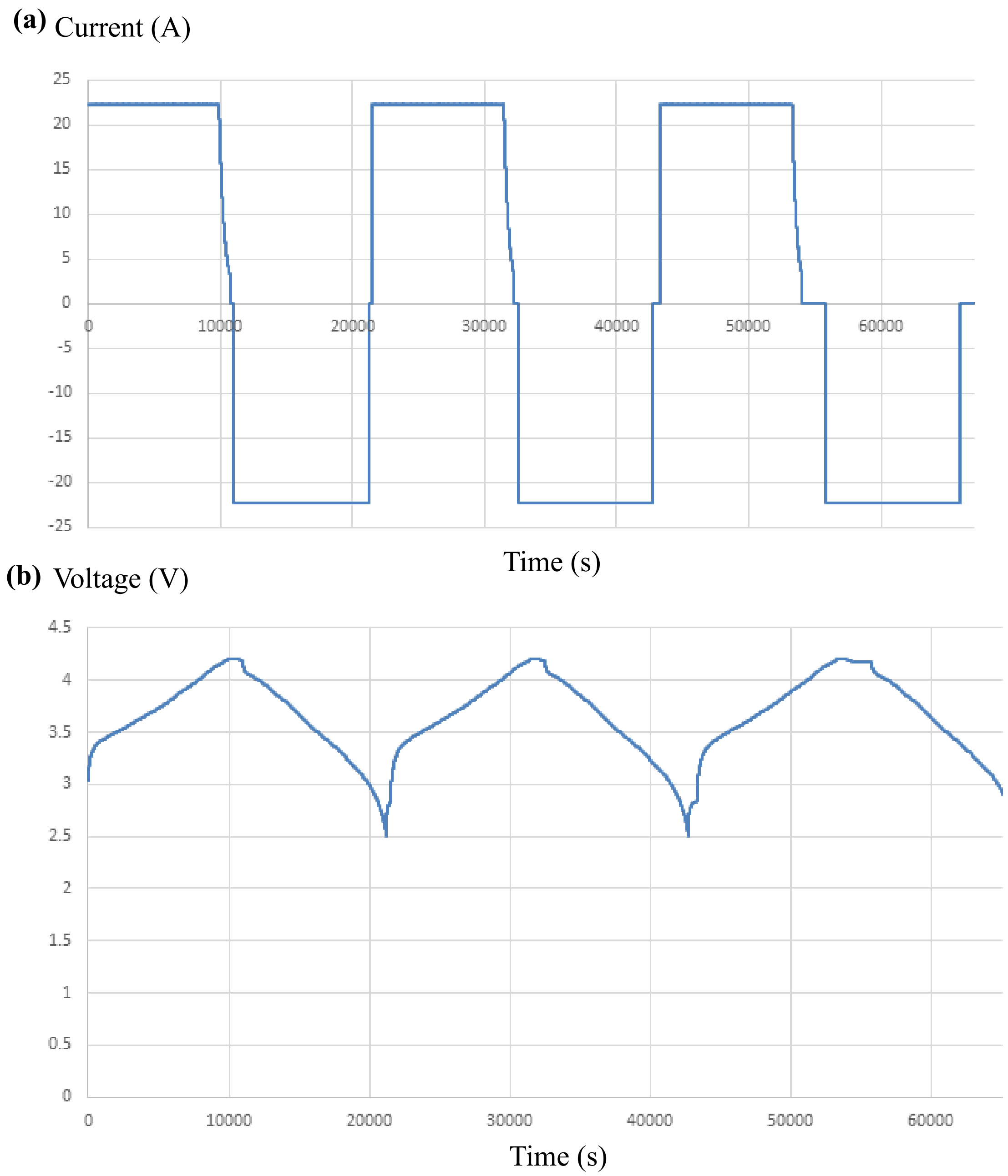


Figure 3.6 A3 working condition test report

3.2 Datasets Treatment

Before importing input data, we need to prepare the following raw datasets based on three different current and voltage pulse profiles. First, the charge capacity is converted to SOC by Eq.(1.1) in section 1.2.4. Second, current and voltage were normalized and translated [Eq.(2.1) and Eq.(2.2)] to meet the high gain interval of activation function, which is between -1 and 1. Third, the accumulated time (**Table 3.1**) is also considered because of the polarization effect, which happens when the anode's potential is higher than the cathode's.[12] The way of considering accumulated time is when the current is equal to zero, the Step_Time of last second (e.g., 10,821.35828) is used as a factor.

$$\text{Shift I}=\mathbf{2} * \frac{[\mathbf{Current(A)}]-(-\mathbf{25A})}{\mathbf{25A}-(-\mathbf{25A})} - \mathbf{1} \tag{2.1}$$

$$\text{Shift V}=\mathbf{2} * \frac{[\mathbf{Voltage(V)}*\mathbf{1000}]-\mathbf{2000mV}}{\mathbf{5000mV}-\mathbf{2000mV}} - \mathbf{1} \tag{2.2}$$

Table 3.1 The value of accumulated time assumed by how long the step time is

Step_Time(s)	Accumulated time(s)	Current(A)
10806.83525	0	3.494346142
10807.84931	0	3.484650373
10808.86308	0	3.45556283
10809.8769	0	3.445866823
10810.89113	0	3.474954367
10811.90511	0	3.426475286
10812.91906	0	3.426475286
10813.93303	0	3.465258598
10814.94711	0	3.445866823
10815.96099	0	3.407083511
10816.97501	0	3.377995968
10817.98894	0	3.426475286
10819.00301	0	3.407083511
10820.01689	0	3.377995968
10821.03093	0	3.358604193
10821.35828	0	3.348908424
1.013835842	10821.35828	0
2.027809214	10821.35828	0
3.041781903	10821.35828	0
4.055755959	10821.35828	0
5.069750201	10821.35828	0
6.083774891	10821.35828	0
7.097840292	10821.35828	0
8.111753452	10821.35828	0
9.125739483	10821.35828	0
10.13970259	10821.35828	0
11.15359557	10821.35828	0
12.16765002	10821.35828	0

3.3 Inputs and Hyperparameters

Before training our datasets to fit the neural network models, we have to select what features to be our inputs. For A1 and A2 working conditions in respectively section 4.1 and section 4.2, inputs include SOC, I, Temperature (T). For A3 working conditions in section 4.3.1, inputs have SOC, I, T, accumulated time (t_{Acc}). In section 4.3.2 and 4.3.3, inputs contain SOC, I, T, t_{Acc}, and the last output with SOC(k-1), I(k-1), T(k-1), V(k-1).

Table 3.2 shows an example of several hyperparameters that need to be decided for the neural network models such as layers, neurons, the range of characteristics (xlRange), DATA1_input, DATA1_target, the number of training data points, and the number of testing data points. Above these, layers, neurons, and activation function are the key factors that need to be adjusted.

Table 3.2 The list of hyperparameters and inputs that were used in the experiments.

Hyperparameters and Inputs	Value
Layers	3
Neurons	10, 5
xlRange	322-45,662 (total number of data = 45,340)
The Number of Training Data Points	40,806
The Number of Testing Data Points	4,534
DATA1_input	SOC, I, T (three inputs)
DATA1_target	V (one output)

Chapter 4: Results and Discussion

4.1 A1 Working Conditions

Figure 3.4 is the dataset which is applied to section 4.1. According to the references [1] and [12], SOC, I, T were selected as inputs to train model as seen in **Figure 4.1**. After training, testing data points based on 10% of the entire datasets, which has been optimized and reported in the literature, were used to estimate the prediction voltage. Then the training error and testing error were obtained to see how well the feed-forward neural network model of the backpropagation algorithm perform by comparing the prediction voltage with the true voltage value, which is gained from experimental data.

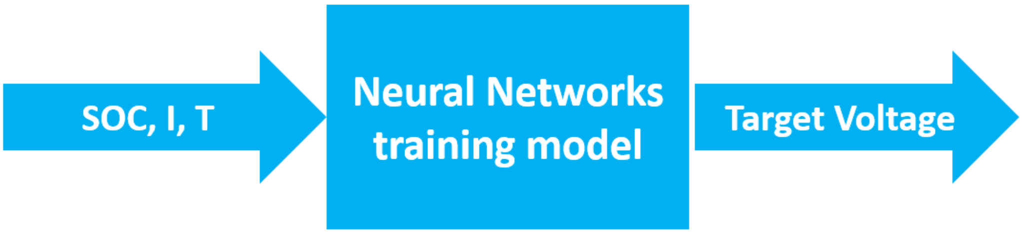


Figure 4.1 The procedures of the feed-forward neural network model of the backpropagation algorithm with SOC, I, and T as inputs, and voltage as the output

4.1.1 Hyperparameters and Inputs Based on Literatures

In **Table 4.1**, hyperparameters and inputs have to be decided to train the datasets. Hyperparameters were assigned including layers, neurons, xlRange (the number of training data points and the number of testing data points). For inputs, there were SOC, I, T. For the output, there is V. In the reference, most of the papers show the feed-forward neural network model of the backpropagation algorithm have better performance with three layers. After the training process, the testing errors of ten, five, or four layers (each layer with ten neurons) were not in the acceptable range, and the reason why they do not generalize well may be the training model overfits the datasets, therefore causing a high testing error for the new datasets. Thus, three layers were applied. The resulting diagram comparing predicted voltage values and measured voltage values while charging in a period is as shown in **Figure 4.2**. **Figure 4.3** and **Figure 4.4** show how the training and testing errors perform. In **Figure 4.3**, the training errors come with the maximum error=8.46 mV and mean error=0.76 mV. In **Figure 4.4**, the testing errors come with the maximum error=6.22 mV and mean error=0.38 mV.

Table 4.1 Hyperparameters and inputs before training

Hyperparameters and Inputs	Value
Layers	3
Neurons	10, 5
xlRange	322(at 3.0V)-45,662(at 3.7V)
The Number of Training Data Points	40,806
The Number of Testing Data Points	4,534
DATA1_input	SOC, I, T
DATA1_target	V

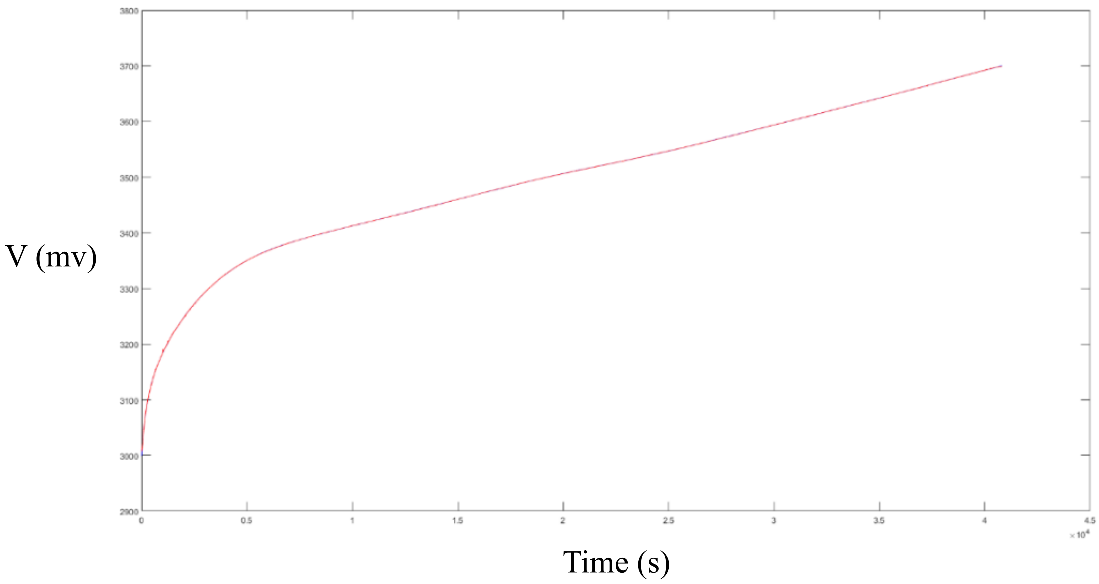


Figure 4.2 The voltage profile under A1 working conditions

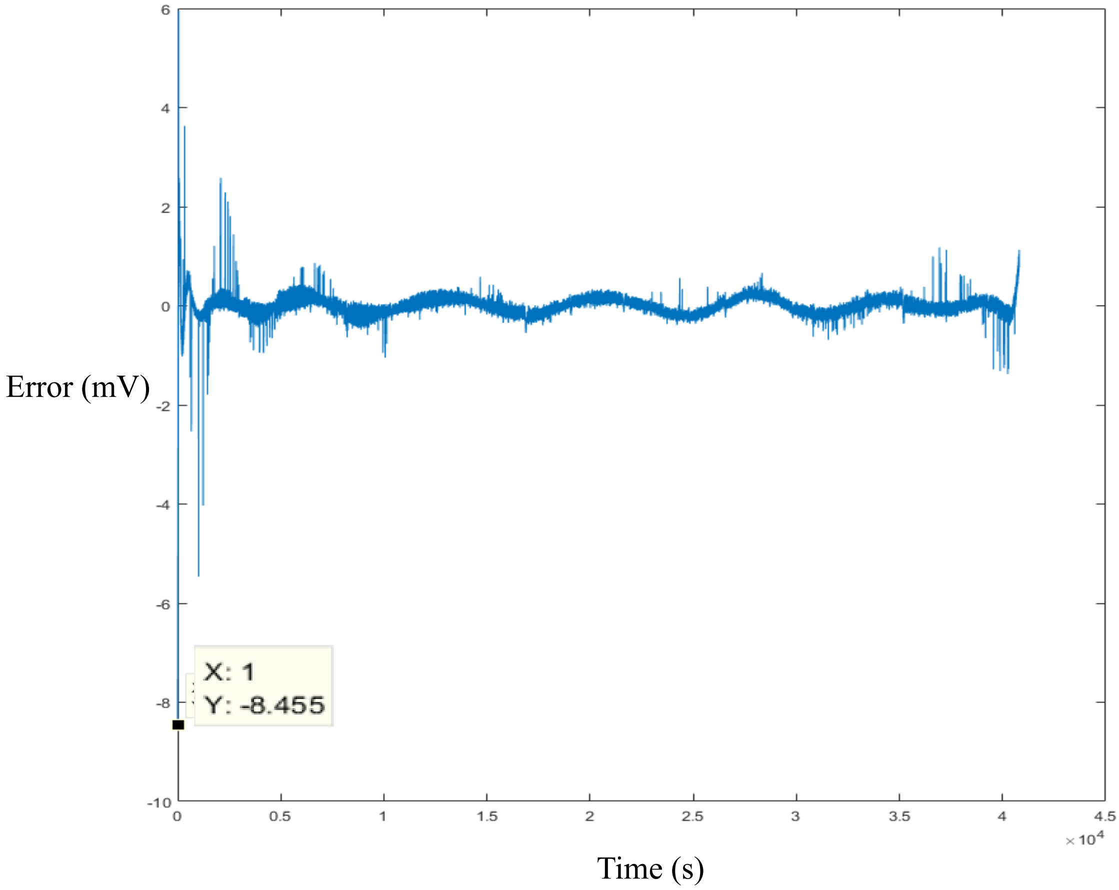


Figure 4.3 The training errors of real voltage vs. estimated voltage based on the ANN model

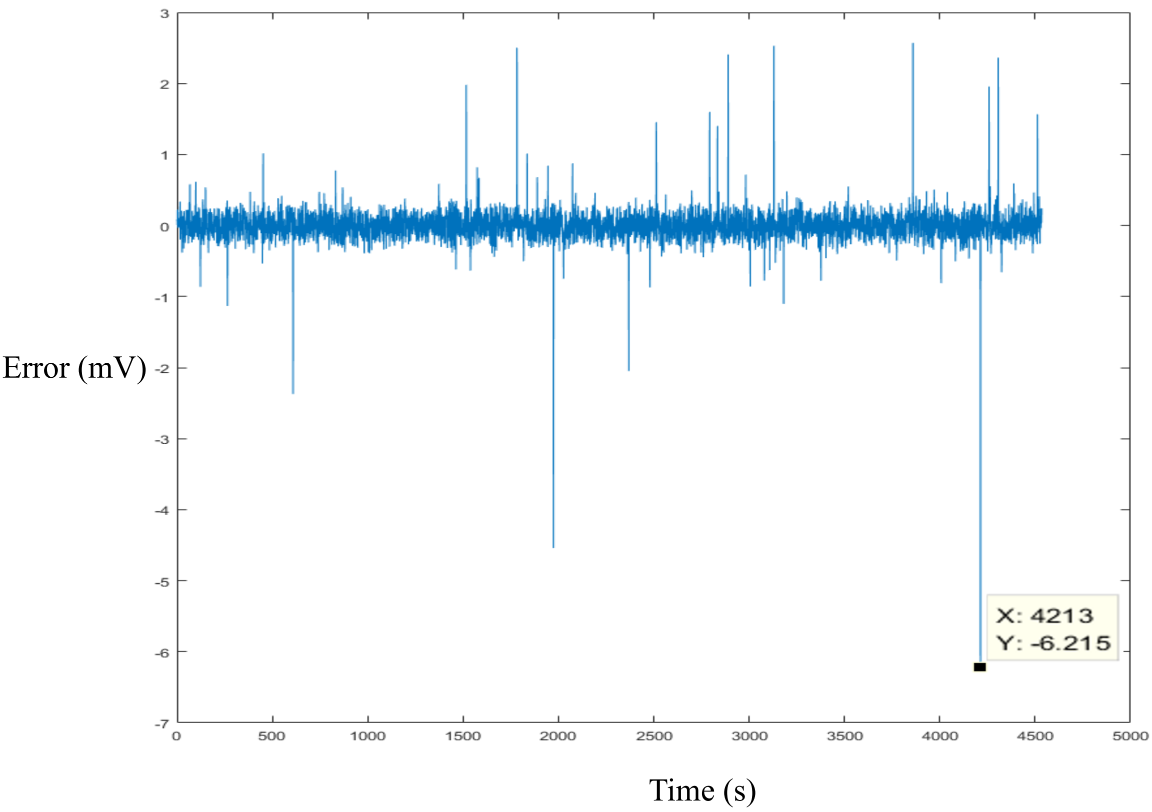


Figure 4.4 The test errors of real voltage vs. estimated voltage based on the ANN model

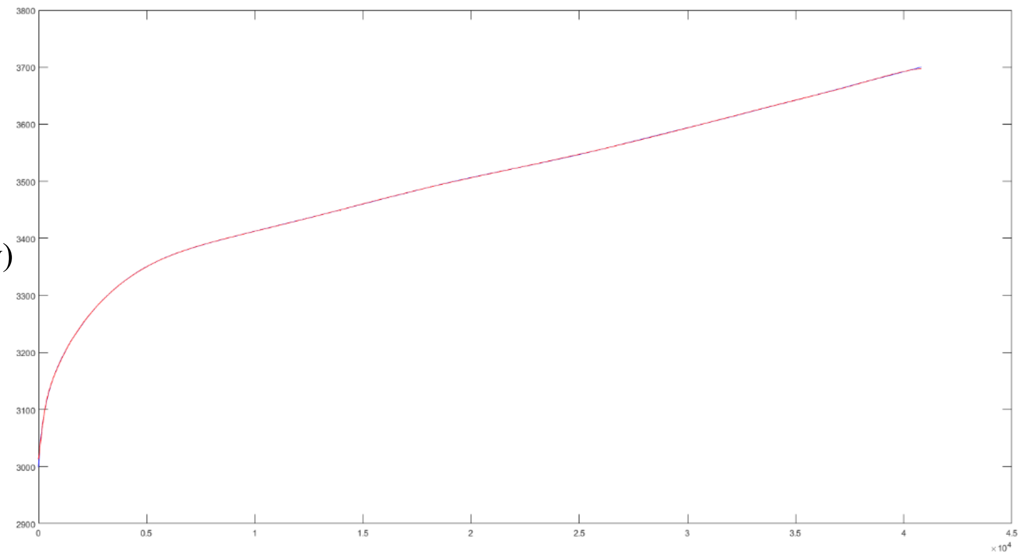
4.1.2 Adjustment of Layers

Table 4.2 shows that we lower the number of layers to lessen the burden of computation resource. **Figure 4.5** presents the result by comparing the measured voltage with the estimated by the adjusted layers. **Figure 4.6** and **Figure 4.7** show how the training and testing errors perform. In **Figure 4.6**, the training errors come with the maximum error=13.71 mV and the mean error=0.77 mV. In **Figure 4.7**, the testing errors come with the maximum error=11.41 mV and mean error=0.53 mV.

Table 4.2 Hyperparameters and inputs before training

Hyperparameters and Inputs	Value
Layers	2
Neurons	10
xlRange	322(at 3.0V)-45,662(at 3.7V)
The Number of Training Data Points	40,806
The Number of Testing Data Points	4,534
DATA1_input	SOC, I, T
DATA1_target	V

V (mv)



Time (s)

Figure 4.5 The voltage profile under A1 working conditions

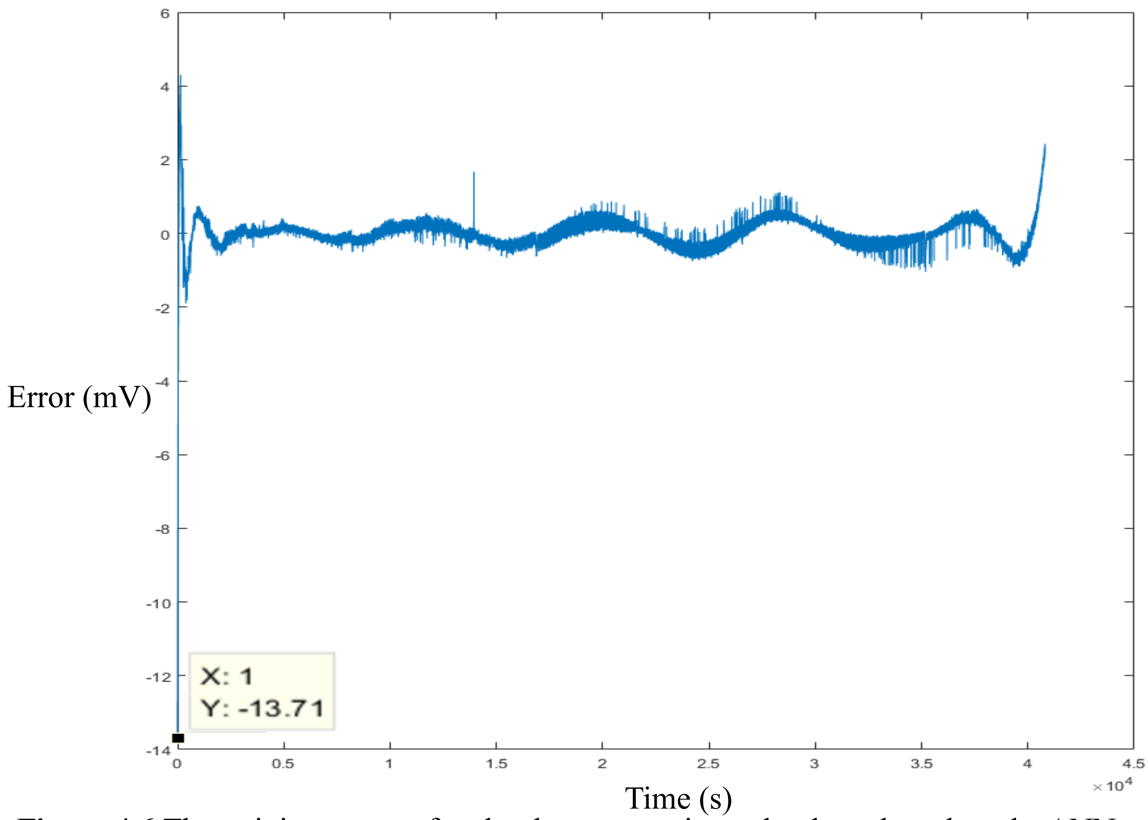


Figure 4.6 The training errors of real voltage vs. estimated voltage based on the ANN model

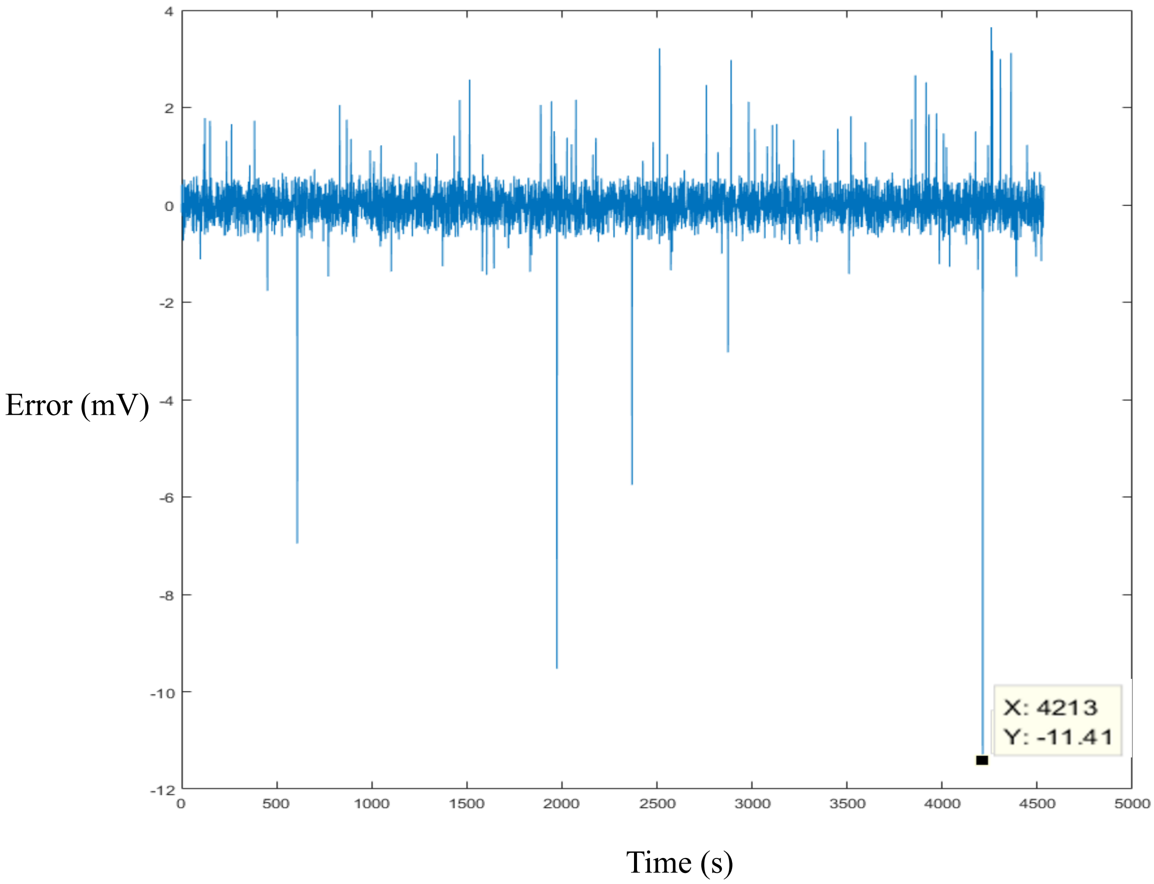


Figure 4.7 The test errors of real voltage vs. estimated voltage based on the ANN model

4.1.3 Comparison

Table 4.3 demonstrates the underfitting problem. For instance, the use of two layers in hidden layers instead of three layers increased the maximum error by 62% even though the mean square error remains stable in the training errors and the maximum error by 83% while the mean square error rose by 39% in the testing errors. The above comparison suggests that three layers are proved to be a possible number of the hidden layers for voltage prediction. However, the bouncing voltage curves, which cause significant errors, remain unsolved in hyperparameter with three layers.

Table 4.3 The results of the training errors and testing errors under assigned hyperparameters and inputs

Hyperparameters and Inputs				Train		Test	
Capacity (Ah)/ T (℃)	**Working Conditions**	**Layers**	**Neurons**	**Max Error (mV)**	**Mean Error (mV)**	**Max Error (mV)**	**Mean Error (mV)**
67/25	A1	3	10, 5	8.46	0.76	6.22	0.38
		2	10, 10	13.71	0.77	11.41	0.53

4.2 A2 Working Conditions

In this section, the results of section 4.1 will be applied to the A2 working condition datasets as seen in **Figure 3.6**.

4.2.1 Adoption of the Best Hyperparameters in 3.1 with A2 Working Conditions

The hyperparameter of three layers has better results in section 4.1, so this hyperparameter is used in section 4.2 with A2 working conditions as seen in **Table 4.4**. The resulting diagram comparing predicted voltage values and measured voltage values while charging in a period is as shown in **Figure 4.8**. **Figure 4.9** and **Figure 4.10** show how the training and testing errors perform. In **Figure 4.9**, the training errors come with the maximum error=7.93 mV and mean error=2.14 mV. In **Figure 4.10**, the testing errors come with the maximum error=7.94 mV and mean error=2.15 mV.

Table 4.4 Hyperparameters and inputs before training

Hyperparameters and Inputs	Value
Layers	3
Neurons	10, 5
xlRange	20,098, 21,149(at SOC=20%)- 45,662, 46,332(at SOC=80%)
The Number of Training Data Points	45,672
The Number of Testing Data Points	5,075
DATA1_input	SOC, I, T
DATA1_target	V

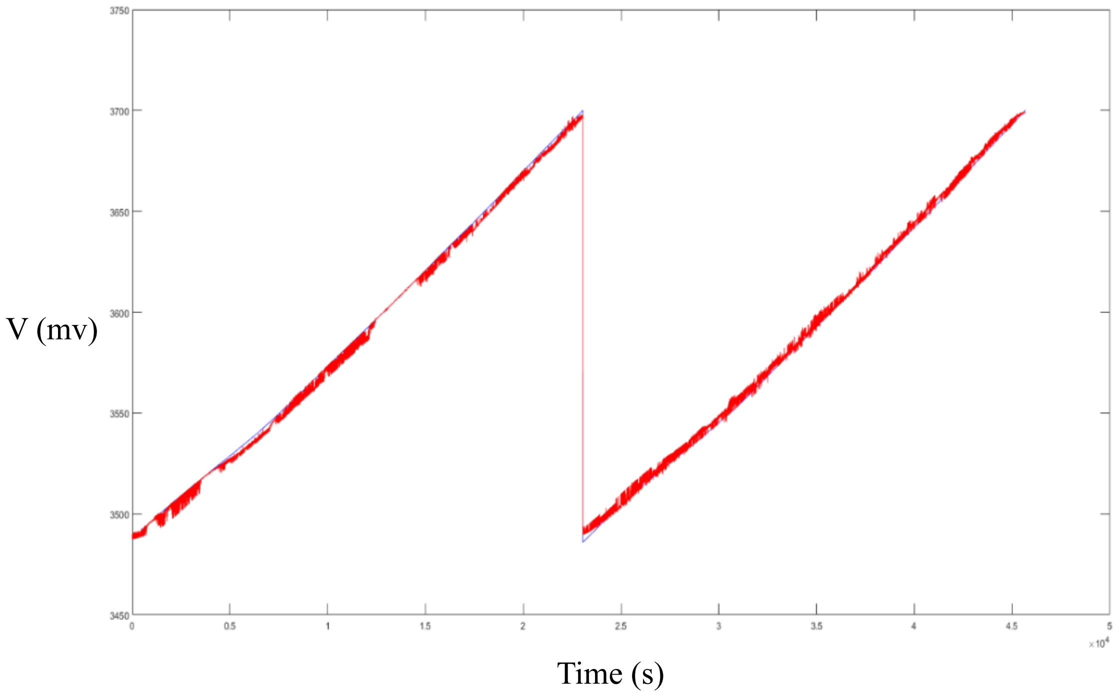


Figure 4.8 The voltage profile under A2 working conditions demonstrated by two discontinuous datasets sheets

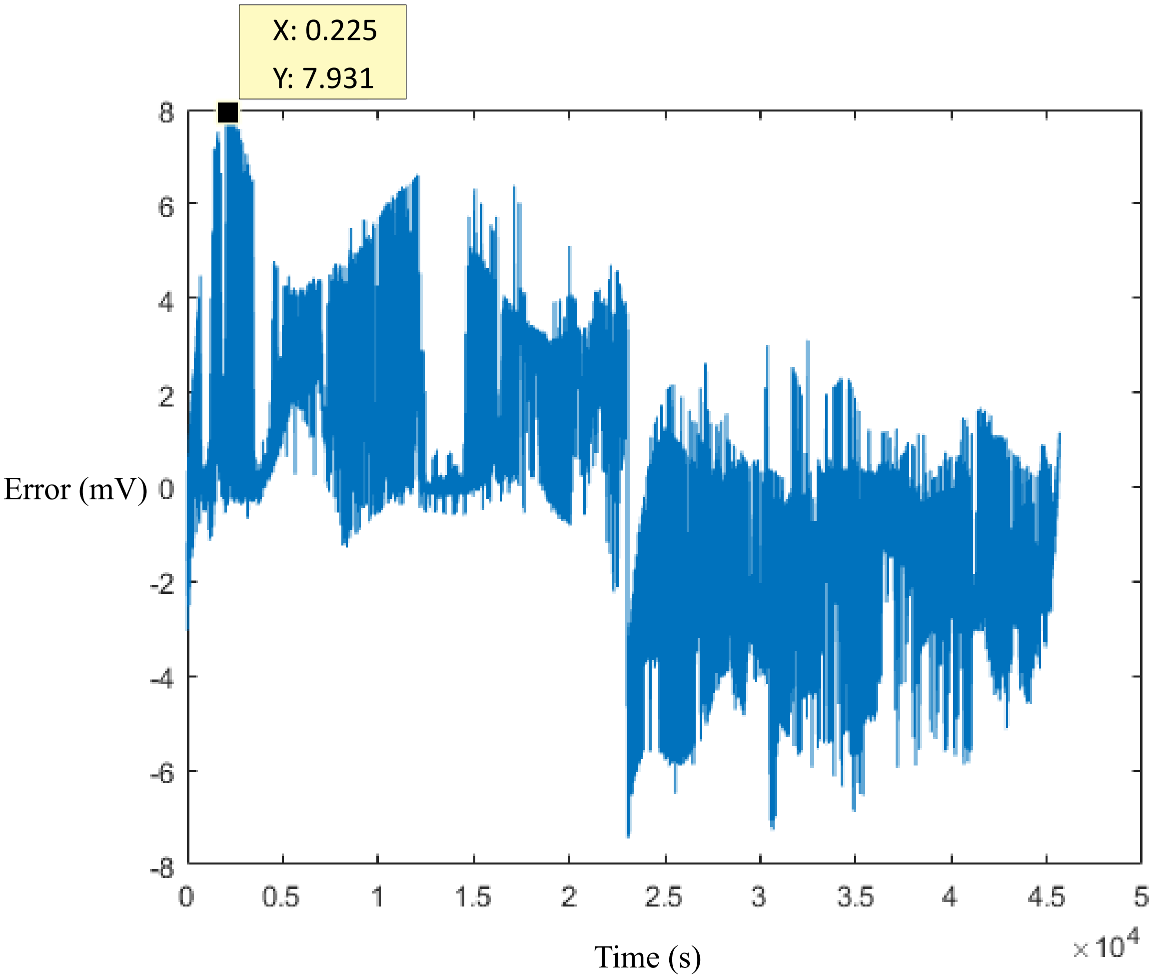


Figure 4.9 The training errors of real voltage vs. estimated voltage based on the ANN model

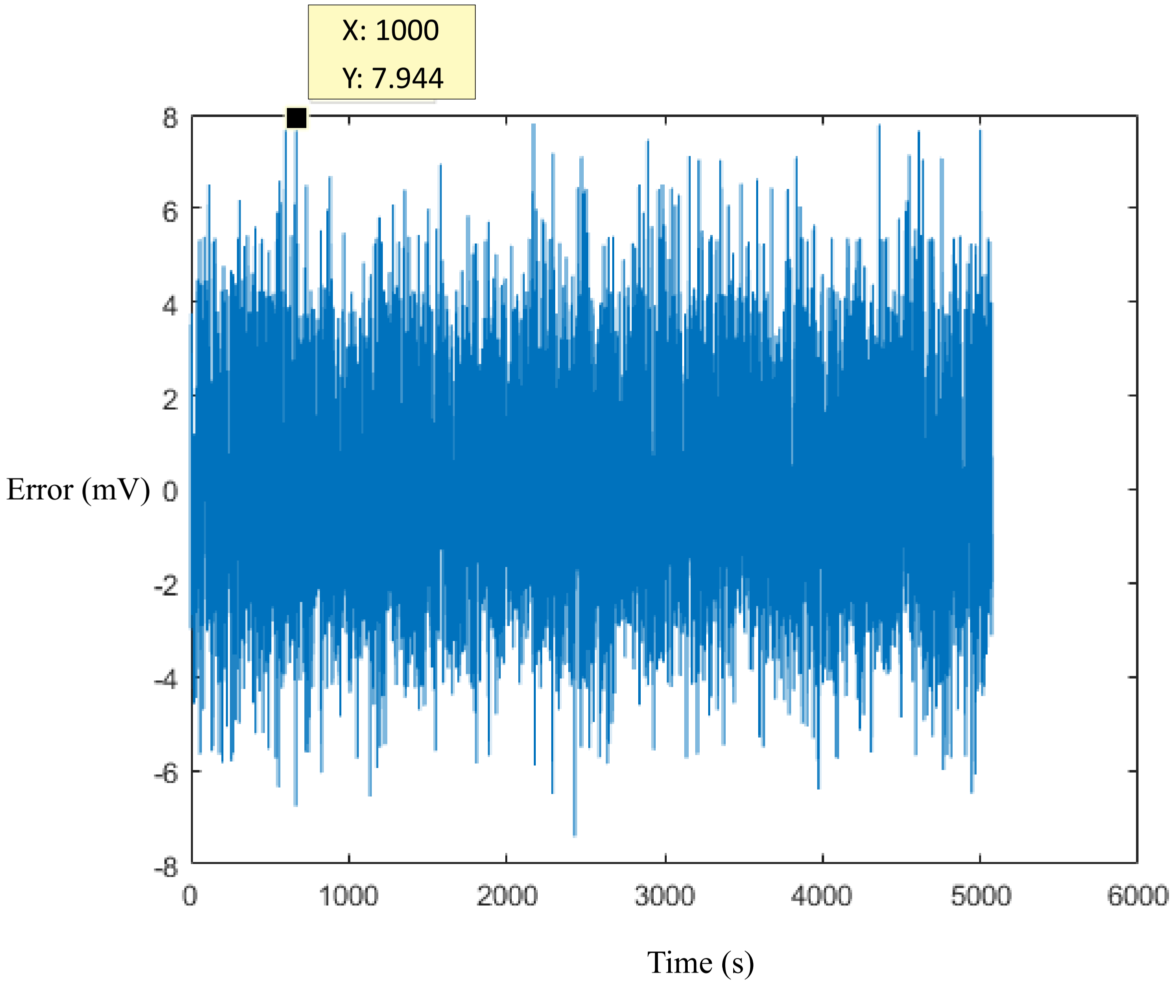


Figure 4.10 The test errors of real voltage vs. estimated voltage based on the ANN model

4.2.2 Adjustment of Neurons

Based on section 4.2.1, the number of neurons is lowered to six and three corresponding to the first layer and second layer (**Table 4.5**) to increase the spare computation resource. The resulting diagram comparing predicted voltage values and measured voltage values while charging in a period is as shown in **Figure 4.11**. **Figure 4.12** and **Figure 4.13** are demonstrated how the training and testing errors perform. In **Figure 4.12**, the training errors come with the maximum error=8.84 mV and the mean error=3.59 mV. In **Figure 4.13**, the testing errors come with the maximum error=8.72 mV and the mean error=1.82 mV.

Table 4.5 Hyperparameters and inputs before training

Hyperparameters and Inputs	Value
Layers	3
Neurons	6, 3
xlRange	20,098, 21,149(at SOC=20%)- 45,662, 46,332(at SOC=80%)
The Number of Training Data Points	45,672
The Number of Testing Data Points	5,075
DATA1_input	SOC, I, T
DATA1_target	V

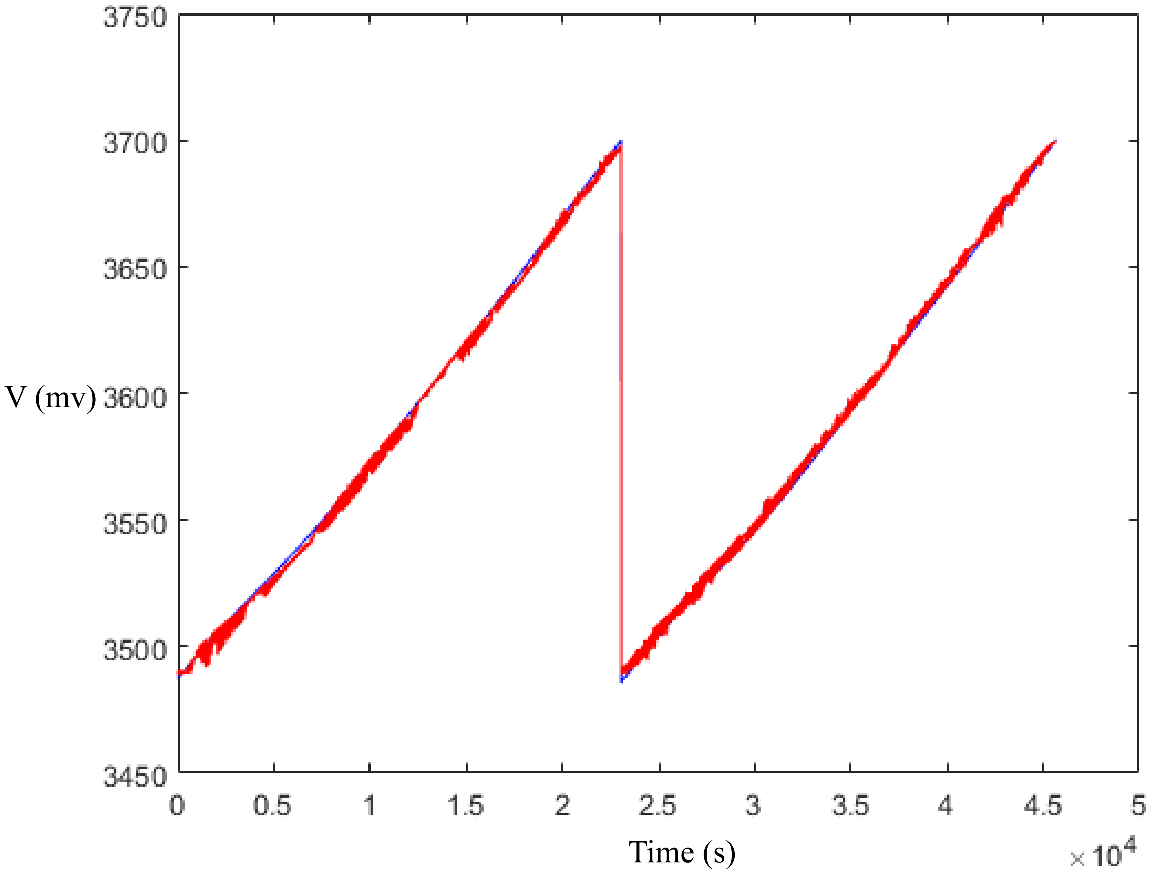


Figure 4.11 The voltage profile under A2 working conditions demonstrated by two discontinuous datasets sheets

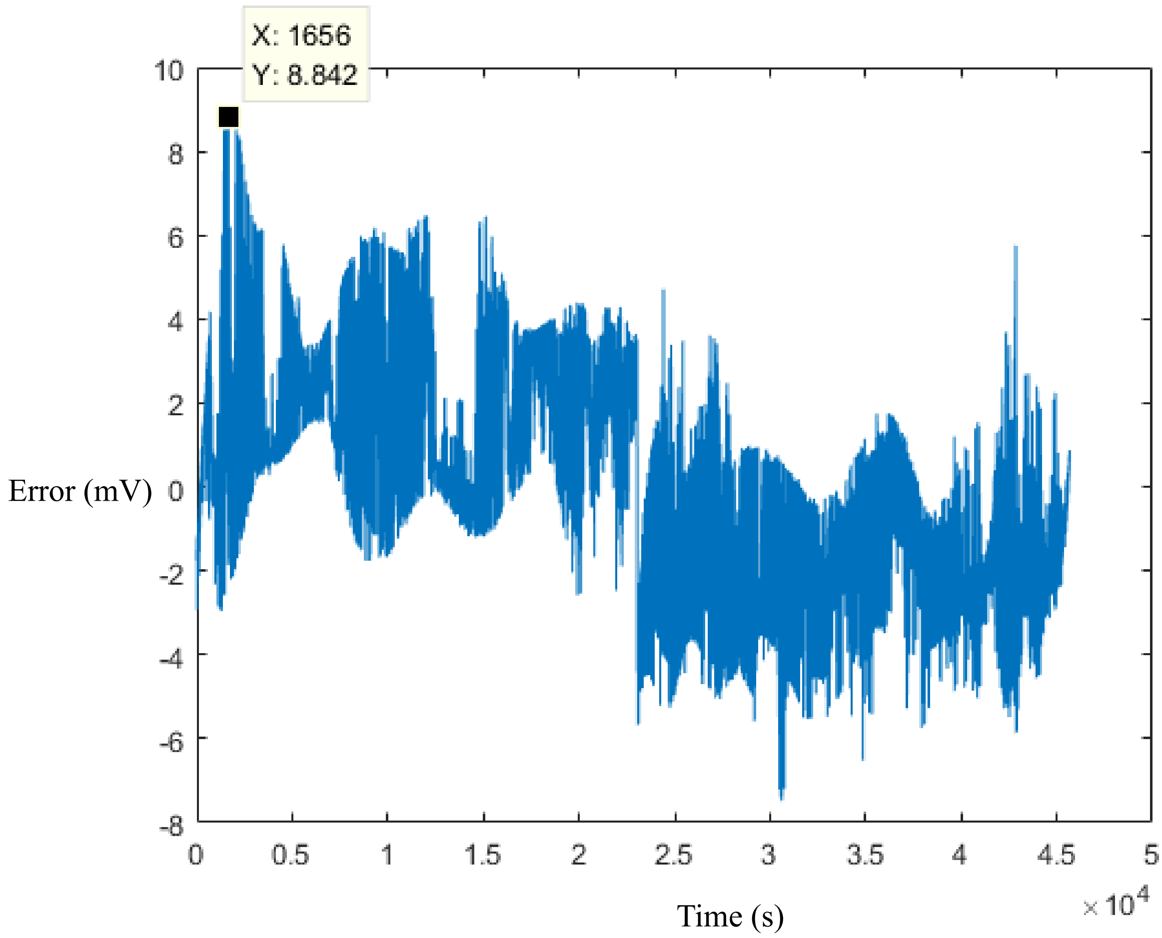


Figure 4.12 The training errors of real voltage vs. estimated voltage based on the ANN model

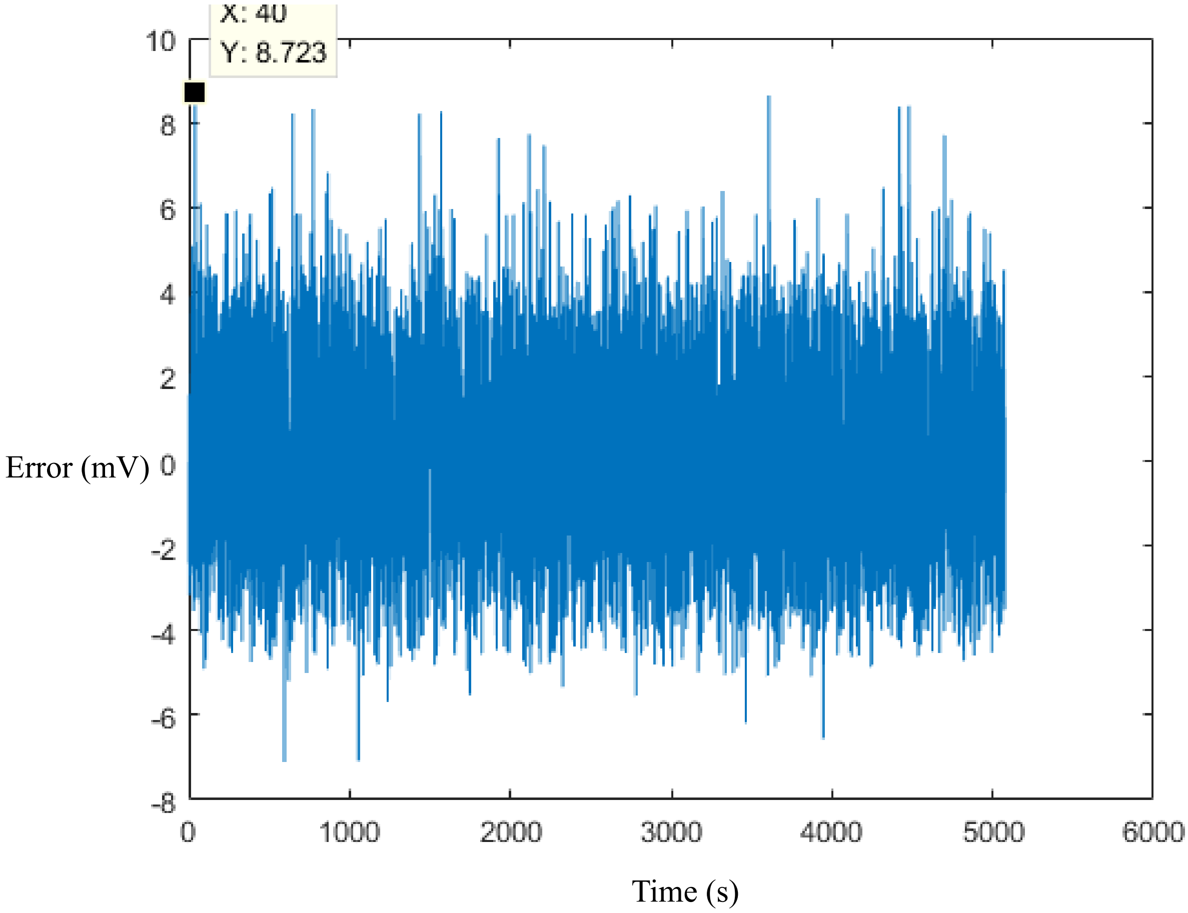


Figure 4.13 The test errors of real voltage vs. estimated voltage based on the ANN model

4.2.3 Comparison

Table 4.6 shows that the number of neurons with six and three for first and second layers in the neural network, and the training errors indicate that the maximum error increased by 11% while the mean error rose by 68%. The testing errors show that the maximum error raised by 10% while the mean error decreased by 15%. These results illustrate that the training errors and testing errors are still in the acceptable range.

Additionally, although the less number of neurons present slightly worse performances, the lower number of neurons can help to decrease the computation resource. Therefore, these hyperparameters were applied to section 4.3.1. However, the bouncing voltage curves still occur in A2 working condition datasets. Thus, more features should be input to fit the portions of the bouncing voltage curves better.

Table 4.6 The results of the training errors and testing errors under assigned hyperparameters and inputs

Hyperparameters and Inputs				**Train**		**Test**	
Capacity (Ah)/ T (℃)	**Working Conditions**	**Layers**	**Neurons**	**Max Error (mV)**	**Mean Error (mV)**	**Max Error (mV)**	**Mean Error (mV)**
67/25	A2	3	10, 5	7.93	2.14	7.94	2.15
		3	6, 3	8.84	3.59	8.72	1.82

4.3 A3 Working Conditions

In section 4.3.1, the accumulated time has to be input because of the electrode polarization effect [**Figure 4.14 (a)**]. According to the literature, SOC(k-1), I(k-1), T(k-1), and V(k-1) were considered to improve the voltage prediction in section 4.3.2 (**Figure 4.14 (b)**). Those inputs were applied in A3 working conditions (**Figure 3.6**).

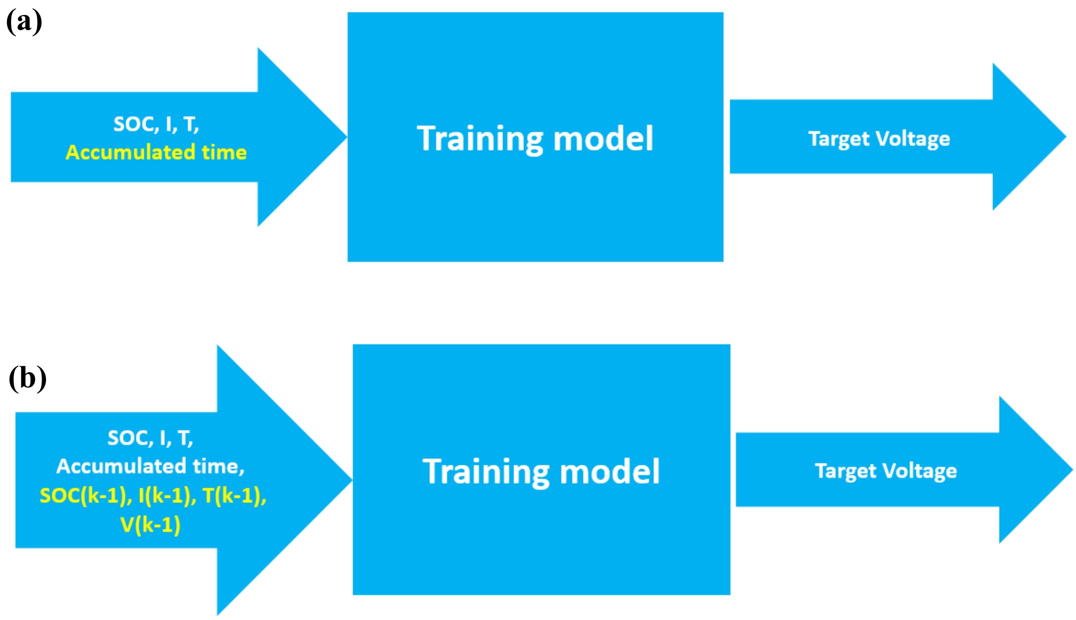


Figure 4.14 (a) The procedures of the feed-forward neural network model of the backpropagation algorithm including accumulated time as the additional input in 3.3.1, and **(b)** SOC(k-1), I(k-1), T(k-1), V(k-1) as additional inputs in 3.3.2

4.3.1 The Import of Accumulated Time Input with A3 Working Conditions

Table 4.7 shows that the number of layers and neurons were applied to the A3 working conditions based on section 4.2. The resulting diagram comparing predicted voltage values and measured voltage values with charging, resting, and discharging procedures is as shown in **Figure 4.15**. **Figure 4.16** and **Figure 4.17** show how the training and testing errors perform. In **Figure 4.16**, the training errors come with the maximum error=502.00 mV and the mean error=9.92 mV. In **Figure 4.17**, the testing errors come with the maximum error=300.60 mV and the mean error=16.21 mV. The errors are quite large. Hyperparameters optimized in the A2 current and voltage profiles, which includes charging procedure, were applied in A3 current and voltage profiles. These likely result from the fact that significant errors are that two current and voltage profiles contain different procedures.

When the switch between charging and discharging, the unexpected change of current may cause a significant change in voltage. This phenomenon is called the Hysteresis phenomenon, which is recognized as the most critical impact on the dynamic lithium-ion battery. This originated with the response of interior hyperparameters, especially the internal ohmic resistance. In an open circuit, the electrochemical effect gradually changed the voltage in the internal battery.[17]

Table 4.7 Hyperparameters and inputs before training

Hyperparameters and Inputs	Value
Layers	3
Neurons	6, 3
xlRange	2-66,010
The Number of Training Data Points	59,407
The Number of Testing Data Points	6,601
DATA1_input	SOC, I, T, t_{Acc}
DATA1_target	V

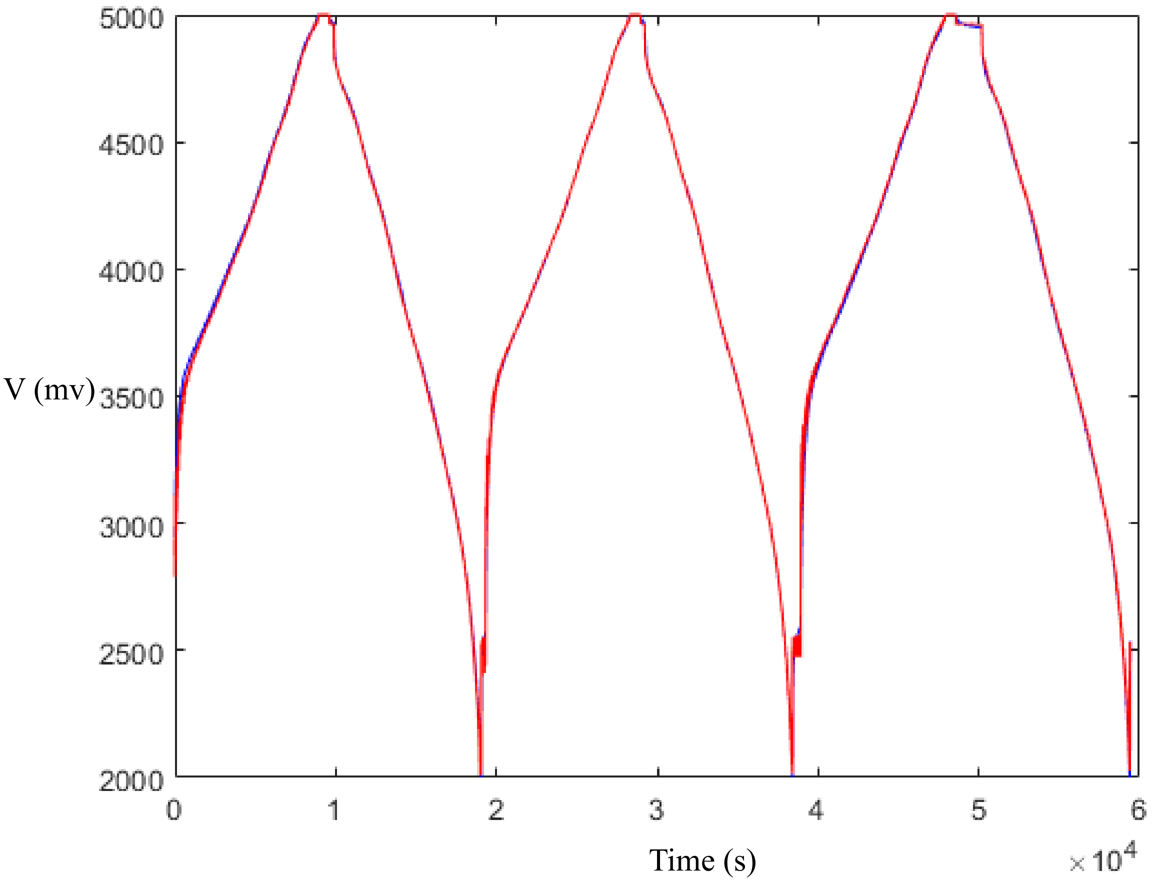


Figure 4.15 Charging, discharging, and resting diagram of the voltage profile under A3 working conditions demonstrated by continuous dataset sheets.

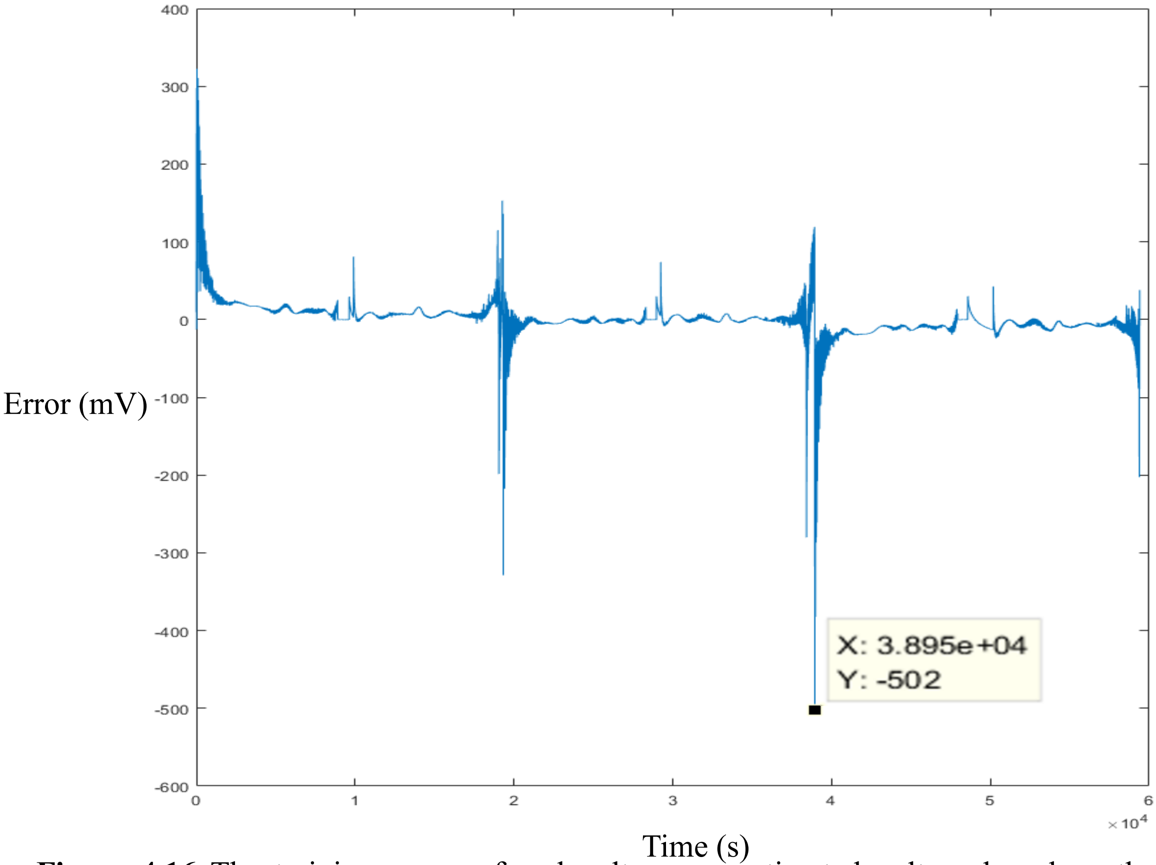


Figure 4.16 The training errors of real voltage vs. estimated voltage based on the ANN model

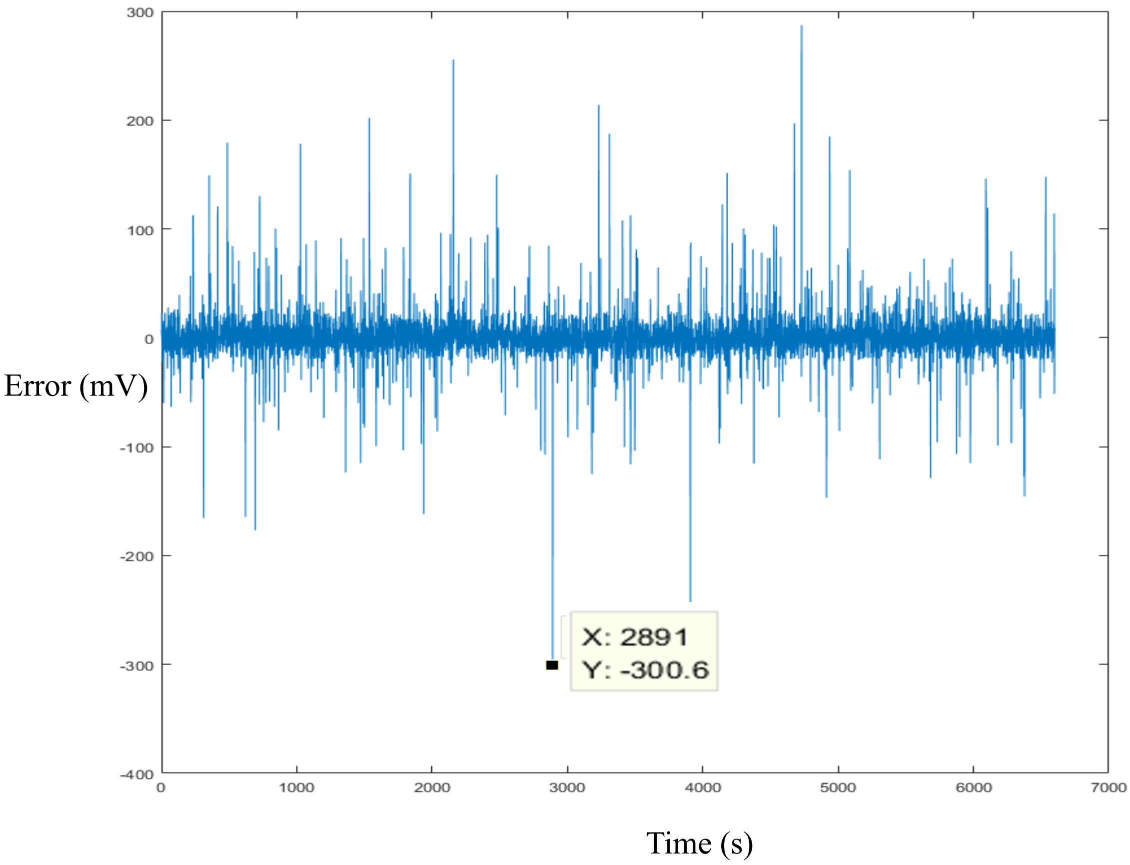


Figure 4.17 The test errors of real voltage vs. estimated voltage based on the ANN model

4.3.2 The Import of Time Delay Input

In **Table 4.8**, SOC(k-1), I(k-1), T(k-1), V(k-1) were considered based on the results in section 3.3.1. The resulting diagram comparing predicted voltage values and measured voltage values with charging, resting, and discharging procedures is as shown in **Figure 4.18**. **Figure 4.19** and **Figure 4.20** show how the training and testing errors perform. In **Figure 4.19**, the training errors come with the maximum error=107.30 mV and the mean error=0.90 mV. In **Figure 4.20**, the testing errors come with the maximum error=11.34 mV and the mean error=0.28 mV.

Table 4.8 Hyperparameters and inputs before training

Hyperparameters and Inputs	**Value**
Layers	3
Neurons	6, 3
xlRange	2-66,010
The Number of Training Data Points	59,407
The Number of Testing Data Points	6,601
DATA1_input	SOC, I, T, t_{Acc}, SOC(k-1), I(k-1), T(k-1), V(k-1)
DATA1_target	V

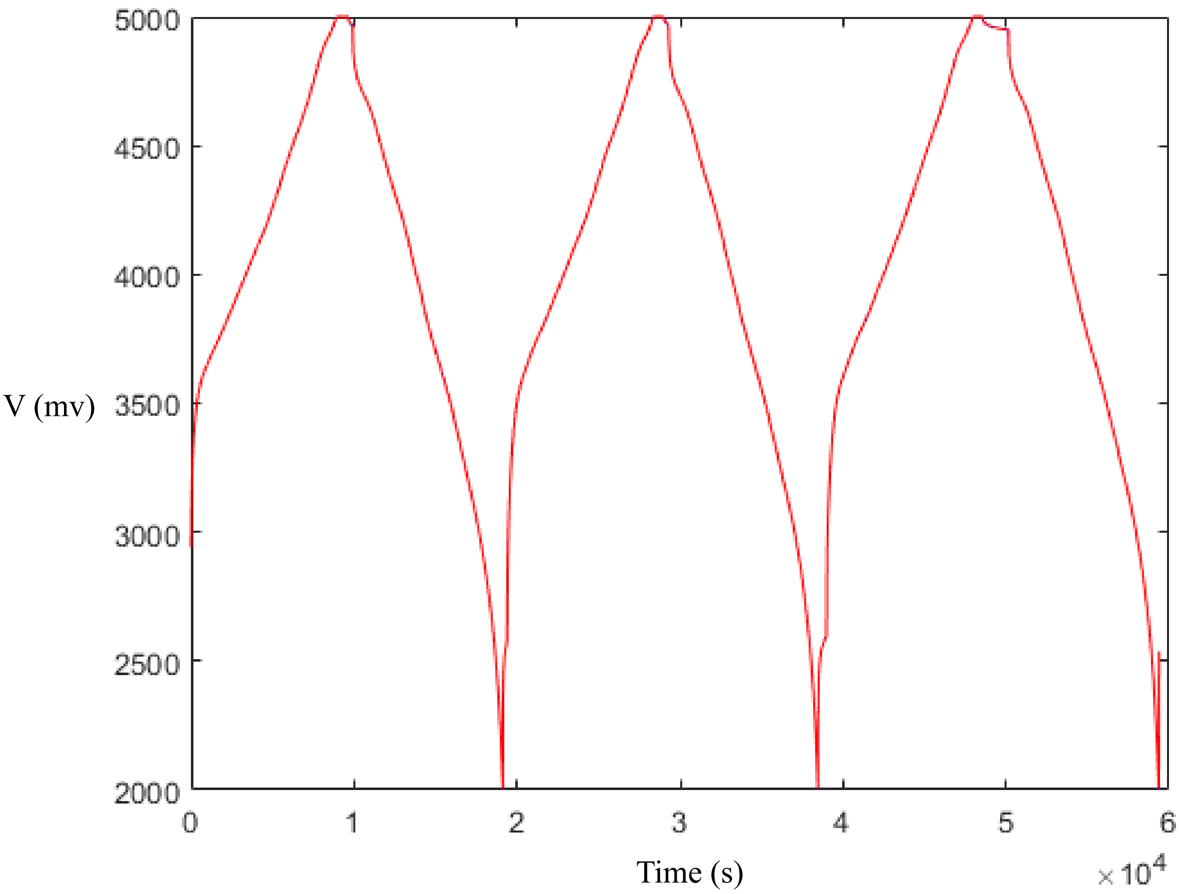


Figure 4.18 Charging, discharging, and resting diagram of the voltage profile under A3 working conditions demonstrated by continuous dataset sheets.

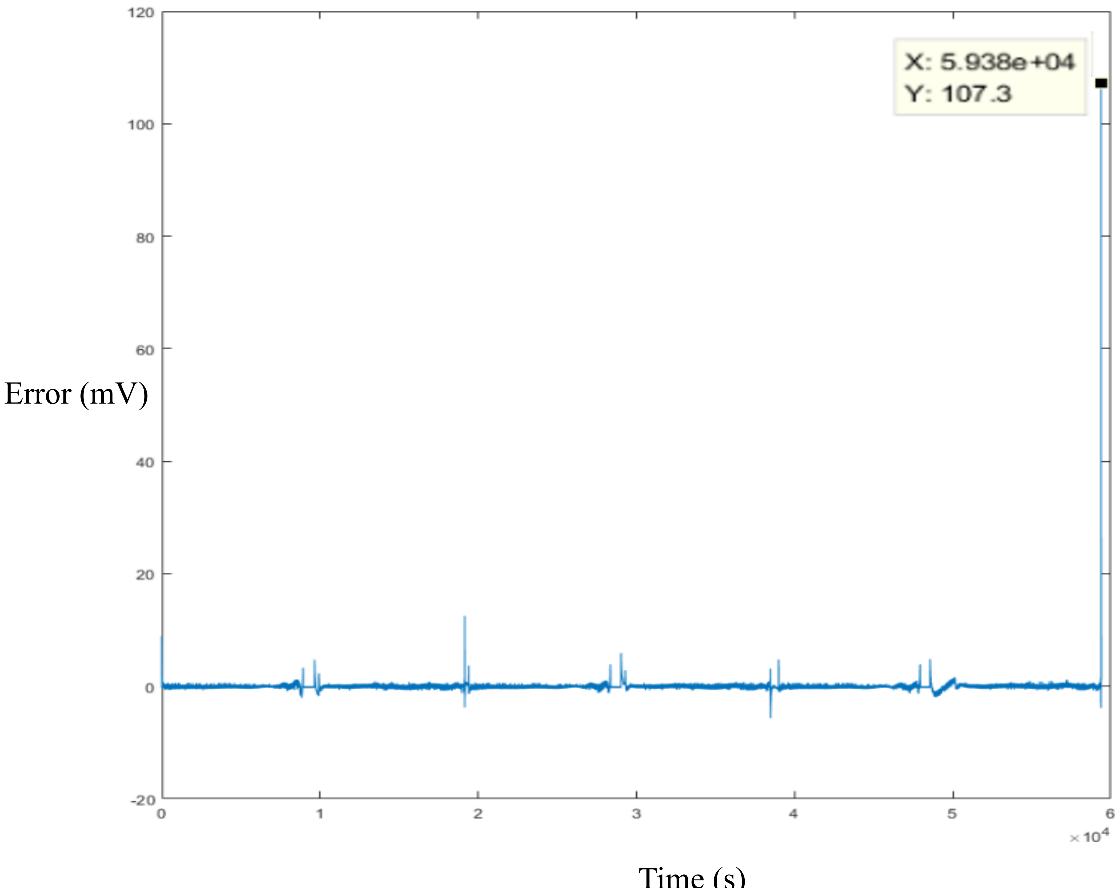


Figure 4.19 The training errors of real voltage vs. estimated voltage based on the ANN model

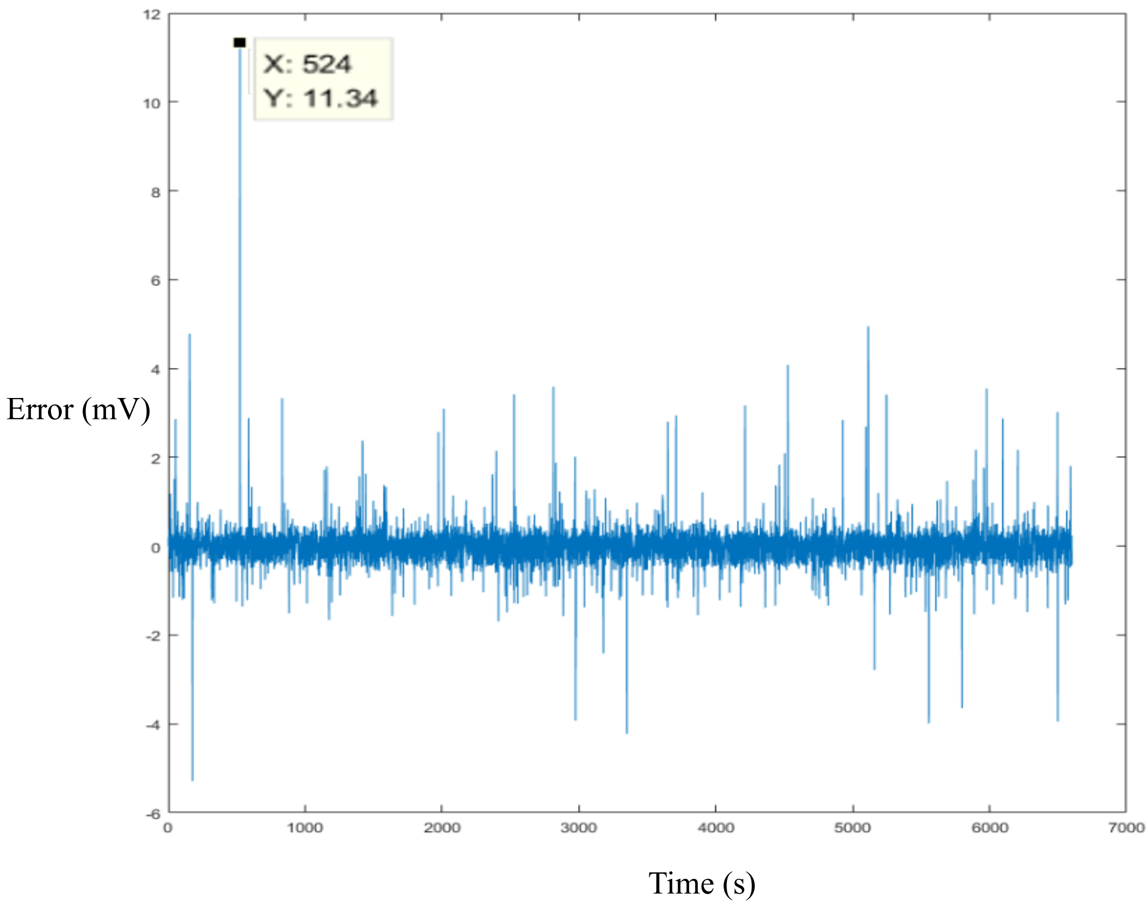


Figure 4.20 The test errors of real voltage vs. estimated voltage based on the ANN model

4.3.3 Hyperparameter Adjustment of Layers

Because the results in section 4.3.2 do not reach our tolerant range, the number of layers was increased (**Table 4.9**). The resulting diagram comparing predicted voltage values and measured voltage values with charging, resting, and discharging procedures is as shown in **Figure 4.21. Figure 4.22** and **Figure 4.23** show how the training and testing errors perform. In **Figure 4.22**, the training errors come with the maximum error=8.15 mV and the mean error=0.27 mV. In **Figure 4.23**, the testing errors come with the maximum error=7.75 mV and the mean error=0.22 mV.

Table 4.9 Hyperparameters and inputs before training

Hyperparameters and Inputs	Value
Layers	4
Neurons	10, 10, 10
xlRange	2-66,010
The Number of Training Data Points	59,407
The Number of Testing Data Points	6,601
DATA1_input	SOC, I, T, t_{Acc}, SOC(k-1), I(k-1), T(k-1), V(k-1)
DATA1_target	V

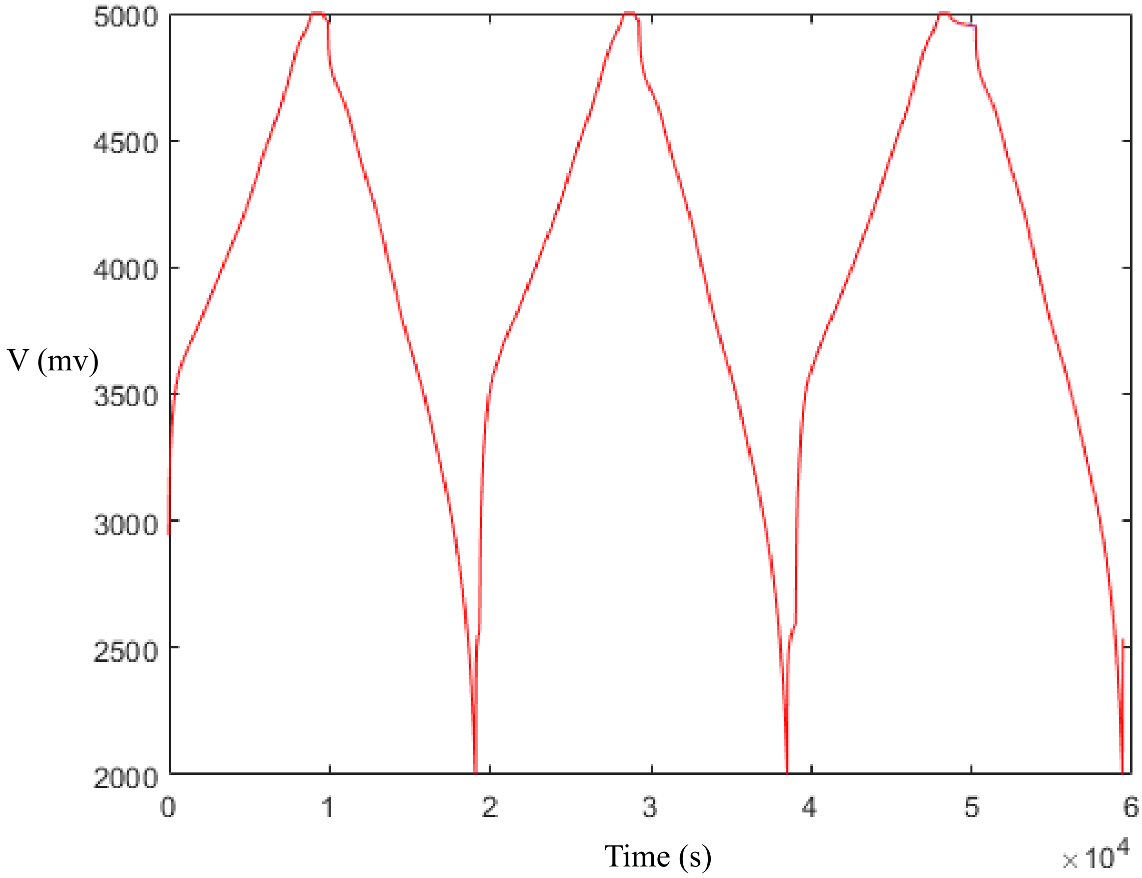


Figure 4.21 Charging, discharging, and resting diagram of the voltage profile under A3 working conditions demonstrated by continuous dataset sheets.

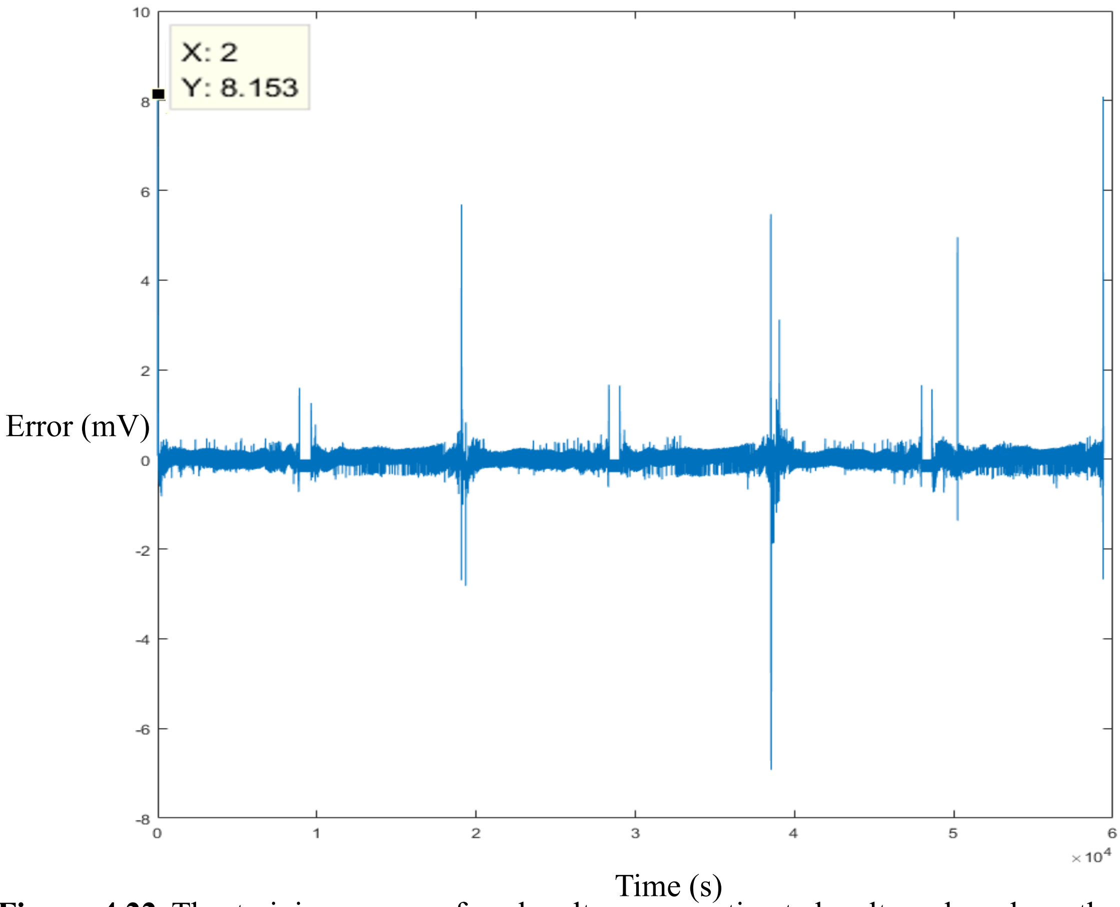


Figure 4.22 The training errors of real voltage vs. estimated voltage based on the ANN model

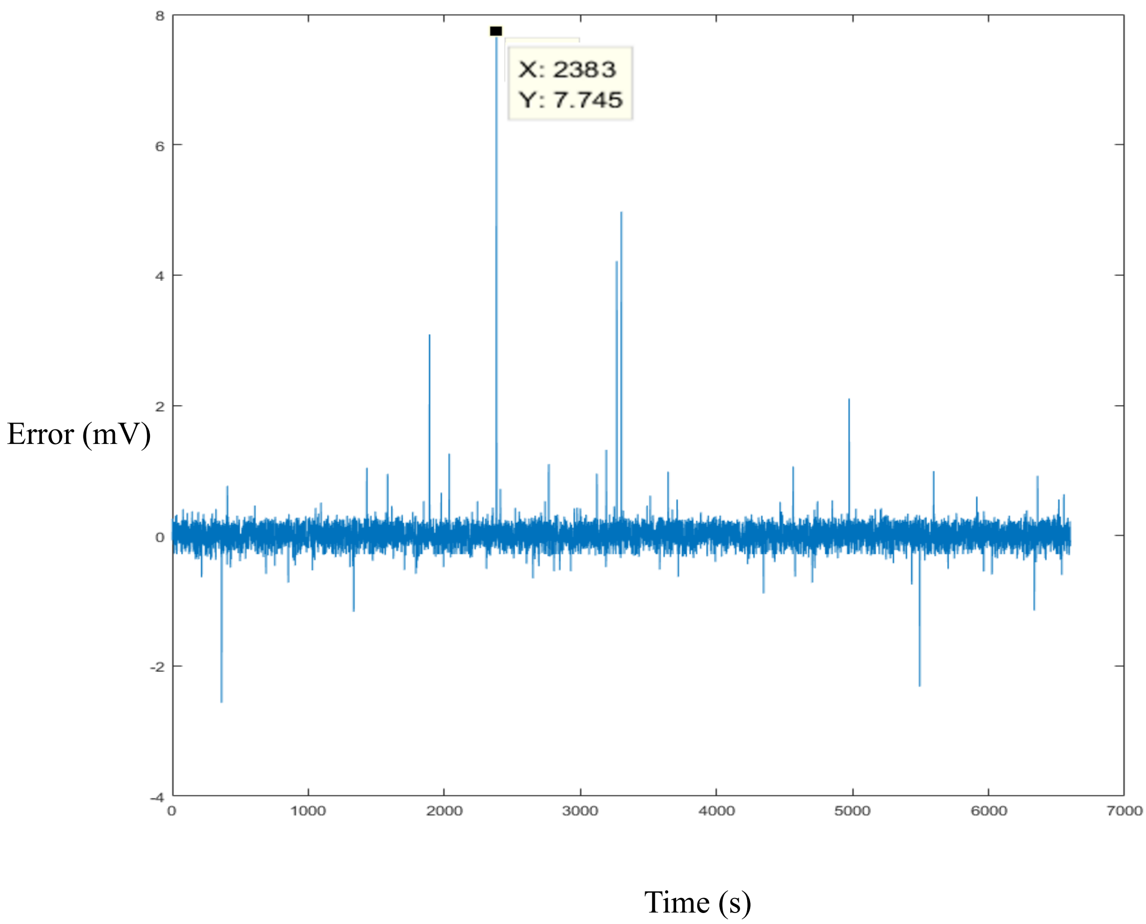


Figure 4.23 The test errors of real voltage vs. estimated voltage based on the ANN model

4.3.4 Comparison

In **Table 4.10**, when the time delay was considered as inputs in the neural network, the training errors reveal that the maximum error declined by 79% while the mean error decreased by 91%. The testing errors show that the maximum error lowered by 96% while the mean error reduced by 98%. The number of layers was increased to four layers in the feed-forward neural network model of the backpropagation algorithm to improve the performances of the neural network. The training errors demonstrate that the maximum error dropped by 92% while the mean error shrank by 70%. The testing errors indicate that the maximum error declined by 32% while the mean error lessened by 21%.

Table 4.10 The results of the training errors and testing errors under assigned hyperparameters and inputs

Hyperparameters and Inputs						**Train**		**Test**	
Capacity (Ah)/ T (℃)	**Working Conditions**	**Accumulated Time**	**Time-delay**	**Layers**	**Neurons**	**Max Error (mV)**	**Mean Error (mV)**	**Max Error (mV)**	**Mean Error (mV)**
67/25	A3	Yes	No	3	6, 3	502.00	9.92	300.60	16.21
		Yes	Yes	3	6, 3	107.30	0.90	11.34	0.28
		Yes	Yes	4	10, 10, 10	8.15	0.27	7.75	0.22

4.4 Analysis of A1, A2, and A3 Working Conditions

Overall, we chose the best number of three layers based on articles in the A1 working conditions. Then, we optimized neurons to six and three in the A2 working conditions. Finally, we adjusted to four layers and gained better error results.

Table 4.11 shows that the training errors (the maximum error= 8.15 mV and the mean error= 0.27 mV) are back to the stable performance similar to section 4.1 or 4.2 results, which had reached a local minimum when four layers were applied in the neural network. It is observed that the output voltage from the model is very close to the real voltage with the maximum error of 7.75 mV and the mean error of 0.22mV in testing errors, respectively. This performance has achieved our goal, which is that the output voltage error does not exceed 30 mV (between 20% and 80% SOC) and 50 mV (below 20% and above 80% SOC).

Table 4.11 The overall results of the training errors and testing errors under assigned hyperparameters and inputs

Hyperparameters and Inputs						Train		Test	
Capacity (Ah)/ T (℃)	**Working Conditions**	**Accumulated Time**	**Time-delay**	**Layers**	**Neurons**	**Max Error (mV)**	**Mean Error (mV)**	**Max Error (mV)**	**Mean Error (mV)**
67/25	A1	No	No	3	10, 5	8.46	0.76	6.22	0.38
		No	No	2	10, 10	13.71	0.77	11.41	0.53
	A2	No	No	3	10, 5	7.93	2.14	7.94	2.15
		No	No	3	6, 3	8.84	3.59	8.72	1.82
	A3	Yes	No	3	6, 3	502.00	9.92	300.60	16.21
		Yes	Yes	3	6, 3	107.30	0.90	11.34	0.28
		Yes	Yes	4	10, 10, 10	8.15	0.27	7.75	0.22

Chapter 5: Conclusion and Recommendation

5.1 Conclusion

The feed-forward neural network model of the backpropagation algorithm based voltage prediction performance demonstrated that we found that four layers and ten neurons for each layer have excellent outcomes, which is better than any other method for lowering the voltage error. We lowered the voltage error under 5.00 mV among 20 % and 80 % SOC, and we lowered the voltage error under 8.15 mV for the rest. Second, we lowered the maximum voltage error by 25 times and the average voltage error by 273 times using feed-forward neural network models of the backpropagation algorithm in comparison to the equivalent circuit model for electric-vehicle battery at CATL. This allowed obtaining the correct input voltage for driving an electric motor from a simulation battery model, which can also predict next 10s or 20s voltage, at the early stage of designing a vehicle.

5.2 Future Work

Current work will need to be improved if we want to ace this solution: the approach of the weight adjustment, which is initialized randomly, of the neural network should be further advanced. Next, by applying Python instead of MATLAB, it will increase the flexibilities to import new tools like TensorFlow to fit our model better. Additionally, by introducing a graphics processing unit to raise computing rate, this allows us to increase the layers and neurons to lower errors. Last, to improve the voltage accuracy, we can select potential features like the factors in the state of health and state of power, or use other models like recurrent neural network (RNN) to simulate the problem of bouncing voltage curve.

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