

## SHORT COMMUNICATION

# Evaluation of battery modules state for electric vehicle using artificial neural network and experimental validation

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**Abstract**

This work undertakes research problem on prediction of state of battery modules used in electric vehicle. Past studies focussed extensively on the estimation of state of charge and state of health of a single cell/battery. However, the focus on the estimation of state of entire battery module is hardly studied. During the actual operation of electric vehicle, the environmental conditions (road slope and climate) and factors such as abnormal voltage and temperature conditions causes the deviations among the battery modules from its equilibrium state. As a result, its power efficiency and the life-cycle decreases. One of the reasons of deviation is the defects in manufacturing of a battery module. For this purpose, the evaluation and estimation of state of battery modules is a priority to have information on which module among the given ones should be discharged first. Therefore, this study proposes the methodology for the evaluation of state of battery modules based on its current and temperature. Firstly, the rules are defined based on experiments to determine the priority for the discharge of each of the six modules. Dataset of 6000 samples obtained comprises of the 12 inputs (temperature and current) and 6 outputs (on-off state of switch). Each output represents the priority of module to be discharged. To analyze this multi-input multi-output dataset, the popular artificial intelligence algorithm namely, artificial neural network with three training algorithms (Levenberg, Scaled conjugate and Bayesian regularization), using a number of neurons from 2 to 20 in the hidden layer is used. It was found that the model obtained using Levenberg algorithm performs the best.

**KEYWORDS**

battery modules, electric vehicle, energy storage system, state of charge, state of health

## 1 | INTRODUCTION

Within the last two decades, energy storage systems such as lithium ion batteries (LIBs) have been widely used in large-scale electric storage applications, such as for mobile phones, electric vehicles, and renewable power stations because of their excellent features of small size, high energy density,

long life cycles, high voltage, and low self-discharge. Among these, the research on Li-ion Battery packs used for electric vehicles (EVs) is vital to ensure its safe, reliable, and longer usage with an improved vehicle and road safety. In other words, the efficient design and management of Battery packs is critical for the higher performance and reliability of the EVs.<sup>1-3</sup> The significant research attempts have been made in solving

the problems such as the overcharging, self-discharging, capacity fading, impedance increase, thermal runaway, shocks, aging (calendar and cyclic), etc.<sup>4,5</sup> in the battery packs. To counter these problems, researchers attempted to design the battery management system (Figure 1) that incorporates the battery modeling methods<sup>6,7</sup> and the mechanical designs for road safety purpose. Battery modeling methods are based on the physics based models, empirical models, equivalent circuit models, and fusion models for estimating the battery states such as SOC and SOH. The mechanical designs of the Battery packs incorporate the cooling/heating systems by air/liquid media to operate in extreme cold temperatures and prevent self-discharging and thermal runaway, addressing the suitable location of battery pack to minimize the danger of explosion on sudden impact/collision and the suitable materials for design of the battery pack box.<sup>8-12</sup>

Among these two procedures, the extensive focus was paid on battery modeling methods to estimate the battery states (SOC, SOH) in real time. This is because almost most of the problems listed have direct or indirect relationship with SOC and SOH. Therefore, the real-time estimation of SOC or SOH can be useful for mitigating safety risks and ensure smooth and reliable driving. State-of-the-art studies that illustrate the role of battery modeling methods in estimation of battery states and fault diagnosis are as follows. Young et al<sup>8</sup> reviewed the recent trends in battery technology development and classified the battery models into electrochemical and equivalent circuit models. To understand the physics and the fundamental aspects of battery mechanisms,

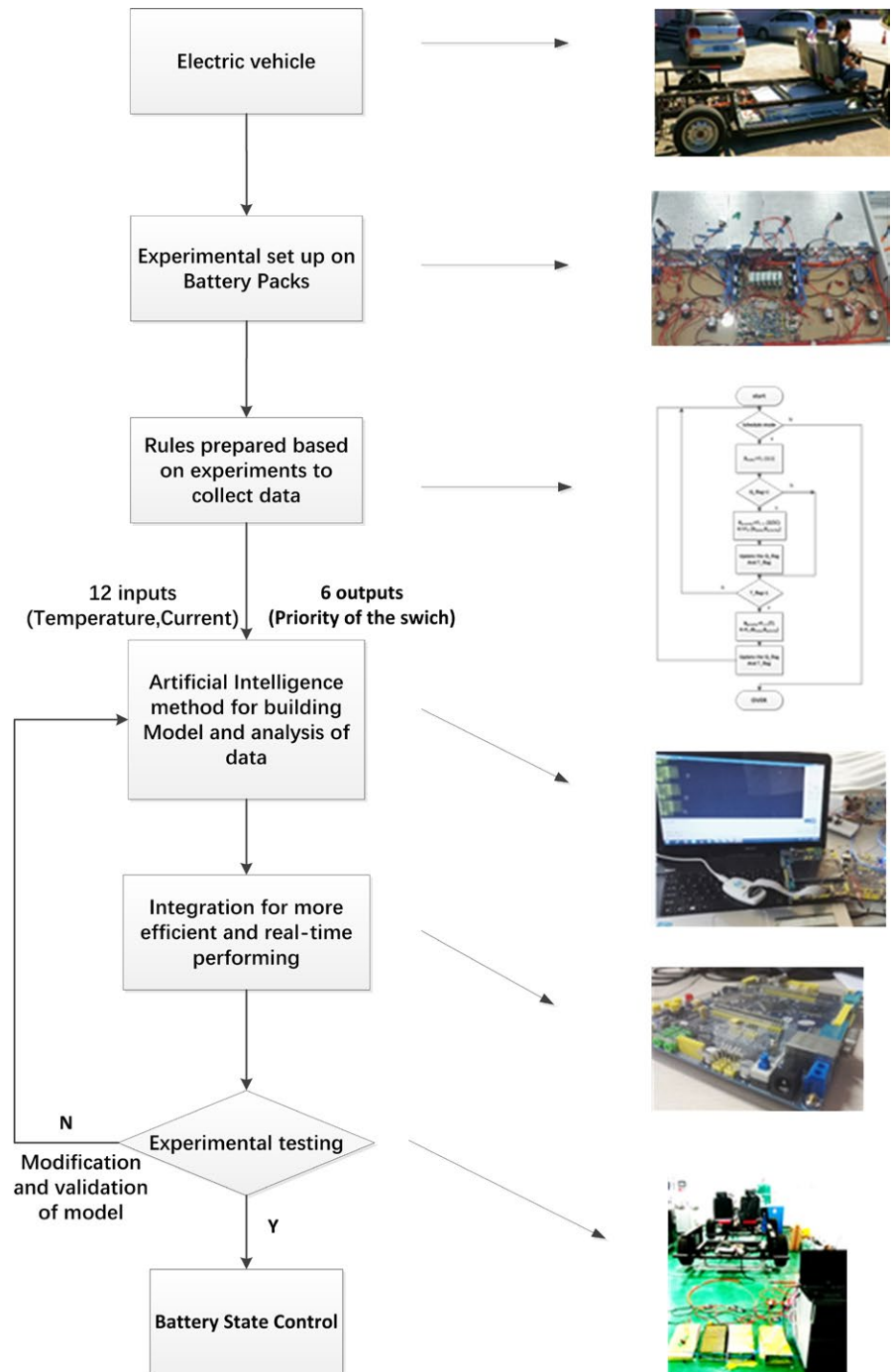
the electrochemical models based on finite element analysis/differential equations are important but their use is restricted due to its computational complexity.<sup>13,14</sup> On the other hand, the equivalent circuit models are lumped-parameter models and can be used for long-term simulation studies. Besides, several research studies ranging from the lead acid battery modelling to the advanced finite element modelling of Lithium-ion battery were discussed broadly in era 2000-2012.<sup>15-19</sup> The physics-based models developed using the finite element software's were used to understand the physical/chemical (fundamental) aspects at cell level. The artificial intelligence (AI) methods such as those based on artificial neural network (ANN), genetic programming, is considered as an effective way for estimation purpose.<sup>20</sup> Among them, ANN has advantages in nonlinear system modeling, specifically as predictive tools, Gandomi et al<sup>21</sup> predict the peak ground acceleration (PGA) utilizing a hybrid method coupling artificial neural network (ANN) and simulated annealing (SA). In battery research, ANN was used to estimate the temperature,<sup>22,23</sup> current, voltage, SOH, and SOC of battery cell. In brief, a number of studies conducted relating to problems such as thermal runaway, states estimation, rupture, etc. were conducted on a single battery/single cell.<sup>15,19,22-25</sup>

Studies on measuring the state (SOC/SOH) of a battery module comprising of hundreds of cells is paid less attention. It is necessary to understand that the fundamental need for measuring SOH/SOC is due to the deviations of battery modules from its equilibrium state. One such reason for deviations could be the defects in manufacturing of a battery module. During the actual operation of an electric vehicle, the environmental conditions and the factors such as abnormal voltage and temperature conditions causes the deviations among the battery modules from its equilibrium state. The preliminary tests (Figure 1) are performed to validate the hypothesis that the state (capacity) of modules varies significantly from its equilibrium state for the given power demand based on the temperature, current, and voltage. As a result, its power efficiency and the life-cycle decreases. Therefore, it is necessary to control the state of the battery modules.

For this purpose, the evaluation and estimation of the state of battery modules is a priority to have information on which modules among the given ones should be discharged first. Therefore, this study proposes the methodology (Figure 2) for the evaluation of state of battery modules based on its current and temperature. Since, it is difficult to estimate SOH of a module, therefore this work uses current and temperature as the inputs for measuring the state of battery module. Firstly, the rules are defined based on experiments to determine the priority for the discharge of each of the six modules. Dataset of 6000 samples obtained comprises of 12 inputs (temperature and current) and 6 outputs (on-off state of switch). Each output represents the priority of module to be discharged. To analyze this multi-input-multi-output dataset,



**FIGURE 1** A, Battery enclosure comprising of battery modules. B, Battery enclosure used in Electric vehicle for collecting data



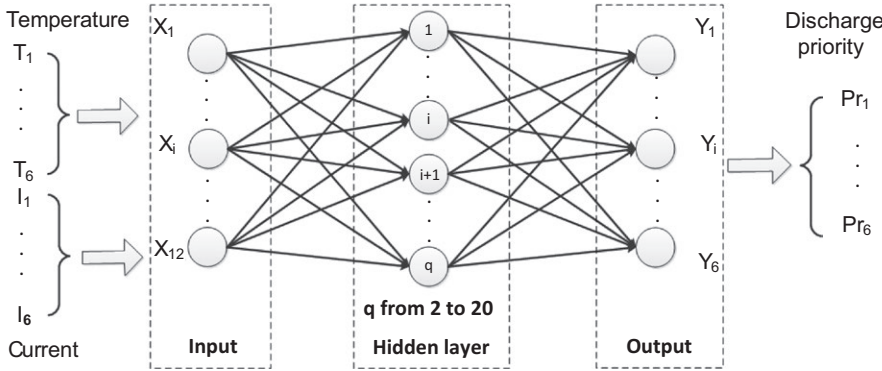
**FIGURE 2** Holistic methodology based on experiments and simulation for control of battery module state

an artificial neural networks (ANN) with three training algorithms (Levenberg, Scaled conjugate and Bayesian regularization), using a number of neurons from 2 to 20 in the hidden layer is used (Figure 3).

## 2 | RESEARCH PROBLEM STATEMENT

The battery pack comprised of several modules in parallel is used for powering the electric vehicle. During the operation

of battery modules connected in parallel, the environmental and road conditions can cause differences in its state resulting in decline of its power efficiency and life-cycle.<sup>20,21</sup> Therefore, it is necessary to control the state of the battery pack. The state of the battery modules connected in parallel is divided into an equilibrium state and the nonequilibrium state, where the nonequilibrium state implies that the battery modules have the power output difference or the temperature difference exceeding a certain threshold value. In the equilibrium state, the battery modules discharge without any control mechanism in place. However, in the nonequilibrium state,



**FIGURE 3** Discharge priority modeling with ANN

given with the requirement of load and safety, the regulation and control of the battery pack is necessary for the modules to return to its equilibrium state (as shown in Figure 4). For the modules to return to its equilibrium state, it is necessary to define the priority of which module should be discharged first. The priority of the module to be discharged is determined based on the parameters such as the temperature, the voltage and its current. This is an important aspect of efficient management and prolonged life of battery modules because over discharging results in degradation of cycle life of the battery module and hence can cause several undesired consequences (overheating problems, fire, etc.).

## 2.1 | Research problem formulation

When the battery modules are in an equilibrium state, they discharge freely without any control mechanism. The main objective of systems modeling is to regulate and control the pack so that the battery modules return to its equilibrium state. For the battery pack in the nonequilibrium state, the multi-input single-output model is set up for the scheduling control to make the battery modules return to their equilibrium state. The input parameters of the system considered are the load parameters (battery voltage  $U$  and discharge

current  $I$ ) and the state parameters of each battery (including SOC, SOH), and the output is the on-off state of the battery modules.

Assuming that there are  $N$  parallel battery modules, where the  $i$ -th one is called  $B_i$ , the voltage of the  $i$ -th battery module is  $U_i$  at a given time, the current is  $I_i$ , the remaining charge is  $SOC_i$ , the health state is  $SOH_i$ ,  $K_i$  is the on-off state of battery circuit:

$$\mathbf{K} = F(\mathbf{U}, \mathbf{I}, \mathbf{SOC}, \mathbf{SOH}, \dots) \quad (1)$$

Among them,  $\mathbf{K}$ ,  $\mathbf{U}$ ,  $\mathbf{I}$ ,  $\mathbf{SOC}$ ,  $\mathbf{SOH}$  is  $N$ -dimensional vector of the corresponding  $N$  battery modules.

As the way to measure SOH of the module is difficult, hence, to simplify the problem, the temperature  $T$  of battery modules is set as an input instead of SOH.

$$\mathbf{K} = F(\mathbf{U}, \mathbf{I}, \mathbf{SOC}, \mathbf{T}, \dots) \quad (2)$$

Therefore,  $\mathbf{K}$ ,  $\mathbf{U}$ ,  $\mathbf{I}$ ,  $\mathbf{SOC}$ , and  $\mathbf{T}$  is the  $N$ -dimensional vector of the corresponding  $N$  battery modules.  $T$  is the temperature of each battery module.

Given with the load demand, at least  $M$  ( $M \leq N$ ) set of battery modules are powered to meet the required demand. In order to maintain the power efficiency of the battery pack and improve its life cycle, the  $M$  modules with good status (higher SOC...) should be selected.

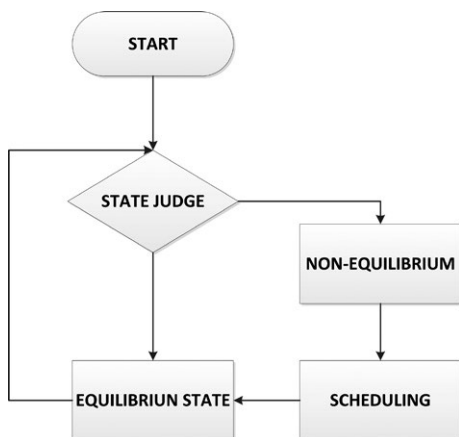
Good status means high SOC and low temperature (when it is above  $20^\circ\text{C}$ ). But SOC plays a more important role than temperature to calculate the priority.

The  $N$  battery modules are sorted by SOC in descending order, so the  $j$ -th SOC in the sequence is  $SOC^j$  ( $j \in [1, 2, \dots, M]$ ), and the temperature of the corresponding battery module is  $T^j$ ,

Therefore, the SOC of the adjacent two battery modules can be expressed as  $SOC^j$ ,  $SOC^{j+1}$ , and the temperature can be expressed  $T^j$ ,  $T^{j+1}$ , respectively. By assuming  $SOC^j > SOC^{j+1}$ ,

1. When  $Th_1 < SOC^j - SOC^{j+1} < Th_2$

If  $T^j - T^{j+1} \leq Th_T$ , the priority of the corresponding battery modules should be



**FIGURE 4** Scheduling mechanism for changing battery modules from nonequilibrium state to an equilibrium state



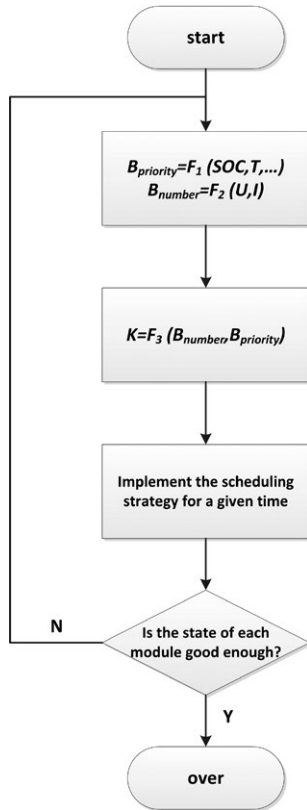


FIGURE 5 Flow diagram in nonequilibrium state

$$Pr^j = j, Pr^{j+1} = j + 1;$$

If  $T^j - T^{j+1} > Th_T$ , the priority of the corresponding battery modules should be

$$Pr^j = j + 1, Pr^{j+1} = j.$$

2. When  $SOC^j - SOC^{j+1} < Th_1$

If  $T^j$  is higher,  $Pr^j$  will take the smaller value, where  $Pr \in [1, 2, \dots, n]$

Finally,  $M$  battery modules with the smallest  $Pr$  value will be taken.

The above formula  $Th_1, Th_2$  is a function of temperature  $T$ , and often difficult to find. Hence, ANN with a set of given inputs and outputs data should be considered to find the relationship between inputs and outputs.

The key point of control process is the determination of the battery module on-off state. In order to determine the on-off state (output  $K$ ) of the battery module during the operation, this problem can be divided into two parts as follows:

1. The priority of on-off of the battery modules is determined by the state of the battery module parameters, included SOC,  $T$ , and so on;
2. The number of on-off of the battery modules is determined by the given load, and hence, the equation (2) can be split into two parts:

$$B_{priority} = F_1(SOC, T, \dots) \quad (3)$$

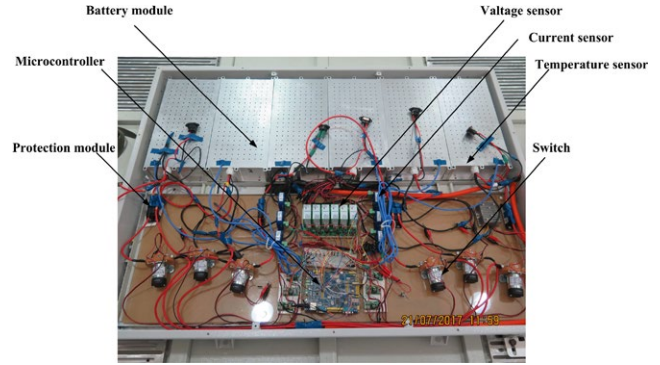


FIGURE 6 Six battery modules connected in parallel

$$B_{number} = F_2(U, I) \quad (4)$$

$$K = F_3(B_{number}, B_{priority}) \quad (5)$$

By combining (3) (4) and (5):

$$K = F_3(F_1(SOC, T, \dots), F_2(U, I)) \quad (6)$$

where,  $B_{number}, B_{priority}$  are on-off number and on-off priority of battery modules, respectively, and each of them is an  $N$ -dimensional vector.

As shown in Figure 5, in the nonequilibrium state, the controller will automatically figure the needed number of the battery module based on the SOC and  $T$ , and then it will calculate the priority of each module based on the  $U$  and  $I$ . After that, with the parameter of priority and number of the module, scheduling strategy can be determined. According to the scheduling strategy, the battery module will be controlled for a given time and then check whether the state of the battery modules good enough and return to the equilibrium state.

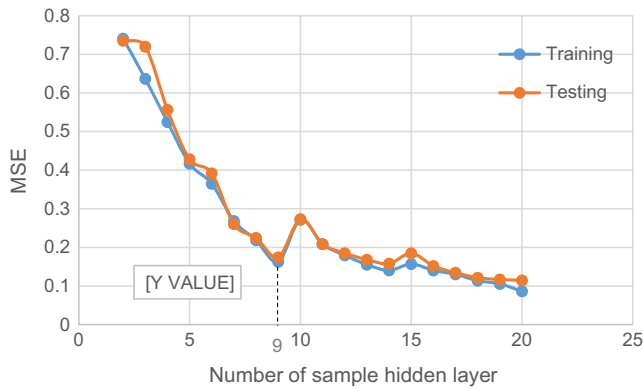
The input parameters considered are the state of charge (SOC) and temperature ( $T$ ). It is known that the larger the SOC, the higher the battery circuit open circuit voltage. In addition, in parallel structure higher is the circuit voltage of the battery pack, higher is the working current. Thus, there is a certain relationship between the SOC and the working current  $I$ . The higher is the working current  $I$ , the larger is the SOC. SOC is not measured directly, while the current  $I$  can

TABLE 1 Parameters of battery module in experiment

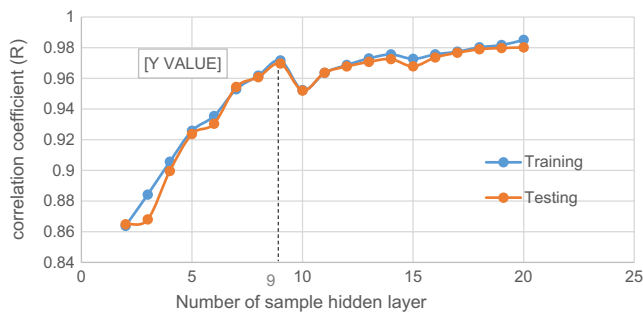
Battery module	Scope or value
Nominal Voltage	72 V
Nominal Capacity	22 Ah
Max continuous discharge current	20 A
Max instantaneous discharge current	40 A
Temperature	-10 to 60

TABLE 2 6000 data samples collected from Experiment

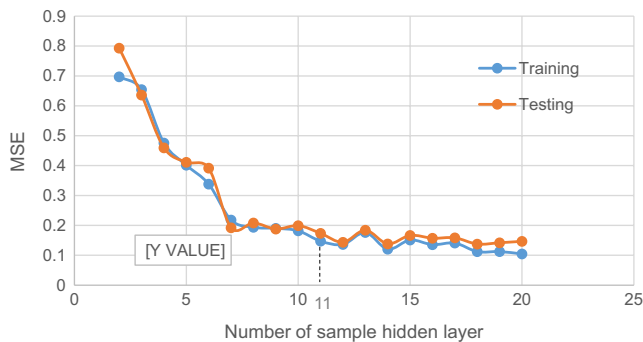
	Current (A)						Temperature (°C)						Priority of battery					
	I1	I2	I3	I4	I5	I6	T1	T2	T3	T4	T5	T6	K1	K2	K3	K4	K5	K6
1	19.7	13.55	12.6	9.8	4.1	3.7	21.63	23.6	28.9	31.3	32.3	37.9	1	2	3	4	5	6
2	17.8	15.8	12.4	9.1	6.6	3.8	20.4	28.8	31.3	32.9	36.2	23.4	1	2	3	4	6	5
3	18.1	14.8	10.5	8.6	5.0	2.2	20.2	28.8	29.9	37.5	25.1	33.8	1	2	3	5	4	6
4	18.2	14.3	10.9	7.5	6.2	3.4	36.5	22.9	28.6	30.7	33.8	24.5	2	1	3	4	5	6
5	16.4	14.9	12.3	8.7	6.7	2.0	32.5	37.5	21.7	31.5	28.9	24.1	1	3	2	4	5	6
6	5.0	1.0	1.0	1.0	1.0	1.0	36.9	22.1	21.0	22.7	20.9	20.6	1	2	3	4	5	6
7	6.0	2.0	2.0	2.0	2.0	2.0	37.9	20.4	22.5	21.7	21.8	22.3	1	2	3	4	5	6
8	7.0	6.9	3.0	3.0	3.0	3.0	36.4	35.6	25.3	23.5	25.0	24.8	1	2	3	4	5	6
9	8.0	7.9	4.0	4.0	4.0	4.0	37.9	35.2	23.8	24.7	24.3	23.4	1	2	3	4	5	6
10	9.0	8.7	8.6	5.0	5.0	5.0	36.4	37.9	34.8	26.4	26.5	28.8	1	2	3	4	5	6
11	10.0	9.9	9.5	6.0	6.0	6.0	36.7	35.5	36.4	28.1	27.4	28.5	1	2	3	4	5	6
12	11.0	10.8	10.65	10.4	7.0	7.0	37.5	37.5	35.5	34.2	29.1	30.1	1	2	3	4	5	6
13	12.0	11.8	11.5	11.4	8.0	8.0	37.1	37.8	35.5	34.2	29.1	30.1	1	2	3	4	5	6
14	13.0	12.9	12.8	12.7	12.56	9.0	37.6	37.2	37.2	35.5	36.5	29.7	1	2	3	4	5	6
15	14.0	14.0	13.9	13.8	13.6	10.0	37.2	36.9	36.0	35.8	36.6	31.8	1	2	3	4	5	6
16	13.7	13.4	13.0	12.8	12.4	12.1	25.6	27.3	22.5	28.7	35.4	20.1	3	4	2	5	6	1
17	9.6	9.4	9.0	8.8	8.4	8.3	21.3	22.1	23.3	26.5	34.3	26.7	1	2	3	4	6	5
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
6000	18.9	18.3	18.5	18.1	17.9	17.7	23.3	33.4	35.6	25.3	37.8	23.8	1	4	5	3	6	2



**FIGURE 7** The relation between the MSE and the number of neurons in hidden layer on training and testing data with Levenberg algorithm



**FIGURE 8** The relation between the  $R$  and the number of neurons in hidden layer on training and testing data with Levenberg algorithm



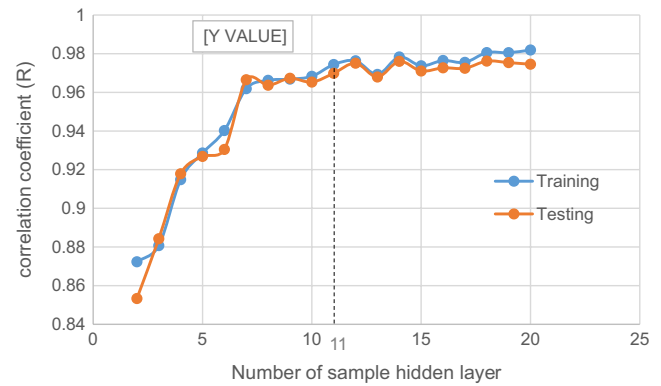
**FIGURE 9** The relation between the MSE and the number of neurons in hidden layer on training and testing data with Bayesian regularization algorithm

be directly measured, so it is reasonable to provide working current  $I$  as the input parameters of the neural network instead of the SOC.

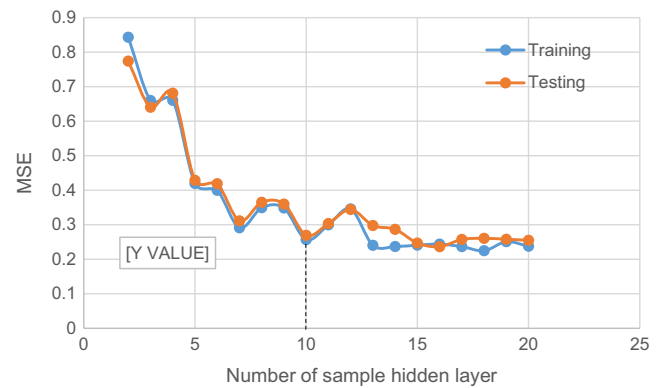
So, formula (6) could convert to:

$$\mathbf{K} = F_3(F_1(\mathbf{I}, \mathbf{T}, \dots), F_2(\mathbf{U}, \mathbf{I})) \quad (7)$$

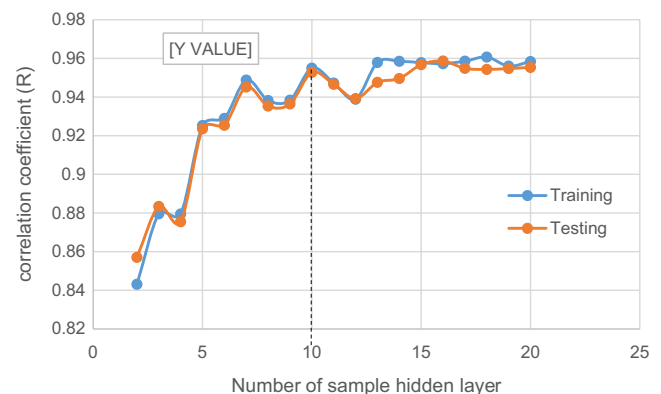
In equation (7), it is possible to find  $F_2()$ . However, it is very difficult to find the  $F_1()$  to calculate the priority of



**FIGURE 10** The relation between the  $R$  and the number of neurons in hidden layer on training and testing data with Bayesian regularization algorithm



**FIGURE 11** The relation between the MSE and the number of neurons in hidden layer on training and testing data with Scaled conjugate algorithm



**FIGURE 12** The relation between the  $R$  and the number of neurons in hidden layer on training and testing data with Scaled conjugate algorithm

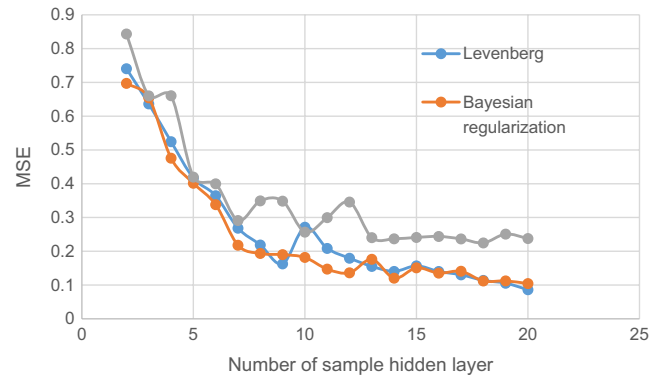
the battery modules because of higher number of inputs and complexity of the battery pack system.

In this case, as shown in Figure 6, considering 6 set of battery modules ( $B_1, B_2, B_3, B_4, B_5, B_6$ ), there are 12 inputs including  $T_i$  and  $I_i$  ( $i = 1, 2, 3, 4, 5, 6$ ) which will be collected

by the temperature sensor and current sensor, and 6 outputs  $K_1, K_2, K_3, K_4, K_5, K_6$  ( $K$  means the on-off state of battery switch at next moment). The data of inputs and outputs is recorded and sent to the computer by the microcontroller. Based on some safety rules (depend on battery electric parameters) and the rules to reduce the difference in temperature and current between battery packs simultaneously, data of 12 inputs and 6 outputs is selected. Given the set of 12 inputs and 6 outputs, artificial neural network (ANN) can be used to develop relationship and find out  $F_1$ . ANN code in MATLAB can be further converted into C/C++ files readable by microcontroller for battery managing.

### 3 | MIMO DATA MODELING USING ANN

The determination of priority of battery module to be discharged first is a nonlinear problem of Multi-input Multi-output (MIMO) data. ANN has the function of approximating MIMO and adapting to the nonlinearity of the data. Artificial neural network is a popular AI method for modelling complex systems whose behavior is uncertain and unknown. ANN consists of three parts: input layer, hidden layer, output layer. The input layer consists of the number of neurons same as the number of inputs, including temperature and current. The output layer consists of  $N$  group of priority of the battery



**FIGURE 13** The relation between the MSE and the number of neurons in hidden layer on testing data

models. The hidden layer consists of the unknown number of neurons. The number of neurons in the hidden layer are set by using the variety of training algorithms. The activation function in the hidden layer and output layer transforms the weighted summation of data into a crisp value.

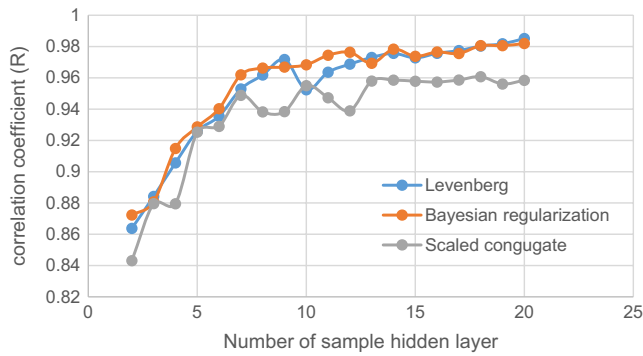
In this case, the input of the ANN consists of 12 group of parameter including  $T_i$  (temperature) and  $I_i$  (current), ( $i = 1, 2, 3, 4, 5, 6$ ) and output consists of 6 groups of on-off state of battery switch  $K_i$ . 6000 data as shown in Table 1

The settings to be varied for the ANN approach includes the number of neurons in the hidden layer and the selection of the training algorithm. In this study, three training algorithms

Sample	Levenberg		Bayesian		Scaled conjugate	
	MSE	$R$	MSE	$R$	MSE	$R$
2	0.735185	0.864838	0.793088	0.853323	0.774215	0.857062
3	0.719769	0.868002	0.636089	0.884263	0.640509	0.883401
4	0.556381	0.899578	0.459442	0.917883	0.681235	0.875478
5	0.428139	0.923697	0.411122	0.926861	0.428817	0.923573
6	0.391806	0.930414	0.391621	0.930468	0.418962	0.925403
7	0.260021	0.954397	0.191985	0.966535	0.311242	0.945207
8	0.224508	0.960743	0.208099	0.963696	0.365065	0.935340
9	<b>0.174318</b>	<b>0.969656</b>	0.187724	0.967304	0.359775	0.936422
10	0.273166	0.952032	0.199051	0.965328	<b>0.269171</b>	<b>0.952792</b>
11	0.208176	0.963652	<b>0.173398</b>	<b>0.969879</b>	0.303496	0.946596
12	0.184963	0.967776	0.143433	0.975103	0.344199	0.939185
13	0.168062	0.970761	0.18397	0.967952	0.297737	0.947615
14	0.157840	0.972565	0.137956	0.976067	0.286680	0.949591
15	0.184795	0.967839	0.166384	0.971064	0.246849	0.956781
16	0.151766	0.973638	0.157048	0.972705	0.236360	0.958649
17	0.134221	0.976721	0.158360	0.972475	0.257436	0.954863
18	0.121357	0.978979	0.137374	0.976186	0.260550	0.954316
19	0.116852	0.979767	0.141783	0.975411	0.257829	0.954779
20	0.114494	0.980183	0.146575	0.974576	0.254877	0.955347

**TABLE 3** The comparing of testing results among three algorithm (row number highlighted in bold shows the best model)





**FIGURE 14** The relation between the  $R$  and the number of neurons in hidden layer on testing data

(Levenberg, scaled conjugate and Bayesian regularization) were used. A single hidden layer with number of neurons from 2 to 20 is used in this study.

## 4 | RESULTS AND DISCUSSIONS

The analysis of ANN approach on the data set (Table 2) collected from the experiment is shown in Figures 7-12. MSE (mean square error) and correlation coefficient ( $R$ )

are the key statistical parameters for determining the performance of ANN. The lower the MSE and higher the  $R$  values, higher is the performance/accuracy of the model. If the ANN architecture has same accuracy for different number of neurons in the hidden layer, the model with the lower number of neurons in the hidden layer is chosen as the best model.

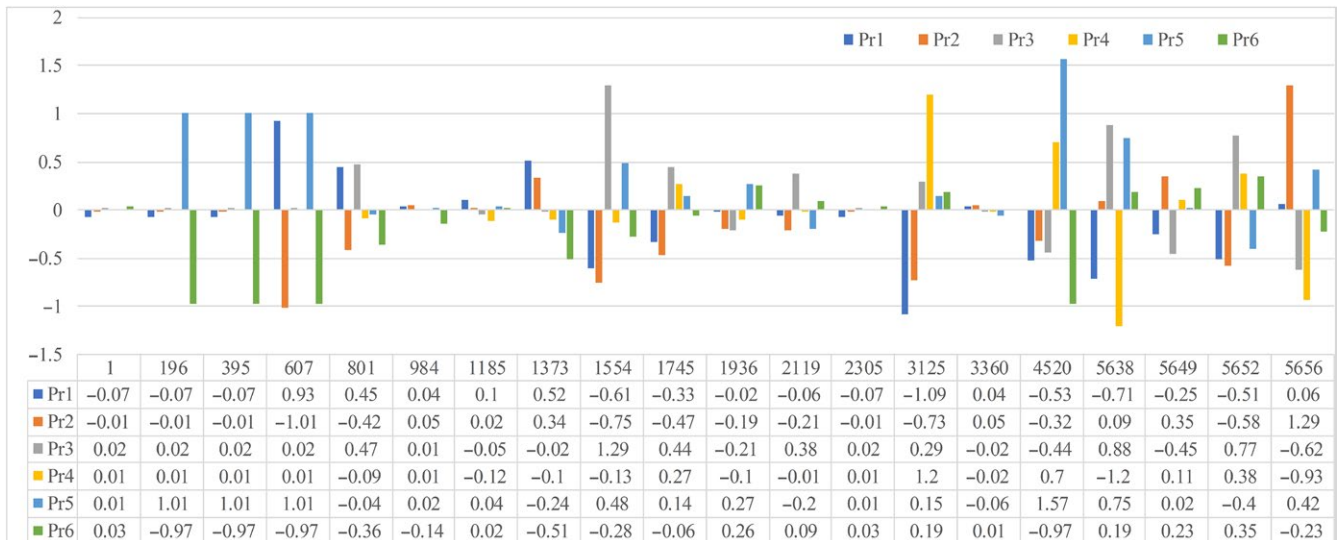
From Figures 7 and 8 using Levenberg algorithm for training of ANN, the best model selected has number of neurons in the hidden layer of 9,  $R$  value of 0.96 and a MSE value of 0.17. From Figures 9 and 10 using Bayesian regularization algorithm, the best model selected has the  $R$  value of 0.96, MSE of 0.17 and the number of neurons in the hidden layer is 11. From Figures 11 and 12, using the Scaled conjugate algorithm, the best model selected has  $R$  value of 0.95, MSE of 0.26 and the number of neurons in the hidden layer is 10. Based on the comparison among the three training algorithms (Table 3, Figures 13 and 14), the best model among the three best is the one trained, using Levenberg algorithm because it has the lower number of neurons (simpler) in the hidden layer with accuracy at par with other two algorithms.

Table 4 and Figure 15 shows the performance of ANN using Levenberg algorithm on the training, validation and

**TABLE 4** Performance of Levenberg algorithm in ANN using 9 neurons on training data

Serial number	Actual output						Target output					
	Pr <sub>1</sub>	Pr <sub>2</sub>	Pr <sub>3</sub>	Pr <sub>4</sub>	Pr <sub>5</sub>	Pr <sub>6</sub>	Pr <sub>1</sub>	Pr <sub>2</sub>	Pr <sub>3</sub>	Pr <sub>4</sub>	Pr <sub>5</sub>	Pr <sub>6</sub>
1	0.93	1.99	3.02	4.01	5.01	6.03	1	2	3	4	5	6
196	0.93	1.99	3.02	4.01	7.01	4.03	1	2	3	4	6	5
395	0.93	1.99	3.02	4.01	7.01	4.03	1	2	3	4	6	5
607	2.93	-0.01	3.02	4.01	7.01	4.03	2	1	3	4	6	5
801	6.45	0.58	2.47	2.91	3.96	4.64	6	1	2	3	4	5
984	1.04	2.05	3.01	4.01	5.02	5.86	1	2	3	4	5	6
1185	1.10	2.02	2.95	3.88	5.04	6.02	1	2	3	4	5	6
1373	1.52	2.34	2.98	3.90	4.76	5.49	1	2	3	4	5	6
1554	0.39	1.25	4.29	3.87	5.48	5.72	1	2	3	4	5	6
1745	0.67	1.53	3.44	4.27	5.14	5.94	1	2	3	4	5	6
1936	0.98	1.81	2.79	3.90	5.27	6.26	1	2	3	4	5	6
2119	0.94	1.79	3.38	3.99	4.80	6.09	1	2	3	4	5	6
2305	0.93	1.99	3.02	4.01	5.01	6.03	1	2	3	4	5	6
3125	1.91	3.27	5.29	7.2	1.15	2.19	3	4	5	6	1	2
3360	1.04	2.05	2.98	3.98	4.94	6.01	1	2	3	4	5	6
4520	1.47	2.68	3.56	5.7	7.57	0.03	2	3	4	5	6	1
5638	1.29	4.09	6.88	-0.2	5.75	3.19	2	4	6	1	5	3
5649	4.75	6.35	0.55	3.11	2.02	4.23	5	6	1	3	2	4
5652	0.49	3.42	3.77	6.38	1.60	5.35	1	4	3	6	2	5
5656	4.06	3.29	0.38	4.07	3.42	5.77	4	2	1	5	3	6

The italic values in Table 4 shows the matching of the actual and estimated.



**FIGURE 15** Error between the actual and the target output

testing data, respectively. The italic values in Table 4 shows the matching of the actual and estimated (target) output values and Figure 15 show the absolute difference between the actual and the target output. It is noted that there is still great scope for improvement of improving the accuracy of the ANN algorithm.

## 5 | CONCLUSIONS

The present work highlights the research problem on determining the priority discharge of battery modules for obtaining its equilibrium state during the electric vehicle operation. In this context, this work proposed a methodology for the evaluation of state of battery modules based on its current and temperature values. The set of rules were formulated based on experiments to determine the priority for the discharge of six modules. 6000 data samples comprising of 12 inputs (temperature and current) and 6 outputs (discharge priority) were then fed into ANN architecture. ANN models were then trained using three training algorithms (Levenberg, Scaled conjugate and Bayesian regularization) with number of neurons from 2 to 20 in the hidden layer. It was found that the ANN model obtained, using Levenberg algorithm performs the best with  $R$  value of 0.96 and MSE value of 0.17. The chosen model when integrated with the microcontroller can estimate the priority of discharge of the module, which could result in improving the life cycle and efficiency of the battery modules. There is still some scope for improving the accuracy of the models and the computational time. Therefore, the future work for authors is to work on developing a holistic integrated solution<sup>26-28</sup>, which can accurately estimate the state of a battery module in a minimum computational time.

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## NOMENCLATURE

U	Voltage [V]
I	Discharge current [A]
T	Temperature [°C]

## ACRONYMS

ANN	Artificial neural networks
LIB	Lithium ion battery
EV	Electric vehicle
SOC	State of charge
SOH	State of health
AI	Artificial intelligence
Pr	Discharging priority
B	Battery

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