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The Estimation of Battery State of Charge using Corny Network

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Abstract*: State of charge (SOC) estimation of lithium-ion batteries has been extensively studied and the estimation accuracy was mainly investigated through the development of various battery models and dynamic estimation algorithms. All battery models, however, contain inherent model bias due to the simplifications and assumptions, which cannot be effectively addressed through the development of various conventional computation and intelligent computation. Consequently, some existing methods performed battery SOC estimation using conventional and intelligent computation have not very accurate to predict the SOC battery characteristics. There some drawbacks in employment deep learning to estimate SOC battery, such as complicated algorithm or network, over fitting and so on. The proposed method, the Corny architecture has narrow layers design. This design has low cost computation and prevent over fitting. The result shows the accuracy of method is very high. The predicted and targeted values are almost merged in a single line. The RMSE and MAX error indexes are very low. That the accuracy of the model is acceptable. The electric vehicle battery can estimate to life longer and more reliable to perform mobility task. Finally, this method also show the accuracy of estimation SOC battery of electric vehicle can be solved by narrow learning layers.

***Keywords*: Battery, Corny Architecture, Electric Vehicle, State of Charge**

I. INTRODUCTION

The increase of carbon emission as waste of a vehicle running on the work of Internal Combustion Engines (ICE) required an alternative source of vehicle working. Electric Vehicle (EV) is an impeccable solution to handle this problem, thus reducing the environmental damages. In operating Electric Vehicle, the most important part of EV is energy storage devices [1] [18][19][20]. The Energy storage devices and power supply used in high power EV applications is batteries. The cutting edge battery technology offers a wide range of advantages including high energy density, low environmental pollution and long cycle life. When attached to the load, the efficiency of the battery depends on the chemical reactions that occur in the batteries. The boom in the EV industries needs the significant demand for an effective battery management system. The battery management system includes battery monitoring. The performance parameters of the lead acid battery are most influenced by the temperature and other atmospheric variables. Further, the battery monitoring is a vital task in most EVs, because it influenced the operation of the battery, personal security and EV's life. This monitoring contributes to governing the condition of battery within the stated safety limit of operation. There were many methods available to monitoring state of charge (SOC) of the battery so far. The management of battery system using interleaved pulse charging proposed to monitor battery management. It includes fast charging, battery aging diagnosis and charge estimation and balancing. This method used a single inductor single input dual output architecture [2]. It as shown in Fig. 1 below.

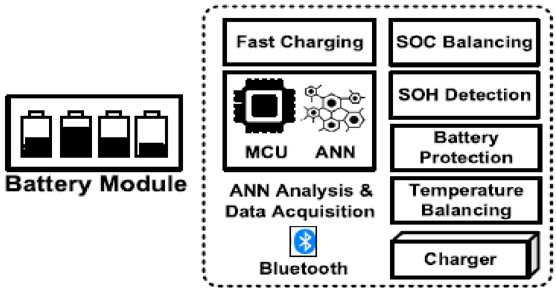

Fig. 1: The Battery Management System [2]

Interleaved pulse charging is intended to generate fast charging process and delay aging battery process. The aging battery is influenced by many surrounding factors such as variation cell temperatures. This method also significantly suppresses the temperature fluctuation of cell surface. That it can make charge balancing of the battery. This method used artificial neural network to detect the state of health (SOH) of battery cells and improves the accuracy of the state of charge (SOC) estimation. The detail of the architecture is as shown in Fig. 2.

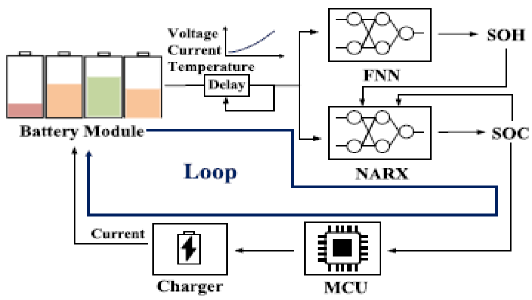

Fig. 2: The use of CNN to SOH Architecture [2]

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Fig. 2 shows a ANN with input delay feedforward is employed. The ANN process collected data from ADC on the MCU, including output voltage V_{cell}, charging current I_{module} and temperature of each battery cell V_{tem}. The sample data is sent in ANN model to estimate SOC and SOH. The other method estimated battery state of charge is the multi-timescale estimator. This method has accurate and robust estimation of state of charge and state of energy in battery management system [3]. The estimator can predict SOC and SOE under dynamic operation and different temperatures. The predictor uses dual H infinity filter. The block diagram of this method is as shown in Fig. 3 below.

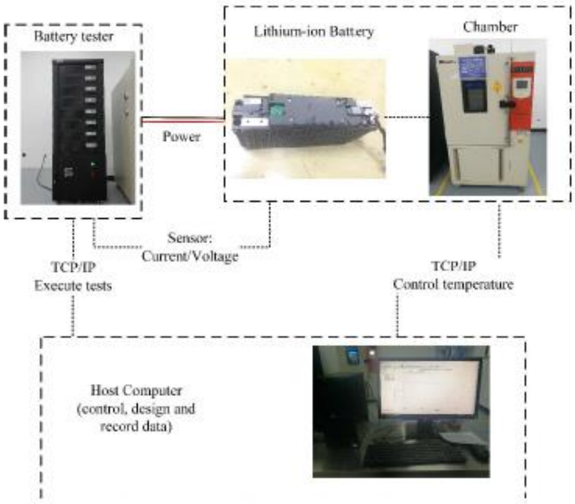

Fig. 3: The Block Diagram of Dual H Infinity Filter [3]

Fig. 3 shows block diagram of experiment to obtain the experimental data. The data consists of terminal voltage, current and OCV. The PC is used to control and store the data. Thermal chamber is used to set up temperature of battery, battery tester performs the strategy charging and recharging with wide range of temperature levels, and TCP/IP module used for data transmission. The result shows the prediction of SOC and SOE have error rate more or less 1.5%. Further, other method used fractional Kalman filter to estimate state of charge in battery management system, especially for lithium-ion battery[4]. The purpose od this method is to reflect the dynamic characteristic of the battery. Moreover, fractional orders were identified using genetic algorithm. It is as shown in Fig. 4 below.

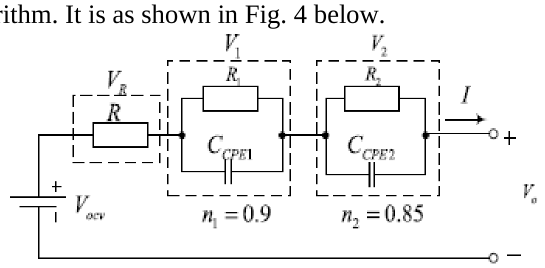

Fig. 4: The Fractional Kalman Filter [4]

Fig.4 shows the fractional Kalman filter circuit is based on second-order RC model. Where V_o is the terminal battery voltage, V_{ocv} is battery open-circuit voltage, V_R is the battery internal resistance voltage, and R is the internal resistance of the battery. The error rate of the terminal voltage is 0.014 V. This accuracy is considered reliable. The importance of good battery management system especially in electric vehicle is to keep the health of battery with long life utility. Furthermore, there are many vital roles to be supported by the battery. They are monitoring voltage and current, estimating charge and discharge, equalizing and protecting the battery, managing temperature and data, and so on[5]. That the battery modelling, states estimation, and battery charging are crucial. The standard of electric vehicle is as shown in Fig. 5 below.

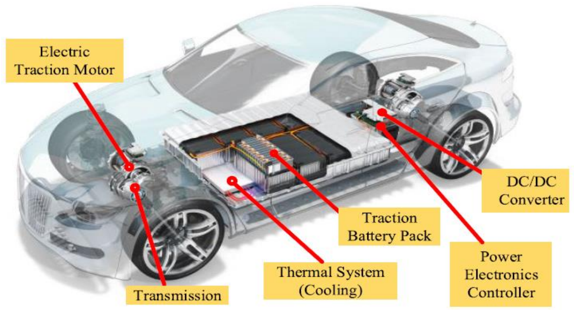

Fig. 5: The Standard of Electric Vehicle [5]

Fig.5 shows the layout of EV functional components standard. The layout offers safety and reliability EV for driving and other usage. The other important thing to make the long useful life of battery is through charge balancing among battery cells. The unbalancing charging among cells can reduce battery capacity, accelerate battery degradation, and even cause some safety hazards [6][22]. In order to handle this problem, the using of battery charging equalization system BCE) is needed. This method considers the battery as a series of cells. This circuit is termed as battery module. Module level equalizers are connected to each pair of consecutive battery modules. These connected modules composed a new architecture is called BCE system. It is as shown in Fig.6.

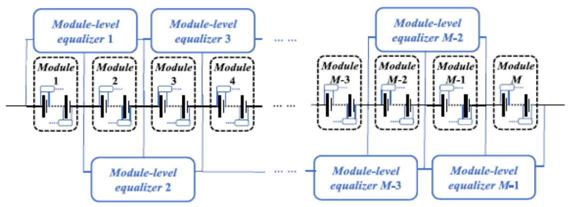

Fig. 6: The Architecture of BCE System [6]

The mathematical model of BCE system is presented in Eq. 1, Eq.2 and Eq. 3. Charge transfer rate k_i^{cl} is according to Eq.1.

$$K_i^{cl}(n)=\begin{cases} \operatorname{sgn} l(-\Delta_i^c(n-1), l_c) r_c, if, i-1>(\Gamma_\beta^i)B, \\ 0, otherwise \end{cases} \quad (1)$$

$$K_i^{cr}(n)=\begin{cases} \operatorname{sgn} l(-\Delta_i^c(n-1), l_c) r_c, if, i-1>(\Gamma_\beta^i)B, \\ 0, otherwise \end{cases} \quad (2)$$

Where

$$\operatorname{sgn} l(u,v)=\begin{cases} -1, & \text{if } u<0, \\ 0, & \text{if } u=0, \\ 1-v, & \text{if } u>0, \end{cases} \quad (3)$$

$$\Delta_h^c(n-1)=x_h(t_{n-1})-X_{h-1}(t_{n-1}) \quad (4)$$

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Thus,

$$K_i^{ml}(n) = \begin{cases} \operatorname{sgn} l(-\Delta_i^c(n-1), l_m) r_m, if, i-1>(\Gamma_\beta^i)-1>0, \\ 0, otherwise \end{cases} \tag{5}$$

$$k_i^{mr}(\mathrm{n}) = \begin{cases} \operatorname{sgn} l(\Delta_{1+b}^m(n-1), I_m) r_m, \text{ if } \Gamma\frac{i}{B}+1 \geq M, \\ 0, \quad \text{otherwise} \end{cases} \tag{6}$$

$$\Delta_h^m(n-1) = \sum_{j=(\lceil \frac{h}{B} \rceil -1)B+1}^{\lceil \frac{h}{B} \rceil B} X_j(t_{n-1}) - \sum_{j=(\lceil \frac{h}{B} \rceil -2)B+1}^{(\lceil \frac{h}{B} \rceil -1)B} X_j(t_n - 1) \tag{7}$$

Based on above equations, the SOC changes from i-th cell, that,

$$k_i^{net}(n) = k_i^{cl}(n) + k_i^{cr}(n) + k_i^{ml}(n) + k_i^{mr}(n) \tag{8}$$

Eq.8 shows the cell SOC evolution during each working cycle.

$$X_i(t) = x_i(t_{n-1}) + \frac{K_i^{net}(n)}{\tau}(t - t_{n-1}), \tag{9}$$

$$t \in (t_{n-1}, t_n], \ \mathrm{n}=1,2,3,...)$$

Based on Eq. 9, the system is able to reach charge equalization. Then fully charge and discharge together without having overcharging and overdischarging. A joint state of charge (SOC) and state of available power (SOAP) are the method to estimate battery model parameters identification. The SOAP of battery is estimated, then joint SOC is performed [7]. The method gained the joint SOC and SOAP obtained higher accuracy than the Adaptive Battery State Estimator (ABSE) method. The ABSE algorithm errors come from identification internal resistance (Rp). Where the identified values is much higher than actual values when the battery is charged /discharged in at a high current. The circuit of the estimation model is as shown in Fig. 7 below.

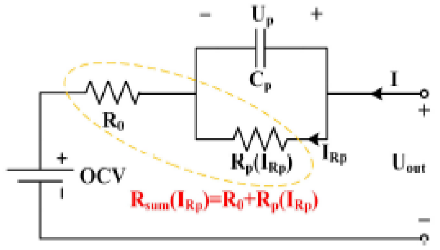

Fig. 7: The Circuit Model of Joint SOC and SOAP Method [7]

The testing of joint SOC and SOAP is performed according to below schematic diagram. It is shown in Fig. 8.

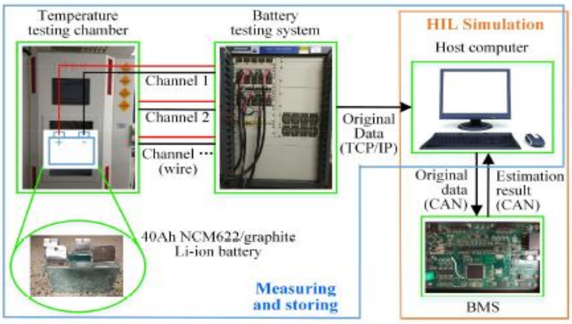

Fig. 8: Schematic Diagram of Battery Test Bench [7]

This estimation was more accurate compared to ABSE method. The other method to estimate SOC battery was using typical extended Kalman filter. This method was improvement of Kalman filter algorithm or particle filtering algorithm. This method generate error about 5% to 10% depend on battery characteristics [8]. The typical extended Kalman filter has flow chart with four phases. The flow chart is as shown in Fig. 9 below.

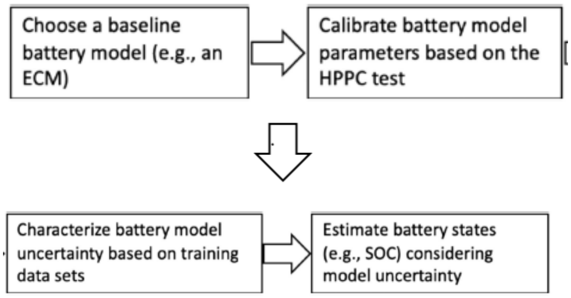

Fig. 9: Flow Chart of Joint SOC [8]

The improvement can be done using Gaussian filter and polynomial regression model. This technique can examine the effect of SOC and SOAP methods on typical battery circuit model. The increasing of large-scale electric vehicle makes charging/discharging voltage fluctuated. It is needed a method to stabilize the voltage of battery. That the improvement of battery lifecycles can be reached. The SOC need to work more high end. It is need to monitor the frequency of the charging/discharging voltage[9]. The detailed of optimized SOC has the scheme as shown in Fig. 10.

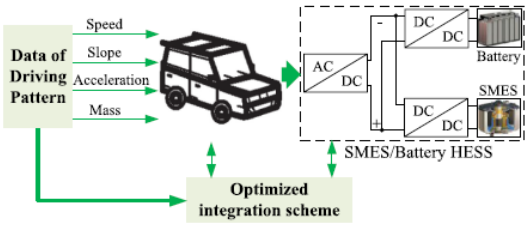

Fig. 10: The Optimized SOC [9]

The development of SOC scheme used unscented Kalman filter (UKF) method, and used extended Kalman filter to estimate internal resistance of battery. The method is able to estimate system parameters and state of battery. The test bench of the method is as shown in Fig. 11.

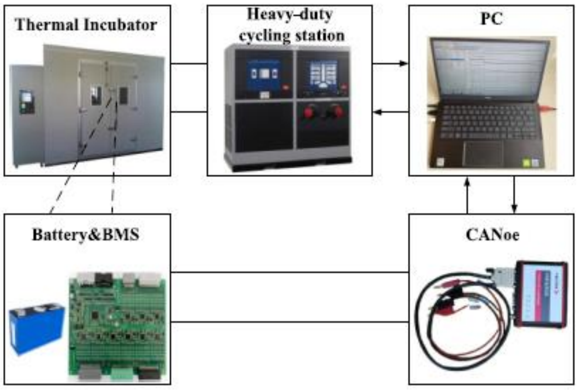

Fig. 11: The Test Bench of UKF Model [9]

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The monitoring and estimation of reliance batteries was urgent, especially for lower energy and power density. This kind of battery prone to aging and performance degradation over time, and restricts their mainstream adoption [10]. The method used for handling above task is Digital Twin (DT)[10]. This method was applied to difficulty of onboard computation for incremental SOC and SOH. The schematic of DT is as shown in Fig. 12.

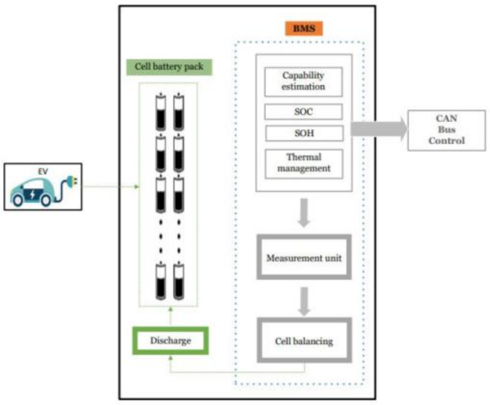

Fig. 12: Schematic diagram of DT [10]

The electrical circuit model of the battery is as shown in Fig. 13.

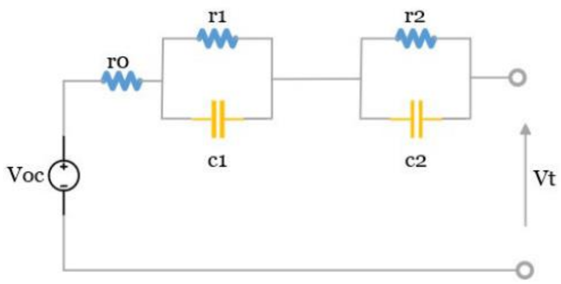

Fig. 13: The Circuit Model of ECM Structure [10]

In order predict the SOH and SOC, the mathematical formulation is according to Eq.10

$$(SOC)_{\tau} = 1 - \int_0^T \delta \frac{i}{c_n} dt \qquad (10)$$

This method is useful for managing batteries and full life cycle statistics that the batteries can upgrade path.

II. DEEP LEARNING ON BMS

Deep leaning is derived from conventional neural network but outperforms its predecessor [11]. Deep learning employs transformations and graph techniques simultaneously in order to build up multilayers training models. There were many method of deep learning in BMS system. The use deep learning based on transformer model trained with self-supervised learning (SSL). The SSL framework generated estimation with the accuracy rood mean square (RMS) of 0.9 [12]. The use neural network with Elman architecture use to estimate SOC and SOH lithium-ion cell. The multi-objective optimization approach based on Particle Swarm Organization (PSO) to training in order obtaining lower root mean square (rms). The optimization of neural network characteristics are influenced by number of hidden layers, activations functions, bias values, and the weights of inputs and outputs [13]. The detail of Elman architecture is as shown in Fig. 14.

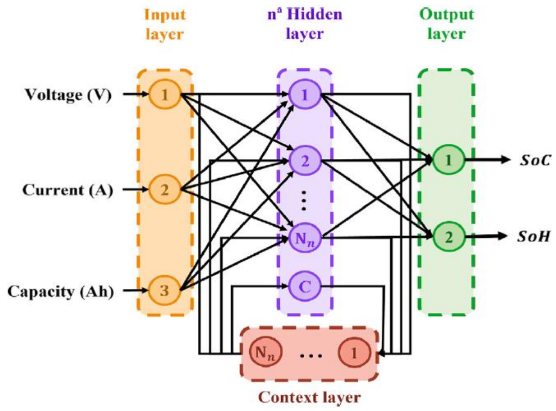

Fig 14. The Elman Architecture [13]

The use of Kalman filter and deep learning form hybrid method to estimate SOC of Li-ion batteries. The first CNN was combined with different version of RNN including LSTM to obtain SOC [14][21]. This method could shorten computation cost. State of art in determining SOC and SOH of battery is very important because it can optimizing the battery energy strategy [15]. This method can estimate to non-linear and time varying charging/discharging characteristics of battery. The other method using deep learning with optimization using Evolutionary Mating Algorithm (EMA). EMA algorithm is used for optimization DL parameters to estimate SOC of a battery for an Electrical Vehicle [16]. It can employ as a proficient technique to accurately estimate SOC of electric vehicle batteries.

III. METHOD

The proposed method uses deep learning with narrow learning layers. It is called corny learning architecture. This corny model contains sequence input, fully connected layer, activation function (tanh function), fully connected layer, ReLu layer, fully connected layers, Relu layer, and regression output layer. This typical model enables the model adapts to varied data. The learnerable layers responds quickly every changes of the fluctuated input. The use of some fully connected layers generate the function form accurate weight faster. The detail of filter size architecture is as shown in Table 1.

Table 1. The Filter Size of Each Layer Corny Model

sequenceinput Sequence input with 5 dimensions	5(C) × 1(B) × 1(T)
fc_1 55 fully connected layer	55(C) × 1(B) × 1(T)
layer Hyperbolic tangent	55(C) × 1(B) × 1(T)
fc_2 55 fully connected layer	55(C) × 1(B) × 1(T)
leakyrelu Leaky ReLU with scale 0.3	55(C) × 1(B) × 1(T)
fc_3 1 fully connected layer	1(C) × 1(B) × 1(T)
clippedrelu Clipped ReLU with ceiling 1	1(C) × 1(B) × 1(T)
regressionoutput mean-squared-error	1(C) × 1(B) × 1(T)

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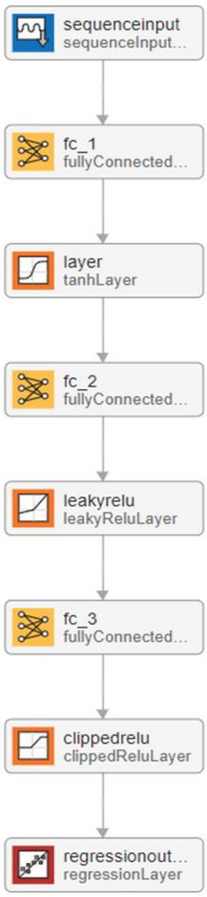

Fig. 15: The Corny Architecture Model

Figure 15 shows the sequence of proposed method. It starts with input layer, fully connected layer, activation layer, 2nd fully connected layer, 2nd activation layer, 3rd fully connected layer, 3rd activation function layer and regression layer. This architecture does not have convolutional layer, pooling layer and batch norm layer. The regression layer predicts the values of target. The architecture has two dimension filters. It does not have depth dimension. The prediction value is a number. This task is performed by regression layer. The data is taken from Lithium-ion dataset. It contains voltage , current, temperature and capacity of the battery[17]. The model generated from the training data influenced by input parameters. It is as shown in Fig. 16.

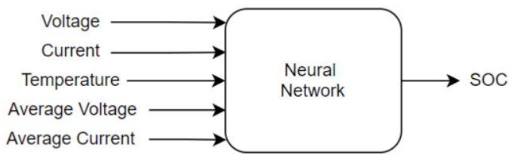

Fig. 16: The Model Architecture of Corny Model

The characteristic battery is varied refers to some external influences. Due to the nonlinear temperature, health, and SOC dependent behavior of Li-ion batteries, This method enriched the previous deep learning methods with more simple architecture. The more complete architecture might be undergo over fitting problem and high cost. Then, it is also complicated to training since the setting of dataset and filter banks size is very crucial in deep learning. This method prevents the complexity and possible over fitting problem occurred as long as training process takes place. The training sample trains a neural network to predict the state of charge of a Li-ion battery, given time series data representing various features of the battery such as voltage, current, temperature, and average voltage and current (over the last 500 seconds). It contains a sequence of data collected while the battery powered an electric vehicle during a driving cycle with an external temperature of 25 degrees Celsius. The test data contains four sequences of data collected during driving cycles at four different temperatures. They are 0 degree C, 10 degree C, 25 degree C, 20 degree C and 40 degree C. Further, the training hyperparameters are train for 1200 epochs with mini-batches of size 1 using the "adam" solver. To prevent the gradients from exploding, set the gradient threshold to 1. Specify an initial learning rate of 0.01, a learning rate drop period of 400 and a learning rate drop factor of 0.1. Specify a validation frequency of 30. The initial learning rate of 0.01 and the learning rate drop factor of 0.1 together minimize the validation error.

IV. RESULT

The training process has the progress as shown in Fig. 17.

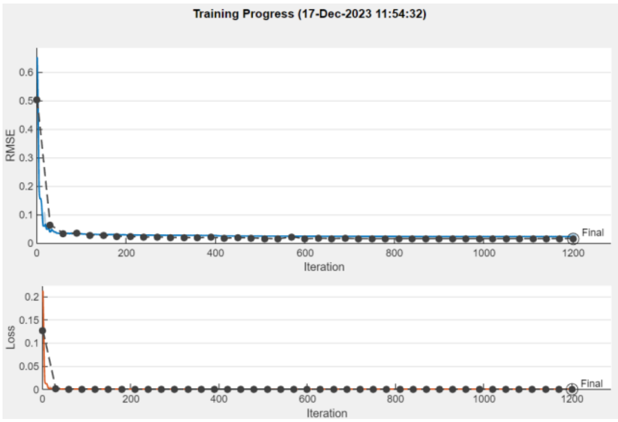

Fig. 17: The Progress of Training Process

Based on the previous hyperparameters and input data, the training process generates error rate less than 0.02. Further, the losses obtained very closes to zero and might be zero. It means that every input data offered the accuracy at 1200 iterations is 100%. That the estimation of the SOC is accurate. It is as shown in Fig.17. It also shows that the training process reaches low RMSE very fast. It needs only less than 50 iterations. At 30th iteration, it reaches MRSE about 0.05 %, then at 60th iterations, it reaches MRSE less than 0.025 and it goes steadily for next iterations at about less than 0.001 of MRSE index.

Furthermore, the same MRSE characteristic also take place to loss index progress. The training process with 1200 iterations produces a fast speed of reaching low loss index. Fortunately, It can reaches the lowest value or zero. The fast movement of decrement loss index happen at about 30th iterations. For the next remaining iterations, the loss index exists at zero values. In order to reassure the generated model is accurate, the other testing data employed to the model according to various environment temperatures. The result is as shown in Fig. 18 below.

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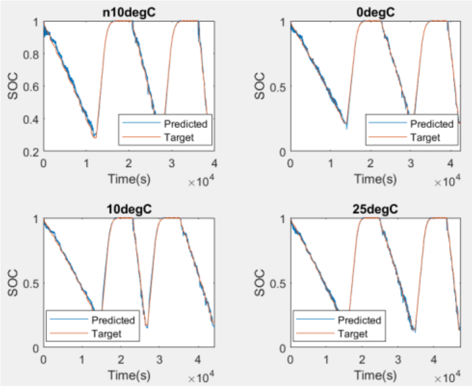

Fig. 18: The Estimation of SOC Battery at Various Temperatures

The Fig. 18 shows graph with predicted and target SOC at different temperatures. The blue graphs is estimation values while the red one is target values. The highest accuracy achieved when the blue and red graphs are merged. Nevertheless, the bad accuracy when the red and blue graphs are separated with curtained distance.

When the measurement of error is assessed by different methods. They are rood mean square error (RMSE) and maximum absolute error (MAX) in different temperatures. The lower the value index at same plot temperature, the accurate the estimation is. The proposed method has RMSE and MMAX indexes as shown in Fig. 19.

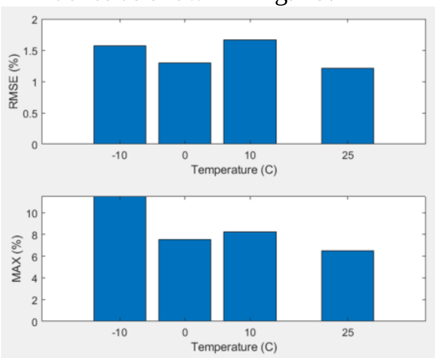

Fig. 19: The RMSE and MAX Indexes of Corny Model

Fig. 19 shows the RMSE index of proposed method is very low. It has range between 0 – 1.5. The plot with lower index is measurement performed at 0 degree C and 25 degree C. Nevertheless, the temperature 10 degree and -10 degree C have the higher RMSE. This nature also happens to maximum absolute error index.

Finally, the proposed method, Corny model is able to estimate accurate HOC of electric vehicle.

V. CONCLUSION

The measurement of SOC and HOC of battery is very important, especially at electric vehicle usage. It determine the long-life and reliable of the battery.

In this paper, SOC and HOC of battery estimation method for lithium-ion batteries based on typical deep learning architecture was proposed. Firstly, the data contains some parameters such as temperature, capacity, voltage, and current of Li-ion battery are labelled. Then, based on those properties, the designing model architecture is performed. The architecture network is very narrow to prevent high cost and over-fitting problem. This Corney model is able to estimate SOC of the Li-ion battery type very accurate. The RMSE and MAX indexes are very low. Thus, the temperature also influence the MRSE and MAX indexes of the Li-Ion battery. This accuracy and lower cost index are the two advantages of proposed method. Besides, the simply designing and can understand by person who no-prior experiences on deep learning programming.

acknowledgment.

DECLARATION STATEMENT

Authors are required to include a declaration of accountability in the article, counting review-type articles, that stipulates the involvement of each author. The level of detail differs; Some subjects yield articles that consist of isolated efforts that are easily voiced in detail, while other areas function as group efforts at all stages. It should be after the conclusion and before the references.

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Ethical Approval and Consent to Participate	This article does not require ethical approval and consent to participate.
Availability of Data and Material/ Data Access Statement	The data is obtain from mendeley dataset as cited in the article.
Authors Contributions	The first author has major contribution in this article, the other four authors have equal participation at minor portion.

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