A Comparative study on state of charge estimation techniques for Lithium-ion Batteries

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***Abstract*— State of Charge (SOC) estimation is significantly important for the optimal utilization and protection of batteries. This paper implements and compares the performance of a neural network (NN) algorithm and Coulomb Counting method for estimating state of charge (SOC) for batteries. This algorithm is applied to a battery management system (BMS) in electric vehicles. Accurate SOC information can avoid over charging and over discharging of battery, and thus increase battery life. Also, control system uses accurate SOC information to make rational decisions to save energy in electric vehicles. The advantage of NN model over Coulomb Counting method is it can be implemented in BMS Hardware where online measurements like current, voltage and temperature are available. The feature of this neural network approach is that it optimizes two important hyper-parameters to achieve a reasonable MAPE error. The performance of the proposed method is tested using two Datasets for city driving conditions. The results reveal that both methods (NN and Coulomb counting) can predict SOC with reasonable error (<6%). However, Coulomb counting outperforms Neural network MAPE for both Datasets.**

Keywords—Electric Vehicles, Battery Management System, Lithium-ion batteries.

I. INTRODUCTION

Lithium ion batteries is adopted because it brings higher terminals voltage and higher power and energy density to its application in electric vehicles. Accurate state estimation model is required as an aid in circuit design process to forecast, display and manage energy consumption of battery. State of charge (SOC) and state of health (SOH) are two critical parameters required for Battery Management System (BMS). SOC is a runtime battery gauge that indicates the remaining charges relative to the rated capacity. SOH is another parameter that shows the performance level of the battery relative to the beginning of life conditions. Difficulties obtaining SOC and SOH is that its needs prediction methods and models to estimate as it deteriorates over its discharging/charging cycles.

There are many types of Model methods and Hybrid methods in literature. Therefore, Model methods are categorized as white-box models (electro-chemical) and grey-box models (equivalent-circuit) and some/many Hybrid methods are categorized as black-box models. The white-box is based on physical characteristics and first principle modelling [1]. The black-box proposes a much simpler structure based on statistical or mapping models [1]. Grey-box model is a combination of both black-box and white-box models [1]. This paper [2] uses electro-chemical model to recast cell into complex high dimensional equations as spatially distributed system. By defining constant parameters of cell and by building constant matrices of state space electro-chemical model, SOC is obtained. A drawback of this approach is substantial effort is required to parameterize the electro-chemical model [3]. Equivalent-circuit models used in literature are internal resistance (Rint), resistor-capacitor (RC), Thevenin and Partnership for new generation of vehicles (PNGV) models. An improved Thevenin model is used in this paper [4] to estimate SOC. The battery equivalent-circuit parameters based SOC method is developed in this paper [5]. This original approach combines data points obtained from enhanced multiple hybrid pulse power characterization (EMHPPC) tests. To improve the accuracy higher degree equivalent circuit model is used [6]. However, this increases the complexity of design. Hybrid methods are also employed in literature [7] for SOC estimation. This method improves accuracy of estimation however this too over complicates the design and/or requires higher complexity of BMS.

This paper investigates feed forward neural network architecture. The neural network is optimized by hyperparameter tuning to estimate SOC. Firstly, the structure of feedforward neural network model for SOC estimation is designed. Secondly, the feedforward model is trained and optimized using by splitting dataset into training and validation set. Finally, the error for validation data is forecasted. In this research, for measuring consistency, two discharging profile datasets is used. The first dataset is the neural network drive cycle set. Neural Network drive cycle consists of combination of portions of US06 and LA92 drive cycles. The second dataset is the UDDS drive cycle. Both datasets (and all three drive cycles) represent typical driving conditions in a city. In this paper, the results for two datasets is evaluated and compared with each other. Finally, the efficacy of the neural network method is compared with the Coulomb Counting method in this paper.

II. SOC ESTIMATION METHODS

Figure 1 illustrates the key SOC estimation methods. The first method for SOC estimation is the Coulomb Counting method. The formula for discretised SOC is given in equation 1.

$$SOC(k) = SOC(k-1) + I(k-1).\ \Delta t/(Q_{rated}) \quad (1)$$

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Where, Q_{rated} is rated capacity (Ah), I is current (A), Δt is change in time (h). Drawback for Coulomb counting method is it requires live time stamped parameters.

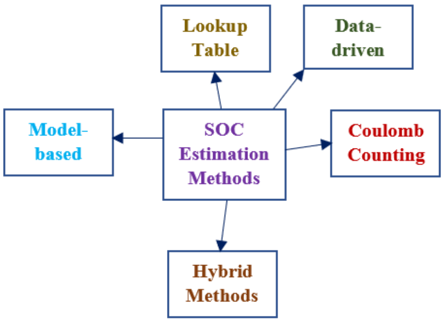

Fig. 1. SOC estimation methods (Adapted from [3])

The look-up table method directly maps relationship between SOC and the external characteristics parameters. The parameters can be open-circuit voltage (OCV) or impedance of battery. The measured parameters can be used to correlate with SOC through the lookup table [3]. The drawback of this method is it is limited to battery in laboratory conditions and not suitable to battery in online battery management system [3].

Four model based estimation methods are applied to estimate the SOC of Li-ion batteries [8]. The first order RC model is utilized to describe the equivalent-circuit behavior of battery. However, this method suffers from problem of relatively large errors [8]. To improve the accuracy higher degree equivalent-circuit model is used. However, this increases the complexity of design. Model based electro-chemical model has been described, in the above section [2]. Electro-chemical model suffers from substantial effort required to parameterize the model. Survey of literature [7, 9] shows hybrid methods used to estimate SOC. However, implementation of hybrid method complicates design and/or complicates the BMS hardware.

The following Data-driven approaches are investigated with drawbacks of each method:

Fuzzy Logic – Fuzzy logic method is a data driven method where the discharge current and temperature is used as fuzzy inputs and (SOC) as fuzzy output using the min-max inference method in fuzzy inference system as is highlighted in this paper [10]. The estimation error is still relatively high, however from knowledge of theory, learning mechanism can be implemented to reduce error.

Support Vector Machines - SVMs are a set of related machine learning methods used to approximate this regression problem to high level of accuracy [11]. The Support Vector machine (SVM) also uses measurement like voltage, current and temperature. SVMs are not very computationally efficient, when using observation of more than one thousand rows in dataset.

Deep Learning Deep neural network predicts the SOC to reasonable accuracy. According to this paper [12] four hidden layers is optimum number of layers after training network.

Feed forward neural network model achieves same ballpark figure error as deep neural networks (Feed forward network: 3%, deep neural network: 3.68% [12, 13]) without its complexity. Cited papers [13, 14] use feedforward model to predict SOC with an established number of hidden neurons. However, proposed research extends to tuning hyperparameters such as learning rate as well as hidden neurons. This paper [15] uses advanced Backtracking Search Algorithm (BSA) to tune hyperparameters. Proposed algorithm uses simpler grid search to perform the same task.

III. COLOUMB COUNTING AND FEEDFORWARD NEURAL NETWORK WITH HYPERPARAMETER TUNING

Battery discharging load profile data is obtained from battery degradation experiment from the Panasonic 18650PF Li-ion - Mendeley Datasets. A reasonable sized data samples is extracted from two datasets representing typical city driving conditions. The Datasets consist of discharge current (I), terminal voltage (U), temperature (T) and state of charge from raw data consisting of large samples of time, voltage, current, temperature and time stamped Amp hour (Ah) capacity. Eq (1) is used to calculate SOC using Coulomb counting method for each Dataset.

The Feedforward Neural network architecture (Figure 2) is employed to forecast test error after training and validation in MATLAB. This architecture has 5 features (Input), hidden neurons, weights, activation functions and 1 dependant variable (Output). The default bias is used. The 5 features are U(k), and T(k) from current sample and U(k-1), I(k-1) and T(k-1) from previous sample. The dependant variable is SOC.

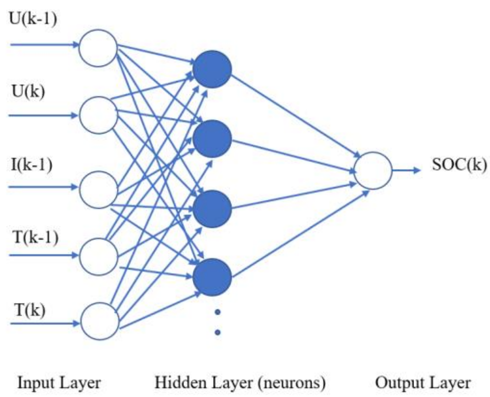

Fig. 2. Proposed Feedforward Neural network (Adapted from [16])

The Flow diagram of neural network algorithm is shown in Figure 3. The neural network main code uses the backpropagation algorithm to adjust random weights, and the goal is to reduce the error until the neural network learns the training data. The forward propagation and back propagation of signals represent this neural network learning process. The hidden activation function used in this architecture is the sigmoid function. Data must be divided in two sets: training and validation. The training is performed to minimize error. And validation is performed to select the optimum number of iterations to avoid overlearning. Validation set is implemented on unseen data. This network algorithm ends up going over the entire training set and completes iteration, batch and epoch. When maximum iterations reached and the requirements of training/validation is met, network generalizes. The idea of learning from some data and applying the gained knowledge on other unseen data is called generalization.

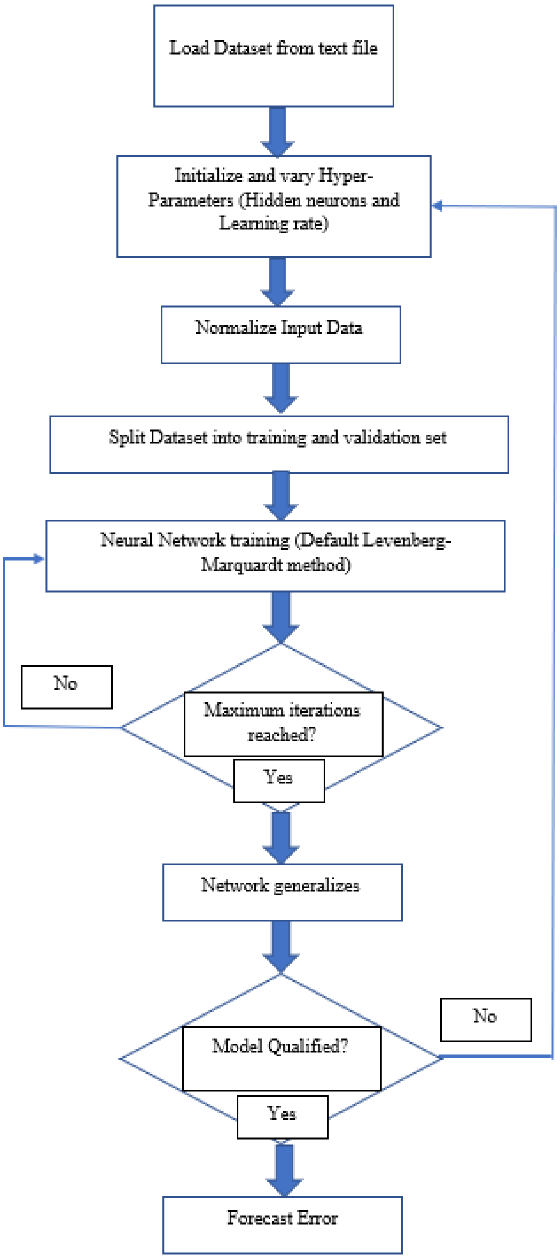

Fig. 3. Flow diagram of Neural Network Algorithm

The hyper-parameter pairs (learning rate and hidden neurons) are varied with two for loops at start of the code until the neural network model is fully qualified. The main body of code is represented by flow chart. Thus, learning is performed in training phase, generalization and forecasting in validation phase.

IV. SIMULATION RESULTS

A "grid search" is used to find the optimal hyper-parameters (learning rate and hidden neurons) that yield the neural network model with best predictive performance after training. The accuracy of prediction is measured in validation phase by two forms of error. Normalised root mean squared error (NRMSE) and Mean absolute percentage error (MAPE) is shown in equation 2 and 3 respectively [17, 18].

$$NRMSE = \sqrt{\frac{1}{n}.\sum_{k=0}^{n}\left(\frac{y-\hat{y}}{y}\right)^2}\ x\ 100\% \qquad (2)$$

$$MAPE = \frac{1}{n}.\sum_{k=0}^{n}\left(\frac{|y-\hat{y}|}{y}\right)\ x\ 100\% \qquad (3)$$

Where,

y is actual output, $\hat{y}$ is predicted output, n is number of samples.

The proposed neural network results of NRMSE and MAPE error of test dataset 1 and 2 is shown in Figure 4, 5, 6 and 7.

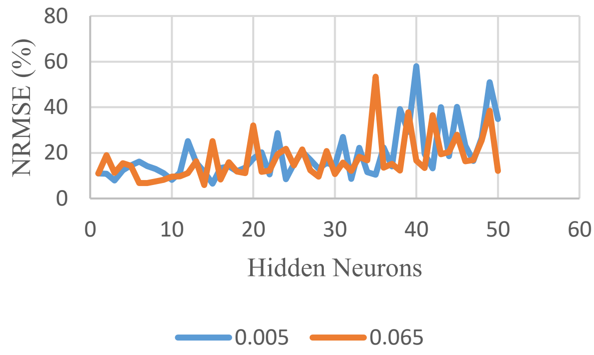

Fig. 4. Dataset 1: NRMSE versus Hidden neurons for Learning rates 0.005 (Blue) and 0.065 (Red)

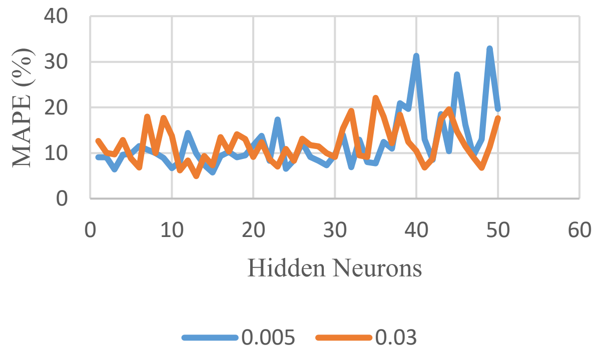

Fig. 5. Dataset 1: MAPE versus Hidden neurons for Learning rates 0.005 (Blue) and 0.03 (Red)

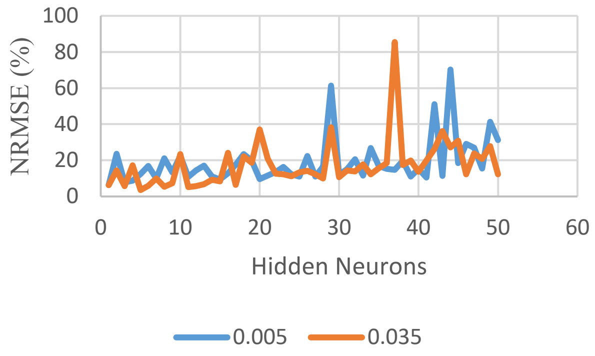

Fig. 6. Dataset 2: NRMSE versus Hidden neurons for Learning rates 0.005 (Blue) and 0.035 (Red)

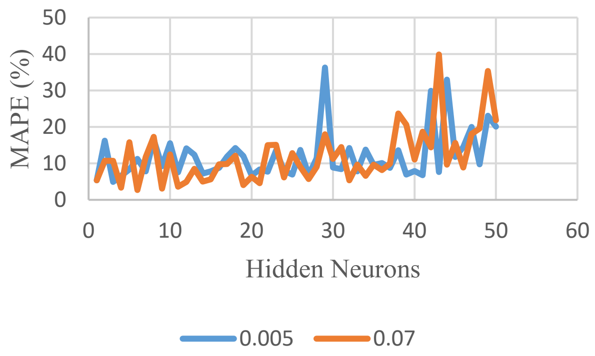

Fig. 7. Dataset 2 MAPE versus Hidden neurons for Learning rates 0.005 (Blue) and 0.07 (Red)

Table I shows comparison of SOC prediction method errors. The degree to what network weights are updated during training is referred as the learning rate. A learning rate that is too large causes the model to converge too quickly to non-optimal value. Whereas a learning rate that is too small causes the program to get stuck and freeze. That's why learning rate of moderate range of 0.005-0.075 is selected for simulation. After hidden neurons, learning rate is the most important hyper-parameter in neural network optimization.

Table I. Comparison of SOC Prediction Methods

SOC Prediction Method	**NRMSE (%)**	**MAPE (%)**
Coulomb Counting method (Dataset 1)	2.75	1.89
Coulomb Counting method (Dataset 2)	1.63	0.78
Neural Network method (Dataset 1)	5.89	4.93
Neural Network method (Dataset 2)	3.55	2.70

Optimum hyper-parameters for NRMSE and MAPE is presented in Table II.

Table II Optimum hyper-parameters for NRMSE and MAPE

	NRMSE		**MAPE**	
Dataset	**Learning Rate**	**Hidden Neurons**	**Learning Rate**	**Hidden Neurons**
1	0.065	14	0.03	13
2	0.035	5	0.07	6

NRMSE gives a relatively high weight to large errors. This means that NRMSE is more suitable when maximum errors are significant. The linear scoring is attributed to MAPE is better indicator at revealing error where minimum error is significant. Thus, NRMSE is eliminated from this investigation because the maximum error is not significant in this nature of research. Both datasets represent typical driving conditions in a city. In this paper, the results for two datasets is evaluated and compared with each other. Coulomb counting outperforms Neural network for both Datasets. Because the optimized MAPE error is reasonably low, typical simulation of predicted neural network SOC tracking the actual SOC is shown in Figure 8. Neural network achieves a reasonable tracking MAPE of 5.95% with non-linear tracking pattern.

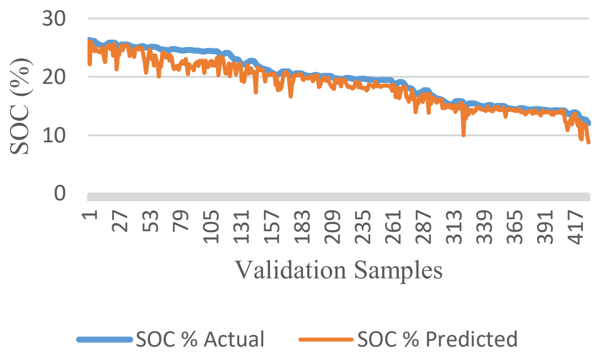

Fig. 8. Typical simulation of predicted neural network SOC (Red) tracking the actual SOC (Blue)

V. CONCLUSION AND SIGNIFICANCE OF RESEARCH

This paper uses feed forward neural network architecture. The neural network is optimized by hyperparameter tuning to estimate SOC. NRMSE is eliminated from this investigation because maximum errors is not significant in this nature of research. Both datasets used in this research represent typical driving conditions in a city. In this paper, the results for two datasets is evaluated and compared with each other. Coulomb counting outperforms Neural network for both Datasets. The measure of consistency is verified by outcome of both Datasets. To contribute to future impact of this research, proposed neural network method can be tested on Hardware-In-Loop (HIL) platform by applying MicoLabBox hardware controller. The HIL results can be used to verify the effectiveness of the proposed design in real-time systems with reasonable error.

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