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Particle Swarm Optimized Back Propagation Neural Network for State of Health Estimation of Lithium-ion Battery

Afida Ayob[a*], Shaheer Ansari[a] , Aini Hussain[a] , Mohamad Hanif Md Saad[b] & M. S. Hossain Lipu[c]

[a]*Department of Electrical Electronics and System Engineering, Universiti Kebangsaan Malaysia, Bangi, 43600, Selangor, Malaysia*

[b]*Department of Mechanical and Manufacturing Engineering, Universiti Kebangsaan Malaysia, Bangi, 43600, Selangor, Malaysia*

[c]*Department of Electrical and Electronic Engineering, Green University of Bangladesh, Dhaka, 1207, Bangladesh*

[*]*Corresponding author: afida.ayob@ukm.edu.my*

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ABSTRACT

The assessment and monitoring of battery health is very crucial for the maintenance and safety of battery-powered applications such as Electric vehicles (EVs). To conduct appropriate battery operation in EVs, the battery capacity should be estimated accurately. In this regard, the State of health (SOH) estimation is conducted for evaluating the battery aging status. This work proposes a hybrid backpropagation neural network (BPNN) and particle swarm optimization (PSO) technique for SOH estimation. A multi-feature input data framework is constructed with 31-dimensional features for the model training by using 4 battery datasets from NASA i.e. B5, B6, B7 and B18. The acquisition of the data samples has been performed with a systematic sampling technique. The presented work is conducted with a training testing ratio of 70:30 and validated with the MIT Stanford battery dataset. The experimental outcomes demonstrated high SOH estimation accuracy compared with the conventional BPNN model. In the case of battery B5, it was observed that RMSE, MSE and MAPE for the BPNN-PSO model are 0.6791, 0.0046, 0.3203 compared with the conventional BPNN model i.e. 0.8796, 0.0077, 0.4881 respectively. Furthermore, the significance of capacity regeneration in B7 and B18 results in high-performance metrics compared with other battery datasets. The research conducted would be beneficial to estimate the battery status regarding battery health i.e. SOH accurately in Battery System Management (BMS) based EV application.

Keywords: Lithium-ion battery; state of health; back propagation neural network; particle swarm optimization; electric vehicles

INTRODUCTION

Presently, the increased exploitation of fossil-based automotive application has triggered several concerns worldwide consisting of increased global temperature, global warming and health hazards respectively (Ansari et al. 2021a). To overcome these concerns, the application of Electric vehicles (EVs) has been greatly researched worldwide due to its various benefits such as reliability, simplicity, comfort, and improved efficiency (Tu et al. 2020)the upstream emissions from electricity generation cannot be ignored. In this study, a heuristic algorithm was designed to optimize regional electric vehicle charging schedules with the objective of minimizing greenhouse gas emissions from electricity generation. Our study is set in the Greater Toronto and Hamilton Area. Emissions from the charging demand are estimated by a marginal emission model calibrated with historical data for Ontario electricity generation. The results illustrate that the optimized plan can reduce greenhouse gas emissions by around 97% compared to a base case, where vehicles are powered by gasoline. Four other charging scenarios (home, out of home, after trip, and after 3am. Furthermore, the application of lithium-ion battery system in EV application has been one of the reasons for its substantial progress. The lithium-ion battery system is utilized due to its various benefits such as being lightweight, high energy density, and long-span for charging and discharging (He et al. 2011). However, the timely maintenance and examination of lithium-ion battery with regard to State of health (SOH) should be conducted. This is due to the continuous battery degradation which occurs during charging and discharging operations. The battery is intended for replacement due to safety issues once the 70% or 80% of its initial capacity has been used. The battery degradation may result in a substantial loss in terms of economic loss and system loss. Therefore, it becomes crucial to estimate the SOH of lithium-ion battery by developing intelligent models and frameworks.

Currently, various SOH estimation techniques have been developed which are categorized as model-based and data-driven based respectively. The model-based techniques comprise of electrochemical model and equivalent circuit model (ECM) which is based on developing a mathematical model and analyzing the internal battery features. Goebel et al. (2008) developed a SOH estimation technique by considering the negative linear relationship between capacity and internal impedance. The internal impedance was calculated by utilizing the electrochemical impedance spectrometry (EIS) method. Daigle and Kulkarni (2016) constructed a capacity estimation model. The capacity estimation was conducted by utilizing battery parameters such as internal impedance and diffusion constant respectively. The model-based methods deliver sufficient information for battery dynamics but suffers from computational complexity to solve partial differential equations.

Whereas, the data-driven model are based on estimating SOH by evaluating the historical data and do not requires to solve complex mathematical equations. Primarily, methods such as Particle filter (PF), Kalman filter (KF) etc. have been employed for SOH estimation of lithium-ion battery (Plett 2004; Guha and Patra 2017)power fade, capacity fade, and instantaneous available power. The estimation mechanism must adapt to changing cell characteristics as cells age and therefore provide accurate estimates over the lifetime of the pack. In a series of three papers, we propose methods, based on extended Kalman filtering (EKF. Additionally, other data-driven methods such as Support vector machine (SVM), Artificial neural network and Deep learning (DL) techniques have been introduced to estimation the SOH of the battery (You et al. 2017; Patil et al. 2015; Ansari et al. 2021b; Qu et al. 2019) diagnosing battery states, such as state of health (SOH. Feng et al. (2019)which reflects the intrinsic characteristics of the Li-ion battery, are determined from the charging data of fresh cells. Furthermore, the coefficients of the SVMs for cells at different SOH are identified once the support vectors are determined. The algorithm functions by comparing partial charging curves with the stored SVMs. Similarity factor is defined after comparison to quantify the SOH of the data under evaluation. The operation of the algorithm only requires partial charging curves, e.g., 15 min charging curves, making fast on-board diagnosis of battery SOH into reality. The partial charging curves can be intercepted from a wide range of voltage section, thereby relieving the pain that there is little chance that the driver charges the battery pack from a predefined state-of-charge. Train, validation, and test are conducted for two commercial Li-ion batteries with Li(NiCoMn proposed a SVM based SOH estimation technique by utilizing the partial charging segment. The proposed experiment was conducted under the constant current charging for calibrating the battery capacity. Ansari et al. (2021) developed a Cascaded forward neural network (CFNN) for to estimate capacity and remaining useful life (RUL) of the battery. In recent times, You et al. (2017)diagnosing battery states, such as state of health (SOH presented a capacity estimation model based on battery voltage and current. The discussed data-driven methods delivered satisfactory outcomes based on capacity estimation, however, appropriate volume of dataset is necessary for the model to train effectively. Moreover, the model hyperparameter adjustment requires significant human intervention and time loss depicting their drawbacks.

Therefore, in this paper, Particle swarm optimization (PSO) technique based Back propagation neural network (BPNN) is utilized for capacity estimation where suitable battery parameters such as temperature, capacity, voltage and current with appropriate volume of dataset is considered for effective model training. Furthermore, the PSO technique is employed for suitably selecting the BPNN model hyperparameters for satisfactory outcomes.

DATA EXTRACTION TECHNIQUE

The proposed PSO-BPNN model has been constructed by utilizing the NASA battery dataset acquired from NASA prognostics Centre of Excellence Data Repository (“Prognostics Center of Excellence - Data Repository” n.d.). The database consists of 4 battery datasets namely B5, B6, B7 and B18 respectively. Each battery dataset consists of two operating profiles namely charging and discharging. The acquisition of various battery parameters such as voltage, current, capacity etc. is acquired under the environment of Constant Current Constant Voltage (CCCV) principle. The capacity profile of the acquired battery datasets has been shown in Figure 1. The operating profiles of the battery datasets i.e. charging and discharging was analyzed and charging profile battery parameters i.e.

temperature, voltage and current were selected along with discharge capacity data. The acquisition of battery parameters was considered from charging profile as it is based on set pre-set guidelines while the process of battery discharging is random.

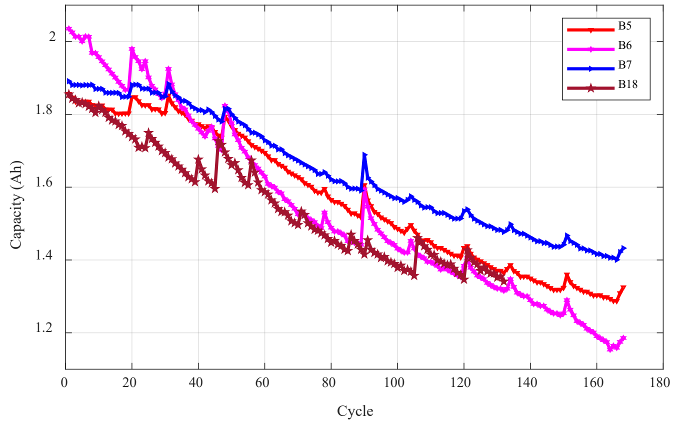

FIGURE 1. Capacity degradation curve for B5, B6, B7 and B18

PROPOSED METHODOLOGY

Primarily, the proposed method for SOH estimation of lithium-ion battery has been developed by considering the BPNN model and PSO technique. The data extraction to develop the data framework for the PSO-BPNN model training has been conducted with systematic sampling technique.

At first, BPNN model is constructed which consists of 3 layers namely input layer, hidden layer and output layer. The input layer consists of 4 neurons with input as temperature, capacity, voltage and current. The hidden layer consists of suitable hidden neurons which is selected with PSO technique. The estimated capacity is achieved from the output layer with 1 neuron. The basic structure of the BPNN model for the proposed SOH estimation technique has been presented in Figure 2.

Secondly, the PSO technique is employed to select the suitable BPNN model hyperparameters such as hidden layer neurons and learning rate. The PSO technique was developed by Eberhart and Kennedy in 1995 and is usually applied for solving the non-linear function (Kennedy and Eberhart 1995). The construction of the PSO technique is concentrated on swarm behavior such as bird flocking and schooling in nature. The objective function of PSO technique is achieved by swarm population based on local best and global best. The PSO technique selects the best possible outcomes based on the swarm's optimal position and velocity through the movement in the search space. The swarm position and their respective velocity to achieve the optimal results is calculated by the following equations:

$$V^{k+1} = W * V^{k} + C_1 * r_1^{k} (pbest^{k} - x^{k}) + C_2 * r_2^{k} (gbest^{k} - x^{k}) \tag{1}$$

$$x^{k+1} = x^{k} + V^{k+1} \tag{2}$$

where, V^{k+1} and V^{k} relates with updated and current velocity, the learning factor is c_1, c_2. W is weight factor, r_1^k and r_2^k is the variables ranging between 0 to 1. X^k and X^{k+1} depicts the present and updated position. The objective function employed to optimize the hidden layer and learning rate was mean square error (MSE).

Lastly, the appropriate acquisition of the data samples from various battery parameters such as temperature, voltage and current is achieved using the systematic sampling technique. The systematic sampling technique was utilized to obtain 10 samples of temperature, voltage and current from each charging cycle. The data samples obtained from the systematic sampling is arranged in the appropriate format to develop the proposed data framework for model training.

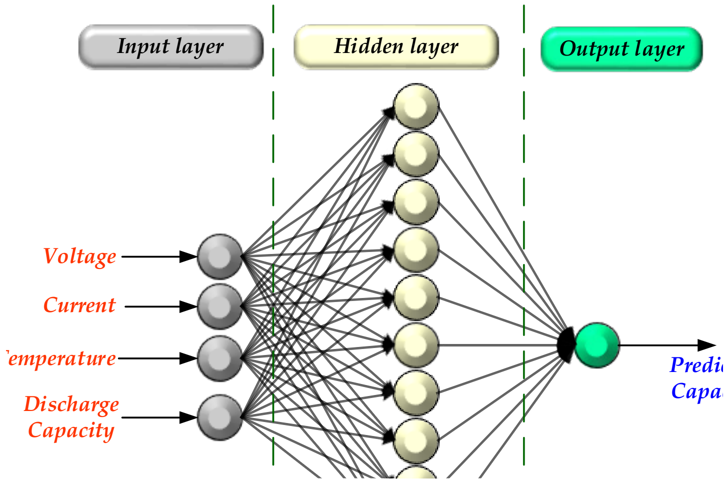

FIGURE 2. BPNN model for the proposed SOH estimation technique

RESULTS AND DISCUSSION

In this proposed work, a PSO optimized BPNN model is proposed for SOH estimation of lithium-ion battery. The battery data has been acquired from NASA Prognostics Centre of Excellence Data Repository and MIT Stanford. Four battery datasets from NASA and MIT have been selected for the experimental work. The NASA battery datasets includes B5, B6, B7 and B18 battery datasets and MIT Stanford dataset includes c33, c34, c35 and c36 battery datasets. Additionally, various battery parameters such as temperature, capacity, voltage and current were extracted by systematic sampling technique to develop suitable data framework for model training. The training of the model was performed by splitting the data in 70:30 ratios i.e. 70% for training and 30% for testing. The PSO-BPNN model has been validated against conventional BPNN model by various performance metrics such as RMSE, MSE and MAPE. At first, the proposed method is evaluated by considering the NASA battery dataset. The performance metrics for different battery dataset has been presented in Table 1. It is observed that PSO optimized BPNN model outperforms conventional BPNN model. It is evaluated that proposed model accuracy was highest with battery B5 whereas least with battery B7 and B18. This is due to low training cycles and capacity regeneration phenomena in battery B18. The RMSE, MSE and MAPE for B5 is 0.6791, 0.0046, 0.3203 while it is 2.1357, 0.0456, 0.8891 for B18 respectively.

Additionally, compared with BPNN model, the proposed PSO-BPNN delivers more accurate outcomes. The capacity estimation curve for NASA battery datasets has been presented in Figure 3. It is seen that capacity estimation curve depicts linear characteristics with battery B5 whereas it shown significant non-linearity with battery B7 and B18. Figure 4 depicts the SOH estimation error for various battery datasets depicting the error shown by BPNN model and PSO-BPNN model. From the above discussion, it is concluded that highest accuracy for PSO-BPNN model was shown with battery B5 while the lowest capacity estimation accuracy was depicted in battery B7 and B18 as shown in Figure 5.

TABLE 1. SOH estimation outcomes for NASA batteries

Battery	Model	Performance Metrics		
		RMSE	MSE	MAPE
B5	BPNN	0.8796	0.0077	0.4881
	BPNN-PSO	0.6791	0.0046	0.3203
B6	BPNN	1.5147	0.0229	0.6792
	BPNN-PSO	1.6100	0.0259	0.7596
B7	BPNN	2.3890	0.0571	1.2850
	BPNN-PSO	1.8256	0.0333	0.7776
B18	BPNN	2.6999	0.0729	1.3877
	BPNN-PSO	2.1357	0.0456	0.8891

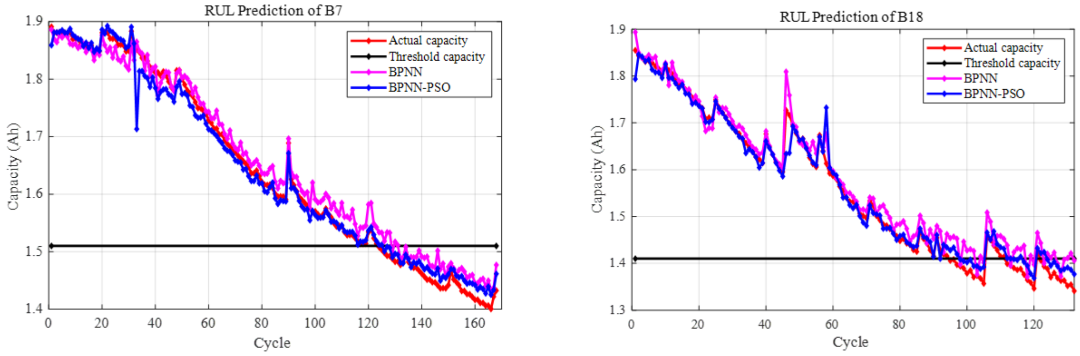

FIGURE 3. Capacity estimation curve for B5, B6, B7 and B18

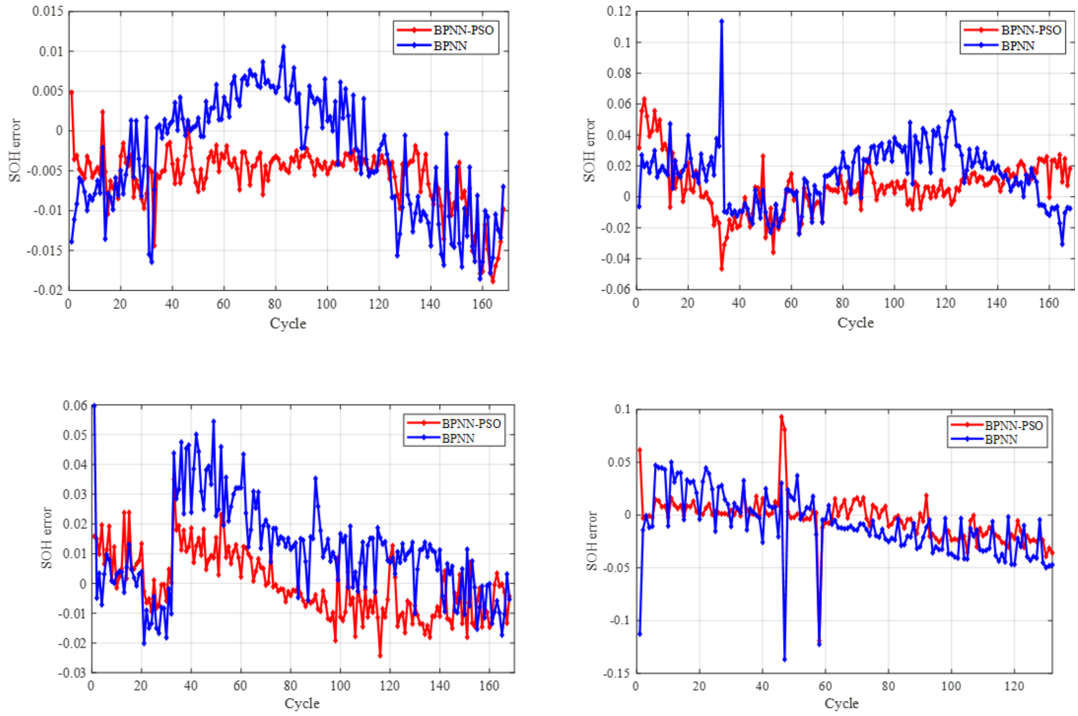

FIGURE 4. SOH estimation error curve for B5, B6, B7 and B18

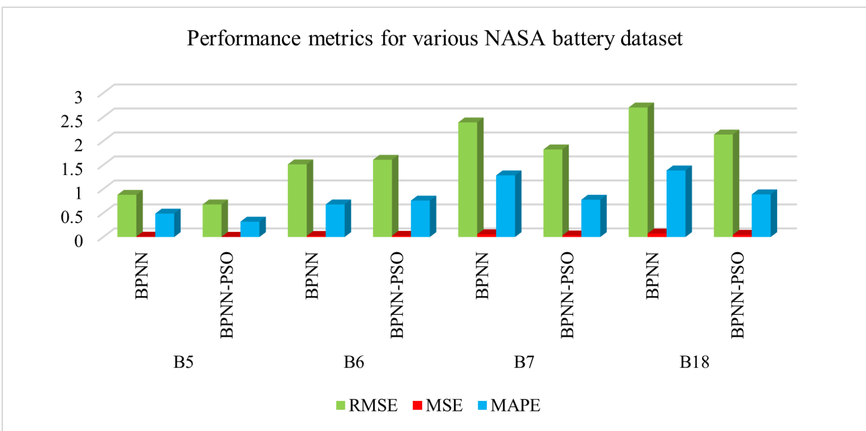

FIGURE 5. Performance metrics for B5, B6, B7 and B18

The proposed PSO-BPNN model was validated with MIT Stanford battery dataset consisting of four battery dataset with similar features (Severson et al. 2019). The PSO-BPNN model outperforms the conventional BPNN model in all case of battery datasets. Furthermore, the proposed model demonstrated highest estimation accuracy with C33 dataset while the lowest estimation accuracy was shown with C36 battery dataset as shown in Table 2. In case of C33, the performance metrics such as RMSE, MSE and MAPE with proposed PSO-BPNN model was 0.1597, 2.5494*10-4, 0.0416 compared with BPNN model which was 0.1740, 3.0275*10-4, 0.0888. The capacity estimation curve for different MIT battery datasets has been shown in Figure 6. It is seen that due to the phenomena of capacity regeneration in C36, the estimated capacity curve is highly disoriented compared with other battery capacity curves.

TABLE 2. SOH estimation outcomes for MIT batteries

Battery	Model	Performance Metrics		
		RMSE	MSE	MAPE
C33	BPNN	0.1740	3.02*10-4	0.0888
	BPNN-PSO	0.1597	2.54*10-4	0.0416
C34	BPNN	0.1982	3.92*10-4	0.1323
	BPNN-PSO	0.0711	5.04*10-4	0.0549
C35	BPNN	0.5254	0.0028	0.2459
	BPNN-PSO	0.9087	0.0083	0.1459
C36	BPNN	2.8360	0.0804	1.9152
	BPNN-PSO	0.7381	0.0054	0.4896

The SOH estimation error for C33, C34, C35 and C36 has been depicted in Figure 7. The PSO-BPNN model attains high accuracy in all cases compared with BPNN model.

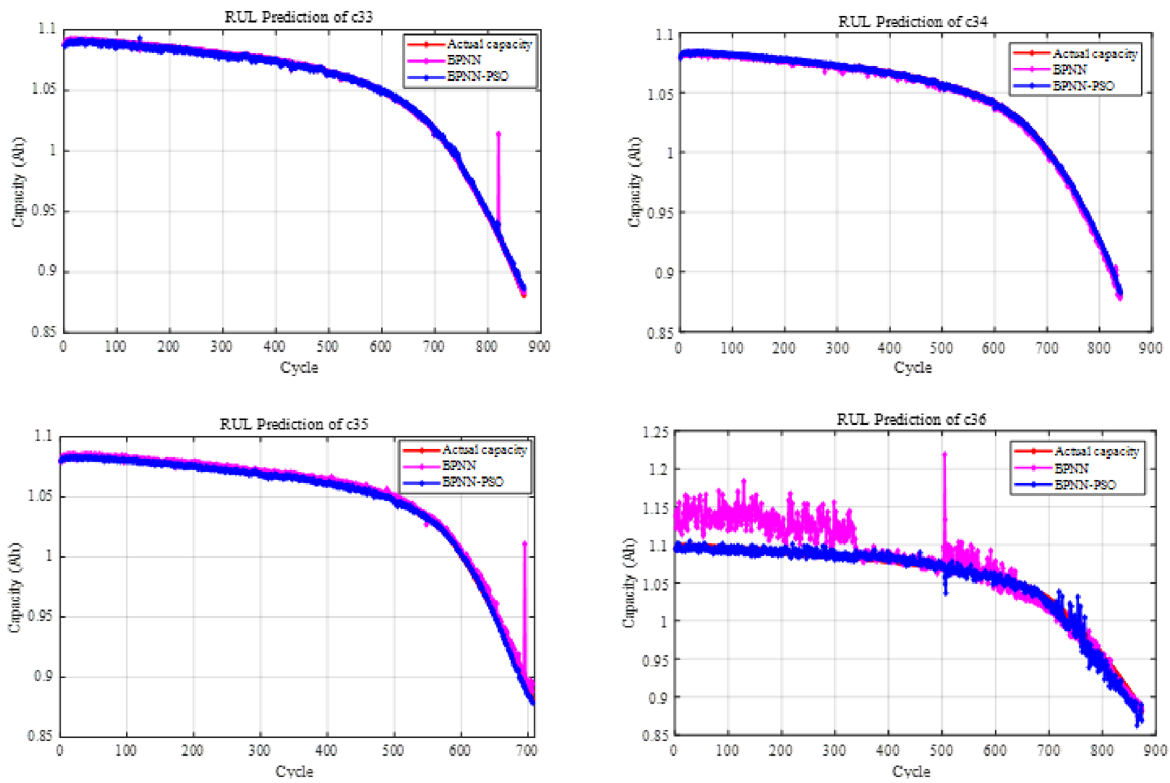

FIGURE 6. Capacity estimation curve for C33, C34, C35 and C36

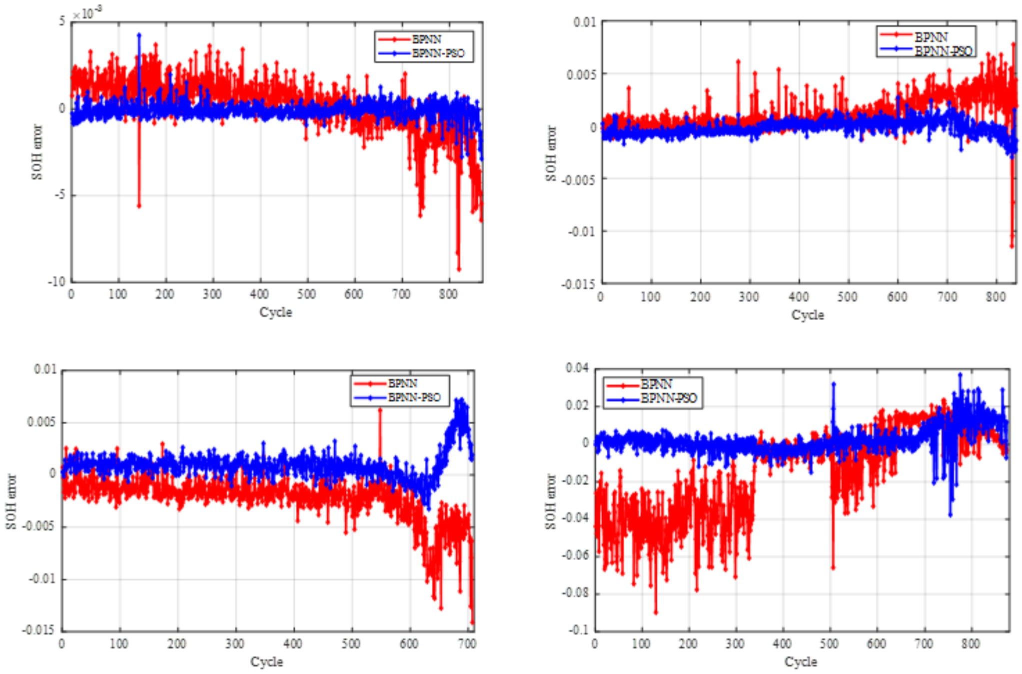

FIGURE 7. SOH estimation error curve for C33, C34, C35 and C36

From the above discussion and results, it is concluded that PSO-BPNN based model performs with high accuracy and estimates capacity degradation of various battery datasets accurately. Figure 8 presents the bar graph of various performance metrics to depict the performance of BPNN and proposed PSO-BPNN model.

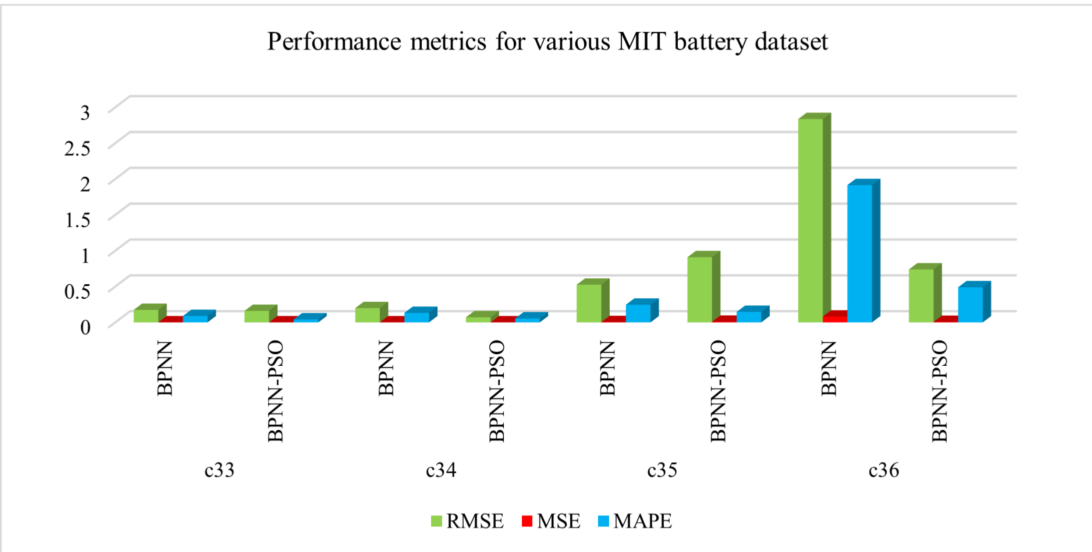

FIGURE 8. Performance metrics for c33, c34, c35 and c36

CONCLUSION

In this work, a PSO optimized BPNN model is proposed for SOH estimation of lithium-ion battery. The proposed model was built with NASA battery datasets consisting of four datasets. In addition, the battery parameters such as temperature, capacity, voltage and current profiles were extracted by systematic sampling technique to develop a data framework for model training. The proposed PSO-

BPNN model was validated with the conventional BPNN model and MIT Stanford battery dataset. It is studied that performance metrics such as RMSE, MSE and MAPE attained with the proposed model for battery B5 were 0.6791, 0.0046, 0.3203 as compared to 0.8796, 0.0077, 0.4881 for the BPNN model. Furthermore, due to the phenomena of capacity regeneration in B18 and B7, the performance error was higher compared with other battery datasets. Additionally, the validation of the proposed PSO-BPNN model delivered significant outcomes. In the future, the proposed model will be validated with other meta-heuristic optimization techniques.

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DECLARATION OF COMPETING INTEREST

None.

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