Multi-Channel Profile Based Artificial Neural Network Approach for Remaining Useful Life Prediction of Electric Vehicle Lithium-Ion Batteries

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Abstract: Remaining useful life (RUL) is a crucial assessment indicator to evaluate battery efficiency, robustness, and accuracy by determining battery failure occurrence in electric vehicle (EV) applications. RUL prediction is necessary for timely maintenance and replacement of the battery in EVs. This paper proposes an artificial neural network (ANN) technique to predict the RUL of lithium-ion batteries under various training datasets. A multi-channel input (MCI) profile is implemented and compared with single-channel input (SCI) or single input (SI) with diverse datasets. A NASA battery dataset is utilized and systematic sampling is implemented to extract 10 sample values of voltage, current, and temperature at equal intervals from each charging cycle to reconstitute the input training profile. The experimental results demonstrate that MCI profile-based RUL prediction is highly accurate compared to SCI profile under diverse datasets. It is reported that RMSE for the proposed MCI profile-based ANN technique is 0.0819 compared to 0.5130 with SCI profile for the B0005 battery dataset. Moreover, RMSE is higher when the proposed model is trained with two datasets and one dataset, respectively. Additionally, the importance of capacity regeneration phenomena in batteries B0006 and B0018 to predict battery RUL is investigated. The results demonstrate that RMSE for the testing battery dataset B0005 is 3.7092, 3.9373 when trained with B0006, B0018, respectively, while it is 3.3678 when trained with B0007 due to the effect of capacity regeneration in B0006 and B0018 battery datasets.

Keywords: lithium-ion battery; remaining useful life; electric vehicles; backpropagation neural network; multi-channel input (MCI) profile

1. Introduction

The increased number of fossil-based vehicles has significantly triggered global temperature rise, environmental pollution, and health hazards [1]. To address these issues, electric vehicles (EVs) have been extensively exploited among researchers and automobile engineers due to their reliability, simplicity, comfort, and improved efficiency [2]. In addition, EVs offer several potential benefits, such as improved energy storage management, increased usage of renewable power, and lower dependence on fossil-fuel-based energy generations. Moreover, the successful implementation of EV technology is important towards achieving United Nations Sustainable Development Goals (UN SDGs) by 2030 [3]. In this regard, there has been substantial progress in hybrid EVs due to their advanced battery and propulsion systems [4]. The application of advanced battery technology in EVs and hybrid EVs with regard to low or zero emissions permits the automobile industries to develop an advanced battery technology compared to conventional engines based on
fossil fuels [5,6]. Among the various energy sources, lithium-ion batteries play a major role in providing storage as well as energy in the automotive industry due to their various benefits such as being lightweight, high energy density, and long-span for charging and discharging [7,8]. Lithium-ion batteries have also found applications in various other fields such as energy storage, electrical power system, telecommunication, and aerospace [9–12]. In continuation with Industrial Revolution 4.0, vast research is currently undertaken by several industrialists and researchers for optimizing the capabilities of systems while reducing their costs. Additionally, it is worth noting that maintenance expenses typically amount to more than one-third of total operating costs [13]. With regard to the efficient and robust performance of EVs, the state of health of the battery needs to be carefully examined regularly. This is because the battery is subjected to degradation after some time owing to several physical and chemical changes inside the battery which occur due to regular battery operations. The degradation of battery life could result in major breakdown, economic loss, and safety issues [14,15]. Therefore, it is important to predict the RUL of the battery and this is an area that is currently receiving huge attention [16,17]. Additionally, RUL prediction is necessary to predict the battery lifetime towards achieving safe and reliable operation of EVs. As the battery undergoes charging and discharging, it begins to degrade. When the capacity of the battery remains at 70% or 80% of the initial capacity, it is recommended to replace the battery for safety issues [18]. Therefore, the development of an intelligent framework for predicting the RUL of lithium-ion batteries is crucial for the safe operations of EVs. In recent times, several methods have been proposed in estimating the RUL of the battery consisting of experience-based, physics (model) based, and data-driven methods [19–21].

Specifically, experience-based methods are applied for less complex systems and predict the RUL of the battery by utilizing stochastic deterioration distribution. Experience-based models require expert knowledge and engineering experience to predict the RUL of the battery. The experience obtained by solving the previous problem is applied in solving similar problems. These models heavily depend on a set of rules for the system from domain experts. These models are also incapable of real-time monitoring [22]. On the other hand, the physics-based model predicts the RUL of batteries by building a mathematical description of the battery degradation process. The behavior of the system is significantly characterized by utilizing physics or the first principles [23]. However, physics-based models are not suitable for complex systems due to the lack of understanding of battery failure modes.

On the other hand, data-driven methods depend solely on historical data consisting of current, voltage, capacitance, temperature, impedance, etc., for the RUL prediction compared to the other models discussed above. This method predicts/extrapolates the degradation of the battery parameters to calculate the RUL and does not require explicit mathematical models or internal change/mechanism of the battery degradation [16]. Data-driven methods are more accurate, faster, and less complex. Earlier works on data-driven methods utilize conventional techniques to predict the RUL of batteries. Zhou and Huang [24] presented an Ensemble Empirical Mode Decomposition (EEMD) and Auto-Regressive Integrated Moving Average (ARIMA) based method for the prediction of the battery RUL. In this method, EEMD is used initially to decompose the data into multiple components and then ARIMA is utilized for prediction. The results are merged to estimate the final prediction of RUL. Although the RUL prediction in the proposed method is satisfactory, the probability density function (PDF) with ARIMA is unobtainable. In addition, Zhang et al. [25] designed a method based on Box-Cox Transformation (BCT) and Monte Carlo (MC) simulation for the RUL prediction of the battery. A linear model was developed by BCT to predict RUL and then, the RUL prediction uncertainties were generated using the MC simulation. This developed method can perform offline data training efficiently but sophisticated modeling ability for the complex nonlinear system is absent.
Additionally, kernel-based methods such as Support Vector Machine (SVM) and Relevance Vector Machine (RVM) have also been implemented by some researchers. Nuhic et al. [26] proposed a combined SVM and machine learning method to predict the state of health (SOH) and RUL of lithium-ion batteries. However, SVM has some limitations such as difficulty to estimate loss function and penalty factor. Qin et al. [27] presented the RVM based method for the prediction of SOH and RUL of lithium-ion batteries. RVM is applied to compute the relationship between monitoring parameters and capacity data. In comparison with SVM, RVM possess high efficiency and low complexity.

Currently, artificial neural network (ANN) based methods are quite popular among researchers due to their high computational speed, low complexity, and high efficiency. Wu et al. [28] developed a feed-forward neural network (FFNN) with importance sampling for predicting battery RUL. The author analyzed battery terminal voltage curves under different cycle numbers during the charging process for predicting RUL. Shaheer et al. [29] developed a cascaded forward neural network for RUL prediction under different input profiles. A comparative study was conducted to evaluate the performance of the proposed algorithm with different charging profiles. In recent work, Malek and Marciniak [30] developed a recurrent neural network (RNN) based AI technique for predicting the performance of EVs. The presented ANN techniques are simpler but lacked suitable hyperparameter adjustment resulting in a high error. Even though these mentioned works delivered satisfactory results, a suitable volume of critical data is required to train the network efficiently. Additionally, the use of various parameters from the operating profile of the lithium-ion batteries was not taken into consideration due to the lack of training capability of the algorithms. Hence, it is important to study critical parameters of the operating profiles and extract key samples for training the proposed network towards obtaining better RUL prediction results.

Currently, most of the work on RUL prediction of lithium-ion batteries is based on single input (SI) or single-channel input (SCI) profile [31–33]. SI refers to the single input for training the network such as voltage or capacity whereas SCI involves the inclusion of one battery dataset for training purposes. The utilization of the SI or SCI profiles results in high error metrics due to the lack of data dimensionality required to train the network. Therefore, the development of an MCI profile with several batteries and diverse datasets to train the network efficiently towards delivering satisfactory results is essential.

In this paper, the ANN-based RUL framework is established to predict RUL using diverse lithium-ion battery datasets. The MCI profile-based RUL prediction accuracy is analyzed and compared with the SCI profile. The training of the proposed MCI based ANN technique is conducted under various combinations of battery datasets. The contributions of this paper are highlighted below,

- Unlike work-related to Single Channel Input (SCI) profile or One-to-One input profile consisting of a single input [34,35], an improved back propagation neural network (BPNN) framework based on MCI profile for RUL prediction under various combinations of datasets is presented.
- The proposed method considers input parameters from the charging profiles such as voltage, current, and temperature along with discharge capacity degradation profile.
- In addition, the method employs systematic sampling to obtain critical sample values of input parameters from each charging cycle at equal intervals. Due to the inclusion of systematic sampling, it is easy to reconstitute or redesign the prediction curve while training the algorithm.
- The novelty of the proposed work lies in the development of an intelligent framework for RUL prediction of lithium-ion batteries as well as training the algorithm with various dataset combinations provided by NASA. The performance of the system is evaluated using various statistical error terms. The effectiveness of the presented algorithm is verified by training the model with various dataset combinations.

The rest of the paper is as follows: Section 2 describes the acquisition of battery data and the importance of capacity regeneration. Section 3 presents the methodology for RUL
prediction. Section 4 presents the proposed research framework of the MCI profile-based BPNN algorithm. Section 5 covers experimental results followed by the conclusion in Section 6.

2. Battery Data Preparation

The preparation of battery data was performed using the NASA Prognostics Centre of Excellence Data Repository dataset. Several important battery operating profile parameters such as voltage, current, temperature, and capacity were considered when preparing the dataset to train the proposed algorithm.

2.1. Lithium-Ion Battery Dataset

Battery data by NASA Prognostics Centre of Excellence Data Repository [36] were used and these datasets consist of four lithium-ion batteries (B0005, B0006, B0007, and B0018) that run through three different operational profiles, i.e., charging, discharging, and rest period, at room temperature. The experiments consist of applying the repeated charging and discharging cycles to commercially available 18650 lithium-ion cells for achieving accelerated aging. Batteries were charged by the constant current constant voltage (CCCV) principle at a constant current of 1.5 A until the voltage reached the cell’s upper voltage limit of 4.2 V, then constant voltage was applied until the current dropped to 20 mA. The battery discharging was carried out at the constant current of 2 A until the cell voltage fell to 2.7, 2.5, 2.2, and 2.5 V for all four batteries. The results are presented in Table 1. A capacity degradation curve for various batteries is shown in Figure 1. The experiments continued until the batteries reached a 30% reduction of the rated capacity.

| Battery No. | Charging | Discharging | Operating Condition |
|-------------|----------|-------------|---------------------|
|             | Constant Current (A) | Upper Voltage Limit (V) | Cut off Current (mA) | Constant Current (A) | Cut off Voltage (V) | Initial Capacity (Ah) | Capacity Retention |
| B0005       | 1.5      | 4.2         | 20                  | 2                   | 2.7                | 1.86                 | 70.5 |
| B0006       | 1.5      | 4.2         | 20                  | 2                   | 2.5                | 2.04                 | 57.7 |
| B0007       | 1.5      | 4.2         | 20                  | 2                   | 2.2                | 1.89                 | 75.2 |
| B0018       | 1.5      | 4.2         | 20                  | 2                   | 2.5                | 1.86                 | 73.0 |

Table 1. Specification of NASA batteries under various charging and discharging profiles [37].

![Capacity degradation curve](image)

Figure 1. Capacity degradation curve of various batteries [38].
2.2. Data Extraction from the Charging Profile

During the charging and discharging process of the lithium-ion battery, Li\(^{+}\) ion charges are scattered irregularly across the battery surface particles. The larger the unevenness, the more battery particles are influenced and hence the life of the battery becomes shorter. The data needs to be characterized during the charging as well as discharging processes. The variation of the current is rapid in discharging and hence it becomes difficult to obtain internal parameters. On the contrary, electrical parameters can be easily obtained in the charging process as it is based on preset protocols. Hence for this proposed method, battery parameters were leveraged from the charging profile. From Figure 2, it is found that the aged battery (with more charge–discharge cycles) reaches the voltage mark of 4.2 V much earlier compared to new batteries. In addition, the value of current drops quicker in aged batteries than in fresh ones. Lastly, the aged battery reaches the maximum temperature at a faster rate in comparison to a fresh battery.

Figure 2. Battery parameters during the charging process: (a) voltage; (b) current; (c) temperature [39].

2.3. Importance of Capacity Regeneration Phenomena

The phenomena of capacity regeneration are observed during the rest time between charging and discharging processes. It is realized that lithium-ion moves from the negative electrode to the positive electrode during discharging to generate electricity and vice versa. During the movement of lithium ions, the capacity of the battery lowers due to the occurrence of a secondary reaction on the electrode surface and hence reduces battery performance. Furthermore, it is seen that when the battery rests in between charging and
discharging processes, a residual reaction occurs between the active material and relaxation of gradient produced leading to an increase in the capacity of the battery. Hence, the phenomena of capacity regeneration can alter the capacity degradation and hence RUL of batteries. Therefore, it is important to consider the capacity degradation curve as an important Health Indicator (HI) for predicting the RUL of the battery.

3. RUL Prediction Algorithm Based on BPNN with MCI Profile

The following section presents the proposed methodology for the RUL prediction of lithium-ion batteries. Primarily, the proposed framework consists of a neural network model for predicting RUL. Secondly, feature selection consisting of a systematic sampling technique is elaborated and lastly, the execution processes for the MCI profile-based algorithm are presented.

3.1. Back Propagation Neural Network Algorithm

BPNN algorithm with multi-layer perceptron is one of the most extensively utilized ANN models in the field of forecasting and prediction. In addition, BPNN is utilized for supervising in solving nonlinear problems. The operation of an artificial neuron includes a nonlinear element with an activation function and two parameters including the weight (W) and bias (b). The optimum weight and bias in BPNN are achieved by utilizing the Levenberg Marquardt Algorithm (LMA). In the proposed method, the framework of BPNN consists of three layers, one input layer consisting of 4 neurons with 10 samples of voltage, current, and temperature and a single discharge capacity from each cycle. In addition, the model consists of a single hidden layer with 10 neurons each and lastly an output layer for characterizing the output variable, i.e., capacity, as shown in Figure 3.

![BPNN Structure for RUL Prediction of Lithium-Ion Batteries](image)

Figure 3. BPNN structure for RUL prediction of lithium-ion batteries [40].

The hyperparameters of the BPNN were selected by validating with various combinations to obtain the minimum performance function ‘mse’. The hyperparameter validation includes learning rate, number of iterations, number of epochs, and hidden neurons. It is realized that the minimum value of mse is reported when the number of iterations is 20 with 10 hidden neurons, 1000 epochs, and 0.005 learning rate by performing the hit and trial
method. Training of the BPNN model is divided into various steps as presented in Figure 4. A comprehensive explanation of each step is presented in the following diagram [40].

![Training methodology for the BPNN model](image)

**Figure 4.** Training methodology for the BPNN model [40].

The steps involved in the training are:

**Step 1:** Initialize the value of weight and bias with random variables.

**Step 2:** The transfer function utilized in the hidden layer is a log-sigmoid function which is expressed as:

\[
B_{(net)} = \frac{1}{1 + e^{-net}}
\]  

(1)

For input variable \(a\), the \(x\)-th input layer node holds \(X_{a,x}\). The net input and output to the \(y\)-th node in the hidden layer are expressed as

\[
net_{(j)} = \sum_{i=0}^{n} W_{g,x}X_{a,x} + \theta_{g,x}
\]  

(2)

\[
X_{a,y} = B_{y} \left( \sum_{i=0}^{n} W_{g,x}X_{a,x} + \theta_{g,x} \right)
\]  

(3)

where \(W_{g,x}, \theta_{g,x}\) denote the weight and bias from input to hidden layer, respectively. The net input and output to the \(z\)-th node in the output layer are written by the following expressions,

\[
net_{(y)} = \sum_{i=0}^{n} W_{z,y}X_{a,y} + \theta_{z,y}
\]  

(4)

\[
O_{a,z} = B_{z} \left( \sum_{i=0}^{n} W_{z,y}X_{a,x} + \theta_{z,y} \right)
\]  

(5)

where, \(W_{z,y}, \theta_{z,y}\) refer to the weight and bias from the hidden layer to the output layer, respectively.

**Step 3:** The value of error is estimated and propagated backwards from the output to the hidden layer. The magnitude of error in the output layer is calculated as:

\[
\partial_{z} = B_{z}(1 - B_{z})(T_{z} - B_{z})
\]  

(6)

where \(T_{z}\) refers to the true value of the output layer. The magnitude of error in the hidden layer is expressed as

\[
\partial_{y} = B_{y}(1 - B_{y})\partial_{z}W_{z,y}
\]  

(7)
Step 4: To minimize the error, the weights are updated by the following equations,

\[ \Delta W_{z,y} = \alpha \partial_z B_y \]  \hspace{1cm} (8)

\[ W_{z,y} = W_{z,y} + \Delta W_{z,y} \]  \hspace{1cm} (9)

\[ \Delta W_{y,x} = \alpha \partial_y X_a \]  \hspace{1cm} (10)

\[ W_{y,x} = W_{y,x} + \Delta W_{y,x} \]  \hspace{1cm} (11)

where \( \alpha \) represents the learning rate. The biases are updated by the given expressions:

\[ \Delta \theta_{z,y} = \alpha \partial_z \]  \hspace{1cm} (12)

\[ \theta_{z,y} = \theta_{z,y} + \Delta \theta_{z,y} \]  \hspace{1cm} (13)

\[ \Delta \theta_{y,x} = \alpha \partial_y \]  \hspace{1cm} (14)

\[ \theta_{y,x} = \theta_{y,x} + \Delta \theta_{y,x} \]  \hspace{1cm} (15)

3.2. Input Selection for RUL Prediction

The input selection for the training of the proposed algorithm is carried out by applying a systematic sampling technique or probability sampling. Systematic sampling consists of selecting the number of samples from an ordered sampling frame with fixed sampling intervals. The sampling interval is achieved by dividing population size with sampling size. In this work, a systematic sampling approach is applied to extract the input samples of the charging profile parameters such as voltage, current, and temperature. In total, 10 samples of the mentioned parameters from each charging cycle are obtained to develop a framework of 30 samples. Additionally, the battery discharge capacity is also considered as one of the input parameters for training the algorithm which comprises 31 samples. The sample extraction process is explained below.

Let the total number of samples of voltage, current, and temperature from each charging profile be expressed as:

\[ V_a = V_{a1}, V_{a2} \ldots \ldots \ldots V_{an} \]  \hspace{1cm} (16)

\[ I_a = I_{a1}, I_{a2} \ldots \ldots \ldots I_{an} \]  \hspace{1cm} (17)

\[ T_a = T_{a1}, T_{a2} \ldots \ldots \ldots T_{an} \]  \hspace{1cm} (18)

where \( V_{a1}, I_{a1}, T_{a1} \) are the initial sample and \( V_{an}, I_{an}, T_{an} \) denote the final samples of the parameters in a specified charging cycle. \( a \) represents the number of charging cycles where \( a = 1, 2, \ldots, 168 \) for batteries B0005, B0006, B0007 and \( a = 1, 2, \ldots, 132 \) for battery B0018. The sample extraction to develop the proposed framework is carried out by dividing total samples by sampling size. While considering Equations (16)–(18), the 10 samples can be extracted as:

\[ v = \frac{V_a}{10} * j \]  \hspace{1cm} (19)

\[ i = \frac{I_a}{10} * j \]  \hspace{1cm} (20)

\[ t = \frac{T_a}{10} * j \]  \hspace{1cm} (21)

where the value of \( j \) is varied from 1, 2, \ldots, 10. The extracted 10 features from voltage, current, and temperature can be expressed as,

\[ v = \left\{ \frac{V_a}{10} * 1, \frac{V_a}{10} * 2 \ldots \ldots \frac{V_a}{10} * 10 \right\} \]  \hspace{1cm} (22)
\[ i = \left\{ \frac{I_a}{10} * 1, \frac{I_a}{10} * 2 \ldots \frac{I_a}{10} * 10 \right\} \]
\[ t = \left\{ \frac{T_a}{10} * 1, \frac{T_a}{10} * 2 \ldots \frac{T_a}{10} * 10 \right\} \]  

(23)  

(24)  

The obtained input vector framework with 30 features can be expressed as

\[ I = \left\{ \frac{V_a}{10} * 1, \frac{V_a}{10} * 2 \ldots \frac{V_a}{10} * 10 \right\} \left\{ \frac{I_a}{10} * 1, \frac{I_a}{10} * 2 \ldots \frac{I_a}{10} * 10 \right\} \left\{ \frac{T_a}{10} * 1, \frac{T_a}{10} * 2 \ldots \frac{T_a}{10} * 10 \right\} \{C_d\} \]

(25)  

while considering the discharge capacity feature, the proposed input vector can be written as

\[ I_{new} = \left\{ \frac{V_a}{10} * 1, \frac{V_a}{10} * 2 \ldots \frac{V_a}{10} * 10 \right\} \left\{ \frac{I_a}{10} * 1, \frac{I_a}{10} * 2 \ldots \frac{I_a}{10} * 10 \right\} \left\{ \frac{T_a}{10} * 1, \frac{T_a}{10} * 2 \ldots \frac{T_a}{10} * 10 \right\} \{C_d\} \]

(26)  

where \( C_d \) is the discharge profile capacity. \( a \) denotes the number of discharge cycles, i.e., 168 for batteries B0005, B006, B0007 and 132 for battery B0018. Therefore, the complete 31-dimensional input feature vector can be generated by assigning \( a = 1, 2, \ldots, 168 \) for batteries B0005, B0006, B0007 and \( a = 1, 2, \ldots, 132 \) for battery B0018.

\[ I_{total} = \]

\[ \left\{ \frac{V_{a1}}{10} * 1, \frac{V_{a1}}{10} * 2 \ldots \frac{V_{a1}}{10} * 10 \right\} \left\{ \frac{I_{a1}}{10} * 1, \frac{I_{a1}}{10} * 2 \ldots \frac{I_{a1}}{10} * 10 \right\} \left\{ \frac{T_{a1}}{10} * 1, \frac{T_{a1}}{10} * 2 \ldots \frac{T_{a1}}{10} * 10 \right\} \{C_{d1}\} \]

\[ \left\{ \frac{V_{a2}}{10} * 1, \frac{V_{a2}}{10} * 2 \ldots \frac{V_{a2}}{10} * 10 \right\} \left\{ \frac{I_{a2}}{10} * 1, \frac{I_{a2}}{10} * 2 \ldots \frac{I_{a2}}{10} * 10 \right\} \left\{ \frac{T_{a2}}{10} * 1, \frac{T_{a2}}{10} * 2 \ldots \frac{T_{a2}}{10} * 10 \right\} \{C_{d2}\} \]

\[ \vdots \]

\[ \left\{ \frac{V_{a168}}{10} * 1, \frac{V_{a168}}{10} * 2 \ldots \frac{V_{a168}}{10} * 10 \right\} \left\{ \frac{I_{a168}}{10} * 1, \frac{I_{a168}}{10} * 2 \ldots \frac{I_{a168}}{10} * 10 \right\} \left\{ \frac{T_{a168}}{10} * 1, \frac{T_{a168}}{10} * 2 \ldots \frac{T_{a168}}{10} * 10 \right\} \{C_{d168}\} \]

(27)  

In the SCI profile, the model is trained with a single battery dataset which proves insufficient for accurate prediction. The structure of the SCI profile consisting of a single battery dataset for training the algorithm is presented in Figure 5. As observed, due to the insufficient volume of data for training the model in the SCI profile comprising a single battery dataset, the accuracy and error metrics are compromised. Therefore, the MCI profile is considered for training the model to predict the RUL accurately by considering a large amount of data from various batteries. The structure of the proposed method with an MCI profile consists of several battery datasets for the training model. The structure of the proposed multi-channel input profile is presented in Figure 6. In both SCI and MCI profiles, careful observation is carried out to extract the critical samples of various parameters from the charging profile of the batteries.

**Figure 5.** Single channel input profile consisting of a single battery dataset.
4. Research Framework and Execution of MCI Profile Based BPNN Algorithm for RUL Prediction

The proposed methodology/algorithm for predicting the RUL of the battery by utilizing BPNN consists of three major levels which include (i) feature extraction and data pre-processing, (ii) data split and model training, and (iii) prediction and analysis. In the first level, data is extracted from the NASA database consisting of B0005, B0006, B0007, and B0018 battery datasets. The extracted datasets are analyzed to obtain the important parameters for training the algorithm. The important parameters for training are obtained from the charging profiles of the battery consisting of voltage, current, and temperature. In total, 10 critical samples of the parameters from each charging cycle are extracted by employing a systematic sampling technique. Additionally, the capacity degradation data is achieved from the discharge profile. The 10 critical samples of voltage, current, temperature along with single capacity data are framed to develop a 31-dimensional input vector framework for training the model. In addition, the generated data is normalized by utilizing min–max normalization. In the second level, data is separated into training data and test data while assigning target values simultaneously. The selection of hyperparameters is carried out by the hit and trial method while LMA is applied as a training function for the BPNN model. In the third level, BPNN based algorithm is employed to estimate capacity as well as evaluate different error metrics such as RMSE, MSE, MAPE, MAE, and SD. Additionally, the proposed MCI based BPNN technique is validated with SCI profile and consequently, a comparative study is undertaken to evaluate the performance of the proposed model against various combinations of battery datasets. The implementation processes of the proposed methodology are shown in Figure 7. Furthermore, the threshold value at which the battery needs replacement is assigned individually to each battery while analyzing the results.
4.1. Feature Selection and Data Pre-Processing

At first, the NASA battery dataset was examined and important battery parameters were selected from the charging profile. Suitable features/samples of the parameters from each charging cycle were acquired by systematic sampling method. It is preferable to
include the important sampling values from each charging cycle of various influential parameters to train the BPNN algorithm to obtain accurate results. Hence, 10 sample values of voltage, current, and temperature were selected from each charging profile along with discharge capacity, as performed in [37,38]. Parallel to this, the single capacity data was extracted from the battery discharging profile. The developed 31-dimensional input vector framework underwent data pre-processing and cleansing to discard undesirable data. After data pre-processing, the extracted data was normalized by utilizing a min–max data normalization process, as shown in the following equation,

\[ Z_{ks} = \frac{x_k - \min(x)}{\max(x) - \min(x)} \]  

(28)

where \( x \) denotes the sum of charging cycle \( x_k \), \( s \) refers to the number of charging cycles, \( \max(x) \) and \( \min(x) \) represent the maximum and minimum value of the sample data, respectively [41]. The data normalization was performed to remove data redundancy so that only relevant data was present for training and testing.

4.2. Data Split Method

Primarily, the NASA dataset is utilized as a common reference for RUL prediction of battery [17,39,42]. The SCI-based model is trained by employing a conventional 70:30 ratio for each battery [43]. For instance, in the case of B0005, 70% of the data is utilized to train the model while 30% data is employed for testing. In the proposed MCI based technique, four battery datasets were employed to develop a 31-dimensional input vector profile framework as shown in Figure 8. For training and testing, one battery dataset was considered as a test dataset while others were considered as a training dataset. For instance, while B0005 was selected as a test battery dataset, various combinations of other batteries were utilized as training datasets such as B0006 B0007 B0018, B0006 B0007 B0007 B0018, B0006 B0018. Additionally, the same test battery dataset was trained with a single battery dataset such as B0006, B0007, and B0018, respectively. The same procedure for the training and testing applies to other batteries as well. The hyperparameters of the BPNN model were selected through hit and trial method including number of hidden layers, hidden layer neurons, number of iterations, and the learning rate. Each learning method was implemented by MATLAB 2018a with the Intel(R) Core (TM) i7-4790 CPU at 3.60 GHz with installed RAM of 10 GB. At first, 20 iterations with 1000 epochs and ‘mse’ as the performance function were assigned. LMA was utilized to train the neural network and estimate the capacity for RUL prediction of lithium-ion batteries. The error metrics such as RMSE, MAPE, MAE, and SD were evaluated. The expressions for various performances indicators are shown in the following equations,

\[ \text{MAPE} = \frac{1}{n} \sum_{n=1}^{n} \frac{|c_k - \hat{c}_k|}{c_k} \]  

(29)

\[ \text{RMSE} = \sqrt{\left( \frac{1}{n} \sum_{n=1}^{n} |c_k - \hat{c}_k|^2 \right)} \]  

(30)

\[ \text{MAE} = \frac{1}{n} \sum_{n=1}^{n} |c_k - \hat{c}_k| \]  

(31)

\[ \text{MSE} = \frac{1}{n} \sum_{n=1}^{n} |c_k - \hat{c}_k|^2 \]  

(32)

\[ \text{SD} = \sqrt{\left( \frac{1}{1-n} \sum_{n=1}^{n} |c_k - \hat{c}_k|^2 \right)} \]  

(33)

where \( c_k \) is actual capacity, \( \hat{c}_k \) is predicted capacity, and \( n \) is the number of cycles.
4.3. RUL Prediction and Analysis

The results were obtained for four battery datasets B0005, B0006, B0007, and B0018 under various training datasets. As the target values were set and BPNN was trained by utilizing several combinations of datasets obtained from NASA, the output of the algorithm yielded the estimated capacity in the form of output. The RUL prediction of the lithium-ion battery was examined from the initial cycle, i.e., 1st cycle and hence different error metrics were calculated. The threshold value of the capacity at which the battery needs replacement was assigned to each battery while plotting the graph. In addition, SCI profile results were displayed to prove the competency of the MCI profile.

5. RUL Experimental Results and Validation

The BPNN algorithm was implemented to evaluate the battery RUL based on various error metrics such as RMSE, MAPE, MSE, MAE, and SD. Each performance index was calculated for a different combination of training data sets keeping the target dataset constant. To verify the accuracy and effectiveness of the proposed MCI based technique, a comparative analysis was performed with the SCI technique. The robustness of the MCI technique was examined by training the BPNN model with a combination of various battery datasets.

Figure 8. MCI profile configuration for 31-dimensional input data, training data format, and testing data.
datasets. The training dataset was varied and the results were predicted. A 31-dimensional input data framework was generated for training the BPNN model. In terms of the RUL prediction curve, the capacity threshold limit was assigned for B0005, B0006, B0007, and B0018 battery datasets.

5.1. RUL Prediction by SCI Profile

Here, the SCI profile was implemented by using the methodology described earlier. For B0005, the RMSE, MSE, MAPE, MAE, and SD obtained are 0.5130, 0.0028, 0.2153, and 0.5131 while it is 2.4247, 0.0588, 1.0869, 0.8352, 2.2040 for B0006, as shown in Table 2. The error metrics are higher in B0006 and B0018 due to the occurrence of capacity regeneration phenomena. Additionally, the graph of B0018 is not smooth due to the lesser training data as compared with other datasets. The plot of capacity estimated for various battery datasets under the SCI profile is shown in Figure 9. The prediction accuracy for the BPNN model accurately redesigns the predicted curve against the actual capacity curve due to the application of systematic sampling.

| Battery | Error Metrics |
|---------|---------------|
|         | RMSE  | MSE  | MAPE  | MAE  | SD   |
| B0005   | 0.5130 | 0.0028 | 0.2153 | 0.3007 | 0.5131 |
| B0006   | 2.4247 | 0.0588 | 0.8352 | 1.0869 | 2.2040 |
| B0007   | 0.7091 | 0.0050 | 0.2552 | 0.3812 | 0.6881 |
| B0018   | 2.6604 | 0.0708 | 0.7300 | 0.1849 | 2.3292 |
| Average | 1.5018 | 0.0343 | 6.0357 | 0.4884 | 1.4336 |

Figure 9. RUL prediction curve from various batteries under SCI profile.
5.2. RUL Prediction by MCI Profile

Consequently, MCI profile-based methodology was utilized in training the model for RUL prediction as well as to evaluate the performance metric. It was found that for battery B0005, the error metrics are drastically reduced when trained with more datasets in the MCI profile compared to the SCI profile. In addition, the prediction curve shows more convergence when trained with more datasets as shown in Figures 10–12. Furthermore, in the proposed MCI profile method, training of the BPNN model is based on combined and individual datasets rather than training and testing data in percentage. For each case of the battery, the BPNN model was trained with different datasets and the RUL prediction was explored. It was seen that as the size of training data is reduced, the accuracy and the efficiency to predict the RUL also decrease.

![Figure 10. RUL prediction curve of various batteries under MCI profile when trained with three datasets.](image1)

![Figure 11. Cont.](image2)
5.2.1. Prediction When Trained with Three Datasets

Firstly, the algorithm was trained by utilizing three different battery datasets and the error metrics were studied. As seen from Table 3, when battery B0005 is tested while training with a combination of three datasets (B0006 B0007 and B0018), it is found that RMSE, MSE, MAPE, MAE, and SD are 0.0819, 6.7114 \times 10^{-5}, 0.0423, 0.0681, and 0.0717, respectively. The error metrics were examined while batteries B0006 and B0018 under test show a high error because of capacity regeneration phenomena as shown in Figure 10. The RMSE observed for B0006, B0007, and B0018 is 0.4247, 0.0995, and 0.5608, respectively, as shown in Table 5. For the same battery type and NASA datasets we employed.

To conduct a fair comparative analysis, the same battery type and NASA datasets were employed. Comparative approaches such as particle filtering (PF), Support Vector Machine (SVM), Artificial neural network (ANN), and Random Vortex Machine (RVM) were used to perform the validation, the accuracy of error metrics in the prediction of battery RUL is affected by varying the volume of training data as well as the inclusion of capacity regeneration phenomena as shown in Figure 12. In addition, the average error obtained for different error metrics is higher compared to the SCI profile. It can be concluded that RUL prediction is accurate when the model is trained by employing an MCI profile with a large amount of data.
average error of the error metrics such as RMSE, MSE, MAPE, MAE, and SD are 0.2917, $2.5 \times 10^{-3}$, 0.1136, 0.1679, and 0.2865, respectively.

Table 3. RUL prediction for MCI profile when trained with three datasets.

| Testing Battery Dataset | Training Battery Dataset | Error Metrics |
|-------------------------|--------------------------|--------------|
|                         |                          | RMSE  | MSE   | MAPE  | MAE   | SD    |
| B0005                   | B0006, B0007, B0018      | 0.0819| 6.714 $\times 10^{-5}$ | 0.0423| 0.0681| 0.0717|
| B0006                   | B0005, B0007, B0018      | 0.4247| 0.0018| 0.1247| 0.2066| 0.4219|
| B0007                   | B0005, B0006, B0018      | 0.0995| 9.8968 $\times 10^{-5}$ | 0.0451| 0.0451| 0.0968|
| B0018                   | B0005, B0006, B0007      | 0.5608| 0.0031| 0.2423| 0.3894| 0.5558|
| Average error           |                          | 0.2917| $2.5 \times 10^{-3}$  | 0.1136| 0.1679| 0.2865|

5.2.2. RUL Prediction When Trained with Two Datasets

The algorithm was trained by utilizing two datasets from different batteries for training the BPNN model. It is found that as the training dataset is decreased, the values of the error metrics decrease. In the case of B0005, when the BPNN model is trained with a combination of datasets, i.e., B0006 and B0007, B0007 and B0018, and B0006 and B0018, the values of the error metrics are examined as shown in Table 4. The values of RMSE, MSE, MAPE, MAE, and SD obtained while training the BPNN with two datasets (B0006 B0007) are 0.1746, 1.0154 $\times 10^{-4}$, 0.0913, 0.1423, 0.1348, respectively. For training with B0007 and B0018, the error metrics observed are 0.1669, 2.7843 $\times 10^{-4}$, 0.0836, 0.1306, 0.1550, respectively, and while training with B0006 and B0018, they are calculated as 1.2866, 0.0169, 0.7790, 1.1782, and 0.5885, respectively. As seen from the prediction curve in Figure 11, the model shows low convergence when it is trained with a combination of B0006 and B0018 in comparison to other combinations of training datasets. In addition, the error metrics are higher when the model is trained with B0006 and B0018 due to the effect of capacity regeneration and low training data. Similarly, the performances of other batteries such as B0006, B0007, and B0018 were examined under the combination of the various datasets and the prediction errors are presented. It was analyzed that the average value of error metrics increased by about four times when the training datasets were reduced from three to two. For instance, the average error for the error metrics increased to 0.9848 for RMSE (trained with two datasets) as compared with 0.2914 (trained with three datasets).

Table 4. RUL prediction for MCI profile when trained with two datasets.

| Testing Battery Dataset | Training Battery Dataset | Error Metrics |
|-------------------------|--------------------------|--------------|
|                         |                          | RMSE  | MSE   | MAPE  | MAE   | SD    |
| B0005                   | B0006, B0007             | 0.1746| 1.0154 $\times 10^{-4}$ | 0.0913| 0.1423| 0.1348|
|                         | B0007, B0018             | 0.1669| 2.7843 $\times 10^{-4}$ | 0.0836| 0.1306| 0.1550|
|                         | B0006, B0018             | 1.2866| 0.0169| 0.7790| 1.1782| 0.5885|
| B0006                   | B0005, B0007             | 0.4651| 0.0022| 0.1736| 0.2714| 0.4665|
|                         | B0007, B0018             | 0.4771| 0.0023| 0.2134| 0.3032| 0.4699|
|                         | B0005, B0018             | 1.5211| 0.0231| 0.5998| 0.9371| 1.5092|
| B0007                   | B0005, B0007             | 0.2440| 5.9554 $\times 10^{-4}$ | 0.1127| 0.1821| 0.2289|
|                         | B0006, B0018             | 2.4424| 0.0597| 1.2529| 2.0233| 2.4482|
|                         | B0005, B0018             | 1.3147| 0.0173| 0.5669| 0.9532| 1.2805|
| B0018                   | B0005, B0006             | 1.1827| 0.0140| 0.4154| 0.6576| 1.1867|
|                         | B0006, B0007             | 2.5091| 0.0630| 1.2325| 1.8611| 2.2680|
|                         | B0005, B0007             | 2.2096| 0.0488| 0.9112| 1.4495| 2.2022|
| Average error           |                          | 0.9848| 0.0157| 0.4408| 0.6878| 0.8937|
5.2.3. RUL Prediction When Trained with One Dataset

When training of BPNN is executed with a single battery dataset, the accuracy of RUL prediction is the lowest compared to other training datasets. The values of RMSE, MSE, MAPE, MAE, and SD obtained for B0005 with one dataset when trained with B0006 are 0.6624, 0.0044, 0.3115, 0.4979, 0.6624, respectively, as shown in Table 5. For the same case with B0005, the prediction errors are higher when trained with B0007 and B0018. Due to the lower volume of training data, i.e., a single battery dataset and the influence of capacity regeneration in B0018, the prediction efficiency of the BPNN model is the lowest amongst other training datasets. It is also examined that the prediction curve shows less convergence when the model is trained with B0006 and B0018 due to the significance of capacity regeneration phenomena as shown in Figure 12. In addition, the average error increases to more than 10 times when the model is trained with one dataset in comparison to training the model with three datasets. For instance, the average value of RMSE is 0.2917 when trained with three datasets which increases to 3.5714 when trained with only one dataset. Hence, the accuracy of error metrics in the prediction of battery RUL is affected by varying the volume of training data as well as the inclusion of capacity regeneration phenomena. However, in the case of MCI profiles trained with single datasets, the average error obtained for different error metrics is higher compared to the SCI profile. It can be concluded that RUL prediction is accurate when the model is trained by employing an MCI profile with a large amount of data.

Table 5. RUL prediction for MCI profile when trained with one dataset.

| Testing Battery Dataset | Training Battery Dataset | Error Metrics |
|-------------------------|--------------------------|---------------|
|                         | RMSE | MSE  | MAPE | MAE  | SD  |
| B0005                   | 3.7092 | 0.1376 | 1.8156 | 2.8964 | 3.7077 |
|                         | 3.3678 | 0.1140 | 2.0337 | 3.0532 | 3.3228 |
|                         | 3.9373 | 0.1550 | 2.1278 | 3.4206 | 2.2033 |
| B0006                   | 2.6744 | 0.0715 | 1.5379 | 2.3424 | 1.3287 |
|                         | 3.120 | 0.1305 | 1.8588 | 2.9353 | 3.4052 |
|                         | 3.4729 | 0.1206 | 0.9298 | 1.5688 | 3.4528 |
| B0007                   | 2.4065 | 0.0579 | 1.0860 | 1.8607 | 1.9955 |
|                         | 4.3247 | 0.1870 | 1.8260 | 3.0315 | 4.2578 |
|                         | 4.9945 | 0.2450 | 2.4701 | 4.0452 | 4.9640 |
| B0018                   | 1.9564 | 0.0383 | 0.9709 | 1.5528 | 1.5764 |
|                         | 4.5414 | 0.2062 | 2.3562 | 3.6030 | 3.9198 |
|                         | 3.9374 | 0.2255 | 2.5342 | 3.9374 | 4.6883 |
| Average error           | 3.5714 | 0.1407 | 1.7955 | 2.8539 | 3.2272 |

5.3. Comparative Validation with the Existing Works

Apart from the various existing datasets used to perform the validation, the accuracy of the presented technique was compared with other conventional, model-based, and intelligent approaches such as particle filtering (PF), EEMD, ARIMA, SVM, and RVM, as shown in Table 6. To conduct a fair comparative analysis, the same battery type and NASA datasets were employed.

The key important features related to RUL prediction of lithium-ion batteries such as input features and output, capacity, battery type, and error metrics are considered in the comparative study. For instance, Li et al. [44] presented a PF-based technique for RUL prediction and calculated RMSE of 0.04408. Further, Gao and Huang [45] proposed the hybrid SVM and particle swarm optimization (PSO) technique for RUL prediction which delivered 0.0213 and 0.0514. Additionally, the Zhou and Huang [24] model based on EMD-ARIMA delivered RMSE below 1%, while for RVM [46], the relative error was estimated under 1%. In contrast, satisfactory results in terms of accuracy, adaptability, and robustness based on the BPNN model are achieved by employing a novel multi-channel input profile...
technique consisting of 31-dimensional input features. Even though the prediction results obtained are higher while training with the low volume of data, the training ability of the BPNN model is better compared to other techniques.

Table 6. Comparative performance analysis of various techniques for RUL prediction.

| Reference | Algorithm | Input Feature and Output | Battery Type | Validation | Performance Metrics | Research Gap |
|-----------|-----------|--------------------------|--------------|------------|---------------------|--------------|
| [44]      | Linear PF | -[Input] = Impedance, aging, number of charging cycle -[output] = Capacity | -18650 lithium ion battery | NASA battery dataset | RMSE 0.2902 | -Charging and discharging profile parameters can be considered for better predictability. |
| [45]      | Hybrid PSO and SVM | -[Input] = Discharge cycle data -[output] = Capacity | -18650 lithium ion battery | NASA battery dataset | MSE 0.0213 | -Increased computational burden, variability in the outcomes during optimization. The validation of the technique could be performed with data-driven models. |
| [47]      | SVM       | -[Input] = Voltage, current, temperature, capacity and time -[output] = RUL | -18650 lithium ion battery | NASA battery dataset | RMSE 0.2159, 0.3108 | -Employment of low volume of training data, validation with other model-based technique is needed. |
| [48]      | EMD and RVM | -[Input] = Capacity -[output] = RUL | -18650 lithium ion battery | NASA battery dataset | MSE 4.4972 × 10^{-5}, 1.6437 × 10^{-5} (battery 5 and 18) | -Employment of low volume of training data, validation with other model-based technique is needed. |
| [28]      | FFNN      | -[Input] = Voltage -[output] = RUL | -18650 lithium ion battery | NASA battery dataset | MAE 29.4218 | -Very high error, requires hyperparameter adjustment. |
| [31]      | Deep neural network | -[Input] = Voltage, current, temperature, capacity -[output] = RUL | -18650 lithium ion battery | NASA battery dataset | RMSE 3.427 | -Computational burden and high error. |
| Proposed method | BPNN | -[Input] = Voltage, current, temperature, capacity -[output] = RUL | -18650 lithium ion battery | NASA battery dataset | RMSE 0.0819, MSE 6.7114 × 10^{-5} | -The accuracy of the model can be further improved by utilizing optimization techniques. |

6. Conclusions

This work developed and evaluated an ANN-based intelligent algorithm for RUL prediction of lithium-ion batteries under various training datasets. The battery dataset for training the model was acquired from the NASA Prognostics Centre of Excellence Data Repository. Compared to the other methodology employing the SCI profile, the MCI profile was applied to achieve better results in predicting the RUL under different combinations of battery datasets. Various significant parameters such as voltage, current, and temperature samples were obtained from the charging cycles for the accurate prediction of the RUL of lithium-ion batteries. Due to the employment of a systematic sampling approach for critical data extraction, it is easy to reconstitute the predicted capacity curve while training with various combinations of battery datasets. The major findings of this work are summarized below,

- The proposed model delivers accurate results with regard to RMSE while training with MCI based technique with three datasets as compared to the training with two datasets and one dataset, respectively. For B0005, the RMSE is calculated to be 0.0819 while training with three datasets, however, the RMSE decreases to 0.1746, 0.1669, and 1.2866 when trained with three combinations of two datasets.
- The effect of capacity regeneration phenomena was also assessed while training the model with B0006 and B0018 which lowers the prediction accuracy of the model. While training the MCI model with three datasets for B0005, the RMSE is estimated to be 0.0819 while that for B0006 is 0.4247. The same pattern of prediction error was studied in other cases of battery as well.
- Additionally, the average value of various error metrics is the lowest when the model is trained with large training data, i.e., three datasets. While training with SCI, the
average error for RMSE is 1.5018. When the MCI profile is used, the error declines to 0.2917 and 0.9848 with three and two datasets, respectively.

Although the proposed algorithm trains efficiently with a large volume of training datasets, the prediction accuracy is low with a small volume of training datasets. In future, the proposed MCI profile framework-based RUL prediction of the lithium-ion batteries could be employed using more efficient ANN models such as recurrent neural network (RNN), nonlinear autoregressive network (NARX), and deep learning techniques. Parallel to that, the RUL prediction of the battery can be implemented with other battery profiles such as discharging, impedance and accordingly, the verification of the results could be performed.

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**Abbreviations**

| Abbreviation | Description                             |
|--------------|----------------------------------------|
| ANN          | Artificial Neural Network              |
| ARIMA        | Auto-Regressive Integrated Moving Average |
| BCT          | Box-Cox transformation                  |
| BPNN         | Back Propagation Neural Network         |
| EEMD         | Ensemble Empirical Mode Decomposition  |
| EV           | Electric Vehicle                        |
| FFNN         | Feed Forward Neural Network             |
| HI           | Health Indicator                        |
| LMA          | Lavenberg Marquardt Algorithm           |
| MAE          | Mean Average Error                      |
| MAPE         | Mean Absolute Percentage Error          |
| MC           | Monte Carlo                              |
| MCI          | Multi-Channel Input                     |
| MSE          | Mean Square error                       |
| NARX         | Nonlinear Autoregressive Network        |
| PDF          | Probability Density Function            |
| PF           | Particle Filtering                      |
| PSO          | Particle Swarm Optimization             |
| RMSE         | Root Mean Square Error                  |
| RNN          | Recurrent Neural Network                |
| RUL          | Remaining Useful Life                   |
| RVM          | Relevance Vector Machine                |
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