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Analysis of Optimal Machine Learning Approach for Battery Life Estimation of Li-Ion Cell

PRAKASH VENUGOPAL[1], S. SIVA SHANKAR[1], C. PHILLIP JEBAKUMAR[1], RISHAB AGARWAL[1], HASSAN HAES ALHELOU[2,3], (Senior Member, IEEE), S. SOFANA REKA[1], AND MOHAMAD ESMAIL HAMEDANI GOLSHAN[3], (Senior Member, IEEE)

[1]School of Electronics Engineering, Vellore Institute of Technology, Chennai 600127, Tamilnadu, India
[2]Department of Electrical Power Engineering, Faculty of Mechanical and Electrical Engineering, Tishreen University, Lattakia 2230, Syria
[3]Department of Electrical and Computer Engineering, Isfahan University of Technology, Isfahan 84156-83111, Iran

Corresponding author: Hassan Haes Alhelou (alhelou@ieee.org)

ABSTRACT State of health (SOH) and remaining useful life (RUL) are two major key parameters which plays a major role in battery management system. In recent years, various machine learning approaches have been proposed to estimate SOH and RUL effectively for establishing the battery conditions. In the proposed work establishes an effective method to predict the battery aging process with accurate battery health estimation with real time simulations and hardware approach. This paper effectively exhibits a process to estimate SOH and RUL of a Li-Ion 18650 cell which are based on various factors like state of charge, discharge voltage transfers characteristics, internal resistance and capacity. To identify an optimal SOH and RUL machine learning based estimation approach, various battery's statistical models are developed and implemented on a standalone hardware platform. The experimental results in this real time application shows that SOH is predicted by deep neural network approach which are found to be within the accepted error rate of ±5% and long short time memory neural network model estimates a battery's RUL effectively with an accuracy of ±10 cycles. This approach exhibits various machine learning models in an realistic hardware platform which establishes optimal battery life.

INDEX TERMS Battery management system, deep neural network, Li-ion batteries, long short time memory, state of health, remaining useful life, state of charge.

LIST OF ABBREVIATIONS

BMS –	Battery Management System resistive-capacitive (RC).
LSTM–	Long Short Time Memory.
SOH –	State of Health.
SOC-	State of Charge.
RUL –	Remaining useful life.
VTC-	Discharge Voltage Transfer characteristic.
DNN –	Deep Neural Network.

I. INTRODUCTION

Li-ion Batteries (LiB) is one of the primary energy storage units widely used in many electrical and electronic applications due to its high life cycle, high capacity, high energy density and high specific energy. Majority of the devices are powered by a Li-ion based cell or battery with varying capacity for many applications including cell phones, spacecraft, electric vehicles. When compared to other types of batteries, Li-ion batteries require more advanced monitoring system to ensure safe operation of the battery with the help of battery management system (BMS). Various functions of BMS strongly depends on the complexity of the specific application. Understanding and analyzing the remaining life expectancy of the battery are greatly important to ensure proper functioning of them. An optimal method of battery life estimation for a Li-Ion cell [1] are needed to make efficient use of most of the electronic appliance. As example, single batteries in cell phones uses simple technique which estimates the battery states by measuring voltage, current and temperature of the battery. However, for complex application like electric vehicle, BMS requires advanced algorithms to accurately estimate various battery states along with aforementioned battery parameters. The state of health (SOH) parameter is an indication of current health of a battery with respect to the unused state and can be predicted by using the

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battery cycle, measured voltage, measured current, measured temperature, ambient temperature, load current, load voltage and capacity. The remaining useful life (RUL) indicates the durability of the battery, which gives the number of charge and discharge cycles using SOH [2]. Each application has its own load capacity that drains the battery in a variable rate. Thus, by proposing an efficient intelligent method to find the state of health and remaining usage life of the battery increases the efficiency of the system in a larger aspect can be established.

Various models have been proposed to estimate SOH and RUL by analyzing the aging process of lithium batteries in literature. This includes different parameters ranging from the physical measurement to the analytical model. The battery is constructed as a resistive-capacitive (RC) circuit that takes internal resistance, time, voltage into consideration and a continuous time analysis is done to predict its life [3]. In [4], a novel SOH estimator by using the partial constant-voltage (CV) charging data is suggested. A novel model-based voltage construction method for robust SOH estimation of lithium-ion batteries using incremental capacity analysis are proposed in [5] and [6]. The RUL of the Li-Ion battery is estimated by measuring the growing DC resistance of the battery [7]–[9] while on usage. The precise prediction of SOH of Li-ion batteries performed using probabilistic neural network (PNN) is to avoid unexpected malfunction of cells [10]. To predict the SOH, experimental dataset are obtained by using constant current and constant voltage methods with continuously charging and discharging of the battery. The PNN is trained on 100 pieces of battery cell and the last 10 pieces are utilized for verifying and testing the model.

A dynamic long short-term memory (DLSTM) based model is proposed for RUL prediction of Li-Ion batteries in satellite [11]. An indirect health indicator (HI) on the basis the Spearman correlation analysis method is extracted from the battery discharge voltages, and polynomial fitting is used to establish relationship between Indirect HI indices and the capacity of the battery. A data driven prognostic Deep Neural Networks (DNN) are used to estimate the SOH and the RUL of the battery based on a battery dataset obtained from the NASA Prognostics Center of Excellence (PCoE) database with acceptable accuracy range [12], [13]. A Coulomb counting method combined with back propagation neural network (BPNN) approach is used to calculate the SOC first and then SOH is computed based on the dataset is acquired with the hardware using a PIC based controller [14].

A novel quantum behaved particle swarm optimization (QPSO) based Support Vector Regression (SVR) method is used to estimate the remaining capacity of Lithium-Ion battery with a root mean square error (RMSE) of 1.5-1.8% based on the starting cycle of battery [15]. A deep learning approach has been applied to estimate RUL based on the battery features extracted from the NASA dataset separately for charging and discharging of battery at a particular interval [16]. With the help of principal component analysis and an auto encoder model 15 layers of data are fused together followed by data normalization. Then the model is trained by using deep neural network model with rectified linear unit (ReLU) as the activation function. Unlike conventional neural network approach, an independent recurrent neural network (IndRNN) is used for estimating the SOH of the Li-ion battery under variable load conditions [17]. The experimental results prove that the IndRNN system delivers better performance than Gated Recurrent Units (GRU) and Long Short Time Memory (LSTM).

In this work, an Extended Kalman Filter (EKF) based filter takes the battery measurements as input and provides the SOC of the battery [18]–[20]. A batch of optimized OCV values and pairing SOC values are utilized as input for a parameter varying approach based algorithm, which revises the SOH function. An equivalent circuit model is created for the battery and the constant current of the charging and discharging profiles are considered to approximate the Open-circuit voltage (OCV)-SOC function [21]. An Independent Component analysis model is used to apply the capacity model of battery to directly define the dependence of OCV on SOH estimation. It proposes an unrequired learning method with parameters to changes based on maximum capacity to estimate SOH. A brute force nearest neighbor search is used to predict the long-term evaluation of aging characteristics that serve as an important benchmark for SOH and RUL prediction proposed in [22]. The Lithium ion Battery is described as an equivalent RC model and altered into a mathematical model by using least squared method and forgetting factor recursive least square algorithm and then Laplace transform is used on the equations. A discrete space state equation is used to get the relation between state variables and SOC. Then Dual Extended Kalman Filter (DEKF) algorithm is used to approximate SOH of the battery. In DEKF using ampere hour integral priori estimation of SOH is done using the ohmic resistance and SOH is calculated [23].

An efficient particle filter for any kind of probability distribution is used to predict and estimate SOC and SOH for a Lithium ion Phosphate battery.an open circuit voltage hysteresis is modelled by multimodal probability function to estimate SOC [24]. The results are validated for photovoltaic profile, electric vehicle profile and nondeterministic behaviour. To estimate the capacity in batteries a popular regression technique called the least square estimation based weighted ordinary least square and weighted total least square (WTLS) proposed to consider all the errors and variances into consideration and are used to calculate the SOC for an EV profile [25]. From this value SOH or capacity are further estimated by using WLTS approach [26]. Partial charge voltage and current is used to estimate SOH applying support vector machine (SVM) with kernel function as radial basis function (RBF) [27]. For the SVM model, identification of optimal kernel parameter is done by grid search method but estimation precision can be affected by various factors like sampling rate and error, temperature and other factories.

A multilayer perceptron model is used to predict the SOH of the battery by generating the data with the help of simulated model of an equivalent circuit model [28]. Time series classification is used with a windowing technique for the obtained data, which is then trained in a multi-layer model with SoftMax function as top layer. Dynamic driven Neural network model with exogenous inputs is designed for estimating SOC and SOH [29]. A combination of Back propagation with multilayer perceptron is used for the training model for SOC and SOH. A Global feedback theorem is used which increases the robustness and computational intelligence. A snapshot-based approach is used where there is a layer of LSTM followed by a polling layer to estimate SOH of the battery using Urban Dynamometer Drive Schedule [30]. Three different model are used which compromise of both unidirectional and bidirectional LSTM. A RUL prediction framework is developed with LSTM and three-fold cross validation (CV) is employed in the testing and training process to get the best statistical model. The online calculation process conducts the RUL predictions using the obtained best model on a battery model developed with the help of Centre for Advanced Life Cycle Engineering (CALCE) dataset [31].

A neural network degradation model is used to predict the RUL along with bat-inspired particle filter [32], [33]. The particle filter is optimized by using random uniform distributed function. To predict the RUL state space equation is calculated for which the state is updated by the particle filter and then the RUL is predicted by neural network. Some of the common issues found in various previous work that has been carried related to estimation of SOH and RUL of an Li-Ion battery are mentioned as

(1) Effectiveness of most of the SOH and RUL algorithm proposed in existing literatures are verified only through simulation but failed to implement it on a real-world hardware platform
(2) There is no unified hardware platform implemented to analyze and validate the effectiveness of various machine learning models for SOH and RUL of Li-ion battery
(3) Different authors use different datasets to train and validate their approach hence it is difficult for other researchers to verify the effectiveness of the proposed approach and apply it to their application

In this work, various battery models are developed and supported with a hardware setup to validate the efficiency of the proposed system and implemented on the hardware. However, compared to other models which had been considered for study, the statistical models are found to be modified to different batteries and they also can perform with the characteristics of the real time aging process diagnosis in an effective way. Therefore, in order to overcome the above mentioned research gap, this research work is aimed to develop, analyze and compare various machine learning models by porting into the hardware computational device in order to identify an optimal SOH and RUL estimation approach for a single Li-ion battery thereby estimation accuracy of each statistical model is verified in a more practical way. The key contributions of this research work are,

(i) Implementation of most commonly used machine learning approaches related to SOH and RUL estimation on one common hardware platform thereby recommendation made to researchers the most suitable approach for real-world implementation.
(ii) The effectiveness of various machine learning models for SOH and RUL has been analyzed based on its performance metric to suggest an optimal SOH and RUL estimation approach.
(iii) As NASA's battery dataset is the most commonly used dataset for SOH and RUL estimation, a method to identify and extract vital battery parameters is proposed and utilized to develop various machine learning model for an uncompromised comparison.

The rest of the paper is organized into following sections. Section II shows the system model explaining the proposed methodology with the hardware implementations. Section III exhibits the model implementations with the analysis of Machine learning approaches with practical approaches. Section IV depicts the results and discussions of the model with machine learning (ML) analysis with hardware approach. Section V completes with the conclusion and future work approaches.

II. PROPOSED METHODOLOGY

The proposed design follows a step-by-step methodology. At the onset, NASA datasets for the 5 batteries are converted from mat to CSV format using python script. Then the data is cleaned by using algorithms specific to the fields of our interest. Then in the process optimization is done where the search for parameters which requires to minimize or maximize our function are done. Furthermore, in the process, a suitable predictive algorithm like Artificial Neural Network (ANN), Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), Deep Neural Network (DNN), Linear Regression (LR), LSTM is used to train the data. Then the model is tested using another dataset and the results are validated. From the dataset acquired from NASA prognostics center, the data indicates that the battery degradation process is stochastic in nature. The data is segregated into charge and discharge cycles and numbered by the cycle. The initial analysis phase consists of implementing existing benchmarks methods. The proposed models include LSTM, GRU, ANN, CNN with varying parameters including Current, voltage, capacity, impedance.

The data acquisition design approach is shown in Fig.1 The hardware is designed such that it obtains the real-time dataset with the values of various parameters used for the prediction of SOH and RUL. The dataset was collected manually from 'Panasonic NCR18650B' batteries using a setup consisting of voltage and current sensors. This method is more similar to a case where this research might be applied where there are interferences from external factors like wind, ambient temperature and noise which might result in better results compared to the existing methods which require precise data measurements and isolated an environment. It consists of various sensors connected to Arduino which then acquires the data and sends it to Raspberry Pi to be stored as CSV which is later used by the trained model to train and test for the SOH and RUL, to measure the current, voltage and internal resistance of the battery at a particular value and store it.

The stand-alone hardware where the entire work is implemented is the Raspberry Pi. The Raspberry Pi is used to train the model and test the efficiency of the model for the real-time datasets of the test battery. A hardware model is developed with sensors and controllers to acquire the data and create datasets for the test battery that is used to test the developed model on hardware. Two voltage sensors and a current sensor forms the hardware along with the load resistors and the battery in this system.

The battery is connected to a combination of resistors to get a combined resistance of 5Ω. Voltage sensor 1 is connected to the battery to measure the voltage in the battery with load. After the combination of resistors, the current sensor ACS712 is connected in series which completes the circuit and to get the current drain by the battery in the circuit. The voltage sensor 2 is connected across the combination of resistors to get their voltage drop across them. This drop in voltage is used to calculate the battery's internal resistance.

The hardware implementation of the proposed system is presented in Fig. 2. The voltage sensor is used to measure the voltage across resistors, it must be connected in the polarity corresponding to the current flow. The current sensor works in a different mechanism unlike the voltage sensor that just takes the value across the voltage divider and maps the value and points out the voltage measured. The current sensor takes around 150 samples for a reading and takes it average to accurately get results. The average of 150 samples is converted as a digital value from analog inputs by multiplying it 5 as 5.0V is the input and dividing it by 1024 as it is 10-bit precision. The resulting value is subtracted from 2.5V which is considered as offset and it is divided by 0.066 as 66mv is the rise in input when 1A current flows via it.

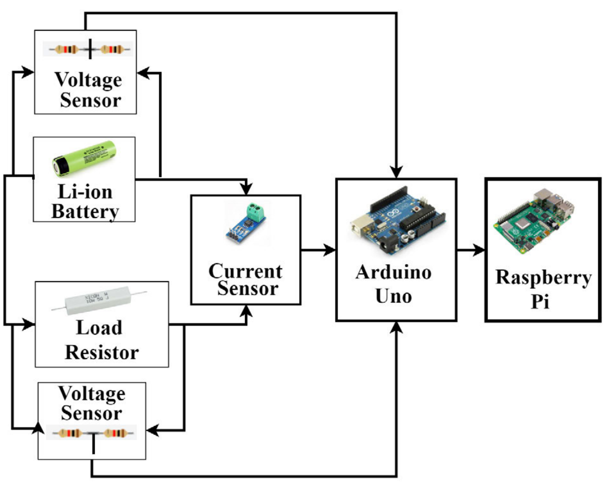

FIGURE 1. Hardware design.

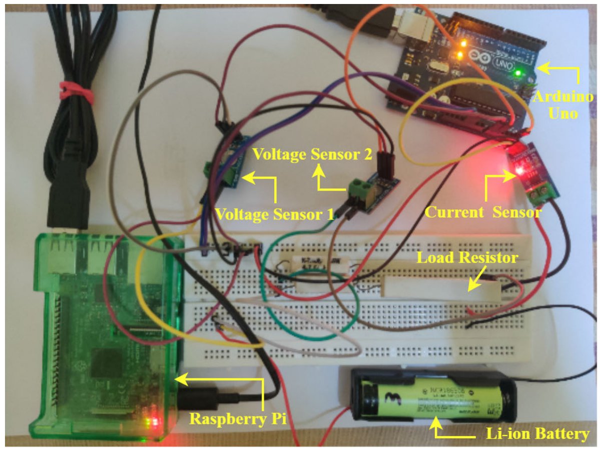

FIGURE 2. Hardware implementation.

The Voltage sensors are connected to A0 and A1 pins of the Arduino Uno board and the current sensor is connected to A5 pin of the Arduino board. The internal resistance of the battery is measured by modelling the battery as shown in Fig. 3. Without connecting any load, the battery voltage is measured which is open circuit voltage. When there is zero current flow, the voltage drop is zero. So, the open circuit voltage is equal to ideal battery voltage. This drop is analyzed by the Internal resistance. Internal resistance is calculated as shown in Fig. 4. The voltage drops across the resistors when added up found to be equal to the voltage of the ideal voltage of the battery. The voltage drops across the internal resistor and the current through it in the system.

The Arduino is connected to the universal serial bus (USB) port in Raspberry Pi 3 as in Fig. 5 in a serial interface which is an Asynchronous communication mechanism between the both boards. The data is generated at rate of 700ms from the Arduino side. There is a slight delay of around 10% in the serial communication as it is asynchronous. The Raspberry Pi is configured using a header less connection using shell script and it is Wi-Fi enabled to make it be accessed in a wireless.

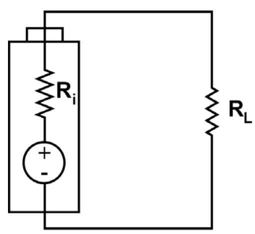

FIGURE 3. Battery model.

In the Raspberry Pi the serial port is continuously monitored and the value out of it is taken as a string that is basically separated by spaces. It is then processed by the python csv libraries and it is then stored as a column-based comma separated values (CSV) file in the Raspberry Pi which has time, Voltage, Current, Internal resistance and total current drawn. The dataset is collected for each discharge cycle for a

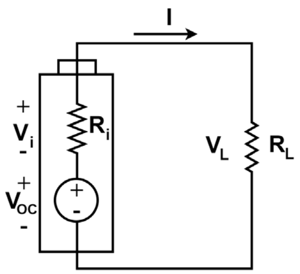

FIGURE 4. Battery with current flow and load.

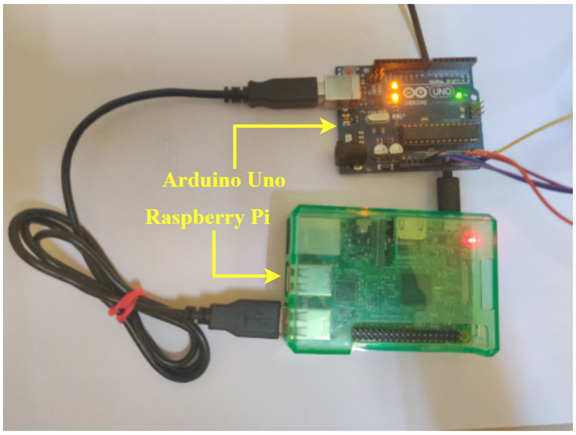

FIGURE 5. Arduino to raspberry Pi communication.

battery until the open circuit voltage drops just below 2.70V in the entire hardware set up.

III. SYSTEM IMPLEMENTATION

In this research work, the battery model is developed based on NASA's battery ageing data set which is a highly recommended and most commonly used dataset by many researchers for SOH and RUL estimation [34]. In the dataset, a set of four Li-ion batteries were able to run through in three different operational profiles -charge, discharge, and impedance at room temperature. The charging is done at a constant current of 1.65A followed by constant voltage after a threshold. This dataset is used for the prediction of both the remaining charge (for a given discharge cycle) and RUL The model is mainly trained on main features like Voltage, current, impedance and Capacity (for RUL). Among the available battery samples, training is done using batteries B0005, B0006, B0018 and the battery B0007 is used to validate the trained model. This indicates that 75% of data is used for training and the remaining 25% is used for testing which is the most acceptable ratio of training and testing data for developing machine learning models. Also, it is necessary to highlight that each battery sample consists of good enough data samples to represent the battery ageing process. In order to achieve better accuracy, all necessary parameters required to develop various battery models are considered during the training process. Initially all the datasets are converted from. mat to.csv file format using python script. The NASA dataset are present as a.mat file. As the data is converted, the data is cleaned according to the required parameters needed for our training. After cleaning of all the data, the summary of battery 5,6,7,18 is plotted based on all the factors included in the dataset and each parameter are noted and analyzed for further usage. To train the model the data from the battery are analyzed. So, for the benchmark in the hardware set up, commonly used models like ANN, CNN, RNN and DNN and other models like LSTM [35]–[38] for forecasting are implemented. Training is done using battery B0005, B0006, B0018 and the battery B0007 is used to test the trained model. To analyze the predictors better, the change in capacity for every cycle for all the three battery is plot to see the trend of change in each battery are represented in Fig. 6. From the analysis a generally decreasing trend with a few irregular peaks in-between is observed clearly.

A. CONVOLUTIONAL NEURAL NETWORK

CNN is based on a unique and special type of linear operation known as convolution. CNN are basically neural networks that use convolution functions in place of some other general matrix multiplication and similar function in at least one of their layers. A convolutional neural network also called convnet at least consists of an input and an output layer, as well one or more multiple hidden layers of one or more types. The hidden layers typically are a series of convolutional layers that convolute with a multiplication matrix function or other dot product. The activation function is commonly a rectified linear unit (ReLU) layer, and is followed by many other layers such as normalization layers, pooling layers, and fully connected layers as shown in Fig. 7. Typical ways of generally avoiding overfitting are regularization, and adding some form of method of measurement of weights in the network are done to the loss function. The steps in CNN are shown in Fig. 8. Although CNN is the most preferred choice for coupling factor analysis such as classification and segmentation in image applications, in recent years CNN is also employed for SOH and RUL estimation [39], [40].

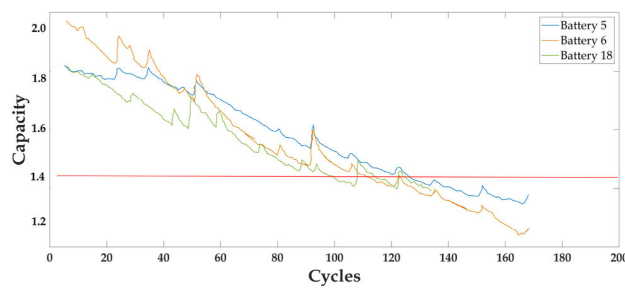

FIGURE 6. Battery 5,6,18 plotted (capacity vs. cycle).

This is mainly due to the ability of the CNN model to capture local capacity regeneration, thus improving the overall prediction accuracy of the model. In addition, pooling and

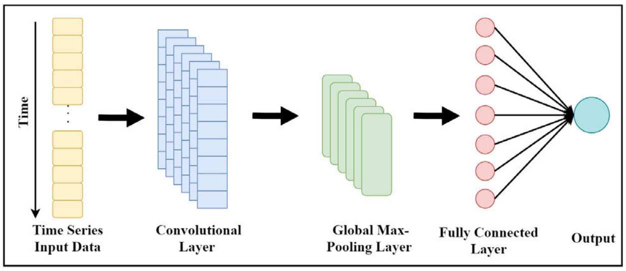

FIGURE 7. CNN architecture.

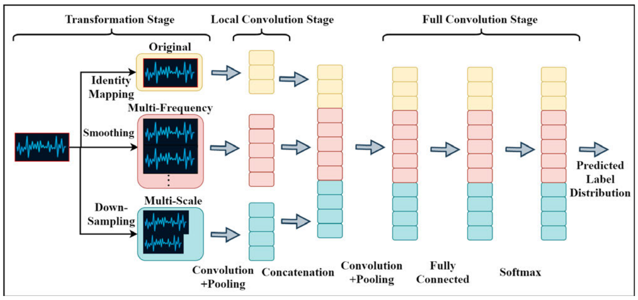

FIGURE 8. Steps in CNN.

dropout layers helps to improve the training speed of the model and avoid overfitting in a deep network.

B. RECURRENT NEURAL NETWORK

RNN is a type of artificial neural network in which connections between nodes form a directed graph along a time-based sequence. This allows it to exhibit temporal dynamic behavior. RNNs can be considered a method for forecasting in this case. RNNs can use their set internal memory to process different lengths of input sequences. RNN architecture is explained in Fig. 9. RNNs have variants like fully recurrent, independently RNN, Elman and Jordan networks, LSTM and others. Any common LSTM unit is composed of a cell, an output gate, input gate and a forget gate. The cell stores values from random time periods and the three other gates manage the flow of information in and out of the cell.

C. DEEP NEURAL NETWORK

A DNN is an ANN with multiple hidden layers between the input and output layers. DNNs are composed of multiple levels of nonlinear operations, such as neural nets with many hidden layers'' [41]. Like shallow ANNs, DNNs can also model complex non-linear relationships between different parameters. The model is trained using multiple hidden layers (DNN) [42]–[45] having different method of weight initialization and activation functions. In this process, a model is trained with 5 layers and in which 4 layers are of dense as shown in Fig. 10. The model is trained on 217 parameters. ReLU is the activation function for the layers of dense and then at last the results are compiled using Adam Optimization. There are large number of core types of layers present for Standard Neural Networks. Some of the most useful types chosen are:

- Dense Layer: Fully connected layer with highest demand and most useful Layer.
- Dropout Layer: Layer setting the fraction and minuet values to zero helping in reducing overfitting.
- Merge Layer: It helps to combine input from different model and resulting to one single model.

For transforming the summed weight input from one node into activation of the node activation functions are used. The Rectified Linear Activation function is a piecewise linear function that will result the input directly if it is positive ($x > 0$), otherwise, it will output as zero. ReLU has become one of the most used activation functions for many types of neural networks because a model that uses this is easier to train and often achieves better performance.

As the model with different layers and activation function is defined, it needs to be compiled. While compilation it has to keep note of the attributes to be taken care of like Loss functions, Metrics and optimizers.

1) MODEL OPTIMIZERS

Model optimizer is a search technique used to update the weight in the model. Optimizer are object with self-defined argument and learning rate [46] but as of the market Adam Optimizer is the best gradient descent optimizer present there. As the optimization algorithm can make difference between good result by minutes, hours or days choosing the best optimizer is a great task.

2) ADAM OPTIMIZER

Adam optimizer is the extension of stochastic gradient It is different from the stochastic gradient procedure to update network weight iterative used while training data. It maintains a single constant learning rate for all the weight updates which improves performance on problem with the sparse gradient. Adam used advantages of the two gradient decent that are Adaptive Gradient Algorithm (AdaGrad) and Root Mean Square Propagation (RMSProp) [47]–[50] which are algorithms with constant learning rate which means the algorithm perform perfectly on online and non-stationary problems.

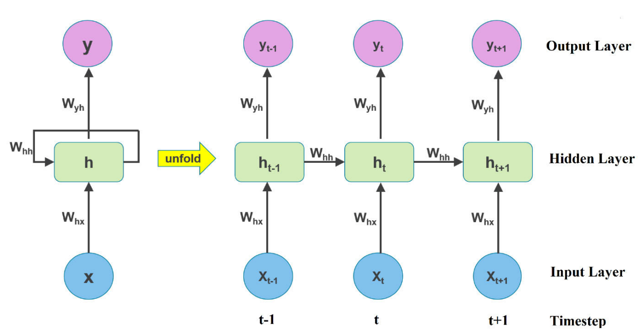

FIGURE 9. RNN architecture.

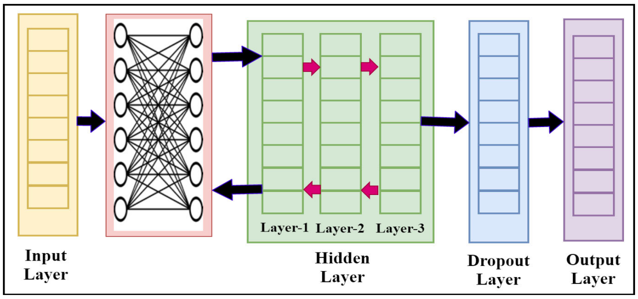

FIGURE 10. DNN architecture.

```
Model: "sequential_8"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_32 (Dense)             (None, 8)                 64
_________________________________________________________________
dense_33 (Dense)             (None, 8)                 72
_________________________________________________________________
dense_34 (Dense)             (None, 8)                 72
_________________________________________________________________
dropout_8 (Dropout)          (None, 8)                 0
_________________________________________________________________
dense_35 (Dense)             (None, 1)                 9
=================================================================
Total params: 217
Trainable params: 217
Non-trainable params: 0
_________________________________________________________________
```

FIGURE 11. Model architecture for SOH and DNN.

Hence, a model with all the multiple hidden layers were build which include the best suitable functions and algorithm and keeping all the different constrain in mind. The resultant model as shown in Fig.11 was compiled using the best optimizer present and the resultant model was used to predict the SOH of the testing battery dataset and the final result was noted for accuracy and further conclusion.

D. LONG SHORT TIME MEMORY

An LSTM has a similar control flow as a recurrent neural network. It processes data passing on information as it propagates forward. The differences are the operations within the LSTM's cells as shown in Fig. 12. The core concepts are the cell state, and various gates. It consists of a forgot gate which decides if the information must be kept or discarded. Then to update the cell state we have the input gate. Then the sigmoid function is applied on the gate with the previous hidden state. Then the cell state is calculated. At the end an output gate is used to decide what the next hidden state is.

Then the new cell stare is carried over to the next time step. To estimate the RUL, a similar model is obtained with Adam optimizer and uses back propagation for the same. A total of 1124201 parameters are considered for training. It consists of 4 LSTM layers,4 dropout layers and a dense layer the architecture of model shown in Fig. 13.

IV. RESULTS AND DISCUSSIONS

The sensors are calibrated and are used to collect the data. The collection has been implemented as step-by-step method.

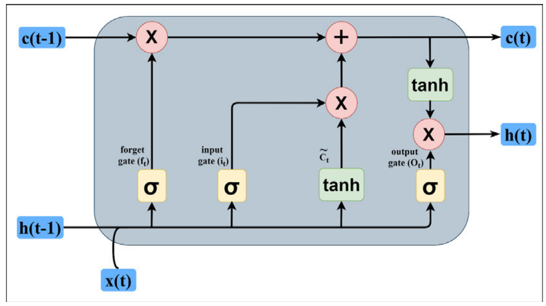

FIGURE 12. LSTM architecture.

```
Model: "Sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_4 (LSTM)                (None, 10, 200)           161600
_________________________________________________________________
dropout_5 (Dropout)          (None, 10, 200)           0
_________________________________________________________________
lstm_5 (LSTM)                (None, 10, 200)           320800
_________________________________________________________________
dropout_6 (Dropout)          (None, 10, 200)           0
_________________________________________________________________
lstm_6 (LSTM)                (None, 10, 200)           320800
_________________________________________________________________
dropout_7 (Dropout)          (None, 10, 200)           0
_________________________________________________________________
lstm_7 (LSTM)                (None, 200)               320800
_________________________________________________________________
dropout_8 (Dropout)          (None, 200)               0
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 201
=================================================================
Total params: 1, 124, 201
Trainable params: 1, 124, 201
Non-trainable params: 0
_________________________________________________________________
```

FIGURE 13. Model architecture for RUL using LSTM.

First the data are verified by only using Arduino for verification. Fig. 14 shows the data obtained in the serial monitor of Arduino. the data is in the order of time taken, Voltage across the battery with load, Current drawn by the battery, internal resistance of the battery and the cumulative capacity. Each of these battery parameter plays a vital role in determining SOH and RUL hence they all considered in developing the battery model. There are minor fluctuations in the reading of the voltage and current and readings are not strictly increasing or decreasing due to some extra resistance put in by the wires and other components. These fluctuations does not exhibit a problem when considering the data for one whole discharge cycle. Thereby, the Arduino are connected to Raspberry Pi in a serial port and the reading were verified. In order to generate a dataset required to perform the estimation of SOH and RUL in the proper format a.csv file is created by appending the values received serially from Arduino. Otherwise, the training and testing process involved in developing the battery model can't be achieved.

Fig. 15 shows the result of python script indicates the values that is got from its serial port separated by spaces. Fig. 16 shows a data which is stored in the Raspberry Pi as a csv file with all the variable in it. The battery model used for predicting SOH was trained using B0006 only. The trained model resulted to a new SOH values which was compared to the original i.e. actual SOH. Fig. 17 shows the comparison results of actual SOH and predicted SOH under its first run. From this result, it can be inferred that actual and predicted SOH maintain a lesser error percentage during the initial battery cycle (up to 25). Later, the developed battery model failed to maintain a minimum error percentage between the predicted SOH value and the actual SOH value. In order to verify the effectiveness of the DNN model, RMSE was calculated and the error was found to be around 9.088% in its second run as shown in Fig. 18, which implies that the accuracy of the DNN prediction is close to 91%. Here, actual SOH is represented as SOH and estimated SOH is denoted as NewSOH. Also from the result shown in Fig. 18 it shows that the DNN model tries to achieve the best accuracy from the beginning by matching the predicted SOH value near to its estimated SOH value.

Similarly, the DNN model were trained on B0005, B0006, B0018 battery dataset and battery B0007 was used to predict the model's accuracy. The error was found out to be around 5.9% as shown in Fig. 19 which means the accuracy of the model is around 94%. This gave an improved SOH result over previous tries due increase in the number of battery samples considered for training the battery model for SOH prediction hence significant improvement was made on the accuracy level. Although during the initial battery cycle, this battery model struggles to maintain minimum RMSE later it achieves better performance with an approximately 5.6% as error rate.

Fig. 20 presents the SOH estimation of various machine learning models which includes ANN, CNN, RNN, LR and DNN. Table 1 presents the accuracy of different learning models in terms of RMSE value. From the obtained results it can be inferred that DNN delivers better performance than other learning models by predicting the SOH value very close to the actual SOH value. Meanwhile, LR yields the worst accuracy when compared to others with an error rate of 18.9% which is very high and not suitable for real-world implementation. The number of hidden layers in DNN also influence the model's accuracy. With a number of hidden layers as one and two, the DNN model exhibits under fit with large error. However, with three hidden layers the DNN model achieves the best fit as shown in Fig 21.

T	V	I	Ri	C
146668	3.47	0.92	77.24	29.84
147340	3.47	0.92	72.58	30.76
148013	3.44	0.92	73.17	31.68
148684	3.47	0.92	77.24	32.59
149356	3.44	0.92	73.17	33.51
150028	3.47	0.91	72.58	34.42
150700	3.47	0.92	77.24	35.34
151372	3.47	0.91	77.24	36.25
152044	3.47	0.92	77.24	37.17
152716	3.44	0.92	73.17	38.09
153388	3.47	0.91	77.24	39.00
154060	3.44	0.92	73.17	39.92

FIGURE 14. Sensor readings recorded in Arduino (T = Time, V = Voltage, I = Current, RI = Internal resistance, C = cumulative capacity).

Also, it is essential to mention that beyond three hidden layers, the DNN model encounters over fit condition.

```
  T    V    I    RI    C
b'5001 3.66 0.25 63.91 2.54\r\n'
b'5672 3.61 0.26 60.61 2.80\r\n'
b'6344 3.61 0.24 60.61 3.04\r\n'
b'7016 3.61 0.25 64.89 3.29\r\n'
b'7688 3.61 0.25 60.61 3.54\r\n'
b'8359 3.61 0.24 60.61 3.78\r\n'
b'9031 3.59 0.25 61.07 4.03\r\n'
b'9703 3.64 0.25 64.39 4.28\r\n'
b'10375 3.61 0.25 60.61 4.53\r\n'
```

FIGURE 15. Running of python script in raspberry Pi to generate dataset.

T	V	I	Ri	C
b'969'	b'3.56'	b'0.39'	b'65.89'	b'0.39'
b'1641'	b'3.59'	b'0.39'	b'69.77'	b'0.78'
b'2313'	b'3.64'	b'0.38'	b'77.52'	b'1.16'
b'2984'	b'3.52'	b'0.39'	b'58.14'	b'1.55'
b'3656'	b'3.59'	b'0.38'	b'69.77'	b'1.94'
b'4329'	b'3.64'	b'0.35'	b'64.39'	b'2.29'
b'5001'	b'3.66'	b'0.25'	b'63.91'	b'2.54'
b'5672'	b'3.61'	b'0.26'	b'60.61'	b'2.80'
b'6344'	b'3.61'	b'0.24'	b'60.61'	b'3.04'
b'7016'	b'3.61'	b'0.25'	b'64.89'	b'3.29'
b'7688'	b'3.61'	b'0.25'	b'60.61'	b'3.54'

FIGURE 16. Data stored as a csv in raspberry Pi.

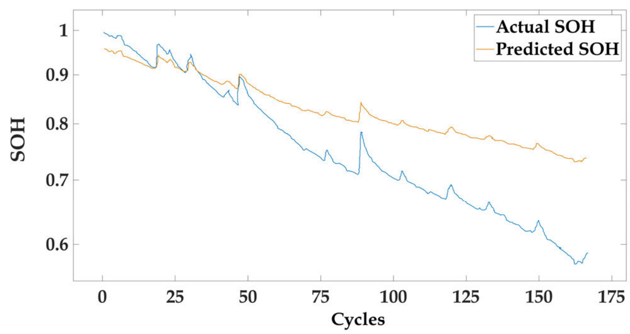

FIGURE 17. First run SOH predicted for B0006 using DNN.

```
(50285, 1)
   cycle       SoH     NewSoH
0      1  1.000000  0.959172
1      2  0.994990  0.956460
2      3  0.989185  0.953311
3      4  0.989165  0.953293
4      5  0.982898  0.949908
5      6  0.989467  0.953456
6      7  0.989075  0.953246
7      8  0.967304  0.941484
8      9  0.966997  0.941313
9     10  0.961625  0.938410
Root Mean Square Error:  0.09088712307694548
```

FIGURE 18. Predicted SOH and RMSE for second time prediction of B0006 using DNN.

TABLE 1. RMSE for various algorithms in SOH estimation.

	LR	ANN	RNN	CNN	DNN
RMSE	0.189	0.141	0.094	0.165	0.059

The results for each layer's accuracy of the DNN model along with the error difference under each layer is presented in Table 2. For finding out the RUL an efficient model of LSTM is employed, and the result was found to be as shown

```
(50285, 1)
   Cycle       SOH    NewSoH
0      1  1.000000  1.045082
1      2  0.994492  1.040318
2      3  0.994506  1.040699
3      4  0.994563  1.041457
4      5  0.993865  1.041479
5      6  0.994526  1.043849
6      7  0.994121  1.043126
7      8  0.994953  1.042896
8      9  0.988704  1.036756
9     10  0.988895  1.037450
Root Mean Square Error: 0.05986816859511503
```

FIGURE 19. Predicted SOH and SOH, RMSE value of battery B0007.

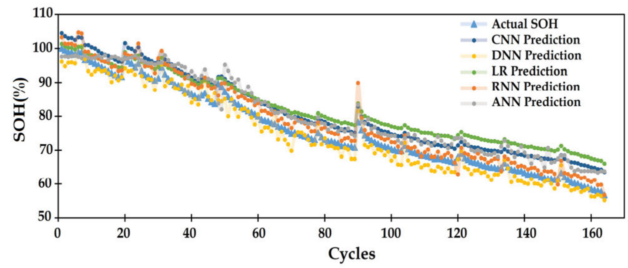

FIGURE 20. SOH prediction using different approaches.

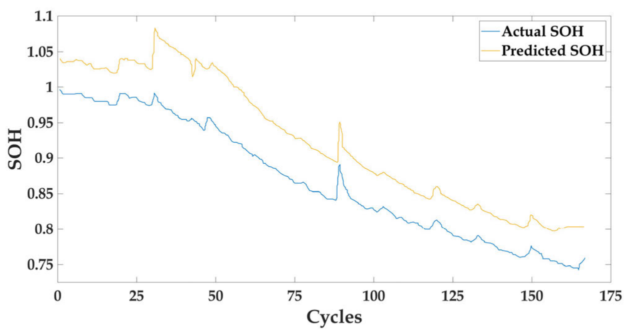

FIGURE 21. Result with 3 hidden layers in DNN.

in Fig. 22. From Fig. 22, it can be inferred that the LSTM model makes its best efforts to match the predicted RUL cycle with the actual cycle of battery fail condition. As RUL prediction is based on the previously predicted SOH, the error is not always the same and it is dependent on the previous prediction. Although the RUL error range is inconsistence when the same learning model is made to run at different time instances, the performance of the LSTM model is much better than other learning models. Fig. 23 illustrates the error for the same RUL prediction under different instances with 3 cycle error difference for the best case and -8 cycle error difference as the worst case. This main objective of this research work is to develop, analyze and compare various machine learning models on hardware in order to identify an optimal SOH and RUL estimation approach for a single Li- ion battery hence the computation complexity involved is very negligible. This can be verified by running the model at different time instant, and the system is able to provide the estimation result instantly. However, if the given approach is extended for a large volume of LiB like a battery pack or battery module then the computation complexity may increase. Since each battery model delivers SOH and RUL prediction result with different time duration at different time instance hence it is not presented in the result section. However, all machine learning models are able to deliver the estimation result within less than 1 second. Hence, it can be concluded that the computation time cost involved in various machine learning models implemented is insignificant. In this research work, NASA's battery aging process dataset collected is utilized to construct the battery model using various data-driven based machine learning algorithms. From the dataset, vital battery parameters which influences battery health conditions such as voltage, current, impedance and capacity are considered to develop the battery model. Since data-driven based approach is applied in this research work, irrespective any battery dataset is employed, the procedure followed will remains the same irrespective of any battery chemistries.

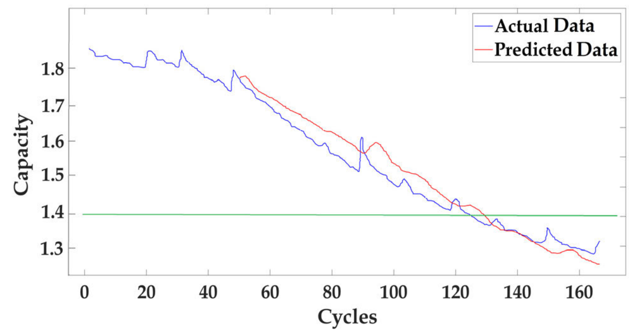

FIGURE 22. RUL prediction.

```
The Actual fail at cycle number: 128
The predictionfail at cycle number: 131
The error of RUL= 3 Cycles(s)
```

```
The Actual fail at cycle number: 128
The predictionfail at cycle number: 120
The error of RUL= -8 Cycles(s)
```

FIGURE 23. Error in RUL prediction.

TABLE 2. RMSE for different hidden layers in DNN SOH estimation.

Number of Hidden Layers	RMSE	Error difference (%)
1	0.09088	-
2	0.06750	2.33
3	0.05986	0.76

V. CONCLUSION

This main objective of this research work is to develop, analyze and compare various machine learning models on hardware platform in order to identify an optimal battery life estimation approach for Li-ion battery. In order to achieve this objective, a unified standalone hardware is developed using a Raspberry-Pi and various machine learning models such as LR, ANN, CNN, RNN, DNN and LSTM are analyzed by determining SOH and RUL. To verify the effectiveness of each learning model, models were tested against a real-world data acquired from a Panasonic NCR18650B battery. From the obtained experimental results, it can be concluded that DNN learning model outperforms other learning model in SOH estimation with maximum RMSE error of 5.9%. Similarly, by considering SOH and battery capacity as a key feature, RUL of the battery is predicted. Although, RUL error range is inconsistence when same learning model made to run at different time instances, the performance of the LSTM model is much better than other learning model. The main limitations of the above approach are it is verified only on a single battery cell hence computation complexity and computation time involved is very negligible. However, if the same approach are followed for battery pack or battery module it may increase. To overcome this limitation, a better hardware setup can be used in ideal conditions to increase the rate of prediction and decrease the prediction time with faster computational mechanisms.

REFERENCES

[1] D. Linden, *Linden's Handbook of Batteries*. New York, NY, USA: McGraw-Hill, 2010.

[2] R. Spotnitz, "Simulation of capacity fade in lithium-ion batteries," *J. Power Sources*, vol. 113, pp. 72–80, Jan. 2003.

[3] G. Livint, M. Ratoi, V. Horga, and M. Albu, "Estimation of battery parameters based on continuous-time model," in *Proc. Int. Symp. Signals, Circuits Syst.*, Jul. 2007, pp. 1–4.

[4] H. Ruan, H. He, Z. Wei, Z. Quan, and Y. Li, "State of health estimation of lithium-ion battery based on constant-voltage charging reconstruction," *IEEE J. Emerg. Sel. Topics Power Electron.*, early access, Jul. 21, 2021, doi: 10.1109/JESTPE.2021.3098836.

[5] X. Bian, Z. Wei, J. He, F. Yan, and L. Liu, "A novel model-based voltage construction method for robust state-of-health estimation of lithium-ion batteries," *IEEE Trans. Ind. Electron.*, vol. 68, no. 12, pp. 12173–12184, Dec. 2021.

[6] J. He, Z. Wei, X. Bian, and F. Yan, "State-of-health estimation of lithium-ion batteries using incremental capacity analysis based on coltage–capacity model," *IEEE Trans. Transport. Electrific.*, vol. 6, no. 2, pp. 417–426, Jun. 2020.

[7] L. Lam and P. Bauer, "Practical capacity fading model for Li-ion battery cells in electric vehicles," *IEEE Trans. Power Electron.*, vol. 28, no. 12, pp. 5910–5918, Dec. 2013.

[8] M. A. Patil, P. Tagade, K. S. Hariharan, S. M. Kolake, T. Song, T. Yeo, and S. Doo, "A novel multistage support vector machine based approach for Li ion battery remaining useful life estimation," *Appl. Energy*, vol. 159, pp. 285–297, Dec. 2015.

[9] J. S. Goud, R. Kalpana, and B. Singh, "Modeling and estimation of remaining useful life of single cell Li-ion battery," in *Proc. IEEE Int. Conf. Power Electron., Drives Energy Syst. (PEDES)*, Dec. 2018, pp. 1–5.

[10] H.-T. Lin, T.-J. Liang, and S.-M. Chen, "Estimation of battery state of health using probabilistic neural network," *IEEE Trans. Ind. Informat.*, vol. 9, no. 2, pp. 679–685, May 2013.

[11] C. Wang, N. Lu, S. Wang, Y. Cheng, and B. Jiang, "Dynamic long short-term memory neural-network-based indirect remaining-useful-life prognosis for satellite lithium-ion battery," *Appl. Sci.*, vol. 8, no. 11, p. 2078, Oct. 2018.

[12] P. Khumprom and N. Yodo, "A data-driven predictive prognostic model for lithium-ion batteries based on a deep learning algorithm," *Energies*, vol. 12, no. 4, p. 660, Feb. 2019.

[13] C. Lin, A. Tang, and W. Wang, "A review of SOH estimation methods in lithium-ion batteries for electric vehicle applications," *Energy Proc.*, vol. 75, pp. 1920–1925, Aug. 2015.

[14] A. Ganeshan and R. Shanmughasundaram, "Estimation of SoC and SoH using mixed neural network and Coulomb counting algorithm," *Int. J. Innov. Technol. Exploring Eng.*, vol. 8, pp. 2557–2561, Nov. 2019.

[15] Z. Wang, S. Zeng, J. Guo, and T. Qin, "Remaining capacity estimation of lithium-ion batteries based on the constant voltage charging profile," *PLoS ONE*, vol. 13, no. 7, Jul. 2018, Art. no. e0200169.

[16] L. Ren, L. Zhao, S. Hong, S. Zhao, H. Wang, and L. Zhang, "Remaining useful life prediction for lithium-ion battery: A deep learning approach," *IEEE Access*, vol. 6, pp. 50587–50598, 2018.

[17] P. Venugopal, "State-of-health estimation of Li-ion batteries in electric vehicle using IndRNN under variable load condition," *Energies*, vol. 12, no. 22, p. 4338, Nov. 2019.

[18] M. Galeotti, L. Cinà, C. Giammanco, S. Cordiner, and A. Di Carloac, "Performance analysis and SOH (state of health) evaluation of lithium polymer batteries through electrochemical impedance spectroscopy," *Energy*, vol. 89, pp. 678–686, Sep. 2015.

[19] M.-H. Hung, C.-H. Lin, L.-C. Lee, and C.-M. Wang, "State-of-charge and state-of-health estimation for lithium-ion batteries based on dynamic impedance technique," *J. Power Sources*, vol. 268, pp. 861–873, Dec. 2014.

[20] S. Tong, M. P. Klein, and J. W. Park, "On-line optimization of battery open circuit voltage for improved state-of-charge and state-of-health estimation," *J. Power Sources*, vol. 293, pp. 416–428, Oct. 2015.

[21] X. Bian, L. Liu, and J. Yan, "A model for state-of-health estimation of lithium ion batteries based on charging profiles," *Energy*, vol. 177, pp. 57–65, Jun. 2019.

[22] M. Huang and M. Kumar, "Electrochemical model-based aging characterization of lithium-ion battery cell in electrified vehicles," in *Proc. Dyn. Syst. Control Conf.*, vol. 51913, Sep. 2018, Art. no. V003T29A002.

[23] L. Fang, J. Li, and B. Peng, "Online estimation and error analysis of both SOC and SOH of lithium-ion battery based on DEKF method," *Energy Proc.*, vol. 158, pp. 3008–3013, Feb. 2019.

[24] S. Schwunk, N. Armbruster, S. Straub, J. Kehl, and M. Vetter, "Particle filter for state of charge and state of health estimation for lithium-iron phosphate batteries," *J. Power Sources*, vol. 239, no. 1, pp. 705–710, 2013.

[25] E. Bakas, B. Rosca, S. Wilkins, and T. Donkers, "Least-squares-based capacity estimation for lithium-ion battery cells," in *Proc. EEVC*, 2017, pp. 1–6.

[26] P. Ananto, F. Syabani, W. D. Indra, O. Wahyunggoro, and A. I. Cahyadi, "The state of health of Li-Po batteries based on the battery's parameters and a fuzzy logic system," in *Proc. Joint Int. Conf. Rural Inf. Commun. Technol. Electr.-Vehicle Technol. (rICT ICeV-T)*, Nov. 2013, pp. 1–4.

[27] Z. Chen, M. Sun, X. Shu, R. Xiao, and J. Shen, "Online state of health estimation for lithium-ion batteries based on support vector machine," *Appl. Sci.*, vol. 8, no. 6, p. 925, Jun. 2018.

[28] J. Kim, J. Yu, M. Kim, K. Kim, and S. Han, "Estimation of Li-ion battery state of health based on multilayer perceptron: As an EV application," *IFAC-PapersOnLine*, vol. 51, no. 28, pp. 392–397, 2018.

[29] H. Chaoui and C. C. Ibe-Ekeocha, "State of charge and state of health estimation for lithium batteries using recurrent neural networks," *IEEE Trans. Veh. Technol.*, vol. 66, no. 10, pp. 8773–8783, Oct. 2017.

[30] G.-W. You, S. Park, and D. Oh, "Diagnosis of electric vehicle batteries using recurrent neural networks," *IEEE Trans. Ind. Electron.*, vol. 64, no. 6, pp. 4885–4893, Jun. 2017.

[31] Y. Liu, G. Zhao, X. Peng, and C. Hu, "Lithium-ion battery remaining useful life prediction with long short-term memory recurrent neural network," in *Proc. Annu. Conf. PHM Soc.*, vol. 9, no. 1, 2017, pp. 1–7.

[32] Y. Zhang, R. Xiong, H. He, and M. G. Pecht, "Long short-term memory recurrent neural network for remaining useful life prediction of lithium-ion batteries," *IEEE Trans. Veh. Technol.*, vol. 67, no. 7, pp. 5695–5705, Jul. 2018.

[33] J. Wu, Y. J. Wang, X. Zhang, and Z. H. Chen, "A novel state of health estimation method of Li-ion battery using group method of data handling," *J. Power Sources*, vol. 327, pp. 457–464, Sep. 2016.

[34] B. Saha and K. Goebel, *Battery Data Set*. Moffett Field, CA, USA: NASA Ames Research Center, NASA Ames Prognostics Data Repository, 2007. [Online]. Available: http://ti.arc.nasa.gov/project/prognostic-data-repository

[35] S. Albawi, T. A. Mohammed, and S. Al-Zawi, "Understanding of a convolutional neural network," in *Proc. Int. Conf. Eng. Technol. (ICET)*, Aug. 2017, pp. 1–6.
[36] Q. V. Le, N. Jaitly, and G. E. Hinton, "A simple way to initialize recurrent networks of rectified linear units," 2015, *arXiv:1504.00941*.
[37] V. Nair and G. E. Hinton, "Rectified linear units improve restricted Boltzmann machines," in *Proc. ICML*, Jan. 2010, pp. 807–814.
[38] A. L. Maas, A. Y. Hannun, and A. Y. Ng, "Rectifier nonlinearities improve neural network acoustic models," in *Proc. ICML*, vol. 30, no. 1, Jun. 2013, p. 3.
[39] S. Hong, M. Kang, H. Jeong, and J. Baek, "State of health estimation for lithium-ion batteries using long-term recurrent convolutional network," in *Proc. IECON 46th Annu. Conf. IEEE Ind. Electron. Soc.*, Oct. 2020, pp. 1929–1934.
[40] D. Zhou, Z. Li, J. Zhu, H. Zhang, and L. Hou, "State of health monitoring and remaining useful life prediction of lithium-ion batteries based on temporal convolutional network," *IEEE Access*, vol. 8, pp. 53307–53320, 2020.
[41] X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," in *Proc. 13th Int. Conf. Artif. Intell. Statist.*, Mar. 2010, pp. 249–256.
[42] S. Ruder, "An overview of gradient descent optimization algorithms," 2016, *arXiv:1609.04747*.
[43] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," 2014, *arXiv:1412.6980*.
[44] Y. Bengio and Y. LeCun, "Scaling learning algorithms towards AI," *Large-Scale Kernel Mach.*, vol. 34, no. 5, pp. 1–41, 2007.
[45] R. DiPietro and G. D. Hager, "Deep learning: RNNs and LSTM," in *Handbook of Medical Image Computing and Computer Assisted Intervention*. New York, NY, USA: Academic, 2020, pp. 503–519.
[46] T. K. Gupta and K. Raza, "Optimization of ANN architecture: A review on nature-inspired techniques," in *Machine Learning in Bio-Signal Analysis and Diagnostic Imaging 2019*, Jan. 2019, ch. 6, pp. 159–182.
[47] Y. Takagishi, T. Yamanaka, and T. Yamaue, "Machine learning approaches for designing mesoscale structure of Li-ion battery electrodes," *Batteries*, vol. 5, no. 3, p. 54, Aug. 2019.
[48] T. Yamanaka, Y. Takagishi, and T. Yamaue, "A framework for optimal safety Li-ion batteries design using physics-based models and machine learning approaches," *J. Electrochem. Soc.*, vol. 167, no. 10, Jun. 2020, Art. no. 100516.
[49] I. Babaeiyazdi, A. Rezaei-Zare, and S. Shokrzadeh, "State of charge prediction of EV Li-ion batteries using EIS: A machine learning approach," *Energy*, vol. 223, May 2021, Art. no. 120116.
[50] V. Kannan, A. Fisher, and E. Birgersson, "Monte Carlo assisted sensitivity analysis of a Li-ion battery with a phase change material," *J. Energy Storage*, vol. 35, Mar. 2021, Art. no. 102269.

PRAKASH VENUGOPAL is currently a Faculty Member with the School of Electronics Engineering, Vellore Institute of Technology, Chennai. He has published many research papers in the high-quality peer-reviewed journals and international conferences. His major research interests include embedded system design, real-time operating systems, battery management system in electric vehicle, smart grid, the Internet of Things, and machine learning.

S. SIVA SHANKAR is currently pursuing the bachelor's degree with the School of Electronics Engineering, Vellore Institute of Technology, Chennai. His major research interests include embedded system design, real-time operating systems, and the Internet of Things.

C. PHILLIP JEBAKUMAR is currently pursuing the bachelor's degree with the School of Electronics Engineering, Vellore Institute of Technology, Chennai. His major research interests include computer vision and automotive applications of Industrial IoT.

RISHAB AGARWAL is currently pursuing the bachelor's degree with the School of Electronics Engineering, Vellore Institute of Technology, Chennai. His major research interests include embedded system design, the Internet of Things, and machine learning.

HASSAN HAES ALHELOU (Senior Member, IEEE) is currently a Faculty Member with Tishreen University, Lattakia, Syria. He is also with IUT, Iran. He was with University College Dublin, Ireland. He has participated in more than 15 industrial projects. He has published more than 160 research papers in the high quality peer-reviewed journals and international conferences. His major research interests include power systems, power system dynamics, power system operation and control, dynamic state estimation, frequency control, smart grids, micro-grids, demand response, load shedding, and power system protection. He was a recipient of the Outstanding Reviewer Award from *Energy Conversion and Management* Journal in 2016, *ISA Transactions* Journal in 2018, *Applied Energy* Journal in 2019, and many other awards. He was also a recipient of the Best Young Researcher in the Arab Student Forum Creative among 61 researchers from 16 countries from Alexandria University, Egypt, in 2011. He is included in the 2018 and 2019 Publons List of the Top 1% Best Reviewer and Researchers in the field of engineering. He has also performed reviews for high prestigious journals, including IEEE TRANSACTIONS ON POWER SYSTEMS, IEEE TRANSACTIONS ON SMART GRID, IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS, *Energy Conversion and Management*, *Applied Energy*, and the *International Journal of Electrical Power and Energy Systems*.

S. SOFANA REKA is currently working as an Assistant Professor (Senior) with the School of Electronics Engineering, Vellore Institute of Technology, Chennai. She has published various international journals with high impact factor in her credit. Her research interests include smart grid, embedded systems, machine learning, the Internet of Things, and cyber physical systems. She is also a reviewer of many SCI journals.

MOHAMAD ESMAIL HAMEDANI GOLSHAN (Senior Member, IEEE) received the B.Sc. degree in electrical engineering from the Isfahan University of Technology, Isfahan, Iran, in 1987, the M.Sc. degree in electrical engineering from the Sharif University of Technology, Tehran, in 1990, and the Ph.D. degree in electrical engineering from the Isfahan University of Technology, in 1998. He is currently a Full Professor with the Department of Electrical and Computer Engineering, Isfahan University of Technology. His major research interests include power system analysis, power system dynamics, power quality, dispersed generation, flexible ac transmission systems and custom power, and load modeling.