Journal of Energy Storage 40 (2021) 102741

Contents lists available at ScienceDirect

Journal of Energy Storage

journal homepage: www.elsevier.com/locate/est

Battery monitoring system using machine learning

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A R T I C L E I N F O

Keywords:
Battery
BMS
Lithium-ion
Rechargeable
LSTM
Health

A B S T R A C T

Battery life prediction helps in smooth and uniform functioning of the battery-operated systems. Although, the capacity of the battery can be monitored by some devices, they cannot estimate how long the battery can work before a failure occurs. The technique that we have proposed here, estimates the life span of a battery using Long Short Term-Memory (LSTM), an artificial Recurrent Neural Network (RNN) architecture in Machine Learning (ML). The battery life is measured by considering each cell voltage, load voltage, temperature of the battery and charge-discharge cycle. The voltage and temperature of the battery cells are measured by a thermistor and microcontroller. The voltage values fetched by the micro controller are sent to a web server and these values are displayed on a web based mobile phone application. Balance charging of the battery cells and over charge protection is provided by constantly monitoring the battery status. This paper includes explanation on different circuit parts, algorithm used in training the model, Graphical User Interface (GUI) and the test results.

1. Introduction

The progress in the field of rechargeable batteries has garnered it a wide popularity among different energy storage systems. The renewable energy sources require an energy storage system (ESS) to support a reliable and smooth supply to the customer. Among different energy storage systems, Li-ion battery is preferred over other batteries in many fields owing to its high reliability, efficiency, power and energy density, long lifespan and low discharge rate. If a circuit can equalize the charge within the cells of a battery, the performance can be increased even if the cells differ with capacities [1–3]. Battery Management System (BMS) is a vital and an essential element in any battery driven system to assure the safety, reliability, efficiency and long-last operation of a Li-ion battery. Each cell in a battery pack has different temperature though they have an effectively built cooling system [4]. Hence, the cells deteriorate unevenly and cell capacity variation occurs [5,6]. The BMS senses the voltage and current of the battery cells and its corresponding temperature to prevent over-charge and over-discharge conditions which occurs when the battery is connected to a load. These measured variables are employed in estimating the Li-ion battery states i.e., the State of available Power (SOP), State of Charge (SOC), State of Life (SOL) and State of Health (SOH) [7–9].

Early detection of inadequate performance facilitates timely maintenance of battery systems. This reduces operational costs and prevents accidents and malfunctions [10]. Modeling the battery behavior using ML has been increasing over the years. Most ML methods cover SOC prediction through neural networks [11], deep neural networks [12], LSTM cells [13,14]. ML could be a promising modeling approach to estimate the SOH, SOC and remaining useful life of batteries. The two widely studied types of battery models for prediction of state of battery are equivalent circuit and physics-based models. Due to their limitations, we use the ML technology for fast and better efficient battery state prediction [15–18]. Lithium batteries require constant and accurate monitoring to check their condition, specifically, the level of the remaining available energy, indicated by the SOC. An accurate and reliable knowledge of the SOC mitigates psychological factors such as the range anxiety [19]. Precise SOC estimations are a crucial and consequential concern in designing a BMS. Accurate and precise estimations can not only evaluate the battery reliability but also impart the information on the unexploited energy with its useable time [20]. The SOC cannot be directly measured, and its value can only be estimated from the measurement of other battery parameters, such as current, voltage, internal resistance, and temperature [21].

Approaches using statistical and machine learning techniques to predict cycle life are attractive, mechanism-agnostic alternatives [22]. As the battery state of health is highly non-linear ML is an appropriate approach. ML can significantly accelerate calculations to improve prediction accuracy and make optimized decisions for real time management. Vidal et,al presented a paper on comparison of SOC models based on FNN,RNN and Kalman filter models and their studies showed that

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https://doi.org/10.1016/j.est.2021.102741
Received 15 December 2020; Received in revised form 12 May 2021; Accepted 17 May 2021
Available online 31 May 2021

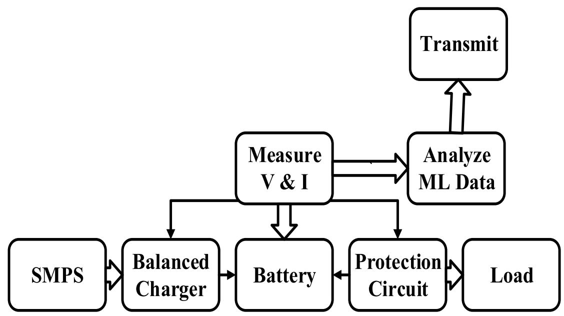

Fig. 1. Block Diagram of the proposed System.

RNN delivers better results [23]. The comparisons were made in terms of data quality, inputs and outputs, test condition and battery types. Considering all the above stated requirements in batteries, a system was designed to monitor the battery which will inform the user about the battery cell health and its range i.e., lifespan. This is done by using Long Short Term-Memory (LSTM) architecture in Machine Learning [24,25]. Knowing cell health and lifespan of the battery will be helpful in replacing the battery well in advance to evade any kind of harm to the battery driven system and its smooth functioning. Even charging of all the cells of the battery will help in increasing the life span of a battery and efficiency. The designed BMS circuit can protect the battery from over charging, over voltage, over discharge, imbalance charging and discharging of the battery cells and also predict how long the battery will last before failure. The concept of equalizing the charge within the cells of a battery by continuously monitoring the battery status is also been implemented in this paper. This project will help Unmanned Ariel Vehicle (UAV)s, Electric Vehicle (EV)s, inverters and other battery-operated devices to function smoothly for a long time.

2. Methodology

Fig. 1 shows the functional block diagram of the proposed BMS using ML system. Here, 'Measure V & I' block corresponds to the microcontroller and 'Transmit' block corresponds to ESP8266 Wi-Fi microchip. Analog - Digital Converter (ADC) of the microcontroller measures the voltage state of battery. The voltage values fetched by the microcontroller is sent to a local server by ESP8266, a Wi-Fi microchip.

Machine Learning algorithm analyses the data stored in the web server to estimate life span of the battery cells. This result along with cell voltage and temperature is displayed in the web based mobile phone application. Long Short Term-Memory (LSTM), a feedback Machine Learning algorithm which is an artificial RNN architecture involving memory directed cycles giving excellent performance for sequential pieces of figures is used in this system [26,27]. Balance charging of the battery cells and other charging protections are provided by the BMS circuit itself.

2.1. Battery Management System (BMS)

BMS is a system that manages a battery. It monitors constant charging and discharging of the battery and also ensures equal charge on each cell of a battery during charging and discharging mechanism. BMS comprises both, hardware and software. The software instructs the hardware components. An efficient BMS,

i) Forfends the battery
ii) Maintains safe operation of the battery within the rated current, voltage, temperature
iii) Measures and evaluates battery states.

A BMS includes measuring, balancing and protection circuit. The voltage and current measurement section measure the voltage and current values of each cell in the battery pack and that of the whole battery. The temperature control section measures the temperature of each cell of the battery pack and also monitors the cooling system [20]. Balancing circuit ensures even charging and discharging of the battery cells so that they don't get over charged or discharged. Protection circuit provides protection to the battery from different threats. Fig. 2 is the general diagram of a BMS with its different working units.

In a battery pack where cells are in series relation, cells which have uniform capacity, drastically lose their capacity after being used for a long period of time. In Fig. 3, Cell i, Cell ii and Cell iii have a capacity of 10 Ah initially and are healthy. In the long run of use, Cell i will have its original capacity 10 Ah preserved, Cell ii with 8 Ah capacity and Cell iii with only 6 Ah capacity left. This imbalance in capacity results in imbalance charging-discharging. Now, the unhealthier Cell iii will be charged up to 4.2 V which is the limit to avoid overcharging, faster than Cell i and Cell ii which will have only 3.8 V and 4.0 V respectively at the time taken by Cell iii to reach its maximum voltage, leaving 25% and 15% correspondingly unoccupied capacity. Likewise, the Cell iii will be discharged to 2.8 V which is the under-charging limit, at a rate faster than Cell i and Cell ii which will reach 3.1 V and 3.0 V respectively leaving 25% and 15% capacity unexploited. This will result in Cell i and Cell ii in the battery pack merely exploiting 50% and 70% of their capacity respectively. Hence, the overall battery capacity will be very low proving that balanced charging is essential.

Strategy is prerequisite in designing a balancing circuit. The circuit that we have designed has Atmega328p at the core as microcontroller controlling all the components and functions. The reason for choosing Atmega328p over other micro controllers is, it costs less and has the required number of Analog and Digital pins. Atmega328p has 10-bit ADC and 8-bit ADC. We have chosen 10-bit ADC in this project as it has better resolution than 8-bit but its speed is slower than the 8-bit ADC. Fig. 4(a) shows pin configuration of the Atmega328p. Multiplexer CD74HC4067 is used which is a MUX and DEMUX with four select lines [28]. These select lines are connected to the microcontroller Atmega328p. Voltage value obtained from the cell is translated to actual voltage using the voltage divider ratio,

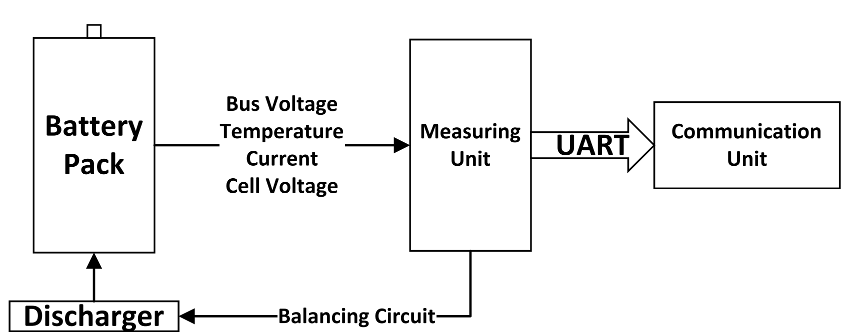

Fig. 2. General diagram of a BMS.

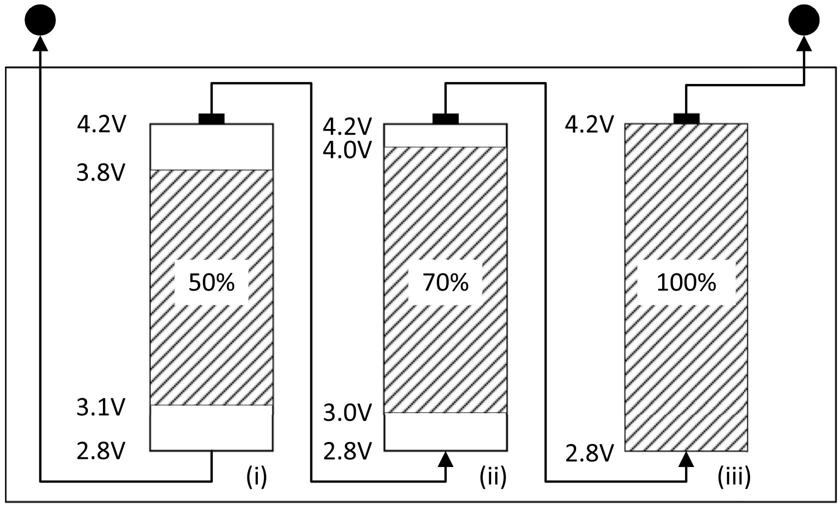

Fig. 3. Unbalance among cells in the battery set.

$$V_{actual} = V\left(\frac{R_7 + R_{25}}{R_{25}}\right) \tag{1}$$

The voltage and temperature value obtained are then sent to ESP8266 which appends data related to the URL, posts the URL request and waits for the confirmation from the server. Fig. 4(d) shows the pin configuration of the Multiplexer CD74HC4067.

2.1.1. *Pre-Processing of Battery Voltages and Temperature*

The protection circuit consists of a MOSFET which cuts off the connection from the battery if the voltage exceeds or goes below the threshold voltage and also if the battery is fully charged or the battery voltage goes low. In the Fig. 4(e), the terminals b_1 to b_8 are connected to the positive terminal of 8-cell battery pack. The terminals c_1-c_{16} are connected to multiplexer. The terminals of female header are used to connect to a 10k Ω thermistor. R_7 to R_{14} with R_{25} to R_{32} form voltage divider network (1) and R_{15} to R_{22} with thermistors connected at the header terminal forms voltage divider network (2) which gives proportional voltage of the battery under 3.3 V. The following equations give voltages across the above-mentioned voltage divider networks respectively.

$$V_{c1} = \frac{b_1 R_{25}}{R_7 + R_{25}} \tag{2}$$

$$V_{t1} = \frac{V_{cc} R_{t1}}{R_{t1} + R_{25}} \tag{3}$$

2.1.2. *Temperature Control Circuit*

The temperature control circuit is shown in Fig. 4(e). It includes a thermistor with voltage divider network which measures the temperature of the battery. Thermistor is a small device with metallic oxide encapsulated by epoxy or glass, which gives temperature value corresponding to the variation in its resistance. If the temperature exceeds the threshold limit, this circuit cuts-off the battery connection until the temperature becomes normal. The temperature senor is calibrated by measuring two known temperatures and the voltage is scaled accordingly. This voltage and temperature value is converted into string and sent to ESP8266 Wi-Fi microchip [29].

2.1.3. *Balancing Circuit*

The balancing circuit has an optocoupler along with IRLZ44N MOSFET to isolate the GND with respect to MOSFET as shown in Fig. 4 (c) [30]. This circuit checks the voltages of individual cell in the battery and ensures that they all have the same voltage. This is an important factor to be observed because if one cell's voltage drops or increases above the required voltage range, the battery may get damaged. As the battery reaches the threshold 4.2 V, the MOSFET is triggered and the battery is connected to a 2 Ω resistor which will reduce the voltage from 4.2 V and charging the battery is carried by maintaining 4.2 V across all the cells. The resistor is chosen in such a way that the charging current does not increase more than the voltage of the battery. Once all the cells of the battery are charged to 4.2 V, the charging mechanism is stopped by the circuit.

2.1.4. *Protection Circuits*

The BMS circuit provides following protections to the battery:

a) **Over Charge Protection** – when all the cells of the battery are charged to the maximum voltage i.e., 4.2 V, the supply is cut-off by this circuit.
b) **Over Discharge Protection** – when one of the cell potential drops below the minimum voltage i.e., 3.6 V, the load connection is cut-off from the battery by this circuit
c) **Over Voltage Protection** – if the battery is being charged at a voltage greater than 33.6 V (in case of 8-cell battery pack where each cell is charged up to 4.2 V), the supply is cut-off by this circuit.
d) **Over Current Protection** – if the current at which battery is charged is greater than the rated input current, supply is cut-off.
e) **Short Circuit Protection** – if the current at which battery is discharging is greater than the rated output current, load is cut-off.

2.1.5. *ESP8266*

ESP8266 Wi-Fi microchip takes the temperature and voltage value from the microcontroller in the form of strings and appends it with the URL data, posts it and waits for approval from server as 'OK' success response. If approved, it is inserted in the table else, ESP tries again by sending request. The circuit in Fig. 4(b) shows an ESP module connected to an opto-coupler which is done to isolate the transmission and reception (TX, RX) pins.

2.2. *LSTM*

Recurrent neural network is a segment of machine learning involving memory directed cycles giving excellent performance for sequential pieces of figures. LSTM is applied to avoid long term dependency as LSTM's default behavior is remembering information for long term, which reduces the vanishing gradient problem [3,13,25]. A simple LSTM component contains a block, an input, output and forget gate as shown in the Fig. 5. The LSTM block stores values over random duration and 3 gates regulate the bidirectional information flow of the block.

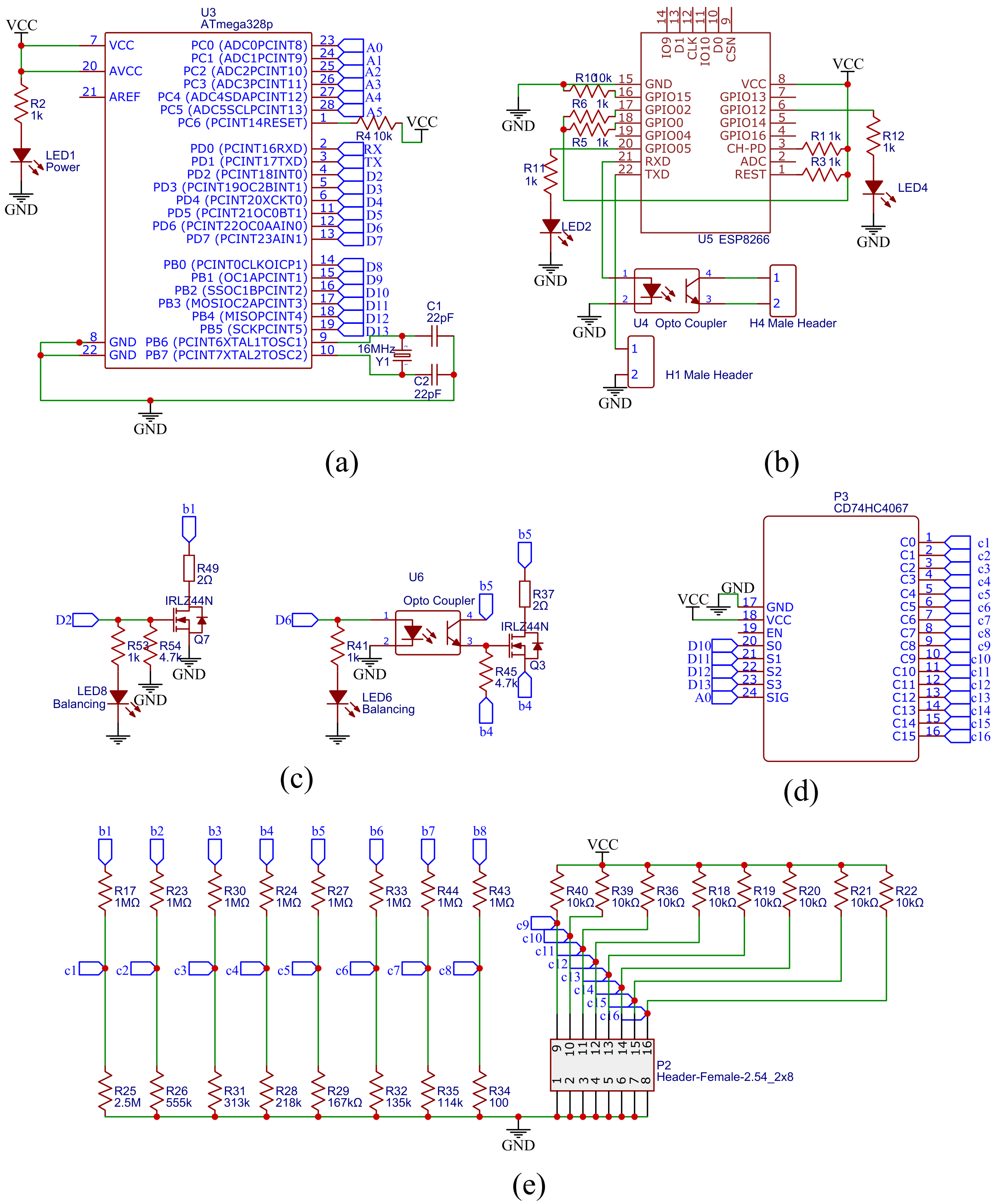

Fig. 4. BMS Components: (a) Pin diagram of Atmega328p (b) ESP Board schematic (c) Balancing Circuits (d) Pin diagram of Multiplexer CD74HC4067 (e) Voltage Divider Network with temperature measurement.

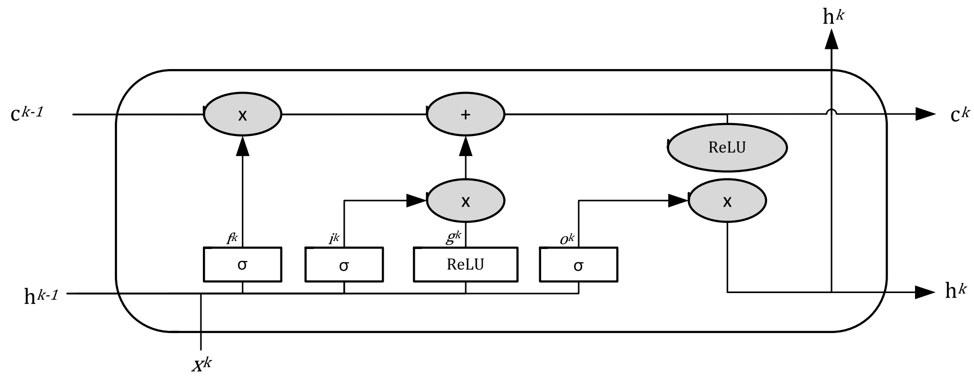

Fig. 5. The Block Structure of LSTM [31].

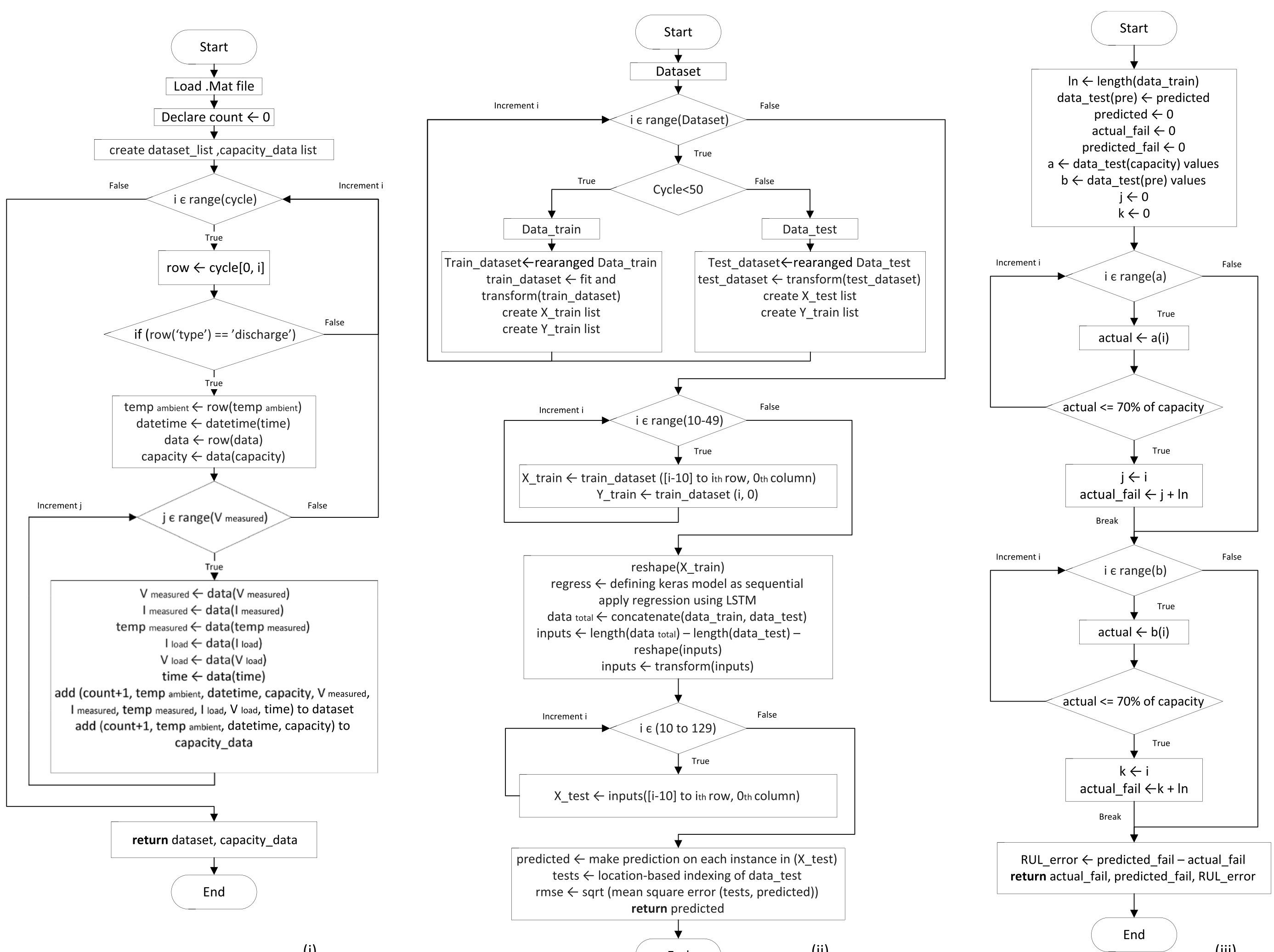

Fig. 6. Flowchart of the Machine Learning Model.

LSTM defines an internal storage block state to store information for a larger period of time. The storage block state links with the previous output and next input to update, maintain or erase among the existing elements [4].

In Fig. 5, the forget gate f_k, which is the first section of LSTM, together with the input gate i_k, decides what information is to be stored. The new entry, g_k is a short-term value which is discarded as soon as a new block state is added. At each stage, h_{k-1} and x_k arrive as input values. The output is computed using the frameworks of weights and biases with the Rectified Linear Unit (ReLU) activation function. ReLU activation function is used to vanquish the vanishing gradient problem. Computation of gates is by

$$f_k = \sigma\left(W_x^f X_k + W_k^f h_{k-1} + b^f\right) \tag{4}$$

$$i_k = \sigma\left(W_x^i X_k + W_k^i h_{k-1} + b^i\right) \tag{5}$$

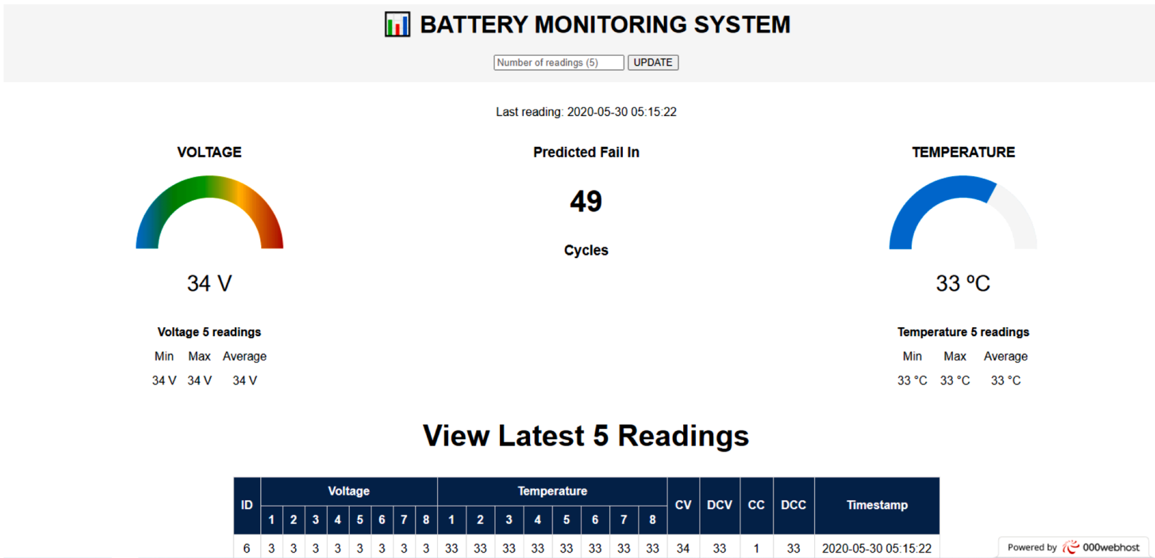

Fig. 7. Web Application Interface.

$$g_k = ReLU\left(W_x^g X_k + W_k^g h_{k-1} + b^g\right) \tag{6}$$

The forget gate f_k is multiplied with the block state c_{k-1} which is previous time step, by Hadamard product, a matrix multiplication where corresponding elements of two matrices with same dimensions are multiplied. Similarly, the input gate i_k is multiplied with new entry g_k [31]. The sum of these elementwise products gives the block state c,

$$C_k = f_k \odot C_{k-1} + i_k \odot g_k \tag{7}$$

The output gate O_k decides the information to output and is calculated as shown below:

$$O_k = \sigma\left(W_x^o X_k + W_k^o h_{k-1} + b^o\right) \tag{8}$$

At the end, the hidden state h_k is computed by

$$h_k = O_k \odot ReLU(C_k) \tag{9}$$

2.3. Data Procurement and Model Training

Battery data sets that were given by Prognostics centre of Excellence (NASA) Data Repository were utilized in training the LSTM model. The data set contains a couple of lithium-ion batteries that were operated at three main working profiles, charge, discharge and idle, all at 24°C temperature. The observation was performed on commercially available 18,650 Li-ion cells to achieve accelerated aging. The experiment involved discharging and charging of batteries. Batteries were charged by an appropriate battery charger using the principle Constant Current Constant Voltage (CCCV) [32,33]. Current of 1.5 A was applied till the battery reached 4.2 V and then a constant voltage was applied until the current dropped to 0.020 A [34]. Discharging was done with the help of variable load to maintain a constant current of 2000 mA until the cell voltage fell to 2.2 V, 2.5 V and 2.7 V, for different batteries. The experiments were performed until the batteries had only 70% of its original life of the rated capacity, i.e., 1.4 Ah [35]. The flowcharts shown in Fig. 6 explains how the machine learning model works. Two sets of data have been used at a time in this model. Based on the length of the training dataset, around 40 iterations for training the data from (0–50) of set 1 and 29 iterations for training the data from (51–90) of set 2 with 200 epochs respectively were performed. The length of the data could be anywhere from 200 cycles to few thousand cycles depending upon the availability of large capacity batteries with large cycle numbers.

The algorithm takes voltage values from dataset as input parameters with first 50 entries for training data and rest of the entries for testing the data. Flowchart (i) shows how the LSTM model accepts dataset. Flowchart (ii) prepares train and test set from the input dataset values. Flowchart (iii) shows how the input data is processed to predict battery fail cycle number.

2.4. Displaying Data on Graphical User Interface

The data obtained from the battery cells are updated in the web application. The data from the microcontroller is converted to string and is sent to web server through ESP8266 which is connected to Wi-Fi. The data from the web server i.e., data base, is sent to the web application using POST method where information is shared via HTTP headers and encoding by URL encoding scheme.

We used Hostinger to create web page. The PHP code fetches the values from the URL and updates the database table. A unique API key is assigned to user table which is used in updating the table values. The values stored are then displayed on the webpage by another code which is a combination of HTML and CSS. The user interface of the webpage is shown in Fig. 7. After running the machine learning algorithm over battery cells and updating the result in the database table, user can see the result on the webpage by entering. The webpage shows the average voltage and temperature values, charging voltage (CV), discharging voltage (DCV), charging current (CC), discharging current (DCC), number of readings (ID). Fig. 7 shows result of a sample battery with 8 cells under test. Its charging voltage is 34 V at an average temperature of 33 °C. The battery under test will start losing its full capacity at 49th cycle of charging and discharging.

3. Test Results and Discussion

The Machine Learning model was trained over the data sets from NASA and evaluated. On evaluation, the obtained result for known batteries were accurate i.e., charge and discharge cycles and lifespan. We have used SHAP to plot the outcome. Force and Summary plots are plotted using the training data. SHAP shows the impact of different features in the model. Fig. 8(a) and 8(b) shows the result of the Machine Learning model tested over two different datasets, set1 and set2. The test result of set1 predicted that the battery capacity will reduce i.e., efficiency will decrease after 117 cycles of charging and discharging (Fig. 8a) and for set2, the efficiency will decrease after 112 cycles of charging and discharging (Fig. 8b). The data sets set1 and set2 were taken from two exhausted batteries which had shown variation in their efficiency i.e., battery capacity started deteriorating at their 128th and

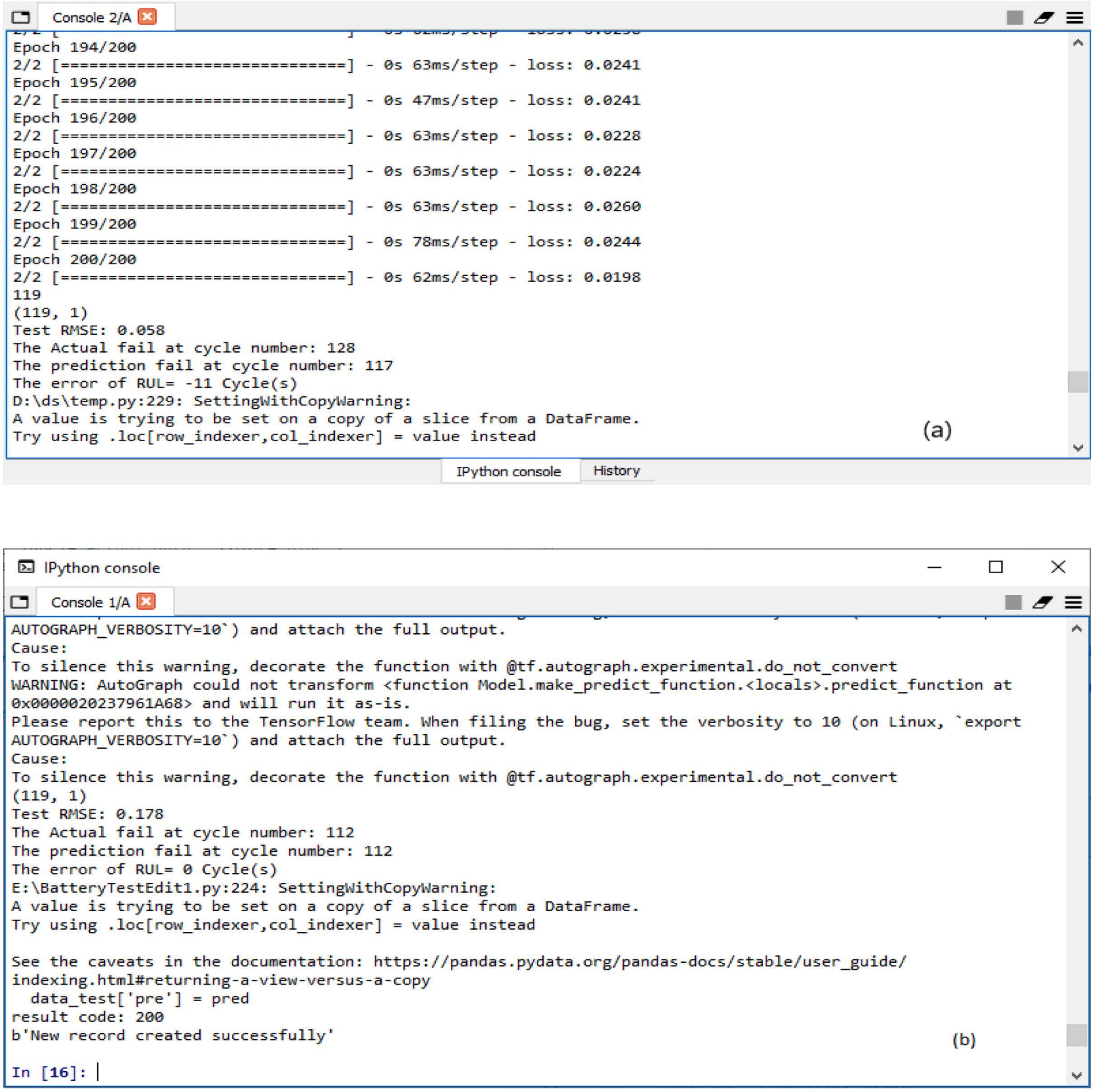

Fig. 8. The machine learning model output: (a) Life Cycle analysis of a known Battery Dataset Result 1 (b) Life Cycle analysis of a known Battery Dataset Result 2.

112th cycle respectively. The result obtained over a number of data set and iterations show an efficiency of more than 90%.

The graph shown in Fig. 9(b) is Force plot of set2 which shows the capacity of the battery over a number of charge-discharge cycles. Initially, the capacity is constant but after certain number of cycles, it reduces. The graph area in pink has more impact on the prediction and area in blue has less impact. The point at which color transition takes place is the point of mean capacity of the battery. Fig. 9(a) is summary plot of set2 and it shows that capacity and ambient temperature had no effect on the prediction as the battery taken for test had 18,650 Li-ion cells and temperature was maintained at 24 °C.

The novelty of this research is to provide an optimized strategy to charge the battery using BMS. The paper helps in predicting how long the battery will last before failure. The concept of equalizing the charge within the cells of a battery by continuously monitoring the battery status is also been implemented in this paper which is currently not used in conventional rechargeable batteries. The battery chargers that are being used now, are equipped with BMS which monitor each cell in the battery while charging. Once battery is disconnected from the charger, the discharging value that battery gives is of the whole battery and not of each cell. Hence, there are chances of a cell draining more voltage than other cells. The work presented in our paper BMS-ML will monitor each cell in a battery, thereby maintaining constant utilization of each cell. This will increase the overall lifespan of the battery. Also, lifespan prediction of a battery will be useful in avoiding situations pertaining to failures of battery. The accuracy of the ML prediction can be increased if the model is trained with larger datasets.

The BMS-ML system that we have developed, works for a battery pack with up to 8 cells only. If a battery has more than 8 cells, a greater number of Atmega microcontrollers are needed to be connected in series with the ESP8266 as a single Atmega chip cannot handle more than 8 cells.

4. Conclusion

The proposed technique includes an optimized strategy to charge the battery using BMS to predict how long the battery can be used i.e., charge and discharge without affecting the performance. The designed

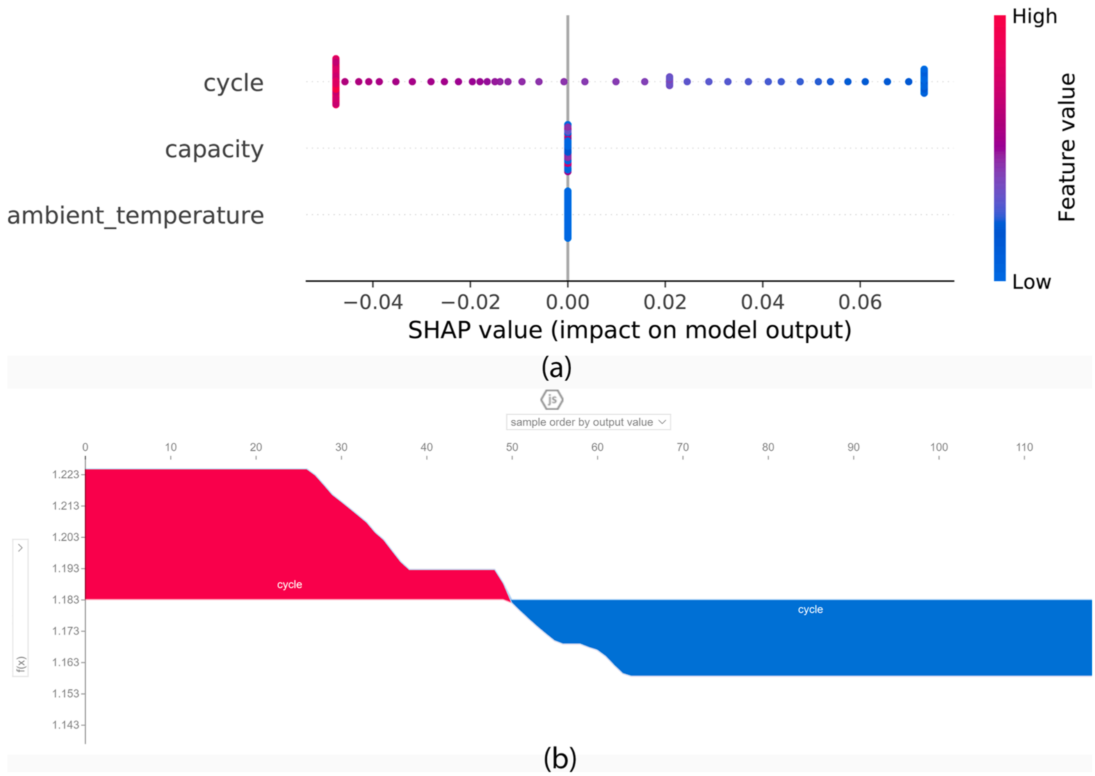

Fig. 9. Machine Learning model output analysis: (a) Summary plot showing impact of different features on the prediction (b) Force plot of Cycle v/s Capacity of the battery under test.

BMS circuit can protect the battery from over charging, over voltage, over discharge, high temperature, imbalance charging and discharging of the battery cells. The designed circuit is compact and its functioning was verified by charging the batteries. The data obtained from the battery was successfully stored in the data base by ESP8266 connected to a Wi-Fi and displayed in the web application. The LSTM model used in the Machine Learning cleared the test when run over a known battery's data, accurately. Thus, the idea of battery monitoring using Machine Learning has proved efficient and effective in predicting the life span of the battery.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

All persons who have made substantial contributions to the work reported in the manuscript (e.g., technical help, writing and editing assistance, general support), but who do not meet the criteria for authorship, are named in the Acknowledgements and have given us their written permission to be named. If we have not included an Acknowledgements, then that indicates that we have not received substantial contributions from non-authors.

Appendix

Algorithm 1 Algorithm 2 Algorithm 3

Algorithm 1
Data conversion.

Input: Dataset in mat format, positive integers i and j
Output: dataset, capacity_data
mat ← load mat file
count ← 0
create dataset list
create capacity_data list
for i ϵ range(cycle) **do**
row ← cycle[0, i]
if row('type') == 'discharge' **then**
temp $_{ambient}$ ← row(temp $_{ambient}$)
datetime ← datetime(time)
data ← row(data)
capacity ← data(capacity)
for j ϵ range(V $_{measured}$) **do**
V $_{measured}$ ← data(V $_{measured}$)
I $_{measured}$ ← data(I $_{measured}$)
temp $_{measured}$ ← data(temp$_{measured}$)
I $_{load}$ ← data(I $_{load}$)
V $_{load}$ ← data(V $_{load}$)
time ← data(time)
add (count+1, temp $_{ambient}$,datetime, capacity, V $_{measured}$, I $_{measured}$, temp $_{measured}$, I $_{load}$, V $_{load}$, time) to dataset
add (count+1, temp $_{ambient}$, datetime, capacity) to capacity_data
count + 1
end for
end if
end for
return dataset, capacity_data
end

Algorithm 2
Splitting into train-test sets and training

Input: train_dataset, test_dataset, positive integer i
Output: predicted
data_train ← dataset(cycle<50)
train_dataset ← rearrange data_train
data_test ← dataset(cycle>=50)
test_dataset ← rearrange data_test
train_dataset ← fit and transform(train_dataset)
test_dataset ← transform(test_dataset)
create X_train list
create Y_train list
for i ϵ (10 to 49) **do**
X_train ← train_dataset ([i-10] to i^{th} row, 0th column)
Y_train ← train_dataset (i, 0)
end for
reshape(X_train)
regress ← defining keras model as sequential
apply regression using LSTM
data $_{total}$ ← concatenate(data_train, data_test)
inputs ← length(data $_{total}$) – length(data_test) – 10
reshape(inputs)
inputs ← transform(inputs)
create X_test list
for i ϵ (10 to 129) **do**
X_test ← inputs([i-10] to i^{th} row, 0th column)
end for
predicted ← make prediction on each instance in (X_test)
tests ← location-based indexing of data_test
rmse ← sqrt (mean square error (tests, predicted))
return predicted
end

Algorithm 3
Counting prediction values

Input: data_test() values from data_test, positive integer i
Output: actual_fail, predicted_fail, RUL_error
ln ← length(data_train)
data_test(pre) ← predicted
predicted ← 0
actual_fail ← 0
predicted_fail ← 0
a ← data_test(capacity) values
b ← data_test(pre) values
j ← 0
k ← 0
for i ϵ range(a) **do**
actual ← a(i)
if actual <= 70% of capacity **then**
j ← i
actual_fail ← j + ln
break
end if
end for
for i ϵ range(a) **do**
predicted ← b(i)
if predicted < 70% of capacity **then**
k ← i
predicted_fail ← k + ln
break
end if
end for
RUL_error ← predicted_fail – actual_fail
return actual_fail, predicted_fail, RUL_error
end

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