Electric Vehicle Lithium-ion Battery Ageing Analysis Under Dynamic Condition: A Machine Learning Approach

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***Abstract*—Currently, the smart cities, smart vehicles, and smart gadgets will improve the way of living standard. Cloud connectivity of IoT sensed devices will capture real-time data in the cloud which helps to improve the system performance and quick response to queries. Electric Vehicle battery health diagnosis plays an important role in the proper functioning of the battery management system, guarantees safety, and warranty claim. Society 5.0 develops with the advancement in the road, infrastructure, better connectivity, transportation, and options available to purchase. Battery health cannot be measured directly. There are internal and external factors that affect battery health such as State of Charge, model parameters, charging/discharging method, temperature, Depth of Discharge, C-rate, battery chemistry, form factor, thermal management, and load change effect. Battery degrades due to both calendar ageing and cyclic ageing. Artificial Intelligence plays a significant role in Battery management system due to the non-linear behavior of lithium-ion battery. Prediction of battery health accurately and in due time will reduce the risk of recklessness. Timely maintenance will reduce the risk of fatal accidents. This paper presents different batteries analysis under different discharge voltage and capacity conditions. Different machine learning algorithms such as Neural Network, Modified Support Vector Machine (M-SVM) and Linear Regression are used to predict state of health. The proposed M-SVM performs well with less error for all four-battery discharge data.**

***Index Terms*—Battery ageing, Support Vector Machine, Linear Regression, Neural Network, Capacity fading**

I. Introduction

IN 20th century, when there were very few gadgets or machines that can talk among themselves, at that time solving machine or system problems takes time to resolve that problem. However nowadays with the help of Society 5.0 cities are becoming smart. There are various energy storage devices available, among them battery is the most convenient and high energy density.

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Battery can be big or small capacity based on application or power drawn requirement. Battery health estimation is necessary for Society 5.0 because most of the devices are connected to sensors and sensors have low battery issue. In order to run IoT sensor system, proper maintenance of sensor battery have to be taken care. People are more aware of their health-related issues, advancement in technology leads to improve facility. Smart city consists of smart vehicles, smart homes, smart hospital, and smart gadgets. Bad air quality will affect the lungs and breathing problems. Clean and green energy consumption will lead to a sustainable environment. Petrol and diesel vehicles emission harmful gases which is polluting the environment. Electric vehicles, CNG vehicles and fuel cell vehicles do not emit harmful gases and hence lead to sustainability.

Lithium-ion batteries are popular nowadays due to high energy density, lightweight, price of lithium-ion batteries is less, long life cycle, and low self-discharging rate. Few years ago, Battery operated Electric Vehicles (BEVs) were operated by Lead-acid battery due to being cheap in cost and safer to use. As the research work progresses in energy storage, the lithium-ion battery performs better than lead-acid battery. Researchers have done extensive research on different materials for cathode, anode, and electrode. Some of the popular and highly demanding lithium-ion chemistries used in BEVs are lithium nickel manganese cobalt oxide (NMC), lithium iron phosphate (LFP), lithium-nickel-cobalt-aluminium oxide (NCA), lithium titanate (LTO), lithium-ion manganese oxide (LMO), and lithium cobalt oxide (LCO). LMO has high nominal voltage as compared to other chemistries whereas LTO can operate in a wide range of temperatures and best for low temperatures. Lithium-ion battery are explosive in nature and catches fire easily during summer. For better thermal management, power management and control, Battery management system (BMS) plays a significant role in BEVs. BMS comes with battery pack while purchasing. Lead-acid battery is safe to use therefore BMS is not required in this battery. Whereas lithium-ion battery can easily change its characteristics and easily get exploded therefore BMS is necessary to use in this battery. Main functions of BMS are to diagnosing the states, cell balancing, safety alerts, communicating with other parts of the vehicle, connectivity with the cloud, and data transferring. Fig.1 shows IEA report of battery demand by different regions. China has highest battery demand and then followed by Europe [1].

In 1976, the COSMOS-839 satellite was fragmented due to battery malfunction. In 1985, the NOAA-8 satellite was exploded due to Ni-cd battery overcharged. In 2010, Boeing 747 in UAE was destroyed due to an Uninterrupted power supply caught fire. In the Federal Authority report mentioned that 280 incidents occurred during 2006-2020 due to lithium-ion battery on aircraft or in airport. Due to this many events related to lithium-ion battery, BMS functioning has to be improved and robust so that in future any damage related to battery should not happen. Lithium-ion battery health depends on internal and external factors

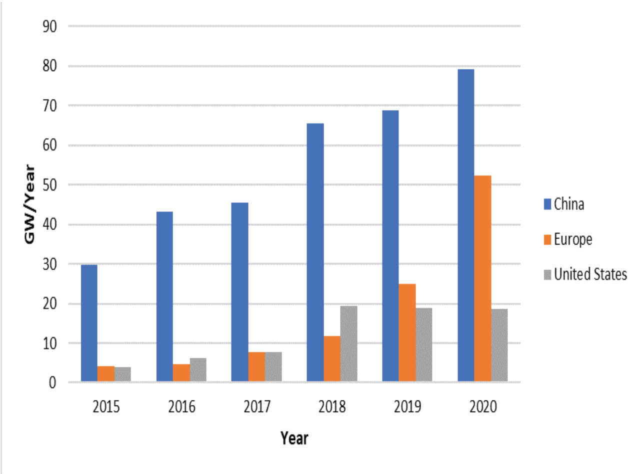

Fig.1 IEA report of battery demand by different regions.

Due to high cycling rate, metallic loss of active material takes place. Due to high State of Charge (SOC) deposition in calendar ageing, lithium-ion loss takes place. Due to overcharging and over-discharging of BMS, loss of active material and current collector corrosion takes place respectively. Due to high and low temperature of battery, solid electrolyte interface decomposition takes place and lithium plating occurs in later respectively. SOC estimation plays a significant role in BMS. Based on the charging level of individual cells, battery pack SOC will be decided. If unbalance in the charging level of individual cells which degrades the capacity hence degrades the life of the battery takes place [33]. Accurate SOC estimation is necessary for improving driver's safety, re-routing, control and protecting from full discharge of battery. Proper predictive maintenance is required, forecasting of SOC using ML algorithms like ARIMA, LSTM and XGBoost are carried out in [34] paper where XGBoost and ARIMA shows less error as compared to LSTM. Driving EV at high SOC has most significant impact on battery aging, driving at high cycling rate or fast charging leads to high discharge current and even damage of the material composition of lithium battery [35]. There are many research questions that can be answered in this paper:

Q1. What is the importance of BMS?

Q2. Why battery health diagnosis is important?

Q3. Which are the factors which cause battery ageing?

Q4. How machine learning (ML) can be useful in predicting battery health?

Q5. Which ML method gives good accuracy for battery health prediction?

A. *Contribution of the Paper*

In order to address the above issues related to battery health, Modified Support Vector Machine (M-SVM) based on regression is established to estimate the battery SOH in this paper. The proposed method not only perform in one battery cell but also performs well for other cells with different operating conditions. This shows that our proposed model is robust in different conditions for the estimation of battery health. Whereas other regression methods like linear regression (LR) and neural network (NN) underperform in different conditions of different battery cells. NN takes a long time to execute as compared to LR and M-SVM. Our contributions are summarized as:

- M-SVM is proposed for SOH estimation which shows robustness for different lithium-ion battery cells at different operating condition.
- Extensive experiments have been performed to verify that our model is flexible, performing better than NN and LR.

B. *Organization of the Paper*

This paper is organized into four sections: Section-I deals with the introduction of the battery, BMS and related problems. Section-II discusses work related to battery health diagnosis and prediction. Section-III discusses an experimental analysis of different batteries under dynamic conditions and results. Section-IV deals with the conclusion of the experiment results and future directions.

II. Related Work

A. *Research Trend*

Fig.2 shows the research trend analysis in web of science database related to battery state of health in different ML methods. Most of the research work in battery state of health has been done related to neural network (NN) followed by linear regression (LR) than Gaussian process regression (GPR), Support-vector-machine (SVM), long-short-term-memory (LSTM), random forest (RF), Bayesian network (BN), ensemble learning (EL) and very few research work related to decision tree. Digital-twin concept is started in the robotics, mechanical domain, medical domain, and in electrical domain. Creating a virtual environment that behaves similar to the real, with high accuracy and precision in the real world itself is an achievement. In the year 1990, machine learning concept came into picture. In 1959 the term machine learning was coined by Aurthur Samuel. Keywords that are frequently used by authors in their documents are represented by the word cloud in fig.3. This data is extracted from SCOPUS database. This figure shows words related to the state of health, battery management systems, lithium-ion batteries, charging(batteries), health, ions, state of charge, and electric batteries are frequently used by authors in their document.

B. *Literature Review*

Battery state of health (SOH) is termed as the ratio of present available-capacity of battery to the actual initial-capacity of battery. Indication of battery ageing is reflected when capacity fades or increase in resistance. Battery health can be modelled by electrochemical equations or by equivalent-circuit-model (ECM) or by data-driven-method. Electrochemical-based modelling and data-driven modelling gives the more accurate result as compared to ECM. But the

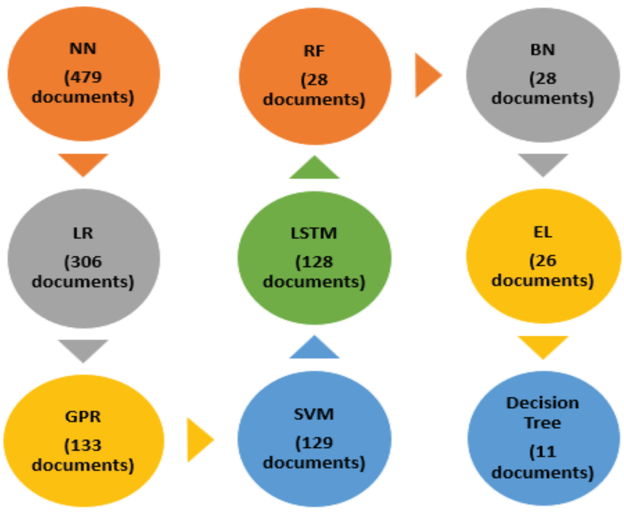

Fig.2 Research trend of battery state of health-related to ML methods.

computational effort increase is more in electrochemical modelling [2].Fig.4 shows the summary of the literature review. There are different categories in the literature summary such as goals, challenges, techniques, application areas and research trends are discussed. The primary goals of SOH are to predict early lifecycle, withstand warranty claims, for scheduling maintenance and also to visualize user driving behaviour. There are various challenges faced while estimating SOH such as real-time analysis is difficult, there is no direct method to estimate SOH, battery-pack analysis is lacking, and there are various features that affect battery health selection of significant features is difficult. There are various techniques such as model-based, data-driven and adaptive filter based for the estimation of SOH. Battery health estimation can be used in different applications such as EV, electric boats, mobile phones, satellite, defence equipment and static energy storage. Latest research trend is to find high accurate and robust model which can withstand dynamic conditions and predict accurate health status of battery.

Equation (1) shows general formula to calculate SOH by two ways [25].

$$\left\{ \begin{array}{l} SOH = \frac{C_{old}}{C_{in}} \times 100\ \% \\ SOH = \frac{R_{Present}}{R_{in}} \times 100\ \% \end{array} \right\} \qquad (1)$$

Where, C_{old} = reduced capacity after certain interval

$R_{Present}$ = increase in resistance after certain interval

C_{in} , R_{in} = initial or nominal capacity, initial or nominal resistance respectively.

SVM is used for SOH capacity estimation as well as SOH resistance estimation presented in [6]. In [6], the author has acquired vehicle charge/discharge battery data operated under different temperature conditions.

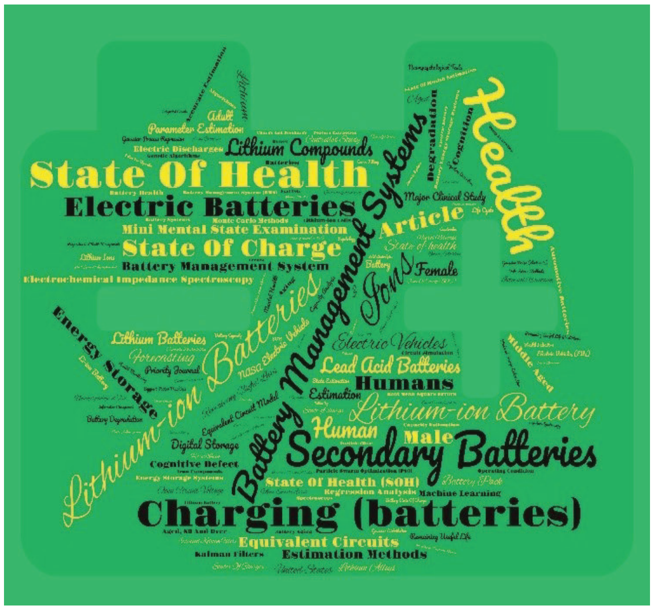

Fig.3 keywords word cloud related to battery state of health.

SVM is trained to calculate battery voltage drop during 10sec discharge pulse for SOH resistance estimation and C/3 partial and full discharge pulse is used for SOH capacity estimation. RMSE for SOH resistance estimation is 6.2% and RMSE of SOH capacity estimation is 0.63%. In [7], the author has discussed SVM along with ECM, Relevance Vector Machine and Particle Filter. In [9], the author has used LSTM for SOC and SOH resistance estimation both in a single model. In [10], the author has used EL method for SOH estimation. EL works faster than SVM, Artificial Neural Network (ANN), LS-SVM but it requires large amount of training dataset. In [11], SVM is used with Radial Bias Function for online SOH estimation. In [18], Genetic Algorithm is used for finding capacity fading of lithium-ion battery under different temperature condition.

By using different cathode electrode combination, cathode anode combinations or different concentration proportion of cathode material for cell manufacturing will change the cycle life of battery. Estimation error of battery capacity is less than 1%. In [19], fusion-based feature selection is done from measured and calculated health indicators. Three publicly available datasets were used for the analysis. Machine learning techniques such as ANN, GPR, SVM, and RVM are used for carrying out this analysis. Out of this four ML techniques GPR shows good performance in this paper. In [20], forward neural network is used for capacity estimation of 18650 lithium-ion battery under different temperatures. 0.66% lowest RMSE error is achieved at 25^{0}C. in [21], review of different ML algorithms used for state of charge and state of health are discussed. FNN, SVM, RBF, RNN, and hamming network are discussed in depth. One very interesting topic that is data quality is discussed in this paper. Because if the dataset is not properly pre-processed then chances of getting high error is high. After completion of first lifecycle of li-ion battery, used for second life use case and their issues-challenges are discussed in [31]. Apart from lithium-ion battery, flexible zinc battery characteristics is discussed in [32].

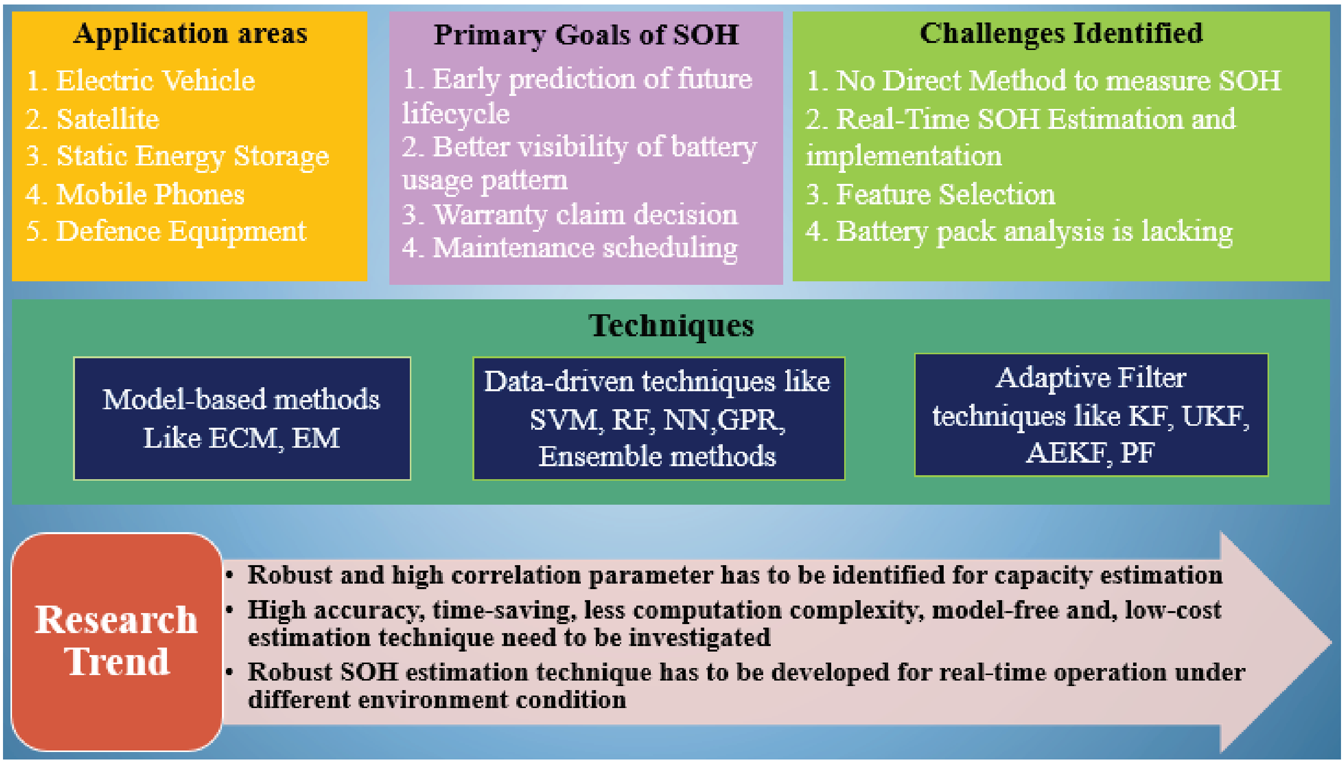

Fig.4 Summary of literature review.

III. Experimental Analysis and Result Discussion

For conducting battery health analysis, various tests on batteries are done. Characteristic test of battery consists of static-capacity test, efficiency test, hybrid pulse power-test, open-circuit-voltage/state of charge test, and lastly loading or driving profile test. These tests are repeated for different temperatures [3]. For this paper analysis, a publicly available NASA Li-ion battery aging dataset is used [5]. Other authors also used same dataset [8]. The procedure for conducting battery ageing test used in this paper is mentioned in Fig. 5 [4]. The cycling procedure is started from cycle i=0 and ended when End of Life (EOL) is reached. Generally, we say EOL when battery capacity is reached 80% of the nominal capacity. This dataset was collected by charging-discharging at different temperatures. This dataset consists of 34 cylindrical cells having form factor of 18650 with different nominal capacities that have been cycled to 70% to 80% of beginning capacity. Cycling of battery consists of three different operational types: charging mode, discharging mode, and impedance mode. Charging at CC-CV at a constant current of 1.5A until 4.2V is reached, then maintaining the constant voltage and decreasing the current to 20mA. This data was divided into 6 groups, 6^{th} group dataset was chosen for this analysis which was taken in the year 2008 at 24^{0}C temperature. Four different batteries were analysed that is B0005, B0006, B0007 and B0018. There are other group of datasets which was conducted at different temperatures. Table 1 shows dataset explanation. Discharging at constant-current (CC) of 2A until battery voltage declined up to 2.45V, 2.12V, 1.737V and 2.349V for 5^{th}, 6^{th} ,7^{th} and 18^{th} batteries respectively. During CC charge, battery charges rapidly and when it reaches near max. capacity then transferred to CV mode for charging further to full capacity. Charging through CC charge to full capacity will heat the battery rapidly and liberates stored energy therefore now-a-days multi-step CC charging is preferred to further reduce the losses while charging. In [22], ensemble learning method (ELM) is used for mapping between health indicator and SOH. By using Pearson correlation, highly correlated health indicator is selected. Duration of same charging voltage range (DSCVR) shows a high correlation or sensitive to battery health. ELM works faster due to fast learning rate and has faster computation power. ELM is trained by different models and gives high weight to that model which performs well. ELM can be applied for classification and regression problems.

Two public datasets that is NASA and CALCE are analysed by ELM for predicting battery SOH. In [23], partial discharge features were selected which shows high sensitivity to SOH. SVM is used for classification of cycles into different groups and then predicting SOH through regression. This classification and regression of SVM model will help in early prediction of SOH.

This dataset is analysed by using Orange Tool of 3.31 version. This tool does not need coding, by using dragging and dropping of blocks and tuning of parameters gives result easily. Popular machine learning approaches NN, M-SVM and LR are used for comparison. For analysis discharging curve data of different batteries is taken. Different batteries were discharged to different voltages and also had different initial capacities selected for battery health prediction analysis. This dataset consists of 11 features, out of which 3 features are removed and one target is set. Fig. 6 (a)-(d) shows capacity versus cycle relation of B0005, B0006, B0007 and B0018 respectively. The color variation shows battery health. As the cycle number increases capacity of battery fades. Based on SOH range, capacity is fades and blue color indicates End of Life while yellow color indicates fresh battery good in condition. Green color indicates moderate battery health. Battery B0018 shows fast degradation of battery health and gaps in the end of life shows missing data.

TABLE 1 DATASET EXPLANATION.

Battery Number	Total Data	Cycles	Ambient Temp	Discharge Current	Discharge Voltage	Initial Capacity
B0005	50284	168	24^0C	2A	2.45V	1.8564Ah
B0006	50284	168			2.12V	2.0353Ah
B0007	50284	168			1.737V	1.891Ah
B0018	34865	132			2.349V	1.855Ah

This section is further divided into three subsections. These three subsections are 1) Linear Regression, 2) Support Vector Machine, and 3) Neural Network, which are categories of machine learning algorithms.

A. Linear Regression

Multiple LR is used for estimating battery SOH is discussed in [16]. In this paper [16], Principal Component Analysis (PCA) is used for feature selection. Basic LR is used for finding the best fit line for the model values. This method is fast but less accurate as compared to other ML methods. In [17] IoT-enabled microcontrollers are used for battery parameter estimation.

B. Support Vector Machine

SVM is one of the most popular ML methods used for regression and classification both. SVM is suitable for small datasets as well. The model of SVM is discussed in [12] below equation (2):

$$\gamma = w^T * \varphi(x) + b, x \in R^d, \varphi(x) \epsilon R^{d'}, b \in R \quad (2)$$

Where, φ(x) = map input linear data into a new feature space with dimension d'.

C. Neural Network

The SOH estimation by the convolutional neural network, artificial neural network, and recurrent neural network are discussed in [13-15] respectively. The neural network has hidden layers, as the number of hidden layers is increased then computational complexity also increases with the model accuracy which is represented in fig.7. In [24], author has proposed LSTM- GPR for remaining useful life (RUL) prediction. Empirical modelling of battery is used in this paper for NASA and CALCE dataset.

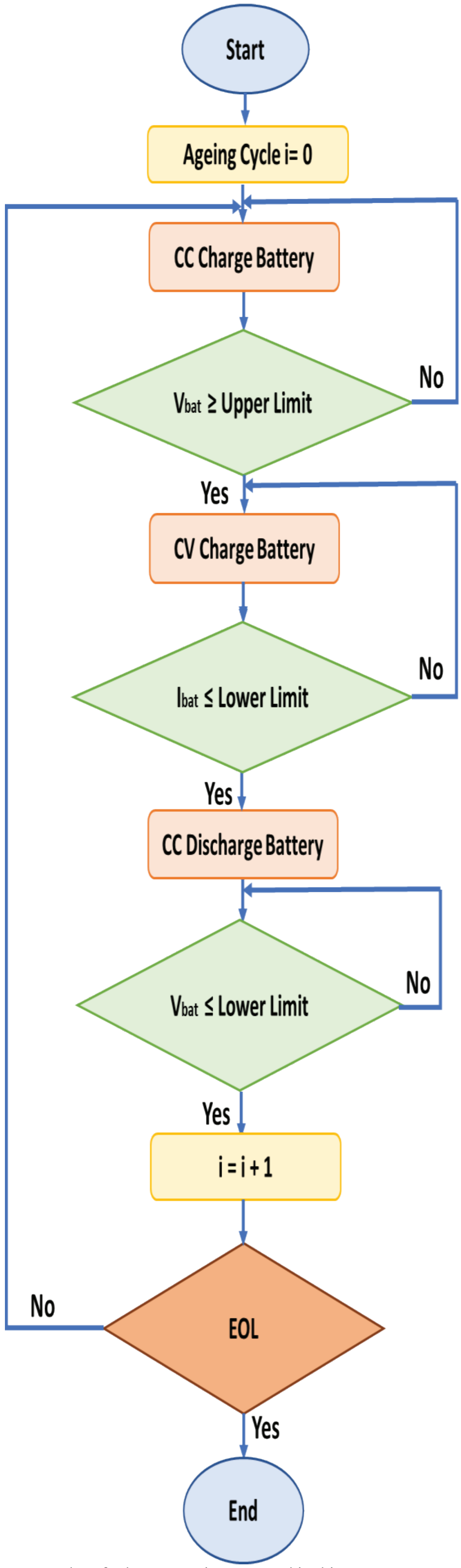

Fig.5 Procedure for battery ageing test used in this paper.

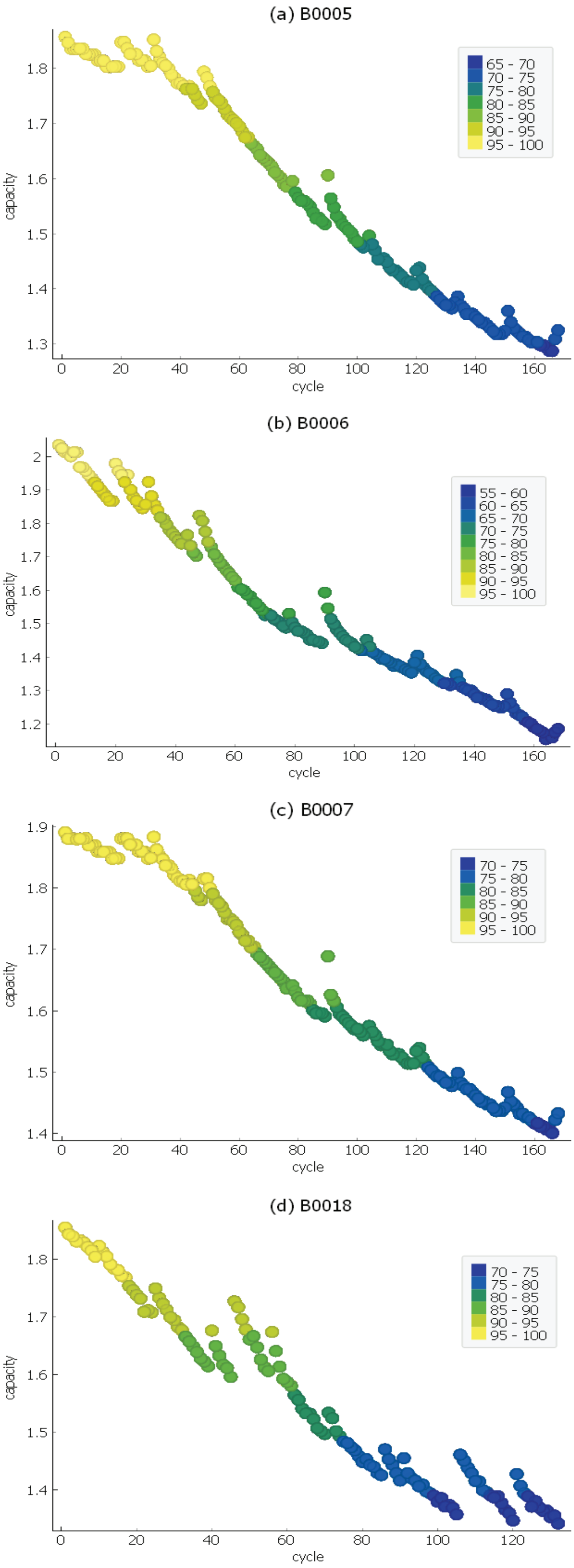

Fig.6 The capacity versus cycle relation of (a) B0005, (b) B0006, (c) B0007, and (d) B0018.

In [26], author has used classification method based on linear and non-linear nature of the electrochemical battery. Taking 25 cycles for early-stage prediction of battery ageing and finding whether battery behaviour is showing Solid Electrolyte Interfacing (SEI) or lithium plating. In [27], author has performed hybrid pulse power test (HPPC) of battery for finding battery ECM parameters that is internal resistance. Then three-layer backward propagation neural network is used for estimating capacity. This model is also validated in static and dynamic current profiles.

In [28], ECM-based modelling and health prediction is done based on particle swarm optimization and genetic algorithm. Battery modelling parameters of first-order or second-order R-C circuit varies with temperature or SOC value. Tuning of parameters is necessary for the prediction of battery health. In [29], Artificial neural network is used for SOH estimation and achieved RMSE of 1.17%. calendar cycle or storage condition of battery is used as input and SOH as output. Based on different storage conditions (fully or partially charged), different temperature condition, different current, and voltage this analysis is done. In [30], review of different models like modelling approach, data-driven approach, and hybrid approach is discussed. Their advantages, disadvantages and future direction are mentioned.

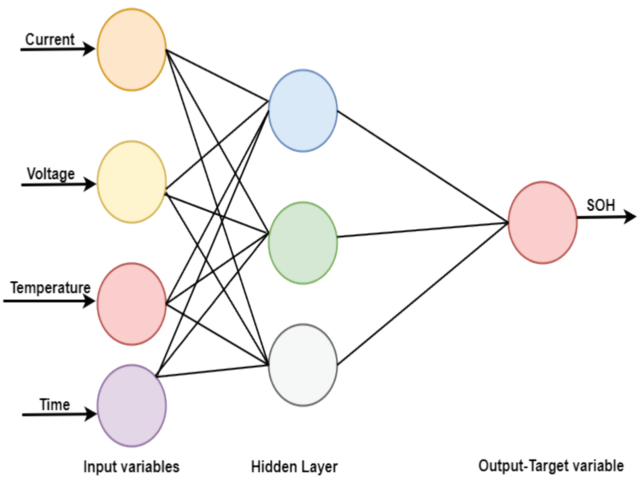

Fig.7 Neural network workflow.

Orange Tool is a freely available software used for data analysis and prediction analysis without using coding.

Dragging and dropping widgets then connecting sequentially and then tuning parameters or hyper-parameters will lead to more accuracy. Training and testing of random

sampling of data doesn't require cross validation of data. In this model 80% of the data is provided for training and 20% of the data is used for testing. Fig.8 shows different Battery health prediction connections by using LR, M- SVM, and NN.

D. Results and Discussion

- From Pearson Correlation, SOH is highly correlated to capacity (+1.00), cycle (-0.98) and moderately correlated to load current (-0.4).
- For all the batteries same parameters are set for comparison.

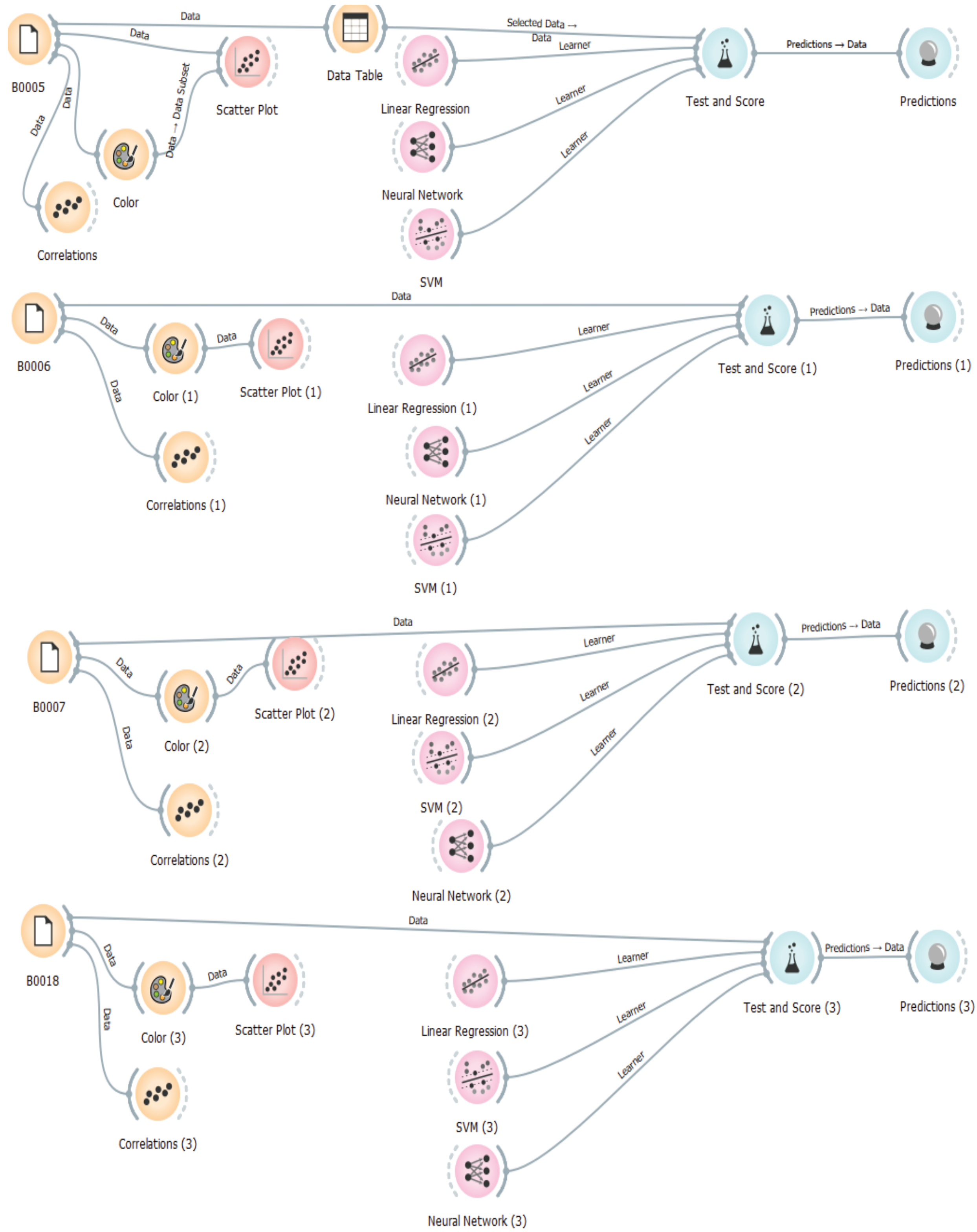

Fig. 8 Different battery (B0005, B0006, B0007 and B0018) health prediction connections by using LR, M-SVM, and NN.

- The setting of LR model: Elastic net regression is selected as regularization, alpha is taken as 0.0006 and elastic net mixing is taken as 50%.
- The setting of M-SVM model: Linear kernel, SVM type is selected, tolerance set at 0.001, and 100 iterations are set

- The setting of NN model: no. of hidden layers is set as 10, activation is ReLu function, solver is Adam, alpha is 0.0006 and 100 no. of iterations are set.
- Table 2 shows the comparative error analysis of different batteries.
- Low Mean Squared Error (MSE) ensures that trained model has no outlier with high error rate and highly sensitive to outliers. MSE is calculated by average of squared errors. MSE can overestimate or under estimate the model if the error is very high or very low.
- Root Mean Square Error (RMSE) is significant when large errors are infelicitous and gives high weightage to large error. RMSE is calculated from square root of MSE. RMSE illustrates error distribution. RMSE tells concentration of data around the line of best fit. Square root of MSE is done for scaling all the errors in same scale as of target value scale.
- Mean Absolute Error (MAE) gives linearity of score which means all the individual differences are weighted equally in the average. This MAE is not sensitive to outliers therefore used for dataset which is having outliers.
- R2 also known as goodness of fit or coefficient of determination. By adding new feature R2 is increasing or remains constant but never decreases. R2 is the ratio of sum of square regression to sum of square total. Greater the value of R2 means MSE is smaller, better will be the regression model.
- M-SVM has fewer errors for all the batteries and is considered a good fit for the dynamic discharge profile of different batteries. Whereas NN takes more time to execute and has more errors as compared to M-SVM. LR has highest error among all three ML models therefore not suggested for prediction of dynamic discharge of battery.

TABLE 2 ERROR RESULT COMPARISON.

Battery Number	ML Technique	MSE	RMSE	MAE	R2
B0005	LR	0.183	0.427	0.358	0.998
	M-SVM	0.06	0.244	0.17	0.999
	NN	0.053	0.23	0.165	0.999
B0006	LR	0.092	0.304	0.235	0.999
	M-SVM	0.016	0.125	0.097	1
	NN	0.041	0.202	0.136	1
B0007	LR	0.194	0.441	0.362	0.997
	M-SVM	0.017	0.131	0.101	1
	NN	0.025	0.159	0.101	1
B0018	LR	0.316	0.368	0.317	0.998
	M-SVM	0.007	0.083	0.067	1
	NN	0.113	0.336	0.257	0.998

IV. Conclusion and Future perspective

Every device is connected to each other nowadays with the help of IoT. Smart battery is also needed for energy storage and communication with other attached devices. A smart battery must have smart BMS. Society will grow when infrastructure, facilities, and technology will develop. The proposed Support Vector Machine performs better than the other two ML models (LR and NN). NN is time-consuming and gives less accurate results than M-SVM. Capacity decreases as the number of cycles increases. B0018 reaches the end of life quickly as compared to B0005, B0006, and B0007. When internal resistance of battery reaches twice the initial resistance value then that battery is stated as reached its end of life. Old battery cells charge fastly and discharge fastly.

There are various measured and calculated features that can be used to improve the model accuracy. Some of the features are peak charge curve, peak discharge curve, min. discharge curve, min. charge curve, the time interval of equal voltage increase, SOC, and temperature. While the testing battery in the laboratory, long rest period has to be maintained so that lithium-ions can settle down. Hence, including rest period in analysis will regenerate power in battery. Real-time analysis is lacking. Terminal voltage drop plays a significant role in SOH estimation [36]. As battery ages, cycle no. increases with increase in voltage drop and capacity decreases. Taking peak voltage change, minimum voltage changes in voltage graph and change of graph from mean voltage features would add advantage to the analysis of battery health. High-frequency IoT connected devices are required for more accurate analysis. Machine learning plays a significant role in battery health diagnosis hence by optimizing the extracted features and model accuracy will be improved.

Conflict of Interest

The authors state that there is no conflict of interest related to the topic and publication of this paper. This manuscript has not been submitted to any other journal for review and publication.

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