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A Comprehensive Exploration on Different Machine Learning Techniques for State of Charge Estimation of EV Battery

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***Abstract*—The State of Charge (SoC) is a measurement of the amount of energy available in a battery at a specific interval of time, mostly expressed as percentage. Proportional relationships between the electromotive force of a battery, current, terminal voltage and temperature determine the SoC. There can be a considerable error in the calculations due to a sharp drop of the terminal voltage at the end of discharge. This research has explored how important SoC is, as a factor in Battery Management Systems. The work focuses on using machine learning techniques to obtain an accurate and reliable status of battery charge, this includes Random Forest, Decision Tree, Gradient Boosting, Support Vector Regression, Polynomial Regression and Multilayer Perceptron. In this paper, these techniques are tested and compared with two real world captured datasets of Lithium-ion batteries which includes LG Battery and Unibo Powertools Battery. For supporting this study, statistical methods like K-fold cross validation and Grid Search cross validation techniques are used to estimate the skill of machine learning models. After implementing these techniques, it is found that Random Forest model returns the best Accuracy and Decision Tree returns the least Mean Absolute Error.**

Keywords—State of Charge (SoC), Lithium-Ion Batteries, Battery Management Systems, Electric Vehicles Machine Learning.

I. INTRODUCTION

Lithium-ion batteries have made a considerable progress since their introduction to the commercial market in the early 1990s. Since the modern world is becoming fully automated with huge rise in technological advances in research and technical fields, as well as day to day lives of an average human, our dependency and reliability on power sources have exponentially bloomed in recent years. Currently, the significant markets are driving little electronic devices such as cell phones, portable computers and cameras. All are aware of how much of a daily utility device have become so important. They have transformed from a want into a need along with time. This has resulted in the rapid growth of the mobile electronics and communication sectors. Furthermore, lithium-ion technology is a rapidly growing market which is gaining huge market share in the power tools market. These types of batteries have recently undergone significant development efforts for stationery and traction applications, for which we have got promising results. Currently, only prototypes of high-capacity lithium-ion batteries are available. Future battery, hybrid powered car introductions could pave the way for completely new business models for electric utilities. This means that electric vehicles will be connected to the grid which can act as a load management buffer system known as the V2G (Vehicle to Grid). Scalability of EV's in the future can open a wide range of business models, which will eventually bloom along with it.

At present, some of the biggest challenges for these material batteries in the field of power is their short lifetime when stored under full charge circumstances. Moreover, the primary concerns with using them is safety and protection. A requirement for launch in the vast market for elevated energy grade of these batteries will be the innovative development of non-hazardous and secure materials for battery construction. Therefore, there is now ongoing research on the use of these Lithium-Ion batteries as a method of electric grid's storage energy or electric mobility. If there is a battery, then to ensure its proper working, there is a need for robust battery management system, that has so many parameters to be calculated. One such important parameter is called State of Charge (SoC) which is the main investigation in this paper using various data driven models for comparison and finding the optimum method to estimate its value.

II. RELATED WORK

Nowadays electric vehicles are getting more popular due to better battery specifications and the most commonly used battery is Lithium-ion battery. So, to get the maximum out of it, there is research going on continuously. In [1] authors have made a SoC comparison between equivalent circuit battery model and machine learning approaches like Support Vector Regression (SVR), neural networks. The problem with the equivalent circuit battery model is that high level of technical knowledge is required but still data driven models get very close to it or sometimes, even beats it. Authors of

[2], [3] explains the whole idea behind SoC estimation from traditional to recent trends using various methods and has a detailed survey about these techniques. [4], [5] gives an outlook about support vector regression model usage to calculate the SoC and parameters that helps it to achieve good Mean Absolute Error and Mean Squared Error. It also depicts that lower temperatures affect battery performance. In today's world, batteries due to incorrect usage especially in power systems start to degrade much before their original deadline, so to estimate the suitability of those batteries, authors in [6] proposes a solution using linear regression, SVR, Random Forest (RF), Gaussian Process Regression (GPR) out of which the latter had the lowest Mean Absolute Error (MAE) of 0.0204. Hybrid machine learning techniques are something that has only picked up in recent times for other applications, in [7] authors discuss how RF and Gaussian filter can be combined to yield better outcomes than if performed individually. Gradient Boosting (GB) is discussed in detail in [8] and it shows that this technique outperforms SVR for SoC estimation. In [9] researchers show differential search optimized RF method to scout for trees and leave's ideal values. It comes out with a lower error rate and it is also the one of the major highlights of the paper. Artificial neural network implementation has been clearly demonstrated in [10] using Panasonic battery dataset and it shows how much computational power is saved using this method compared to Kalman filter technique. Convolutional neural network model architecture is designed in [11] with 7 layers to get a Mean Absolute Percentage Error (MAPE) of 0.4159% in SoC estimation at 25°C. A totally different approach called impedance spectroscopy is applied in [12] to take those features which are highly correlated with SoC estimation and GPR is used to estimate final outcome. All these works prove that there is an evergreen opportunity for development in this field as it is constantly improving over time to extract the best efficiency out of batteries.

III. SoC Estimation Methods

State of Charge, in simple terms can be expressed as,

$$SoC = Q/Q_{MAX} \quad (1)$$

where, Q is the remaining capacity and Q_{MAX} is the rated capacity in (1). For its Estimation, there are so many methods available as shown in Figure 1.

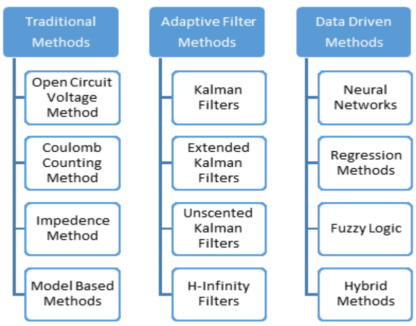

Figure 1. Different Methods for SoC Estimation

The traditional and adaptive filter methods usually dive deep into technical knowledge to the extent of every single cell's chemistry. They all use the Li-ion battery equivalent circuit model for analysis which is shown in Figure 2.

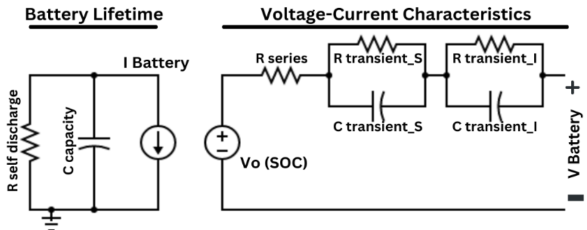

Figure 2. Equivalent Circuit Model of Li-Ion Battery

As opposed to that, the machine learning driven models [13,14] purely work on given parameters of cell like voltage, current, temperature and yield results that are astonishingly similar to that of the previous two methods. That's the reason why there is growing popularity to follow machine learning approaches as it saves a lot of time and effort.

IV. Dataset Description

The research team have used two types of datasets in the paper for applying the proposed algorithms. They are LG and UNIBO battery dataset.

A. LG 18650HG2 Li-ion Battery Dataset

The Mendeley data website provided the LG dataset that is used here. This dataset is known as LG 18650HG2 Li-ion Battery Dataset, it was issued by Kollmeyer, Vidal, Naguib, and Skells [15] and is accessible to public. It provides results from experiments conducted at a number of temperatures. The test was performed on a brand-new 3Ah LG HG2 cell in an 8 cubic feet thermal chamber using a channel of a 75 ampere, 5-volt Digatron Firing Circuits Universal Battery Tester with 0.1% of full-scale voltage and current accuracy. Prior to each discharge test, battery was charged at a rate of 1C to 4.2V with a 50mA cutoff. The values recorded throughout the discharge cycles are sampled every 0.1 seconds. Additionally, a variety of power profile data from automotive industry's accepted drive cycles, including UDDS, LA92, US06, HWFET, and HPPC, as well as a mixed dataset encompassing all of them, are used in discharge testing. To understand the real-world performance of Li-ion batteries that may actually be utilized in electric vehicles, the authors of this paper examined the mixed dataset corresponding to temperatures of 0°C, 25°C, and 40°C. The number of entries in the dataset ranges from 60000 to 80000. Figure 3 illustrates the different LG cell parameters at 25°C which have been used in the paper.

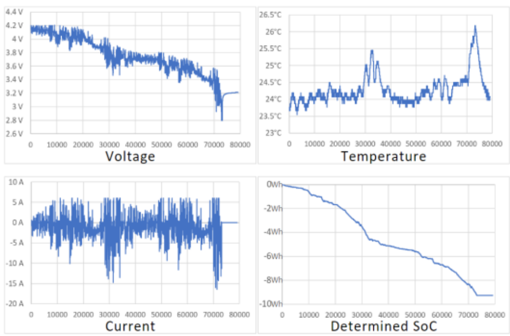

Figure 3. LG 18650HG2 Cell Parameters at 25°C

B. *UNIBO Powertools Battery Dataset*

The Mendeley data website was used to access the UNIBO Dataset also that is utilized. The values in this dataset [16,17] were obtained from 27 distinct battery cells from an Italian equipment manufacturer that were designed to power a variety of electrical products. The use of batteries from several manufacturers with differing nominal capacity and the cycle phases being carried out till the end of life of cell are the main highlights. As a result, it has information from several life stages that can be used to evaluate how the age of the cell affects SoC. It has around 417000 entries of data. Three different types of tests are carried out, including the normal test, in which the battery was discharged during main cycles at a current of 5A, the high current test, in which the battery was discharged during main cycles at a current of 8A, and the preconditioned test, in which the battery cells were kept at a high temperature for 90 days prior to the test. The sampling time taken in this case is 10 seconds for discharging. 100 times each of the charge and discharge main cycles were performed. The following methodology was employed to obtain the dataset:
(1) Charge cycle includes Constant Current-Constant Voltage (CC-CV) at 1.8A and 4.2V (100mA cut-off)
(2) Discharge cycle includes Constant Current until cut-off voltage (2.5V)
(3) Measurement of capacity at discharge CC 0.1A 2.5V and Charge CC-CV 1A 4.2V (100mA cutoff)

V. PROPOSED METHODOLOGY

In this paper, six various machine learning techniques were utilized to determine State of Charge through regression. The proposed methodology is given with the help of flowchart as shown in Figure 4.

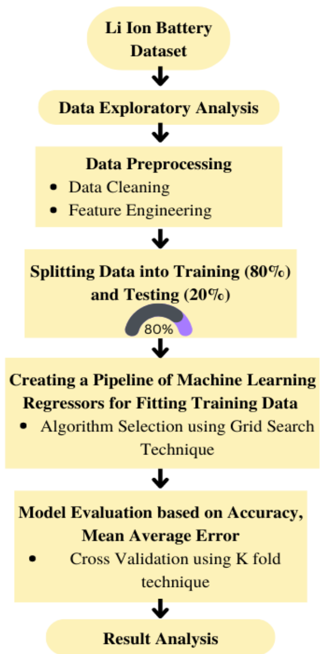

Figure 4. Flowchart of the Proposed Methodology

In the dataset, three parameters are considered to be input, namely Voltage, Current, Temperature and output is calculated SoC. The data pre-processing stage first has the data cleaning in which the duplicate entries are dropped to make the model save a lot of time. Then, features are engineered by appending each data column into the table and also calculating the mean voltage to use later as it is the most important factor than the rest of inputs. Splitting of data is done next where we have given 80% to training and 20% to testing. Since, six machine learning models are designed at the same time, a pipeline is created using them which include random forest, decision tree, gradient boosting, support vector regression, polynomial regression and multilayer perceptron. The hyperparameters for each model is given and it is being fit in a grid. Then, the whole pipeline is trained on initialized training sets one by one. Finally, each model's output is predicted and directly compared with testing set of data. Each model's accuracy and Mean Absolute Error (MAE) is calculated and again verified with K fold cross validation technique. All these models are applied on LG dataset and the best two methods are applied on Unibo dataset. Each of them is discussed in a detailed manner below.

A. *Random Forest Algorithm*

Originally based on Ensemble Learning, Random Forest is a method that builds several decision trees and integrates their results to produce more accurate predictions. A random subset of the features that are accessible and a subset of the training data are used to construct each tree. The technique generates a decision tree using a subset of the features that is randomly chosen during training. The procedure is performed numerous times, and the predictions from each tree are pooled to create the final result. The end result is a model that, in our situation, is effective for regression problems because it is less prone to overfitting and more robust to noise.

B. *Decision Tree Algorithm*

The Decision Tree is a predictive modelling tool applied to different areas. Typically, it is created using an algorithmic strategy that looks for possible conditions to divide a data set based on given rules. The root is first assumed to be the entire training set. Then, feature values that can be classified are provided. If the values do not seem discrete, they are discretized before employing statistical techniques. These decision rules, which are applied in non-linear decision making with a straightforward linear decision surface, are more equivalent to if-then-else statements. There are two nodes, namely decision and leaf nodes. In contrast to the latter, which are results and have no additional ends, the former is used to make decisions and have several branches.

C. *Support Vector Regression*

Another well-known approach for supervised learning is Support Vector Regression or SVR, which chooses the extreme points/vectors known as support vectors, to help in creating the hyperplane, hence the algorithm is named as Support Vector Machine. The SVR method aims to create the most precise decision boundary that can form classes in n-dimensional space by dividing so that fresh data points can be placed in the appropriate category in the future. Here, the hyperplane is a decision boundary that is almost perfect.

D. Polynomial Regression

A special type of multiple linear regression where dependent and independent variables are converted to polynomial of certain degree. Linear relationship will not be applicable if conditional expectation of dependent variable changes proportionally to the independent variable. This can be solved by using a quadratic method. From the estimation point of view, all the models are in linear form. The function of regression is linear based on the unknown parameters. Thus, by using multiple regression method polynomial regression can be solved by considering the variables as particular independent variables.

E. Gradient Boosting Algorithm

Another kind of ensemble approach is gradient boosting in which multiple weak models are designed, then they are combined to get better performance as a whole. Here, each predictor actually corrects the error of the predecessors. In contrast to Adaboost, tweaking does not happen to the training occurrences' weights. Instead, each predictor will be trained using the labels from past residual errors. CART (Classification and Regression Trees) is the default learner utilized. Additionally, shrinkage happens implying each tree's prediction is reduced after being multiplied by the earning rate (eta), which runs from 0 to 1. In the end, the number of estimators and eta are in compromise; to get the best yields, the learning rate must decline while the number of estimators must increase. As more trees get trained in this way, predictions can be made on the model.

F. Multilayer Perceptron

A Multilayer perceptron (MLP) refers to artificial neural networks composed of multiple layers of perceptron or McCulloch-Pitts neuron with specific activation layers which is used here. A Perceptron is a supervised learning algorithm made of a function known as a binary classifier which determines if a vector of integers representing an input is a member of a particular class. It has three layers: the input layer, the hidden layer, and the output layer. Each node, with the exception of the input nodes, is a neuron that employs a nonlinear activation function. Back propagation is a supervised machine learning approach that is used by MLP for training. MLP differs from a linear perceptron in that it does not use linear activation and several layers. It can distinguish between data that is inseparable linearly.

VI. Hyperparameters Optimization

The optimisation of the hyperparameters is crucial for determining effectiveness of the algorithm. Grid Search CV technique, which essentially attempts all conceivable combinations of parameter values for a specific model and yields the set with the best degree of correctness, is used here to customise the algorithm for a specific case. The Grid Search method's number of fold for cross validation is given as 10 as the dataset is large and this is able to give good results. Moreover, for all models 123 is given as the random state. The general parameters used on Machine Learning techniques include learning rate, number of estimators, maximum features, kernel, C, and gamma(ɣ).

$$K(x,x') = \exp\left(-\frac{||x-x'||^2}{2\sigma^2}\right) \quad (2)$$

$||x-x'||^2$ gives the Euclidean squared distance joining any two particular points in (2). ɣ greatly aids in finding how the kernel is distributed throughout the decision-making region. For extremely low values, it begins to widen in the region while the boundary's curvature is reduced, and vice versa. For multilayer perceptron model, parameters like hidden layer sizes and Sigmoid, ReLU activation which is given by (3), (4) respectively are used. The graphical representation of these functions in given in Figure 5.

$$\sigma(z) = \frac{1}{1+e^{-z}} \quad (3)$$

$$R(z) = \max(0, z) \quad (4)$$

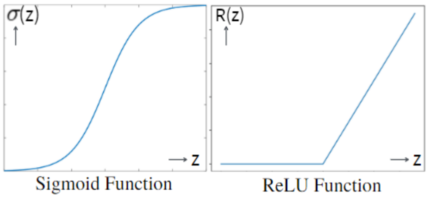

Figure 5. Activation Functions

VII. Model Evaluation and Results

For evaluation of models, calculation of the predicted outcomes of the model with testing data and comparison with original ones is done first. But, to understand the true efficiency of the model and to ensure every set of data is covered with no irregularities, K fold cross validation is further used in this paper. Accuracy and Mean Absolute Error (MAE) are the primary indices used to assess the performance. In Equation (5), y shows predicted value, x shows actual value, and n denotes number of samples.

$$MAE = \frac{1}{n}\sum_{i-1}^{n} |yi - xi| \quad (5)$$

A. LG 18650HG2 Li-ion Battery Dataset Results

Using above methods, the results are tabulated as given below for the all the proposed algorithms for a specific LG battery mixed dataset containing data from different drive cycles to simulate real world scenarios at three different temperatures that is 25°C, 40°C and 0°C separately. A scatter plot is also plotted for each to visualize the results with X axis as predicted values for that algorithm and Y axis as actual values. So, a linear line y equals x in the first quadrant on the scatter plot means that the prediction is perfectly aligned with the actual results and any point away from this line shows the deviation between the two results corresponding to the values in the table.

Table 1. LG Dataset Results at 25°C

LG DATASET (25°C)		
METHOD	ACCURACY	MAE
Random Forest	99.95%	1.65%
Decision Tree	99.90%	1.21%
Multilayer Perceptron	99.72%	10.09%
Support Vector Machine	99.72%	10.35%
Polynomial Regression	99.67%	11.17%
Gradient Boosting	99.42%	14.47%

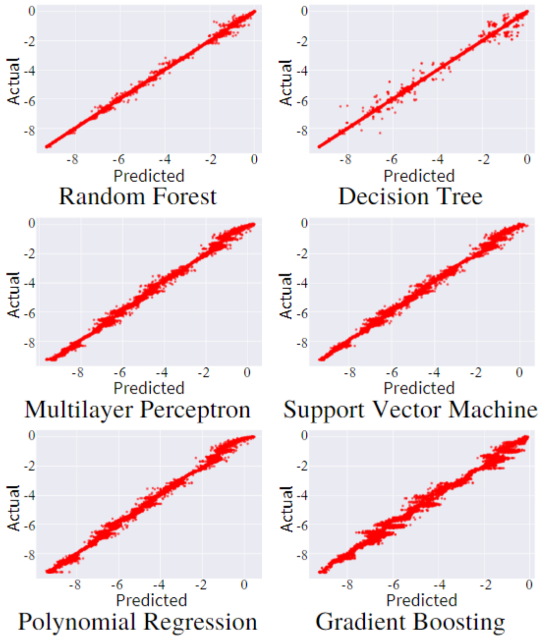

Figure 6. LG Predicted vs Original SoC Graph (25°C)

Table (1) shows the results at 25°C in which Random Forest comes out with Highest Accuracy at 99.95% and Decision Tree comes out with Least Mean Absolute Error at 1.21%.

Table 2. LG Dataset Results at 40°C

LG DATASET (40°C)		
METHOD	ACCURACY	MAE
Random Forest	99.96%	1.27%
Decision Tree	99.92%	0.96%
Multilayer Perceptron	99.83%	6.39%
Support Vector Machine	99.83%	6.80%
Polynomial Regression	99.71%	8.69%
Gradient Boosting	99.49%	12.02%

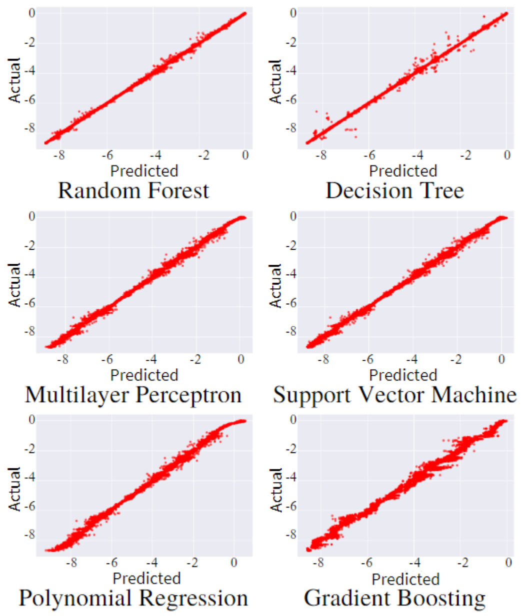

Figure 7. LG Predicted vs Original SoC Graph (40°C)

Table (2) shows the results at 40°C in which Random Forest comes out Highest Accuracy at 99.96% and Decision Tree comes out with Least Mean Absolute Error at 0.96%.

Table 3. LG Dataset Results at 0°C

LG DATASET (0°C)		
METHOD	ACCURACY	MAE
Random Forest	99.88%	1.95%
Decision Tree	99.76%	1.28%
Multilayer Perceptron	99.36%	10.85%
Support Vector Machine	99.13%	14.16%
Polynomial Regression	98.79%	17.93%
Gradient Boosting	98.59%	18.72%

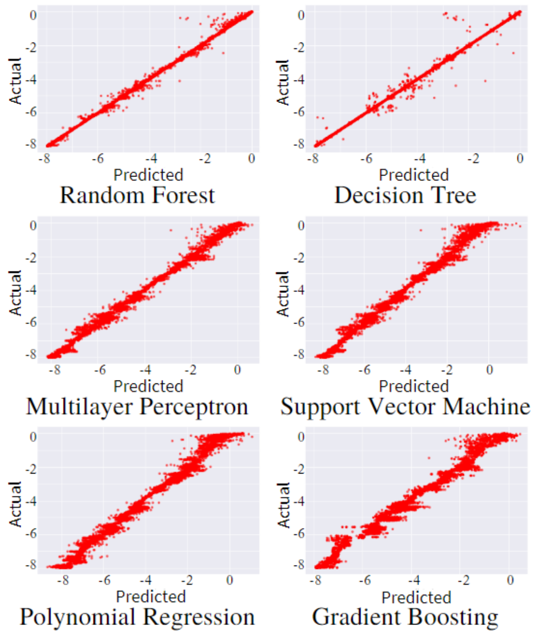

Figure 8. LG Predicted vs Original SoC Graph (0°C)

Table (3) shows the results at 0°C in which Random Forest comes out with Highest Accuracy at 99.88% and Decision Tree comes out with least Mean Absolute Error at 1.28%. The figures 6, 7, 8 also visualize the results in form of scatter plots for 25°C, 40°C and 0°C respectively and they also show that these two methods have the least scattering among all. The other four methods have a good Accuracy in comparison but show a minimum of 5% higher MAE at 40°C and 8.5% higher MAE at 0°C, 25°C.

B. UNIBO Powertools Battery Dataset Results

From previous result, it is found that first two models are giving best accuracy and least mean average error. These two are only used in this dataset to check their performance. Here, it is obtained at normal room temperature only.

Table 4. UNIBO Dataset Results

UNIBO DATASET		
METHOD	ACCURACY	MAE
Random Forest	99.16%	13.26%
Decision Tree	98.15%	12.55%

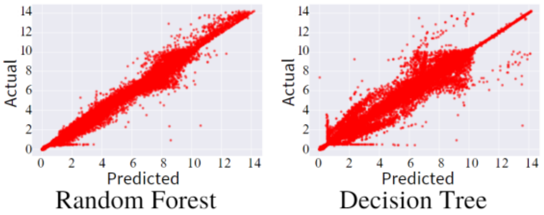

Figure 9. UNIBO Predicted vs Original SOC Graph

Table (4) shows the results in which Random Forest comes out with Highest Accuracy at 99.16% and Decision Tree comes out with the least Mean Absolute Error at 12.55%. This dataset is nearly six times larger and consists of many cycles in comparison to the LG dataset. So, only the best models are applied and as expected, there is a drastic difference in the value. It should also be noted the SoC scatter plot obtained from this dataset in Figure 9 is more scattered than those obtained using previous dataset.

VIII. Conclusion and Discussions

From the results shown above, at all the three temperatures in the LG Dataset, Random Forest turns out to be the one with the Highest Accuracy and Decision Tree has the Least Mean Absolute Error. There is also a considerable gap in mean absolute error when these two are compared to the rest of the methods used in LG Dataset. Then, for the more complex bigger UNIBO dataset, only these two methods are used to save time and computation power as they both perform way better from the previous results. The results obtained here dataset have considerable difference with LG dataset especially for mean absolute error where the change is nearly ten percent. But still, it also reiterates that Random Forest is the winning algorithm. Other than these two best models, multilayer perceptron comes at third, support vector machine at fourth, polynomial regression at fifth and gradient boosting at the last showing that it is least suitable. It is also realized that at 0°C, the results are at their lowest values compared to higher temperatures, making it difficult to predict accurate values of State of Charge. This can be due to many reasons at lower temperatures like the kinetic energy at the atomic scale reduces which can affect the rate of chemical reactions and it also increases the internal resistance of the battery leading to reduced capacity. All these factors can have a direct impact with prediction of SoC at different temperatures. At 40°C, the results are most accurate and at 25° C, it gives results that are intermediate between those two suggesting that temperature and SoC estimation have an inverse relationship between each other. Overall, six machine learning models are implemented to estimate SoC and the results are compared with two different datasets of Lithium-ion Battery in this paper.

IX. References

[1] F. A. Barrios et al., "Comparing Traditional and Machine Learning Models for Battery SoC Calculation," 2022 IEEE Transportation Electrification Conference & Expo (ITEC), 2022, pp. 125-130, doi: 10.1109/ITEC53557.2022.9813753

[2] C. Mehta, P. Sharma and A. V. Sant, "A Comprehensive study of Machine Learning Techniques used for estimating State of Charge for Li-ion Battery," 2021 International Conference on Artificial Intelligence and Machine Vision (AIMV), 2021, pp. 1-6, doi: 10.1109/AIMV53313.2021.9671010.

[3] P. A. Satyan and R. G. Sutar, "A Survey on Data-Driven Methods for State of Charge Estimation of Battery," 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), 2020, pp. 996-1004, doi: 10.1109/ICESC48915.2020.9155926.

[4] A. Upashrutti and K. C. S. Thampatty, "Estimation of State of Charge of EV Batteries-A Machine Learning Approach," 2022 IEEE IAS Global Conference on Emerging Technologies (GlobConET), 2022, pp. 70-76, doi: 10.1109/GlobConET53749.2022.9872510.

[5] S. Jumah, A. Elezab, O. Zayed, R. Ahmed, M. Narimani and A. Emadi, "State of Charge Estimation for EV Batteries Using Support Vector Regression," 2022 IEEE Transportation Electrification Conference & Expo (ITEC), 2022, pp. 964-969, doi: 10.1109/ITEC53557.2022.9813811.

[6] I. Babaeiyazdi, A. Rezaei-Zare and S. Shokrzadeh, "State-of-Charge Prediction of Degrading Li-ion Batteries Using an Adaptive Machine Learning Approach," 2022 IEEE Power & Energy Society General Meeting (PESGM), 2022, pp. 01-05, doi: 10.1109/PESGM48719.2022.9916995.

[7] M. S. Sidhu, D. Ronanki and S. Williamson, "State of Charge Estimation of Lithium-Ion Batteries Using Hybrid Machine Learning Technique," IECON 2019 - 45th Annual Conference of the IEEE Industrial Electronics Society, 2019, pp. 2732-2737, doi: 10.1109/IECON.2019.8927066.

[8] E. Ipek, M. K. Eren and M. Yilmaz, "State-of-Charge Estimation of Li-ion Battery Cell using Support Vector Regression and Gradient Boosting Techniques," 2019 International Aegean Conference on Electrical Machines and Power Electronics (ACEMP) & 2019 International Conference on Optimization of Electrical and Electronic Equipment (OPTIM), 2019, pp. 604-609, doi: 10.1109/ACEMP-OPTIM44294.2019.9007188.

[9] M. S. Hossain Lipu et al., "Differential Search Optimized Random Forest Regression Algorithm for State of Charge Estimation in Electric Vehicle Batteries," 2021 IEEE Industry Applications Society Annual Meeting (IAS), 2021, pp. 1-8, doi: 10.1109/IAS48185.2021.9677106.

[10] N. A. Sârbu and D. Petreuş, "State of Charge Estimation of Li-Ion Batteries using Artificial Neural Networks," 2022 45th International Spring Seminar on Electronics Technology (ISSE), 2022, pp. 1-8, doi: 10.1109/ISSE54558.2022.9812815.

[11] H. S. Bhattacharyya, A. Yadav, A. B. Choudhury and C. K. Chanda, "Convolution Neural Network-Based SoC Estimation of Li-ion Battery in EV Applications," 2021 5th International Conference on Electrical, Electronics, Communication, Computer Technologies and Optimization Techniques (ICEECCOT), 2021, pp. 587-592, doi: 10.1109/ICEECCOT52851.2021.9708055.

[12] Iman Babaeiyazdi, Afshin Rezaei-Zare, Shahab Shokrzadeh, “State of charge prediction of EV Li-ion batteries using EIS: A machine learning approach”, Energy, Volume 223, 2021, 120116, ISSN 0360-5442, https://doi.org/10.1016/j.energy.2021.120116.

[13] Ali Ghorbani Kashkooli, Hamed Fathiannasab, Zhiyu Mao and Zhongwei Chen, “Application of Artificial Intelligence to State-of-Charge and State-of-Health Estimation of Calendar-Aged Lithium-Ion Pouch Cells”, 2019 The Electrochemical Society, Journal of the Electrochemical Society, Volume 166, Number 4, Ali Ghorbani Kashkooli et al 2019 J. Electrochem. SoC. 166 A605 doi: 10.1149/2.0411904jes

[14] Vidal, Carlos & Kollmeyer, Phil & Naguib, Mina & Malysz, Pawel & Gross, Oliver & Emadi, Ali. (2020). Robust xEV Battery State-of-Charge Estimator Design Using a Feedforward Deep Neural Network. 10.4271/2020-01-1181.

[15] Kollmeyer, Philip; Vidal, Carlos; Naguib, Mina; Skells, Michael (2020), “LG 18650HG2 Li-ion Battery Data and Example Deep Neural Network xEV SoC Estimator Script”, Mendeley Data, V3, doi: 10.17632/cp3473x7xv.3

[16] Bosello, Michael; Pau, Giovanni (2021), “UNIBO Powertools Dataset”, Mendeley Data, V1, doi: 10.17632/n6xg5fzsbv.1

[17] Kei Long Wong, Michael Bosello, Rita Tse, Carlo Falcomer, Claudio Rossi, Giovanni Pau. 2021. Li-Ion Batteries State-of-Charge Estimation Using Deep LSTM at Various Battery Specifications and Discharge Cycles. In Conference on Information Technology for Social Good (GoodIT ’21), September 9–11, 2021, Roma, Italy. ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3462203.3475878