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Estimation of State of Charge of EV Batteries-A Machine Learning Approach

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***Abstract*— The automotive industry is witnessing a major technology shift from internal- combustion engine-based vehicles to electrified hybrid models like the plug-in hybrids and battery electric vehicles. As the industry progressively move towards electrification of vehicles, challenges in terms of implementation of the technology are foreseen. Batteries are the key component in an electric vehicle and thereby require accurate real-time supervising and monitoring State of charge is chosen as the vital battery parameter as every battery management system continuously keeps evaluating for the driver. The weather and climatic conditions the vehicle will be exposed to must be considered. Temperature is derived to be the right parameter for analyzing battery parameters as it plays a major role in SOC estimation accuracy. This study aims to estimate the battery SOC based on current through and the voltage across a battery using Support Vector Regression (SVR) after considering adverse temperature change and varied power discharge. This Data-driven model uses Grid Search to find the hyperparameter and obtain accurate results. The Mean absolute error and Mean square error is acquired for different temperature.**

Keywords*— Electric vehicle, Lithium-ion batteries, State of Charge, Depth of Discharge (DoD), Support Vector Machine, Support Vector Regression, Grid search

I. INTRODUCTION

Most of the existing battery models are impractical for automotive applications which require detailed and extensive analysis of the chemistry behind Li-ion cells. As these battery models are oblivious to changes that occur in these cells due to temperature which affects the cell chemistry. In a real-life implementation of these battery models for automotive purposes, it poses a need to ensure the safety of the driver of the electric vehicle. State of Charge is an indicator of the available runtime of the battery. It is equivalent to the fuel level gauge in internal-combustion engine powered vehicles. Accurate battery state estimates not only aids in providing information about the battery's current and remaining output, but also ensure the safe operation of electric vehicles (EV). Safety should be the utmost concern in a vehicle. When Design Failure Mode and Effect Analysis (DFMEA) is done for an electric vehicle, inaccurate and slow-processed SOC and SOH might cost the life of the driver. As the automotive market is transitioning towards electrification is important to make the new buyers feel safe and ensure safety in their new vehicles. Therefore, this highlights the need to adopt effective ways of estimation techniques.

There are various analytical methods of estimation state of charge of Li-ion battery like Coulomb Counting method, Open circuit voltage, and Unscented Kalman filter (EKF). We should include the ambient temperature for the estimation of SOC as it is difficult to measure the temperature of the battery. The Coulomb counting approach is the easiest and often used method but it is observed that the SOC values are inaccurate not only because of the temperature effect but also due to varying power requests and the aging effect which acts as the main challenge for accurate measurement.

OCV method requires a rest time and it is not possible in the real-time estimation of Li-ion batteries. It is also noted that SOC is not linear for Li-ion batteries but whereas Lead-acid is linear. So, it is easy to estimate it for Lead-acid rather than Li-ion. Kalman Filter produces good accuracy but it involves rigorous computation and a convoluted processor which are expensive. Thus, there is a need for a new model of the battery where the temperature effect and aging can also be included for the estimation of SOC. In this paper estimation techniques have been approached from a data-driven perspective using machine learning algorithms such as support vector regression which has faster computation and higher accuracy than analytical methods.

Wang et al., have analyzed the most common seven types of kernel functions namely Linear kernel function, Polynomial

kernel function, Radial basis function (RBF), Sigmoid kernel function, Fourier kernel function, B-spline kernel function, and Wavelet kernel function, and a new kernel function combines three different types of conventional kernel functions to improve generalization and learning is adopted [1]. Surendar V et al., have used Support Vector Regression (SVR) to estimate the State of Charge of the battery. The test runs are done in SIMULINK using a Lead-acid Battery, but this method can be used to estimate the State of Charge of any lithium-ion battery type. In this paper, the hyperparameters for SVR regression were decided by grid search and Particle Swarm Optimization (PSO) [2].

Haq I. N et at., have estimated the State of Charge of LiFePO4 Battery through Support Vector Regression (SVR) by using the charging and discharging testing cycles to derive the lookup table of Open Circuit Voltage (OCV) and the State of Charge by keeping the current and voltage as independent variables [3]. Edison F et al., have estimated the battery's State of Charge, taking into consideration the unbalanced voltage between cells and energy efficiency. In this paper, experiments were conducted on Lithium Nickel Cobalt Aluminium Oxide (LiNiCoAlO2) to get the lookup table for SVR [4].

Temperature is derived to be the right parameter for analyzing battery parameters. As the battery temperature and aging factors play a major role in estimating SOC. Usable capacity is affected by the usage of the battery and number of cycles, it affects the SOC estimation accuracy as it is a function of usable capacity. This project deals with the SOC estimation using Support Vector Regression (SVR) based Machine Learning Approach which concentrates on the temperature and other conditions like a battery being subjected to a variable power discharge. Thus, the accuracy is higher and the error percentage is very less.

II. LI-ION BATTERY MODELING

The commonly used type of battery used in EV is Li-Ion battery in which the anode is generally Graphite and Hydrogen-containing Carbon materials and the Cathode is made of Cobalt, Nickel and Manganese and mostly lithium-cobalt oxide ($LiCoO_2$). The electrolyte liquid is Lithium Hexafluoro- Phosphate. Nominal voltage, energy, and power density vary with the materials used. Li-ion cells are to be operated at a safe operating voltage range preventing them from overcharging and overheating or else the battery will fire. So, the Lithium-Ion batteries should be operated within the range not exceeding the safe voltage limit. Also, the cells should operate within the safe temperature limit.

The cell model that is developed comprises SOC-dependent open-circuit voltage. By varying the state of charge (SOC) and current, the parameters are set according to battery behavior. The equivalent circuit model used in the mattery modeling is shown in Fig .1. Fig.2 is the proposed dynamic

model of the battery.

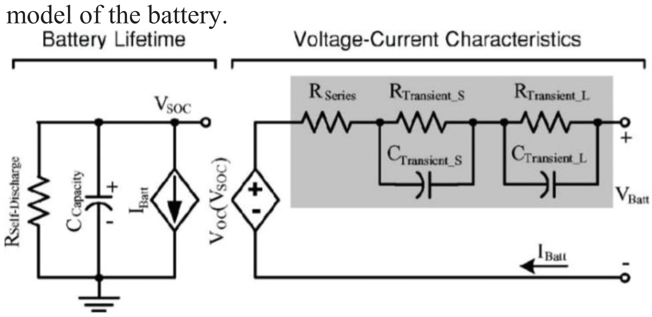

Fig. 1. Battery Equivalent circuit model[5]

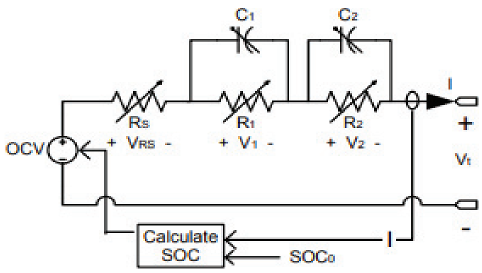

Fig. 2. Dynamic circuit model of battery

The model circuit consists of a dc voltage source, a series resistance, and two RC parallel networks. The open-circuit voltage (OCV) of the battery is represented by the DC voltage source, internal DC resistance is represented by series resistance (RS) and transient response of voltage and terminal voltage are characterized by RC parallel networks (R1, C1, R2, C2) [6]. In this model rate capacity effect is considered by varying the usable capacity with the current. Based on the value of usable capacity, the SOC of the battery is calculated. In this model, all parameters are dependent on SOC and current.

The SOC calculation is given in Eqn.1 [5].

$$SOC = SOC0 - \int_0^t \frac{I*100}{\propto u*360}\, dt \tag{1}$$

In Eqn. 1, 'I' stands for new, SOC0 represents the initial SOC, and 'u' stands for available power. The initial SOC (SOC0) and current SOC are given as inputs (I). The usable capacity (αu) of a battery is used to describe the rate capacity effect, which varies with the magnitude of the current. The real-time SOC is the performance of this subsystem [5]. The open-circuit voltage(OCV) of the battery is calculated as a function of SOC as given in Eqn.2

$$OCV = -1.031 * e^{-35SOC} + 3.685 + 0.2156*SOC - 0.1178*SOC2 + 0.3201*SOC3 \tag{2}$$

The OCV curve is unique for each battery which can be affected by the aging of the battery. SOC has a fixed relationship with OCV under certain temperatures.

The variation of OCV with respect to SOC is shown in Fig.3

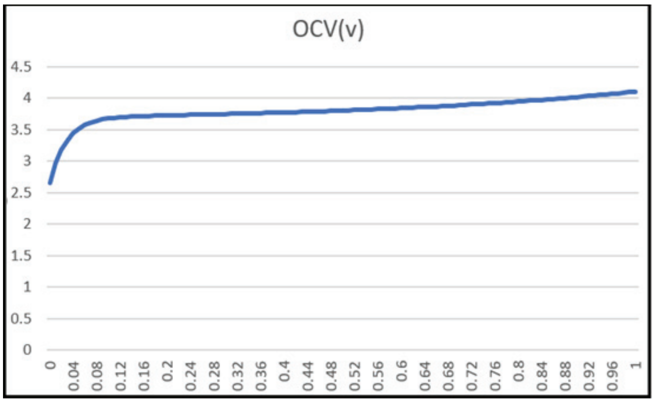

Fig. 3. Variation of OCV with SOC

The values of the RC parallel network are dependent on SOC. The model parameters are calculated using the Eqn. 3 to 6 [5]. These calculated values are consolidated in Table 3.1. The model parameter equations are a function of SOC.

$$R1 = 0.3208*e-29.14\ SOC + 0.04669 \tag{3}$$

$$C1 = -752.9 * e^{-13.51SOC} + 703.6 \tag{4}$$

$$R2 = 6.603 * e^{-27.21SOC} + 0.04984 \tag{5}$$

$$C2 = -6056 * e^{-27.12SOC} + 4475 \tag{6}$$

The value of % SOC is varied with the step of 0.01 from 0 to 100. The RC values are then calculated and plotted. . Using the interpolation-extrapolation lookup method, the best value for the parameters is calculated. Outside the known sequence, the values are calculated by expanding the given values in extrapolation, while values between two known values in a sequence of values are estimated in interpolation. The variation of the battery parameters R1, R2, C1, and C2 shown in Fig.4

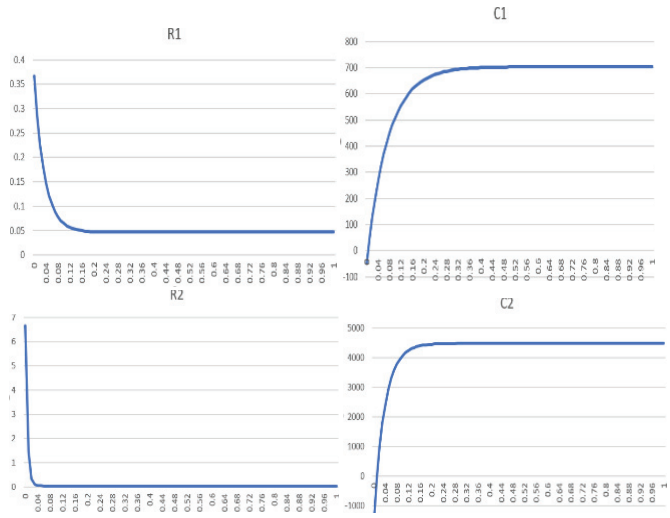

Fig. 4. Variation of the battery parameters with %SOC

The voltage across the battery internal resistance is represented as Vrs. Where the internal resistance Rs is dependent on SOC. The calculation of internal resistance, voltage across the internal resistance, and the terminal voltage of the battery is shown in Eqn. 7 to 9

$$Rs = 0.1562 * e^{(-24.37 * SOC)} + 0.07446 \quad (7)$$

$$Vrs = I * Rs \quad (8)$$

$$Vt = OCV - V1 - V2 - Vs \quad (9)$$

For predicting battery cycle lids and calculating the remaining usable energy, the thermal behavior of these batteries must also be taken into account to help in predicting the performance of the Li-ion Cell batteries [7]. The depletion of a battery's usable power due to time, temperature, and cycle number are referred to as capacity fading. The battery degrades as a result of this permanent loss.

The losses can be classified into two, Calendar life losses and Cycle life losses. These losses increase with time and the effect of temperature must be considered too. The calendar life losses and cycle life losses can be termed together as capacity correction factor (CCF) [7] which is expressed in Eqn. 10.. The usable capacity can be defined as a function of CCF as given in Eqn. 11.. The calendar losses are mathematically modeled as given in Eqn. 3.15. The cycle life losses can model as negative electrode SOC, the rate of change is dependent on the number of cycles and given in Eqn. 3.16. The average SOC and SOC variance Eqn. s are given above in Eqn. 3.17, 3.18 [8].

$$CCF = 1 - (\text{Calendar life losses} + \text{Cycle life losses}) \quad (10)$$

$$C_{usable} = C_{initial} \times CCF \quad (11)$$

$$\%\ \text{Storage Loss} = 1.544 \times 10^{7} * e^{(40498/8.3143 \times T))} * \frac{d\theta_n}{dN} \quad (12)$$

Where $\frac{d\theta_n}{dN} = N\,K1 + K2,$

$K_1 = 8.5 \times 10^{-8}$, $K_2 = 2.5 \times 10^{-4}$

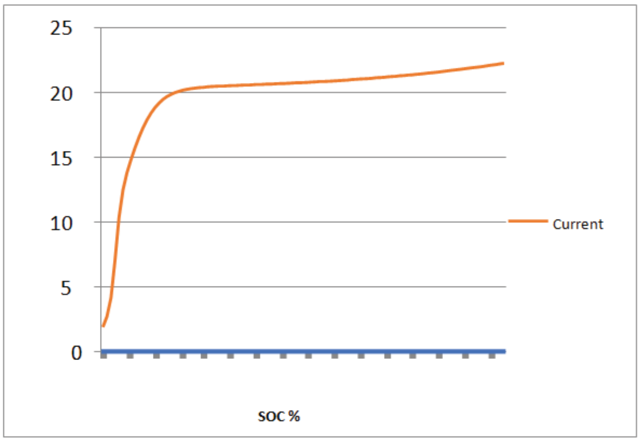

Fig. 5. The current flowing through the battery varies with respect to SOC

Lithium-ion batteries have a fairly constant internal resistance from empty to full charge. Around 0% and 30% SoC, the most significant changes occur as shown in Fig. 6. The internal resistance of a battery varies depending on its charge level. Resistance is maximum when the battery is at a low state of charge. Lithium-ion batteries' resistance rises as they are discharged. The battery resistance limits the power delivery capability when connected in series. Significant variations in battery resistance cause non-uniform current loads resulting in temperature gradients. Therefore, the SOC relationship is dependent on ambient temperatures and aging stages [6].

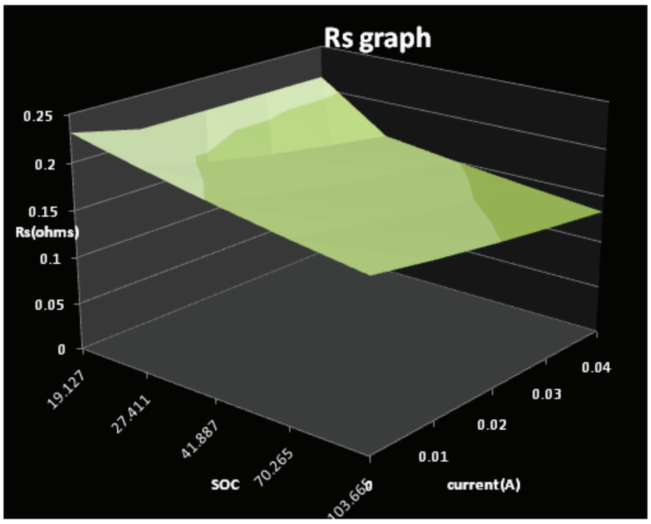

Fig. 6. Variation of % SOC with internal resistance and battery current under 25°C temperature

During charging and discharging of the battery, the variation of %SOC with respect to current is different as shown in Fig. 7 and 8Fig. 7. Variation of % SOC with charging resistance and battery current at 25°C temperature

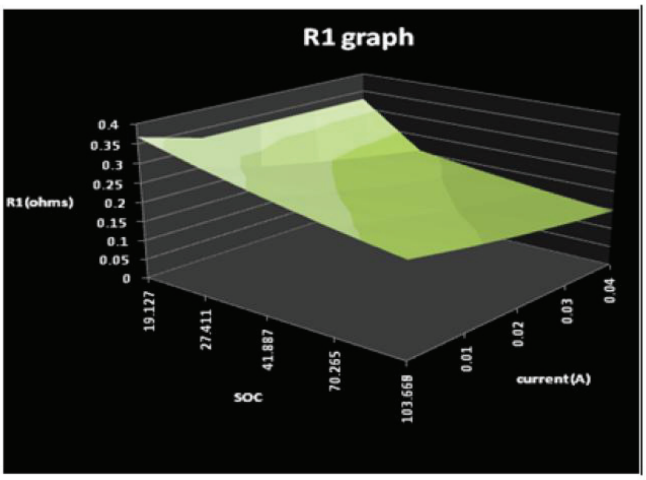

Fig. 7. Variation of % SOC with charging resistance and battery current at 25°C temperature

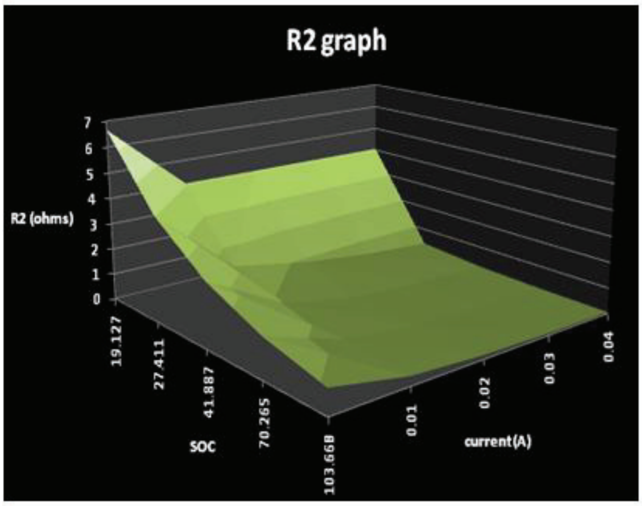

Fig. 8. Variation of % SOC with discharging resistance and battery current at25°C temperature

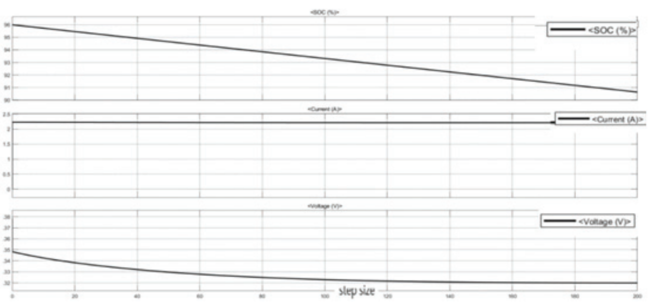

Fig. 9. a) Variation of % SOC b) Variation of current c)Variation of voltage of the Li-Ion battery at 25°C temperature

As the operating temperature changes, all the characteristics of the battery change. From all the analysis conducted on Li-ion battery, it has been observed that during discharge the voltage and charge present the battery drops quickly. As the charge drops the current also decreases. When the battery is discharging the battery, temperature increases therefore increasing the internal resistance allowing the current and SOC to decrease. Whereas during charge the voltage and charge present in the battery increase gradually. The charge presents the battery increases, therefore, increasing the battery current. This is how the SOC, battery current change during charging and discharging.

III. BACKGROUND

In this section, we first present the data to be used for developing and validating the proposed approach. Then, the SOC estimation problem for different temperatures is carried out. The ambient temperature has a significant effect on the SOC estimation accuracy, depth of discharge, and control of charging/discharging of the battery. In this study, an open-source data set provided in [9], which considers A123 cells at different environmental conditions ranging from 0°C to 50°C and also subjected to, two dynamic tests namely, Dynamic Stress Test (DST) and Federal Urban Driving Schedule (FUDS) which are the field data. Therefore we consider the data which is subjected to all these test conditions. The dynamic stress test (DST) is that the battery is subjected to several DST cycles that are to a variable power discharge which is then scaled to a percentage of the maximum rated power with SOC operational range from 90% to 20%. The battery demonstrated reasonable cycle-life and high energy. At different DST conditions such as lower, intermediate, and higher Depth of Discharge (DoD). Long-term tests are needed to determine the DST cycle at very low DoD. Federal Urban driving schedule (FUDS) is the defined speed-time history of the driving schedule for various stop-to-stop cycles which allows deriving additional characteristics of the battery. Data collected can procure a relation from the vehicle's fuel consumption at any urban speed and also the remaining unused energy at the end of a discharge when the vehicle fails the requirement of the driving schedule. In short, DST helps to identify the model parameters, and FUDS is used to validate the performance of the SOC estimation. The final data after the dynamic test contains Voltage, Current, and Time for different temperatures with varied step sizes.

IV. MACHINE LEARNING APPROACH FOR THE ESTIMATION OF EV BATTERY SOC

Machine learning is the process of parsing data, learning from it, and then making a decision or prediction about something in the real-world using algorithms. It helps us to automatically respond to new data and make conclusions and recommendations based on thousands of estimates and analyses. SOC estimation is divided into two groups, open-loop models and closed-loop models. Even though there are various methods for estimating SOC, here is the list of the most popular SOC estimation methods used in Electric vehicles.

1. Coulomb Counting SOC estimation method
2. Support Vector Regression SOC estimation method
3. Kalman Filtering SOC estimation method
4. Open Circuit Voltage SOC estimation method

The conventional method of finding SOC is that the Open Circuit Voltage (OCV) method which is in the Equivalent circuit-based model. Machine learning has become a popular computational tool for determining the level of charge, health, and remaining usable life of batteries in the field of energy storage. In a stable battery management scheme, a precise SOC calculation is crucial. In this study Support Vector Regression, SOC estimation method is used

A. *Support Vector Regression*

Support vector regression is one of the most well-known applications of the supervised Machine Learning technique. We might call it one of the most effective models for solving classification problems or classifying data that isn't linearly separable.

SVR is a useful method for estimating real-value functions. The Support Vector is a vector that is used to represent the hyperplane or to put it another way, these are the dataset's extreme data points that help classify the hyperplane. Support Vector Machine (SVM) is similar to SVR where the support vectors are used to characterize the hysteresis. SVR aims to fit as many data points as possible into the available space while staying within the margin of error. Therefore, SVR is a powerful method that lets us pick how much error is tolerated, both in terms of an acceptable error margin and our tolerance for slipping outside of that acceptable error rate. It is also unaffected by outliers, add to that the decision model can be quickly updated and many classifiers can be trained on various types of data using probability laws. It can improve prediction accuracy and needs less computing than other regression models and it is easy to implement [10]. There are two approaches in nonlinear support vector regression, mapping the non-linearly separable dataset to a higher dimension and getting a linearly separable dataset and by using the kernel trick. In this paper, we follow the kernel trick. The Kernel is diversified and most commonly known are polynomial, sigmoid, and Radial Basis Function (RBF). In this paper, RBF and linear kernels are used for finding the hyperplane using the grid search method.

Fig.10 is a flowchart representing a constructive approach for SOC estimation using the Support Vector Regression Machine Learning Algorithm.

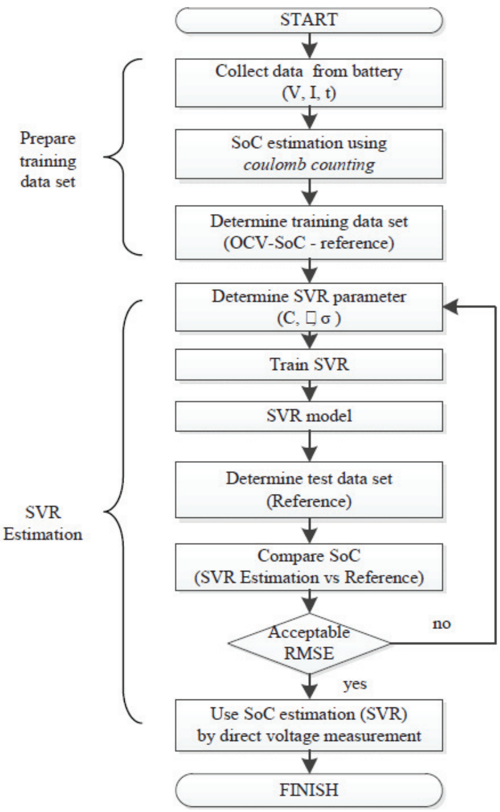

Fig. 10. Flow chart for the execution of SVR algorithm [11]

B. *Hyperparameter Optimization*

Tuning the hyperparameters plays a key role in determining the efficiency of the algorithm. When an algorithm is being tailored for a particular situation using grid search, you tailor the hyperparameters of the chosen model such that the most accurate outcomes are obtained. The parameters used here are C, ɣ, and kernel. The dataset of the battery chosen is not linear, radial basis function is chosen.

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

$||x - x'||^2$ is the Euclidean squared distance between two specific points. ɣ helps in understanding how the kernel is spread over the region of decision. When this value is very less, it broadens the region while lowering the curvature of the boundary and similarly the vice versa.

The main indices used in the performance evaluation of the proposed algorithm are Mean absolute error and mean squared error as given in Eqn in 13 and 14 respectively

$$MAE = \frac{1}{n}\sum_{i-1}^{n}|y_i - x_i| \quad (13)$$

$$MSE = \frac{1}{n}\sum_{l=1}^{n}|y_i - x_i|^2 \quad (14)$$

Where y is the predicted value, x is the actual value and n is the number of samples

V. Result and Discussion

Python libraries have been used to construct the SVR algorithm. Python is a sophisticated language with an open-source development environment, the necessary training and test data are prepared using Python and its development environment. The battery voltage, step time, and current measurements are used as input variables for the SVR model. The right hyperplane for class separation is found by tuning hyperparameters using the GridSearch CV method available in python. The dataset provided in [1], for operating temperatures 10 ℃, 20°C, and 30℃, has been used to train and test the SVR model for SOC estimation. The estimated SOC and original SOC have been compared for each temperature separately, as shown in Fig 11, Fig 12, and 13 respectively.

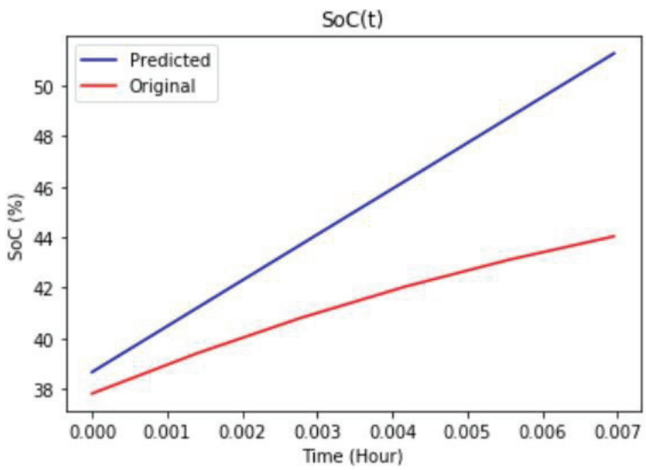

Fig. 11. %SOC vs Time (Hour) operating at temperature 10℃

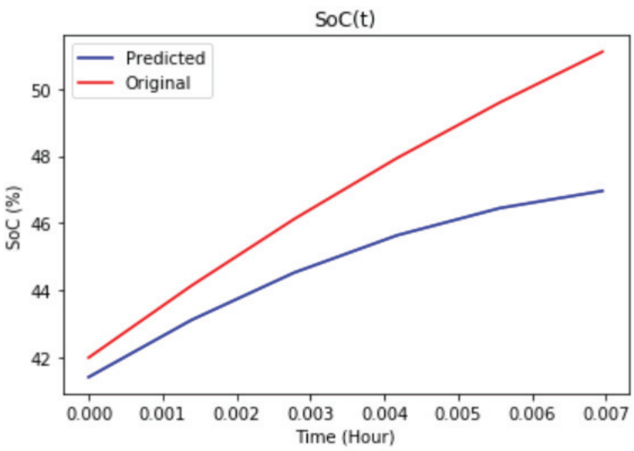

Fig. 12. %SOC vs Time (Hour) operating at temperature 20℃

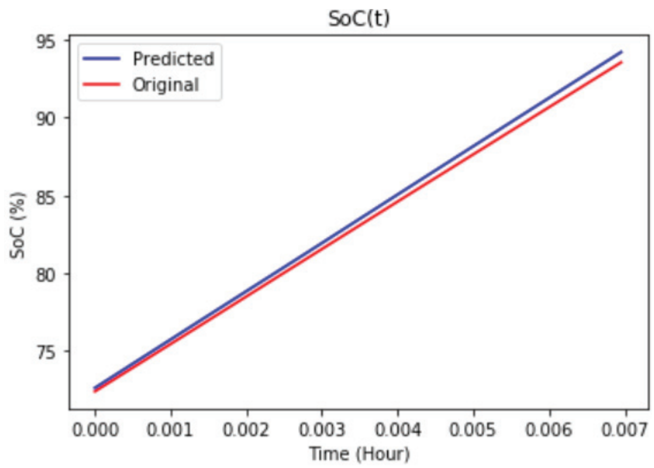

Fig. 13. %SOC vs Time(Hour)operating at temperature (30^0C)

The Mean Absolute Error (MAE) and Mean Squared Error (MSE) for each temperature have been calculated using sklearn.metrics python library.

MAE and MSE is calculated at different temperature level as shown in Table 1

TABLE I. MAE AND MSE AT DIFFERENT TEMPERATURES

Temperature	Mean Absolute Error	Mean Squared Error
10℃	0.215	0.660
20℃	0.037	0.190
30℃	0.028	0.114

From Table I, it is inferred that the error values for lower temperatures are higher compared to the higher temperature. Temperature, as a key aspect, has a major effect on the capacity of lithium-ion batteries, as well as limiting their use. The electrolyte's properties would be affected by the low temperature. The viscosity of the electrolyte can increase as the temperature drops, lowering the ionic conductivity. In the graphs, the predicted value of SOC (Fig.11, Fig.12, Fig.13) is more similar to the true value under operating temperature 30 ℃, compared to that of the graphs under 20 ℃ and 10℃.

VI. CONCLUSION AND FUTURE SCOPE

Based SOC estimation is of great importance when developing a battery management system. It provides an overview of the short- and long-term state of the battery. The battery SOC estimation reflects the reality of the battery including the impact of adverse temperature dependencies and variable power discharges cycles. The machine learning models are the most effective due to their intensive computing and learning process. This SVR method is a good trade-off of the accuracy in estimating SOC by this proposed algorithm as it has achieved good real-time performance and high accuracy.

The accuracy can further be increased by integrating the effect of degradation of the battery. This will enhance the performance of battery management systems.

On the presented research work in this paper, the estimated SOC can be used to find the SOH of the battery. However, this accuracy can further be increased by integrating the effect of degradation of the battery.

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