"Develop and Validate the Machine LearningAlgorithms of SOC Estimation for Solar Assisted Three-Wheeler"

[1]Mangesh Maurye*,[2]Prof.Shashank Gawade,[3]Prof. Neha Zope, [4]Prof. Manisha Shitole
[1,2,3,4]P[2]Mechanical Engg.Dept., School of Engineering & Sciences, Pune, Maharashtra, India, School of Engineering & Sciences, Pune, Maharashtra, India
[1]mangeshmaurya28@gmail.com

***Abstract*— The SOC (State of Charge) of lithium-ion battery packs indicates their currently charged energy level or capacity. Many battery-operated systems use SOC to determine energy availability. Early methods like open-circuit voltage, Coulomb counting, Kalman filters, Data-Driven Approaches, and Real-Time Updates are used to estimate SOC in battery packs. SOC estimation in battery packs has had inaccuracies and accuracy issues in recent years with these old approaches. Two-wheeler, three-wheeler, and four-wheeler electric vehicles have SOC estimation issues. In recent years, AI&ML algorithms are used everywhere for accuracy, solutions, and more to solve this challenge. The Security Operations Centre is optimised via machine learning.Reinforcement learning, unsupervised learning, and supervised learning can improve machine learning SOC. Choosing battery pack algorithms for precise State of Charge (SOC) predictions is one of the best techniques. In machine learning, we choose supervised algorithms. Currently, research will focus on SOC Estimation using a Supervised Machine Learning Algorithm. This approach uses Decision Trees, Bagging, Extra Trees, K-Nearest Neighbours, and Random Forest regression.The algorithms are meant to accurately assess the state of charge (SOC) of lithium-ion battery packs. Machine learning approaches were used to improve State of Charge (SOC) estimation in the Solar Assisted Three-Wheeler (E-Rickshaw) and validate data.**

Keywords— State of Charge (SOC), Machine Learning Algorithm, Lithium-ion (Li-ion) Battery, Accurate Soc Estimation, Solar Panels

I. INTRODUCTION

Electric vehicles (EVs) are a revolutionary and rapidly evolving class of vehicles that are changing the landscape of transportation by offering a cleaner, more sustainable alternative to traditional internal combustion engine (ICE) vehicles. EVs are powered by electricity stored in on-board batteries, which drive electric motors to propel the vehicle. This innovation addresses many of the environmental, economic, and energy challenges associated with conventional gasoline or diesel-powered vehicles [1]. In Electric Vehicles the State of Charge (SOC) Estimations determine the battery's current energy level, which is a vital component of electric vehicles (EVs). SOC is a crucial variable for controlling and enhancing the efficiency, longevity, and range of EV batteries. Drivers and system controllers may make wise choices about charging, driving style, and energy usage with the help of accurate SOC estimations.

SOC represents the remaining energy capacity of an EV battery as a percentage of its total capacity. For example, a SOC of 50% indicates that the battery is halfway discharged, while a SOC of 80% suggests that the battery still has 80% of its energy available. The amount of energy stored in a battery at a specific time is predicted using SOC estimate methods using a variety of methodologies, frequently involving mathematical models, measurements of battery voltage and current, temperature adjustment, and occasionally machine learning algorithms. To avoid over-discharging (which might harm the battery) and underutilization (which might leave wasted energy capacity), accurate SOC calculation is crucial [2]. Battery Voltage When there is no current flowing (open-circuit conditions), battery voltage is frequently utilized as a substitute for SOC calculation. It's important to characterize the relationship between voltage and SOC thoroughly.

The battery's state of charge (SOC) is affected by the flow of electric current that is either entering or leaving the battery. An estimate of the state of charge (SOC) can be obtained through the precise measurement and integration of the current over time (coulomb counting), despite the fact that it requires rigorous calibration and error handling. Temperature has a significant impact on the performance and behaviour of the battery, which makes temperature an important factor. It is necessary to have temperature adjustment in order to take into account variations in capacity and capacity efficiency. Estimation techniques for state of charge (SOC) should take into account the temperature of the battery and how it may influence the voltage and capacity of the battery..

Initially, the SOC Knowledge for estimating algorithms, such as being aware of the starting SOC (for instance, at the beginning of a trip), is a good location to begin developing this knowledge. Through the utilization of inaccurate initial SOC values, it is possible to introduce errors into the estimation [3]. When the voltage-SOC relationship fluctuates over time as a result of factors such as temperature, battery ageing, and cycling, which is one typical source of the mistake, Voltage Drift occurs. Voltage Drift is caused by malfunctions or inaccuracies in State-of-Charge (SOC) calculations. In the event that it simply takes into account the pack, the SOC estimating approach could generate estimations that are not trustworthy.

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II. TRADITIONAL METHOD FOR SOC ESTIMATIONS:

State of Charge (SOC) in an electric vehicle refers to the measurement of the current energy level or capacity of the vehicle's battery pack, typically expressed as a percentage. It represents the remaining available energy in the battery relative to its total capacity. SOC is a crucial parameter in electric vehicles as it provides information about the battery's charging status and helps determine the range or distance the vehicle can travel before requiring a recharge. A higher SOC indicates a more fully charged battery, while a lower SOC indicates that the battery has discharged and requires recharging. Various methods can be used to estimate SOC, including open circuit voltage (OCV) measurement, coulomb counting, and model-based approach

1) Coulomb Counting: coulomb counting is a widely employed method for SOC estimation, based on integrating the current flowing in and out of the battery over time. The basic equation for Coulomb counting is as follows: SOC(t) = SOC(t-1) + (∫I(t) dt) (Q nominal) In this equation, SOC(t) represents the SOC at a time 't', SOC(t-1) is the SOC at the previous time step, I(t) am current at a time 't', ∫I(t) dt represents the integral of the current over time, and Q - nominal is the nominal capacity of the battery

$$SOC(t) = SOC(to) + \frac{\int_{to}^{to+\tau} I_{bat}.d\tau}{Q_{rated}} \times 100\% \qquad (1)$$

SOC	State of Charge
I_{bat}	Battery Current Value
Q_{rated}	Rated capacity

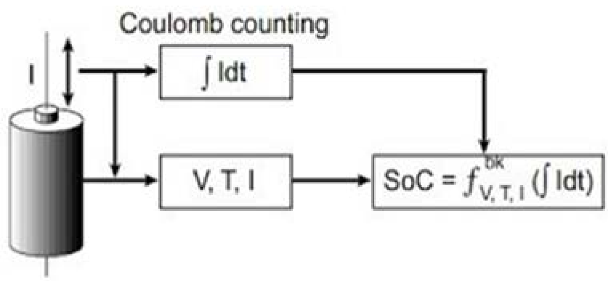

Fig1. Coulomb counting Method [4]

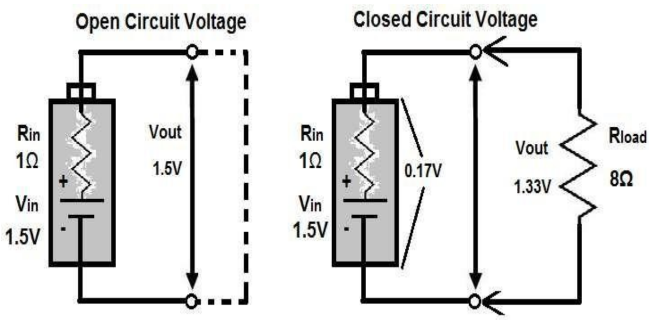

Fig2. Open-circuits methods [4]

2) Open-Circuit Voltage (OCV) Method: The Open-Circuit Voltage method estimates SOC by measuring the battery's voltage when it is at rest and relating it to SOC using a per-determined voltage-SOC relationship The Equation for SOC Estimation using the OCV method is typically represented as: SOC = f(OCV)

3) Model-Based Approaches: A Study of Machine Learning Algorithms in State of Charge (SOC)Estimation MIT School of Engineering & Science, M-Tech Mechanical (Electric Vehicles) 4 Model-based approaches utilize mathematical models that represent the battery's behavior and characteristics to estimate SOC.

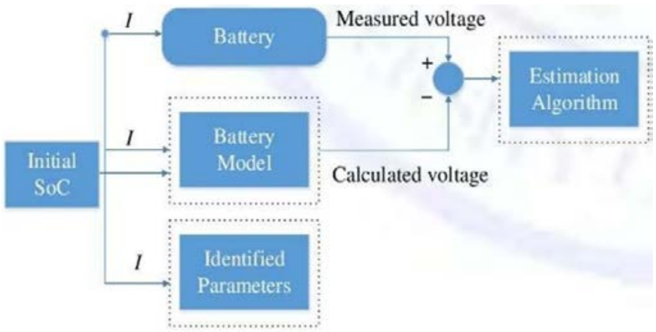

Fig3.Model-Based Methods [4]

4) Extended Kalman filter (EKF) In indirect methods, SoC is evaluated using information from other estimated quantities. SoC can be computed starting from open circuit voltage (VOCV) measurement [3]. Lead-acid and Li-ion batteries VOCV is a direct function of SoC and this relationship is usually experimentally evaluated.

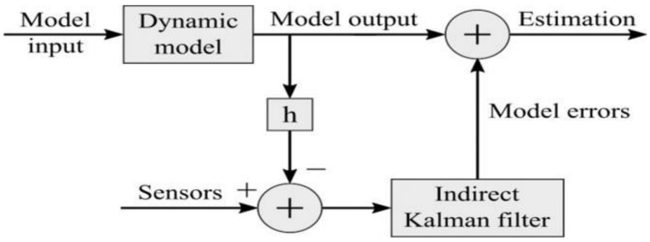

Fig4.EKF Methods [5]

III. SOC Estimations Errors Manipulated by Machine Learning Methods:

Machine learning is a subfield of artificial intelligence (AI) that focuses on developing algorithms and models that enable computers to learn patterns and make decisions without being explicitly programmed. Here is a broad overview of machine learning Supervised Learning: In supervised learning, the algorithm is trained on a labeled dataset, where the input data is paired with the corresponding desired output. The goal is to learn a mapping function that can accurately predict the output for new, unseen inputs. Unsupervised Learning:

Unsupervised learning involves working with unlabeled data. The algorithm explores the inherent structure in the data to find patterns or relationships without explicit guidance on the output. Semi-Supervised Learning: This type of learning combines supervised and unsupervised learning. The algorithm is trained on a dataset containing labeled and unlabelled data, allowing it to leverage the labeled data for supervised learning and the unlabelled data for unsupervised learning. Reinforcement Learning: Reinforcement learning involves training an agent to make decisions within an environment[5]. The agent receives feedback in the form of rewards or penalties based on its actions, and the goal is to learn a policy that maximizes the cumulative reward over time. Algorithm Machine learning algorithms are the mathematical models or sets of rules that enable computers to learn patterns and make predictions. Examples include decision trees, support vector machines, and neural networks. Model:

A model is the learned representation of patterns in the data. It can be a mathematical equation, decision tree, neural network, or any other structure that captures the relationships in the training data. Features are the variables or attributes of the input data that the algorithm uses to make predictions. Feature engineering involves selecting, transforming, or creating features to improve the model's performance. Training data is the dataset used to train the machine learning model. It consists of input-output pairs for supervised learning or just input data for unsupervised learning

The loss function measures how well the model's predictions match the actual outcomes. During training, the algorithm adjusts its parameters to minimize the loss, improving the model's accuracy Hyperparameters are configuration settings external to the model that are set before training. Examples include learning rates, regularization parameters, and the architecture of a neural network [6]. The earlier Method for calculating SOC Estimations by Traditional Methods Such as an open circuit voltage, Columb counting method, Model-based approaches, and Indirect Kalman filter. While in this method there are errors to find in SOC estimations such as errors in Model Accuracy, Parameter Accuracy, Operating Conditions, Degradation Effects, and Cyclic Variations SOC is an important factor for many battery-operated systems since it shows how much energy is available for usage.[7]

SoC Estimation is required in a battery it may manipulate the driver's real-time conditions to avoid this problem Soc estimation uses machine learning algorithms to improve Accuracy and estimate it. In Machine Learning Algorithms we select Supervised Learning in that there are regression and Classification we compared five algorithms Decision Tree, ExtraTreesRegressor, Bagging Regressor, Neighbour's Regressor, and Random Forest Regressor. These five algorithms compare and select the best algorithms and implement on to improve the soc estimation and accuracy [8].

III. ANALYTICAL APPROACH

The methodology in this current project work is divided into two parts, first generating data using an analytical approach and later validating it with an experimental approach. The analytical method starts to generate data from the Test Rig experiment setups such as current, temperature, voltage, and Soc Precisely calculating a battery's state of charge (SOC) is essential in many situations, particularly when dealing with electric cars (EVs) and other battery-operated devices [9]. While non-invasive estimation via direct measurement is impractical, machine learning (ML) provides strong tools. BTMS and become a more economical and sustainable solution.

Gathering of Data: Collect information from a range of sensors and measurements, including temperature, voltage, current, and perhaps other environmental elements that have an impact on battery operation [10].

Engineering Features: Extrapolate pertinent characteristics that reflect the status of charge from the gathered data. Voltage characteristics, charge and discharge rates, temperature dependencies, and other factors pertinent to the particular battery chemistry and application are examples of features [11]

Selecting a Machine Learning Model: Select the right machine learning methods to estimate SoC. Typical options consist of Regression algorithms including support vector, polynomial, and linear regression [12].

Training Models: Utilizing the information gathered, train the chosen machine learning models. Make use of methods like cross-validation to assess and enhance model performance[13].

SoC Estimation: Use the machine learning models that have been trained to estimate the condition of charge in real time[14]. As new data becomes available, update and enhance the models frequently to increase accuracy and make them more flexible to changing operational conditions.

A. DATASETS

Above data sets Load, Time, Speed, and Crr to test and create data sets for Soc Outputs.

Table 1. Data Sets

Load	Time	Speed	Crr
60.0	43	30	0.1
70.1	18	45	0.1
70.1	67	15	0.1
70.1	67	45	0.1
70.1	18	15	0.1
102.5	43	10	0.1
102.5	43	30	0.1

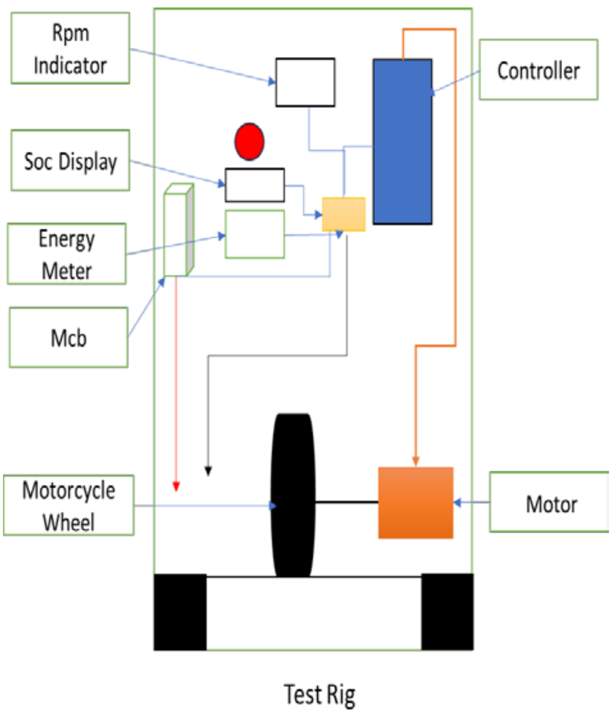

Fig5. Experiments Setups

Table 2. Soc Output

Sr No	Current	Voltage	Temperature	SOC Output %
1	21.88	50.08	29	84
2	21.71	50.11	29	84
3	21.51	50.08	29	84
4	21.22	50.01	29	84
5	21.27	50.02	29	83.91
6	21.88	50.08	29	83.91

Above the Test Rig setup is designed and developed for nalysis of the load and speed effects on the motor. The Rig indicates the Current, Temperature, Voltage, and Soc Display.

IV. RESULTS AND DISCUSSIONS

We are using Python software for analytical purposes and testing your data sets to run the models and tests and train the models using machine learning algorithms. Using Python is compatible with users for ML coding and libraries. Etc Bagging Regressor, KNeighborsRegressor, and andom Forest Regressor

The Test Rig System is used to generate the Data of Differents loads, speeds, Time, and Table.1, The test Rig tests the motor efficiency, VI characteristics, heat, and motor Performance. In this setup, we record and generate data such as current, temperature, and voltage. Show in Table.2

Testing RMSE: 1.37

Training Accuracy: 0.99

Testing Accuracy: 0.99

The above Machine Learning Code compares the five algorithms as DecisionTreeRegressor, ExtraTreesRegressor,

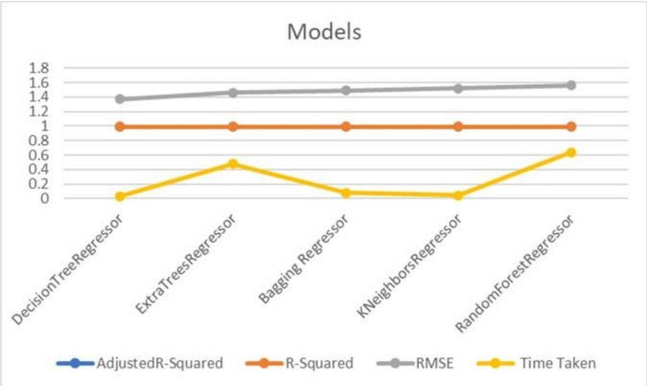

Fig6. Represents the Graph comparing Five Models

The comparison of Five Machine learning algorithms as per given data and finalizing theDecision Tree Regressor.

1. The percentage of a dependent variable's variance that is explained by one or more independent variables in a regression model is expressed statistically as R-squared (R^2)[15]. It has a range of 0 to 1, where 1 denotes that the independent variable(s) fully explains the variance in the dependent variable and 0 denotes no explanatory power[16].

1) A modified form of R-squared that accounts for thenumber of predictors in the model is called adjusted R-squared (also known as adjusted R^2)[17]. It discourages overfitting by penalizing the inclusion of pointless predictors in the model. When a more informative predictor is introduced to the model, the adjusted R-squared usually increases or stays the same. However, if a less informative predictor is included, it usually drops[18].

2) The difference between values predicted by a model or estimator and the observed values is measured by the Root Mean Squared Error or RMSE[19]. It is the square root of the mean squared discrepancies between the actual observation and the prediction. RMSE gives a general idea of the size of the error in the model and is measured in the same unit as the dependent variable [20].

Fig7. Decision Tree Regressors

The Above Fig shows the suitability of your data sets and provides the best accuracy for Soc estimations.

V. CONCLUSION AND FUTURE SCOPE

The results obtained from the Machine learning model are shown in the above figure. These results are verified against the previous literature. The study will also aid in understanding how the Improve the Soc Estimation of Battery Packs. Some key points first generate data major factors for soc data are current, voltage, and temperature. SOC is linearly proportional and voltage is in continuous form. The system will get more accurate as well as increase the battery life cycle, over and under voltage protections.

The best-suited ML from the analytical calculations of Datasets was found to be Decision Tree Regressors

The battery Soc Accuracy improves by using ML Algorithms to select a Decision Tree (0.99,1.37,0.03) an analytical approach that motivates its use in experimental analysis.

The future scope of the work also lies in validating the analytical results obtained for Bid Data Sets at different Battery Loads and comparing them using the results obtained through experimental analysis.

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