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Enhancing Estimating the Charge Level in Electric Vehicles: Leveraging Force Fluctuation and Regenerative Braking Data

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Abstract:- Accurate determination of the state of charge is vital to optimize the performance and lifespan of electric vehicle batteries. Traditional methods which rely on battery models and direct measurements can be error-prone due to fluctuating operating conditions and battery degradation over time. Regenerative braking systems are crucial in electric and hybrid vehicles for improving energy efficiency by transforming kinetic energy into electrical energy during braking. However, force fluctuation is a challenge that can affect the performance and comfort of regenerative braking. It is known to us that electric motors and generators used in regenerative braking have non- linear torque characteristics, especially at low speeds, leading to inconsistent braking force. Variations in road conditions, such as wet or uneven surfaces, can affect the grip of the tires, leading to fluctuations in deceleration. Interactions of regenerative braking system with conventional friction brakes can cause force fluctuations, especially during the transition between the two systems. This study introduces an improved state of charge estimation technique based on force fluctuation and a regenerative braking system. This research shows that this approach significantly enhances state of charge accuracy compared to traditional methods, especially in urban driving conditions with frequent braking. The findings underscore the potential of using regenerative braking as well as force fluctuation condition data as a valuable input for state of charge estimation, ultimately leading to better battery management and an extended electric vehicle range.

***Keywords*:-** *Electric Vehicle (EV), Regenerative Braking, State of Charge (SOC).*

I. INTRODUCTION

The state of charge (SOC) of an electric vehicle's (EV) battery is a crucial indicator of the battery's residual capacity, similar to a fuel gauge in traditional vehicles. Ensuring precise estimation of SOC is essential for the efficient operation, well-being, and long-lastingness in EV batteries. Traditional methods for SOC estimation typically depend on measurements of voltage, current, and temperature, combined with battery models that consider the battery's characteristics and behavior under various operating conditions. However, these conventional methods encounter several challenges. SOC estimation accuracy can be significantly impacted by factors such as battery aging, temperature fluctuations, and dynamic load conditions. Inaccurate SOC estimation can lead to suboptimal battery management potentially decreasing overall battery performance and lifespan and affecting the driving range and reliability of the EV. Regenerative braking, a feature in modern EVs, offers a unique opportunity to enhance SOC estimation. During regenerative braking, electric motor serves as a generator, transforming kinetic energy to electrical energy and storing of the same in the battery. This process along with improving energy efficiency, also provides with valuable data which can be used to enhance SOC estimation accuracy. This paper proposes an enhanced SOC estimation method that incorporates regenerative braking information. We aim to achieve increased dynamic and precise evaluation of battery's state. This research work explains that this approach significantly improves SOC estimation accuracy, particularly in urban driving conditions where frequent braking occurs. The incorporation of regenerative braking data not only enhances the reliability of SOC measurements but also contributes to better battery management strategies, ultimately extending the driving range and lifespan of EV batteries. In the following sections, we detail the methodology of our SOC estimation technique and present the findings & outcomes of our tests.

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II. REGENERATIVE BRAKING SYSTEM

The flowchart illustrates a control mechanism for regenerative braking in a single-axle electric vehicle (EV). Regenerative braking captures kinetic energy when slowing down, converting it to electric power for recharging battery. When the brake signal is received, the system initiates by determining the required 'demand brake force' for deceleration. It then decides on the optimal 'brake force distribution' between the front and rear axles to maintain vehicle stability. The flowchart then branches depending on whether regenerative braking is feasible: if the vehicle speed is below 5 km/h or the battery is nearly full (SOC > 0.95), regenerative braking is bypassed, and the system moves to 'close regenerative mode'. Conversely, if regenerative braking is possible, the system calculates the highest regenerative braking torque that the electric motor can apply to slow down the vehicle, considering system and battery limitations. This torque is then translated into peak Regenerative braking forces for the front and rear wheels. Depending on whether regenerative braking is enabled or not, the flowchart determines either zero regenerative braking torque in 'close regenerative mode' with a calculation of hydraulic braking forces or applies the previously calculated regenerative braking forces to the wheels. The flowchart outlines a control strategy that prioritizes regenerative braking when conditions allow, ensuring a seamless transition to traditional hydraulic braking when necessary.

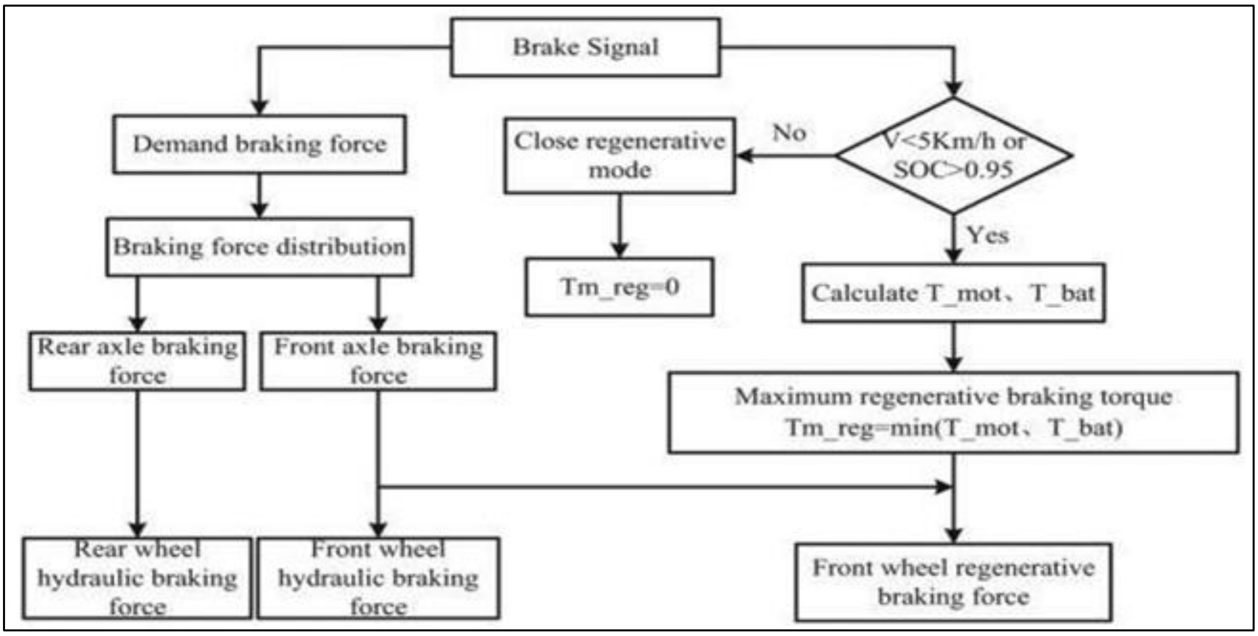

Fig 1. Working of Regenerative Braking System

III. METRICES

A. Root Mean Squared Error (RMSE):

RMSE is a way for measuring how accurate a prediction model is, especially in regression issues. It's basically the mean of squared differences among estimated and original observations, but with the square root taken at the end. Just like MSE, a lower RMSE is better and shows the predictions are on target. A higher RMSE means more misses from the model. Although RMSE is always non-negative, it has the same unit as what you're trying to predict, making it easier to understand. One thing to watch out for with both RMSE and MSE is that they are heavily influenced by outliers because of the squaring involved.

B. Mean Absolute Error (MAE):

MAE is a different way to check how accurate your prediction model is. It simply averages the amount of difference between what you predicted and what actually happened, without considering if the prediction was too high or too low. A low MAE means your predictions are on average close to reality, signifying a good model. The opposite holds true for high MAE. MAE is always non-negative because it uses absolute values, and it shares the same units as what you're trying to predict, making it easy to understand. An advantage of MAE over MSE and RMSE is that it's less swayed by extreme mistakes since it doesn't square the errors.

IV. LITERATURE REVIEW

In recent years, researchers have made significant strides in improving the accuracy of state of charge (SOC) estimation for electric vehicle (EV) batteries. One notable approach involves the use of a Random Forest (RF) model, which has demonstrated superior performance in real-world conditions. This model leverages machine learning to establish robust correlations between various input parameters and SOC values. The RF model has shown exceptional accuracy and reliability across diverse driving scenarios, outperforming other models in rigorous testing. For instance, in k-fold cross-validation, the RF model achieved lower mean absolute error (MAE) and root mean squared error (RMSE) compared to the

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Extreme Learning Machine (ELM) model [1]. Another innovative method for online SOC estimation utilizes vector-type recursive least squares (VRLS). This approach identifies ECM characteristics that change at different rates by employing multiple forgetting factors. The VRLS algorithm has demonstrated high estimation accuracy and significant resilience to disturbances in various testing scenarios [2]. Researchers have also explored the combination of neural networks and Kalman filtering for dynamic SOC estimation. One study developed a NN-EKF model that incorporates Extended Kalman Filter (EKF) estimations into a neural network. This approach was tested on different battery types and showed promising results, particularly when incorporating temperature data [3]. The application of EKF has been further refined in a physics-based model for lithium polymer batteries. This method, which employs a simulated annealing technique for parameter determination, has shown reduced errors for both continuous and pulsed currents compared to the battery model alone [4]. A structured approach combining model uncertainty considerations with a joint EKF has been proposed to simplify observer tuning. This method adjusts EKF equations to accommodate cross-correlated disturbances and introduces a forgetting factor, resulting in a single-parameter tuning process regardless of battery model complexity [5].Digital twin models have also been explored for parameter identification and SOC estimation. One such model uses an EKF with a state-space model of an EV battery, enabling monitoring of both current and historical SOC values [6]. Researchers have also focused on addressing parametric uncertainty and measurement noise in SOC estimation. One study developed an observer based on Kalman Filter Theory, demonstrating accurate SOC estimation while highlighting the trade-off between estimation accuracy and convergence speed [7]. An enhanced Kalman filter using an approximation of a micro-macroscopic lithium-ion battery model has been proposed to make solid concentration estimation more practical [8].To address battery model inaccuracy, researchers have developed a Model Error estimate Observer (MEO) based on Kalman Filter theory This approach disentangles the combined KF method into parallel components for SOC and model error estimation, showing improved performance under various dynamic loading profiles [9]. Finally, researchers have explored the application of continuous discrete Kalman filter (CDKF) and extended Kalman filter (EKF) techniques for recursive SOC estimation in battery electric vehicles (BEVs). This approach uses a first- order RC model to simulate battery dynamics and an Adaptive Sliding Mode Observer (ASMO) for parameter identification [10]. These advancements in SOC estimation techniques demonstrate the ongoing efforts to improve the accuracy and reliability of battery management systems in electric vehicles, contributing to the overall enhancement of EV technology and performance.

V. MACHINE LEARNING ALGORITHMS APPLIED IN OUR STUDY

A. Linear Regression:

Linear regression is a key method in machine learning for predicting continuous values based on one or more independent variables. It determines the best-fit straight line via. data points, representing the linear association between the unconstrained variables and the constrained variable. This line’s equation serves as a guide for making predictions. Once this equation is determined, its accuracy can be assessed employing benchmarks such as R-squared and Mean Squared Error (MSE).

B. K-Nearest Neighbors:

K-Nearest Neighbors (KNN) is a popular, straightforward algorithm used in machine learning in both tasks of classification and regression. It works by measuring the distances among new data point with all existing data points. K-Nearest Neighbors (KNN) determines the labels of the nearest neighbors. The fresh data point adopts the most common label among the nearest neighbors of it. For example, if most neighbors are classified as “cats,” the new point is likely classified as “cats” too. K-Nearest Neighbors (KNN) computes the average values of its nearest neighbors. This average value is then used as the predicted value for the new data point in regression tasks. Linear regression is a key technique in machine learning for predicting continuous values based on one or more independent variables. It determines the best-fit straight line via. data points, representing linear association among the unconstrained variables and the constrained variable. This line’s equation serves as a guide for making predictions. Once this equation is determined, its accuracy can be assessed by benchmarks like R- squared and mean-squared error (MSE).

C. Decision Tree:

It is a fundamental machine-learning tool which employs hierarchical, tree-like structure for making forecast. It operates in supervised learning scenarios, where it learns from labeled data to classify new instances. The algorithm constructs the tree by iteratively dividing the data into tinier subsets based on the highest important characteristic at every node. This division continues until each leaf node contains predominantly one category, ensuring homogeneity. Decision trees are versa- tile and applicable to both classification and regression tasks. Excessively intricate decision trees can result in a phenomenon known as over fitting. This occurs when the model becomes too specialized to the specific patterns and nuances of the training dataset. While such a model may demonstrate excellent performance on the data it was trained on, it often struggles to generalize effectively when presented with new, unseen information. This lack of generalization ability limits the model's practical usefulness in real-world applications where it must handle novel data points. Techniques like pruning are used to mitigate this issue.

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VI. OVERVIEW OF THE APPROACH

This research estimates the state of charge (SOC) of an electric vehicle (EV) battery employing machine learning Techniques such as decision trees, K-Nearest Neighbors (KNN), and linear regression. The trait of the training data determines the effectiveness of this technique. Noise, irrelevant information, and errors are to be encountered inevitably. So, these are considered at the time of tutoring and evaluating phases. So influence of these can be diminished as they are also to be accounted for. The research utilizes an actual dataset from 70 trips driven in a BMW i3 EV that has a 60 Ah battery pack installed. This information was gathered via the car's OBD port at a rate of one hertz (Hz) comes from sensors installed in the car. There may be missing values in the dataset due to measurement errors or other issues, necessitating thorough preprocessing to clean the data. The dataset contains two SOC attributes: one that the car manufacturer estimates and another displayed to the user. This research selects producer's estimated SOC as the goal attribute for instruction and assessment. The models, aim to faithfully reproduce the manufacturer's estimations and use them as an authenticated source in the EV sphere. Input variables for the models include measured voltage, current, battery pack temperature, ambient temperature, regenerated braking system, motor torque, and elevation. To assure precise SOC estimation, extensive data preparation addresses missing values and remove noise or inconsistencies. Using actual data of BMW i3, alongside Decision Tree, K-Nearest Neighbors (KNN), and Linear Regression, and diverse data attributes, it is anticipated to provide resilient SOC forecasts, advancing battery state estimation in EVs. Including ambient temperature, regenerated braking system, motor torque, and elevation as an input variable was a deliberate decision, recognizing its critical impact on the productivity of lithium-ion batteries that are used in EVs. Temperature significantly affects battery capacity, charge/discharge rates, along with overall health. Since temperature variations are common in real-world EV applications, accounting for ambient temperature helps create a robust SOC estimation model adaptable to different climates and conditions. This choice enhances the precision and dependency of SOC evaluation, reflecting practical considerations in EV operations where ambient temperature, regenerated braking system, motor torque, and elevation are easily measurable. Overall, incorporating ambient temperature into the model acknowledges its significant influence on battery performance and its role in improving SOC estimation.

VII. APPROACH

A. Dataset

This research aims to estimate the battery of electric vehicle (EV) and its state of charge (SOC) employing machine learning methods such as decision trees, K-Nearest Neighbors (KNN), and linear regression. The traits of the training data determines the effectiveness of this technique. Noise, irrelevant information, and errors are to be encountered inevitably. So, these are considered at the time of tutoring and assessing phases. So the influence of these can be diminished, as they are also to be accounted for. The research utilizes an original dataset from 70 journeys made by one BMW i3 EV equipped with 60 Ah battery pack. The data, collected at a 1 Hz rate through the vehicle's OBD port, comes from sensors installed in the car this research utilizes a dataset from a BMW i3 electric vehicle, which may contain missing values due to various factors, requiring thorough preprocessing. The study focuses on the manufacturer's estimated State of Charge (SOC) as the target variable, aiming to replicate and validate these estimations within the EV domain. Input variables for the models encompass measured voltage, current, battery pack temperature, ambient temperature, regenerated braking system, motor torque, and elevation. The inclusion of these variables, particularly ambient temperature, regenerated braking system, motor torque, and elevation, is a strategic choice acknowledging their significant impact on lithium-ion battery performance in EVs. Extensive data preprocessing will address missing values and remove inconsistencies to ensure accurate SOC estimation. The research employs Decision Tree, K-Nearest Neighbors (KNN), and Linear Regression models with varying data characteristics to generate robust SOC predictions. By incorporating real-world data and considering critical factors like ambient temperature, which affects battery capacity, charge/discharge rates, and overall health, the study aims to develop a model adaptable to diverse climatic conditions and reflective of practical EV operations. This approach is expected to advance battery state estimation in EVs, enhancing the accuracy and reliability of SOC predictions in electric mobility applications.

B. Data Pre-processing and Feature Extraction:

This phase includes refining and organizing the data to prepare it for integration into the machine learning model. Tasks may include eliminating irrelevant data, standardizing. Data formats, and identifying key features from the dataset. Features represent the specific attributes of the data that the model will utilize for making predictions.

C. Training:

This is the phase where the machine learning model learns from the facts in hand. The preprocessed data is divided into two subsets: a tutoring set and an evaluation set. The tutoring set is employed to practice the model, while the evaluation set assesses the model's productive output. The diagram depicts teaching for three distinct models: linear regression, decision tree regression, and K-Nearest Neighbors (KNN) regression. Each model employs a unique algorithm to glean insights from the data.

D. K-Fold Cross Validation:

This technique evaluates the performance of a machine learning algorithm by partitioning the training dataset into a specified number of equal segments, often referred to as folds. In each iteration, the model is trained using all but one of these segments, with the excluded segment serving as the validation set. This process is repeated until each segment has been used exactly once for validation. By cycling through all possible combinations, this method provides a

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robust assessment of how well the model can adapt to and perform on previously unseen data. This approach offers a comprehensive evaluation of the model's ability to generalize, helping to identify potential over fitting or under fitting issues and ensuring that the model's performance is consistent across different subsets of the data.

E. Test Data:

This dataset has been employed to evaluate the productivity of the trained model. The model is not trained using this data, and it has not been exposed to this dataset previously. The effectiveness of the technique is measured based on its capability for making precise estimations on the evaluation data.

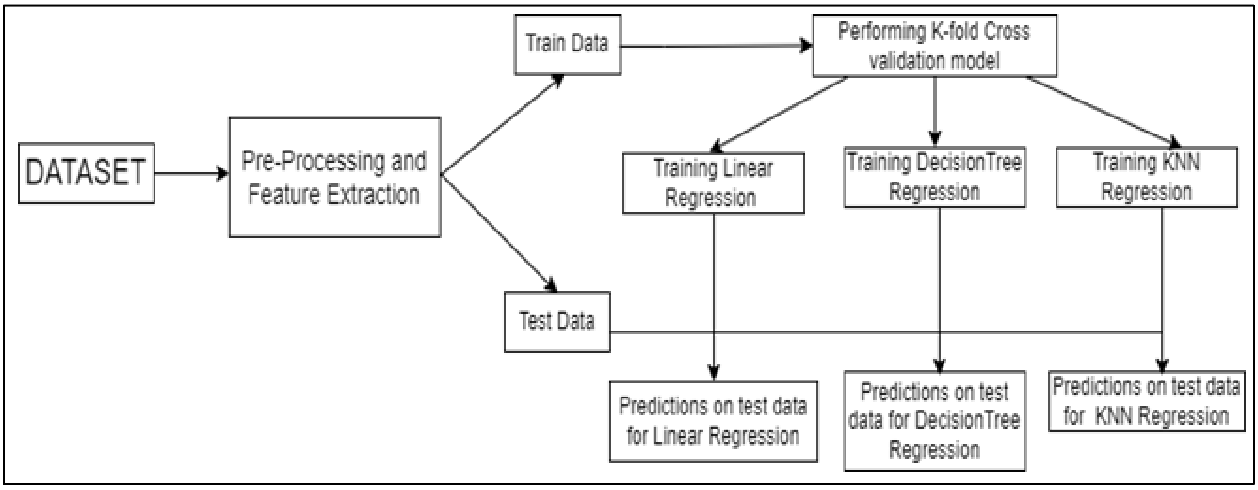

Fig. 2. Workflow of the Proposed Scheme

F. Making Predictions:

After being trained, the model is capable of generating predictions on new data. In the diagram, each of the three trained models generates This is the initial set of data gathered for training the model, sourced from various origins and potentially requiring pre-processing before utilization. Predictions on the test data.

VIII. RESULTS

This experiment aimed to evaluate the importance of a precise state of charge (SOC) estimate in maximizing the lifespan and performance of electric vehicle (EV) battery systems. Google Colab was used to conduct all of the study's results on an equipped PC with a 2.40 GHz quad-core Intel Core i5 processor, 7th Generation, and 8 GB of RAM. Using actual data of a BMW i3 EV, this study provided models for decision trees (DT), K-Nearest Neighbors (KNN) s, and linear regression (LR) to reliably predict state of charge (SOC) in EV batteries. During thorough k-fold cross-validation analyzing, the model achieved a Root Mean Square Error (RMSE) of 5.0850 and Mean Absolute Error (MAE) of 4.1217. This illustrates the competitive precision and accuracy of the method.

Table 1. Performance Metrics of the Approach for SOC Estimation

Parameter	LR	KNN	DT
MAE	4.1316	4.1217	4.1278
RMSE	5.0850	5.5692	5.8272
MAX. VAL.	22.9245	23.9296	23.0758
STD. DEV.	5.8028	5.8745	5.8448

IX. CONCLUSION

The SoC estimation approach has significant practical implications for the electric vehicle industries. By enhancing the precision of EV range forecast and overall battery health, it the potential to completely transform battery management. Examine in the real world electric vehicle applications, the machine learning model's precision and resilience suggest considerable advantage for maximum battery consumption and prolonging battery life span this development helps sector archives and its objective increasing sustainability and electric mobility.

X. FUTURE SCOPE

This work can be further improved in the future by incorporating feature selection approaches, examine a wider range of input parameters, and investigating various input output configurations suited to particular driving scenarios. Through these initiatives, the deep learning approach's accuracy and usefulness in real-world electric vehicle scenarios could be substantially enhanced. To sum up the suggested SoC estimate approach offers a strong answer to important problems with EV battery management Opportunities for further include incorporating feature selection techniques, adjusting input-output relationship for different setting sand investigating others factor.

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