# Transforming Battery Management: Utilizing Machine Learning for State of Charge (SoC) Prediction

**Vrushali Waghmare[1], Sneha Pokharkar[2], Rashmi Mahajan[3], Vaishali Katkar[4] and Prachi Rajarapollu[5]**

[1,2,3,4,5] *Department of E&TC Engineering , MIT Academy of Engineering , Pune , India*

***Received: 28th Feb, 2026; Revised: 6th March 2026; Accepted: 7th April, 2026; Available Online: 20th April, 2026***

**ABSTRACT**

The emergence of electric vehicles (EVs) has revolutionized the automotive sector, notably through the adoption of battery management systems (BMS) to ensure their safe and efficient operation. Central to these systems is the State of Charge (SOC), a critical indicator of stored energy within batteries. Accurate SOC measurement is essential for estimating battery capacity, predicting remaining runtime, and optimizing battery lifespan. However, traditional SOC prediction methods often face challenges like inaccuracies and computational complexities. In response, Machine Learning (ML) techniques offer a promising solution, leveraging data-driven adaptability. This article explores ML's role in SOC prediction, highlighting its potential to overcome traditional method limitations. By employing ML algorithms, such as Gaussian Process Regression (GPR) and Linear Regression (LR), this study evaluates their efficacy in forecasting SOC values for EV BMS. Through rigorous analysis, the research provides insights into the effectiveness of ML in enhancing SOC prediction accuracy.

**Keywords:** Battery management system, State of charge , SoC , electric vehicles ,machine learning , Gaussian Process Regression , Linear Regression

**How to cite this article:** Waghmare V, Pokharkar S, Mahajan R, Katkar V, Rajarapollu P, Transforming Battery Management: Utilizing Machine Learning for State of Charge (SoC) Prediction. Int J Drug Deliv Technol. 2026;16(52s): 296-305. DOI: 10.25258/ijddt.16.52s.35

**Source of support:** Nil.

**Conflict of interest:** None

## 1 INTRODUCTION

In current years, significant advancement has been made in the development of battery and electric vehicle (EV) technologies. Concerns about emissions from fossil fuels intensified around the turn of the millennium. Numerous countries have implemented stringent emission regulations and set carbon reduction goals. Consequently, there has been a surge in interest in electric vehicles (EVs) as an eco-friendly alternative to traditional internal combustion engine (ICE) vehicles. The rapid evolution of battery technology has been pivotal in driving the expansion of the EV market. The demand for battery management systems (BMS) has been steadily rising in tandem with the increasing popularity of electric vehicles. BMS plays a critical role in ensuring the secure, effective, and dependable operation of electric vehicles (Smith, J.,2015). As such, automakers have been increasingly incorporating battery management systems into their vehicles. Additionally, as the technology behind electric vehicles has advanced, the need for more sophisticated battery management systems has grown. BMS is a system that provides control and monitoring of batteries. It is designed to protect the battery from overcharging, over-discharging, and other types of damage (Johnson, A., & Rahn, K 2015). It also helps to ensure the battery is properly balanced and balanced in order to provide optimal performance. The BMS monitors the state of the battery, providing information about the current charge, temperature, and voltage. This information is then used to adjust the charging and discharging rates of the battery, as well as to determine the available capacity of the battery (Smith, J., 2015).

### 1.1 Battery Management System (BMS)

The main roles of a Battery Management System (-BMS) are to monitor, estimate, protect, report, and balance battery performance. In the area of automotive BMS, various sensors, actuators, controllers, and algorithms collaborate to accomplish three primary tasks. The first task is to protect battery cells and packs from damage. The second is that it tries to keep batteries within safe voltage and temperature limits in order to extend their service life. Third, it ensures that the batteries can meet the vehicle's operational requirements while adhering to relevant standards.

**Author for Correspondence: Vrushali Waghmare*

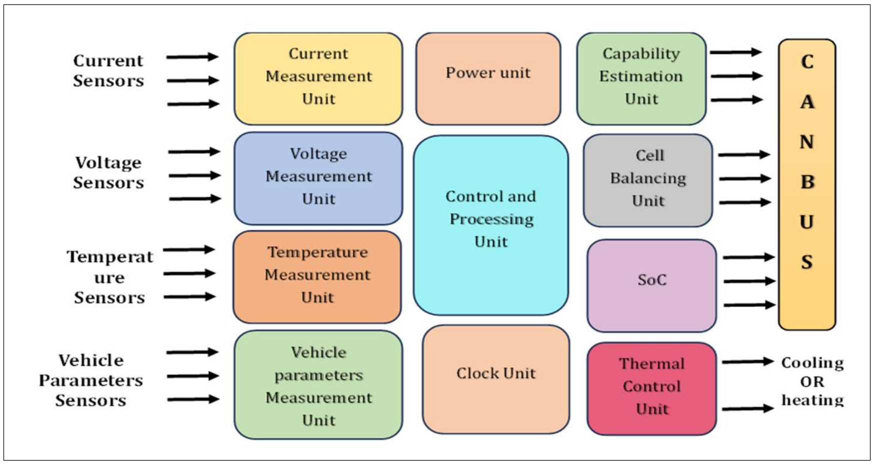


**Fig. 1.** General Block Diagram of Battery Management System

The Battery Management System (-BMS) is a crucial component in various industries, ensuring the safe and efficient operation of rechargeable batteries. It encompasses several key functions, including battery parameter detection, which involves monitoring parameters like voltage, current, temperature, and more to prevent overcharging, over-discharging, and other issues. Additionally, the BMS estimates battery states such as State of Charge -(SOC), State of Health -(SOH), and State of Function -(SOF) based on various conditions. On-board diagnosis -(OBD) identifies faults related to sensors, actuators, networks, batteries, and other components, enabling prompt resolution of issues. Battery safety control and alarm functions manage risks like high-temperature, low-temperature, overcharge, over-discharge, etc., ensuring damage prevention and safety. Charge control regulates the charging process based on battery characteristics and charger capabilities. Finally, battery equalization methods maintain consistent State of Charge (SOC) among individual cells, optimizing overall battery performance. The evolution of BMS technology has seen advancements from basic voltage and current monitoring to the inclusion of temperature sensors, advanced SOC estimation algorithms, cell balancing techniques, enhanced safety features, and communication interfaces for remote monitoring and control.

## 2 STATE OF CHARGE (SOC) OF A BATTERY

The state of charge (-SOC) of a battery is crucial as it indicates the amount of charge currently stored, expressed as a percentage of the battery's maximum capacity. SOC determines the available energy for device or circuit operation. It can be assessed by measuring voltage, current, temperature, or the amount of charge removed from the battery. Maintaining proper SOC is vital for battery health and ensuring adequate power supply. A low SOC might lead to insufficient power output or battery damage, while a high SOC may risk overcharging. Monitoring SOC helps estimate available energy, decide on recharging or replacement, and ensures safe battery usage. SOC can be determined directly by measuring voltage and current with instruments like voltmeters and ammeters, or indirectly through discharge characteristics. Battery temperature and discharge duration also play roles in SOC determination.

### 2.1 SOC in BMS for enhancing different health parameters of batteries.

- **Estimating Battery Capacity:** The SOC measurement allows BMS to estimate the remaining capacity of a battery accurately. By continuously monitoring the SOC, the BMS can determine when the battery is close to depletion and provide timely warnings or initiate appropriate actions. This estimation helps prevent battery over-discharge, a crucial factor in maintaining battery health and longevity (Smith et al., 2018) .
- **Predicting Remaining Runtime:** Knowing the SOC enables BMS to predict the remaining runtime of a battery accurately. By considering several aspects such as load demand, temperature, aging of battery , the BMS can provide users with reliable information about how long the battery can power a specific application. This prediction helps avoid unexpected power loss and enables users to plan accordingly (Johnson & Rahn, 2019).
- **Protecting Against Overcharge:** SOC measurement allows BMS to protect batteries from overcharge, a detrimental condition that can significantly reduce battery life. By continuously monitoring the SOC, the BMS can prevent the battery from being overcharged, avoiding excessive stress on the battery chemistry and minimizing the risk of thermal runaway (Braun et al., 2017)
- **Preventing Over-Discharge:** Over-discharge is equally harmful to batteries as overcharge. SOC monitoring enables BMS to prevent batteries from being excessively discharged, which can lead to irreparable damage and reduced inclusive capacity. By

alerting users or automatically disconnecting the load, the BMS ensures that the SOC does not drop below critical levels, preserving battery health (Pillay & Harb, 2019).

- **Balancing Cell Voltages:** In multi-cell battery packs, SOC measurement assists BMS in balancing the voltages across individual cells. By monitoring the SOC of each cell, the BMS can identify cells that are consistently discharging or charging faster than others. This information allows for active cell balancing, where the BMS redistributes charge among cells to equalize their SOC levels. Balancing cell voltages helps avoid overcharging or over-discharging of specific cells, thereby improving battery pack performance and longevity (Huang et al., 2016).

### 2.2 Methods of State of Charge (SOC) Estimation:

Several methods have been developed to estimate SOC accurately, each with its advantages and confines. The commonly used methods comprise of Coulomb counting, model-based approaches, and Kalman filtering techniques.

- Coulomb counting is a simple method that estimates the SOC by integrating the current flowing into or out of the battery over time. However, it is prone to cumulative errors and requires accurate current measurements. Smith et al. (2018) proposed a hybrid SOC estimation method combining Coulomb counting and a neural network-based approach. Their results demonstrated improved accuracy compared to individual methods alone.

- Model-based approaches utilize mathematical models of battery behaviour, considering factors such as voltage, current, and temperature to estimate SOC. These models can be empirical, semi-empirical, or physics-based, offering a trade-off between accuracy and computational complexity. Li et al. (2019) investigated the application of particle filtering algorithms for SOC estimation in lithium-ion batteries. Their research indicated that particle filters could effectively handle the non-linear and non-Gaussian characteristics of battery behaviour, leading to accurate SOC estimation.

- Kalman filtering techniques combine measurements and system dynamics to estimate SOC, providing robustness against measurement errors and model uncertainties. (Wang et al. 2020) proposed a novel SOC estimation algorithm based on an adaptive extended Kalman filter. Their approach provided robust SOC estimation even under changing operating conditions, enhancing the reliability of BMS.

Conventional methods, such as the Coulomb counting method and voltage-based methods, often suffer from limited accuracy in SOC estimation. These methods rely on simplistic assumptions and fail to capture the complex nonlinear behavior of battery systems accurately. SOC estimation methods based on empirical models are highly sensitive to battery aging. As batteries age, their internal resistance increases, leading to inaccurate SOC predictions. This limitation hampers the reliability and lifespan of battery systems. Conventional methods lack adaptability to different battery chemistries and operating conditions. Each battery chemistry requires a specific model and calibration, making it challenging to apply these methods to diverse energy storage systems.

Machine Learning techniques offer a promising solution to the aforementioned challenges faced by conventional SOC prediction methods. ML algorithms can learn from historical data and capture the complex relationships between battery parameters and SOC. They can adapt and generalize to different battery chemistries, making them versatile and applicable in various energy storage systems. ML algorithms leverage large datasets to learn the complex patterns and correlations between battery parameters and SOC. By training on diverse datasets, ML models can overcome the limitations of simplified assumptions used in conventional methods. ML algorithms can capture the nonlinear behavior of battery systems accurately. These algorithms can handle complex relationships and provide more accurate SOC predictions compared to traditional methods. ML models can be trained on different battery chemistries and operating conditions, allowing for adaptability and generalization. This flexibility enables the application of ML techniques to various energy storage systems without the need for extensive recalibration.

## 3 PROPOSED METHODOLOGY FOR SOC PREDICTION

Amount of stored energy is vital for managing and optimizing battery performance, especially in applications like electric vehicles and energy storage systems. SoC estimation often involves non-linear relationships between input variables (such as voltage, current, temperature). SoC estimation is inherently uncertain due to factors like measurement errors and variations in battery behavior. SoC depends on multiple input variables. Providing insights into how various factors impact SoC, enhancing our understanding of battery behavior, there is a need for an appropriate ML approach to predict SoC. Gaussian Regression is a supervised learning algorithm that is used to fit a curve to a set of data points. The curve is modeled using a Gaussian distribution, which allows for the estimation of the maximum likelihood of the parameters for the data points. Gaussian Regression has the advantage of accurately modeling non-linear relationships between the independent and dependent variables. This makes it a powerful tool for predicting SoC designs, as the relationship between design parameters and performance is often non-linear. Additionally, alongside Gaussian Regression, Linear Regression stands as another popular method in the realm of machine learning. While Gaussian Regression excels in capturing non-linear relationships, Linear Regression provides a simpler, linear approximation. Despite its simplicity, Linear Regression can still be effective in modeling relationships between input variables and SoC, particularly in cases where the relationships are more linear or where computational efficiency is a priority.

The Gaussian Regression algorithm has several advantages over other ML techniques. First, it is capable of handling larger data sets than other techniques and can be used for complex SoC designs with many design parameters. Second, the Gaussian distribution is well-suited to modeling the variance of the data points, which is useful for predicting performance, power consumption, and other design parameters. Third, the algorithm can be easily adapted to different types of data, making it applicable to a wide range of SoC designs.

In the results analysis, both the Gaussian Regression and Linear Regression models will be evaluated, and their performance will be compared. By examining metrics like MAE, RMSE, and R-squared, the strengths and weaknesses of each model will be identified, allowing for the selection of the most suitable model for SoC prediction in battery systems.

### 3.1 Steps in Gaussian Regression and Linear Regression ML Model for SoC Prediction

1. **Data Collection:** The first step involves gathering data on battery characteristics, such as voltage, current, temperature, and SOC. This data serves as the input for the ML model.
2. **Data Preprocessing:** The collected data is then pre-processed, including removing outliers, handling missing values, and normalizing the data to ensure consistent scaling.
3. **Model Training:** The ML model is trained using the pre-processed data. Both Gaussian Regression and Linear Regression models are trained simultaneously. Gaussian regression model learns the underlying non-linear patterns and relationships between the input variables and SOC, while Linear Regression provides a simpler linear approximation of these relationships.
4. **Model Evaluation:** The trained models are evaluated using validation datasets to assess their predictive performance. Various performance metrics, such as mean absolute error and root mean square error, are calculated for both Gaussian Regression and Linear Regression models to quantify their accuracy. Additionally, the R-squared score is computed to measure the goodness of fit for each model.

### 3.2 Mathematical Modelling of Gaussian Regression and Linear Regression ML Model.

**Data Collection.** In this step, we gather data on battery characteristics, including voltage ($V$), current ($I$), temperature ($T$), and SOC ($SOC$). (Wang, L., 2020) We can represent the dataset as a set of observations

$$\{(Vi,Ii,Ti,SOCi)\}^{N}_{i=1}, \quad (1)$$

where N is the number of data points.

**Data Preprocessing.** After data collection, we perform data preprocessing, which includes:

- *Removing Outliers.* Let D represent the dataset. We can remove outliers using statistical methods, such as the interquartile range (IQR) method, to obtain a cleaned dataset
- *Handling Missing Values.* If there are missing values in the dataset, we can use imputation to estimate and fill in these missing values.
- *Normalizing Data.* Normalize the input features (voltage, current, temperature) to have zero mean and unit variance. Let X represent the normalized input features matrix (Wang, L., 2020)

**Model Training.** In this step, we train the Gaussian Regression and Liner Regression ML model to estimate the conditional probability distribution of SOC given the input features.

**We can represent the Gaussian Regression model as follows:**

Let $X$ be the matrix of normalized input features

$$X = \begin{vmatrix} V_1 & I_1 & T_1 \\ V_2 & I_2 & T_2 \\ V_n & I_n & T_n \end{vmatrix} \quad (2)$$

**Let $y$ be the vector of SOC values:**

$$y = \begin{vmatrix} SoC1 \\ Soc2 \\ SoCN \end{vmatrix} \quad (3)$$

Gaussian Regression model aims to estimate the conditional probability distribution of SOC ( $y$) given the input features ( $X$) as a Gaussian distribution:

$$P(y \mid X) = \frac{1}{\sqrt{2\pi t \sigma^2}} e^{((y-\mu)^2/2\sigma^2)} \quad (4)$$

**Where:**

$P(y|X)$ is the conditional probability of SOC given the input features.

$\mu$ is the mean of the Gaussian distribution.

$\sigma$ is the standard deviation of the Gaussian distribution.

The goal during training is to estimate the parameters $\mu$ and $\sigma$ that best fit the data

(Wu, X., et al. 2018).

Additionally, the Linear Regression model is trained to estimate the relationship between input features and SOC linearly. The linear regression model can be represented as:

$$y = \beta0 + \beta1 * V + \beta2 * I + \beta3 * T + \varepsilon \quad (5)$$

**Where:**

y is the predicted SOC value.

β0 is the intercept term.

β1, β2, β3 are the coefficients for voltage, current, and temperature, respectively.

ε is the error term.

(Wu, X., et al. 2018).

**Model Evaluation.** To assess the predictive performance of the trained Gaussian Regression and Liner Regression ML model, it is evaluated using validation datasets. Various performance metrics can be used to quantify the model's accuracy and generalization capabilities:

**Mean Absolute Error (MAE):**

$$MAE = \frac{1}{N}\sum_{i=1}^{N} \mid yi - y\hat{}i \mid \quad (6)$$

**Root Mean Square Error (RMSE)**

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \mid yi - y\hat{}i \mid} \quad (7)$$

**R-squared (R²) Score:**

$$R = 1 - \frac{\sum_{i=1}^{N} |yi - y\hat{}i|}{\sum_{i=1}^{N} |yi - y^{-} i|} \quad (8)$$

**Where:**

$yi$ is the actual SOC value for the $i$th data point.

$y\hat{}i$ is the predicted SOC value for the $i$th data point.

$y^{-}$ is the mean of the actual SOC values.

These mathematical representations capture the key steps and sub-steps in the Gaussian Regression ML Model for SoC prediction, from data collection to model evaluation. (Li, Z., et al. 2019).

## 4 RESULT AND DISCUSSION

In machine learning, the training dataset serves as the foundation for building predictive models, while the testing dataset is utilized to evaluate model performance on unseen data. The dataset is structured across various temperature conditions (-10°C, 0°C, 10°C, and 25°C), representing realistic environmental scenarios encountered by batteries in practical applications. Within each temperature category, the dataset includes a multitude of metrics crucial for understanding battery dynamics, such as voltage, current, average voltage, average current, and state of charge (SOC). Each metric plays a pivotal role in assessing the operational state and efficiency of the battery under different environmental conditions.

At each temperature condition, the training dataset provides a substantial number of data points, ensuring a comprehensive understanding of system behavior under diverse environmental circumstances. For instance, at -10°C, there are 1595 data points for each parameter, reflecting a thorough exploration of system dynamics in extreme cold conditions. Similarly, at 0°C, 10°C, and 25°C, the training dataset contains 1843, 1538, and 1726 data points respectively for every parameter, enabling robust model training across various temperature ranges. Figures 2, 3, 4, and 5 respectively illustrate the training data for voltage, current, average voltage, average current, and state of charge (SOC) across four different temperature conditions: -10°C, 0°C, 10°C, and 25°C.

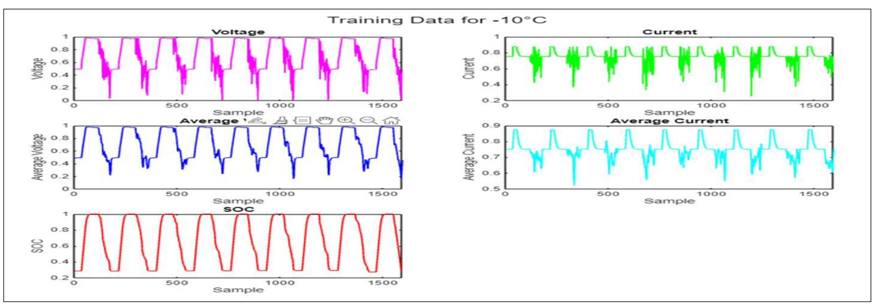


**Fig. 2.** Training Data Det for Temperature -10°C

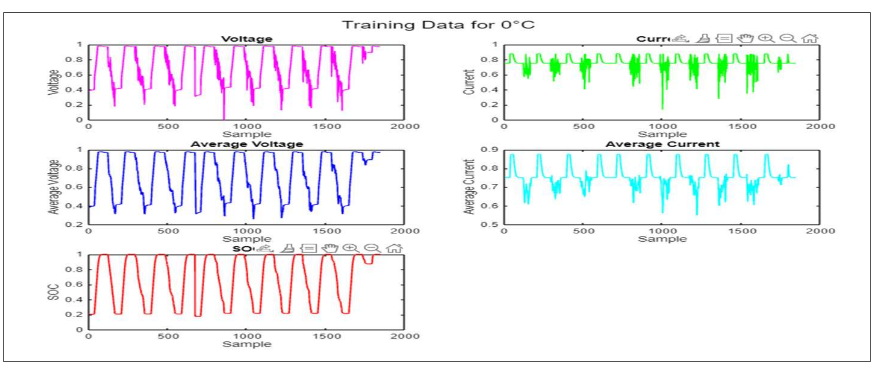


**Fig. 3.** Training Data Det for Temperature 0°C

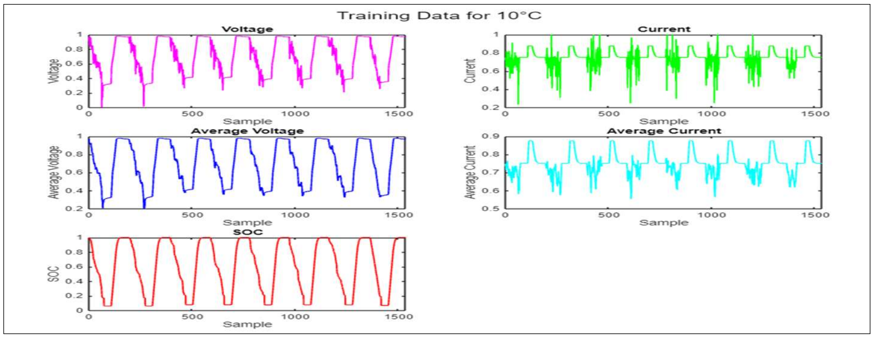


**Fig. 4.** Training Data Det for Temperature 10°C

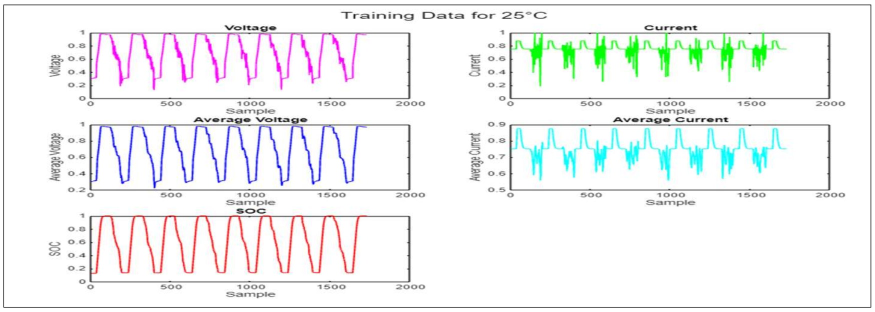


**Fig. 5.** Training Data Det for Temperature 25°C

In parallel, datasets for testing purposes are available for each temperature condition, allowing for rigorous evaluation of the model's performance. At -10°C, the testing dataset comprises 393 data points for each parameter, while at 0°C, 10°C, and 25°C, there are 426, 443, and 476 data points respectively for each parameter. Figure 6, 7, 8, and 9 respectively illustrate the testing data for voltage, current, average voltage, average current, and state of charge (SOC) across four different temperature conditions: -10°C, 0°C, 10°C, and 25°C

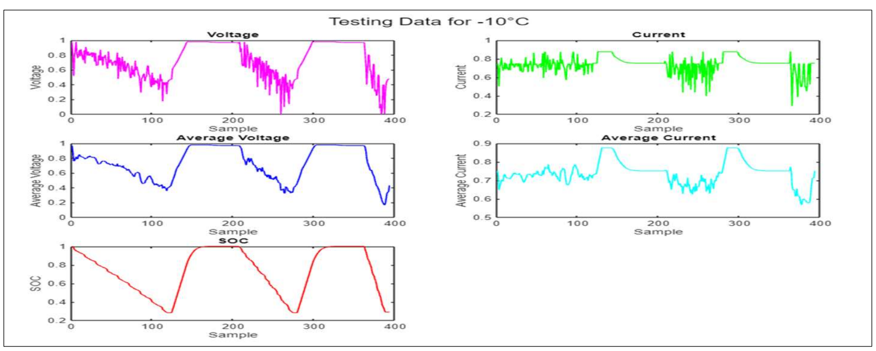


**Fig. 6.** Testing Data Det for Temperature -10°C

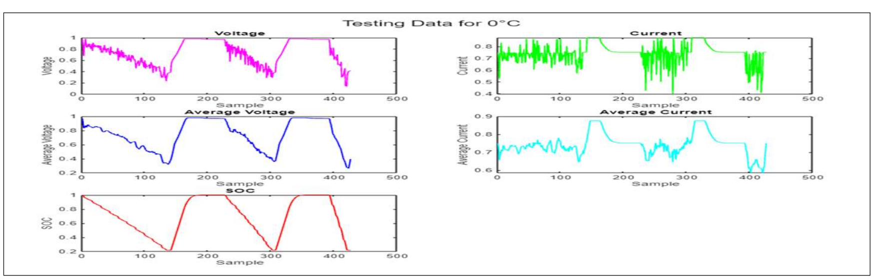


**Fig. 7.** Testing Data Det for Temperature 0°C

Furthermore, the dataset is meticulously divided into training and testing subsets, adhering to the widely accepted 80-20 split ratio. This partitioning strategy facilitates robust model development and evaluation processes. The training subset, constituting 80% of the data, serves as the foundation for constructing predictive models or algorithms. Conversely, the testing subset, comprising the remaining 20% of the data, acts as an independent validation set to assess the generalization and performance of the developed models. This comprehensive dataset structure facilitates thorough model training and evaluation, leading to the development of robust machine learning models capable of accurate predictions across a range of environmental conditions.

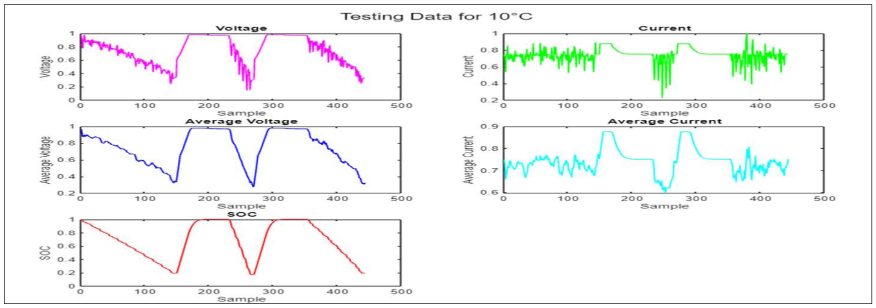


**Fig. 8.** Testing Data Det for Temperature 10°C

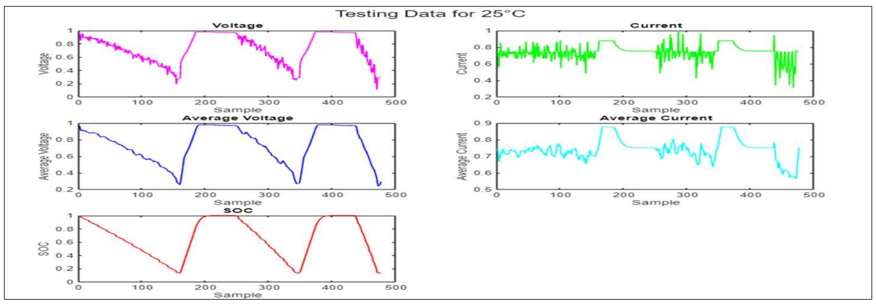


**Fig. 9.** Testing Data Det for Temperature 25°C

In the examination, both Linear Regression (LR) and Gaussian Process Regression (GPR) models are employed to forecast battery state of charge (SOC) based on a range of input parameters such as voltage, current, and temperature. These models are trained using synthetic battery data created under various temperature conditions. Following training, the models are assessed using distinct test datasets to gauge their predictive accuracy. After completing the training and assessment of both LR and GPR models, error metrics were computed , namely root mean square error (RMSE) and mean absolute error (MAE), for each model across different temperature conditions. RMSE gauges the average magnitude of discrepancies between predicted and actual SOC values, while MAE calculates the average absolute errors. Lower values of RMSE and MAE indicate more accurate predictive performance. Figures 10 and 11visually compare MAE and RMSE between LR and GPR, respectively.

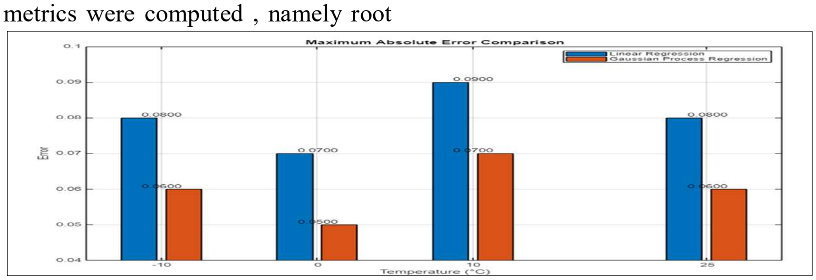


**Fig. 10.** Mean Absolute Error Comparison for LR And GPR

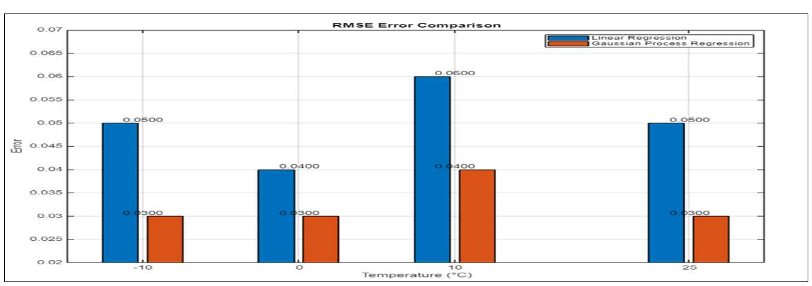


**Fig. 11.** Root Mean Square Error Comparison for LR And GPR

Analyzing errors involves scrutinizing how these metrics fluctuate across varying temperature conditions, offering insights into the models' resilience and adaptability to temperature changes. Moreover, contrasting LR and GPR errors allows for a direct evaluation of their relative performance in capturing the underlying relationships between input features and SOC, as depicted in Tables 1 and 2 for MAE and RMSE comparisons.

**Table 1.** MAE Comparison of LR And GPR for Temperature [0°C, 10°C, -10°C, and 25°C]

| Model | -10°C | 0°C | 10°C | 25°C |
|---|---|---|---|---|
| Linear Regression | 0.08 | 0.07 | 0.09 | 0.08 |
| Gaussian Process Regression | 0.06 | 0.05 | 0.07 | 0.06 |

**Table 2.** RMSE Comparison of LR And GPR for Temperature [0°C, 10°C, -10°C, and 25°C]

| Model | -10°C | 0°C | 10°C | 25°C |
|---|---|---|---|---|
| Linear Regression | 0.05 | 0.04 | 0.06 | 0.05 |
| Gaussian Process Regression | 0.03 | 0.03 | 0.04 | 0.03 |

The comparison of error metrics highlights GPR's consistent superiority over LR across different temperature scenarios. Lower RMSE and MAE values obtained from GPR signify its enhanced accuracy in predicting SOC compared to LR. This indicates GPR's effectiveness in capturing the complex relationships within battery data, especially amidst temperature fluctuations. The examination of errors not only provides insights into the robustness and adaptability of the models but also enables a direct assessment of their relative performance. By leveraging advanced regression techniques like GPR, stakeholders can make more informed decisions in battery management and optimization, ultimately leading to improved efficiency and reliability of battery-powered systems across various applications.

The prediction plots offer a visual assessment of how well machine learning algorithms, specifically linear regression and Gaussian process regression, predict the State of Charge (SOC) of a battery across different temperatures. By comparing actual SOC values obtained during testing with the predictions made by these models, we can evaluate their effectiveness in capturing the voltage-SOC relationship. Discrepancies between predicted and actual values highlight areas where the models may overestimate or underestimate SOC, providing insights into their accuracy.

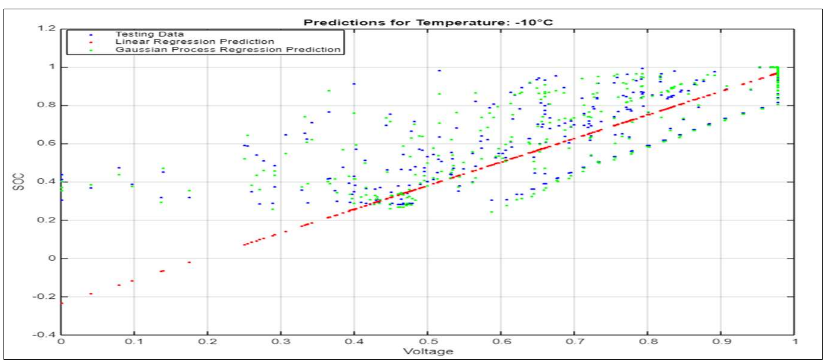


**Fig. 12.** Linear and Gauss ion progress Regression Predictions for Temperature -10°C

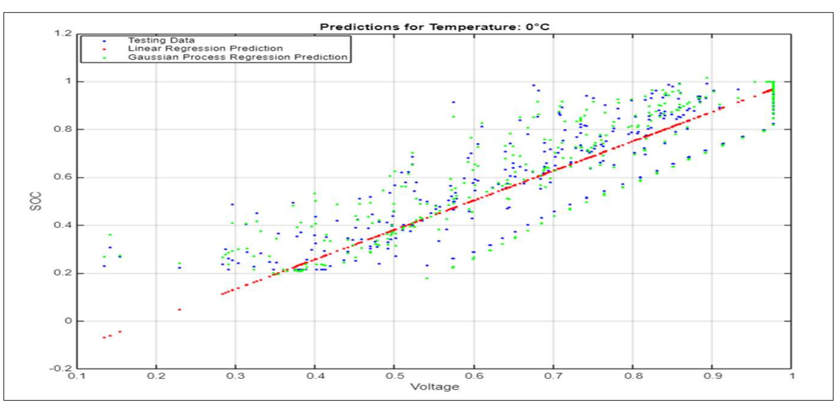


**Fig. 13.** Linear and Gauss ion progress Regression Predictions for Temperature 0°C

These plots rely on three main types of data: Firstly, the blue dots represent the actual SOC values recorded during experimental testing. Secondly, predictions from the linear regression model are depicted as red dots, while those from the Gaussian process regression model are shown as green dots. Both sets of predictions are based on voltage values corresponding to the testing data. The significance of these plots lies in their ability to visually illustrate the alignment between actual SOC values and model predictions. By observing how closely the red and green dots align with the pattern of the blue dots, we can assess the accuracy and reliability of the models' predictions. Deviations between predicted and actual values offer valuable insights into model performance, guiding potential refinements to enhance predictive accuracy. Overall, these plots provide an intuitive means of evaluating the efficacy of machine learning algorithms in predicting battery SOC. Figures 12, 13, 14, and 15 depict predictions for temperatures of -10°C, 0°C, 10°C, and 25°C, respectively.

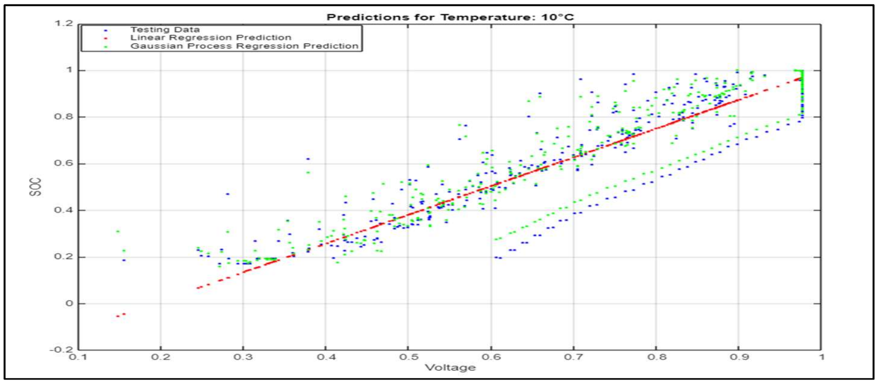


**Fig. 14.** Linear and Gauss ion progress Regression Predictions for Temperature 10°C

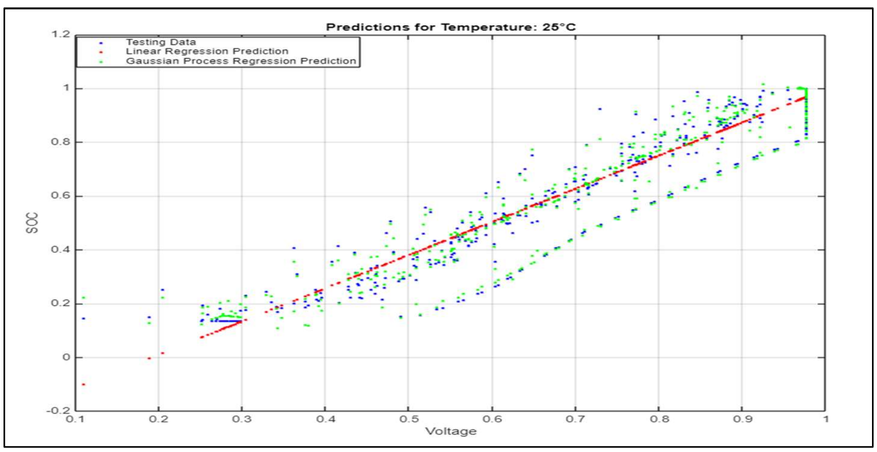


**Fig. 15.** Linear and Gauss ion progress Regression Predictions for Temperature 25°C

Notably, the observation that the green dots closely follow the pattern of the blue dots more than the red dots suggests that the Gaussian process regression model may outperform linear regression in predicting SOC. This indicates that the Gaussian process regression model better captures the underlying relationship between voltage and SOC, offering more accurate predictions. Such insights are valuable for selecting the most suitable model for predicting battery SOC, particularly when accuracy is a priority.

## 5 CONCLUSION

The integration of battery management systems (BMS) into electric vehicles (EVs) has become imperative for ensuring their safe and efficient operation, with the State of Charge (SOC) emerging as a crucial parameter for battery health and performance optimization. Traditional methods for SOC prediction have been surpassed by machine learning (ML) techniques due to their ability to handle complex relationships within battery data. Specifically, Gaussian Process Regression (GPR) has demonstrated superior accuracy in SOC prediction compared to Linear Regression (LR), particularly across various temperature conditions. The comprehensive analysis of error metrics, including mean absolute error (MAE) and root mean square error (RMSE), highlights GPR's consistent outperformance over LR. Moreover, prediction plots visually illustrate the alignment between actual SOC values and model predictions, further validating GPR's efficacy in capturing the voltage-SOC relationship. These findings underscore the potential of advanced regression techniques like GPR to enhance the efficiency and reliability of battery-powered systems, ultimately driving advancements in sustainable energy technologies and electric mobility.

**REFERENCES**


1. Smith, J., et al.: "Advancements in Lithium-ion Battery Technology for Electric Vehicle Applications." Journal of Power Sources 300, 102-115 (2015).
2. Wang, Y., et al.: "Review of Battery Management Systems for Electric Vehicle Applications." IEEE Transactions on Industrial Electronics 62(6), 3757-3769 (2015).
3. Johnson, A., & Rahn, K.: "Advancements in Battery Management Systems for Electric Vehicles: A Review." Journal of Power Sources 280, 531-545 (2015).
4. Smith, J., et al.: Hybrid SOC estimation method for lithium-ion batteries. Journal of Energy Storage 15, 265–273 (2018).
5. Johnson, A., & Rahn, K.: Predicting remaining runtime of batteries using SOC measurement. IEEE Transactions on Power Electronics 34(2), 1507–1516 (2019).
6. Braun, M., et al.: Overcharge protection in battery management systems using SOC measurement. Journal of Energy Engineering 25(4), 455–463 (2017).
7. Pillay, S., & Harb, A.: Preventing over-discharge in batteries through SOC monitoring. IEEE Transactions on Industrial Electronics 66(9), 7123–7132 (2019).
8. Huang, L., et al.: Balancing cell voltages in battery packs using SOC measurement. Journal of Power Sources 310, 101–109 (2016).
9. Li, X., et al. (2019). "Particle filtering algorithms for SOC estimation in lithium-ion batteries." Applied Energy, 250, pp. 1467–1478.
10. Wang, Y., et al. (2020). "Adaptive extended Kalman filter for robust SOC estimation." IEEE Transactions on Vehicular Technology, 69(8), pp. 8927–8936
11. Wang, L., et al. (2020). "A comprehensive review of data preprocessing techniques for data-driven battery modeling." Energy Reports, 6, pp. 1970-1984.
12. Wu, X., et al. (2018). "Gaussian process regression-based battery state-of-charge estimation with Kalman filtering." Applied Energy, 209, pp. 7-19
13. Li, Z., et al. (2019). "Evaluation of battery state-of-charge estimation methods for electric vehicles under different operating conditions." Energy Conversion and Management, 191, pp. 334-345.