State of Charge Estimation of Lithium-Ion Batteries for Electric Vehicle Application Using Gaussian Process Regression Approach

[1]Vinoth Kumar P, [2]Selvarani N, [3]Gunapriya D and [4]Malathy Batumalay
[1]Department of Electrical and Electronics Engineering, Sri Krishna College of Engineering and Technology, Coimbatore, Tamil Nadu, India,
[1]INTI International University, Nilai, Negeri Sembilan, Malaysia.
[2]Department of ECE, PSNA College of Engineering and Technology, Dindigul, Tamil Nadu, India.
[3]Department of Electrical and Electronics Engineering, Sri Eshwar College of Engineering, Coimbatore, Tamil Nadu, India.
[4] Faculty of Data Science and Information Technology, INTI International University, Nilai, Negeri Sembilan, Malaysia.
[1]vinothkumarp@skcet.ac.in, [2]n.selvarani@psnacet.edu.in, [3]gunapriya.d@sece.ac.in, [4]malathy.batumalay@newinti.edu.my

Correspondence should be addressed to Selvarani N: n.selvarani@psnacet.edu.in

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Abstract – For the purpose of ensuring a secure, dependable and affordable performancealong with clean energy in electric vehicles, the estimation of the precise state of charge of LIB is very important. In this article, Gaussian Process Regression with different kernel functions-based SOC prediction is proposed and their performance with good health and well-beingare evaluated and analyzed. A useful benefit of employing GPR is the ability to quantify and estimate uncertainties, allowing for the evaluation of the SOC estimate's dependability. The kernel function serves as a crucial hyperparameter that improves GPR performance. GPR considers the temperature and voltage of the battery, which are independent of one another, as their respective input parametersthat relates Industry, innovation and infrastructure where target-dependent variable is battery SOC. Initially, the training process involves determining the ideal hyperparameters of a kernel function to accurately represent the characteristics of the data. The accuracy of predicting SOC of the battery is evaluated using test data. According to the simulation outcomes, the squared exponential kernel function-based GPR estimates SOC with high accuracy and lower RMSE and MAE which ensures energy efficiency and quality education.

Keywords – State of Charge, GPR, Kernel Function, RMSE, LIB-Lithium Ion Battery, Energy Efficiency and Quality Education.

I. INTRODUCTION

The energy crisis, vehicle emissions, and other associated issues have gained prominence since the turn of the 21st century as related to SDG8-Decent work and economic growth, and as a result, there is now general agreement that carbon emissions must be reduced as stated in SDG11-for Sustainable cities and communities. Ecologically sustainable automobiles demonstrate that transportation has facilitated the emergence of unprecedented growth opportunities [1]. The global interest in new energy cars is attributed to its "zero-emission" characteristic. Moreover, the technological advancement of fully electric vehicles (EV)is remarkably rapid. The major factor contributing to this issue is the core energy storage technology used in EV, specifically the lithium-ion battery (LIB) [2]. With its superior features of large capacity, prolonged cycle life, greater specific energy and power density, and intrinsic absence of memory effect, LIB are expected to supplant alternative battery chemistry and emerge as the most favoured energy source for EV. **Table 1** presents a statistical comparison of LIB and alternative battery chemistry. Implementing specialized management strategies for LIB is essential to reduce the degradation of battery efficiency and avoid the risk of serious malfunctions or explosions [3].

Table 1. Comparison Of Various Batteries Used in EV Application

	Lead acid	Nickle Cadmium	Nickle Metal hydride	LIB				
				LFP	NMC	LTO	LCO	LMO
Specific Power(W/kg)	80-100	120-150	150-450	180-220	180-270	VH	220-330	160-230
Specific energy(Wh/kg)	30-50	35-80	60-120	120-200	150-220	60-110	120-220	250-360
Cycles(*100)	3 to 5	8 to 20	3 to 15	20-80	20-25	40-90	10 to 22	VH
Efficiency	~75	~80	~85	~92	~94	~95	~92	~95
Self-discharge rate	Medium	High	High	Less	Less	Very Less	Less	Very Less
Memory effect	Less	High	High	Very Less	Very Less	Very Less	Very Less	-
Cost(EUR/kWh)	~255	~540	~M-H	~425	~985	~625	~M-H	~M
Operating Range	(-20±45)	(0±50)	(0±50)	(-20±40)	(-20±50)	(-40±60)	(-20±45)	(-40±85)
Toxicity	High	High	Less	Less	Medium	Less	Medium	Less
Recycling level	Complete	Partial	Partial	Partial	Partial	Partial	Partial	-

Accurate monitoring of the state of charge (SOC) of the battery is crucial for enhancing battery efficiency and prolonging battery life [3]. SOC is stated as the ratio of the available useful capacity to the rated battery capacity when the LIB is completely charged.Due to the fact that it has the ability to prevent the battery from being overcharged or discharged, a precise SOC estimate is essential for the battery management system [4].Through the examination of the measurable parameters of the battery, such as its voltage, current, and temperature, it is possible to infer the SOC in retrospect. Variables such as the deterioration of the battery, differences in the temperature of the surrounding environment, a variety of vehicle operating situations, and other components of uncertainty may have an impact on this estimate. Therefore, accurately determining theSOC is an intricate and challenging task [5].

Traditionally, the most common methods for estimating SOC are the lookup table [6] and the Ahmethods [7]. These approaches are well recognized to have specific constraints. To analyse the SOC curve related with open-circuit voltage (OCV), it is necessary to maintain a static situation for a longer period of interval. Conversely, Coulomb counting techniques seek to ascertain the underlying SOC by taking into account the accumulated inaccuracy. Advanced methodologies, such as adaptive filtering algorithms, in conjunction with diverse modelling of battery, are frequently used to compute the SOC of a battery by taking into account of the LIB parameters [8,9]. For instance, the Kalman Filter [10, 11], as well as the Particle Filter [12], and H infinity filter [13]. Despite significant advancements in contemporary sensor technology, it remains unfeasible for model based and filter-based methods to accurately quantify SOC outside laboratories under controlled conditions [14]. The primary high-order algorithms used for predicting SOC are data-based schemes. SOC estimation commonly utilizes machine learning approaches such as deep neural networks [15] and AI algorithms includingSupport Vector Machines [16], Ensembler [17] and Extreme Learning Machine [18].

The major drawback of this algorithms is that they does not explicitly quantify the uncertainty in estimation. Gaussian Process Regression (GPR) method provides a versatile and resilient framework for estimating the SOC forecast probability distribution, as opposed to a single point estimateGPR is trained offline using the prior battery data and further used to predict the SOC online. An intrinsic advantage of GPR is its capacity to provide analytically controllable deduction utilizing complex closed-form equations. Moreover, this approach is crucial data based method that removes the necessity of comprehending the physical battery composition. Henceforth, this method can be utilized with ease in order to compute the SOC of a wide variety of battery types that are equipped with a variety of chemical compositions [19-20]. This paper intends to examine the effectiveness of the SOC estimate approach for LIB batteries using GPR.

Furthermore, we investigate the influence that the selection of the kernel function has on the precision of the estimation performed.

This paper includes five sections including introduction. Section 2 explains the GPR and the section 3 discuss the proposed GPR based SOC estimation. Section 4 presents an examination and analysis of the obtained results, followed by a conclusion drawn in section 5.

II. GAUSSIAN PROCESS REGRESSION

The Gaussian process (GP) regression is a regularly used probabilistic predictive model for regression tasks [21]. Under the premise that the function to be learned is obtained from a Gaussian process, this approach is considered non-parametric. Adopting this assumption enables the model to produce predictions with a well specified degree of uncertainty, which is advantageous for tasks such as active learning and decision making that consider uncertainty.

Formally, the GP regression model may be expressed mathematically as follows. D enote the input data points $x_1,x_2,...,x_n$, where $x_i \in R_d$ is a vector with d dimensions. Designate $y_1,y_2,...,y_n$ as the output values, where ($y_i \in R$) is a scalar. The GP regression model postulates that the function (f), which establishes the relationship between the inputs parameters and target outputs, is derived from a GP characterized by a mean (μ) and a covariance (k). The probability distribution of (f) at a particular test point set(x*) is denoted as

$$f(x^*) \sim N(\mu(x^*), K(x^*, x^*)) \tag{1}$$

Kernel functions are commonly specified to define the mean and covariance. **Table 2** lists the kernel functions utilized in GPR.

Table 2. Various Kernel Functions Of GPR

Exponential	$k(x, x') = exp\frac{x-x'}{l}$
Squared Exponential	$k(x, x') = \sigma^2{}_f \exp\left[-\frac{1}{2}\left(\frac{x-x'}{l}\right)^2\right]$
Matern 5/2	$k(x,x') = \sigma^2\left(1+\frac{\sqrt{5}\Vert x-x'\Vert}{l}+\frac{5\Vert x-x'\Vert^2}{3l^2}\right)\exp\left(-\frac{\sqrt{5}\mid x-x'\Vert}{l}\right)$
Matern 3/2	$k(x,x') = \sigma^2\left(1+\frac{\sqrt{3}\Vert x-x'\Vert}{l}\right)\exp\left(-\frac{\sqrt{3}\mid x-x'\Vert}{l}\right)$
Rational Quadratic	$k(x,x') = \sigma^2\left(1+\frac{\Vert x-x'\Vert^2}{2\alpha l^2}\right)^{-\alpha}$

With the help of Bayesian inference, the GPR model determines the distribution of (f) being probably responsible for the generation of the training data (x, y). The posterior distribution of (f) is calculated from the data as follows:

$$p(f|x,y) = p(y|x,f)p(f)p(y|x) \tag{2}$$

Given the function f, the equation (y|x,f) represents data probability., where The marginal probability of the data is p(y|x) and the prior distribution of f is p(f). Upon obtaining information on the posterior distribution of function f, the model can make predictions at further test points x* by computing the posterior predictive distribution, which is properly defined as:

$$p(f^*|x^*,y,x) = \int p(f^*|x^*,f)p(f|y,x)df \tag{3}$$

This distribution offers a quantification of the inherent uncertainty in the forecast, therefore proving valuable for applications such as active learning and decision making that takes into account uncertainty. Exact specification of the prior mean and prior covariance is required. The specification of the covariance is provided as a kernel object. The optimizer maximizes log-marginal-likelihood to improve kernel hyper-parameters during fitting. This maximization procedure is a non-convex optimization with several local optima, necessitating the restart of the optimizer many times. The first iteration begins with the initial hyper-parameters, and follow iterations employ randomly chosen hyper-parameters within the permissible range.

III. PROPOSED GPR BASED SOC ESTIMATION

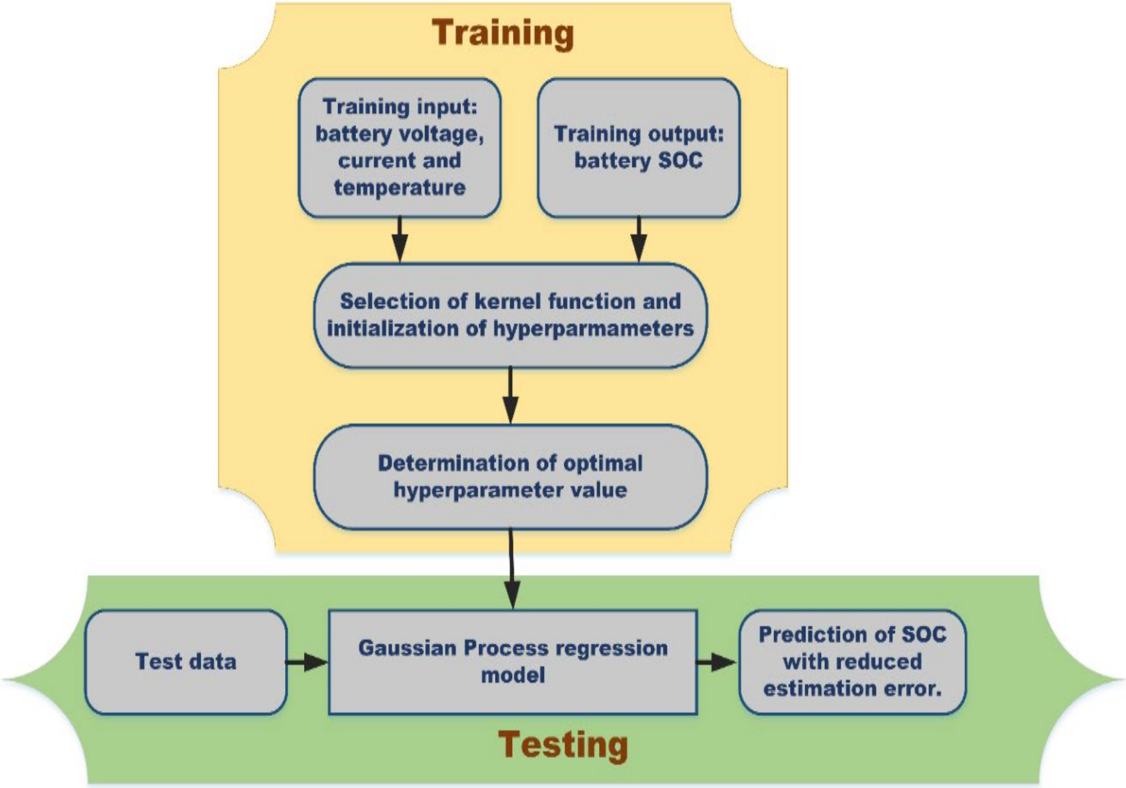

Fig 1. Proposed GPR Based SOC Estimation Methodology.

This section outlines the specifics of the process for estimating the SOC using GPR. As stated in reference [22], the SOC is defined as remaing available capacity of battery. Specifically, the completely depleted battery measures a SOC of 0%, which subsequently rises during the charging process. Accordingly, the completely charged battery achieves a SOC of 100%. As illustrated in **Fig 1**, the approach primarily has two components, namely training and testing. The suitable hyperparameters of the chosen kernel are estimated during the training phase by the conjugate gradient method. Significantly, eliminating the characteristic sample mean standardizes the training dataset SOC values to zero. Subsequently, the SOC is calculated in real-time by analyzing battery parameters namely current, voltage, and temperature [23-24]. In more technical terms, actual SOC is equivalent to estimated SOC. The trained GPR model with reduced error is tested using the new data sets considered under various environmental temperatures [25].

IV. SIMULATION RESULTS AND DISCUSSION

McMaster University in Hamilton provides training and testing data. This study tested a freshly developed 3Ah LG HG2 cell in an eight-cubic-foot thermal chamber utilizing a 75 amp, 5-volt Digatron Firing Circuits Universal Battery Tester channel. This methodology guaranteed that the measurements of voltage and current were precise within a range of 0.1% of the whole scale. The training dataset comprises a single run of experimental data obtained during a driving cycle, in which the battery-powered electric automobile was kept at a constant temperature of 25 degrees Celsius. An estimated 200,000 data points are designated for training purposes, with 30000 specifically dedicated for validation. Each set of four experimental data sequences from driving cycles at -10°C, 0°C, 10°C, and 25°C has about 20,000 data points. The dataset is normalized using min-max normalization before GPR model training and testing. R squared, and MAE are used to evaluate the suggested machine learning algorithms. After creating the model using the training dataset, performance measures were calculated using test data. To reduce overfitting, K-fold cross-validation was devised. K is 7 due to dataset limits. This study uses MATLAB 2024A's machine learning tool for assessment.

An evaluation of the performance of GPR with a Matern52 kernel function is conducted by examining the graph in **Fig 2**. This graph illustrates the correlation between the minimum objective and the number of function evaluations. The minimum objective is the lowest value attained based on the objective function. As the number of function evaluations rises, the minimum objective may demonstrate either a fast or gradual convergence rate. Effective optimization is indicated by the convergence of both observed and estimated minimal objectives to a similar value. Examining the graph, it is evident that the projected objective function has a persistent trend of both growth and decline until the fifth iteration. Later, the observed and estimated values of the function converge to the same value. The maximum number of function evaluations conducted is 30.

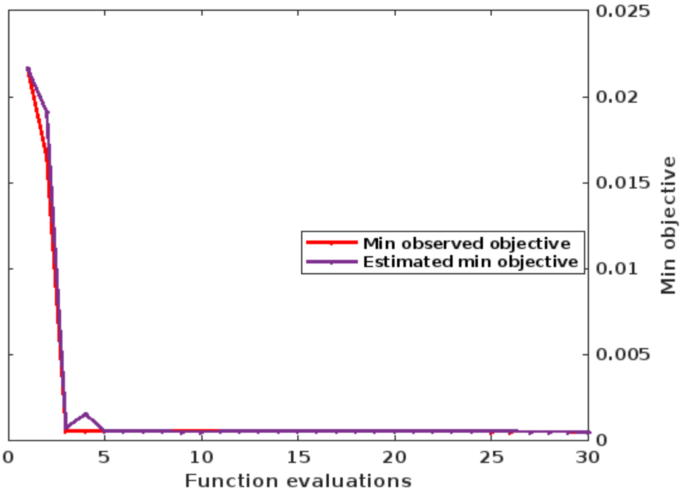

Fig 2. Function Evaluations Vs Minimum Objective Plot Ofgpr with Matern 52 Kernel.

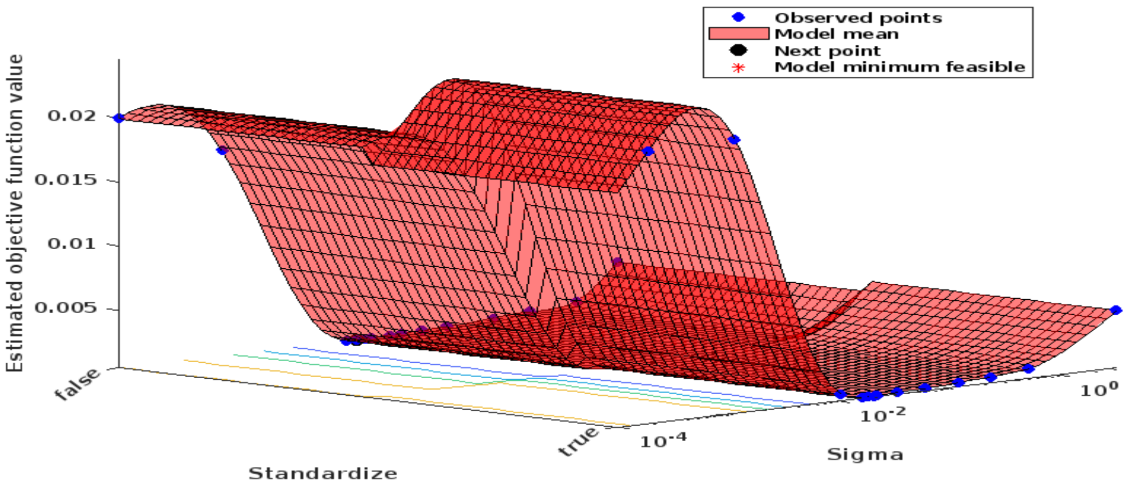

Fig 3. Objective Function Model of GPR With Matern 52 Kernel.

Depicted in **Fig 3** is the objective function model of GPRMatern 52 kernel. The observed data points represent the ensemble of input variables (current, voltage and temperature) that make up the objective function. The model mean is the prediction of the output for a given input using the existing model. Each next point dictates the inputs that are selected for the next optimization, and the next feasible point is chosen by meeting all the optimization requirements.

Similar to GPR with matern52 kernel, GPR is trained with squared exponential and rational quadratic kernel function and their training performance are plotted in **Fig 4 to 7**. **Fig 5** shows Objective Function Model of GPR with Squared Exponential Kernel.

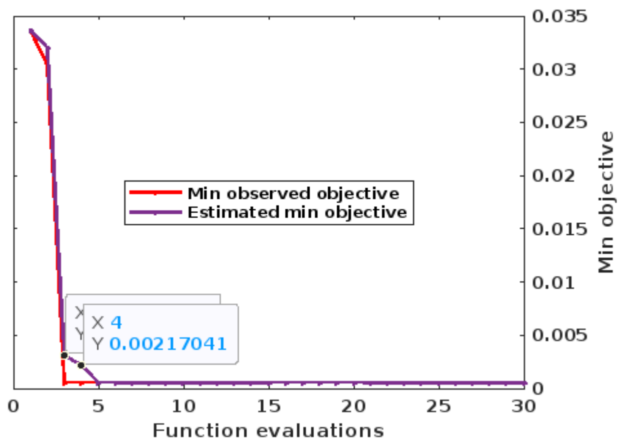

Fig 4. Function Evaluations Vs Minimum Objective Plot of GPR with Squared Exponential Kernel.

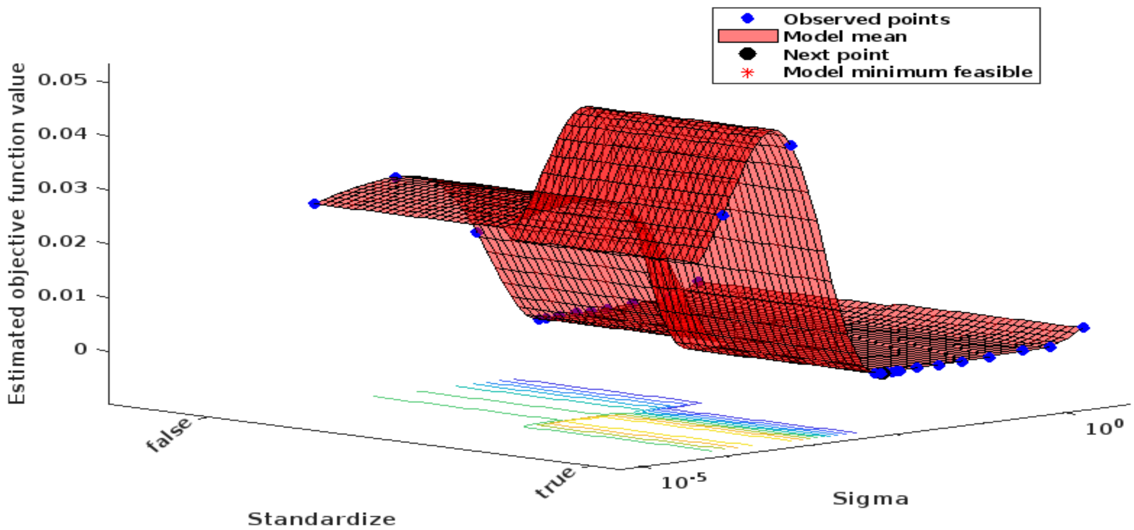

Fig 5. Objective Function Model of GPR with Squared Exponential Kernel.

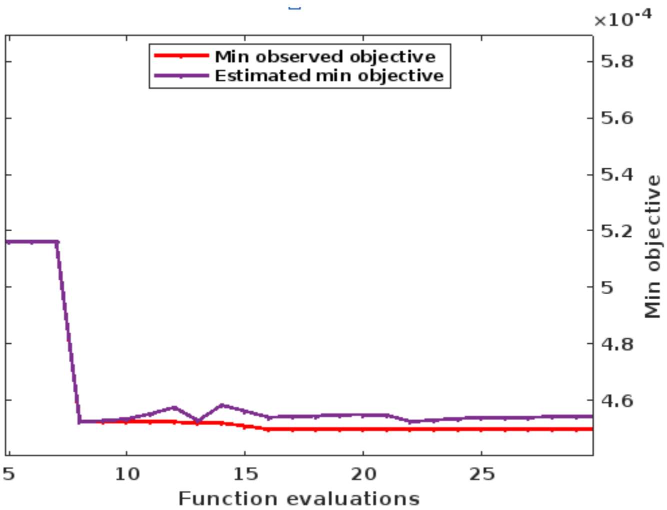

Fig 6. Function Evaluations Vs Minimum objective plot of GPR with Rational Quadratic Kernel.

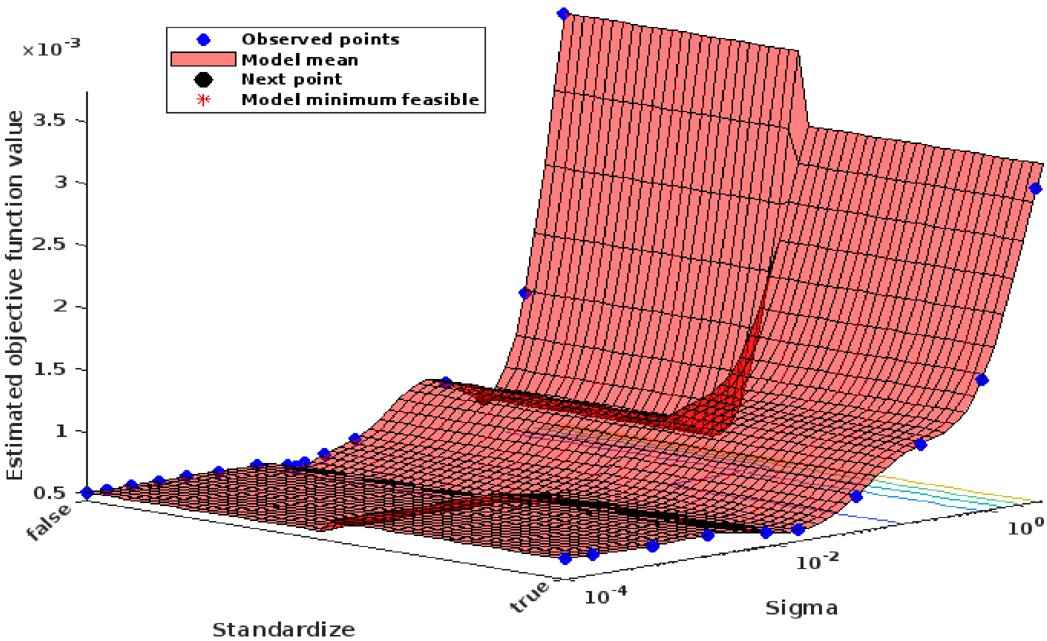

Fig 7. Objective Function Model of GPR With Rational Quadratic Kernel.

Based on the **Fig 6** and **7**, it is evident that the calculated objective and observed objective reach convergence at eighth function evaluations, but fail to converge beyond that point. Significantdisparity exists between the minimum observed objective and the computed minimum objective, suggesting a poor fit. **Fig 8** shows Prediction of SOC using GPR with Matern52 kernel for Testing Datasets At –Various Ambient Temperature. **Fig 9** shows Prediction of SOC using GPR With Squared Exponential Kernel for Testing Datasets at Various Ambient Temperature. **Fig 10** shows **Prediction** of SOC using GPR with Rational Quadratic Kernel for Testing Datasets at Various And 25°C Ambient Temperature.

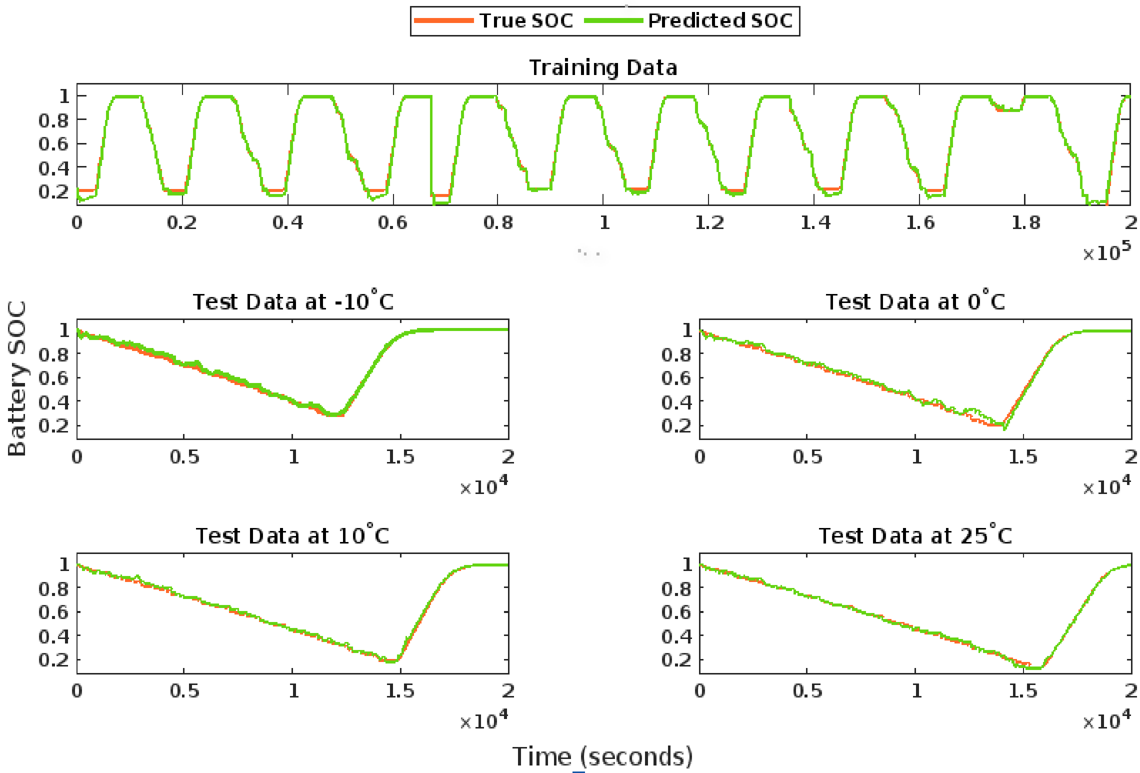

Fig 8. Prediction of SOC using GPR with Matern52 kernel for Testing Datasets At –Various Ambient Temperature.

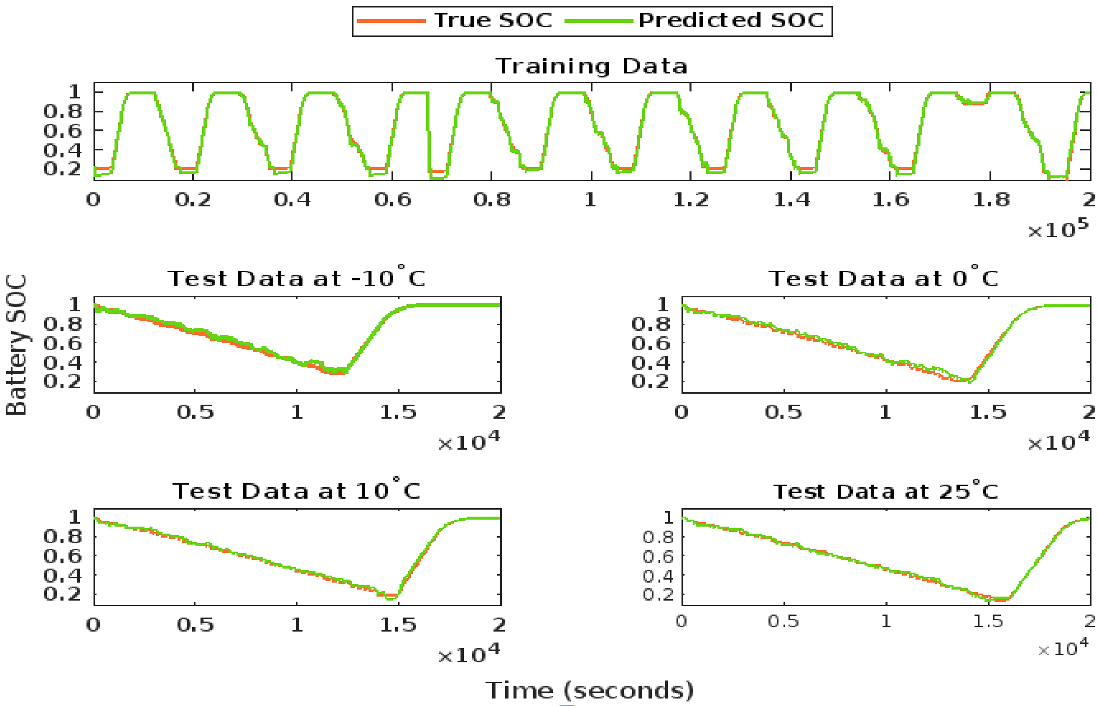

Fig 9. Prediction of SOC using GPR With Squared Exponential Kernel for Testing Datasets at Various Ambient Temperature.

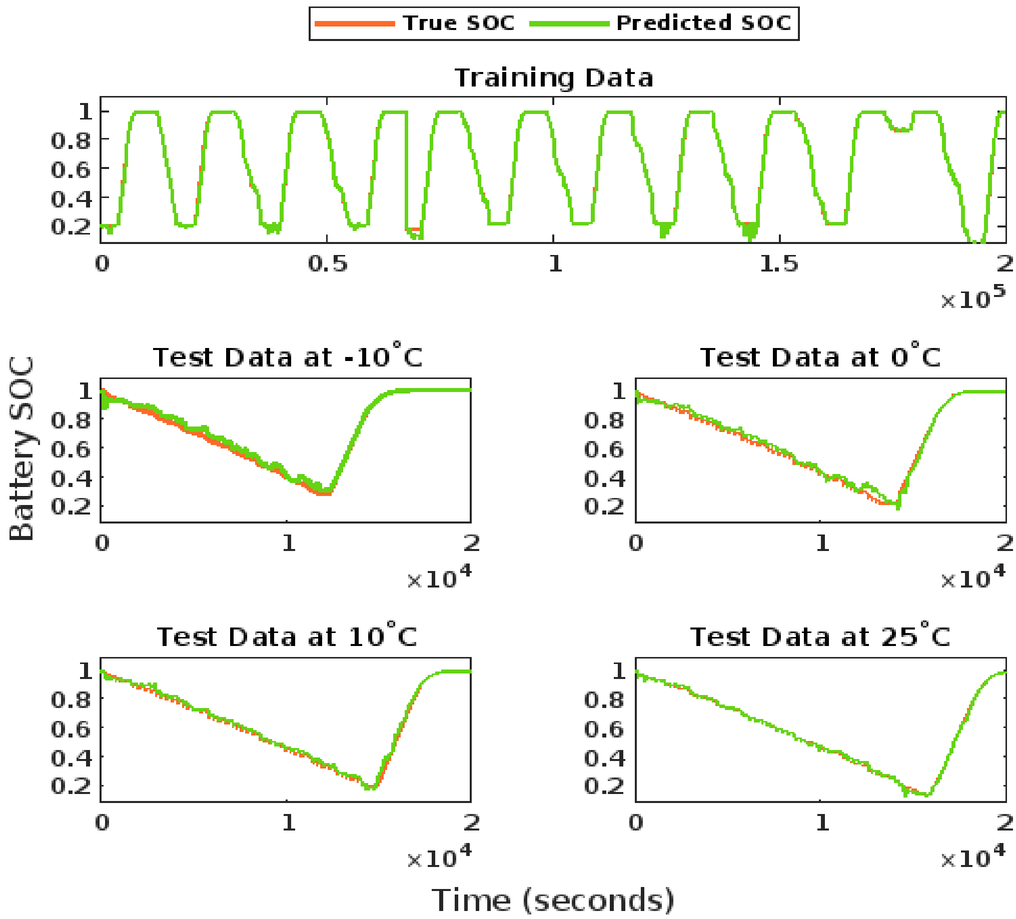

Fig 10. Prediction of SOC using GPR with Rational Quadratic Kernel for Testing Datasets at Various And 25°C Ambient Temperature.

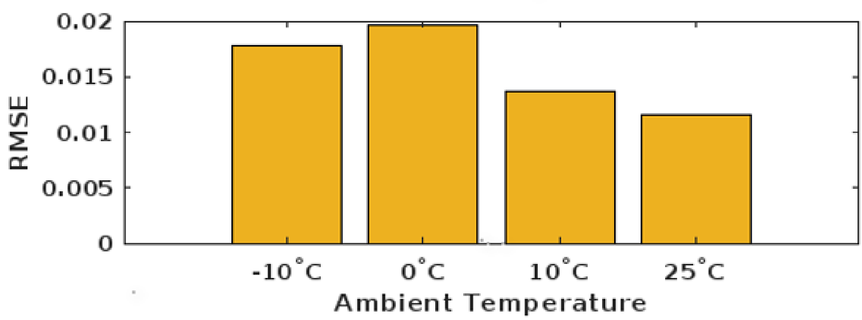

Fig 11. RMSE plot of SOC Prediction Using GPR with Matern52 kernel During Testing.

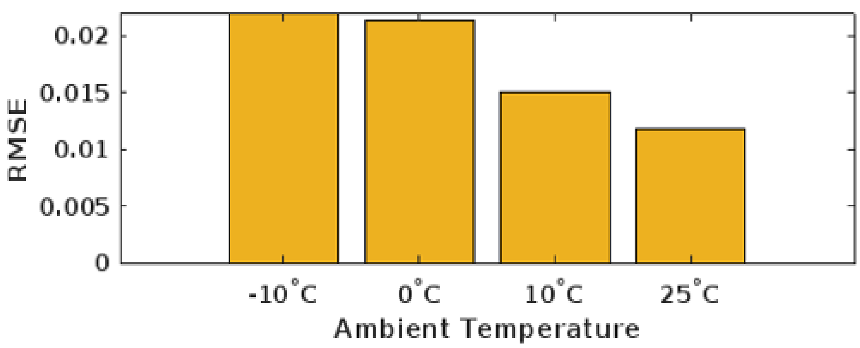

Fig 12. RMSE plot of SOC Prediction Using GPR with Squared Exponential Kernel During Testing.

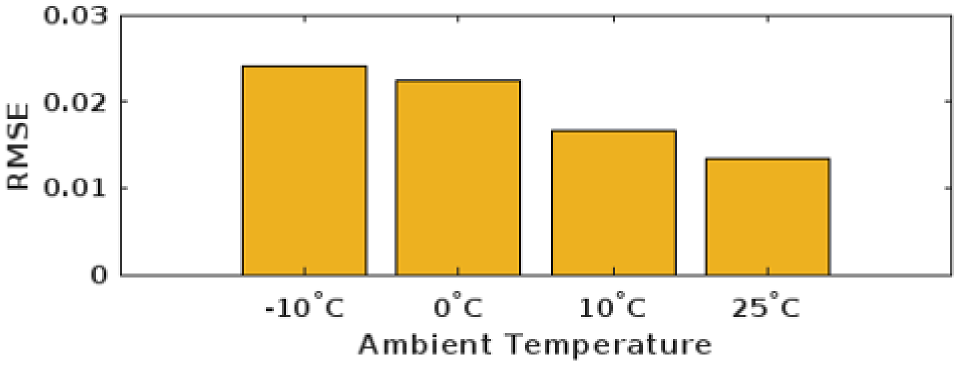

Fig 13. RMSE Plot of SOC Prediction Using GPR With Rational Quadratic Kernel During Testing**.**

The RMSE is used as the performance metric to evaluate the testing performance of GPR in the presence of different kernel functions. **Figs 11-13** presents the visual representation of the findings. The data presented in **Figs 11-13** conclusively demonstrate that the GPR with aMatern52 kernel function effectively evaluates the SOC of the battery with a reduced prediction error.

V. CONCLUSION

A GPR-based SOC estimate approach for Li-ion batteries is tested utilizing multiple kernel functions. The impact of kernel function selection on estimating precision is examined in this work. Simulation findings show that the GPR calculates SOC accurately with an RMSE of less than 0.02 using the Matern 52 kernel for a changing charging-discharging pattern with fluctuating ambient temperature. Furthermore, when employing the squared exponential and rational quadratic methods for a constant charge-discharge current profile, the RMSE is approximately 0.025, surpassing that of the Matern52 kernel. The objective of our future work is to improve the method for SOC using the GPRframework. This will be achieved by including the decrease in battery capacity, therefore effectively tackling the problem of battery aging.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests

There are no competing interests.

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