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SERVICES FOR SCIENCE AND EDUCATION

Machine Learning Based Hybrid State-of-Charge Estimation and Other Battery Parameter Prediction of Commercial EV-Batteries

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ABSTRACT

Electric Vehicles (EVs) are gaining huge attention from researchers due to their importance in environmental sustainability. Accurate and precise EV State-of-Charge (SoC) estimation is the primary challenge for commercial EV Batteries. To address the issue, the researchers have proposed many methods. However, there are a few drawbacks in the existing methods which can be resolved using hybridization of the variants of existing methods. In the previously reported work, the Kalman filter was used for the SoC estimation of EV batteries, which is suitable for linear systems. In most practical cases, the SoC of the EV-Batteries system shows nonlinear behavior. Although there are many other methods, e.g., Extended Kalman and Modified Extended Kalman reported by the researchers with some drawbacks. To resolve the issues, the multi-variable optimization approach can be used to improve the accuracy of the SoC. The present work uses the hybridization of machine learning methods to predict and estimate the SoC for commercial EV batteries. Machine learning methods precisely tune the parameters and optimize the estimation process by iteratively searching for the optimal solution within a defined parameter space. The performance of the proposed method is analyzed using the Jupyter Notebook Platform (Scikit Learn Library). The results prove the superiority of the proposed method.

Keywords: Electrical Vehicles, State-of-Charge estimation, EV Batteries, Machine Learning based SoC, Multi-variable optimization.

INTRODUCTION

Since Electric Vehicles are considered to be environmentally friendly and capable of reducing the consumption of fossil fuels, their popularity is growing. Nevertheless, precise computation of the State-of-Charge (SoC) and other battery parameters is vital to realizing optimal performance and durability in commercial EV batteries. The accurate prediction of state estimation depends on the dependence that is set, based complex electrochemical progressions and efforts such as thermals along with mechanics which makes model alongside parameter precision quite important. Additionally, with the age of batteries, it is necessary to update certain parameters in a model for that accurate performance would be depicted.

To create a hybrid SoC estimation method based on machine learning (ML) and to be able to develop other systems for forecasting battery parameters of commercial EV batteries using ML, one needs to use the most recent studies in this field. A number of studies have considered the integration of state-of-the-art machine learning methodologies to achieve desirable future capabilities and reliable RUL prediction with robust uncertainty handling functions for lithium-ion batteries [1]. In addition to that, realization of online estimations through the generation of a real-time state charge prediction model for lithium-ion battery system by SVM is aimed at alleviating reliance on speed and accuracy in connection with apparatus models [2]. In addition, a research has demonstrated parameter estimation process and state of charge prediction on the life ion batteries by various machine learning algorithms through MATLAB Simulink calculation basis [3].

In addition, for online SoH battery diagnosis a machine learning approach has been suggested which develops the predictive model of future voltage profiles using short-term charging data and positioning itself as an extreme trendy training algorithm [4]. In the recent years, hybrid deep learning models have been introduced. These characteristics of combining multiple machine learning techniques constitute a viable option that could achieve better precision and generalizability in forecasting EV charging status [5]. It is however, that secondary studies lead to changes by substituting machine-learning algorithms for the estimation of optimized maximum battery capacity given specific portions as an input constant-current charging curve [6]. Moreover, a hybrid deep learning prediction method has also been shown to provide fast convergence rate and reduced error numbers when developing state of charge estimates compared to traditional models [7].

In addition, a machine learning algorithm has been built by developing a program that can be trained to forecast the battery's state of health using prior aging data [8]. A machine learning-based component of a suggested 'hybrid' model has been developed based on the awareness about battery state-of-the electrochemistry during charge and discharge operation under actual drive cycles [9]. Furthermore, artificial intelligence and machine learning techniques have facilitated relying on data-driven estimation approaches to assess the SOC of Li-ion batteries which are evolving at an incredible pace [10]. All these studies in conjunction show the applicability of machine learning and therefore develop a versatile system to accurately predict battery parameters live for commercial EV batteries. The novelty and contribution of the proposed work is explained below:

- The main improvement brought by the proposed work is that it overcomes limitations of existing state-of-charge (SoC) estimation methods though hybridization with variations. The purpose of this hybridization approach is to eliminate the constraints implicit with linearity, which are often seen in approaches such as the Kalman filter and improve SoC estimation for EV batteries.
- The previous works were typical in implementing the use of linear models however, unlike those methods; the proposed method identifies that not all was practical on SoC nonlinear characteristic. In recognizing this underlying nature, the research assists in SoC estimation that is more realistic and accurate as aligned with on EV-Batteries systems.

- To mitigate the present limitations of SoC estimation, this work supports a novel multivariable optimization approach. Such novel approach concerns the systematic minimization of numerous variables to increase the accuracy value for SoC prediction. Such an approach represents a comprehensive perspective on the relationship among components of EV-Batteries which is dynamic and multi-dimensional in nature
- The main contribution is to integrate the machine learning approaches to fine-tune parameters carefully for optimal SoC estimation. The method performs iterative search for optimal solutions within a parameter space using machine learning algorithms. This makes this approach adaptive to increase the accuracy and adaptability of SoC predictions.
- The Jupyter Notebook platform and the Scikit Learn library are used to perform a thorough analysis of performance features for the proposed method. This selection of tools provides a solid evaluation, using machine learning libraries which are common to the field. The results prove the success of the solution, offering statistical proof that it is a better approach than its alternatives.

LITERATURE STUDY

The present paper work discusses a literature study that divides itself into two research areas. The first section deals with Kalman based methodologies[11] and the second part focuses on machine learning oriented SoC prediction frameworks [12]. Tian et al. [13] comparatively studied two model-based adaptive algorithms for state of charge estimation in electric vehicles with lithium ion batteries. The article provides some insight into how various adaptive algorithms perform in electric vehicle applications. Chen et al.[14] developed a new algorithm in state-of-charge estimation for lithium ion battery packs used within electric vehicles. Their research helps to increase the accuracy of state-of-charge predictions especially regarding electric vehicle applications. To enhance the performance, a hybrid approach with state-of -charge estimation for lithium polymer batteries [15] [16]. The approach integrates adaptive unscented Kalman filtering and support vector machine procedures to improve the precision of state-of-charge estimation.

Pang et al. [17] did an experimental work for data –driven parameter identification and state of charge estimation using lithium-ion battery equivalent circuit model. The research emphasizes the practical parameter identification that should be considered to make more accurate model of battery. For additional improvement, an advanced model-based self-adaptive filter to online state of charge estimation lithium batteries ion is proposed. The work concentrates on improving the adaptability of this filter in order to achieve precise and real-time state-of charge estimation Moreover, Meng et al. [18] introduced a simplified model-based state-of-charge estimation method for lithium ion batteries based on the dynamic linear model. The study provides information on an efficient and easy-to implement method of state-of-charge estimation.

Peng et al. [19] provided an article on online parameters identification and state-of-charge estimation for lithium ion batteries. The proposed method uses an advanced adaptive dual unscented Kalman filter so that it can properly adjust to real-time changing battery behaviour. According to [20], they proposed a state-of-charge estimation method for lithium ion batteries

using an intelligent adaptive unscented Kalman filter in order to enhance the intelligence of it. The focus of the study is on creating an adaptive and intelligent filter that enhances accuracy for state-of-charge estimation. Another state-of-charge estimation technique for lithium batteries is introduced in [21]. The method is based on extended Kalman filtering and taking into consideration the sensor bias helps to improve accuracy in predicting state-of-charge. Xu et al.[22] developed a state-of-charge estimation method for Li–$NiCoMnO_2$/graphite batteries. The compound method combines an enhanced extended Kalman filter and a long short-term memory network, thereby promoting progress in state-of charge estimation. In order to enhance the performance of extended Kalman filter; a dynamic high-order equivalent modelling approach for lithium-ion batteries is proposed [15]. Their work is based on state-of-charge prediction using a reduced order extended Kalman filtering algorithm.

Li et al. [23] suggested a constrained ensemble Kalman filter for distributed electrochemical state estimation of the lithium-Ion batteries. The research also makes a contribution to developments in distributed estimation methods, electrochemical states. Qian et al. [24] suggested modified dual extended Kalman filters for state-of-charge estimation and online parameter identification of lithium ion batteries. The study merged a gray wolf-optimized algorithm, demonstrating adaptability and enhanced efficiency in practical situations. Shi et al. [25] studies the improvement of state-of-charge and SoH estimation for lithium batteries ion technology. The current study integrates deep learning and Kalman filter methods to improve accuracy in predicting the upcoming conditions of this battery. Yang et al.[26] developed a parameter adaptive approach to the state-of-charge estimation for lithium batteries The proposed study designs an advanced extended Kalman filter, which is more adaptive and accurate for state-of-charge estimation.

METHODOLOGY & MATHEMATICAL MODEL

Discussion on Dataset

For the proposed method, the existing dataset from the measured and simulated values are used [27]. The selected database contains 72 real driving cycles performed with a BMW i3 (60 Ah), which logs almost all types of environment, vehicle states as well as battery and heating circuit. The above datasets are crucial in the development of advanced State of Charge (SoC) prediction models. Some of the environmental data consists of vital aspects like temperature and elevation, whereas vehicle information is made up what may be considered as figures on factors such as speed & throttle facts. Battery data includes voltage, current, temperature SoC and heating circuit has indoor temperature and heating power. The dataset also covers the methods of recuperation electro-thermal and peak power shaving.

Pre-processing of Dataset

The data preprocessing process must be effective enough to guarantee that the quality of the information collected can suffice. Data points that are missing or inconsistent within each class is dealt with during this stage and the features are normalized for standardization. Feature engineering is utilized to create new descriptive features that would take into account complicated cross-dataset interrelationships. Such a scrupulous approach is motivated by the desire to increase the accuracy of models' predictive capabilities taking into account that

driving nature and constant auxiliary consumers, for example, heating or air-conditioning systems are changing.

Decision Tree and SVM Regression Methods and Mathematical Model

The Decision Tree model that can be used for the implementation of SoC prediction is such one, which involves splitting dataset into train and test sets. The fine-tuning of hyperparameters, which are the tree depth and minimum samples per leaf parameters in this case by cross-validation. The metric used to train the model is Mean Squared Error. One of the vital stages is determining important features and understands which key predictors were. This information is then used to optimize the features that are utilized in order to improve on the general performance the model.

A similar procedure is followed with the introduction of an SVR model for Soc prediction. The dataset is split, and SVR hyperparameters are tuned using cross-validation. The tuning parameters like the type of kernel and regularization parameter are essential to achieve outstanding results. Reducing MSE is emphasized during the training phase, and feature selection methods are used to determine which features should be preserved for use in an SVR model.

The evaluation stage will subject Decision Tree and SVR models to thorough testing by use of the dataset. One the other hand, prediction accuracy represented in Figure 1 is evaluated using evaluation metrics such as Mean Squared Error and others related to it. These followed are then discussed in details by carrying out a comprehensive analysis of insights from feature importance analysis and features optimization. The aim is to lower MSE for accurate SoC prediction and obtain the overall best performance in predicting EVB state.

Flowchart of the Proposed Method

The flowchart of the proposed method is shown in Figure 1.

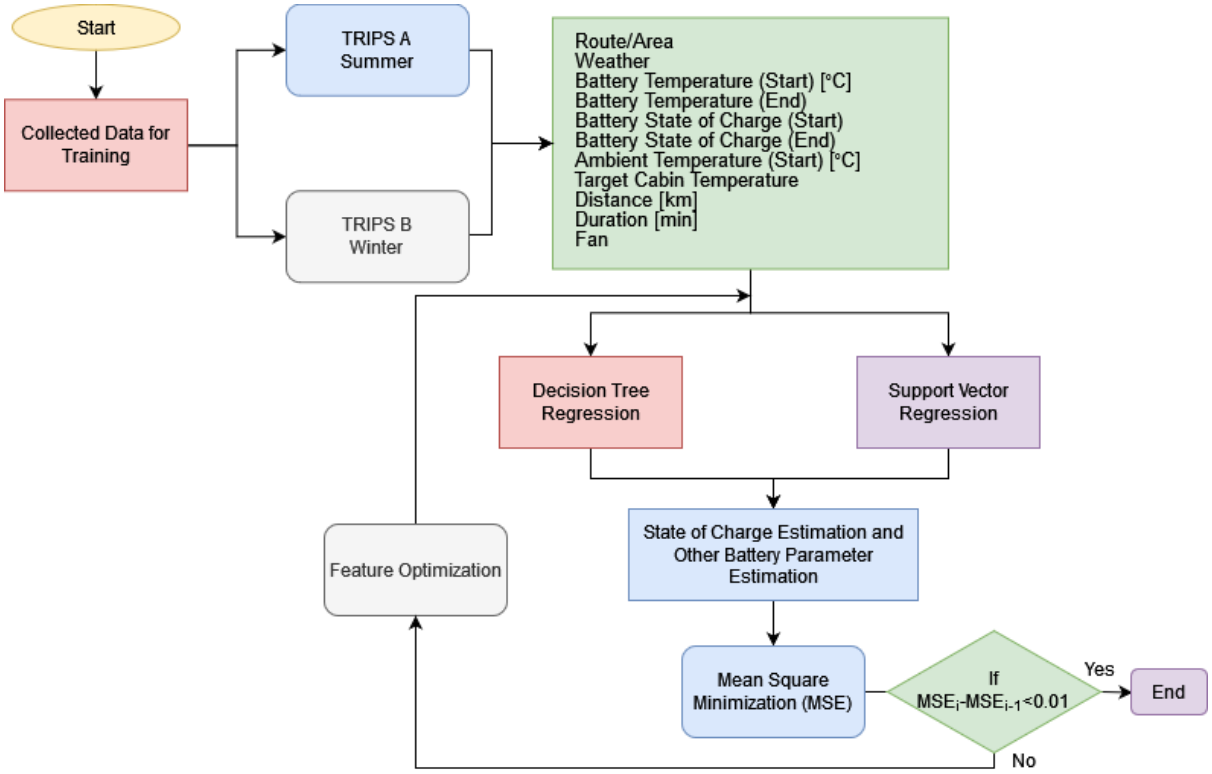


Fig 1: Flowchart of the Proposed Methodology.

Mathematical Model of Decision Tree Regression for EV

For the decision tree various parameters are used for the analysis. The training vector $TV_i \in P^n$, i = 1, … … , n and a label vector $Op \in P^l$ as shown in 3rd block of Fig 1. The data for the individual EV N is represented by D. for each EV division $\beta = (j, Th_N)$ consisting of feature j and threshold Th_N [9]. The data divide into $D_{\mathrm{R}}(\beta)$ and $D_{\mathrm{L}}(\beta)$ [28].

$$D_R(\mathrm{B}) = \mathrm{D}/D_{\mathbf{L}}(\mathrm{B}) \quad \textbf{(1)}$$

$$D_{\mathbf{L}}(\mathrm{B}) = (\mathrm{TV}, \mathrm{OP}) \mid TV_j, \leq Th_N \quad \textbf{(2)}$$

The impurity factor ( ) is defined as given below, the choice depends at the problem (classification or regression).

$$G(\mathrm{D}, \mathrm{B}) = \frac{n_{\mathbf{L}}}{n_N} H(D_{\mathbf{L}}(\mathrm{B})) + \frac{n_{\mathbf{R}}}{n_N} H(D_{\mathbf{R}}(\mathrm{B})) \quad \textbf{(3)}$$

If the continuous value is the goal for regression, then each EV N representing node P_N and η_N observation, mean square error is the common criterion for minimize.

$$C_N = \frac{1}{\eta_N} \sum_{i \in \eta_N} Op_i \quad \textbf{(4)}$$

$$H(TV_N) = \frac{1}{\eta_N} \sum_{i \in \eta_N} (Op_i - C_N)^2 \quad \textbf{(5)}$$

Mathematical Model of SVM Regression for EV

The mathematical model of (6) can be utilised to explain the same concept that is used for support vector machines (SVM) when the sample's linearity is separable [29].

$$\begin{aligned} &\text{MIN} \frac{1}{2} \parallel w \parallel^2 \\ &Op_i[(w \cdot TV_i) + \text{Q}] - 1 \geq 0, i = 1, \dots N \end{aligned} \quad \textbf{(6)}$$

w is the slope of linear discriminant function; Q is intercept; (TV_i, Op_i), $i = 1, \dots N$ is the training sample.

The proper classification of all training samples is the constraint condition of the mathematical model. In practice, meeting this constraint requirement is seldom easy. So variable ξ needs to be introduced. This permits a small number of samples to be incorrectly classified when the classification should comply with (7).

$$Op_j\left[\left(w \cdot TV_j\right) + Q\right] \geq 1 - \xi_i,\ i = 1, \dots N,\ \xi_j \geq 0, i = 1, \dots N \quad \textbf{(7)}$$

By significantly loosening the constraint condition, the new variable is introduced, enhancing SVM's fault-tolerantness and expanding its application domains at the same time. As can be seen from (7), all sample points in the model should have their respective slack variable values set to a minimum in order to minimise the number of wrong sample classifications. For this purpose, penalty term $Py\sum_{i=1}^{N} \xi_i$ can be added on the basis of objective function $\frac{1}{2}|w|^2$. And the new mathematical model of SVM turns into (8).

$$\begin{aligned} &\text{MIN} \frac{1}{2} \parallel w \parallel^2 + Py \sum_{i=1}^{N} \xi_i \\ &Op_j\left[\left(w \cdot TV_j\right) + Q\right] \geq 1 - \xi_i, i = 1, \dots N,\ \xi_j \geq 0, i = 1, \dots N \end{aligned} \quad \textbf{(8)}$$

The SVM's capacity for generalisation considerably increases with the addition of the slack variable. However, this approach is limited to sample data that is separable linear. Many sample data sets, however, are nearly inseparable. For this reason, a certain proper nonlinear mapping $TV \rightarrow \mu(TV)$ can be brought in. It is possible to transform the problem of linear separability in original space into the problem of linear separability in higher space. As a result, the model will further alter as (9), assuming that the sample's linearity is irreducible.

$$\begin{aligned} \text{MIN} \quad & \frac{1}{2} \parallel w \parallel^2 + Py \sum_{i=1}^{N} \xi_i \\ & Op_j \left[\left(w \cdot \mu(TV_j) \right) + Q \right] \geq 1 - \xi_j, i = 1, \dots N \end{aligned} \tag{9}$$

Lagrange function is constituted according to (10).

$$L(w, Q, \alpha, \xi) = \frac{1}{2}|u|^2 + Py \sum_{i=1}^{N} \xi - \sum_{\text{I}=1}^{N} \alpha(Op(w \cdot \mu(TV)) + Q - 1 + \xi) - \sum_{i=1}^{N} \pi\xi \tag{10}$$

$\alpha = (\alpha_1, \alpha_N), \alpha_i \geq 0$ and $\pi = \left(\pi_{1,\dots}\pi_N\right), \pi_I \geq 0$ are Lagrange parameter.

Partial differential of (10) to w, Q, ve can get $\mu(TV)$.

$$w = \sum_{i=1}^{N} \alpha_i Op_i \mu(TV_i) \tag{11}$$

$$Q = Op_i - \sum_{i=1}^{N} \alpha_i Op_i \left(\mu(TV_i) \cdot \mu\left(TV_j\right) \right) \tag{12}$$

Substituting the result of (12) into (9), then we can get the simplified model:

$$\begin{aligned} & \text{MAX} \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{i=1}^{N} Op_j Op_j \alpha_i \alpha_j \left(\mu(TV_i) \cdot \mu\left(TV_j\right) \right) \\ & \sum_{i=1}^{N} Op_i \alpha_i = 0, i = 1, \dots N \\ & \alpha_i \in [0,1], i = 1, \dots N \end{aligned} \tag{13}$$

By comparing (13) with (9), it is shown that nonlinear napping $\mu(TV)$ in (9) appears alone; however in (13), it appears n the form of inner product $\left(\mu\left(TV_j\right) \cdot \mu\left(TV_j\right)\right)$, which means, he decision function can be acquired by figuring out inner roduct $\left(\mu\left(TV_j\right) \cdot \mu\left(TV_j\right)\right)$ of μ(TV) without knowing specific form of $\mu(TV)$. The training of training sample set is conducted via (13) to $\alpha^* = (\alpha_1^*, \dots \alpha_N^*)$ under optimality condition, then ubstituting it into (7) to acquire , Q^* under optimality condition, finally we can get SVR function:

$$f(x) = \sum_{j=1}^{N} \alpha_i^* Op_j \left(\mu(\text{TV}) \cdot \mu\left(TV_j\right) \right) + Op_j - \sum_{j=1}^{N} \alpha_i^* Op_j \left(\mu\left(TV_j\right) \cdot \mu\left(TV_j\right) \right) \tag{14}$$

Based on the function value and optimization, the operation is is performed iteratively multiple times to minimize the error and to improve the accuracy of the proposed method.

RESULTS AND DISCUSSION

The given model is estimated for the conditions of summer and winter. Without loss of general explainability all results are discussed for trips made under summer condition. As for performance optimization, the mean square error of state-of-charge estimation is used to determine accurate training. Regression analysis performance evaluation is done on data set that consists of 32 trips which represent summer trip and have details regarding the percentage State of Charge (SoC). Linear Regression model is used to forecast SoC using different attributes and Mean Square Error for each trip. The outcome accentuates the pre-processing activities such as data value imputation and standardization. The last output of the function is MSEs resulting from individual trips, including a bar chart showing how it spreads through those trips. The average MSE is designated by a red dashed line on top of the plot and presents an at-a-glance metric for how well the model performs over multiple summer trips.

Scenario-1 (Decision Tree)

In the first case, analysis for decision tree is carried out. The objective of the analysis is to review how accurately prediction patterns are identified in regard to SoC as well as determine possible correlations and challenges associated with predicting SoC for different trip scenarios. Fig 2 indicates that, when MSE is optimized for overall trips the mean square error in this point estimates on trip measures to about 0.0118 Figure 4 shows the predicted value of SoC and true value of SoC results for first trip. The resulting MSE offers a numerical approach to measuring the model's accuracy in predicting SoC and gives an idea of how it works with unknown data. In addition to it, concatenating the predicted and real values as an output makes it possible for visual inspection which increases the interpretation of regression results.

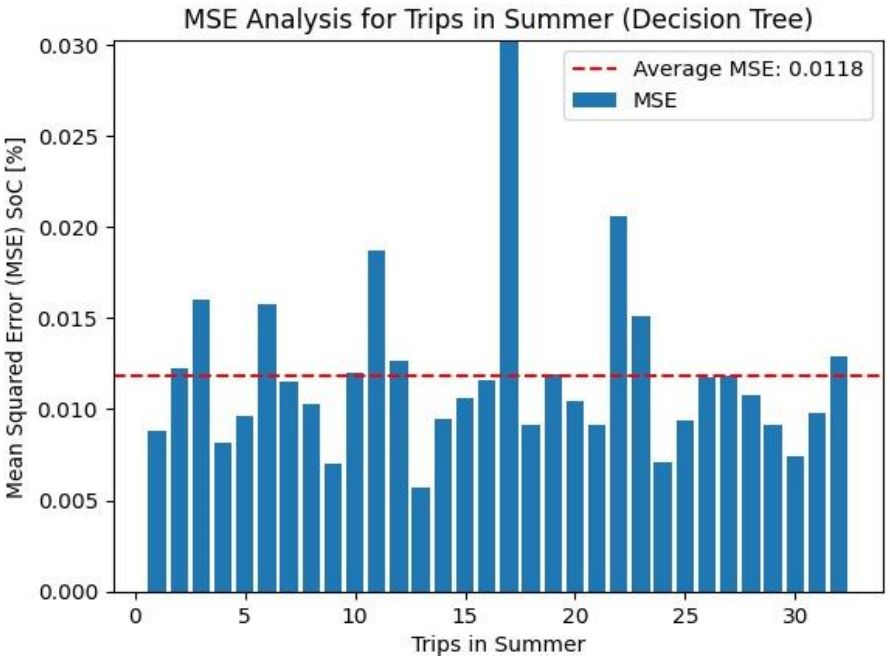


Fig 2: MSE analysis for SoC using Decision Tree

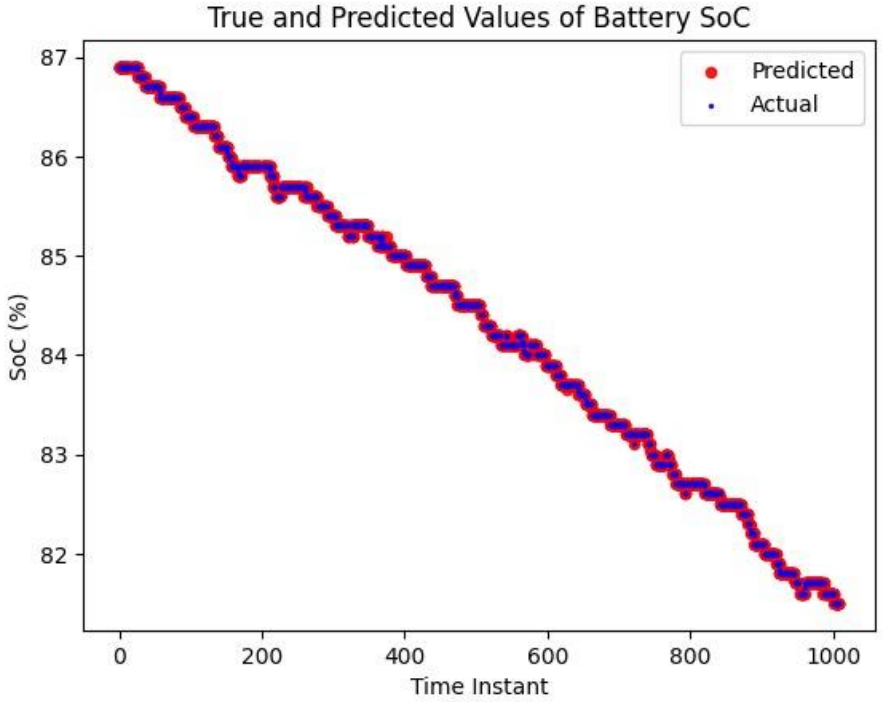


Fig 3: True and Predicted values of SoC using Decision Tree

To further enhance the performance, the battery voltage is also analysed. The MSE for Battery voltage is estimated for all the trips. The average MSE of battery voltage is 0.0977 as shown in Fig 4.

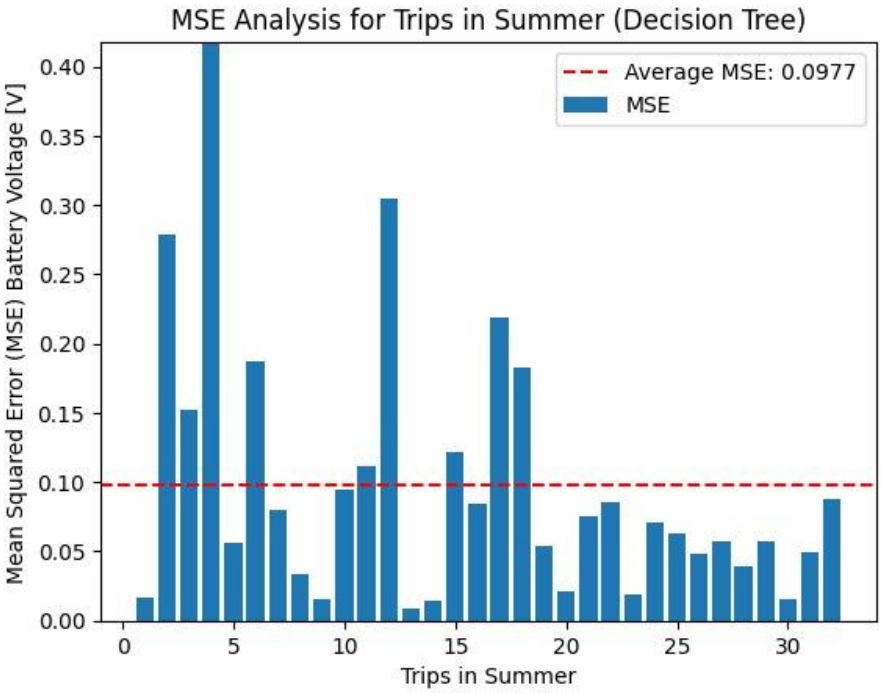


Fig 4: MSE analysis for Battery Voltage using Decision Tree

For the first trip, the predicted value of Battery Voltage and true value of Battery Voltage is shown in Fig 5. The resulting MSE provides a quantitative measure of the model's accuracy in predicting Battery Voltage, offering insights into its performance on unseen data. The resulting MSE, providing a quantitative measure of how well the Decision Tree Regressor performs in predicting Battery Voltage for the test set. The concatenated array of predicted and actual values offers insight into the model's performance on specific instances.

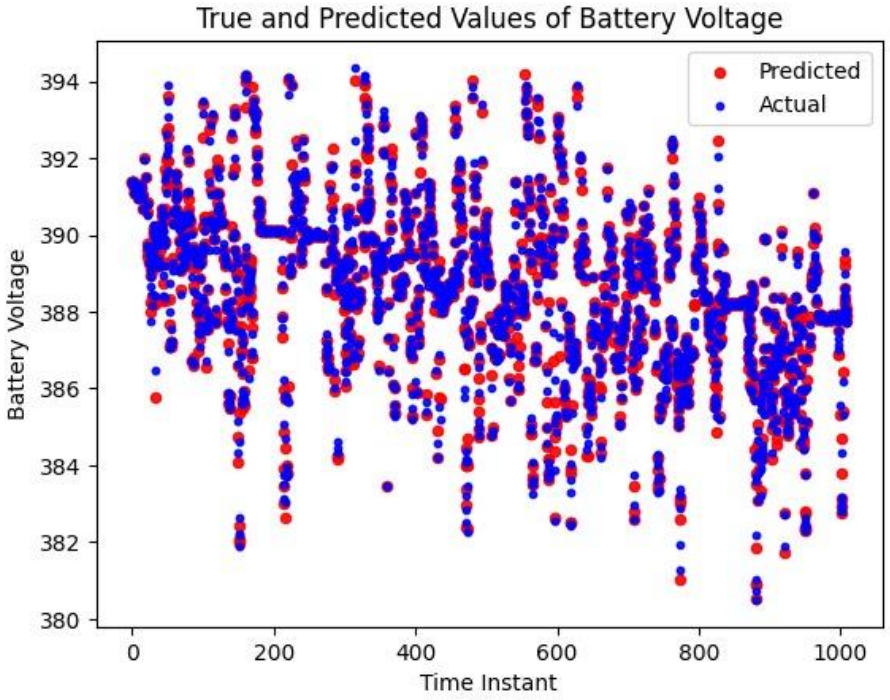


Fig 5: True and Predicted values of Battery Voltage using Decision Tree

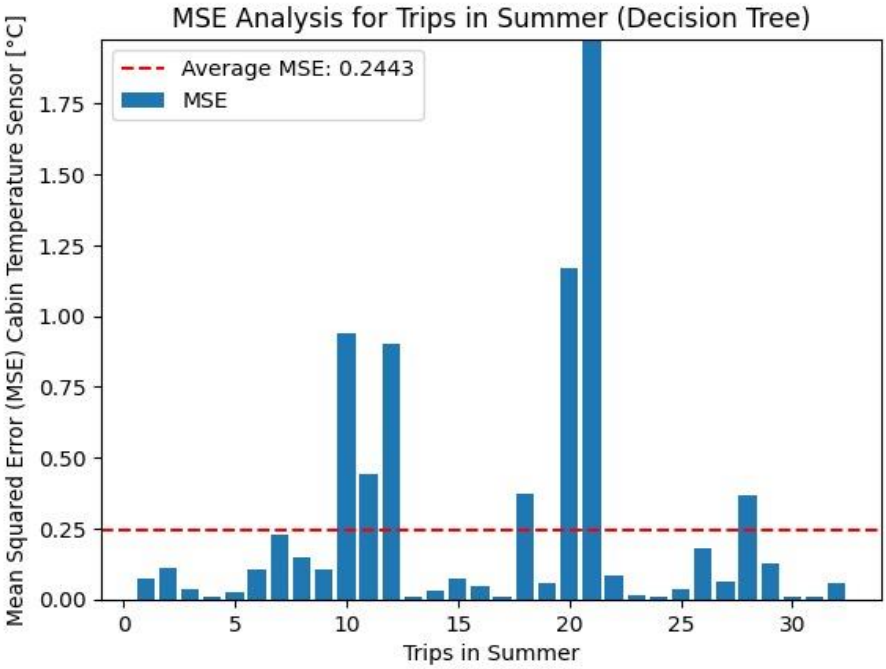


Fig 6: MSE analysis for Cabin Temperature using Decision Tree

The third important parameter is Cabin Temperature. The cabin temperature is analysed for all the trips. The MSE of predicted cabin temperature is little bit higher, i.e., 0.2443 as shown in Fig 6. The true and predicted value of the first trip is analysed for cabin temperature. The results show the deviation is very minor as shown in Fig 7.

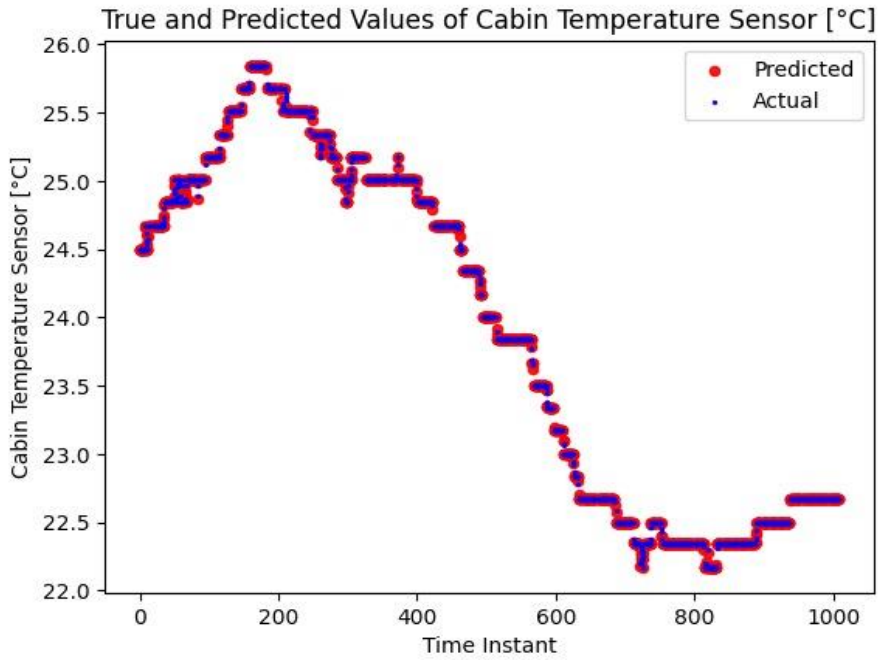


Fig 7: True and Predicted values of Cabin Temperature using Decision Tree

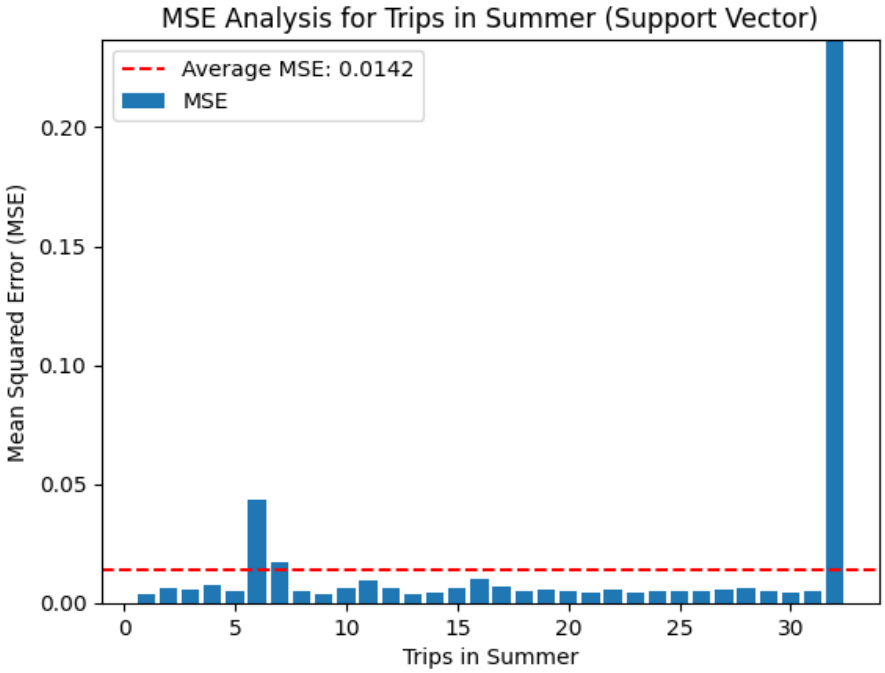


Fig 8: MSE analysis for SoC using SVM

Scenario-2

Before predicting the accuracy of SVM model using different parameters, this paper deals with analysis in which a trip dataset is used. After MSE optimization, the obtained Average Mean Squared Error is 0.0142 for State of charge (SoC) across all trips as shown in Fig-8. A relevant visualization to the model performance on SoC prediction is given below. In the first trip, it is demonstrated how far from agreement were predicted and real SoC values for individual instances Fig 9.

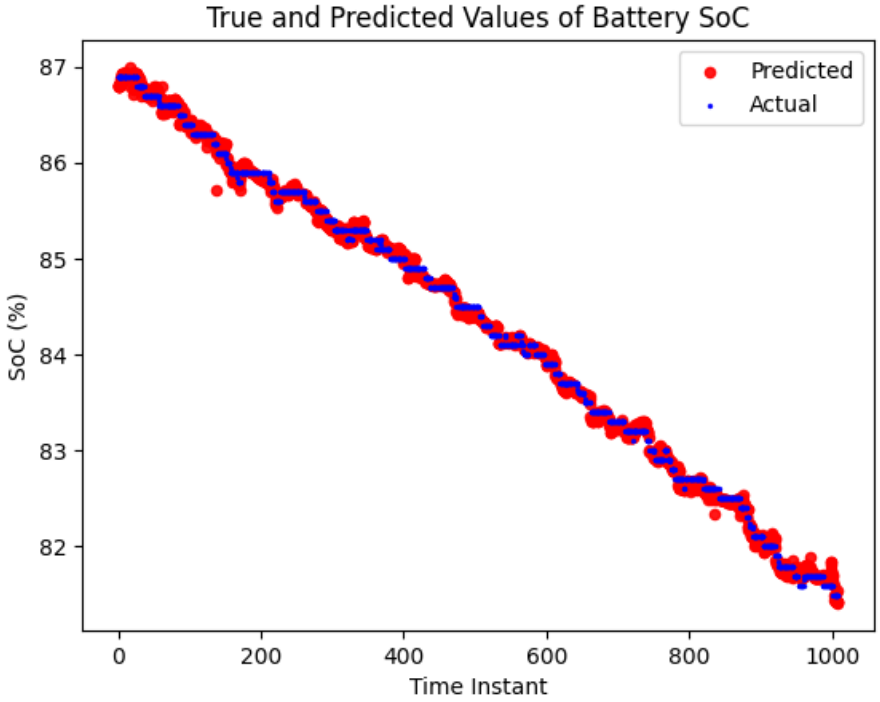


Fig 9: True and Predicted values of SoC using SVM

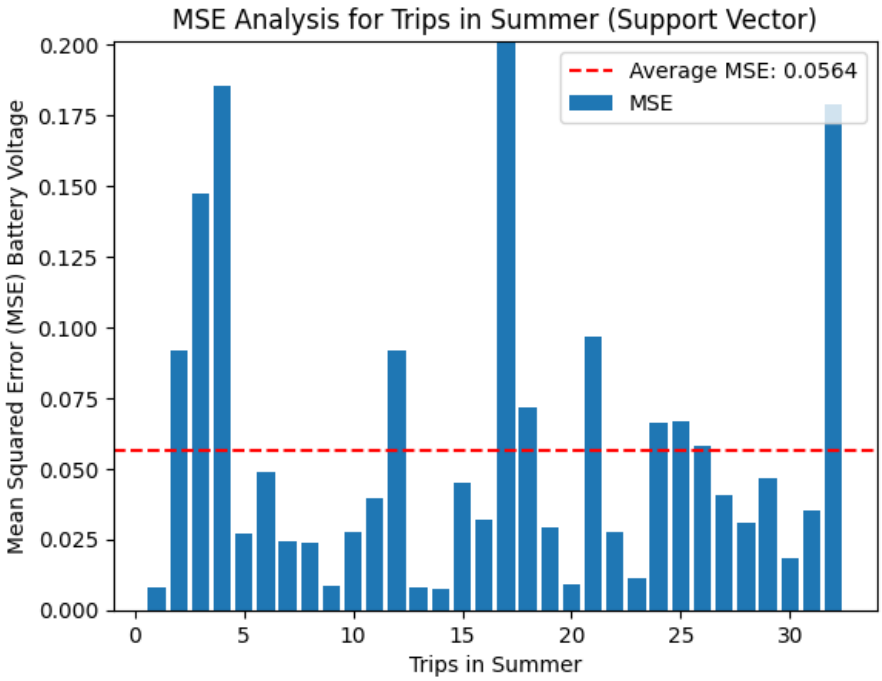


Fig 10: MSE analysis for Battery Voltage using SVM

Similarly, by performing MSE analysis for the battery voltage parameter as shown in Figure 10 this leads to a mean of squared errors value of approximately 0.0564 over all trips. The next

figure, Fig 11 incorporates the actual values of battery voltage and their predictions on a graph for an initial journey thereby explaining how accurate is model in this scenario.

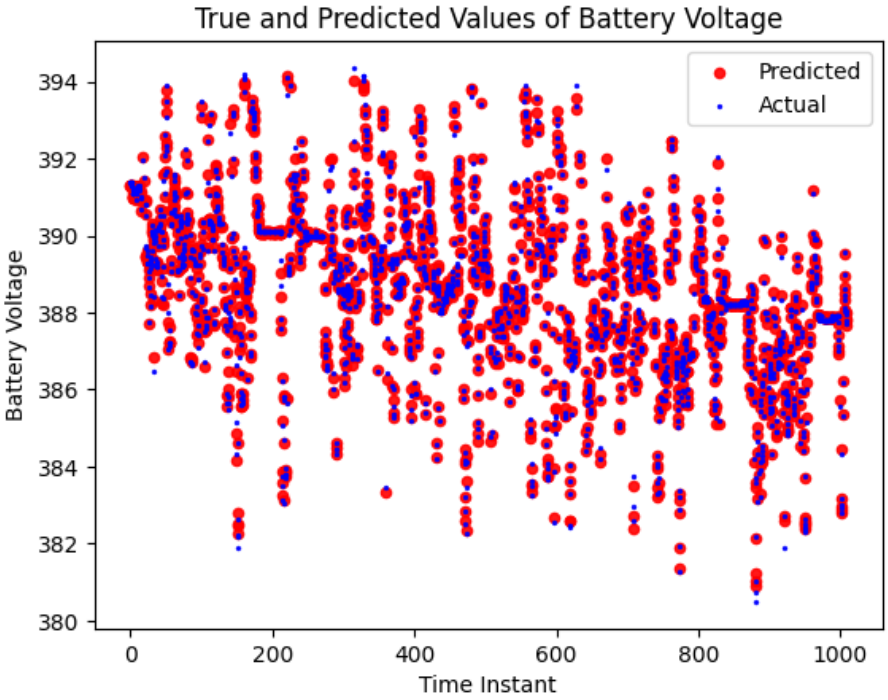


Fig 11: True and Predicted values of Battery Voltage using SVM

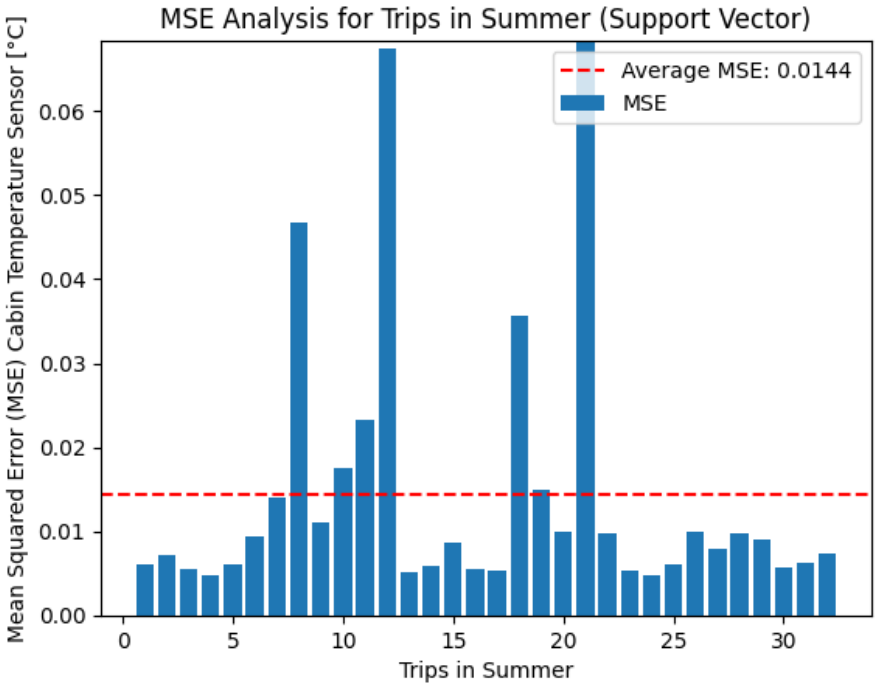


Fig 12: MSE analysis for Cabin Temperature using SVM

In addition, Figure 12 shows the evaluation of Cabin Temperature using SVM model where a marginally low MSE is obtained as compared to Decision Tree. In addition, Fig 13 shows that the disparity between predicted and actual values for Cabin Temperature on first journey is low so it illustrated a good performance of model in predicting this.

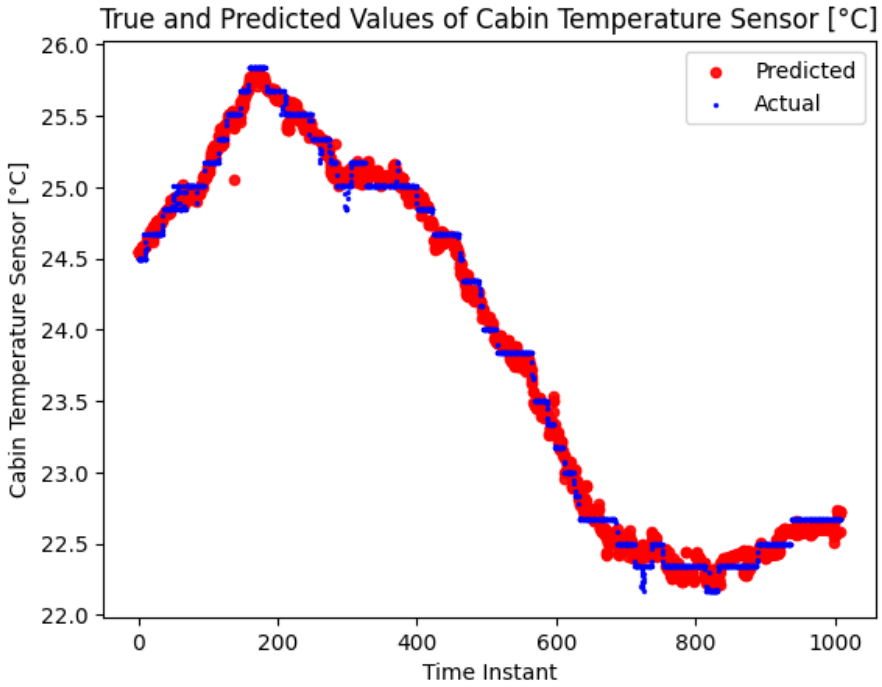


Fig 13: True and Predicted values of Cabin Temperature using SVM

CONCLUSION

This complete study of regression models in forecasting State of Charge (SoC), Battery Volts, and Cabin Temperature under summer trip situations involved the evaluation both Decision Tree and Support Vector Machine model. In the case of decision tree, through Mean Squared Error (MSE) optimization was determined that on an average MSE is found 0.0118 for SoC and 0.0977 for Battery Voltage with minor deviation observed in Cabin Temperature as 0.2443. It was very informative that visualizations such as bar charts and the true-predicted value plots allowed seeing how accurate the models were in specific cases. On the other hand, SVM performs an Average MSE of 0.0142 for SoC and 0.0564 for Battery Voltage with a slightly lower MSE in case of Cabin Temperature over Decision Tree.

From the holistic analysis on different parameters of summer trips, it is clear that Support Vector Machine's (SVM) model provides better results compared to Decision Tree model. For Mean Squared Error (MSE) of State of Charge (SoC) and Battery Voltage, SVM has lower average MSE suggesting better accuracy in prediction of these important parameters. The marginal reduction in MSE for Cabin Temperature is a further testament to the ability of the SVM model to capture intricate relationships within the dataset. In general, such results indicate SVM as a more reliable and effective option to forecast SoC, Battery Voltage, and Cabin Temperature concerning summer trip cases.

References

1. Liu K, Shang Y, Ouyang Q, Widanage WD. A data-driven approach with uncertainty quantification for predicting future capacities and remaining useful life of lithium-ion battery. IEEE Trans Ind Electron. 2020;68(4):3170–80.

2. Li R, Xu S, Li S, Zhou Y, Zhou K, Liu X, et al. State of charge prediction algorithm of lithium-ion battery based on PSO-SVR cross validation. Ieee Access. 2020; 8:10234–42.

3. Surya S, Saldanha CC, Williamson S. Novel technique for estimation of cell parameters using MATLAB/Simulink. Electronics. 2021;11(1):117.

4. Shu X, Li G, Zhang Y, Shen J, Chen Z, Liu Y. Online diagnosis of state of health for lithium-ion batteries based on short-term charging profiles. J Power Sources. 2020; 471:228478.

5. Nagashree R, Gowda K. Electric vehicle charging state predictions through hybrid deep learning: A review. GSC Adv Res Rev. 2023;15(1):076–80.

6. Tian J, Xiong R, Shen W, Lu J, Yang XG. Deep neural network battery charging curve prediction using 30 points collected in 10 min. Joule. 2021;5(6):1521–34.

7. Venkitaraman AK, Kosuru VSR. Hybrid deep learning mechanism for charging control and management of Electric Vehicles. Eur J Electr Eng Comput Sci. 2023;7(1):38–46.

8. Nuroldayeva G, Serik Y, Adair D, Uzakbaiuly B, Bakenov Z. State of Health Estimation Methods for Lithium-Ion Batteries. Siwal SS, editor. Int J Energy Res. 2023 Mar 3; 2023:1–21.

9. Onori S, Pozzato G, Li X, Lee D, Ko J. Accelerating the transition to cobalt-free batteries: a system level solution. 2022 [cited 2024 Jul 15]; Available from: https://www.researchsquare.com/article/rs-2058737/latest

10. Wei M, Ye M, Li JB, Wang Q, Xu X. State of charge estimation of lithium-ion batteries using LSTM and NARX neural networks. Ieee Access. 2020;8:189236–45.

11. Hawsawi T, Alolaiwy M, Taleb Y, Mezaael A, Zohdy M. An Improved Thevenin Model-based State-of-Charge Estimation of a Commercial Lithium-Ion Battery Using Kalman Filter. In: 2023 IEEE Smart World Congress (SWC) [Internet]. IEEE; 2023 [cited 2024 May 17]. p. 735–41. Available from: https://ieeexplore.ieee.org/abstract/document/10448568/

12. Hawsawi T, Zohdy M. Edge Impulse Based ML-Tensor Flow Method for Precise Prediction of Remaining Useful Life (RUL) of EV Batteries. J Power Energy Eng. 2024;12(6):1–15.

13. Tian Y, Xia B, Wang M, Sun W, Xu Z. Comparison study on two model-based adaptive algorithms for SOC estimation of lithium-ion batteries in electric vehicles. Energies. 2014;7(12):8446–64.

14. Chen Z, Li X, Shen J, Yan W, Xiao R. A novel state of charge estimation algorithm for lithium-ion battery packs of electric vehicles. Energies. 2016;9(9):710.

15. Appiah E, Wang S, Zou C, Zhang H, Bobobee ED, Musariri M, et al. A dynamic high-order equivalent modeling of lithium-ion batteries for the state-of-charge prediction based on reduced-order extended Kalman filtering algorithm [Internet]. 2021 [cited 2024 Jul 15]. Available from: https://core.ac.uk/download/pdf/475279930.pdf

16. Meng J, Luo G, Gao F. Lithium polymer battery state-of-charge estimation based on adaptive unscented Kalman filter and support vector machine. IEEE Trans Power Electron. 2015;31(3):2226–38.

17. Pang H, Zhang F. Experimental data-driven parameter identification and state of charge estimation for a Li-ion battery equivalent circuit model. Energies. 2018;11(5):1033.

18. Meng J, Stroe DI, Ricco M, Luo G, Teodorescu R. A simplified model-based state-of-charge estimation approach for lithium-ion battery with dynamic linear model. IEEE Trans Ind Electron. 2018;66(10):7717–27.

19. Peng N, Zhang S, Guo X, Zhang X. Online parameters identification and state of charge estimation for lithium-ion batteries using improved adaptive dual unscented Kalman filter. Int J Energy Res. 2021 Jan;45(1):975–90.

20. Sun D, Yu X, Zhang C, Wang C, Huang R. State of charge estimation for lithium-ion battery based on an intelligent adaptive unscented Kalman filter. Int J Energy Res. 2020 Nov;44(14):11199–218.

21. Al-Gabalawy M, Hosny NS, Dawson JA, Omar AI. State of charge estimation of a Li-ion battery based on extended Kalman filtering and sensor bias. Int J Energy Res. 2021 Apr;45(5):6708–26.

22. Xu S, Zhou J, Zhou F, Liu Y. State-of-charge estimation for LINI $_{0.6}$ CO $_{0.2}$ MN $_{0.2}$ O $_{2}$ /graphite batteries using the compound method with improved extended Kalman filter and long short-term memory network. Int J Energy Res. 2021 Mar 25;45(4):6115–38.

23. Li Y, Xiong B, Vilathgamuwa DM, Wei Z, Xie C, Zou C. Constrained ensemble Kalman filter for distributed electrochemical state estimation of lithium-ion batteries. IEEE Trans Ind Inform. 2020;17(1):240–50.

24. Qian K, Liu X, Wang Y, Yu X, Huang B. Modified dual extended Kalman filters for SOC estimation and online parameter identification of lithium-ion battery via modified gray wolf optimizer. Proc Inst Mech Eng Part J Automob Eng. 2022 Jul;236(8):1761–74.

25. Shi Y, Ahmad S, Tong Q, Lim TM, Wei Z, Ji D, et al. The optimization of state of charge and state of health estimation for lithium-ions battery using combined deep learning and Kalman filter methods. Int J Energy Res. 2021 Jun 10;45(7):11206–30.

26. Yang S, Zhou S, Hua Y, Zhou X, Liu X, Pan Y, et al. A parameter adaptive method for state of charge estimation of lithium-ion batteries with an improved extended Kalman filter. Sci Rep. 2021;11(1):5805.

27. Steinstraeter M, Lewke M, Buberger J, Hentrich T, Lienkamp M. Range extension via electrothermal recuperation. World Electr Veh J. 2020;11(2):41.

28. Nizam M, Mujianto A, Waloyo HT, Purwanto A. Decision tree for state of charge (SOC) prediction of LiFePO4 battery. In: Proceedings of the Joint International Conference on Electric Vehicular Technology and Industrial, Mechanical, Electrical and Chemical Engineering (ICEVT & IMECE) [Internet]. IEEE; 2015 [cited 2024 Jul 15]. p. 359–61. Available from: https://ieeexplore.ieee.org/abstract/document/7496687/

29. Sun Q, Liu J, Rong X, Zhang M, Song X, Bie Z, et al. Charging load forecasting of electric vehicle charging station based on support vector regression. In: 2016 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC) [Internet]. IEEE; 2016 [cited 2024 Jul 15]. p. 1777–81. Available from: https://ieeexplore.ieee.org/abstract/document/7779794