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OPTIMIZING BATTERY THERMAL MANAGEMENT SYSTEMS FOR ELECTRIC VEHICLES USING FIREFLY OPTIMIZATION AND SUPPORT VECTOR MACHINES

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ABSTRACT

Battery Electric Vehicles (BEVs) have a high dependency on effective Battery Thermal Management Systems (BTMS) to guarantee better performance, safety and long-life cycle of lithium-ion battery. Such issues associated with temperatures variations demand efficient thermal control systems. The research paper is carried out under the scope of exploring the applicability of machine learning (especially, Support Vector Machines (SVM) and Firefly Optimization Algorithm (FOA)) in optimising BTMS behaviour in real-time. This combination of techniques enables efficiency and flexibility in manipulating cooling systems in the changing conditions of operation, greatly benefiting efficiency and minimizing the requirements of the costly testing facilities. Findings demonstrate that the proposed model manages to predict and optimize cooling power and Coefficient of Performance (COP) with a relatively low cost and scalable solution of thermal management of BEVs.

KEYWORDS: Battery Electric Vehicles, Battery Thermal Management System, Firefly Optimization Algorithm, Machine Learning, Support Vector Machines.

1. INTRODUCTION

Batteries Electric Vehicles (BEVs) are being regarded as an option with a high potential to minimize the environmental effect of transportation. But excellence, safety, and durability of BEVs are largely based on well-functioning Battery Thermal Management Systems (BTMS). Lithium-ion batteries that are prominent with BEVs are quite sensitive to the changes in temperature. Heat or extreme cooling may result in degradation, impaired performance and even thermally induced catastrophic collapse. Therefore, it is indicated to streamline BTMS so that the functioning of batteries could be optimal in different environments and under different operating conditions.

Older ways of cooling thermal systems, e.g., air cooling and coolers, have some limitations, especially against real life dynamic environments e.g. variable ambient temperatures, vehicle speeds and battery loads. The study examines the use of Machine learning (ML) algorithms which are Support Vector Machines (SVM) and Firefly Optimization Algorithm (FOA) to improve the functioning of BTMS in BEVs. The study will enhance the performance of the system in real-time and efficiencies predicted and also optimized by merger cooling capacity and the copper Coefficient of Performance (COP).

Answering the existing problems of BTMS optimization, the current research presents the solution to the issue via the integration of SVM with FOA. The given model works to change dynamically according to the provided conditions, which guarantees superior performance and increases the lifespan of BEV batteries. It also overcomes the computational and time-intensive issue plaguing conventional experimental methods because it provided a cheaper and larger scale solution.

2. LITERATURE REVIEW

The authors [1] employed machine learning processes to enhance future on-site aspects of Battery Electric Vehicle BTMS systems operation. In this work, Support Vector Regression (SVR) and Particle Swarm Optimization (PSO) was used in predicting the cooling capacity and Coefficient of Performance (COP) of the BTMS. In the findings of the authors, the PSO-SVR model outperformed rather than the conventional regression models in predicting BTMS operational outcomes within diverse settings. The biggest weakness associated with making use of Particle Swarm Optimization is that it is prone to settling at local minima leading to poor optimization values.
In [2], the authors developed the machine learning system to evaluate thermal-related battery lithium-ion battery behavior. In the study, actual EV operation data and battery state data together with temperature dynamics were employed to develop a predictive system of analysis that considered influential factors that influenced battery performance. The validation of the experimental data also proved the usefulness of this model. The primary

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limitation of this approach is that it cannot work without a large size of the dataset but real-life environments may experience difficulties with gathering similar or sufficient data.
In [3], the authors propose an approach to estimating remaining useful life of the lithium-ion batteries based on mutual alignment of the Firefly Algorithm (FA) and Backpropagation Neural Network (BPNN) as well as the K-means clustering. This is an added advantage of the enhanced estimation since it has overcome the problem of parameter selection besides enabling more generalization of predictions. The computational demand of such a method is heavy as it is very complicated thus difficult to implement in real-time estimates.

In [4], a compounded approach is introduced that defers each of the physical simulation-based models with machine learning-based algorithms to predict the malfunctions in batteries that are based on tab failures. The combination of both theoretical and empirical knowledge allows obtaining an improved level of precision in prediction based on the design of this approach. The proper reflection of complex physical working principle by means of the machine learning technology is challenging to accomplish as the flawed performance of initial physical circumstances would yield the flawed outcome of the process.

In a study presented in [5], a Genetic Algorithm (GA) was compared with the Firefly Algorithm (FA) as well as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks in their performance to diagnose faults of lithium-ion batteries. The authors planned the research in order to increase the accuracy of detecting faults in the battery system. The detection algorithm is attractive in its performance but extremely intensive of computation so it hampers on-line applications.

The authors of [6] applied the application of effective machine learning methods in their study that aimed at maximising the control co-design optimisation of vehicle electric thermo management. The authors came up with the concept of reliability-based optimization to ensure the minimal consumption of energy on the one hand and the stability of the thermally reliable management systems on the other hand. High fidelity finite element models were needed when using this method and such models were too costly to apply in the use of wide scale real-time applications.

In [7], the authors proposed an ensemble of a particle filter to estimate state of charge (SOC) of Li-Ion batteries combined with the Firefly Algorithm (FA). Results indicated that the suggested approach could attain superior real-time estimation performance in comparison with existing conventional methods as determined by the authors. The combined algorithm carries out such calculations which result in difficulties of using it in limited resource systems of electric vehicles in short term operations.

In [8], the authors examined the extent to which sophisticated deep learning algorithms can increase simulation and forecasting of battery thermal behaviour. By means of deep learning framework, the authors were able to simulate battery thermal behavior in different scenarios. The reason lies in high data and computing requirements that deep learning models imply and that are a significant obstacle in their practical employment, at least when it comes to real-time operation.

In [9], the authors developed novel thermal management system optimization of electric car using their adapted adapted genetic algorithm based on SVM. The study aim was to develop higher thermal efficiency and consumption of energy. Genetic algorithm and SVM create a complex system that may compromise real-time optimization.

In [10], the authors evaluated Random Forests as a unified method of battery thermal management system temperature prediction. The scholars endeavored to come up with improved battery temperature predictions at various charging loadings. The main disadvantage of the model relies on the usage of voluminous well-prepared training datasets yet relevant real-life implementations have no such sets of data.

In [11], the authors have used combined genetic algorithms along with Support Vector Regression (SVR) to improve the State of Charge (SOC) estimation in lithium-ion battery. The researchers stated that new approach had better predictive outcome as compared to the traditional procedures. The greatest limitation of this method is that it requires heavy computation to train such a model but resources of this kind would not be applicable in real time monitoring systems.

In their paper [12], the researchers provided comprehensive discussion of using machine learning in electric vehicle battery thermal management systems. The discussion in the analysis provided several machine learning processes in the regression and classification and optimization algorithms in BTMS prediction and optimization. The unstable trends in the available datasets impose challenges on these techniques since they undermine the capability of the models of using the acquired knowledge in unknown circumstances.

Research Gap: There is a high number of research gaps needed in the existing implementation of the machine learning (ML) techniques especially in the application of Battery Thermal Management System (BTMS) predictive modelling and optimization. The works that have been carried out up to now treated more traditional and classic approaches, liquid cooling and heat exchangers combined with algorithmic models of forecasting the BTMS cooling capability and COP (Coefficient of Performance). As the key finding of the research, the most of the studies adopt PSO and SVR algorithms in order to fine-tune parameters that lead to the higher accuracy in making predictions. The existing literature shows a significant weakness in the form of failure to apply Firefly Optimization Algorithm (FOA) in conjunction with Support Vector Machines (SVM) to predict the performance. The existing research fails to conduct studies and optimize BTMS work in real-time and implement optimization strategies in the conditions of EV application and changing rapidly temperatures of the system and other parameters. A number of works exploit machine learning to predict battery thermal but there is lack of studies that would identify the interactive effect of ambient temperature with compressor speed combined with air flow rates in BTMS systems. A study should go further to extend the use of various aspects in the integrated optimization platform with sophisticated machine learning techniques. As adjustments in configuration of system in real time is lacking in the existing approach the immediate need is that of improvement. The combined application of Firefly Optimization Algorithm and Support Vector Machines where PSO and SVR can be replaced is the main research goal that gathers the information to increase the prediction accuracy of BTMS and the normalization ability. The analysis of the dynamic optimization method and real-time per-T ration optimization will be performed by conducting the research of different operational parameters. This research will cover specific issues about battery thermal management system to optimize the BEVs with better machine learning strategies towards performance improvement and sustainability and cost-effectiveness of the operation of BEVs.

3. PROPOSED METHODOLOGY

Figure 1 shows the flow diagram for the proposed framework. The methodology used in this research describes the procedure conducted to attain the purpose of the research. It contains the elaborate mechanism of data acquiring and preprocessing that not only guarantees the quality and reliability of the inputs data to train the machine learning models but also prepares the ground to build the machine learning models. A crucial component of the process as well is features engineering, which entails the selection and transformation of the data into a form that can be used in the predictive models. This research also explains the steps that are followed inside the machine learning model development, wherein, SVM is used to establish the relationship between the inputs variables (compressor speed, ambient temperature, airflow rate) and the target variables (cooling capacity and coefficient of performance). Further, hyperparameters of the SVM model are optimized by using Firefly Optimization Algorithm (FOA) so that the model has maximized performance.

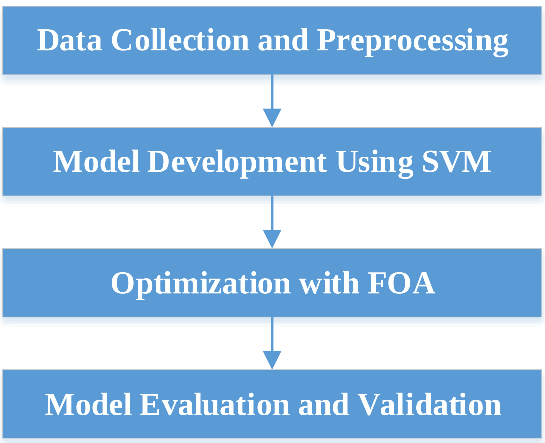

Figure 1: Flow Diagram for Optimizing BTMS Using FOA and SVM

After the development of the predictive models, the technique goes further to optimization, and through it, the performance of the system is improved by continually adjusting to the changing operating conditions. Real-time optimization permits the system to respond in real-time to the changing cooling approaches due to different parameters like temperature variations and driving cycles (inherent in the operation of BEVs). The evaluation parameters that will be used to evaluate the performance of the models mentioned in this research including the Mean Squared Error (MSE), R-Squared (R^2), and cross-validation measures have also been outlined to make sure the models are not over-fitted to the available datasets.

The main idea of the methodology used in this study is to merge the machine learning methodologies to do the predictive modelling and complex optimization algorithms to enhance the efficiency of BTMS. The Support Vector Machines are also applicable in the regression modeling, and the Firefly Optimization can be used to improve the performance of the model in escaping local optima thus giving a better solution in multi-dimensional and larger spaces. Besides, the performance of system remains real-time and it is monitored and adjusted on an ongoing basis, which makes BTMS dynamic and efficient. The given methodology will also help to reduce or even eliminate the necessity of using the conventional experimental method as it is relatively costly and time-consuming as it provides an effective and scalable simulation to thermal problems in BEVs because it is computationally efficient.

The proposed study has aims to achieve a breakthrough in the BEV thermal management with the help of this methodology. This contribution to the optimization and prediction of the liquid-cooled BTMS performance aims to help move towards the future of greener and more sustainable transportation and achieve more energy-saving, safer, and reliable Battery Electric Vehicles. Also, the work highlights the role of real-time optimization, which is an essential peculiarity in the context of the automotive industry that is developing as rapidly today as the ability to respond to the changing situation real-time would be defined as the main prerequisite to the potential success and further rise of BEVs.

3.1 Data Collection and Preprocessing

3.1.1 Description of Dataset

Any machine learning model ultimately depends on how well the data that are used to train and test the model are. The data set is a major factor in the given research, as it will be instrumental in the creation of predictive models to maximize the Battery Thermal Management System (BTMS) in the Battery Electric Vehicles (BEVs). The data that will be used in the study has the input features and target variables all of which are important in establishing the cooling efficiency of the BTMS as well as its capabilities of ensuring the best temperatures of the batteries.

The input parameters include operational parameters, i.e., speed of the compressor (V_{comp}), ambient temperature (T_0), and the rate of airflow (V_{air}), which act in connection to alter the thermal profile of the BTMS. These are the basic cooling system characteristics since the cooling capability is dependent on the speed of the compressor, ambient temperature will be the outside temperature conditions, and the flow rate of air will determine the rate at which heat has to be given out of the system. The performance of the BTMS parameters, which are the cooling capacity and the Coefficient of Performance (COP) are, on the other hand, the target variables.

- **Compressor Speed (V_{comp}):** It is measured in RPM (revolutions per minute) and this value sets the speed of movement of the refrigerant fluid throughout BTMS by the compressor. The speed at which the compressor is running is a direct indicator of the ability of the system to provide cooling since usually high speeds result in higher cooling abilities. The interaction between the speed and the cooling capacity of the compressor is however not linear since there are other factors about which the solution depends; these are the ambient temperature and the airflow rate.
- **Ambient Temperature (T_0):** Temperature of the environment within which an item is located is a major element in heat management. Such ambient temperatures impose a higher thermal load on the BTMS and the system needs greater cooling power. On the contrary, colder than normal temperatures can adversely affect the efficiency of the system since it might require excessive cooling to ensure that the battery is within the required temperature range for the battery.
- **Airflow Rate (V_{air}):** This is the frequency with which air passes through in BTMS which is measured in meters/sec (m/s). The rate of the airflow aids in cooling down the heat retained by the refrigerant and its effect on the cooling capacity is very critical. Improved cooling performance can be achieved with better airflow through but at some limit, the effectiveness will be negatively impacted.
- **Cooling Capacity and Coefficient of Performance (COP)** are the target variables, which depict the performance of the BTMS. The cooling ability is expressed in kilowatts (kW) and how many kilowatts the BTMS is capable of taking out of the battery pack. The small amount of useful cooling to the amount

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of energy the system uses, is a measure of how efficiently the BTMS is doing its job; this is the COP. The higher COP the more efficient the system would be hence using less energy to reach the proposed cooling.

This data plays a central role in the development of machine learning models to forecast these performance indicators given different circumstances. Proper estimation will enable a real-time optimization of BTMS in BEVs, providing proper cooling, and not consuming excessive energy.

3.1.2 Data Preprocessing

3.1.2.1 Data Cleaning

- **Treating Missing Data:** This is not unusual because in some records, some variables might not contain all the data in the dataset i.e., they are missing. The missing data can be caused by failure of the sensors, inadequate data entries and failures in the recording of the data. One can differentiate a few methods of managing missing data:
    - **Deleting the Rows that are Missing:** In case the missing values are few, and in the case where the values of the missing data are not expected to make significant differences in analysis of the whole data, then the rows with missing data are deleted.
    - **Dealing with Missing Values:** Where missing is a relatively high percentage of the data, imputation is used; this is either in the form of the mean imputation or regression-imputation. The mean imputation rests on substitution of missing values with the mean of the existing non-missing and the regression imputation seeks to estimate the missing values based on their relationship with other values.
- **Delete Duplicate:** There is always a possibility of having duplicate records and the same could be a result of having to record the same measurement more than once. These duplicates are capable of biasing model predictions hence they need to be discarded.

3.1.2.2 Normalization of Features

The normalization is done using Min-max normalization in which all features are rescaled to range $[0, 1]$:

$$X_{norm} = \frac{X - \min(X)}{\max(X) - \min(X)} \tag{1}$$

In this formula, every feature will be given the same significance in model training. Min-Max scaling makes sure the model is not biased to a character feature only because of that feature magnitude and it is especially important to such a model as Support Vector Machines (SVM) as they are also sensitive to the scale of the given input data.

3.1.2.3 Feature Engineering

- **Interaction Features:** There can also be non-linearity of relationship between some of the input variables e.g. compressor speed, airflow rate. In order to integrate these interactions, newly constructed features are made through product or a combination of the current features. As an example, a product of compressor speed and the rate of airflow can be critical to the cooling capacity that can be denoted in a new feature:

$$\text{Interaction Feature} = \text{Compressor Speed} \times \text{Airflow Rate} \tag{2}$$

- **Polynomial Features:** When no linear correlation exists between the features and the target variables then the polynomial functions may be applied to the features. As example, squared or cubed factors or variables of the input of the dependency, such as the ambient temperature or compression speed, may be used to capture non-linear dependencies.

3.1.2.4 Transformation of the data

The process of data transformation is included to change the distribution of the features or target variables in such a way that they fit the assumption of machine learning models. To illustrate, the feature distribution (compressor speed, to be precise) can be a much skewed one, and the model can hardly learn in such a fashion. To solve this a change (logarithmic transformation or square root transformation) is done with the skewed features making the value to become more normally distributed.

3.1.3 Outlier Techniques

An outlier is a data point which greatly differs to the rest of the data and it can greatly affect the performance of the model disproportionately.

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3.1.3.1 Outlier Detection

Statistical analysis can be used to detect outliers through use of statistical procedures, which include:

- **Z-Score:** Z-score shows the number of standard deviations a data point differs with the mean of the statistics. When the Z-score is more than 3 or less than -3, then it is usually an outlier.
- **Interquartile Range (IQR):** IQR technique is used to find an outlier using the gap between the 25th and 75th quartiles (Q_1 and Q_3). Any data which is less than $Q_1 - 1.5 \times \text{IQR}$ or greater than $Q_3 - 1.5 \times \text{IQR}$ is regarded as an outlier.

3.1.3.2 Outlier Removal

When outliers have been identified, the following ways can be used to manage them:

- **Outliers Removal:** In those cases where the outliers are found to be incorrect or not reflecting usual circumstances of operation, they are eliminated in the dataset.
- **Capping or Winsorization:** The outliers which are valid but extreme in their nature can be capped, i.e. they can be cut-off at a fixed lower maximum value / upper minimum value so that they cannot distort the results of the model.
- **Transformation:** A logarithmic or a square root transformation may minimize the effect of the outliers by squashing the values to the extreme.

3.2 Feature Engineering

Feature engineering gives set of methods to convert raw data into meaningful features that enhances the precipitous strength of the application. Such transformations are usually associated with the development of new features, coding of the existing ones, or alterations to represent the interactions between variables that are not obvious in raw data. This means that using these techniques, the model will be in a better position to capture the associations that exist in the data and this will eventually yield better predictions of the BTMS performance.

3.2.1 Features Interaction

With regard to optimization of the Battery Thermal Management System (BTMS) of the Battery Electric Vehicles (BEVs), it is important to understand the interaction among features and model them. The connection between the operational variables, which are compressor speed $\left(V_{comp}\right)$, ambient temperature (T_0), and airflow rate (V_{air}) and the target variables and cooling capacity and Coefficient of Performance (COP) cannot be always linear. The above features do interact in a complex fashion and their combined influence on BTMS performance should be clearly incorporated in the model to enhance better predictions.

Broadly speaking, the capacity of cooling and COP does not rely solely on each of this physiological uniqueness but as well as on a combination of two or more. For instance:

- The influence of compressor speed $\left(V_{comp}\right)$ on capacity of cooling could be greater at higher temperature of ambient (T_0).
- The rate of the airflow (V_{air}) might possibly be well-suited at certain compressor rates, since it improves the cooling capacity more proficiently.

In order to capture the interactions between features, interaction terms are introduced as part of feature set. Interaction terms are the collectivity of all the effects of the two or more features on the target variable. As an example, one defines the relationship between compressor speed $\left(V_{comp}\right)$ and airflow rate (V_{air}) described in a form of a new feature:

$$\text{Interaction Term } 1 = V_{comp} \times V_{air} \tag{3}$$

Similarly, the relationship between ambient temperature (T_0), and the compressor speed $\left(V_{comp}\right)$ is graphed as:

$$\text{Interaction Term } 2 = T_0 \times V_{comp} \tag{4}$$

These interaction terms assist the machine learning model to know how a combination of the features works on the system better than each feature being considered in isolation.
Also, higher-order interactions can be modeled by creating the polynomial features. For instance:

$$\text{Interaction Term } 3 = V_{comp}^2 \tag{5}$$

This is because this term in quadratic form represents the non-linearity between compressor speed and the cooling capacity. Even higher order term such as V_{air}^2, T_0^2 can be added to represent more complicated interactions.

3.2.2 Role of the Feature Interaction in Optimization of BTMS

In the case of BTMS in BEVs, the effect injected by the compressor speed $\left(V_{comp}\right)$ to the cooling capacity and COP does not remain unchanged, as it depends on other characteristics associated with the system such as ambient temperature (T_0) or airflow rate (V_{air}). Thus, these interactions of features enable the model to learn formulation of the systems behavior in varied states of operation.

As an illustration, ambient temperature is a dominant factor in establishment of the required amount of cooling. Increasing temperatures may require that the compressor speed is increased but the effect on compressor speed on cooling capacity may be decreased unless the airflow rate is sufficient so that it may increase heat dissipation. On the other hand, at reduced levels of ambient temperatures speed of the compressor might not require to be high although the flow of air might become notable.

Describing these interactions directly, the machine learning model will be able to predict the cooling capacity and COP of the system much better which results in BTMS optimization. This is quite crucial to real-time optimization where the system is forced to change the operational parameters of the systems dynamically as the environment changes, and the operations are changed.

3.2.3 Methods for Capturing Feature Interactions

- **Interaction Terms in the Feature Set:** The easiest way of including interaction is simply creating interaction terms, as was discussed above. Such terms are an impression of the aggregate influence of two or more features on the target variable.
- **Polynomial Features:** With polynomial transformations it is possible to recover interactions among features at a higher order. As an illustration, the squared term V_{comp}^2 enables the model to discover the non-linear connection amid the compressor speed as well as cooling capacity.
- **Radial Basis Function (RBF) kernel in SVM:** A strongly expressive kernel in support all four feature interactions in SVM index of radial basis function (RBF) kernels is the non-linear feature interactions. It is a mapping that occurs during the kernel function to a higher dimensional space as to make the interaction of the features in it linear so that the model can conveniently detect complex relationships.

3.2.4 Example of Feature Interaction in Practice

Practically, compressor speed $\left(V_{comp}\right)$ and ambient temperature (T_0) can be modelled as an interaction term in order to reflect their combined effect to the cooling capacity:

$$\text{Cooling Capacity} = f\left(V_{comp}, T_0, V_{air}, V_{comp} \times T_0\right) \tag{6}$$

This interaction factor unambiguously reflects the response of the cooling capacity to compressor speed variations that varies as a result of the ambient temperature.

3.3 Model Development

To achieve the development of the predictive model of optimizing Battery Thermal Management Systems (BTMS) in Battery Electric Vehicle (BEVs), machine learning algorithms and optimization techniques have to be incorporated. This model has mainly sought to estimate the cooling capacity and Coefficient of Performance (COP) under different working conditions such that the highest performance of this system is achieved. Here, the two fundamental algorithms adopted in the development of the model are described, i.e., Support Vector Machine (SVM) and Firefly Optimization Algorithm (FOA) to optimize hyperparameters.

3.3.1 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a great and extensively applicable machine learning algorithm that performs effectively in the classification as well as the regression problems. It is especially appropriate to the long-discrete problems in which the dependency of output and input variables is not linear. Here, the Support Vector Regression (SVR) will be utilized to envisage the cooling capacity and the Coefficient of Performance (COP) of the Battery Thermal Management System (BTMS) in the Battery Electric Vehicles (BEVs).

3.2.1.1 Concept and Working of SVM

The main idea behind SVM is that a hyperplane (or a decision boundary) is sought in high-dimensional space which best separates or fits the data. However, when dealing with regression, there is no attempt to classify the data, but instead, there is desire to locate a function that would predict continuous values with minimal errors. SVM tries to describe the relationship between input variables and target variables by estimating optimal hyperplane that has minimal error of prediction under a margin ϵ.

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Mathematically, SVR is to minimize the below optimization problem:

$$\min_{w,b,\epsilon} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \epsilon_i \tag{7}$$

Subject to the constraints:

$$\begin{gathered} y_i - w \cdot \phi(x_i) - b \leq \epsilon + \epsilon_i \\ w \cdot \phi(x_i) + b - y_i \leq \epsilon + \epsilon_i \end{gathered} \tag{8}$$

Where:

- x_i is the input of the i^{th} training case.
- y_i is the correct answer of the i^{th} training example.
- The mapping $\phi(x_i)$ is a non-linear projection of the input features into a high dimensional space (through the kernel function),
- w is perpendicular weight vector to a hyperplane,
- b is a bias (or an offset) term,
- The slack variables are ϵ_i, which are the measurements of the deviation to a margin
- The proposed regularization parameter is C, which determines the preference of margins and determines the complexity of a model.

3.3.1.2 Kernel Trick in Non-Linear Regression

The classic SVM model performs well relationship between features and targets is linear, in practice, like in the case of BTMS, the relation between compressor speed, ambient temperature, airflow rate, and the cooling capacity is nearly not linear. In this regard, the kernel trick is utilized. The use of kernel trick is given that the input data is mapped into feature space whose dimension is greater, where the correlation between the input quantities becomes linear and SVM is able to detect the linear hyperplane that is actually able to fit the non-linear data.

Radial Basis Function (RBF) kernel is the most popular kernel function in the SVR that calculates the similarity between two input vectors x_i and x_j in the transformed feature space:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \tag{9}$$

Where:

- The sum of the squared Euclidean distance between input vectors x_i and x_j is the squared Euclidean distance between them, i.e., $\|x_i - x_j\|^2$.
- The parameter σ is known as the width of the Gaussian, and this dictates how smoothly the kernel is.

Such a change allows SVM to learn extremely trivial relationships and non-linear depends between the input characteristics and the desired value.

3.3.1.3 Strengths of SVM Application in BTMS optimization

Application of SVR to predict cooling capacity of the BTMS and COP has some advantages, as follows:

- **Robustness:** SVM has low tendency to over-fitting, particularly in spaces of high dimension, and can deal with fairly small amounts of data, so it is suitable where the cost of gathering data is high or data is limited.
- **Non-Linear Modeling:** SVM with the use of the kernel trick has the capacity to model non-linear relationships that exist between the input data features and the target variables which is needed in the modeling of the BTMS since feature interactions such as compressor speed and airflow rate were found to be non-linear.
- **Generalization:** Unlike typical neural networks, SVM is meant to maximize the margin of the support vectors (that is, the data points nearest the decision surface) and this will allow the model to generalize better in terms of the unknown data.

3.3.2 Firefly Optimization Algorithm (FOA)

Optimization is very important in enhancing the performance of machine learning model. In the study, the use of Firefly Optimization Algorithm (FOA) has been utilized in optimizing the hyperparameters of the SVR model. FOA is a mating-swarming metaheuristic algorithm which was developed on the same pattern as that of the fireflies. The excellence of a solution is associated with brightness of a firefly and all the fireflies are pulled to the brightest (best) firefly so that the solution space is satisfactorily explored throughout the world.

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3.3.2.1 FOA Concept

FOA acts like a firefly that there will be many fireflies that correspond to the possibilities, which are the solutions to the optimization problem. The simple concept is that fireflies will be able to attract other brighter fireflies, and hence the algorithm will prefer those solutions which would have better performance (low error). The object of motion, fireflies, is oriented to brighter solutions on the basis of the following update equation:

$$x_i(t+1) = x_i(t) + \beta e^{-\gamma r^2}(x_j - x_i) + \alpha(rand - 0.5) \quad (10)$$

Where:

- $x_i(t+1)$ denotes a new location of the i^{th} firefly.
- The value of β is attractiveness of the firefly,
- γ is the coefficient of absorption, which regulates the speed of the light taking in,
- r is the distance that separates two fireflies,
- a is a randomisation factor, which assists in search space exploration.
- rand is a number between 0 and 1 which is randomly generated.

The brightness of the fireflies determines its movement which is determined by the fitness function of the optimization problem.

3.3.2.2 FOA for Hyperparameter Optimization

The Support Vector Machine (SVM) model is optimized using FOA in the enhancement of the hyperparameters of the model comprising of the Support Vector Machine (SVM) model. SVM needs the optimum values of:

- **C (Box Constraint):** Regulates the trade-off between both getting a low error on the training data and having a large margin. The higher is C the greater is the penalty for errors.
- **ϵ (Epsilon):** States the level of allowance of error in SVR. It refers to the deviation that is permitted among the predicted and actual values.
- **γ (Kernel Scale):** It regulates the spread of the Gaussian kernel. It establishes the breadth of an impact of one training sample.

The aim is to lower the Mean Squared Error (MSE) which is as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (11)$$

Where:

- y_i is the actual value,
- $\hat{y}_i$ is the predicted value,
- n is the number of data points.

3.3.2.3 The Benefits of FOA in Hyperparameter Tuning

The fact that FOA can effectively optimize hyperparameters is especially due to the fact that:

- **Global Search Ability:** FOA guarantees global search of the hyperparameter space thus evading the limitations of local optima which other optimization strategies easily fall into.
- **Scalability:** FOA can also be utilized in many machine learning models and optimization scenarios with ease, hence quite versatile.
- **Efficiency:** The algorithm is very fast to a desirable solution; therefore, it creates less pressure on the exhaustive grid search algorithms which are of great help; it saves on a large amount of computation space.

3.3.3 Model Training and Optimization

3.3.3.1 SVR Model Training

The following step, after the preprocessing of data and feature engineering, is to retrain the Support Vector Regression (SVR) model. The Radial Basis Function (RBF) kernel is used to train the SVR, because it can seek the complicated dependence of the input attributes on the target variables successfully. Model training engages the following steps of procedure:

- **Input Data:** Input data is the pre-processed and standardized data (compressor speed, ambient temperature and airflow rate) and the associated target vectors (cooling capacity, COP) to the SVR model.

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- **Hyperparameter Tuning:** The hyperparameters, which are C, ϵ, and γ are tuned via firefly optimization algorithm (FOA) in order to make sure that the model can generalize robustly that is, it can produce a small amount of prediction error.
- **Training Process:** The SVR model trains on the mapping between the input feature space and the output variables: it trains to find the optimal hyperplane in a high dimensional feature space. An aim is to reduce the error below the defined tolerance ϵ, as was stated previously in the SVR formulation.

3.3.3.2 Optimization of Hyperparameters Using FOA

The Firefly Optimization Algorithm (FOA) is used to obtain the optimum hyperparameter values C, ϵ, and γ. These parameters directly affect the functioning of the SVR model and the question of determining the optimal values of these parameters is also relevant because it helps to increase the accuracy of the predictions made with the help of the model adopted. The optimization process will consist in:

- **Initialization:** A bunch of fireflies is randomly generated and each of them represents one of the possible solutions (i.e. set of hyperparameters).
- **Evaluation:** The suitability of all fire flies is measured by calculating the MSE of SVR model corresponding to the hyper parameters.
- **Movement:** The fireflies fly to brighter (better) fireflies according the fitness function and the position of the fireflies is updated until convergence.
- **Convergence:** With a number of iterations, the fireflies reach the ideal combination of hyperparameters, so that the SVR model can run the best.

3.3.3.3 Real-Time Optimization

After training and optimization of SVR model, it is tested and applied to the real-time optimization. Operational conditions in the real-world applications are neither very stable nor entirely predictable. As an example, ambient temperature, compressor speed, and amount of airflow vary depending on the driving conditions and due to environmental aspects. In order to display optimal performance, the trained SVR is implemented to forecast cooling capacity and COP of the BTMS in real-time depending on such changing circumstances. Real-time Optimization:

- **Continuous Monitoring:** The system keeps the input features like speed of compressor, ambient temperature and rate of airflow continuously monitored.
- **Real-Time Prediction:** The SVR trained model uses updated inputs and gives predictions to the COP and cooling capacity as per the latest inputs data.
- **Dynamic Adjustment:** The system can dynamically adjust its parameters in real-time using the predicted values and thus makes sure that the BTMS is run at optimum performance in different conditions.

3.4 Model Evaluation

3.4.1 Mean Squared Error (MSE)

One of the most popular evaluation metrics of regression tasks in machine learning is called Mean Squared Error (MSE). It measures the variation between the actual and forecasted values, and it does this by averaging the squared deviations. The lower the MSE, the higher is the predictive power of the model is. MSE is an important indicator of the extent to which the model is accurate in cooling capacity and COP predictions of BTMS in the course of the application of varying conditions. The mathematical formulation for the MSE is already described in Equation (11).

Importance of MSE in BTMS Optimization: In BTMS optimization, the measure of optimality is to be able to predict the cooling capacity and the COP with a given degree of accuracy, in it, the value of MSE can tell us about the capacity of the model to be able to approximate the true behaviour of the system. A reduced MSE implies that the model is capable of forecasting cooling ability and COP with better chances, which is vital to streamline the system efficiency in Battery Electric Vehicles (BEVs) operating under different conditions of use. This measure is especially useful when comparing various models or hyper-parameters because it means the same thing as the amount to which a model can generalize to new data.

3.4.2 R-Squared (R^2)

Another useful metrics that will help in assessment of the performance of the regression models is the R-Squared (R^2). It shows the extent to which the model is useful in explaining variance of the target variable. R^2 gives one the measure of the proportion of variance in the dependent variable caused by the independent variables. The

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higher the value of R^2, the closer is the model fit to data, i.e., the greater is the extent the model can describe the variation in the output.
R^2 value is computed as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (12)$$

Where:
- y_i is actual value of the i^{th} observation,
- $\hat{y}_i$ is the estimated value of the i^{th} observation,
- $\bar{y}$ is the average of the values as they really are,
- n is a total number of data points.

R^2 Interpretation:
- $R^2 = 1$: The model is explaining the whole variance in the target variable and in this case, there is zero error in the model output.
- $R^2 = 0$: The model does not explain any variance so it is useless to use the model to make predictions because they are no better than just predicting the mean of the variable we are trying to predict.
- $R^2 < 0$: It means that the model is inferior compared to a model that just predicts the mean of target variable.

3.4.3 Cross-Validation
In machine learning, cross-validation is a critical mechanism of a machine learning model to evaluate the extent to which it generalizes (can also be called generalisation or generalization) on an unseen dataset. It prevents overfitting and allows having a good model on the untested data. In cross-validation, it is split with a number of subsets and the model is fit on several of the subsets and tested on the other ones.

K-Fold Cross-Validation: Within the K-Fold Cross-Validation the data is randomly divided into K parts or folds that are roughly of the same size. K times and each time the model are trained with $K - 1$ folds used to train the model with the rest of the folds being used to test the model. The measure of performance (MSE or R^2) is computed across all K iterations so that a more definitive indication of performance is obtained. The methodology also contributes to the fact that all the data points will be used to train and test, thus eliminating the bias.
- Partition the data set to K equal segments (folds).
- To every fold, use the rest of the $K - 1$ folds to train the model and use the current fold to test it.
- Write down the performance measure (e.g. MSE or R^2) of any sweep.
- Then calculate the mean performance in each of the folds in order to obtain an accurate estimate of generalization power of the model.

Cross-Validation Mathematic Formulation: Suppose that MSE_k is the mean squared error of fold k, then the average of these MSEs whose number is K can be used as an estimate of the overall result of the model:

$$MSE_{avg} = \frac{1}{K}\sum_{k=1}^{K} MSE_k \quad (13)$$

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4. RESULTS AND DISCUSSION

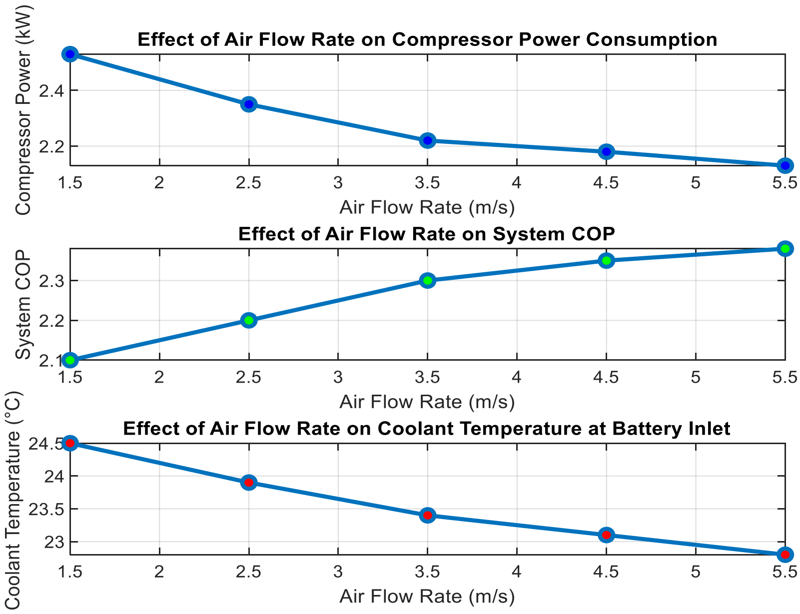

Figure 2: Graphical Comparison for the Effect of Air Flow on Compressor Power Consumption, System Cop and Coolant Temperature at Battery Inlet

As shown in Figure 2 in a graphical and detailed manner, the flow rate of air has impact on three important parameters that include power consumption of compressor, system Coefficient of Performance (COP), and the coolant temperature at the battery inlet. These statistics indicate a definite tendency: the more the air flows, the less the power overhead the compressor spends, and it means that the thermal system of control is performing more efficiency. The reason behind this is that the improved air movement will help in heat dissipation thus reducing the extra effort demanded to the compressor. At the same time the COP of the system also increases with increase in air flow and that implies the system will use less energy and dissipate more heat. Also, better airflow helps to ensure that the coolant temperature at the battery inlet is relatively lower, thus preventing overheating of battery, which subsequently enhances the operation and life of the battery. Based on this analysis, this paper has found that air flow has been of great importance when it comes to maximizing on BTMS since improving airflow within Battery Electric Vehicles (BEVs) is beneficial to energy performance, and temperature management.

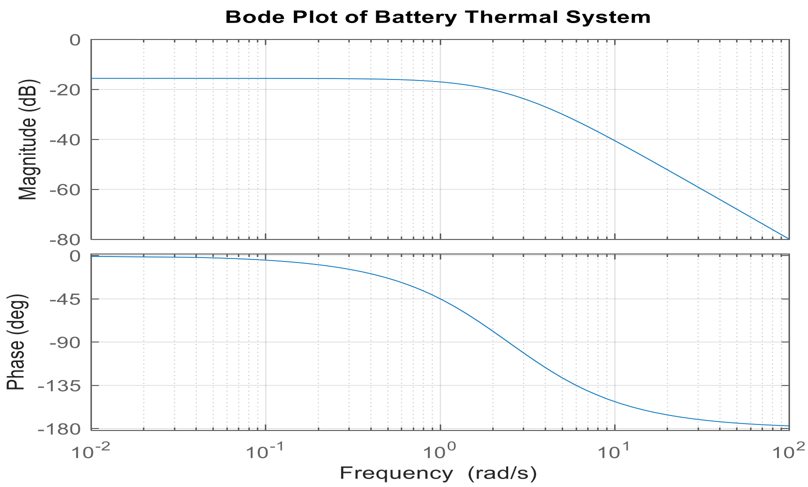

Figure 3: Bode Plot of Battery Thermal System

The frequency response of the battery thermal system as shown in Figure 3 according to a Bode plot (with the gain and phase plot) that depicts the gain and phase of the system referred to frequency. The gain plot gives a measure of the effectiveness of the system to amplify or attenuate thermal fluctuations when these vary with frequency and the phase plot gives the response of the thermal system to the frequency variation. Constant and consistent increase within a wide range of frequencies would mean that the thermal system is able to retain a steady performance even when the conditions are varied. In the present case, the phase plot should be as flat as possible at low frequencies implying that the system would react well to changes in temperature without much noticeable delays. With the rising frequency, there ought to be a slight shift in the phases as would be the case with any system showing a lack of quick responses to dynamic adjustments. In general, Bode plot plays a critical role in the determination of the thermal system stability as well as the sustenance of its optimal operation in the real working conditions which is prone to temperature variations.

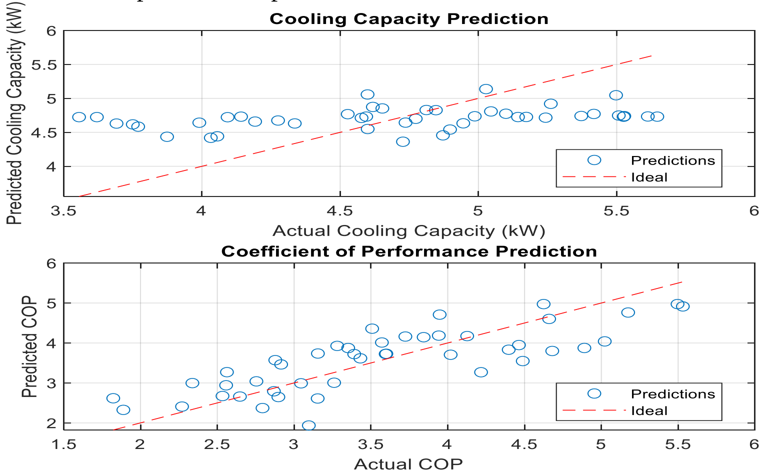

Figure 4: Graphical Analysis of Cooling Capacity Prediction and Coefficient of Performance Prediction

Figure 4 gives the difference between the expected cooling capacity and Coefficient of Performance (COP) of the BTMS. Cooling capacity is also an important parameter that measures the effectiveness with which system can absorb the heat in battery. The graph indicates the positive correlation between the predicted cooling capacity and COP that indicates that the machine learning model is predictable in relation to the system performance that is depicted in the graph. The COP depends on the cooling capacity hence, the higher the cooling capacity the better the COP implying that the system is more energy efficient and is able to pump up a better cooling percentage using a comparatively lower energy. The fact that these two variables correlate well evinces the fact that the model can be trusted with providing predictions about the performance of this system when operated under different loads and also adds to the fact that hopefully, the prediction will bring into play the accuracy required when aiming to optimize BTMS in BEVs. The predictions make the system to be effective and flexible to fluctuations in the real-time of changes in the environmental and functional conditions.

The graphical representation of the frequency response of the battery thermal system is shown in Figure 5 where the frequency response was analyzed into three whole parts (a) the Bode magnitude plot containing SVM predictions, (b) the Bode phase plot and (c) the SVM predictions. The magnitude plot demonstrates system gain responsive to the change in frequencies and SVM predictions are plotted which help in comparing the behavior of the actual system with that which is predicted. When the SVM estimations correspond well with the real data, then the machine learning algorithm can be considered pretty accurate to predict the thermal behavior. The phase plot is an indication of the alteration of the phase shifts with respect to frequency giving an indication in the stability of the system. Large phase margin over all frequencies implies that the thermal system is well tuned and has the capability of managing temperature changes. The SVM estimations also confirm that the system is capable of predicting cooling capacity or COP using frequency data such that the system can achieve maximum level of thermodynamic performance in real-time.

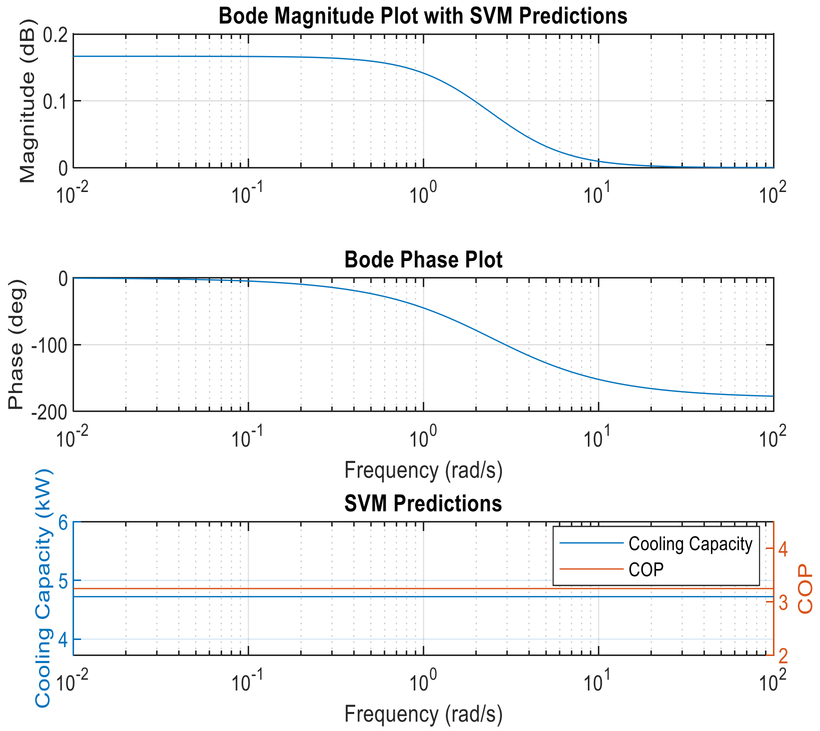

Figure 5: (a) Bode Magnitude Plot with SVM Predictions (b) Bode Phase Plot (C) SVM Predictions

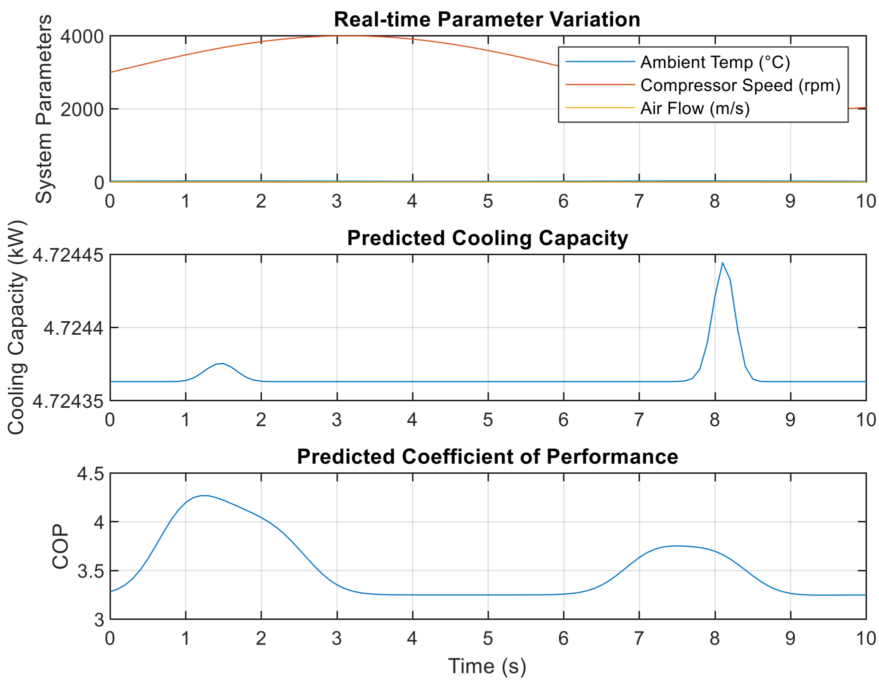

Figure 6: (a) Real Time Parameter Variation (b) Predicted Cooling Capacity (C) Predicted Coefficient of Performance

Figure 6 shows the real-time fluctuation of the main parameters, i.e. the compressor speed, the ambient temperature, and the airflow rate, as well as the estimated cooling capacity and Coefficient of Performance (COP). This value reflects the dynamic character of BTMS, which is based on the fact that the system continuously adapts to changes of operating conditions in order to ensure optimal temperatures setting. Since there is a drop and rise in the compressor speed and airflow rate because of the different driving conditions or environmental conditions, the cooling capacity and predicted COP should also be varying. It means that this prediction is real time, and it signifies that the system will constantly be optimizing itself with the aim of cooling its environment without wasting a lot of its energy. The real-time prediction capability of the cooling capacity and COP with the machine learning model is vital towards adapting to new circumstances in BEVs. Such flexibility assists in enhancing the overall efficiency of the system so that the BTMS would be operating in the most efficient manner in different operation conditions.

Table 1: Model Performance and Optimal Operating Point

Parameter	Value
MSE (Cooling Capacity)	0.3012
R^2 (Cooling Capacity)	0.1346
MSE (COP)	0.3109
R^2 (COP)	0.6361
Compressor Speed	2000 rpm
Ambient Temperature	34 °C
Air Flow Rate	5.0 m/s
Predicted Cooling Capacity	4.73 kW
Predicted COP	5.34

Table 1 provides the index of performance and optimal operating point of the Battery Thermal Management System (BTMS) model. The table here depicts MSE and R^2 of both, cooling capacity prediction and coefficient of performance (COP) prediction. The MSE of cooling capacity is = 0.3012 kW 2, that is the mean squared error of predicted and actual cooling capacity. R^2 value of cooling capacity is 0.1346 and this shows that there will be a relatively low correlation involving prediction and actual values which means that there is an opportunity to increase the accuracy of the model. In the case of COP, the MSE value of 0.3109 and R^2 of 0.6361 would indicate that it fits better than that of cooling capacity prediction indicating that the COP model is relatively more dependable. The table also contains the number of the most favorable point of working of the system which is established in accordance with the predictions carried out by the model. The best setting in this point is compressor speed of 2000 rpm, ambient temperature 34 C and air flow rate of 5.0 m/s. These parameters will provide the estimated cooling power of 4.73 kW and an estimated COP of 5.34 which means that such settings will maximize the BTMS performance. With this table, in one overview, it is possible to see the general performance of the model in its prediction aspects as well as the conditions under which it works during optimal thermal management in Battery Electric Vehicles (BEVs).

5. CONCLUSION

In this paper, the new idea of handling Battery Thermal Management Systems (BTMS) in Battery Electric Vehicles (BEVs) to optimize this technology using machine learning and optimization algorithms is brought to light. Real-time environments and operational conditions change and Support Vector Machines (SVM) and Firefly Optimization Algorithm (FOA) integration enables real-time adaptation to the environment as well as operational input to maximize the performance and life of the BEV battery. Its new methodology is more cost-effective and efficient as compared to the conventional experimental technique and shows potential in the calculation of cooling capacity and Coefficient of Performance (COP). This study leads to the progress of sustainable and energy-efficient transportation since many opportunities exist when utilizing machine learning in the process of optimizing thermal management systems in BEVs.

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