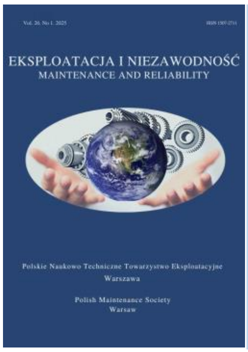

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Temperature Prediction and Performance Comparison of Permanent Magnet Synchronous Motors Using Different Machine Learning Techniques for Early Failure Detection

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Highlights

- KNN Regressor achieved 99.65% training and 98.72% test accuracy for PMSM temperature prediction.
- Machine learning models replace costly sensors, enabling low-cost, real-time motor temperature monitoring.
- Model validation shows RMSE 2.16, R2 score 98.72, and CV R2 97.77%, proving practical effectiveness.

Abstract

Electric motors are increasingly used in various products, including turbines and electric vehicles. Precise temperature measurement is essential for the safe operation of a Permanent Magnet Synchronous Motor. Direct temperature detection of the permanent magnet and stator involves significant costs and hardware requirements. To overcome these challenges, Machine Learning models can eliminate the need for specialized sensors. This study used four diverse regression algorithms: Linear, K-Nearest Neighbor, XGBoost, and AdaBoost. The objective of this study is to model a Permanent Magnet Synchronous Motor used in electric vehicles and predict the temperatures of some of its parameters. The K-Nearest Neighbor Regressor outperformed the other algorithms, achieving a training accuracy of 99.65%, test accuracy of 98.72%, root-mean-square error of 2.16, R^2 score of 98.72, and Cross-Validation R^2 of 97.77%. These results enable low-cost, real-time temperature monitoring of electrical machinery, enhancing power density, safety, and efficiency.

Keywords

machine learning, electric motors, temperature prediction, AdaBoost, K-Nearest Neighbor

1. Introduction

The global demand for renewable energy production and electrification of transportation is increasing, largely due to the need for nations to reduce harmful emissions and meet climate change targets [1-3]. Since electric machines are essential to all of these industries, they must be used effectively and efficiently. Electric machines come in a variety of forms for both transportation and renewable energy applications. The most widely used type of synchronous motor is the permanent magnet synchronous motor (PMSM) due to its high power density, high efficiency and controllability [4-6]. Therefore, the main topic of this thesis is PMSM. The main limitation is the temperature limit of the motor, which must be respected in order to maximize the power density and make the best use of electric machines in these applications. In order to avoid internal short-circuits caused by stator overheating and rotor demagnetization, these limitations must be respected.

The PMSM is the recommended option for automotive motor applications because of the need for high power and torque densities with good efficiency. The enormous thermal stress on failure-prone components such as permanent magnets, which are susceptible to irreversible demagnetization, and stator winding insulation, which is prone to melting, must be

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considered in order to realize the full potential of the motor [7]. The complex internal structure and difficult accessibility of the rotor in electric motors make it economically and technically infeasible to apply sensor-based temperature measurement to the rotor part, even if it allows accurate evaluation of the thermal condition. Stator temperature monitoring is typically accomplished with thermal sensors that are permanently mounted in the stator. This avoids the need to replace the sensors, even in cases where their performance gradually deteriorates. As competitive pressures continue to drive down production costs, there is commercial interest in researching sufficiently accurate real-time temperature predictions [8].

Thermodynamic theory is rarely used in traditional thermal prediction systems, which often rely on thermally sensitive machine characteristics. To determine internal resistances or magnetization levels related to material temperature, signal injection and flux observers are used [9]. However, since both approaches are sensitive to changes in machine parameters during production, signal injection has the potential to increase machine losses and introduce estimation errors. As a result, there is increasing interest in data-driven methods that parameterize computationally lightweight models using empirical data. In particular, these methods use low-rank data-based machine learning (ML) architectures.

It is well known that neural networks are universal generalizers, capable of adapting to progressively higher levels of complexity according to the requirements of the application platform [9]. State-of-the-art methods for classification and prediction performance include Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and regression prediction algorithms, especially in the context of sequence learning tasks. The core idea is to use only experimental data to parameterize neural networks so that their expressive potential can be exploited without the need for domain expertise. Neural networks have been used for PMSM temperature prediction in previous electrical machine research [10]. These networks demonstrated performance comparable to established real-time methods, such as Lumped Parameterized Thermal Networks (LPTNs), when tested on low-dynamic test bench data. However, the effectiveness of these networks was found to be limited to flat architectures, and research was limited to iterative structures.

The main motivation of this work is to apply machine learning techniques to overcome the limitations of traditional methods for temperature prediction of electric motors and to obtain more accurate predictions. This study aims to develop more reliable and efficient models for temperature prediction of internal components of electric motors. The techniques used are expected to predict the temperature in electric motors in real time and prevent safety hazards. Therefore, a detailed analysis and optimization of the techniques in this area is carried out in our study.

This study is based on the global need for increased renewable energy generation and electrification of transportation to reduce harmful emissions and meet climate change targets. Effective and efficient use of electric motors, especially PMSMs, is critical. However, thermal stress from high power and torque densities in PMSMs can lead to component failure, and traditional sensor-based temperature monitoring methods are often inadequate due to the complex internal structure of the rotor and economic limitations. Therefore, there is a need for accurate and cost-effective motor temperature estimation. Machine learning techniques can quickly and accurately model the thermal characteristics of motors, overcoming the limitations of physical sensors. In this study, regression algorithms Linear Regression, K-Nearest Neighbor (KNN) Regressor, XGBoost Regressor, and AdaBoost Regressor are used to predict fluctuating thermal time series in PMSMs. Extensive hyperparameter search and feature engineering were performed to improve the accuracy of the models. The goal is to improve motor temperature prediction using machine learning tools, facilitate real-time simulation of electrical equipment thermal characteristics, and increase power density in various sectors by reducing the thermal margin during operation.

A brief overview of the issue is provided in Section 1 of this paper. The paper is divided into the following sections. The work done to forecast the temperature of electric motors is contained in Section 2. The materials and techniques needed for the applications are in Section 3, and the results and discussion are in Section 4. Future work and conclusions are presented in Section 5.

2. Literature Review

Temperature prediction of the internal components of electric motors is a critical element in ensuring motor performance and safety. Traditional methods are often complex, costly, and require extensive engineering knowledge. In recent years, the use of machine learning and deep learning techniques has played an important role in improving the accuracy and efficiency of these predictions. The existing literature on electric motor temperature prediction covers the application of various machine learning methods. In this section, we present some of the studies in the literature. We also discuss the gaps in the literature and the objectives of our work.

Real-time model development has historically been aided by empirically fitted models. When evaluated on a PMSM, Wallscheid and Backer, for example, showed how particle swarm optimization could modify an LPTN's parameters, producing one of the most accurate models in the literature, as Kirchgassner et al [11] showed. However, the development of such an LPTN requires a large amount of domain knowledge and engineering work. Therefore, supervised machine learning-based data-only models provide a compelling remedy.

To precisely forecast the thermal stress of motors, Kirchgassner et al. carried out a thorough investigation of machine learning models [12]. They investigated the efficacy of several methods, such as neural networks (NN), random trees, KNN, and support vector machines (SVM). The research showed that even with high dynamic driving cycles, temperature profiles could be predicted by traditional supervised learning models with a respectable level of accuracy.

Concurrently, there has been a concentrated attempt to use the potential of Deep Neural Networks (DNNs) to process sequential data, specifically concerning the internal element temperature of PMSMs. To forecast solar power output, Kasburg et al. employed a Long Short Term Memory (LSTM) neural network, which produced a notable improvement over earlier approaches [13]. To estimate the temperature of a reheater system, Gui et al. used a DNN-based model with multi-step feature selection and a Genetic Algorithm (GA)--based solution [14]. Wallscheid et al. used particle swarm optimization to identify appropriate hyperparameters while examining the use of Recurrent Neural Networks (RNNs) for precise temperature prediction in PMSMs [10].

Another approach involves Temporal Convolutional Networks (TCN), as utilized by Kirchgässner et al., achieving a Mean Average Squared Error (MA-MSE) of 3.04 $°C^2$ [15]. Lee et al. proposed a nonlinear auto-regressive exogenous (NARX) based Feed-Forward Neural Network (FNN) to predict the temperature of the permanent magnet and stator winding in PMSMs, asserting that NARX structures provide superior results when the input-output relationship is known compared to RNN and LSTM-based models [16].

Several studies have explored the accuracy of Random Trees, Multilayer Perceptron (MLP) neural networks, K-Nearest Neighbors, Ordinary Least Squares (OLS), support vector regression, and random trees [17]. OLS and MLP models demonstrated excellent accuracy despite their simplistic algorithms, and the prediction accuracy has improved significantly due to sophisticated neural network topologies. Convolutional neural networks (CNN) have shown robust results, approaching LPTN accuracy, although they come with the drawback of a large number of internal weights and longer tuning time [18].

The latest advancement in ML architectures is the Thermal Neural Network (TNN), merging the concepts of LPTNs and universal differential equations, demonstrating top-tier performance among all modeling methodologies [19]. However, the TNN requires substantial adjustment and is anticipated to have similarly long inference times, although no specific data is provided.

The motivation of this work is to apply machine learning techniques to overcome the limitations of traditional methods in temperature prediction of electric motors and to obtain more accurate and reliable predictions. Temperature prediction of electric motors is critical to improve the performance and safety of the motor. In particular, temperature prediction of the internal components of PMSM motors is of great importance in automotive and renewable energy applications that require high power and torque density. The objectives of the research are:

- To perform temperature prediction of internal components of electric motors using machine learning methods.
- Overcome the cost and accessibility challenges of traditional sensor-based temperature measurement methods.

- Improve the performance and efficiency of electric motors by providing highly accurate temperature prediction.
- Improve the thermal management systems of electric motors through real-time temperature prediction, creating safer and more efficient systems.

The contribution of this work to the literature is the effective application of machine learning (ML) based methods for temperature prediction of electric motors, especially PMSM, which are widely used in automotive and renewable energy applications due to their high power density and efficiency. In this study, four different regression algorithms (Linear, K-Nearest Neighbor, XGBoost, and AdaBoost) are used to predict motor temperatures in real-time as an alternative to the cost and accessibility challenges of traditional sensor-based measurements. These methods provide high accuracy in temperature prediction, while offering low cost and real-time monitoring. In particular, the superior performance of the KNN regressor compared to other algorithms proves the applicability and effectiveness of machine learning tools in thermal management systems. In this way, thermal analysis of electrical machines can be accelerated to increase power density and efficiency, contributing to the development of safer and more efficient systems in the renewable energy and transportation sectors.

3. Material and Method

In this study, ML techniques will be used to estimate the parameters of Permanent Magnet Synchronous Motors. Results are obtained by optimizing four different regression models. For the study, the open source dataset shared by the LEA department of Paderborn University for PMSM is used. This section describes the regression models used, the dataset and model validation.

Regression is one of the most effective methods in machine learning for examining the relationship between independent variables and the dependent variable. As a predictive modeling technique, regression uses algorithms to predict continuous outcomes based on this relationship. By understanding how independent variables affect the dependent variable, we can predict outcomes with considerable accuracy. In the context of machine learning, regression analysis plays a critical role in the development of predictive models [20, 21]. It helps predict and predict outcomes by fitting a line of best fit to the data points. The best-fit line is determined by minimizing the distance between each data point and the line itself. This process is fundamental to supervised machine learning, where the primary applications are regression and classification. While regression predicts continuous outcomes, classification assigns objects to categories based on learned attributes. Both tasks involve predictive modeling and rely on labeled input and output training data to function effectively.

For a regression model to accurately predict outcomes, it must understand the relationship between the features and the outcome. This understanding is developed using labeled training data that guides the model in learning this relationship. Once trained, the model can identify gaps in historical data, predict future trends, and predict outcomes from new, unseen data. Thus, regression analysis not only helps understand the relationship between multiple independent factors and the dependent variable, but also trains models to predict specific trends and outcomes based on that understanding. This methodological approach underscores the importance of using labeled data to teach models the intricate relationships within the dataset to ensure accurate and reliable predictions.

3.1. Linear Regression

The relationship between a dependent variable and one or more independent factors (predictor variable) can be modeled statistically using a linear regression model.

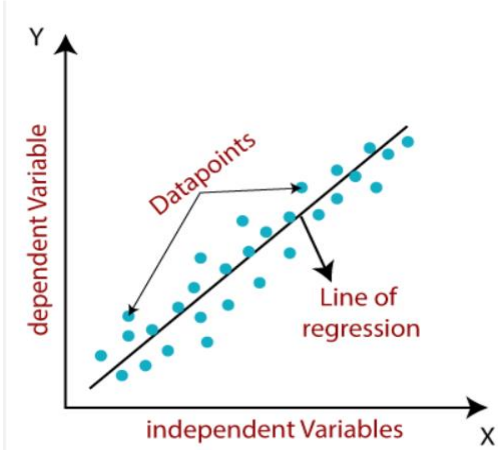


Figure 1. Linear Regressor plot.

Finding the linear equation that best captures the relationship between the variables is the primary goal of linear regression [11]. The linear equation is expressed as follows:

$$Y = b_0 + b_1X_1 + b_2X_2 \dots + b_nX_n \quad (1)$$

Where Y is the response variable, X_1, X_2, X_n, predictor variables, b_0 y-intercept (constant term) and b_1, b_2, b_n coefficients representing the slope of the regression line.

The coefficients are estimated by a method that minimizes the squared differences between the predicted values and the actual values. This process is often referred to as the least squares method. Linear regression is used for a variety of purposes, including predicting outcomes, understanding the strength and direction of the relationship between variables, determining the importance of predictor variables in explaining the variability of the dependent variable. It serves as a fundamental tool in statistics, machine learning and data analysis. However, the assumptions of linear regression, such as linearity, independence, homoscedasticity and normality, must be considered and verified for the model to provide reliable results [22]. A visualization of linear regression is presented in Figure 1.

3.2. K-Nearest Neighbor Regressor

K-Nearest Neighbors A machine learning approach called a regression is used to address regression problems. This algorithm makes predictions using the average of k-nearest neighbors around data points. KNN Regressor is particularly suitable for regression analysis [23]. An important parameter that determines the performance of the KNN Regressor is the k value. This value represents the number of neighbors to be used in each prediction. When choosing the value of "k", it is important to check the tendency of the model to overfit or underfit. The KNN Regressor is known for its ability to understand local structures and complexities in the dataset. However, with large datasets and high-dimensional feature spaces, the computational cost may increase. It can also be sensitive to noise in the dataset. This algorithm can be used to understand whether there is a distinct structure or pattern in the dataset, but it is important to carefully consider the characteristics of the dataset and the parameters of the model before using it. Figure 2 shows the K-Nearest Neighbor Regressor plot.

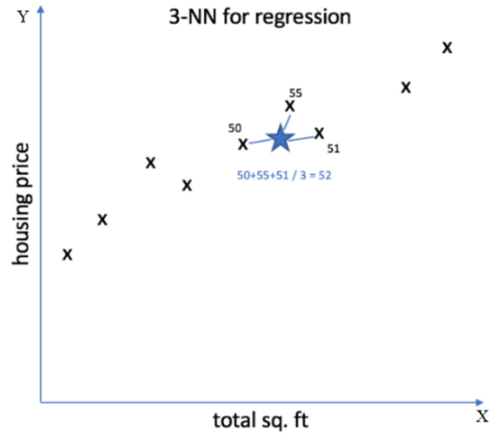


Figure 2. K-Nearest Neighbor Regressor plot

3.3. XGBoost Regressor

XGBoost (Extreme Gradient Boosting) Regressor is a potent machine learning algorithm that is a member of the ensemble learning technique family.

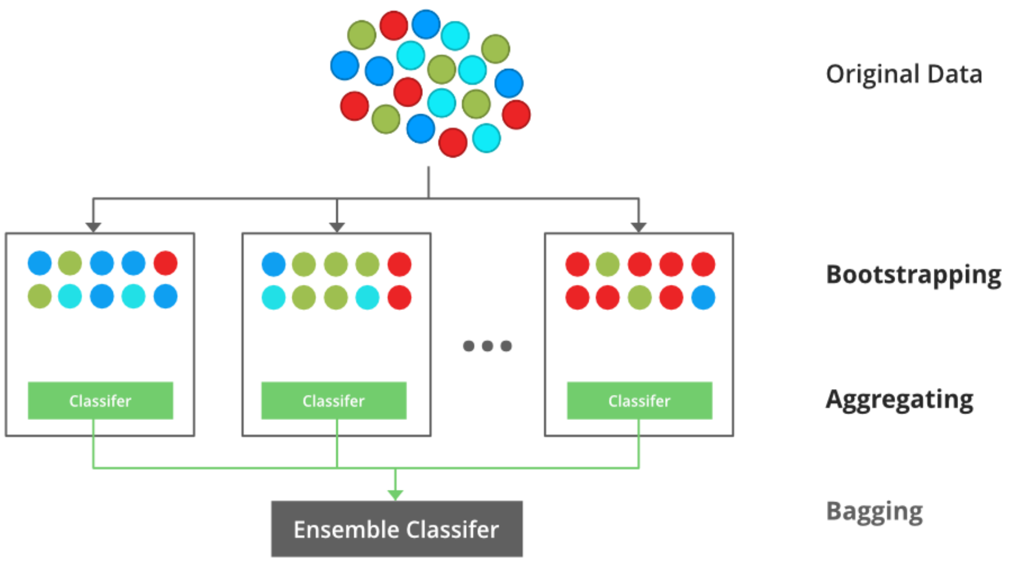


Figure 3. XGBoost Regressor example schematic.

It is made especially for regression issues when the goal is to forecast a continuous output variable. An improvement on the Gradient Boosting method, the XGBoost Regressor is renowned for its accuracy, efficiency, and capacity to handle complex data relationships [24]. To use the XGBoost Regressor effectively, practitioners often perform hyperparameter tuning to find the optimal set of parameters for specific regression tasks. XGBoost has become the algorithm of choice in many machine learning applications, especially where accurate and interpretable regression models are needed. Figure 3 shows an example schematic of the XGBoost Regressor.

3.4. AdaBoost Regressor

AdaBoost Regressor is an adaptation of AdaBoost, one of the ensemble learning methods, for regression problems. This algorithm aims to combine weak regression models to create a stronger regression model [25]. The AdaBoost Regressor is often preferred for its robustness to noise in datasets, high generalization ability and low tendency to over-fit. However, it can be sensitive to over-tuning, so proper hyperparameter tuning is important. Figure 4 shows a diagram of the AdaBoost Regressor.

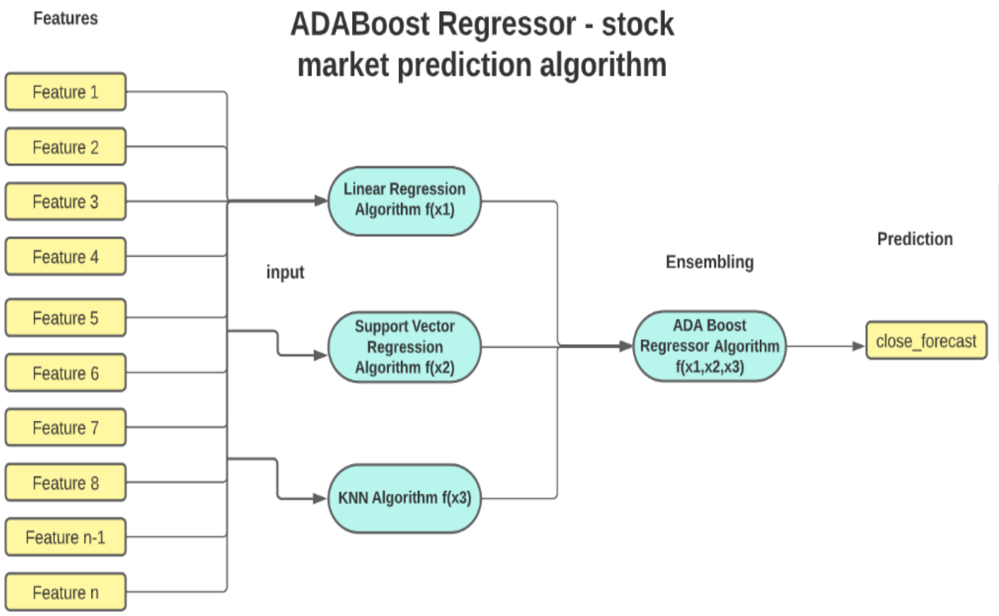


Figure 4. AdaBoost Regressor.

3.5. Model Training

The models were trained with the SciKit Learn package for Python's Linear-Regression, K-Nearest Neighbor Regressor, XGBoost Regressor, and AdaBoost Regressor classes. A random 30-70% split of the dataset for training and testing was applied by applying hot-code coding to qualitative features such as PMSM parameters, stator, rotor, magnet and body style. For regression learning techniques, validation was performed for each regression class.

3.6. Model Validation

The evaluation of the model was performed using the root-mean-square error (RMSE) and the expression is as follows [18]:

$$RMSE = \frac{\sqrt{\sum_{i=1}^{m} \hat{y}_i - y_i}}{m} \tag{2}$$

It's here, $\hat{y}_i$ and y_i stand for the expected and actual values of the model, respectively, while m denotes the total number of observations or data points.

3.7. DataSet

The University of Paderborn's LEA department has gathered sensor data from a PMSM that is utilized in a test bench. This dataset includes a range of data measuring motor behavior such as voltages, currents, motor speed and torque under various driving cycles. The dataset consists of multiple measurement sessions lasting several hours. Pre-planned driving cycles that represented a reference motor speed and torque were used to excite the motor. Because of a typical control method, the resulting currents and voltages are meant to follow the reference speed and torque. The torque and motor_speed columns show the outcomes of this method. This dataset provides a valuable resource for researchers and engineers to study the behavior of PMSMs under various operating conditions and to develop efficient control strategies for these motors [26]. In addition, other information in the dataset is shown in Table 1.

Table 1. Descriptions of the parameters in the dataset [26].

Value	Description	Unit	Range
u_q	Voltage q-component measurement in dq-coordinates	V	-25.3 - 133
coolant	Coolant temperature	°C	10.6 – 102
stator winding	Stator winding temperature measured with thermocouples	°C	18.6 – 141
u_d	Voltage d-component measurement in dq-coordinates	V	-132 - 131
stator tooth	Stator tooth temperature measured with thermocouples	°C	18.1- 112
motor_speed	Motor speed	Rpm	-276 – 6000
i_d	Current d-component measurement in dq-coordinates	A	-278 – 0.05
i_q	Current q-component measurement in dq-coordinates	A	-293 - 302
pm	Permanent magnet temperature measured with thermocouples and transmitted wirelessly via	°C	20.9 – 114
stator yoke	Stator yoke temperature measured with thermocouple	°C	18.1 - 101
ambient	Ambient temperature	°C	8.78 – 30.7
torque	Motor torque	Nm	-246 - 261

4. Results and Discussion

In this section, studies were performed on our dataset with the methods mentioned in the materials and methods section. The results were evaluated and compared with each other. The limitations of the study and future work are discussed.

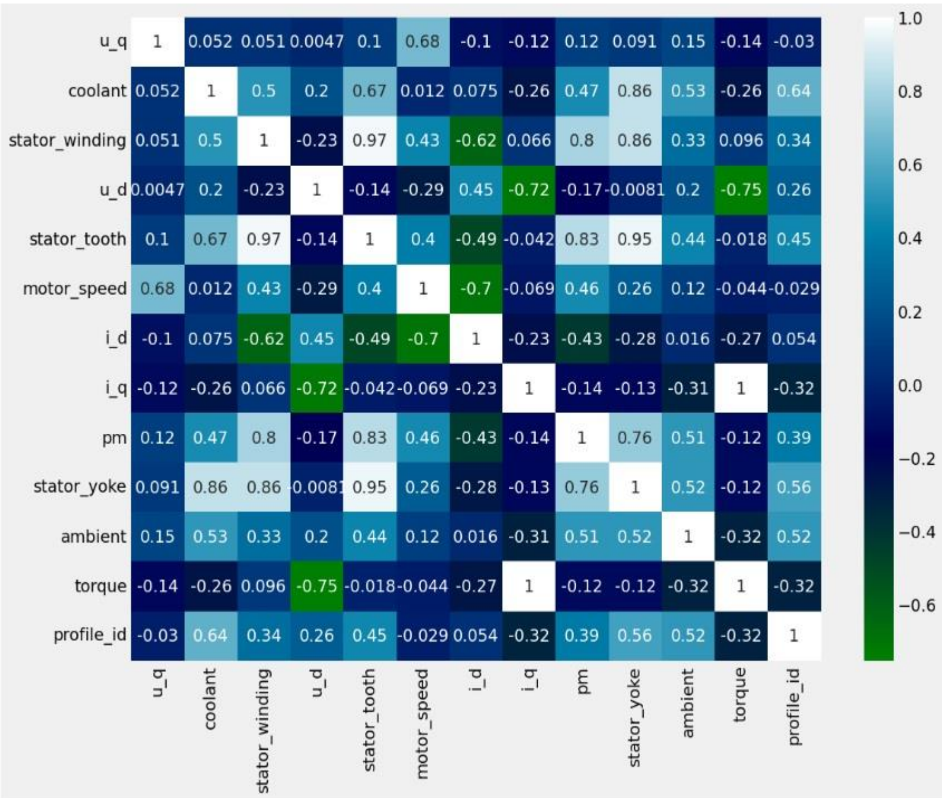


Figure 5. Heat map correlation of all parameters.

Temperature prediction of electric motors using machine learning has found significant application in industrial processes. Machine learning algorithms can predict the temperature state of the motor by analyzing a number of variables such as the operating state of the motor, load conditions and environmental factors. These predictions can provide preventive maintenance by detecting problems such as motor overheating or performance degradation in advance. Furthermore, temperature predictions can optimize operating costs by improving energy efficiency. Temperature prediction of electric motors by machine learning plays an important role in industrial applications by providing reliability and efficiency gains in smart manufacturing processes.

In order to enhance comprehension of the dataset's structure, a heatmap was created by calculating the correlation between every characteristic and visualizing it, as illustrated in Figure 5. Notably, there is a one-to-one association between the two properties, torque and i_q. High correlation values result from the near closeness of specific elements in the PMSM's internal structure, which causes them to undergo similar thermal stress.

Pm, stator_yoke, stator_tooth, and stator_winding are the motor's outputs. These stand for the temperature of the stator winding, PMSM rotor, stator yoke, and stator tooth, in that order. Figure 6 shows the matrix showing the relationship between these parameters.

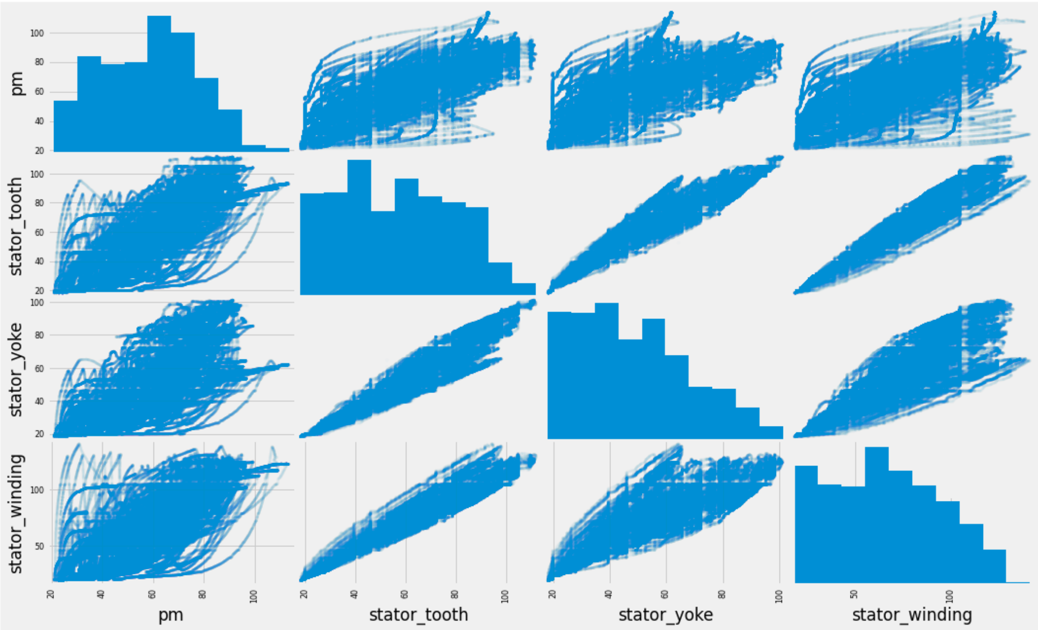


Figure 6. Relationship matrix between pm, stator_tooth, stator, yoke and stator_winding .

Figure 6 is a matrix showing the relationships between the different components in the PMSM. This matrix describes the relationships between pm, stator_tooth, stator_yoke and stator_winding. The relationship matrix in Figure 7 visualizes the thermal and electrical connections between these four components. This matrix shows how the temperature and electrical behavior of each component interacts with the other components. For example, the stator_tooth temperature is directly related to the stator_winding temperature because electric current causes heating as it passes through these windings. Similarly, pm temperature can be related to stator_tooth temperature because magnetic flux circulates between these components. This type of relationship matrix provides critical information to optimize the thermal management of the motor. Accurately monitoring and controlling the temperatures of related components can improve the performance and reliability of the motor. Using this matrix, it may be possible to better understand the thermal stresses in the PMSM and predict potential failures.

The torque-speed parameters of a typical measurement cycle from the experimental dataset are displayed in Figure 7. Specifically, the test profiles utilized for additional comparisons are included in this test set.

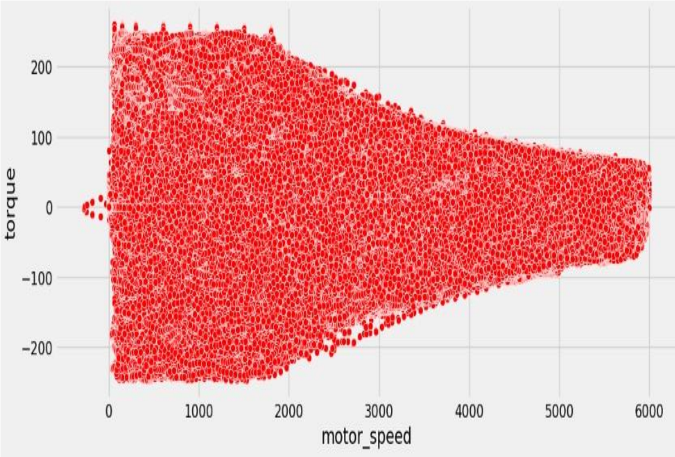


Figure 7. Features of a representative measuring loop's torque-speed relationship.

Tooth temperature, yoke, and stator winding considerably correlate with one another. This is because the stator winding is wound around the stator tooth which is connected to the stator yoke. In order to better understand the relationship between the three properties, the property values of several randomly selected test runs were plotted. The line plots verify that the trend is the same for all three temperatures. The stator winding temperature, stator teeth, and stator yoke, in that order, saw the biggest variations. This is especially noticeable when there is a lot of variation in the stator winding temperature. Another thing to note about the various plots is that occasionally the stator winding and stator yoke temperature are greater. Figure 8 shows the actual motor output temperature of pm, stator_tooth, stator, yoke and stator_winding and Figure 9 shows the predicted temperature. As you can see, all 4 variables related to internal motor temperatures follow the same pattern, although the permanent magnet temperature pm is slightly lagging.

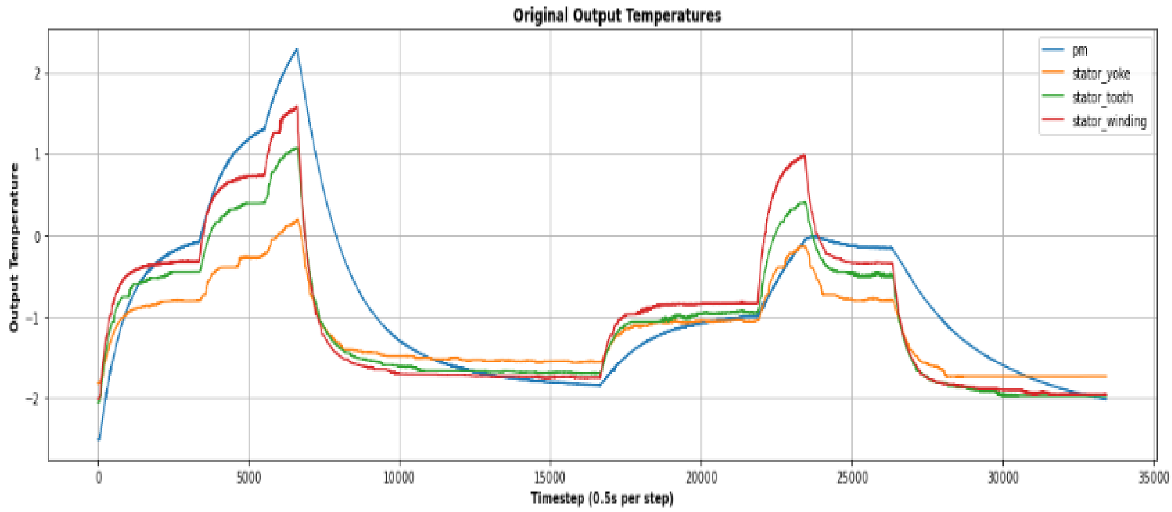


Figure 8. pm, stator_tooth, stator, yoke and stator_winding actual motor output temperature.

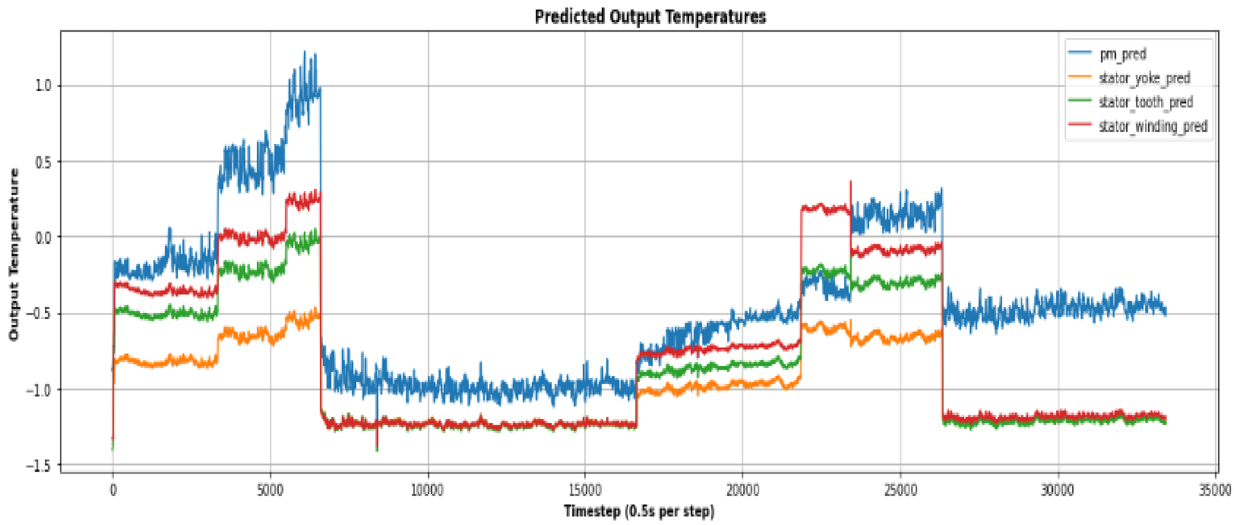
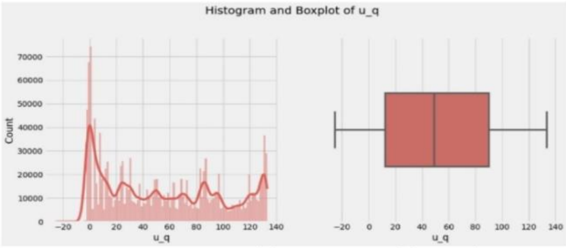
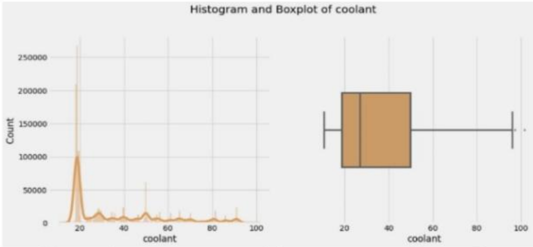


Figure 9. PM, stator_tooth, stator, yoke and stator_winding predicted motor output temperature.

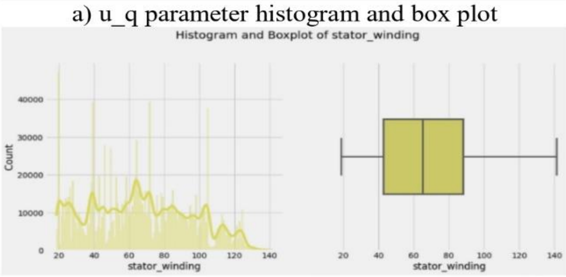
The analysis of temperature prediction includes the analysis of the dataset and the methods applied to improve the model's temperature prediction. These analyses include steps such as understanding the effects of specific operating conditions on engine temperature, feature engineering and building a prediction model. The trend graph showing an example from the training set is presented in Figure 10.



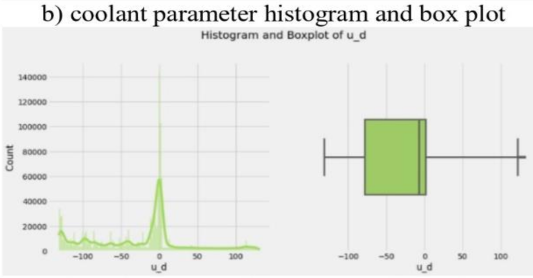
a) u_q parameter histogram and box plot



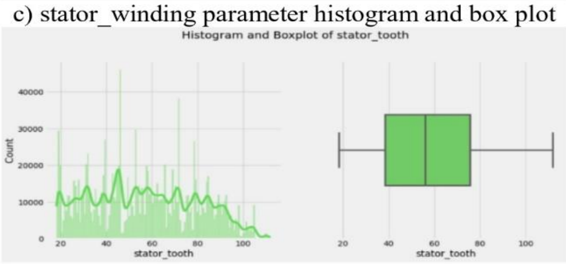
b) coolant parameter histogram and box plot



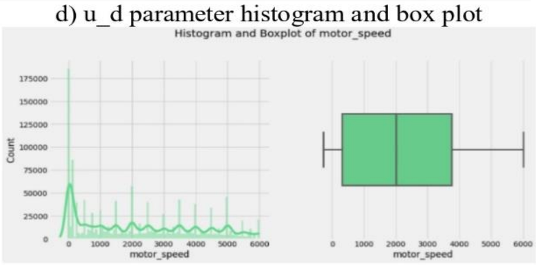
c) stator_winding parameter histogram and box plot



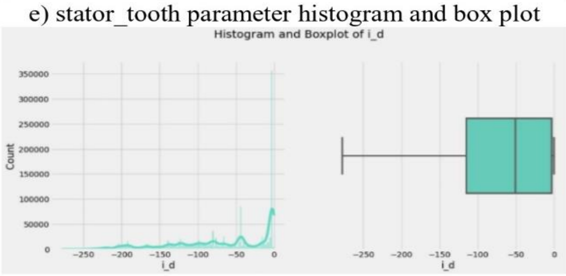
d) u_d parameter histogram and box plot



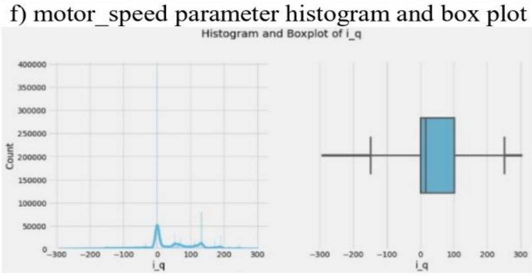
e) stator_tooth parameter histogram and box plot



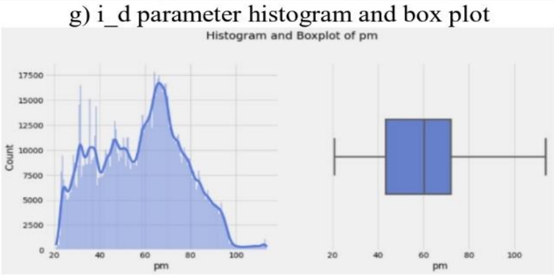
f) motor_speed parameter histogram and box plot



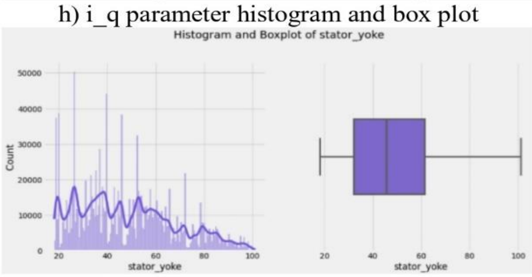
g) i_d parameter histogram and box plot



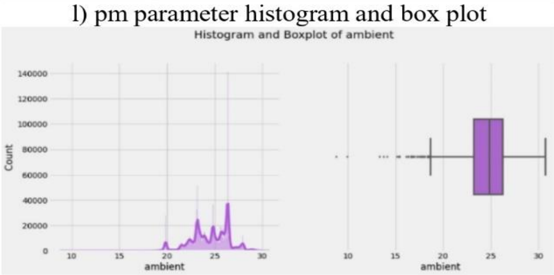
h) i_q parameter histogram and box plot



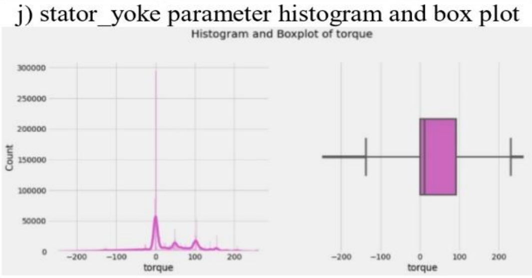
l) pm parameter histogram and box plot



j) stator_yoke parameter histogram and box plot



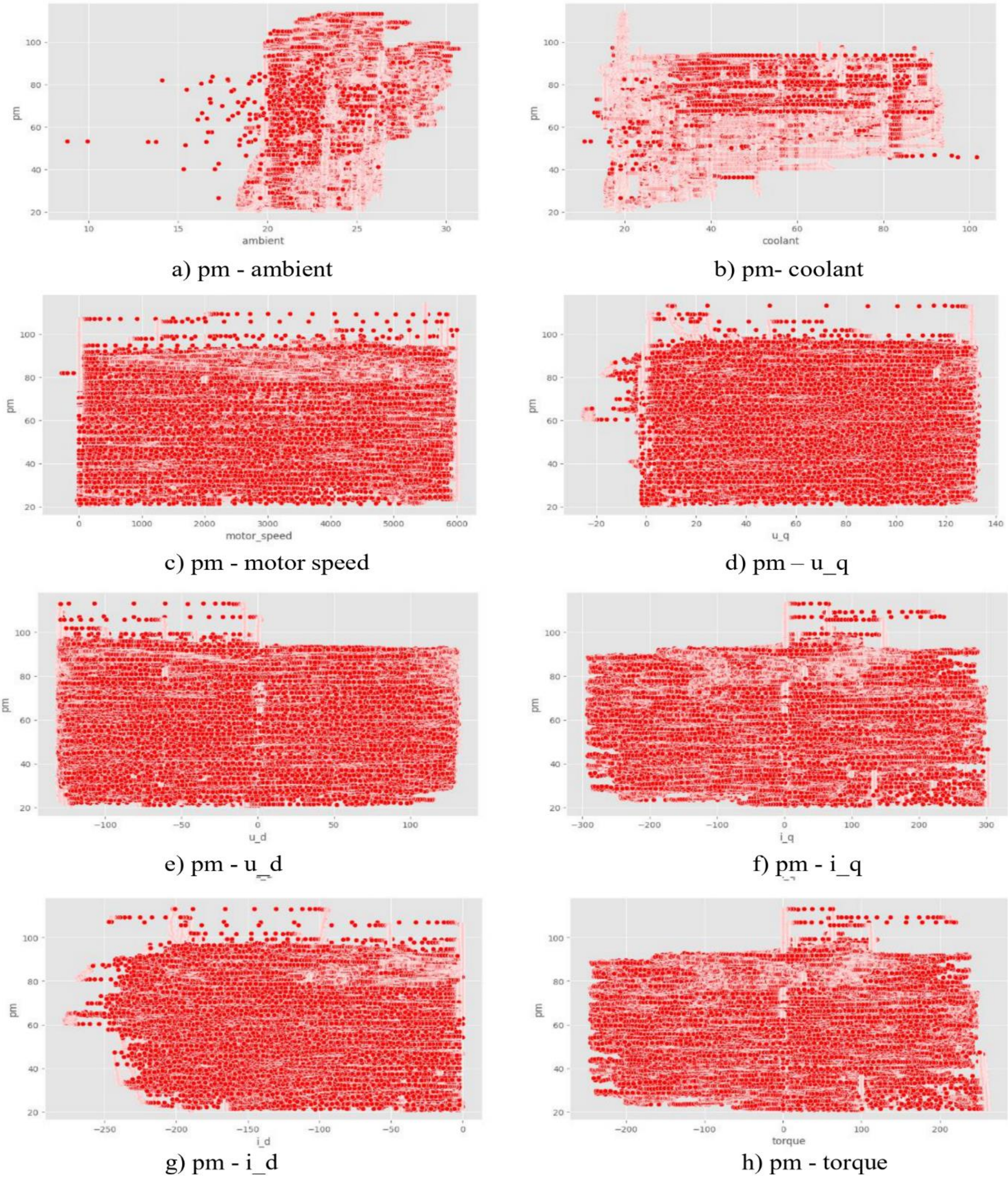
k) ambient parameter histogram and box plot



l) torque parameter histogram and box plot

Figure 10. Histogram and box plots of training set parameters.

Iron losses were shown to be the most advantageous or least unfavorable single loss type for all locations and characteristics within the motor. Even though copper and winding losses have a detrimental effect on yoke and teeth forecasts when used alone, the optimal configuration for stator temperature predictions is the addition of all loss features. This could be explained by the fact that these losses balance out the iron losses, enabling more intricate interactions to be captured by the modified hyperparameter values. The operating point shown in Figure 11 shows the parameters of the engine and the heat map at the operating points.



a) pm - ambient

b) pm- coolant

c) pm - motor speed

d) pm – u_q

e) pm - u_d

f) pm - i_q

g) pm - i_d

h) pm - torque

Figure 11. Engine parameters-temperature relationship graph.

The main evaluation criterion for this work is the mean squared error, which is defined in equation (2) because it deals with regression problems involving true value estimation. A lower mean square error (MSE) score denotes superior model performance. For all Regressor algorithms , 30% of our dataset was used for training and 70% for testing. The parameters used for optimization in the ML models were determined by trial and error. During the analyses, appropriate parameters for each regressor were tested with different values and the optimal values were used. The parameters used in the optimization are shown in the tables.

Table 2. Linear Regressor Parameters.

Parameters	Values
fit_intercept	true
n_job	none
positive	true
copy_X	true

Table 2 shows the hierparameters of the Linear Regressor. The optimization parameters of this model were determined to maximize the accuracy. As a result of the training, the Linear Regressor algorithm achieved 85.59% training performance and 85.54% test performance in predicting electric motor temperature. Root Mean Square Error (RMSE) is 7.28, Mean Absolute Error (MAE) is 5.43, R^2 Score is 85.54 and Cross-Validation (CV) R^2 is 85.54. The graph showing the prediction of engine temperature and actual engine temperature values predicted by the Linear Regressor algorithm is given in Figure 12.a. The actual temperature values in the dataset and the temperature values predicted by the Linear Regressor algorithm are given in Table 7.

Table 3. K-Nearest Neighbor Regressor parameters

Parameters	Values
n_neighbors	9
weights	*uniform*
algorithm	auto
Power(p)	1
metric	*minkowski*

Table 3 shows the hierparameters of K-Nearest Neighbor Regressor. The optimization parameters of this model are chosen to balance both speed and accuracy. As a result of the training, the K-Nearest Neighbor Regressor algorithm achieved 99.65% training performance and 98.72% test performance in predicting the electric motor temperature. RMSE is 2.16, MAE is 0.87, R^2 Score is 98.72 and CV R^2 is 97.77. The graph showing the prediction of engine temperature and actual engine temperature values predicted by the Linear Regressor algorithm is given in Figure 12.b. The actual temperature values in the dataset and the temperature values predicted by the K-Nearest Neighbor Regressor algorithm are given in Table 7.

Table 4. XGBoost Regressor Parameters

Parameters	Values
booster	gbtree
verbosity	1
eta	0.3
learning_rate	0.99
max_dept	6
n_estimators	50

Table 4 shows the hierparameters of the XGBoost Regressor. As a result of the training, the XGBoost Regressor algorithm achieved 98.10% training performance and 92.51% test performance in predicting electric motor temperature. RMSE is 5.23, MAE is 3.68, R^2 Score is 92.51 and CV R^2 is 92.51. The graph showing the prediction of engine temperature and actual engine temperature values predicted by the XGBoost Regressor algorithm is given in Figure 12.c. The actual temperature values in the dataset and the temperature values predicted by the XGBoost Regressor algorithm are given in Table 7.

Table 5. AdaBoost Regressor Parameters

Parameters	Values
Base_estimator	dtree
learning_rate	0.99
loss	linear
n_estimators	50

Table 5 shows the hierparameters of AdaBoost Regressor. As a result of the training, the AdaBoost Regressor algorithm achieved 99.99% training performance and 94.57% test performance in predicting electric motor temperature. RMSE is 4.45, MAE is 1.99, R^2 Score is 94.57 and CV R^2 is 75.14. The graph showing the prediction of engine temperature and actual engine temperature values predicted by AdaBoost Regressor algorithm is given in Figure 12.d. The actual temperature values in the dataset and the temperature values predicted by the AdaBoost Regressor algorithm are given in Table 7.

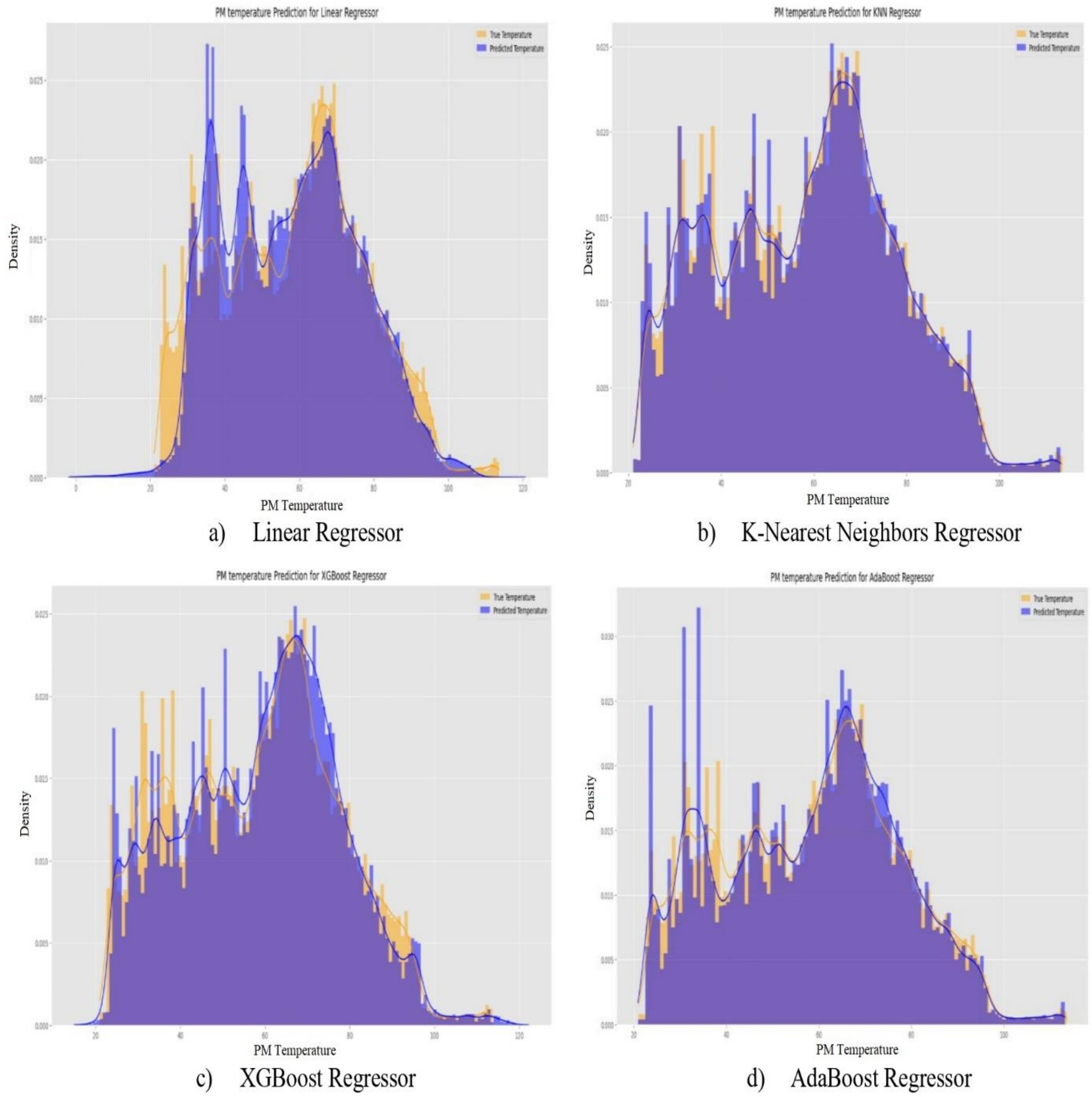


Figure 12. Comparison of predicted and actual engine temperatures with ML models.

PMSM temperature prediction has been realized with 4 different methods. The evaluation metrics of the performance of the regression algorithms and the success scaling of the algorithms are presented in Table 6. As can be seen in Table 6, the worst performance was given by the Linear Regressor algorithm and the best performance was given by the K-Nearest Neighbors Regressor algorithm.

Table 5. Comparison of regression algorithms.

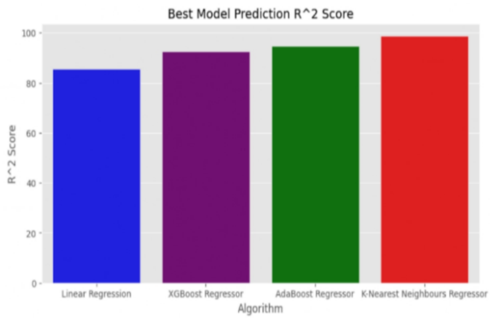
Algorithm	**Training Accuracy**	**Testing Accuracy**	**RMS Score**	**MAE Score**	**R^2 Score**	**CV R^2 Score**
Linear	85.5915	85.5406	7.2816	5.4334	85.5406	85.5406
XGBoost	98.1082	92.5140	5.2393	3.6861	92.5140	92.5140
AdaBoost	99.9999	94.5759	4.4598	1.9953	94.5759	75.1407
K-Nearest Neighbors	99.6537	98.7217	2.1649	0.8749	98.7217	97.7785

Table 7. Actual and predicted temperature values.

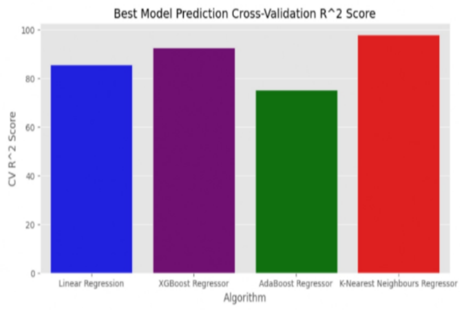
ID	True Temperature	Predicted Temperature			
		Linear Regressor	XGBoost Regressor	AdaBoost Regressor	K-Nearest Neighbors Regressor
1	80.370648	77.170195	66.204575	73.636782	79.546671
2	81.354715	77.506720	84.205383	79.190930	80.277010
3	75.681844	76.630113	74.922043	74.087818	75.712269
4	36.301079	40.731363	40.485966	54.266106	36.172670
5	46.072262	47.081153	45.101055	54.266106	46.970879
6	65.871500	61.895012	68.452187	66.760419	65.842998
7	50.566772	45.415065	46.795605	50.609702	50.616540
8	59.947044	43.458173	73.985504	52.261452	60.024526
9	78.207240	71.715534	75.798790	67.432551	78.292631
10	83.033463	83.745194	83.488167	81.636411	81.839415

The performance of four regression algorithms Linear Regression, XGBoost, AdaBoost, and KNN for predicting the thermal time series of PMSMs is compared in this study. Linear Regression showed the lowest performance with a training accuracy of 85.59% and testing accuracy of 85.54%, along with a relatively high RMS score of 7.28 and MAE score of 5.43. XGBoost improved significantly, achieving a training accuracy of 98.11% and testing accuracy of 92.51%, with an RMS score of 5.24 and MAE score of 3.69. AdaBoost performed even better in training accuracy, reaching nearly 100%, but its testing accuracy was slightly lower at 94.58%, with an RMS score of 4.46 and MAE score of 1.99, indicating some overfitting. KNN outperformed all other algorithms, with a training accuracy of 99.65% and testing accuracy of 98.72%, as well as the lowest RMS score of 2.16 and MAE score of 0.87. The R^2 and CV R^2 scores also highlighted KNN's superior predictive capability, making it the most effective algorithm for real-time temperature prediction in PMSMs among those tested.

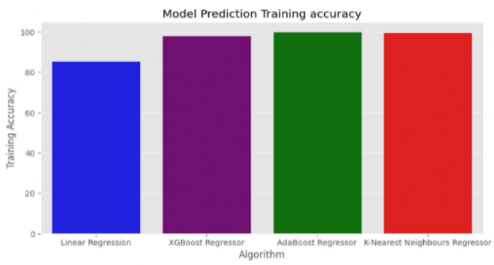
Figure 13 presents graphs that illustrate the effect of multiple independent variables on temperature, with values colored differently based on the regression model that was employed. This information is helpful in understanding the temperature effect of PMSM engines. Among the regression algorithms used experimentally and among all the experiments, the best prediction was obtained with the K-Nearest Neighbor Regressor.



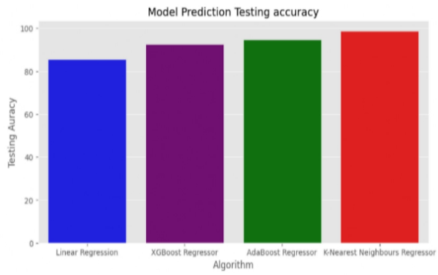
a) R^2 score



b) CV R^2



c) Training Accuracy



d) Testing Accuracy

Figure 13. Performance indicator graphs of regression algorithms.

The limitations of this study revolve around several important factors. This study's primary limitations are related to the range and volume of data sets that were utilized. Since the datasets used in the study are limited, there may be some limitations on the generalizability of the developed models.To assess the suggested models' real-time performance in industrial applications, more investigation is required. Moreover, the performance of the models used in this study is directly related to the quality and diversity of the datasets. There are also some limitations in terms of training time and computational resources of deep learning models.

Future work should aim to improve the generalizability of the models by using larger and more diverse datasets. Further research should be conducted to test real-time applications of the proposed models in industrial settings and evaluate their performance. These studies can also develop various optimization techniques to reduce the training time and computational cost of machine learning models. In addition to machine learning techniques, studies with different artificial intelligence techniques can be conducted.

5. Conclusions

In this study, regression algorithms are used to predict key component temperatures in a PMSM in real time. It is shown that by carefully selecting and designing motor specifications, motor temperatures can be accurately predicted using various machine learning tools. Among the Linear, K-Nearest Neighbor, XGBoost and AdaBoost Regressor algorithms used, the K-Nearest Neighbor Regressor algorithm outperformed the other three regressions due to its locally weighted prediction over nearest neighbors and its consideration of time dependence. As a result of the analysis with the K-Nearest Neighbor Regressor algorithm, the training accuracy was 99.65%, the test accuracy was 98.72%, RMSE was 2.16, the R2 score was 98.72 and the CV R2 was 97.77%. The main limitations of this study include the variety and quantity of data sets used. Further research is needed to evaluate the real-time performance of the proposed models in industrial applications. The performance of the models used in this study is directly related to the quality and diversity of the datasets. The results of this study have demonstrated that creating real-time thermal models of electric machines can be made considerably easier by performing thermal analysis of the motor. This creates new opportunities for predictive thermal management systems and edge computing in the context of thermal modeling of electrical machinery. Future research is planned on the adaptability of the analysis method to different motor types and validation of its accuracy in various scenarios.

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