Temperature Estimation in Permanent Magnet Synchronous Motor (PMSM) Components using Machine Learning

MSc Research Project
Data Analytics

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Temperature Estimation in Permanent Magnet Synchronous Motor (PMSM) Components using Machine Learning

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Abstract

The ubiquitous adoption of permanent magnet synchronous motors (PMSMs) as the electric motors of choice for traction drive applications especially in manufacturing and the electric vehicle industries birthed the need for monitoring the temperatures of its critical components to control the effects of overheating. In proffering solutions, several techniques have been employed by researchers spanning decades. These include the sensor-based method, methods based on classic thermal theory, electric circuit theory and the hybrid lumped-parameter thermal networks (LPTNs). These however have deficiencies ranging from requiring expertise for efficient modelling to one or the other of lacking interpretability and not meeting reliability requirements. Recent studies have seen an increased application of machine learning techniques to other fields like healthcare with convincing results. In this work, several machine learning (ML) models were evaluated on their estimation error after training on test bench data from a PMSM for the task of predicting the temperatures of the rotor, stator yoke, stator tooth and stator winding. Diverse regression algorithms were applied and include linear regression (LR), k-nearest neighbours (kNN) regression, random forest (RF) and decision tree (DT). It is observed that the stator yoke records the least error of prediction while the pm records the highest and in general, the stator components record the least error compared to the rotor component.

Keywords– permanent magnet synchronous motors, machine learning, linear regression, temperature estimation, random forests

1 Introduction

An electric motor is an electric machine that converts electrical energy into mechanical energy through the interaction of the electric current in the rotor windings of the motor and the stator magnetic field to generate rotational force in the shaft (Tounsi; 2015). They, like the electric generator, operate on the principle of magnetism except that the electric generator conversely converts mechanical energy into electric energy.

High torque and power densities together with high efficiency are basic requirements in most industrial and automotive applications. For this reason, the permanent magnet synchronous motor (PMSM) is widely used in industrial and automotive applications. The need to stay competitive and control rising manufacturing costs especially in the automotive sector often leaves engineers at the risk of compromising safety in materials when designing motors. To avoid this, the utilization of the motor must be maximized during design using a control strategy that reduces the thermal stress on the motor components with the highest risk of thermal failure. Some of the motor components most sensitive to failure are the permanent magnets in the rotor which may suffer irreversible demagnetization from exposure to excessive heat and the stator end windings which may melt from the effect of high temperatures. This necessitates the measurement and control of temperatures in these components.

1.1 Background and Motivation

For maximum return on investment in electric motors, the critical components such as the winding insulation which may melt from high heat and the permanent magnets which may become irreversibly demagnetized have to be consistently monitored for high thermal stress due to high temperatures. Temperature is the primary indicator of the presence of a fault or problem in an electric motor and this further introduces the problem of energy wastage where 25% of all energy consumption is in industry of which 70% of that energy is used in motor-based systems (Waide and Brunner; 2011). Also, electric motors find their biggest applications in industrial settings where they account for two thirds of electrical energy used and consume 45% of total electric energy consumption and constitute in industrial settings Waide and Brunner (2011), making it pertinent to control the energy loss from motors by monitoring the component temperatures.

From [1]Figure 1 below , stator related faults together with rotor related faults make up about 50% of all faults in electric motors. Test bench data containing sensor-based temperature measurements taken from a PMSM includes data on various factors and the temperatures of the rotor, stator yoke, stator tooth and stator winding components.

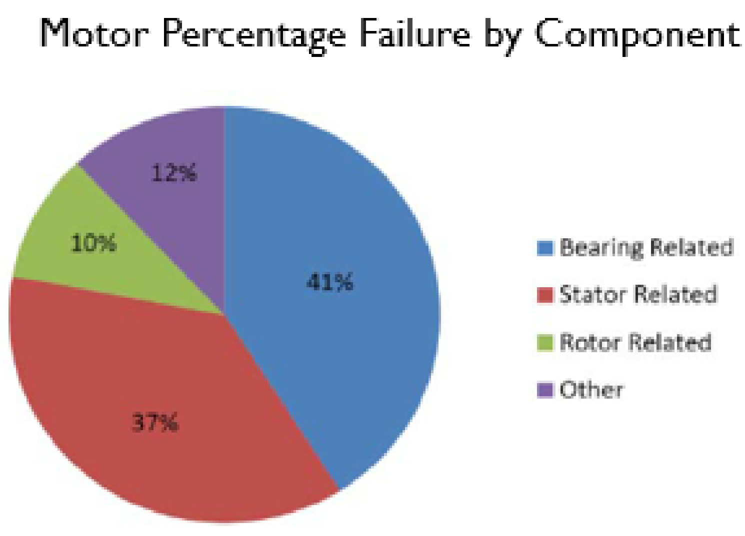

Figure 1: Motor percentage failure by component (Navarro et al.; 2010)

Permanent magnet synchronous motors make up most motors found in industrial applications due to their ruggedness. Temperature monitoring in electric motors is crucial

[1]Source: https://www.kaggle.com/wkirgsn/electric-motor-temperature/data

as it is the main indicator of a fault or problem with an electric motor Nandi et al. (2005). Several techniques exist for estimating temperature in electric motors and some are not efficient.

1.2 Research Question

Test bench data taken from a PMSM includes data on various factors such as external temperatures and motor electrical characteristics affecting the temperature of a motor. It also includes the corresponding temperatures of four stator and rotor components which are the rotor, stator yoke, stator tooth and stator winding. Given the available data with the objective of this research to estimate the temperatures of motor components by applying ML techniques to the available data, this research proposes to answer the research question:

"To what extent can the temperatures of the rotor, stator yoke, stator tooth and stator winding of permanent magnet synchronous motors be accurately estimated from external temperature factors and motor electrical characteristics using machine learning?"

To answer the research question, the project objectives are outlined below.

1.3 Research Objectives and Contributions

This research work set out with a critical review of literature in the problem domain so as to understand the scope of the work already done to address this problem and to identify gaps for further work leading to the research question. Based on this, this work aims to answer the research question by achieving the following objectives:

- Identify a reliable test bench dataset of a PMSM, perform pre-processing and exploratory data analysis to understand the data and extract preliminary insights.
- Apply linear regression, k-nearest neighbours regressor, random forest regressor and decision trees regressor algorithms to estimate the temperatures of the rotor, stator tooth, stator yoke and stator winding.
- Derive better features from the existing variables through feature engineering.
- Train the models again on the new dataset with derived features.
- Compare and evaluate the results from the two sets of experiments to answer the research question.

This work contributes to the body of knowledge by identifying the motor component that can most accurately be estimated from external temperature factors like ambient temperature and electrical characteristics like voltage and current which indicates the motor component most affected by these variables.

The rest of this paper follows this structure: section 2 critically reviews the related literature, section 3 details the modified CRISP-DM methodology adopted in this research, section 4 shows how the research was implemented, section 5 evaluates and discusses the results in the context of the stated objectives and finally, the study is concluded in section 6.

2 Related Work

Over the years, the importance of monitoring component temperatures as a critical indicator of the performance of electric motors and controlling the consumption of electrical energy necessitated the deep and extensive study of these electrical machines. Several techniques have been applied to measure and control temperature, including direct sensor-based measurements which yield satisfactory results for the stator part (Boglietti et al.; 2009) and is easily implemented on the stator. This is however technically more difficult and economically infeasible to achieve in the rotor due to the difficulty in accessing the sophisticated internal structure of the rotor. Other instrument-based temperature monitoring techniques like infrared thermography (Stipetic et al.; 2011) and the classic thermocouples apart from lacking in real-time temperature monitoring capabilities are also not feasible for industrial scale. Also, the high costs of manufacturing and maintaining these motors in the face of increasing industrial competition further highlight the need to estimate temperature with acceptable accuracy.

Against this background, several literature have been published, proposing different approaches including classical methods based on thermodynamic theory and electric circuit theory. Also, advancements in computational power and knowledge base such as the application of machine learning techniques to problems where data is richly available has led to an increase in popularity in the application of data-based modelling techniques like regression for the estimation and prediction of the temperature of critical components in a PMSM. The following subsections provide a critical review of related literature going back over a decade as a justification of the need for this work and its contribution to the existing body of knowledge.

2.1 A Critical Review of Classical Methods for Temperature Estimation

Considering the drawbacks in the use of physical instruments like the infrared thermography device, including the need for a real-time system, research on estimating rotor temperatures in the last few decades became model-based where in general the models are either thermal models or electrical models. Starting with classical thermodynamic theory, several researchers exploited the heat properties of materials used in motor design for temperature estimation (Boglietti et al.; 2009).

Demetriades et al. (2009) and (Boglietti et al.; 2009) designed a real-time thermal model which was able to estimate the temperature of different components of the motor in transient, steady-state and stall torque operating conditions. They were able to achieve good measurement performance comparable to temperature transducers with their model which was built from discreetly calculated parameters abstracting different components of a PMSM in state-space format and the model order reduced to minimize the complexity. Despite the satisfactory results presented by using this approach, the authors acknowledge that the discretization of the model introduces deviations which impact the consistency and limits its use in industry.

For (Kral et al.; 2013) and (Kral et al.; 2012), a lumped thermal network model for the estimation of the temperatures of the permanent magnets and stator windings in an electric motor was developed and located in the stator of the machine. According to the authors, the model when compared with experimental results from a water-cooled PMSM highlighted the effectiveness of the model. However, the temperature estimates are distorted by the cooling circuit, making the model less reliable for practical applications where accuracy is expected.

Huber et al. (2014) applied the heat equation finite element analysis (FEA) to develop a thermal model while Gedlu et al. (2020) conducted their analysis using computational fluid dynamics (CFD). According to the authors, the two methods recorded high accuracies with good predictions of the thermal behaviours of the motor components during development. However, the heat equation FEA showed limitations in the modelling of convection processes making it impracticable in the context of the electric motor since parts like the motor air-gap and rotating rotor shaft have conventional processes. Despite the high accuracy of CFD methods in thermal motor modelling, they are limited by the enormous computational resources, making them unsuitable for real-time monitoring.

In a bid to estimate the temperatures of critical components of a PMSM, Wallscheid and Böcker (2015) employed a technique named by them as the global identification technique for linear parameter varying systems on a thermal model of a motor. To achieve this, they modelled the critical components of the motor i.e., the stator winding, stator teeth, permanent magnets and stator yoke using a lumped-parameter thermal network (LPTN) comprising four nodes. The system was designed to extend the scope of the model beyond the training domain by accounting for the varying parameters and physical constraints. They were able to achieve a worst-case estimation error of 8^oC.

Despite the significant contributions made by these papers aimed at estimating the temperatures of critical components in PMSMs by modelling their thermal behaviours based on classical thermodynamic theory, they were limited by the need for expert knowledge in the domain and also the impracticality of implementing them for real-time temperature measurements on industrial scales. Seeing the drawbacks of thermal modelling, research efforts shifted from thermodynamic modelling to electrical modelling using electrical model parameters like current and voltage for generating thermal indicators like resistance in windings and flux linkage in permanent magnets. Both cases leverage the thermal properties of parameters in electric models e.g., the flux linkage in permanent magnets or the resistance in windings.

Some methods work with current injection to obtain resistance in the stator windings as in (Reigosa et al.; 2015) while others use voltage injection to vary the magnetization level of the magnets as in (Reigosa et al.; 2010). The authors proposed a method to estimate the temperature of the magnets in permanent magnet machines by injecting a high-frequency signal superimposed on the fundamental excitation allowing the estimation of the stator impedance which is an indicator of the stator temperature. Other methods retrieve the magnet temperature without the need for signal injection or sensors by using an exact flux linkage observer in the fundamental wave domain as done by Wallscheid et al. (2017) and Specht et al. (2014). However, apart from being largely limited by the low sensitivity in temperature dependent parameters leading to model inaccuracies and estimation errors, these methods require domain expertise and the models can hardly be generalized to other cases.

2.2 Data-Based Techniques for Temperature Estimation in electric Motors

In contrast to the previously discussed approaches which are motivated by physical models, current research trends have taken a different approach by exploring data-based models. Unlike the classical thermodynamic and machines theory upon which the model-based techniques are heavily dependent, data-based models apply machine learning (ML) techniques which leverage advancements in computational speed to estimate temperature from test bench data.

Kirchgässner et al. (2019b) proposed an alternative to the LPTN in the form of a simple thermal linear model using linear regression on data pre-processed as exponentially weighted moving averages (EWMA). They were able to show that linear regression performs with similar predictive capability as the LPTNs. Even though linear regression is already a simple technique, they were able to further reduce the computational complexity observing a predictive performance similar to LPTNs and not requiring expert knowledge. However, with the advancements in machine learning research which has seen the development of more advanced techniques for learning from data such as deep learning algorithms, means even better performing models can be developed.

Following the recent trends in deep learning, Kirchgässner et al. (2019a) evaluated cutting-edge deep learning frameworks in the form of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for predicting component temperatures in a PMSM. The temperature profiles of the components were modelled with RNN and CNN techniques using test bench data and the models optimized using Bayesian optimization during training to arrive at optimal hyperparameters. They observed that the mean squared error and maximum absolute deviation performances of both deep RNNs and CNNs measure up to those of LPTNs while offering the further advantage of not requiring domain expertise. These models are however computationally intensive and take a lot of time to run.

2.3 A Review of Evaluation Metrics for Regression Tasks

Willmott and Matsuura (2005) and Willmott et al. (2009) studied the abilities of two of the most commonly used measures of model performance in regression tasks which are the root mean squared error (RMSE) and mean absolute error (MAE). They arrived at a conclusion that the RMSE is an inappropriate measure of the average performance of a model as it is a reflection of 3 different sets of errors instead of one (the mean error), making it an ambiguous measure of average error.

Chai and Draxler (2014) critiqued the claim by Willmott and Matsuura (2005) and Willmott et al. (2009) about the RMSE metric being inappropriate. Although agreeing that the MAE is generally a better communicator of average model performance as opposed to the RMSE which might be an ambiguous measure of model mean error, Chai and Draxler (2014) however concluded that the RMSE is a better representation of the average model performance when a Gaussian error distribution is expected.

Wang and Lu (2018) and Franses (2016) in addition to studying the MAE and RMSE metrics also studied other regression metrics including the mean absolute scaled error (MASE) metric. They observed that the biggest advantage of the RMSE over other metrics including MAE is that RMSEs do not use absolute values which is unrequired in many mathematical computations. This advantage is however nullified by the RMSE outlier sensitivity and the probability that these outliers will be present as shown by the normal distribution.

2.4 Identified Research Gaps and Contribution of this Research

This work adds to the body of knowledge by exploring the PMSM component temperature most accurately affected by external temperature factors affecting the temperatures of PMSM components. All critically reviewed previous publications on this subject aimed exclusively to either reduce model computational demand or increase the accuracy of the predictions thereby trading one important quality for another. This work seeks to bridge this gap by building models of intermediate complexity and computational demand and evaluated on the mean absolute error (MAE).

3 Methodology

The aim of this research is to identify the motor component among other components whose temperature can more accurately be predicted from external temperature variables and electrical characteristics. Machine learning algorithms and techniques were employed for this task due to their success in the last decade at classification tasks and regression tasks as in this case. A slightly modified form of the Cross Industry Standard Process for Data Mining (CRISP-DM) methodology was employed to provide a structured approach for implementing and evaluating this work to achieve the stated goals (Azevedo and Santos; 2008). It consists of the first 5 steps of the standard CRISP-DM which take raw data from the initial point of understanding the task or problem, through implementing a solution by cleaning and preparing the raw data, modelling and finally evaluating the solution. The last step is not included as this work will not be deployed after evaluation.

The modified methodology is illustrated in figure 1 below and explained in the following sections.

Figure 2: Modified CRISP-DM

3.1 Business Understanding

A permanent magnet synchronous motor as with every other type of electric motor is an electric machine that converts electric energy into mechanical force or torque for providing traction. High torque and power densities together with high efficiency are basic requirements in most industrial and automotive applications; for this reason, the permanent magnet synchronous motor (PMSM) is most widely used in industrial and automotive applications. The need to stay competitive and control rising manufacturing costs especially in the automotive sector often leaves engineers at the risk of compromising safety in materials when designing motors. To avoid this, the utilization of the motor must be maximized during design using a control strategy that reduces the thermal stress on the motor components with the highest risk of thermal failure. Some of the motor components most sensitive to failure are the permanent magnets in the stator which may suffer irreversible demagnetization from exposure to excessive heat and the rotor windings which may melt from the effect of hot temperatures. This necessitates the accurate and real-time measurement, monitoring and control of temperatures of these components which has seen the application of several techniques as discussed in the literature review. The task of estimating temperature which is a continuous numerical quantity is a regression task and this understanding guides the data understanding and preparation.

3.2 Data Understanding

With an understanding of the problem from the first stage of the procedure, a dataset containing features relevant to the prediction of the temperature of electric motor components was sourced from Kaggle [2] in a single csv file named pmsm_temperature_data.csv containing 998070 observations and 13 features. The data is comprised of external temperature variables, motor electrical characteristics and target temperature variables to be predicted. To gain proper understanding of the dataset and its properties, initial activities on the dataset sought to create familiarity with the dataset, including identifying data quality issues and exploratory data analysis to uncover first insights and discover interesting patterns if any to aid in answering the research question.

3.3 Data Preparation

Based on the knowledge gained from the business and data understanding stages, this stage of the project cycle involves a series of activities focusing on cleaning, preparing and transforming the raw data to a form more suitable for analysis and model building. The activities include pre-processing and feature engineering which is a technique for improving the performance of the machine learning models.

3.4 Modelling

Several algorithms are applied to know if the prediction accuracy from the data is affected by the choice of algorithm. To build the models for prediction, linear regression, k nearest neighbours regression, random forest regressor and decision tree algorithms are chosen

[2] https://www.kaggle.com/wkirgsn/electric-motor-temperature/data

for their performance on regression tasks, explainable models and use of relatively less computational resources (Zheng and Dagnino; 2014).

3.4.1 Ordinary Least Squares (OLS) Linear Regression

Ordinary Least Squares (OLS) is a linear regression method for developing a model which seeks to estimate a target variable from data features by minimizing the distance between the predicted data and the actual data measured by the sum of the squared errors (Kirchgässner et al.; 2019b). A smaller distance indicates a better performance of the model.

3.4.2 K Nearest Neighbours Regression

The k nearest neighbours regression is an algorithm that estimates a numerical target by getting the average of the k nearest neighbours where the nearest neighbours are determined by a distance function (Dagnino and Cox; 2014). Since the variables in the dataset for this research are continuous, this work uses Euclidean distance,

$$Distance, d = \sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \tag{1}$$

3.4.3 Random Forest Regressor

Random forest regression applies random forests which are an ensemble of learning methods for regression tasks. It works by training several decision trees on different subsets of the data and returning the mean of the predictions of the individual decision trees (Kirchgässner et al.; 2019b).

3.4.4 Decision Trees Regression

Decision trees offer the advantage of less computational demand in addition to high performance, although models built with decision trees are prone to overfitting but this can easily be handled (Kirchgässner et al.; 2019a).

3.5 Evaluation

The objective of this project as a regression task is the estimation of temperatures which are numerical quantities as accurately as possible. The built models will be evaluated on a test dataset using the mean absolute error (MAE) evaluation metric which measures the average of the absolute estimation errors i.e., the average of the difference between the estimated values and the actual values irrespective of the direction of the difference(Kirchgässner et al.; 2019b). This is given mathematically as,

$$MSE = \frac{1}{n}\sum \mid y_i - \hat{y}_i \mid \tag{2}$$

where y_i is the actual value and $\hat{y}_i$ is the predicted value.

The MAE is an indicator of the quality of an estimator; it is always non-negative and the closer the value is to zero, the better. Hence, the objective is to minimize the evaluation errors as the lower the MAE, the better the model performance. 10-fold cross validation (CV) is applied in each experiment prior to calculating the MAE to account for generalizability of the models. This is done by shuffling the dataset and splitting in 10 equal parts with equal sizes and training and testing is carried out 10 times, each time using a different 90% of the data for training and 10% for testing.

4 Implementation

The implementation process flow of this research is illustrated in the diagram below. All the experiments were done in Jupyter Notebook in the Anaconda environment using the Python programming language.

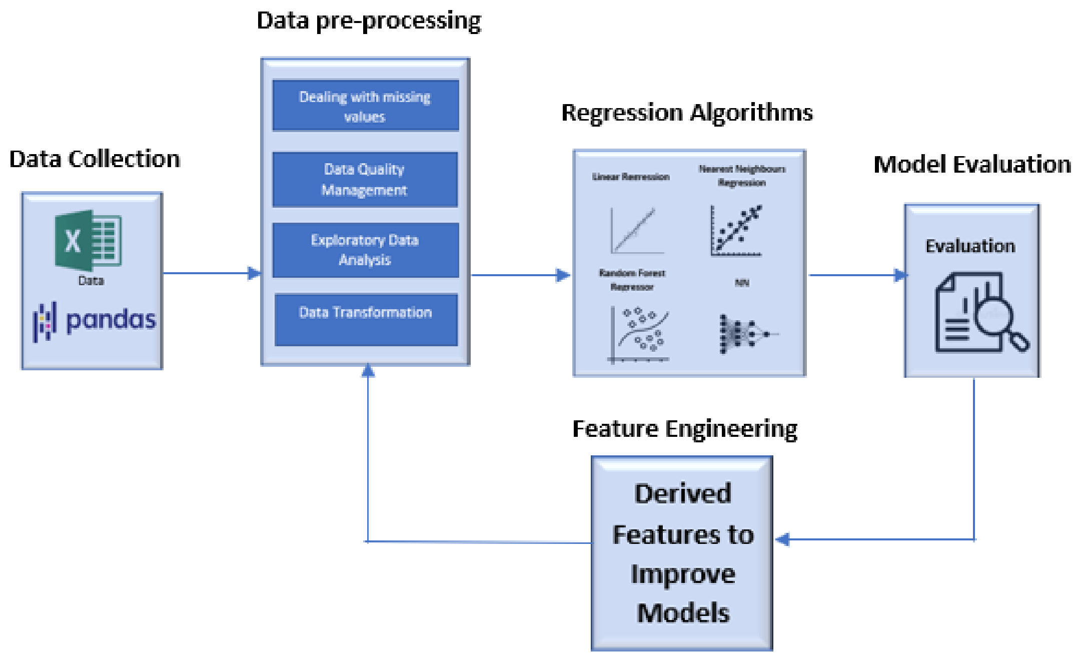

Figure 3: Implementation process flow

4.1 Data Collection and Description

The raw dataset with a size of 127MB is publicly available and was downloaded from Kaggle [3] in a zipped folder. The folder was unzipped to extract the pmsm_temperature_data.csv file which was used as the raw data in this work. The dataset contains standardized measurements including temperature readings of different components collected by aggregating several sensor data from a German OEM's prototype permanent magnet synchronous motor (PMSM) deployed on a test bench. It is mildly anonymized by standardization and the original dataset where the temperature values are in degrees Celsius can be arrived at if the mean and standard deviation of each column is given using the standardization formula:

[3] https://www.kaggle.com/wkirgsn/electric-motor-temperature/data

$$StandardizedValue = \frac{OriginalValue - Mean}{Std\_Dev}$$

The negative values are a result of the standardization.

4.2 Data Pre-processing

The extracted data was loaded into the Jupyter Notebook environment using the Pandas package and basic properties of the dataset are returned using Pandas commands showing it contains 998070 observations and 13 variables. Data quality checks were carried out on the data to ensure the data is in a suitable format for the analysis. The data was checked for missing values in each column and overall to reveal that the dataset contains no missing value in any of the columns and a check on the data types of each column showed that all the variables are numerical and continuous. Since the data contained no missing values, no missing data input technique was applied. Basic descriptive statistics were then computed on the dataset to get an initial understanding of the values and how they are distributed. The mean showing the average value of each variable, the 25th, 50th and 75th quartiles showing the interquartile ranges, the standard deviation showing the spread of the values around the mean in each variable and the minimum and maximum values indicating the full range of values and giving insight into the presence of outliers. The presence of outliers is however visualized during the exploratory analysis using boxplots to verify this observation. Since the dataset was collected for the purpose of estimating any of the temperature values or the torque from the other features, the torque variable was removed as this work is focused on the estimation of the four temperature variables (Wallscheid et al.; 2017). The data was not standardized as the raw form is standardized since the data was mildly anonymized using standardization during collection. After establishing that data passes the preliminary data quality checks, exploratory data analysis is carried out next.

4.3 Exploratory Data Analysis

The data was analytically explored to gain preliminary insights and uncover hidden patterns if they exist in the data. to start with, a correlation analysis was performed to understand the relationships between the variables. From the correlation matrix in Figure 3 below, a perfect positive linear correlation is observed between i_q and torque while u_d is observed to be highly negatively correlated with torque and i_q. The former can be explained by electric drive theory, where either higher torque is exclusively dependent on i_q in case of similar sized inductances in d-axis and q-axis or increasing with higher i_q and slightly decreasing i_d elsewise (more common in practice). The high correlation of torque further corroborates the decision to drop it.

There also exists very strong positive correlations between the stator variables i.e., stator_yoke, stator_tooth and stator_winding. This is expected as these are the temperatures of components in close proximity and sometimes in contact in an electric motor. This is however inconsequential as each of these was considered a response variable to be estimated from other variables in the absence of the other temperature variables.

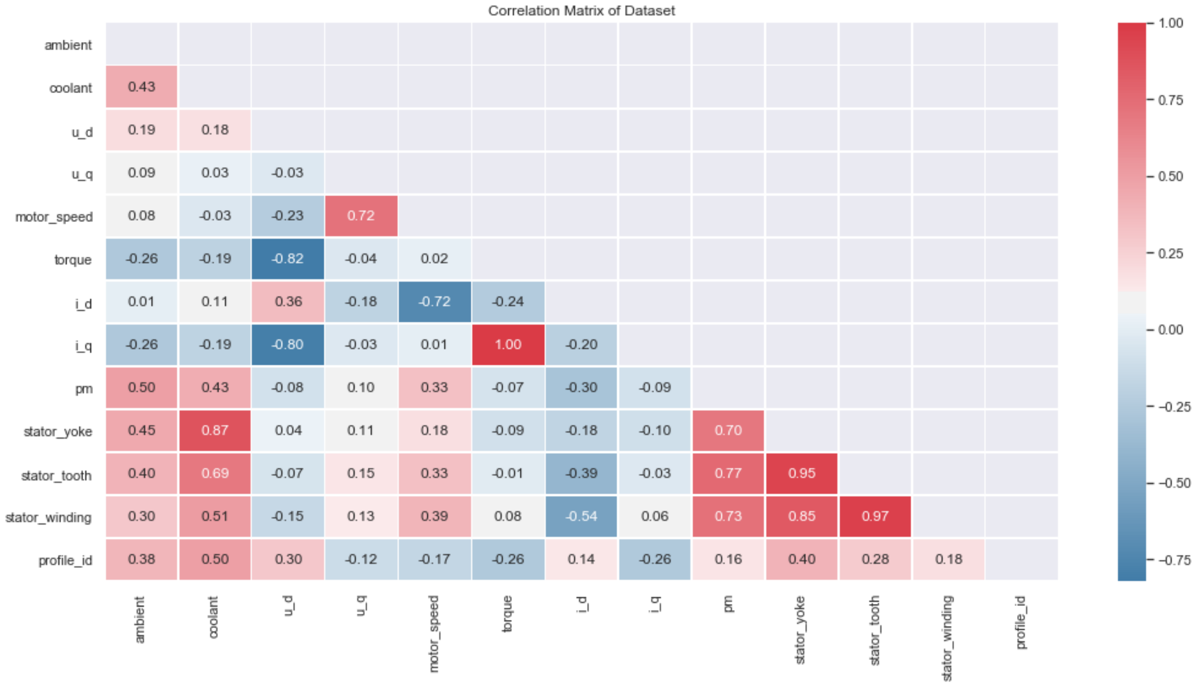

Figure 4: Features correlation matrix

4.4 Feature Engineering

From the correlation analysis carried out during the exploratory data analysis, high correlations were identified which was handled by removing unwanted features. To improve the performance of the models, new features were engineered from the existing ones. Arroba et al. (2015) strongly suggested the creation of new features from existing ones by combining old features mathematically or through a theoretical understanding of the problem. Hence, in this work, the voltage and current components were combined according to (Van Zon et al.; 2004) to obtain their effective magnitudes. The voltage in the d-axis component, u_d and the q-axis component, u_q were combined according to equation 2 to obtain the actual voltage magnitude under which the motor was operating.

$$Voltage\_magnitude, u = \sqrt{u_d^2 + u_q^2}$$

Similarly, the d-axis component current, i_d and the q-axis component current, i_q were combined to obtain the actual current magnitude supplied to the motor at the point the measurement was taken as shown below.

$$Current\_magnitude, i = \sqrt{i_d^2 + i_q^2}$$

Furthermore, the apparent power which represents all power consumed by the motor i.e., the power consumed by the motor and that dissipated in operation was computed from the voltage magnitude and current magnitude as shown below.

$$Apparent\_power, S = u * i$$

The table below shows the features with the derived inputs.

INPUT PARAMETERS	Symbol
Ambient temperature	-
Liquid coolant temperature	-
Actual d-axis voltage component	u_d
Actual q-axis voltage component	u_q
Actual d-axis current component	i_d
Actual q-axis current component	i_q
Motor speed	n
DERIVED INPUT PARAMETERS	Symbol
Voltage magnitude	u
Current magnitude	i
Apparent power	S
TARGET VARIABLES	Symbol
Permanent magnet temperature representing rotor temperature	p_m
Stator yoke temperature	stator_yoke
Stator tooth temperature	stator_tooth
Stator winding temperature	stator_winding

Table 1: Data description including derived features

4.5 Modelling

The sklearn library of machine learning packages was employed for the modelling as it already has optimized implementations of almost all machine learning algorithms as packages containing functions. Implementing any ML algorithm only requires calling the respective algorithm function and supplying the appropriate parameters.

To start implementation, all required packages and functions were imported from the sklearn library into the Jupyter notebook environment using import statements. An instance object of the estimator corresponding to each of the ML algorithm was created for training. For efficient training and model generalizability, the models were trained and evaluated using the k-fold cross validations technique with the value of k=10. This splits the data into 10 equal folds and in the first train-test cycle, trains the algorithm on the first nine parts of the data while testing and evaluating on the 10th part. This process is repeated 9 more times, each time reserving a different tenth fold for testing and evaluation after training with the remaining 9 splits. To implement this, the cross_val_score() function is called from the sklearn.model_selection package and required parameters passed as arguments to it. The parameters are the algorithm instance already created, the train dataset, the target variable, the number of folds i.e., 10 and the metric for scoring i.e., mean absolute error (MAE). The model is trained and evaluated on the MAE while the MAE is returned as an indication of the performance of the model. For experiment 1, the independent variables were as obtained in the original dataset while for experiment 2, the independent variables also include the features derived from feature engineering.

5 Evaluation

The performance of the models was evaluated on their MAEs after training. K-fold cross validation with K = 10 was applied during model training and testing to estimate the errors of the estimated values from the models on various holdouts of the test set (Fushiki; 2011). A value of 10 was chosen for K as it is observed that no significant improvement is made on the model performance for values of K greater than 10 (Yadav and Shukla; 2016). This was performed to ensure the accuracy of the obtained results and avoid overfitting or underfitting. The results of the research experiments are presented in below. They show the MAEs of each model for each of the target variables (component temperatures).

5.1 Experiment 1: Model Results from Original Dataset

The performance of the models from experiment 1 are shown in the table below.

MODEL	pm	stator_tooth	stator_yoke	stator_winding
LR	0.58	0.44	0.31	0.49
kNN	0.71	0.54	0.40	0.59
RF	0.68	0.55	0.41	0.61
DT	0.78	0.64	0.52	0.72

Table 2: Model MAEs from original dataset

5.2 Experiment 2: Model Results from Dataset with Derived Features

The performance of the models from experiment 2 are shown in the table below.

MODEL	pm	stator_tooth	stator_yoke	stator_winding
LR	0.59	0.43	0.31	0.48
kNN	0.73	0.56	0.41	0.63
RF	0.67	0.55	0.41	0.61
DT	0.80	0.66	0.51	0.73

Table 3: Model MAEs from dataset with derived features

5.3 Discussion

Tables 2 and 3 show the results of the experiments conducted to answer the question posed in this research. Table 2 shows the MAEs of the predictions from the first experiment for each of the models built for each of the target variables from the original dataset while Table 3 shows the MAEs of the predictions from the second experiment for each of the models built for each of the target variables from the dataset with derived features. In each of the experiments, the models for predicting each of the four target variables were trained on the training data with four algorithms and evaluated on the test data. This was done 10 times in each case using k-fold cross validation with k=10. The MAEs are computed 10 times for each run of the experiment and the scores recorded. The average of these is obtained and recorded as seen in tables 2 and 3 for comparison.

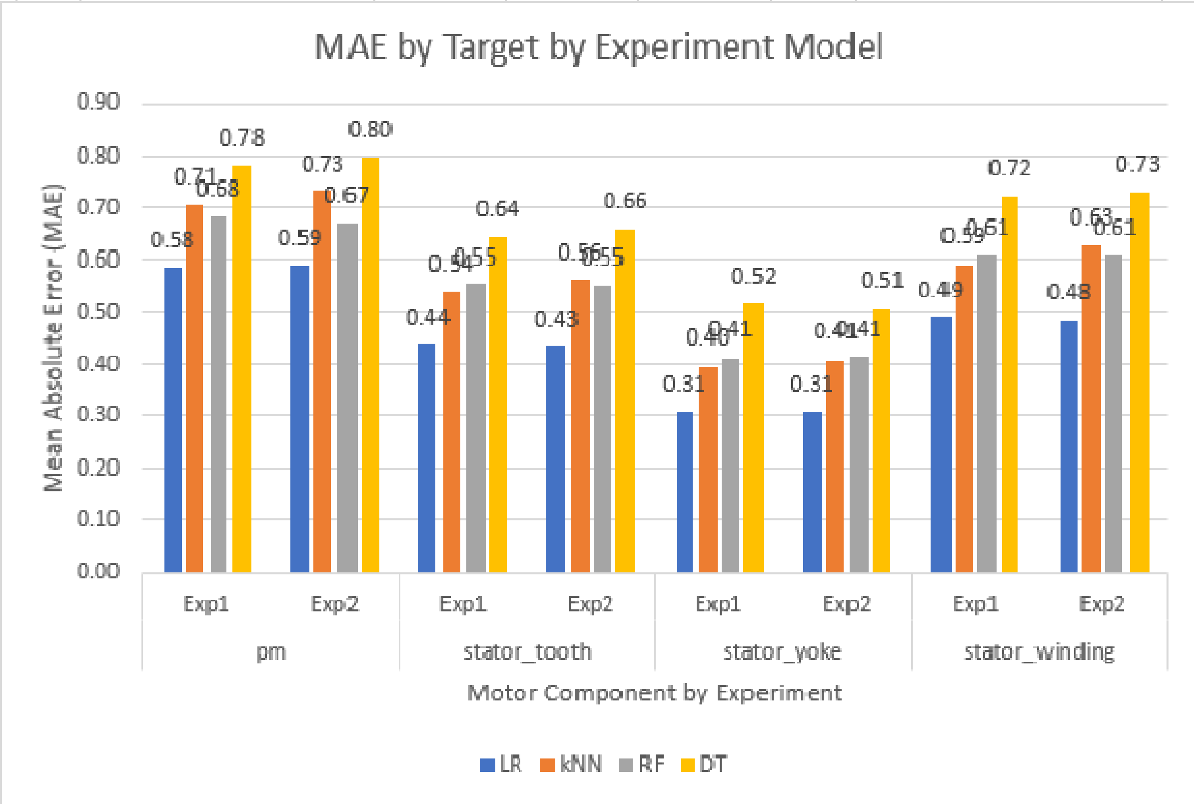

Figure 5: Comparison of model results

The analysis of the results in Tables 2 and 3 are summarized in Figure 5. From the figure, there appears to be no significant change in the performance of each model between experiment 1 and experiment 2 for each of the target variables as shown by their nearly constant MAEs. For target variable pm, there is an increase of 0.1 in each of the models in experiment 2 over experiment 1 except for the random forest (RF) model which shows a decrease of 0.1. For the stator yoke, the linear regression (LR) model shows no change over the two experiments and while there was an increase of 0.1 in the k nearest neighbours (KNN) model, there was however a decrease of 0.1 in the decision tree (DT) model. For the other target variables (stator tooth and stator winding), a similar pattern is observed where there is a small increase in the performance of one model from experiment 1 to experiment 2 but a decrease in another while others remain constant. These patterns suggests that the derivation of new features from existing ones does not have any significant effect on the performance of the models. However, among the four target variables, the stator yoke consistently shows the best performance across each of the models applied both for experiment 1 and experiment 2 with a MAE of 0.31 for LR and 0.41 for RF while the pm shows the worst performance in terms of the MAE with a MAE of 0.58 for LR in experiment 1 and 0.68 in experiment 2.

Having established from the results the insignificance of the engineered features on the performance of the models, with the estimations of the stator yoke consistently performing better than the other target variables irrespective of the applied model or the combination of features, it shows that of the four target variables, the temperature of the stator yoke is the most accurately estimated from data containing external temperature variables (ambient temperature and coolant temperature) and electrical characteristics of the motor (voltage, current and power) while the pm is the least accurately predicted.

A possible interpretation of the better performance of the stator target variables over the rotor is the ease of heat transfer across

6 Conclusion and Future Work

In this paper, test bench data from a permanent magnet synchronous motor (PMSM) was used to estimate the temperatures of the rotor, the stator yoke, the stator tooth and the stator winding in the PMSM by applying machine learning techniques. Linear regression (LR), k nearest neighbours (kNN), random forest (RF) and decision tree (DT) algorithms were employed on the dataset in two different experiments with an objective of determining the extent to which these temperatures can be accurately estimated. The models had varying performances on the task with performance measured by the mean absolute errors (MAEs) of the predictions where a lower MAE indicates a better performance. In the first experiment, models were trained for each of the four target variables using training data and evaluated on the test data using the MAEs, where the dataset was split using k-fold cross validation with k=10. The same process was repeated in experiment 2 with the data however containing derived features.

Comparing by experiment, no significant change in the performance of the models was observed between experiment 1 and experiment 2 for all the target variables while comparing by target variable, the stator yoke shows the best model performance while pm shows the worst performance.

The scope of this work was restricted to the application of simple machine learning algorithms to a PMSM due to data availability. Future work could however aim to generalize across different motor types which will require collecting data more representative of the diverse types of motors.

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