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Improved Accuracy in Estimation of Temperature for Permanent Magnet Synchronous Motor (PMSM) using Machine Learning (ML) method for Electric Vehicle Application

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Abstract— With the advancement of an electrical transportation system, demand for the efficient electric vehicles (EV's) will be more. So, manufacturing industries of EV's are using the latest technologies to design an efficient and reliable electric vehicles for the customers. Since, electric motor is the main driving component of the EVs, so our major concern is to protect the motor from various faults in the very early stage with better accuracy and with minimum error. Various types of faults which mainly oc-curs in the motors are, overheating, bearing fault, insulation breakdown, over speed, vibration, noise etc. So, in this paper Machine Learning (ML) technique is used to analyze various electrical parameters of Permanent Magnet Synchronous Motor (PMSM) taking coolant, ambient temperature, voltage, current, speed and torque as input parameters and winding temperature as output parameter. The test is performed in MATLAB software and the results found with the above method is found more improved and accurate with least error. The proposed method classifies the stator winding temperature into respective classes with 93.13% classification accuracy, sensitivity and specificity are 90.22% and 94.78% respectively.

Keywords- Electric Vehicles, Permanent Magnet Synchronous Motor, Machine Learning, Faults.

I. INTRODUCTION

With the continued growth of electric vehicles (EVs) in the market as a future transportation system, manufactur-ers are now towards the latest technologies in the designing to provide efficient and reliable vehicles to customers [1] [2]. In this regards, various factors which have to be considered before designing the EVs are Efficiency of electric vehi-cles, Faults in various parts of EVs, Battery performance, Dynamic performance etc. [3].

Now a days, faults in the electric vehicles is become the major challenge for the manufactures. Since, with the in-crease in the load capacity, customers also needs high speed and torque with long distance running. So, it become a major task to maintain the performance of the motor [4]. For the general motors, major faults which occurs are bearing fault, stator related faults, rotor related faults and eccentricity related faults [5]. The percentage of occurrence of the faults are given in below figure:

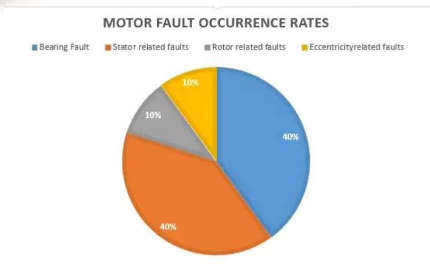

Fig. 1 Major faults occurs in motors

From the above chart, we can say that 40% of faults occurs in the stator part of the motors in the electric vehicles. To analyze

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the temperature estimation, we are considering the permanent magnet synchronous motor (PMSM) for the electric vehicle. Since, PMSM motor is now a days widely used in the electric vehicle applications due to its inherent properties like high torque to current ratio, high power to weight ratio, high efficiency and reliability [6].

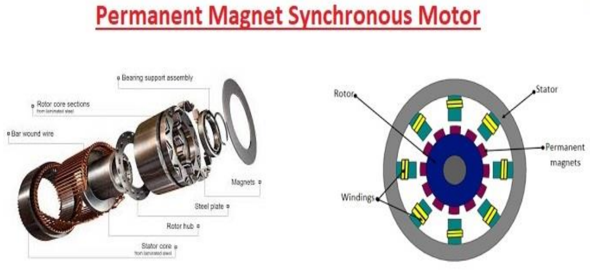

Fig. 2 Construction of PMSM Motor

Since, major parts of PMSM motors are stator, rotor, permanent magnets, bearings and shaft. We are mainly fo-cusing in the stator part of the motor. The stator of the motor also consists various components like, motor frame or yoke, stator tooth, stator winding, bearings and stator slots [7]. Our aim is to analyze the temperature of the stator winding. Due to the continuous running of the electric vehicle, motor gets heated at load condition due to its rated cur-rent which is flowing through the winding of the stator [8] [9]. If fault occurs in the winding part of the stator due to access current flow or overheating, it can affect the insulation of the winding (ageing). Due to the insulation failure, it may cause to short circuit between the windings or between winding and the core. Also it cause to overheating of the motor which indirectly increase the losses in the motor results in poor efficiency [10].

So, there are various machine learning approaches which can be used to analyze the health condition of the stator winding temperature of the PMSM motor. The various algorithms which can be used are, Linear Regression (LR), K-Means Clustering, Random Forest (RF), Naïve Bayes (NB), Decision Tree (DT) etc [11]. So, in this paper Decision Tree approach is used to predict the stator winding temperature.

In the previous researches, prediction of PMSM motor is done using deep neural network approach, in which ac-curacy is predicted to approx. 0.9439 and with the decision tree accuracy is predicted to 0.6616 [12], which is not a good performance. In another paper various machine learning algorithms are implemented and compared for predic-tion of stator winding temperature of PMSM motor, but the accuracy of prediction is approx. 0.73 [13], which is not a better results for prediction.

So, our objective of this research is to estimate the stator winding temperature of the PMSM motor with more ac-curacy with the given real time data. For this, decision tree algorithm is implemented to predict the winding tempera-ture using other input data of the motor.

The processing of the research work using decision tree algorithm can be done step by step from real time setup to extraction of features. The flow chart given below explains the process of our research work [14]. In this, initially real time data is collected, which is than trained using the machine learning algorithm. Data is classified in three catego-ries class 1, class 2 & class 3. Thus, the accuracy of the prediction is done for all the classes of the data.

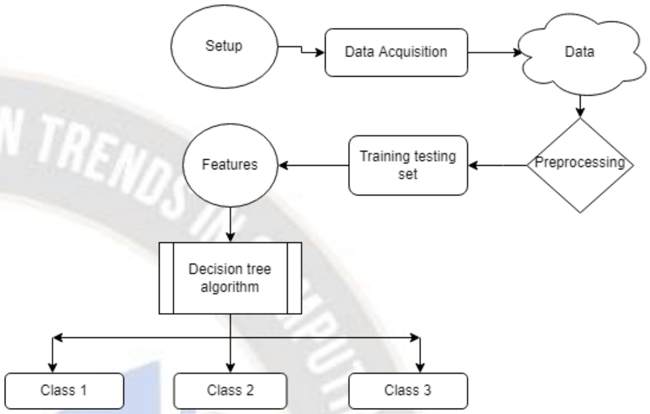

Fig. 3 Flow chart of the research work.

II. MATERIALS & METHODS

For the research work, data is collected for PMSM motor from the Kaggle website dataset [3]. In the given data, various electrical parameters are considered as an input and with the help of the data, output result is predicted. So, in the dataset, important parameters which are considered are given below in table 1.

TABLE 1 IMPORTANT PARAMETER FROM THE DATASET

ambient	coolant	u_d	u_q	motor_ speed	torque	i_d	i_q	pm	stator_ yoke	stator_ tooth	profile _id
-0.75214	-1.11845	0.327935	-1.29786	-1.2224	-0.2502	1.029572	-0.24586	-2.5221	-1.8314	-2.066	4
-0.77126	-1.11702	0.329665	-1.29769	-1.2224	-0.2491	1.029509	-0.24583	-2.5224	-1.831	-2.065	4
-0.78289	-1.11668	0.332772	-1.30182	-1.2224	-0.2494	1.029448	-0.24582	-2.5227	-1.8304	-2.064	4
-0.78094	-1.11676	0.3337	-1.30185	-1.2224	-0.2486	1.032845	-0.24695	-2.5216	-1.8303	-2.063	4
-0.77404	-1.11678	0.335206	-1.30312	-1.2224	-0.2487	1.031807	-0.24661	-2.5219	-1.8305	-2.063	4
-0.76294	-1.11695	0.334901	-1.30302	-1.2224	-0.2482	1.031031	-0.24634	-2.5222	-1.8319	-2.063	4
-0.74923	-1.11617	0.335014	-1.30208	-1.2224	-0.2479	1.030493	-0.24616	-2.5225	-1.833	-2.062	4
-0.73845	-1.11399	0.336256	-1.30515	-1.2224	-0.2483	1.030107	-0.24603	-2.5228	-1.8322	-2.062	4
-0.73091	-1.11183	0.334905	-1.30379	-1.2224	-0.2478	1.029851	-0.24598	-2.5228	-1.8316	-2.062	4
-0.72713	-1.10949	0.335988	-1.30563	-1.2224	-0.2483	1.029636	-0.24589	-2.5227	-1.8314	-2.062	4
-0.72371	-1.10828	0.3354	-1.30456	-1.2224	-0.2479	1.029509	-0.24583	-2.5226	-1.8315	-2.062	4
-0.71775	-1.10859	0.334431	-1.30434	-1.2224	-0.2477	1.029386	-0.2458	-2.5226	-1.8318	-2.062	4
-0.70488	-1.10999	0.336241	-1.30582	-1.2224	-0.248	1.029318	-0.24578	-2.5222	-1.8321	-2.062	4
-0.68253	-1.11136	0.335566	-1.30324	-1.2224	-0.2475	1.029274	-0.24578	-2.5219	-1.832	-2.062	4

From the above table, u_d & u_q are voltages across d and q axis of the motor, i_d & i_q are the currents measured across d and q axis respectively. Other data which are measured are temperature across stator yoke, stator tooth, permanent magnet surface (pm), coolant temperature & ambient temperature. In the dynamic performance, speed and torque is also considered for the prediction. With the help of the given parameters, we have to predict the temperature of the stator winding. Since at the

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running condition, temperature of the stator winding will also change as the parameters will change.

For this, decision tree algorithm is implemented for the prediction of the data. Decision tree algorithm is basically a supervised learning technique. This technique is used for both classification as well as regression problems. But mainly it is preferred to solve classification type problems. Decision tree is basically having a tree type structure having branches & root. Below flowchart is showing the working of decision tree:

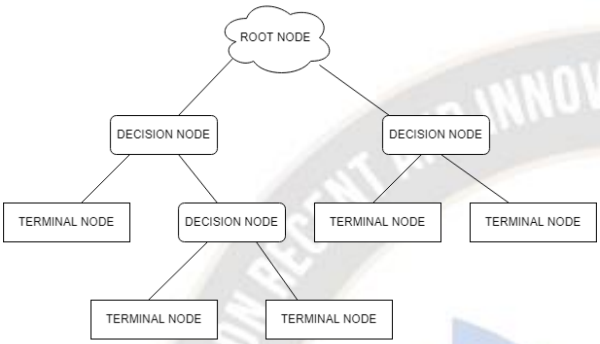

Fig 4. Flow chart of decision tree

There are basic two nodes in decision tree Decision node and Terminal node. Decision node is used to make decisions and it will have other branches. But terminal node is basically an output node and this doesn't have any further branches. In this, root node collect the data and compare with standard dataset and based on this, it further expand the data into homogeneous sub data and so on. This process will continue until it predict the final output or it reaches the terminal node.

2.1 Feature Engineering:

Q_resistance: The ratio of voltage and current of Q-axis is calculated termed as Q_resistance.

Q_resistance= Q_voltage/Q_current (1)

D_resiatance: The ratio of voltage and current of D-axis is calculated termed as D_resiatance.

D_resistance= D_voltage/D_current (2)

Q_power: The power of Q-axis is determined using the following formula:

Q_Power=Q_voltage*Q_current (3)

D_power: The power of D-axis is determined using the following equation

D_Power=D_voltage*D_current (4)

The above calculated features have fed to decision tree neural network for the classification purpose. The classification accuracy of the proposed algorithm with decision tree is found to be 93.13% using ten fold cross validation..

III. RESULTS

The dataset consists of all measurement sessions and features. Sample rate is 2 Hz. The dataset consists of Q axis voltage component, coolant temperature, stator winding temperature, D axis voltage component, stator tooth temperature, motor speed, D axis current component, Q axis current component, permanent magnet temperature, stator yoke temperature, ambient, and torque. Three respective classes have been considered for experiment. These three classes are stator winding temperature below 50℃, between 51℃ to 100℃, and above 101℃. In the proposed methodology features has been calculated using voltage and current component of Q-axis and D-axis. Resistance of Q axis and D axis is calculated which is used as two features for decision tree. Power of Q axis and D axis is calculated which act as another two features for decision tree. Resistance of Q axis and D axis and power of Q axis and D axis is fed into decision tree as an input feature set. The decision tree classified the given data into three respective classes. The figure 5-8 shows the Q and D axis voltage and currents.

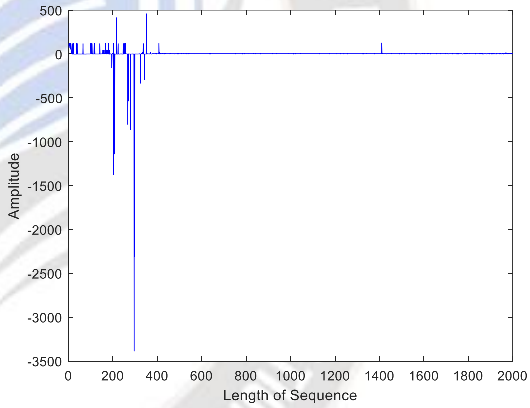

Fig 5. Voltage component of Q axis

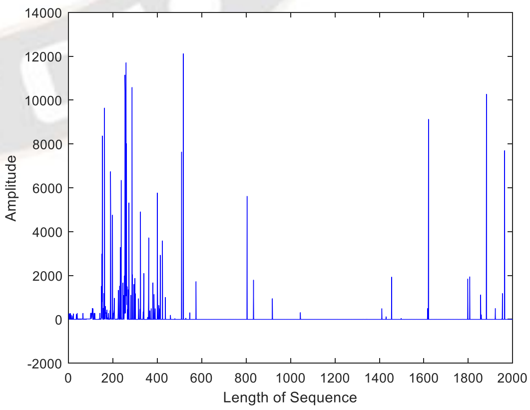

Fig 6. Voltage component of D axis

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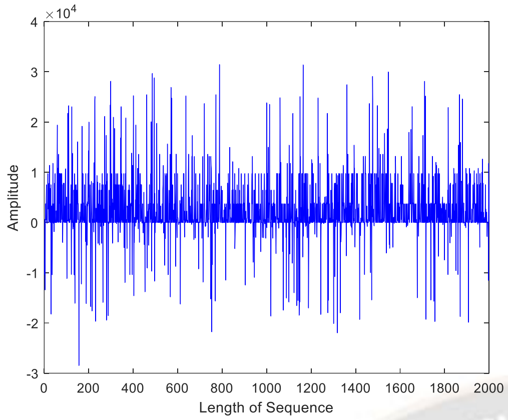

Fig 7. Current component of Q axis

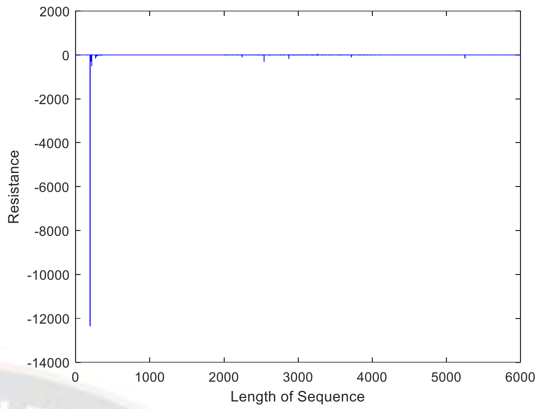

Fig 10. Resistance of D axis

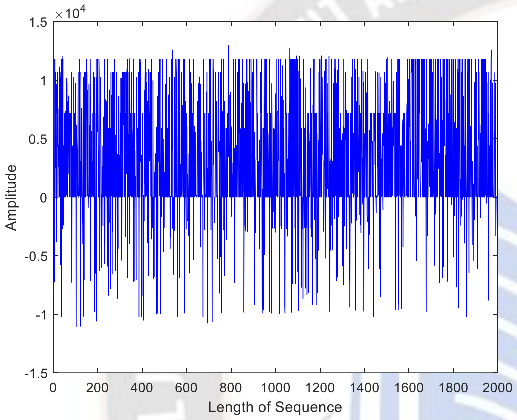

Fig 8. Current component of D axis

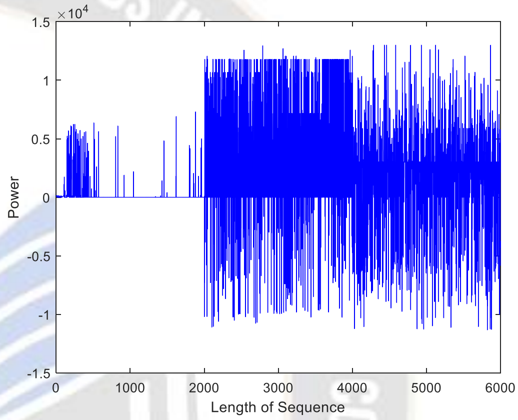

Fig 11. Power of Q axis

The figure 9-12 shows the features calculated using the dataset. Fig 9 and Fig 10 shows the resistance for Q and D axis respectively. Fig 11 and Fig 12 shows the power for Q and D axis respectively.

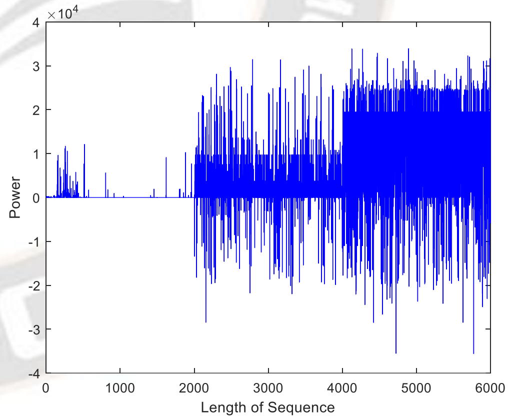

Fig 12. Power of D axis

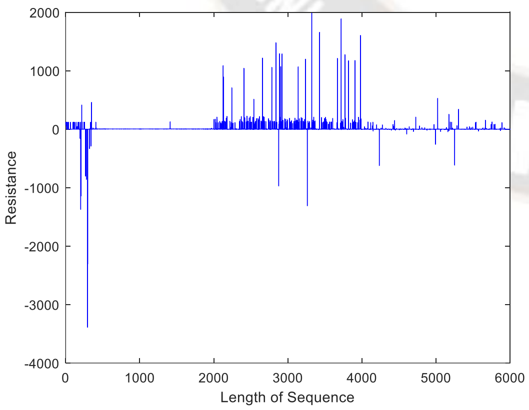

Fig 9. Resistance of Q axis

Decision tree is used to classify the input feature vector into respective classes. The accuracy of the proposed algorithm is found to be 93.13% with ten fold cross validation. Fig 13 shows the confusion matrix of the classification for decision tree. Fig 14 shows the receiver operating characteristic curve for the decision tree using proposed features.

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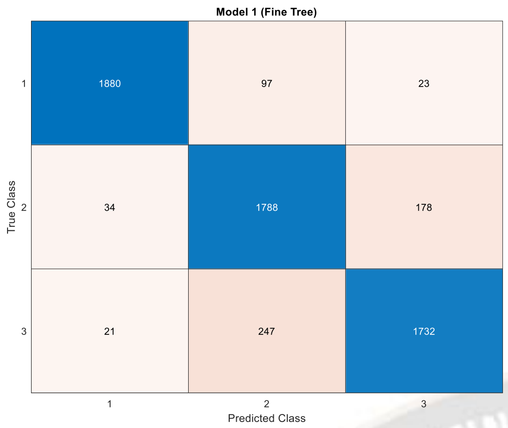

Fig 13. Confusion matrix plot for decision tree

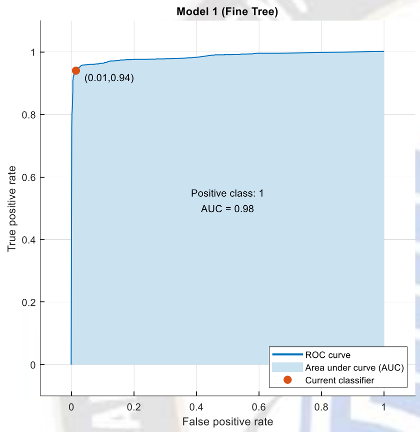

Fig 14. ROC plot for decision tree

The performance parameters for the proposed algorithm are accuracy, sensitivity, and specificity which is calculated using the following equations.

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN) \qquad (5)$$
$$\text{Sensitivity} = TP/(TP+FN) \qquad (6)$$
$$\text{Specificity} = TN/(TN+FP) \qquad (7)$$

Where TP is true positive values, TN is true negative values, FP is false positive values, and FN is false negative values.
The accuracy is 93.13%, sensitivity and specificity are 90.22%, and 94.78% respectively. The table 2 shows the performance parameters calculated for the proposed methodology.

TABLE 2. PERFORMANCE PARAMETERS FOR THE PROPOSED METHODOLOGY

S.No	Parameter	Class 1	Class 2	Class 3	Overall
1	Accuracy	96.80%	90.66%	92.00%	93.13%
2	Sensitivity	97.20%	83.86%	89.60%	90.22%
3	Specificity	96.70%	94.45%	93.19%	94.78%

IV. CONCLUSIONS

Stator winding temperature is an important parameter while determining the performance of the PMSM motor. The determination of stator winding temperature is always an challenging task for the researchers. The proposed method-ology is based on the extraction of features from the dataset which is further utilized as an input parameter for the de-cision tree. Ratio of voltage component and current component of Q axis and D axis is calculated as one feature. The product of voltage and current component of Q axis and D axis is calculated as second feature. The input feature set consists of both the features which is fed to decision tree for classification purpose. The proposed algorithm classify the stator winding temperature into three respective classes that is below 50℃, between 51℃ to 100℃, and above 101℃. The proposed algorithm correctly classified the input feature set with highest classification accuracy of 93.13%, sensitivity and specificity are 90.22% and 94.78% respectively:

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