Application of Machine Learning for Speed and Torque Prediction of PMS Motor in Electric Vehicles

Debottam Mukherjee
Department of Electrical Engineering
Indian Institute of Technology (BHU)
Varanasi, India
debottammukherjee@gmail.com

Samrat Chakraborty
Department of Electrical Engineering
National Institute of Technology
Arunachal Pradesh
Yupia, India
1995samchakraborty@gmail.com

Pabitra Kumar Guchhait
Department of Electrical Engineering
National Institute of Technology
Arunachal Pradesh
Yupia, India
pabitraguchhait@gmail.com

Joydeep Bhunia
Department of Electrical Engineering
Punjab Engineering College
Chandigarh, India
joydeepbhunia05@gmail.com

***Abstract*— Permanent Magnet Synchronous (PMS) motor has huge applications in Electric Vehicles. Therefore, a correct prediction of both speed and torque is required for satisfactory result. A dataset is considered having real time data of ambient temperature, coolant temperature, direct axis and quadrature axis voltage and current, yoke temperature, rotor temperature and stator temperature for prediction of motor speed and torque. This dataset is collected from the test bench of University of Paderbon laboratory. Various machine learning models have been applied on the dataset. The result shows that *Fine Tree* is the best model for prediction of both speed and torque of the permanent magnet synchronous motor having lowest RMSE of 0.029224 and 0.052538 for prediction of speed and torque respectively.**

Keywords—Copula, Forecasting, Machine Learning, Permanent Magnet Synchronous Motor.

I. INTRODUCTION

Recently, the use of electric vehicles in the world has grown up to a promising level. The permanent magnet synchronous motor is used in Electric Vehicles, because of its capable output. By 2030 it has been decided that there will be a 100% shift to Electric Vehicle in Delhi, India [1]. Therefore for using the Electric Vehicle a correct prediction of speed and torque of the permanent magnet synchronous motor is required based on some historic data. This historic data includes: ambient temperature, coolant temperature, direct axis and quadrature axis voltage and current, yoke temperature, rotor temperature and stator temperature.

Many researchers have done work on forecasting of different aspect of PMS motor in the use of electric vehicles. In [2] analysis of temperature sensitivity has been done for PMS motor using the Monte Carlo simulation. The result points that, there is an uncommon relationship between the tolerance of the used sensors and accuracy observed. In [3] the temperature of the magnets and windings of the PMS motor has been estimated by using Lumped-parameter thermal networks (LPTNs). The result indicates that operating range part of the speed and current is accurate enough. The estimation errors for the winding temperature, permanent magnet temperature and end-winding temperature is found to be 6.8°C, 4.7°C and 6.2°C respectively. In [4] estimation for temperature of permanent magnet synchronous motor has been done by using combination of two methods i.e. Permanent Magnet temperature observers (PMTOs) and Lumped-parameter thermal networks (LPTNs). The result shows that execution improvement over the standard topology; especially, a better unsettling influence dismissal than voltage estimation mistakes over the whole working reach. In [5] precise observer for flux method is used to predict temperature of the rotor for dynamic state of the permanent magnet synchronous motor. The result indicated altogether better discretization exactness in contrast with first order standard technique of explicit Euler. In [6] LPT Network is used for global identification of temperatures in permanent magnet synchronous motor. The result shows that model precision is cross-approved with autonomous burden profiles and a most extreme error in estimation (assuming the worst possible scenario) of 8° C in regards to all thought to be machine temperatures is accomplished. In [7] deep learning i.e. LSTM network has been used for prediction of temperatures in permanent magnet synchronous motor. The result shows that the prediction is much more accurate than previous methods and algorithms used for prediction and forecasting of temperatures in PMS motor.

While traction drives are becoming more dependent on PMSMs, monitoring of latent high dynamic temperatures within the EV motor becomes a critical issue. Deep recurrent and convolution neural networks with residual connections has been recently deployed for better understanding of the temperature profiles for the highly utilized PMSM [8]. Classical thermal modeling of with LPTNs can be bypassed with a linear regression approach. Such kind of an approach matches the traditional LPTN for estimation of temperatures within EV motors until the inputs are represented as exponentially weighted moving averages. Thus domain knowledge becomes less important and temperature estimation as well as forecasting depends purely on collected data [9]. A more robust observer topology for temperature estimation than LPTNs with inherent disturbance rejection properties has also been developed. Such kind of observers combines a gopinath type flux observers with traditional LPTN. Such kind of observer fitted with kalman filters is capable of mitigating model uncertain- ties as well as sensor noise [10]. With the rapid use of infrared surface temperature measurement for excitation winding, temperature monitoring of motors are possible. This can be seen as an alternative to digital sensors as

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well for temperature monitoring [11]. Simultaneous research works has also been carried out in PMSMs for estimation of magnet temperatures considering d axis saturation currents in hand. This is done to determine the variations of temperature with respect to magnetization for PMSM [12].

In this research, a dataset of direct axis and quadrature axis voltage and current, yoke temperature, rotor temperature and stator temperature is taken as input data of a permanent magnet induction motor collected from test bench of University of Paderbon, Germany laboratory. Initially 400,000 sample data was collected. Using copula Gaussian multivariate distribution, corresponding 600,000 corresponding synthetic data is generated. Different machine learning model is trained with this total 10,00,000 huge dataset for prediction of both speed and torque in MATLAB environment.

The paper is organized in following fashion: section I indicate the introduction of the paper, section II includes the system data, section III includes machine learning technique, section IV include result part and section IV comprises of conclusion and future works.

II. System Data

A. System Dataset

The data set of a permanent magnet synchronous motor used in electric vehicles consists of direct axis and quadrature axis voltage and current, yoke temperature, rotor temperature and stator temperature. The 400,000 sample size data is taken from the test bench of University of Paderbon, Germany laboratory [6]. Fig. 1 shows the direct axis current scatter plot of current for 400,000 data collected.

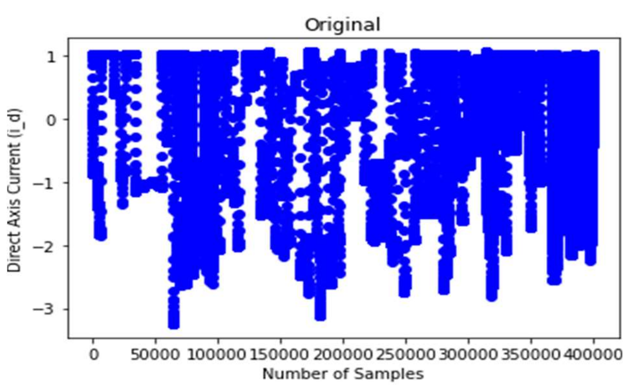

Fig. 1. Direct axis current original data scatter plot of current for 400,000 samples [6].

B. Copula Generated Synthetic Data

Distribution functions whose marginal are known is called copula. Let us consider for instance any continuous joint distribution of multivariate type having n numbers of random variables a_1 , a_2 ,…, a_n

$$F(a_1\,, a_2\,, \dots, a_n) = Prob\{A_1 \le a_1, A_2 \le a_2, \dots, A_n \le a_n\}$$

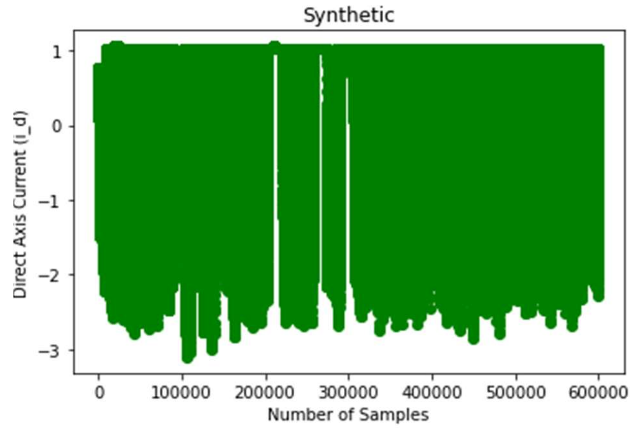

Fig. 2. Direct axis current synthetic data scatter plot of current for 600,000 samples.

is demarcated by C i.e. copula which is the distributional marginal function of:

$$F_{A_i}(a_i) = Prob\{A_i \le a_i\}, i = 1,2, \dots, n; \text{i.e.}$$

$$F(a_1, a_2, \dots, a_n) = C\big(F_1(a_1), F_2(a_2), \dots, F_n(a_n)\big)$$
$$\triangleq C(v_1, v_2, \dots, v_n) \tag{1}$$

here,

$$v_i = F_{A_i}(a_i), i = 1,2, \dots, n \text{ and } C(v_1, v_2, \dots, v_n)$$

is the function which is associated with copula. Moreover, the respective density function after applying chain rule is obtained as:

$$f(a_1, a_2, \dots, a_n) = \frac{\partial^n C(v_1, v_2, \dots, v_n)}{\partial v_1\, \partial v_2 \dots \partial v_n}$$

$$\triangleq c(v_1, v_2, \dots, v_n) \cdot f_1(a_1) \cdot f_2(a_2) \cdot \dots \cdot f_n(a_n) \tag{2}$$

The equation (2) represents the density function jointly in which the marginal product is $f_i(a_i)$, $i = 1,2, \dots, n$ and the corresponding density function for copula is $c(v_1, v_2, \dots, v_n)$.

Let us consider $\mathbf{Z} = (z_{i,j})$, $i = 1,2, \dots, n$, $j = 1,2, \dots, n$ a positive symmetric definite matrix with entry of diagonal unit. Therefore, the definition of *Gaussian copula for multivariate* is [13]

$$C(v_1, v_2, \dots, v_n; \mathbf{Z}) = \phi_{\mathbf{Z}}(\varphi^{-1}(v_1), \varphi^{-1}(v_2), \dots, \varphi^{-1}(v_n)) \tag{3}$$

here, $\boldsymbol{\phi}_{\mathbf{Z}}$ is demarcated by standard normalized multivariate distribution whose matrix for correlation is

$$\mathbf{Z} = (z_{i,j}), i = 1,2, \dots, n, j = 1,2, \dots, n\,.$$

The inverse univariate distribution for standard normal $\varphi(a)$ is $\varphi^{-1}(a)$. The density function is

$$c(v_1, v_2, \dots, v_n; \mathbf{Z}) = \frac{1}{|\mathbf{Z}|^{1/2}} \exp\left(-\frac{1}{2}\boldsymbol{\omega}^T(\mathbf{Z}^{-1} - \mathbf{I})\boldsymbol{\omega}\right) \quad (4)$$

and,

$$\boldsymbol{\omega} = \left(\varphi^{-1}(v_1), \varphi^{-1}(v_2), \dots, \varphi^{-1}(v_n)\right)^T.$$

In this paper, *copula multivariate distribution* is used to generate synthetic data of direct axis and quadrature axis voltage and current, yoke temperature, rotor temperature and stator temperature. From 400,000 original data, 600,000 synthetic data is generated. Fig. 2 shows the synthetic direct axis scatter plot of current for 600,000 samples. In this paper, final dataset of the PMSM is developed with standardization on unit standard deviation of the dataset followed by subtraction of the mean. A detailed procedure of the dataset can be seen in [6].

III. Machine Learning

With the rapid deployment of machine learning models in the domain ofmotor derating forecasting, it becomes a challenging task for the researcher to identify the best model based on RMSE which can fit the model features accurately. The rapid deployment of electric vehicles comes with its ingrained limitations. Our goal here is to forecast the effects of stator temperature, ambient temperature, yoke temperature, rotor temperature, coolant temperature, voltage (d & q components) as well as current (d & q components) on motor speed and torque characteristics. Measurements in the dataset were recorded with a sampling frequency of 2 Hz and temperatures were recorded with use of infrared sensors. The PMSM (permanent magnet synchronous motor) was excited with the aid of hand designed driving cycles indicating a reference motor speed and torque. Measurements were taken from duration of 1-6 hours. These driving cycles signify random walks in the speed-torque hyper-plane so as to emulate the real world driving cycles to a more accurate degree. From the comparative analysis of the several machine learning models *fine tree* based regression model outperforms the other studied models in case both speed and torque forecasting.

Fine Tree based Regression

Tree based regression model can provide a better forecasting than statistical forecasting methodologies like ARIMA, SARIMAX etc. Large feature space based datasets are best suited for such kind of regression models. Such models generally comprises of two major steps.

Dividing the predictor space of feature variables into well-defined non intersecting regions (branches of trees). Prediction subspaces can be defined by any shape, here we have chosen high dimensional rectangular boxes for ease of simplicity and interpretation. The aim is to minimize the objective function as [14]:-

$$z = argmin_{\hat{y}} \sum_{j=1}^{J} \sum_{i \epsilon R_j} (y_i - \hat{y}R_j)^2 \quad (5)$$

where, J is the number of boxes, y_i represents the observed variable at i^{th} instant and yR_j represents the estimated observed output.

For every measurement that comes within this region prediction is done by taking the mean of the responses of the training set in that specific region.

For consideration of every feature space into J boxes it becomes computationally tedious and solutions tends to become infeasible. To overcome such issues a top down greedy approach is adopted which is known as recursive binary splitting (RBS). For this RBS approach we identify and select the predictor and cut points that lead to a better optimal result of the objective function z.

$$R_1(j, s) = \left[X \middle| X_j \leq s\right] \quad (6)$$

$$R_2(j, s) = \left[X \middle| X_j > s\right] \quad (7)$$

The final objective is to minimize the objective function z_1.

$$z_1 = argmin_{j,s} \sum_{i:x_{i \in R_1(j,x)}} (y_i - \hat{y}R_1)^2 + \sum_{i:x_{i \in R_2(j,x)}} (y_i - \hat{y}R_2)^2 \quad (8)$$

This method of RBS being greedy in nature has a tendency of over fitting. This model has a higher variance but a fine tree with fewer splits leads to lower variance but with a higher bias. Thus this tree size is a tuning parameter which is dependent on data. For overcoming over fitting of the model a cost complexity pruning algorithm is also used. This algorithm ascertains the minimum node size which in the other hand stops splitting. A sub-tree T can be obtained by reducing the internal nodes. Terminal nodes are represented by m with each node representing a region R_m. $|T|$ denoting the terminal nodes inT.

$$N = \#[x_i \in R_m] \quad (9)$$

$$\hat{c}_m = \frac{1}{N_m} \sum_{x_i \in R_m} y_i \quad (10)$$

$$Q_m(T) = \frac{1}{N_m} \sum_{x_i \in R_m} (y_i - \hat{c}_m)^2 \quad (11)$$

$$C_\alpha(T) = \sum_{m=1}^{|T|} N_m Q_m(T) + \alpha|T| \quad (12)$$

Tuning parameter (α) is the governing criteria which gives a tradeoff between tree size and goodness of fit of the model. Larger value of α, lead to smaller tree node and vice versa. A is estimated for fine trees with a minimum of tenfold validation.

IV. Machine Learning Regression Results

Several machine learning regression models are trained with the independent variables like direct axis and quadrature axis voltage and current, yoke temperature, rotor temperature and stator temperature for the dependent variable i.e. speed and torque of the permanent magnet synchronous motor. Table 1 shows the parameters of PMSM under test. Related to the optimization results obtained from the machine learning algorithms, top three regression models on the basis of RMSE value is shown for two conditions i.e. speed and torque of the permanent magnet synchronous motor.

TABLE I. PARAMETERS OF THE PMSM UNDER TEST [6]

Item No.	Type	Rating / Nature
1	Maximum Voltage Rating	177 V
2	Current Rating	110-282 A
3	Power Rating	19.6-50.6 W
4	Torque Rating	110-283 Nm
5	Speed Rating	1700-6000 rpm
6	Number of Pole Pares	8
7	Cooling Type	Water Jacketed Cooling
8	Winding Type	Fractional Slot concentrated Winding

A. Machine Learning Result for speed of PMS Motor

The machine learning algorithm shows that *Fine Tree* based method has least RSME value of 0.029224. Table 2 shows the comparative analysis of machine learning algorithm with RMSE (for speed). Fig. 3 shows the *Fine Tree* machine learning algorithm for true and predicted plot of speed. Fig. 4 shows the *Medium Tree* machine learning algorithm for true and predicted plot of speed. Fig. 5 shows the *Coarse Tree* machine learning algorithm for true and predicted plot of speed.

B. Machine Learning Result for torque of PMS Motor

The machine learning algorithm shows that *Fine Tree* based method has least RSME value of 0.052538. Table 3 shows the comparative analysis of machine learning algorithm with RMSE (for torque). Fig. 6 shows the *Fine Tree* machine learning algorithm for true and predicted plot of torque. Fig.7 shows the *Medium Tree* machine learning algorithm for true and predicted plot of torque. Fig. 8 shows the *Coarse Tree* machine learning algorithm for true and predicted plot of torque.

TABLE II. COMPARATIVE ANALYSIS OF DIFFERENT MACHINE LEARNING METHODS (FOR SPEED WITH PCA ENABLED)

Sl. No.	Machine Learning Algorithm	RMSE Value
1	Fine Tree	0.029224
2	Medium Tree	0.029619
3	Coarse Tree	0.031118

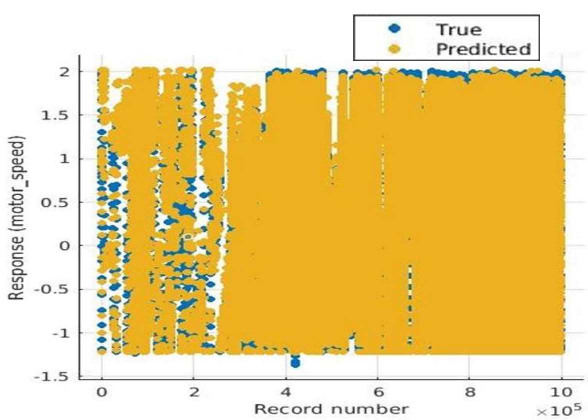

Fig. 3. *Fine Tree* machine learning algorithm for true and predicted plot of speed.

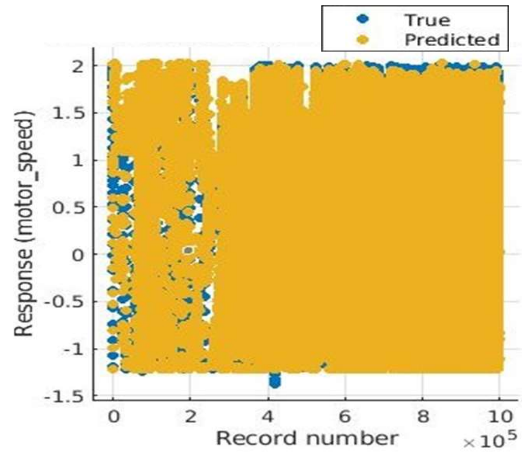

Fig. 4. *Medium Tree* machine learning algorithm for true and predicted plot of speed.

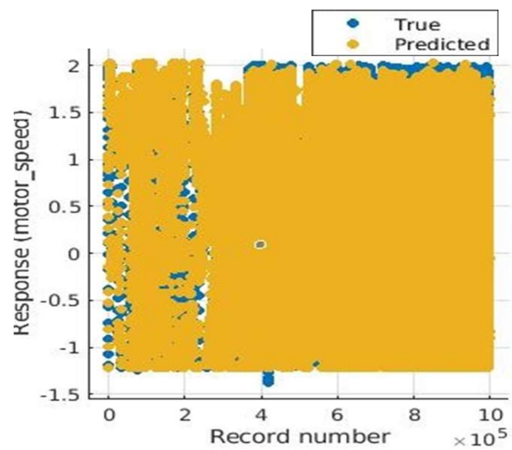

Fig. 5. *Coarse Tree* machine learning algorithm for true and predicted plot of speed.

TABLE III. COMPARATIVE ANALYSIS OF DIFFERENT MACHINE LEARNING METHODS (FOR TORQUE WITH PCA ENABLED)

Sl. No.	Machine Learning Algorithm	RMSE Value
1	Fine Tree	0.052538
2	Medium Tree	0.053787
3	Coarse Tree	0.058067

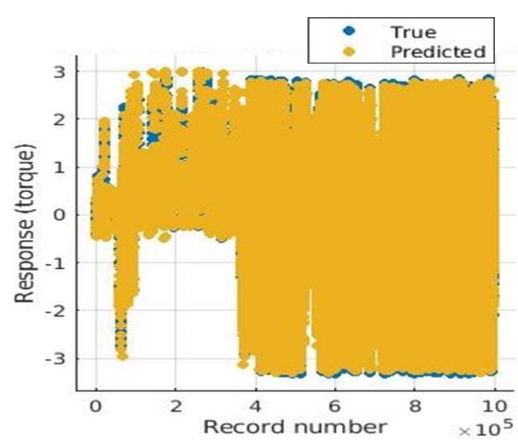

Fig. 6. *Fine Tree* machine learning algorithm for true and predicted plot of torque.

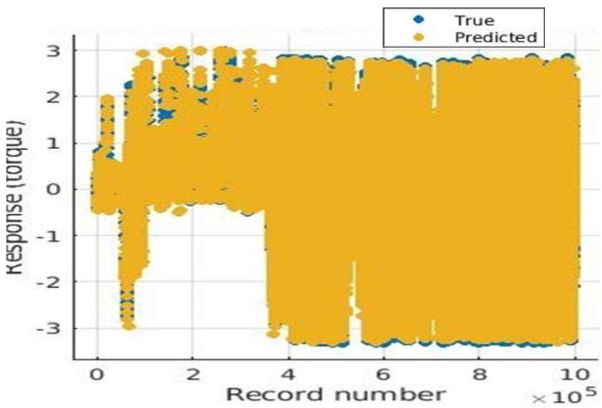

Fig. 7. *Medium Tree* machine learning algorithm for true and predicted plot of torque.

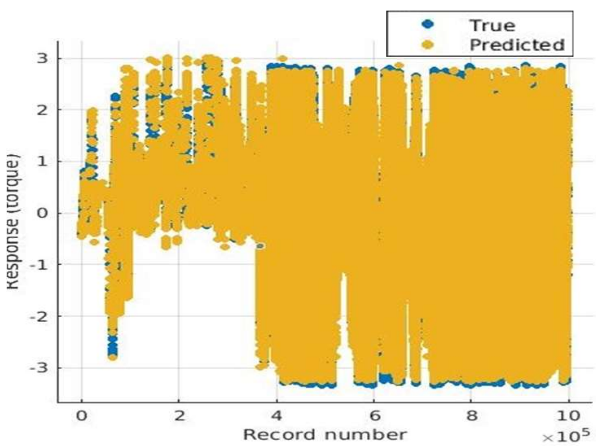

Fig. 8. *Coarse Tree* machine learning algorithm for true and predicted plot of torque.

V. CONCLUSION AND FUTURE WORKS

The machine learning result shows that *Fine Tree* is the best methods for forecasting both the speed and torque of a permanent magnet synchronous motor. This helps in designing an Electric Vehicle more effectively. The best methods are determined on the basis of least RMSE achieved from the result. The less the error is, the more accurate the prediction will be. With the fine tree-based machine learning model trained on a particular dataset of EV prototype model, it remains a question whether such kind of a model is robust enough for other OEMs, or with the same manufacturer but with pre specified parameters of thermal throttling, production tolerances etc. Moreover, such kind of models does not take into account motor aging. This issue can be taken up as future challenges in this area.

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