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Adaptive Model Predictive Control for IPMSM Based on Machine Learning Models

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Abstract: - Accurate torque estimation is necessary for effective management of Interior Permanent Magnet Synchronous Motors (IPMSM) in commercial settings. High computational complexity and model parameter mismatches are common problems with traditional Model Predictive Control (MPC) techniques. This work presents the Random Forest (RF) regression model to estimate important PMSM parameters for precise torque in the shortest amount of time. To accurately forecast electromagnetic torque, the model uses rotor angle ω, voltages, and dq axis currents as input parameters. RF uses a collection of decision trees to increase prediction accuracy with lower variance and overfitting to effectively manage nonlinearities. The model was created in Python programming to increase torque prediction accuracy. With the aid of the RF approach, torque may be estimated, greatly increasing computing efficiency and responsiveness to changes in the load in real time. The suggested approach improves motor control performance and offers a dependable substitute for traditional sensor-based methods.

Keywords: IPMSM, MPC, Random Forest, Torque estimation

1.Introduction

Electric Vehicles (EVs) have emerged as an effective solution to environmental and energy challenges. Among several propulsion systems, Interior Permanent Magnet Synchronous Motors (IPMSMs) are distinguished by their extensive speed range, high power density, and efficiency. IPMSMs produce substantial low-speed torque, making them ideal for urban driving [1]. Precise torque control is crucial for maximizing IPMSM performance in EVs. Diverse control systems, such as Field Oriented Control (FOC) and Direct-Torque Control (DTC) [2], facilitate this objective. Advancements in sensor technology and motor control algorithms have significantly enhanced the accuracy and responsiveness of the IPMSM torque controller, resulting in improved efficiency and overall driving experience [3]. Offline torque estimation, facilitated by torque transducers and sensors, provides essential data for the development of control schemes. This approach guarantees that IPMSMs align with the dynamic power requirements of EV propulsion, enhancing operational efficiency [4]. Simultaneously, online torque estimate methods provide real-time observation and adjustment, ensuring optimal power distribution across diverse driving conditions. These technologies utilize intricate algorithms and sensor data to ensure impeccable electric vehicle performance, particularly in urban environments characterized by rapid acceleration and deceleration. Kriging-based techniques have been developed for real-time torque estimate in brushless DC motors, enhancing IPMSM control [5]. Figure 1 illustrates a block schematic of an IPMSM control system utilizing Model Predictive Control (MPC). Accurate torque estimation is vital to efficient IPMSM management. Online approaches employ real-time electrical parameters to compute instantaneous torque, minimizing complexity and expense..

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2. Proposed Methodology

2.1. Frame work for proposed methodology:

This paper introduces an ML approach for IPMSM torque prediction [6], utilizing cleaned data and R^2 evaluation to optimize motor control efficiency as shown in figure 2.

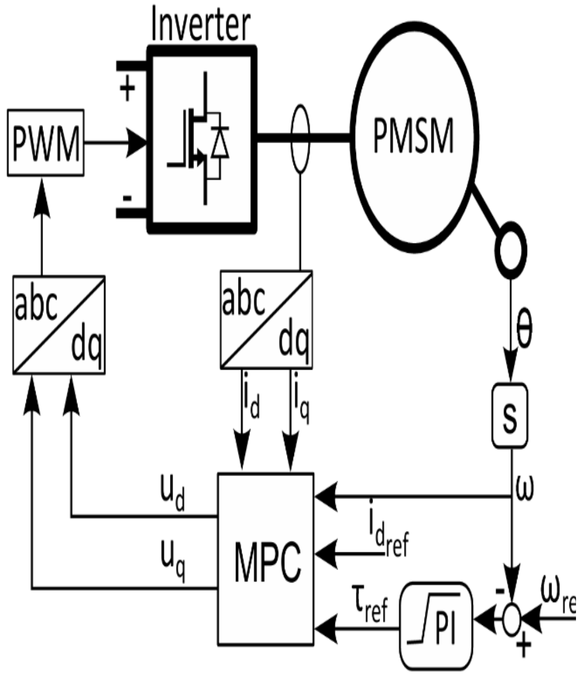

Fig 1: Drive control system with MPC

Fig 2: Flow chart of Proposed Methodology

A typical method uses Clark and Park transformations, simplifying IPMSM models for FOC. Clark transformation translates 3ϕ voltages and currents into a 2ϕ stationary frame, while Park conversion maps them onto a rotating reference frame, as shown in Figure 3. In an IPMSM, L indicates the stator's magnetic flux, whereas u_a, u_b and u_c imply phase voltages. Similarly, i_a, i_b and i_c denote phase currents, whereas R refers to stator winding resistance. The 3ϕ voltage equations are complex differential equations requiring transformation for simplified control. Park and Clark transformations reduce these voltage models into comprehensible forms.

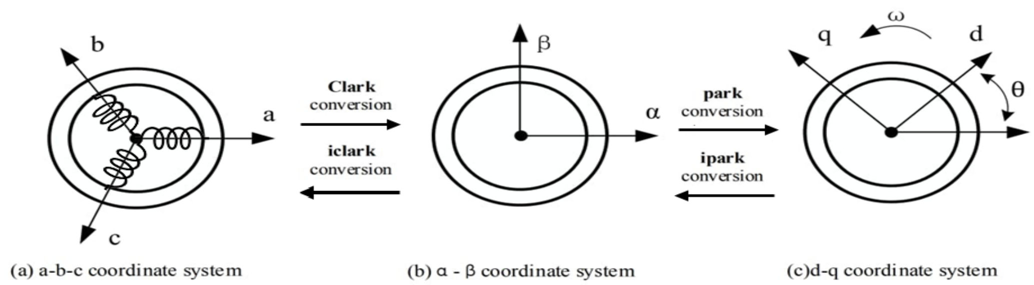

Fig 3: Transformation relationship in IPMSM

$$\begin{bmatrix} u_a \\ u_b \\ u_c \end{bmatrix} = \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} L & 0 & 0 \\ 0 & L & 0 \\ 0 & 0 & L \end{bmatrix} \frac{d}{dt} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \Phi_\omega \begin{bmatrix} \sin \omega t \\ \sin(\omega t - 2\pi/3) \\ \sin(\omega t + 2\pi/3) \end{bmatrix} \quad (1)$$

$$\begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} X \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} \quad (2)$$

$$\begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & 0 \\ -\frac{1}{2} & \frac{\sqrt{3}}{2} \\ -\frac{1}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} X \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} \quad (3)$$

$$\begin{bmatrix} i_d \\ i_q \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} X \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} \quad (4)$$

$$\begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} X \begin{bmatrix} i_d \\ i_q \end{bmatrix} \quad (5)$$

2.2. Implementation of Polynomial Linear Regression Model

PLRM utilises the measured torque and speed as regressors to estimate torque control. The torque curve is presented as equation (6) showcasing the relation between speed and measured torque, can therefore be fitted to the mathematical expectation of higher order items, k = 0. Things with a high order "k" are expected to have a small population. However, the equation (6) for bivariate k^{th}-order PLRM [7] is referred to as

$$T_{cij}=\sum_{\gamma=0}^{k} \sum_{\lambda=0}^{k} \beta_{\gamma\lambda} T_{mij} \lambda + \varepsilon_{ij} \quad (6)$$

Where k should be greater than or equal to 1, i = 1,2,3,……n and j = 1,2,3,…..q

Once ε_{ij} is torque error and $\beta_{\gamma\lambda}$ is required to determine the regression coefficient which has the same distribution and is independent. To obtain second-order polynomials' linear regression. The cost of k in equation (6) is 2. Equation 6 helps in building the bivariate second order regressors of the measured torque and speed.

$$PLRM.T_{cij} = \beta_{00}+\beta_{01}\omega_i + \beta_{02}\omega_i^2 + \beta_{10}T_{mij} + \beta_{11}T_{mij}\omega_i + \beta_{20}T_{mij}^2+\varepsilon_{ij} \quad (7)$$

$$\text{where} T_{mij} = \begin{bmatrix} x_{i100} & x_{i101} & x_{i102} & x_{i110} & x_{i11} & x_{i120} \\ x_{i200} & x_{i201} & x_{i202} & x_{i210} & x_{i211} & x_{i220} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{iq00} & x_{iq01} & x_{iq02} & x_{iq10} & x_{iq11} & x_{iq20} \end{bmatrix} \quad (8)$$

$$\beta=[\beta_{00} \quad \beta_{01} \quad \beta_{02} \quad \beta_{10} \quad \beta_{11} \quad \beta_{20}]^T \quad (9)$$

In equation (8), ω_i has a value of 0. Equation (10) then demonstrates how to use the experimental torque regressor to produce the univariate 2^{nd} order PLRM. Equation (11) illustrates one approach to rewrite equation (9).

$$T_{cij}=\beta_{00} + \beta_{10}T_{mij} + \beta_{20}T_{mij}^2 + \varepsilon_{ij} \quad (10)$$

$$\beta = [\beta_{00} \quad \beta_{10} \quad \beta_{20}]^T \quad (11)$$

2.3. Random Forest (RF) algorithm

RF regression is a combined learning technique that aggregates and averages the output of several decision tree models. The fundamental purpose of RF is to build a massive amount of decision trees, individually trained on an arbitrary chunk from the training data & attributes. The ultimate conclusion of the prediction process is decided by a majority vote on each given tree projection. Two of RF's key strengths are its relative insensitivity to hyperparameter selection and its flexibility to handle a large array of data types and distributions [8]. An ensemble method called RF creates a large amount of decision trees and assesses the average of their projections. Additionally, by offering important insights into the relative values of each component in the forecast, RF helps comprehension of the underlying data patterns. A piece of the training data with replacement and a chunk of the input topographies at each split are needed for each decision tree in the randomly selected RF. This randomization decreases overfitting to the training set and boosts generalization performance on fresh data. The target variable is estimated more precisely and robustly as a result of this merger. The RF regression technique's mathematical form is clearly represented in the equation below [9].

$$\bar{\bar{Y}} = \frac{1}{n}\sum_{k=1}^{n} f_k(X)$$

where $f_k(x)$ the forecast of the k_{th} decision tree, n is the quantity of decision trees in the RF model, and Y represents projected value. Figure 4 depicts the flow chart of RF algorithm.

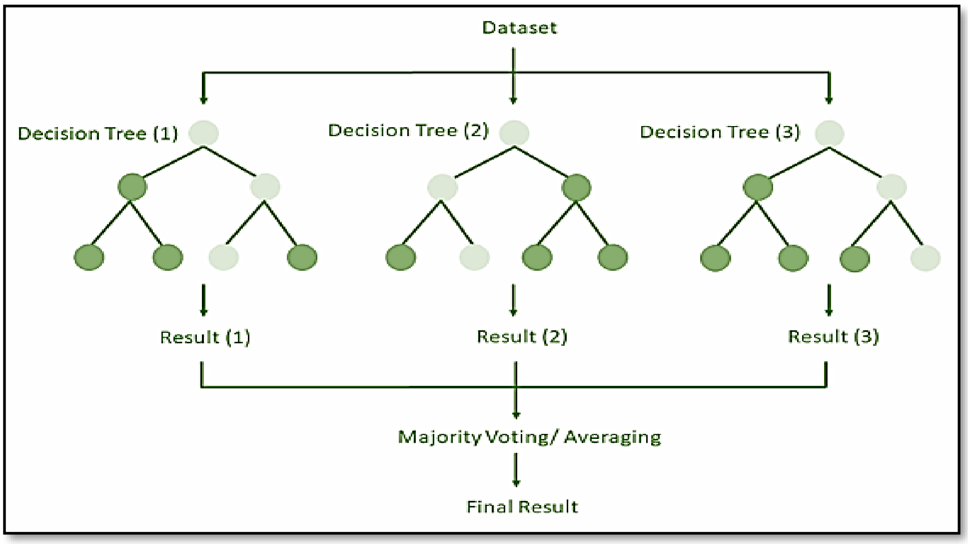

Fig 4: Flow chart for RF algorithm structure

3. Results and Discussion

3.1. Information set

This article gives a detailed study of two datasets, Dataset 1 and Dataset 2, comprising torque T values in Nm. As seen in Figure 5, the dataset statistics well support the recorded torque values and their distribution

Dataset 1 embraces 370 lack samples with a mean torque of -0.86 Nm with an average deviation of 71.39 Nm, fluctuating between -133.90 Nm & 134.07 Nm. The Inter Quartile Range (IQR) spans -56.13 Nm to 55.40 Nm, with a median of -1.08 Nm. Similarly, Dataset 2 has 370 lack samples but a slightly lower mean of -0.90 Nm and 72.51Nm of average deviation. Torque values range from -136.84 Nm to 136.04 Nm, with an IQR of -59.40 Nm to 57.54 Nm and an average of -1.37 Nm

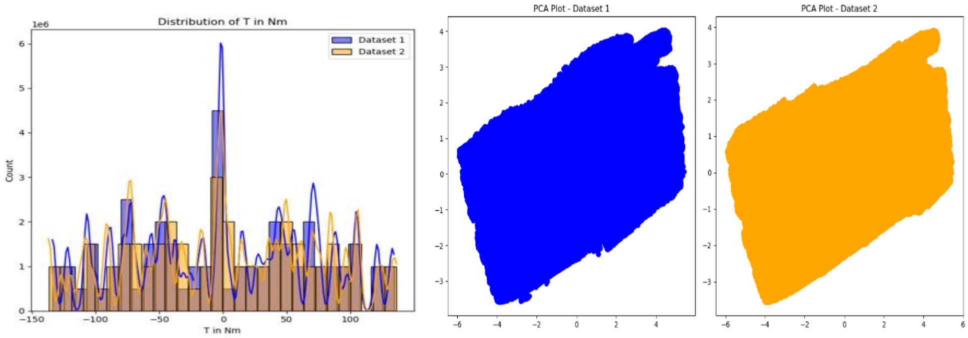

Fig 5: Dataset Visualization

3.2. Results

The performances of polynomial linear regression and RF for torque estimation at two distinct speeds (i.e.,120 RPM and 2000 RPM) are reported in tables 1 and 2 correspondingly. The R-squared values of RF given in table.2 is 0.999 and 0.998 at both speeds accompanying low values of MSE, RMSE and MAE suggests polynomial linear regression and RF for accurate torque estimate. The RF model captures the variance in the dataset and shows that it greater predicting skills over polynomial linear regression model for real time variations in the load.

Table 1: Torque Estimation using PLRM

Speed in RPM	Mean-Square Error (MSE)	RootMean-Square Error (RMSE)	Mean-Absolute Error (MAE)	R^2
120	212.8501	14.5892	10.9491	0.9581
2000	206.0641	14.3543	10.7142	0.9608

Table 2: Torque Estimation using RF

Speed in RPM	Mean-Square Error (MSE)	RootMean-Square Error (RMSE)	Mean-Absolute Error (MAE)	R^2
120	2.4377	0.0049	4.8652	0.9999
2000	10.3538	3.2177	2.4220	0.9980

4. Conclusions

The three-phase currents, voltages, and torque estimations were generated using MATLAB/Simulink and validated against a Kaggle dataset. While MPC ensures accurate torque estimation, it faces challenges like nonlinearities and high computational costs. This study applies a RF regression model using dq axis current, voltage, and rotor angle ω for rapid and precise torque prediction. The research investigated through python programming for predicting torque through RF technique which enhances accuracy, reduces variance, and improves computational efficiency, offering a reliable IPMSM control.

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