

Optimizing KPIs Prediction for Different Motor Geometries: A Gradient Boosting Approach

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This paper presents a novel surrogate modeling approach for electric motor design using Extreme Gradient Boosting (XGBoost). Traditional finite element analysis (FEA) methods for motor performance evaluation are computationally intensive, limiting design space exploration and optimization. To address this challenge, we developed a multi-output XGBoost model that simultaneously predicts seven critical motor performance parameters—torque, torque ripple, copper mass, magnet mass, power factor, Von Mises stress, and winding temperature—based on eight design input parameters. The model demonstrated exceptional prediction accuracy with coefficient of determination (R^2) values consistently above 98% across all output parameters. Feature importance analysis revealed that rotor radius, tooth dimensions, and barrier geometry parameters had the greatest impact on motor performance metrics. By reducing computational time by approximately three orders of magnitude compared to FEA while maintaining high prediction accuracy, the taken approach enables rapid design space exploration and optimization. The model integrates electromagnetic, thermal, and mechanical performance predictions within a unified framework, providing a holistic solution for electric motor design that balances computational efficiency with fidelity to physical constraints.

Index Terms—Data-driven approach, Gradient Boosing, XGBoost, Motor Geometry, Torque, Temperature, Von Mises Stress

I. INTRODUCTION

The electric vehicle (EV) market presents significant challenges for motor design, requiring optimization of multiple conflicting parameters. EV motors must deliver high efficiency, rapid torque response, and substantial power density [1] while minimizing noise, vibration, and harshness [2]. Traditional design methodologies rely on Finite Element Analysis (FEA), which is computationally intensive and time-consuming—limiting design space exploration and optimization capabilities [3]. Surrogate modeling has emerged as a powerful alternative by creating data-driven approximations of high-fidelity simulations, enabling rapid performance predictions without repeated intensive calculations [3], with machine learning integration significantly enhancing these capabilities, particularly in automotive systems [4].

Various surrogate modeling techniques have been explored, including Response Surface Methodology (RSM), Kriging, Artificial Neural Networks (ANNs), and Support Vector Regression (SVR) [5]. Comparative studies have shown varying performance among these techniques, with Kriging demonstrating strong results in certain electric machine applications [6]. Despite advancements, challenges remain, including accuracy limitations for highly sensitive input-output relationships, difficulty capturing complex multiphysics interactions, and the substantial computational cost of generating training data [3].

Machine learning methodologies have proliferated across engineering fields [7], including chip design, civil engineering, manufacturing, and automotive applications [8], with specific exploration in electric motor applications [9]. Extreme Gradient Boosting (XGBoost) has emerged as a powerful machine learning technique offering advantages in handling missing data, scalability, and computational efficiency [10]. Multi-output regression predicts multiple continuous target variables simultaneously [11], using either problem transformation or algorithm adaptation methods [12], with potential benefits

for electric motor design where performance parameters are interrelated [13].

The primary research objective is to develop accurate surrogate models for predicting electric motor performance parameters using XGBoost, hypothesizing that it can provide superior prediction accuracy and computational efficiency compared to conventional techniques. The research proposes that a single multi-output XGBoost model can effectively predict diverse performance parameters simultaneously, including torque, torque ripple, material masses, power factor, mechanical stress, and operating temperature, while incorporating critical physical constraints to ensure the feasibility and reliability of predicted motor designs.

II. METHODOLOGY

XGBoost is used as a Gradient Boosting approach, leveraging Gradient Boosting's structured data efficiency and feature importance analysis [14]. This study aims to develop a predictive model for electric motor performance based on various design parameters. The target is to establish relationships between eight input parameters and seven output parameters of an electric motor. The model enables rapid performance prediction, replacing computationally expensive finite element simulations typically used in motor design optimization.

The dataset was compiled from finite element analysis (FEA) simulations of electric motor designs with varying input parameters. The dataset underwent preprocessing steps including data cleaning, feature selection, and data normalization. After evaluating several regression algorithms, XGBoost was selected for its superior performance in capturing complex, non-linear relationships between motor design parameters and performance metrics. The XGBoost model was configured with hyperparameters including objective function coefficient of determination (R^2), 1000 estimators, maximum tree depth of 6, learning rate of 0.05, subsample ratio of 0.8, and regularization parameters.

III. RESULTS

The XGBoost regression model was implemented to predict seven critical output parameters of electric motor design based on ten variable input parameters. Table I summarizes the R^2 values for each predicted output parameter. The XGBoost model demonstrated exceptional predictive performance across all seven output variables, with R^2 values consistently above 98%. The highest accuracy was achieved for maximum winding temperature prediction (99.94%), followed closely by the mass of winding copper (99.90%). Even the most challenging parameter to predict, power factor, yielded a strong R^2 value of 98.35%.

TABLE I
PREDICTION RESULTS

Parameter	R^2
Torque (T)	99.74%
Torque ripple (T_r)	99.13%
Mass of winding copper (M_{Cu})	99.90%
Mass of rotor magnets (M_{mag})	99.73%
Power factor ($\cos(\phi)$)	98.35%
Von Mises stress (VM)	99.66%
Max winding temperature ($Temp$)	99.94%

Feature importance analysis revealed that rotor radius and tooth dimensions were the most influential parameters affecting multiple output variables. For torque ripple prediction, barrier position (d_a) and barrier shift (dx_{IB}) emerged as dominant factors. The power factor prediction was most heavily influenced by the current phase angle (γ).

IV. DISCUSSION

The observed differences in R^2 scores among the predicted output parameters, though minimal (ranging from 98.35% to 99.94%), can be attributed to several underlying factors related to the diverse amplitude of input parameter ranges. The power factor ($\cos(\phi)$) exhibits the lowest R^2 score (98.35%) likely because it represents a complex nonlinear function of multiple input parameters. Parameters like copper mass (M_{Cu}) and maximum winding temperature ($Temp$) demonstrate exceptionally high R^2 scores (99.90% and 99.94% respectively) because they are governed by more deterministic physical relationships.

The principal innovation of this work lies in several key contributions: simultaneously predicting seven critical motor performance parameters with exceptional accuracy, application of gradient-boosted trees that outperforms traditional neural network methods, integration of electromagnetic, thermal, and mechanical performance predictions within a unified framework, and reduction of computational time by approximately three orders of magnitude compared to finite element analysis, while maintaining accuracy levels above 98%.

V. CONCLUSION

This research has demonstrated the effectiveness of XGBoost as a surrogate modeling technique for electric motor design and performance prediction. The developed model

achieved remarkable prediction accuracy across all seven output parameters, with R^2 values consistently above 98%. By simultaneously predicting electromagnetic, thermal, and mechanical performance metrics, the taken approach provides a comprehensive design optimization framework that eliminates the need for separate domain-specific models. The computational efficiency of the surrogate model enables rapid design space exploration while maintaining high fidelity to physical constraints. The methodology established in this work can be extended to other electric machine topologies and offers a promising alternative to traditional simulation-based approaches.

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