

A Computationally Efficient Approach to Optimizing Axial Flux Permanent Magnet Synchronous Motor for Electric Vehicle Using Initial State Finite Element Analysis and Machine Learning

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This paper proposes a novel design methodology aimed at efficiently reducing the computation costs associated with axial flux permanent magnet synchronous motors (AFPMM). The proposed method utilizes the analysis results of the initial position of the rotor, called initial state finite element analysis (ISF), as a 3-dimensional analysis of AFPMM, and generates a surrogate model using machine learning. This approach can significantly reduce the computation time required to analyze the nonlinear characteristics of the motor, as it eliminates the need for any additional periodic analysis. The performance of ISF will be verified through comparison with full periodic finite element analysis (FPF). The machine learning model used for optimization of the proposed method is LightGBM, and its performance will be verified through comparison with other ML models using test functions. By combining many samples generated at low computational costs through ISF with LightGBM, the method aims to perform optimization and achieve the numerous required performances of electric vehicle (EV) driving motors.

Index Terms—Design optimization, electric vehicle, machine learning, permanent magnet synchronous motor

I. INTRODUCTION

THE shift to eco-friendly motors is accelerating due to global regulations, increasing the demand for compact and lightweight designs. Permanent magnet synchronous motors (PMSMs), particularly axial flux PMSMs (AFPMMs), are gaining attention for their high efficiency and power density [1]. However, AFPMM design requires 3-dimensional finite element analysis (3D FEA) to account for nonlinear output characteristics, which is accurate but computationally expensive. Many studies are being conducted to solve this problem [2]. Unlike that, this paper introduces initial state FEA (ISF), which uses the rotor's initial position analysis instead of full periodic FEA (FPF), significantly reducing computation time while maintaining torque accuracy [3]. A surrogate model generated using machine learning (ML), combined with an optimization algorithm, was applied for AFPMM multi-objective optimization. The overall process of the proposed method is shown in Fig 1. The method reduced computation time and was validated through prototype production, confirming its effectiveness.

II. PROPOSED METHOD

This paper introduces a method for reducing design computation time by utilizing ISF and ML. The target motor is an AFPMM for EV driving, with its shape, design variables, and specifications detailed in Fig. 2 and Table I. This section provides simple explanations of each step.

A. Initial State Finite Element Analysis

ISF is an FEA method that aims to reduce the calculation time by analyzing the electromagnetic field characteristics only at the initial rotor location. The performance of ISF have already been verified in RFPM case [3]. This approach is suitable for the conceptual design stage that requires a lot of case study because it can derive excellent accuracy from torque and

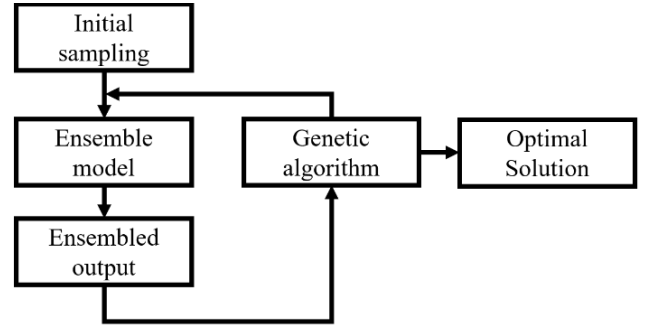


Fig. 1. The overall flow of proposed method.

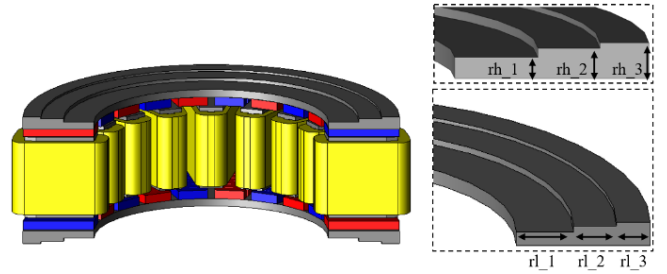


Fig. 2. The target motor shape and design variables.

TABLE I
THE BASIC SPECIFICATION OF TARGET MOTOR

Division	Value
Pole / Slot	20 / 18
Stator inner / outer diameter [mm]	152 / 244
Rotor inner / outer diameter [mm]	152 / 245
Shaft direction length [mm]	75
Air gap [mm]	0.8
Rated / maximum rotate speed [RPM]	2000 / 4000
Rated / maximum torque [Nm]	160 / 200

terminal voltage without performing FPF. This paper will be compared the accuracy of torque and terminal voltage and the computational time in case of 3D AFPMM.

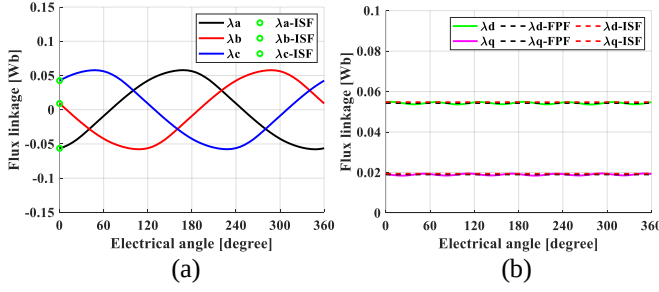


Fig. 3. Examples the flux linkage both ISF and FPF. (a) abc-phase. (b) dq axis.

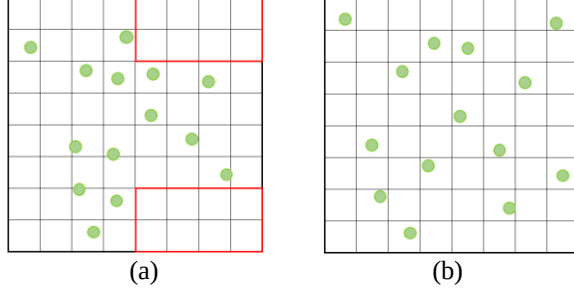


Fig. 4. Distribution example of sampling methods. (a) Random Sampling. (b) Latin Hypercube Sampling.

Before calculating the torque and terminal voltage, the dq-axis flux linkage must be obtained, which can be obtained from the abc-phase flux linkage as shown in equation (1) and Fig. 3 shows the example of the flux linkage both ISF and FPF.

$$\begin{bmatrix} \lambda_{di} \\ \lambda_{qi} \end{bmatrix} = \frac{2}{3} \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} \lambda_{ai} \\ \lambda_{bi} \\ \lambda_{ci} \end{bmatrix} \quad (1)$$

The torque and terminal voltage of PMSM can be obtained as shown in equations (2) and (3), it is confirmed accuracy of the ISF with the results of FPF.

$$T = \frac{3}{2} \frac{P}{2} (\lambda_{di} i_q - \lambda_{qi} i_d) \quad (2)$$

$$V_d = R i_d - \omega \lambda_{qi}, \quad V_q = R i_q + \omega \lambda_{di} \quad (3)$$

B. Sampling method - Latin Hypercube sampling

In motor design, ensuring a uniform distribution of initial solutions across the problem domain is crucial. As shown in Fig. 4(a), randomly generated samples may lead to difficulties in exploring the entire problem domain. Therefore, in this paper, Latin Hypercube Sampling (LHS) is employed to achieve uniform initial sampling, which considers the same probability [4]. For generating surrogate model training data, the number of samples and the range of variables were determined considering electromagnetic performance, productivity, and design experience.

C. Machine Learning - LightGBM

In the design of a motor, FEA is required to accurately analyze nonlinear characteristics, however, the computation time increases proportionally with the number of design variables. To address this issue, a surrogate model using ML has been applied, enabling optimal design without additional FEA. In this paper, LightGBM was selected through a performance comparison of various ML.

D. Optimization Algorithm – Genetic Algorithm

The surrogate model using ML has undergone sufficient parameter tuning for solution exploration, eliminating the need to repeat such processes in the optimization algorithm. The genetic algorithm (GA) is superior ability to explore global optimal solutions without parameter tuning. Therefore, this paper employs the GA, and this section focuses on introducing the objective function, which is critical in the optimization stage, by presenting only the "Fitness Evaluation" step among the various stages.

1) *Fitness evaluation* – In this step, calculate the value of the objective function. In case of the EV driving motors, the torque and power density are the important performance. Therefore, the objective function $f(x_i)$ is defined as follow:

$$f(x_i) = \alpha_1 \times T_{ave} + \alpha_2 \times T_{density} \quad (4)$$

III. CONCLUSION

This paper proposes a novel design method using ISF and ML to reduce computation time. This method demonstrates the accuracy of the torque and terminal voltage calculation of ISF, and can dramatically reduce the time to generate datasets. A surrogate model using ML can derive the optimal design for superior performance without additional FEA. The overall process of the proposed method, and the prototype manufacturing/test results will be described in the full paper.

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