

Topology Optimization of Synchronous Motors using Bayesian Optimization and Variational Auto Encoder

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This paper proposes a new approach for topology optimization of synchronous motors using Bayesian optimization and a variational auto encoder (VAE). The VAE compresses the search space into a latent space, where Bayesian optimization is applied to explore more efficiently. The proposed method obtains a solution 52.3% faster than conventional methods.

Index Terms—Convolutional neural network, topology optimization, Bayesian optimization, synchronous motor.

I. INTRODUCTION

THE electrification of automobiles, aircraft, and factories is accelerating, leading to the widespread adoption of high-efficiency, high-power synchronous motors (SM) and intensifying the development race. Consequently, the development of patentable and high-performance SM shapes and topology optimization has attracted widespread attention [1]. The search space of topology optimization of motors spans several tens to several hundreds of dimensions, leading to increased search times when using methods such as genetic algorithms (GA), which use many intractable search points. Because motor characteristics are analyzed using the finite element method (FEM) for topology optimization, the optimization time is significantly influenced by the number of search points. Therefore, a topology optimization method that compresses latent space using a variational autoencoder (VAE) has been proposed [2]. Exploration within a low-dimensional latent space achieves a short optimization time. Because heuristic algorithms such as GA are employed, a large number of search points is still required.

Therefore, we propose a new topology optimization method that uses Bayesian optimization to search a small compressed latent space. Bayesian optimization uses a probability model to quantitatively evaluate search points throughout space and efficiently search for an optimal solution [3]. This enables a fast search based on a probability model. Generally, Bayesian optimization requires exponentially more computations to update a predictive distribution as the dimensionality of the search space increases. However, the proposed method reduces the search space by utilizing a VAE, allowing Bayesian optimization to leverage its superior search efficiency. We applied the proposed method to rotor topology optimization of an interior permanent magnet (IPM) SM and discussed its performance.

II. PROPOSED METHOD

A. Training VAE

The target IPMSM is illustrated in Fig. 1 (a). This model is the reference model proposed in [4]. The specifications of the IPMSM are listed in Table I. In this study, the 0–45° region of the rotor was used as the design region, and the material

distribution was determined using the normalized Gaussian net (NGnet)-on/off method [1]. The weights of the NGnet were determined using a real-coded GA. The optimization problem for data creation is defined as follows:

$$F = -1.3 \frac{T_{avg}}{T_{avg}^{ref}} + 0.3 \frac{T_{pp}}{T_{pp}^{ref}} \rightarrow \min. \quad (1)$$

$$\text{s. t. } N_{area} = 1$$

Here, T_{avg} , T_{pp} , and N_{area} denote the average torque, torque amplitude, and number of separated rotor cores, respectively. Furthermore, T_{avg}^{ref} (2.06 Nm) and T_{pp}^{ref} (1.13 Nm) are the average torque and torque amplitude of the target model, respectively. The air and iron distributions of the generated individuals are stored as a square bitmap (224 bit * 224 bit * 1 channel), as shown in Fig. 1(b). 25751 data were obtained via optimization. The bitmaps were used to train a VAE that recovered the material distribution.

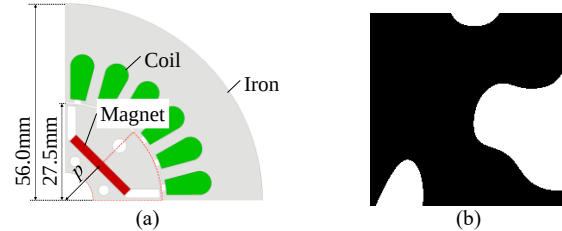


Fig. 1. Target model: (a) IPMSM and (b) example of bitmap.

TABLE I
MOTOR SPECIFICATION

Magnetization [T]	1.25
Core material	50A470
Shaft length [mm]	65
Number of turns [turn]	35
Current [A_{rms}]	3
Current phase angle [deg]	0

B. Bayesian Optimization

An overview of the proposed method is presented in Fig. 2. The training conditions for the VAE are listed in Table II. The proposed method performs Bayesian optimization within a search space $\mathbf{w}$ consisting of the magnet parameter $\mathbf{p}$ and latent space $\mathbf{z}$ constructed by the VAE. The VAE has four convolutional layers, and $\mathbf{z}$ has 16 dimensions. Furthermore, the inverse convolutional layer consists of four layers. $\mathbf{z}$ was trained by assuming a probability distribution. An image expressing the material distribution (iron or air) was generated from $\mathbf{z}$ using a

decoder. The rotor mesh was generated using p . The material distribution in the design region was determined by fitting an image obtained from z . The evaluation value of each individual was calculated using the FEM utilizing the mesh created by these methods. This algorithm evaluates the motor characteristics using the FEM from a low-dimensional w . w can be quickly optimized using Bayesian optimization owing to its low dimensions.

For simple verification, the proposed method was applied to the optimization of the average torque maximization and torque amplitude minimization problems of an IPMSM. We also performed an optimization using the GA at z for comparison. The objective function is the same as that in Eq. (1). The optimization conditions are listed in Table III.

TABLE II
TRAINING CONDITIONS FOR VAE.

Epoch	100
Batch size	64
Loss function	MSE
Optimizer	Adam
Learning rate	10^{-4}

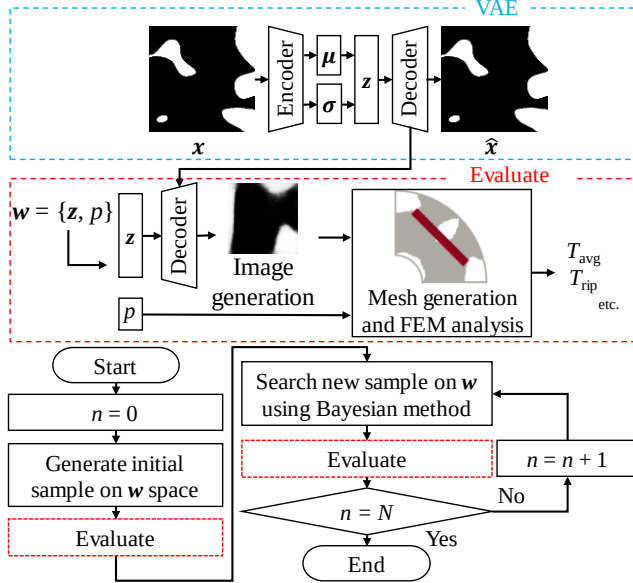


Fig. 2. Overview of the proposed method.

TABLE III
OPTIMIZATION CONDITIONS

	Bayesian optimization	GA
Dimension of w	17	
z range	$-2 \sim 2$	
p range [mm]	$13.86 \sim 22.45$	
Number of initial samples	50	-
Acquisition function	EI	-
Number of populations	-	300
Number of parents	-	30
Number of children	-	60
Number of iterations N	50	100
Method of crossing over	-	REXStar
Optimization method	-	JGG
Total number of evaluations	100	9300
Number of parallel computations	1	30

III. RESULTS

The optimization results obtained using Bayesian optimization and the GA in the w space are shown in Fig. 3. The optimized shapes obtained from both optimizations were evaluated as equivalent. The progression of the evaluation values is shown in Fig. 4. Bayesian optimization reduced the total number of evaluations by 97.8% compared to the GA. The optimization time for Bayesian optimization was 51 min without parallelization, whereas that for the GA was 1 h and 47 min with 30 parallels. The Bayesian optimization was 52.3% faster than the GA, even though it was a single thread.

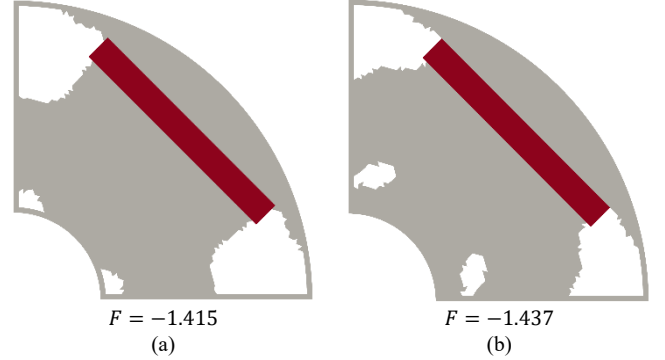


Fig. 3. Optimization results: (a) Bayesian optimization and (b) GA.

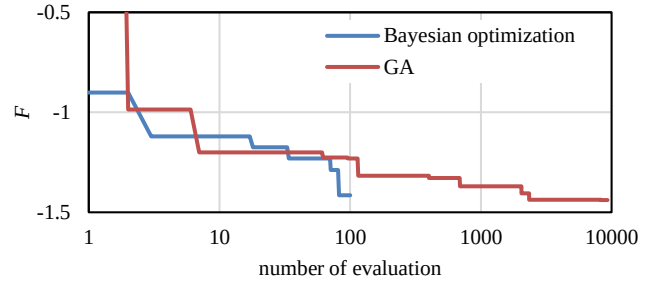


Fig. 4. Convergence characteristics: (a) Bayesian optimization and (b) GA.

IV. CONCLUSION

In this study, we propose a new topology optimization method that efficiently searches for z compressed by a VAE using Bayesian optimization. In the full paper, we will improve the method for generating images for training z and achieve faster model construction. Furthermore, we will consider faster topology optimization using neural networks instead of the FEM. We also plan to optimize other characteristics.

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