

A Data-driven Parameter-Topology Hybrid Optimization of Permanent Magnet Motors Based on Deep Reinforcement Learning

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This paper presents an efficient parameter-topology hybrid optimization method based on a data-driven approach. In the present method, the shapes of the magnets are represented by geometric parameters, and those of the iron cores are determined through topology optimization. Because the magnet and topology parameters are related to each other, their simultaneous optimizations lead to difficult optimization category. The present method relaxes this issue by making the search interval of the magnet parameters small. To find the effective search space for magnet parameters, reinforcement learning is used, that is, effective shapes of the magnets are estimated through the data generated by computationally light evaluations. The reinforcement learning utilizes the data and estimates the effective magnet parameters. Moreover, thanks to the use of the data-driven approach, additional optimization requirements can be processed more quickly.

Index Terms—Evolutionary algorithms, Permanent magnet motor, Reinforcement learning, Topology optimization.

I. INTRODUCTION

ELECTRIC motors are one of the key components to realize mobility electrification. Thus, various numerical optimization methods have aggressively been proposed to develop high performance motors. For example, evolutionary topology optimizations for interior permanent magnet synchronous motors (IPMSMs) are attractive methods. Although these methods are effective for designing iron cores, it is difficult to find appropriate shapes of the magnets due to their high degree of freedom, i.e., overly complex shapes are found as the magnets [1]. For this reason, parameter-topology hybrid optimization methods have been proposed [2], [3]. Namely, the shapes of the magnets are represented by geometric parameters, while those of the iron cores are optimized by topology optimizations. However, because the magnet and topology parameters are related to each other, their simultaneous optimization leads to difficult optimization problem category: strongly non-separable problems. Solving such problems with evolutionary algorithms involves a significant computational burden.

As an efficient parameter-topology hybrid optimization method, we propose a data-driven optimization method based on deep reinforcement learning and evolutionary algorithms. As for the present method, effective magnet parameters are first estimated, and then, iron cores are optimized under the condition that the search interval of the magnet parameters is set small. As a result, the strong non-separability is relaxed. Moreover, by utilizing the data, a candidate design for new design requirements can be estimated.

II. DATA-DRIVEN HYBRID OPTIMIZATION METHOD

A. Problem definition

Here, let $\mathbf{z}$ and $\mathbf{x}$ be the magnet and topology parameters, respectively, as shown in Fig. 1. Note that we assume that the parametric topology optimization method is used [1]. The parameter-topology hybrid optimization problem is defined as

$$(\mathbf{z}_{\text{best}}, \mathbf{x}_{\text{best}}) = \underset{\mathbf{z}, \mathbf{x}}{\operatorname{argmin}} F(\mathbf{z}, \mathbf{x} | \Theta), \quad (1)$$

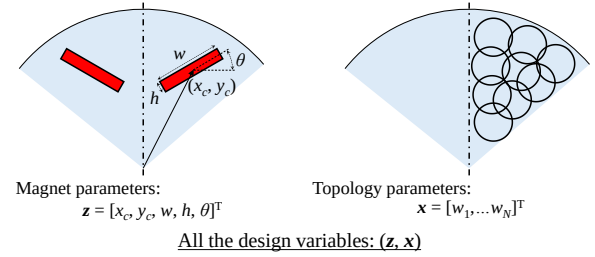


Fig. 1. Parameter-Topology hybrid optimization for IPMSM.

where F is objective function, and Θ denotes a requirement represented as a real vector. It is clear that the appropriate $\mathbf{x}$ strongly depends on the shapes of the magnet: $\mathbf{z}$. Hence, the optimization of $\mathbf{z}$ and $\mathbf{x}$ is the strongly non-separable problem, which is one of the difficult optimization problem classes; evolutionary algorithms request much computational burden to solve such problems.

B. Present data-driven approach

Let us assume that appropriate $\mathbf{z}$ is determined depending on Θ , and appropriate $\mathbf{x}$ depends on $\mathbf{z}$ [4], namely:

$$\mathbf{z} \sim p(\mathbf{a} | \Theta), \quad (2)$$

$$\mathbf{x} \sim p(\mathbf{a} | \mathbf{z}, \Theta), \quad (3)$$

where $p(\mathbf{a} | \mathbf{y})$ is a probability distribution function of $\mathbf{a}$ conditioned by $\mathbf{y}$. To approximate the above two distributions, deep reinforcement learning is introduced. The present reinforcement learning agent is illustrated in Fig. 2. We prepare two kinds of agents. The first agent receives Θ as a state vector and outputs $\mathbf{z}$ as an action. Similarly, the second agent does Θ and $\mathbf{z}$ and outputs $\mathbf{x}$. As a result, one candidate rotor shape of IPMSM can be generated. Its rotor shape is analyzed, and its evaluation result is obtained as a reward. However, the agents

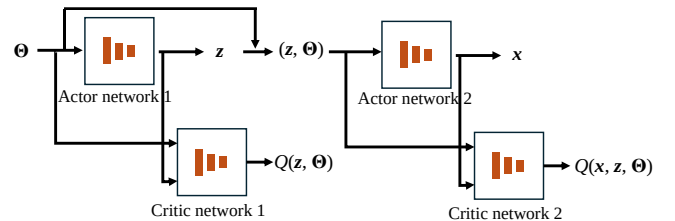


Fig. 2. Basic flow of present reinforcement learning-based shape generation.

would take huge amounts of time to adapt the given requirements by try and error search. To accelerate the generation of appropriate data, therefore, evolutionary algorithms are applied to the optimization of $\mathbf{x}$ and $\mathbf{z}$. Note that the search interval of $\mathbf{z}$ is set small to relax the non-separability. The advantage of this approach is that we can utilize some data that were obtained under computationally light settings. Moreover, effective design data can be utilized to generate some new designs for newly given requirements.

III. NUMERICAL EXAMPLE

We try to optimize the rotor shape of an IPMSM [5] shown in Fig. 3. The dimension of the magnet parameters is 5, and that of $\mathbf{x}$ is 348, where NGnet-based method [1] is used. Hence, 353 design variables are optimized. The optimization problem is defined as

$$F(\mathbf{z}, \mathbf{x} | \Theta) = -T_{ave}/T_{th1}, \quad (4)$$

subject to

$$S \leq \theta_{mag} S_T, \quad (5)$$

$$T_{rp} < T_{th2}, \quad (6)$$

$$\rho_{max} < \rho_{th}, \quad (7)$$

where T_{ave} and T_{rp} denote the average torque and torque ripple, respectively, and S is the magnet area, and ρ_{max} is the maximum von Mises stress for 10000 min⁻¹. Moreover, $S_T=198.72$ mm², $T_{th1}=205.9$ Nm, and $T_{th2}=10.65$ % are the values for the original model, and $\rho_{th}=250$ MPa is a threshold. Moreover, $\Theta=[\theta_{mag}]$ is set as a requirement. The standard feed forward deep neural networks with four layers are defined for the two agents

First, to generate some data, 400 infeasible $\mathbf{z}$ are respectively randomly generated for θ_{mag} is 1.0 and 0.5. The agents are learned through a total of 800 data. Using the agents, five different $\mathbf{z}$ are respectively generated for $\theta_{mag}=0.5$ and $\theta_{mag}=1.0$. Then, $\mathbf{x}$ for $\mathbf{z}$ is optimized. In these optimizations, CMA-ES is used. The number of candidate solutions are set to 160, and optimizations are performed over 200 iterations. Moreover, the search interval of $\mathbf{z}$ is set as $[z-0.5|z|, z+0.5|z|]$. From these optimizations, a total of 10 data are obtained. Through these new data, the agents are again learned. Then, two new $\mathbf{z}$ are respectively generated for $\theta_{mag}=0.5$ and $\theta_{mag}=1.0$. The CMA-ES is applied to them, where optimizations are performed over 500 iterations. Moreover, the search interval of $\mathbf{z}$ is set as $[z-0.2|z|, z+0.2|z|]$. The resultant rotor shapes are shown in Fig. 4, which shows that designs superior to the original model are obtained.

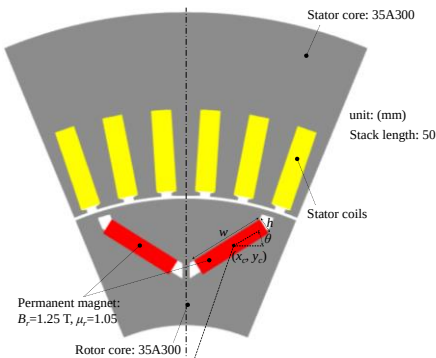


Fig. 3. IPMSM model for optimization.

Finally, we newly set θ_{mag} from 0.5 to 1.2. For these conditions, candidate designs are respectively generated using the agents. The resultant rotors are shown in Fig. 5. It can be seen that the shapes similar to those shown in Fig. 4 are generated when θ_{mag} is 0.5 and 1.0. On the other hand, in other θ_{mag} values, the shapes are gradually modified depending on θ_{mag} . In particular, the magnet area is relatively close to the given condition: $\theta_{mag} S_T$. Although some infeasible magnet shapes are generated, this is because only two effective data are included in the dataset.

In the fullpaper, the present algorithm will be mentioned in detail.

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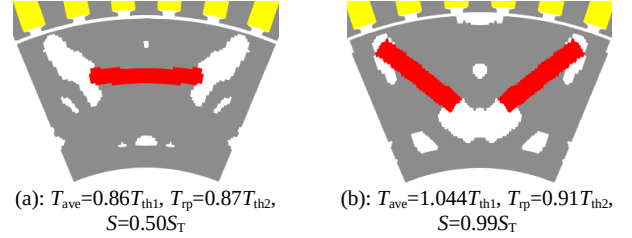


Fig. 4. Resultant rotor shapes for (a): $\theta_{mag}=0.5$, (b): $\theta_{mag}=1.0$.

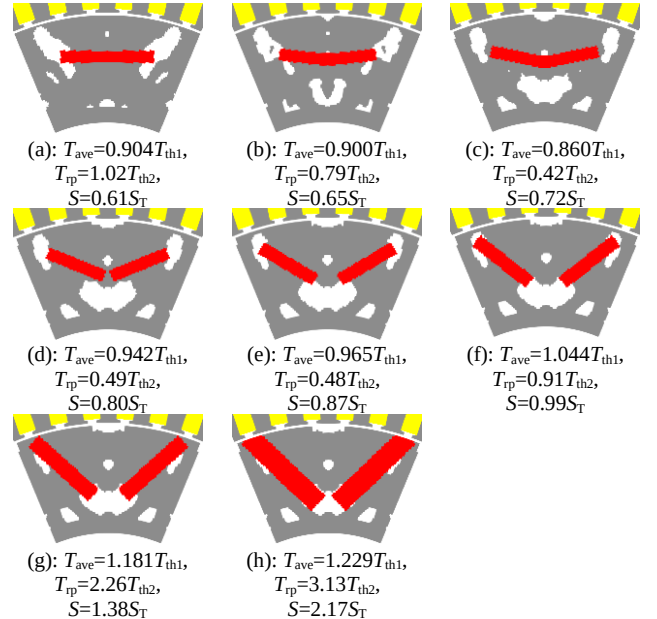


Fig. 5. Rotor shapes generated by actor network for (a): $\theta_{mag}=0.5$, (b): $\theta_{mag}=0.6$, (c): $\theta_{mag}=0.7$, (d): $\theta_{mag}=0.8$, (e): $\theta_{mag}=0.9$, (f): $\theta_{mag}=1.0$, (g): $\theta_{mag}=1.1$, (h): $\theta_{mag}=1.2$.