

Parameter and Topology Optimization for Permanent Magnet Synchronous Motors Using Reinforcement Learning

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In this study, a new optimization method for topology optimization (TO) of permanent magnet synchronous motors (PMSMs) using reinforcement learning is proposed. The method employs the twin delayed deep deterministic policy gradient algorithm, a reinforcement learning approach, for TO. It achieves an 18.7% reduction in computational cost while maintaining search performance compared to the conventional optimization method, under the optimization problem of maximizing average torque and minimizing torque ripple for PMSMs.

Index Terms—reinforcement learning, topology optimization, permanent magnet

I. INTRODUCTION

THE rapid advancement of electric mobility in aircrafts and automobiles necessitates the development of motors with enhanced performance and efficiency tailored to specific applications. In this context, numerical analysis-based optimization techniques, such as the finite element method (FEM), are indispensable for designing motors and other electrical devices. In particular, the rotor structure of a permanent magnet synchronous motor (PMSM), which is expected to be highly efficient, significantly affects the motor characteristics. Consequently, developing a novel, patentable structure is crucial. Topology optimization (TO), which has the potential to produce innovative structures, has therefore attracted considerable attention [1].

Heuristic optimization algorithms such as the covariance matrix adaptation evolution strategy (CMA-ES) and genetic algorithms have been widely employed in TO for PMSM [2]. Despite their efficacy in high-dimensional searches, these methods are inherently computationally expensive and require significant amounts of time in environments where parallel processing is not feasible.

We propose a new TO algorithm for PMSMs using reinforcement learning. The proposed method can search while simultaneously training a model that generates an update policy specific to each problem, thereby reducing search time. The proposed method was applied to maximize the average torque of the PMSM. We also applied the proposed method to simple PMSM parameter optimization to verify its search performance.

II. PROPOSED METHOD

A flowchart of the proposed method is shown in Fig. 1. It is based on a twin-delayed deep deterministic policy gradient (TD3) algorithm [3]. TD3 is a reinforcement learning algorithm designed for continuous action spaces, capable of handling real-valued inputs such as design variables. It enhances search diversity by delaying updates to the actor network and introducing noise to actions. After the initial state is set, the

method selects the next action based on the strategy and calculates the evaluation value. This evaluation serves as the reward in reinforcement learning and is repeated for each episode and step. After the evaluation, the data were stored in a buffer, and mini-batch learning was performed when the amount of data for the batch size was collected.

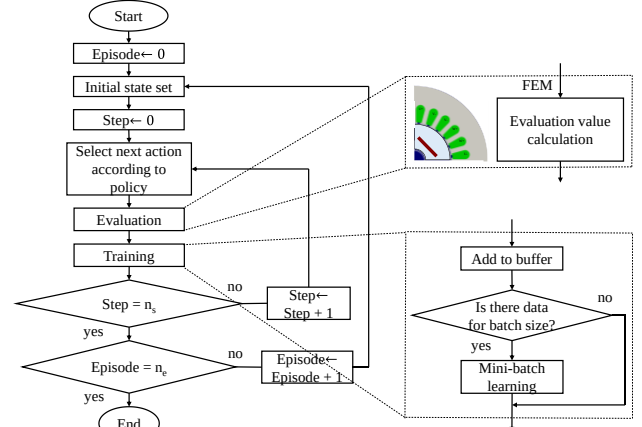


Fig. 1. Flowchart of topology optimization based on TD3 model.

III. ANALYSIS CONDITIONS

The optimized target PMSM is shown in Fig. 2. Fig. 2(a) and (b) show the variable parameters for the PO and the design region for TO, respectively. The motor thickness was 65 mm. The evaluation value was calculated using FEM under a three-phase sinusoidal current input condition. The current amplitude and phase angle are set to 3.0 Arms and 0°, respectively. The training conditions for the proposed method are provided in Table I. The search dimension corresponds to the action and state dimensions. The optimization targets are the six parameters illustrated in Fig. 2(a) for PO. For TO, they are the weights of the 54 Gaussian bases that express NGnet [4], which determines the material distribution in the design region depicted in Fig. 2(b).

In this study, the proposed method was applied to the optimization problem of maximizing the average torque T_{avg}

and minimizing the torque ripple T_{rip} . The objective function F is defined as:

$$\begin{aligned} \max. F &= 1.3 \frac{T_{ave}^{ref}}{T_{ave}} - 0.3 \frac{T_{rip}^{ref}}{T_{rip}}, \\ \text{sub. to. } &\begin{cases} S < S_{ref} \text{ (Parameter optimization)} \\ N_{area} = 1 \text{ (Topology optimization)} \end{cases} \end{aligned} \quad (1)$$

where $T_{ave}^{ref} = 2.06$ Nm and $T_{rip}^{ref} = 0.55$ Nm represent the average torque and torque ripple of the reference model, respectively. Additionally, S , S_{ref} , and N_{area} are the magnetic areas of the individual and reference models and the number of iron areas, respectively. The constraints for the PO and TO are S and N_{area} , respectively. Optimization was performed using the CMA-ES as the comparison algorithm. The optimization settings for the CMA-ES are listed in Table II.

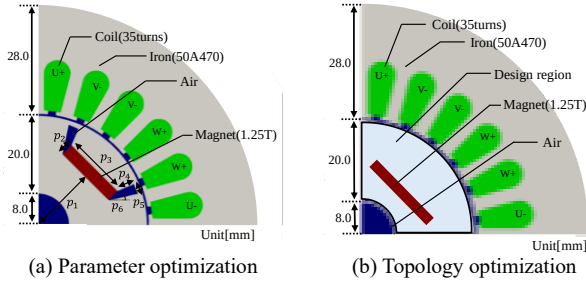


Fig. 2. Permanent magnet synchronous motor.

	Parameter Optimization	Topology Optimization
Episode n_e	5	100
Step n_s		50
Action dimensions	6	54
State dimensions	6	54
Discount rate		0.99
Action range		[-1, 1]
Batch size		16
Loss function		MSE
Optimizer		Adam
Learning rate		3.0×10^{-4}

	Parameter Optimization	Topology Optimization
Number of generations		100
Number of individuals	9	63
Standard deviation		1.0
Initialization area		[-1, 1]
Total number of ratings	900	6300

IV. OPTIMIZATION RESULTS AND CONCLUSION

The optimization results for the PO are presented in Fig. 3. Figs. 3(a) and 3(b) show the optimized shapes obtained using the proposed method and CMA-ES, respectively. The optimized shape from the proposed method exhibited a 9.0% higher evaluation value compared to CMA-ES. The TO results are shown in Figs. 4(a) and 4(b), which display the optimized shapes obtained using the proposed method and CMA-ES, respectively. The optimized shape from the proposed method had an evaluation value closer to that of the shape obtained using CMA-ES. Fig. 5 illustrates the convergence

characteristics based on the number of analyses using FEM. The proposed method achieved an optimized shape with approximately 34.3% of the FEM analyses required by CMA-ES in the PO. Additionally, it obtained an optimized shape with approximately 81.3% of the FEM analyses required by CMA-ES in TO.

In future studies, the proposed method could be applied to simultaneous parameter and topology optimization. Additionally, we plan to extend its application to other characteristic optimization problems.

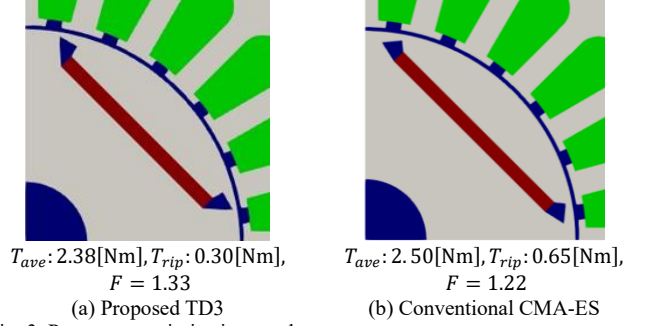


Fig. 3. Parameter optimization result.

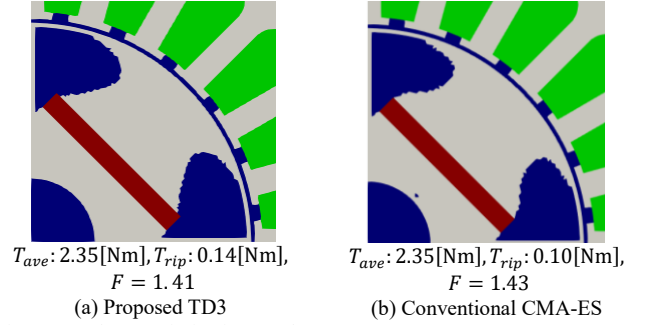
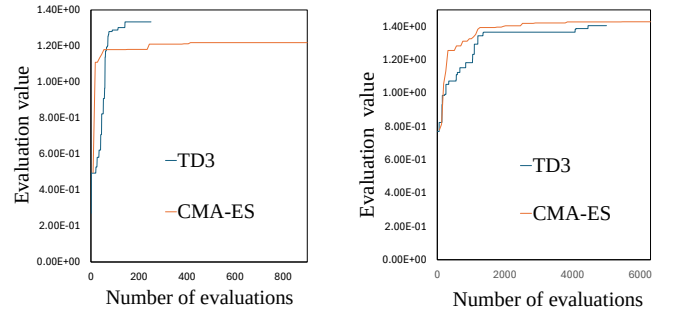


Fig. 4. Topology optimization result.



(a) Parameter Optimization (b) Topology Optimization
Fig. 5. Convergence characteristics by FEM

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