

Data-driven Topology Optimization with Warm Starting CMA-ES for Constraint Optimization of Rotating Machine

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In this paper, a method, which reduce the computational cost for solving constrained optimization, was proposed. In constrained optimization problems, it takes a lot of time to search for a solution that satisfies the constraints function, and the computation time required to improve the objective function increases. Therefore, this study proposes a method based on Warm Starting CMA-ES. By using the proposed method, solutions which satisfy the constraint function can be found quickly, thus reducing computational time for optimization. To validate the effectiveness, the proposed method was applied to the topology optimization problem of interior permanent magnet motor.

Index Terms—Warm Starting CMA-ES, topology optimization, constraint optimization, rotating machine.

I. INTRODUCTION

DATA-DRIVEN techniques, including deep learning, have been widely used in electrical machine designing. In Ref. [1], the motor performance was evaluated without using the finite element method (FEM) using a CNN constructed by offline learning. Although this method was effective in reducing the number of FEM, it could not improve the convergence of the optimization because the algorithm was similar to the classical one. For example, in the actual design of motors, most problems are constrained problems. When genetic algorithms with CNN are used to solve these problems, the initial stage of optimization is devoted to solution search result obtained to satisfy the constraints, and the main object cannot be improved efficiently. The purpose of this study is to propose a novel data-driven optimization method suitable for constrained optimization.

The proposed method was based on the covariance matrix adaptation evolution strategy (CMA-ES) [2]. In the CMA-ES, the population distribution in terms of design variables is represented by a multivariate normal distribution. A solution search is performed by updating the mean and variance of the distribution, and updating is performed to bring the distribution closer to solutions with better performance. For this reason, this method has better convergence than random search-based optimization. In this study, a warm-starting CMA-ES [3] is proposed as an effective optimization method for constraint problems. In warm-starting CMA-ES, the initial values of the mean and variance are determined using existing analysis data. While the warm-starting CMA-ES proposed in the previous study assumed similar optimization problems with the same design variables, transfer learning with CNN is assumed in this study to be effective even when the design variables are different.

Since there are few previous studies on verification of warm-starting CMA-ES in the optimization problem of electrical machine, numerical verification of its validity is cleared in this paper. Rotor shape of an interior permanent magnet motor was optimized using the proposed method. Moreover, the obtained results were compared with those of the conventional CMA-ES.

II. OPTIMIZATION METHOD

A. Conventional -CMA-ES-

In CMA-ES, if the number of variables is N , the parameters used in the search are initialized (mean vector : $\mathbf{m}^0$, scaling factor : σ^0 , covariance matrix $\mathbf{C}^0$), and initial population $\mathbf{z}_i$, whose evaluation function is defined by $f(\mathbf{x}_i)$, is generated based on the following formula.

$$\mathbf{z}_i (i = 1, \dots, \lambda) \sim N(\mathbf{m}^0, \mathbf{C}^0) \quad (1-a)$$

$$\mathbf{y}_i = \sqrt{\mathbf{C}^0} \mathbf{z}_i \quad (1-b)$$

$$\mathbf{x}_i = \mathbf{m}^0 + (\sigma^0)^T \mathbf{y}_i \quad (1-c)$$

Individual generation is performed according to a multivariate normal fraction based on the initialized means and covariances. If the solution distribution is difficult to guess, the $\mathbf{m}^0$ is defined zero vector, and the $\mathbf{C}^0$ is the unit matrix $\mathbf{I}$. After the objective function of the initial population is calculated, they are sorted, and the mean vector is updated with the weighted sums. Since most motor optimization problems have unpredictable solutions, the initial values of the mean vector and covariance matrix may contain many solutions that do not satisfy the constraints. Consequently, in the early stages of optimization, efforts were devoted to searching for a solution that satisfied the constraints, and the objective function could not be improved efficiently.

B. Proposed -Warm Starting CMA-ES-

Warm Starting CMA-ES uses existing data set $\mathbf{z}'_i$, where the objective function is computed by $f(\mathbf{x}'_i)$, to determine the initial population. The optimization parameters ($\mathbf{m}_{WS}^0$, σ_{WS}^0 , $\mathbf{C}_{WS}^0$) are defined by

$$\mathbf{m}_{WS}^0 = \frac{1}{N_y} \sum_{i=1}^{N_y} \mathbf{x}'_i \quad (2-a)$$

$$\Sigma^* = \alpha^2 \mathbf{I} + \frac{1}{N_y} \sum_{i=1}^{N_y} (\mathbf{x}'_i - \mathbf{m}_{WS}^0)(\mathbf{x}'_i - \mathbf{m}_{WS}^0)^T \quad (2-b)$$

$$\mathbf{C}_{WS}^0 = \Sigma^* / \det \Sigma^* \quad (2-c)$$

$$\sigma_{WS}^0 = \sqrt{\det \Sigma^*} \quad (2-d)$$

In the above equation, we use the upper bound of diversion data, γ , α is the regularization term, and should be set to an appropriate value. In this paper, $\gamma = \alpha = 0.3$.

An image of the search result obtained using this procedure is shown in Fig. 1. The purpose of transfer learning is to generate initial solutions that satisfy a constraint function. A pre-constructed dataset should be generated to determine the value of the constraint function. This process is expected to efficiently improve the objective function and convergence of optimization because many solutions that satisfy the constraints are generated from the early stages of optimization.

III. NUMERICAL SIMULATION AND CONCLUSION

A. Optimization problem

In Fig. 2, the optimization model of the IPM motor is shown. The optimization target is flux barrier shape in design domain. The object function is defined below.

$$F = T_{rip} = T_{max} - T_{min} \rightarrow \min. \quad (1)$$

$$G = T_{ave} \geq 9.0 \text{ N.m}$$

In this optimization problem, the torque ripple T_{rip} was minimized with the constraint that the average torque is above 9.0 N.m. In the proposed method (Warm Starting CMA-ES), the optimization results of the non-constraint optimization, in which T_{ave} is maximized, are used to determine the initial values of the mean and variance based on Eqn. (3). The optimization problem used in data-driven has a different objective, and the optimal results have different characteristics. The results obtained by the proposed method are compared with those of the conventional method (CMA-ES) with respect to the number of analyses required to converge the optimization.

B. Optimization results

The optimization results are shown in Fig. 3. The conventional method required 793 analyses until the optimization converged, whereas the proposed method converged after 293 analyses. In other words, the proposed method reduced the number of analyses required for the convergence of optimization by approximately 63.4%. In addition, the performance of the obtained solutions was equivalent for the conventional and proposed methods, and the proposed method improved convergence without any loss in performance. This is because the mean and variance were determined using the results obtained from the torque maximization problem; thus, more solutions satisfying the constraints were generated from the start of the optimization, and the objective function was efficiently improved. Fig. 4 showed the optimized geometry. The solutions obtained by the conventional and proposed methods both had flux barriers formed at both ends of the magnet to suppress the leakage flux. In addition, small bubbles formed in the forward of the magnet, which altered the magnetic flux flow. The flux barrier in front of the magnet was positioned differently for both methods, but its role was considered to be the same.

In the full paper, the details of the proposed method, especially on transfer learning using CNN, will be presented. Moreover, this method will be applied to another type motor.

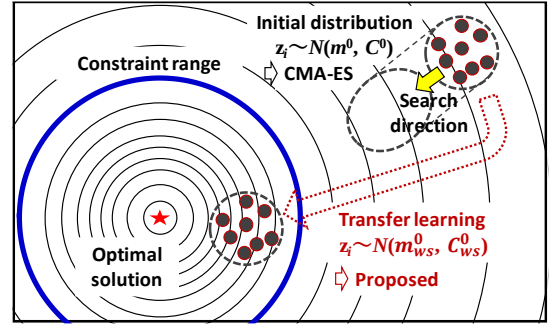


Fig. 1. Image of the proposed method. z_i denotes population.

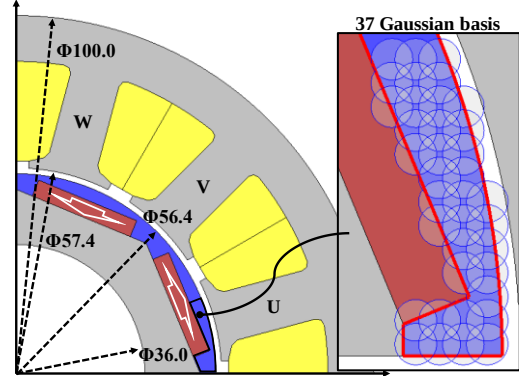


Fig. 2. Optimization model [4].

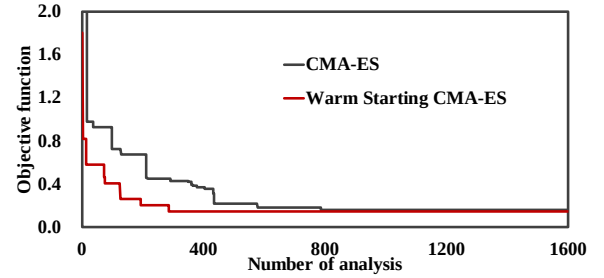
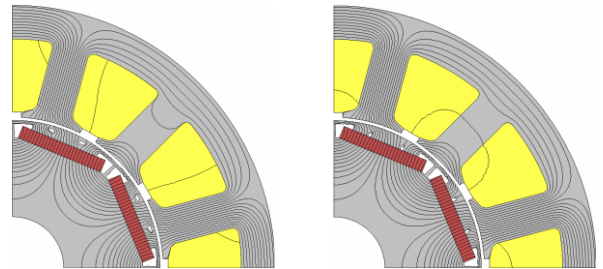


Fig. 3. Optimization history.



(a). CMA-ES. (b). Warm Starting CMA-ES.
Fig. 4. Optimized shapes with flux line.

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