

Fast Shape Optimization with Effective Shape Collapse Prevention for IPM Motors using Machine Learning

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The novel efficient parameter optimization algorithm for interior permanent magnetic motors that prevents shape collapse is proposed. When the shape collapse is detected, the proposed method generates an individual by perturbing a non-collapsed individual. This process reduces the rate of shape collapse compared to randomly generating new individuals. It is numerically shown that the proposed method works 21 times faster than the conventional method while maintaining the optimization performance.

Index Terms—Genetic algorithms, Machine learning, Multilayer perceptrons, Permanent magnet motors.

I. INTRODUCTION

INTERIOR permanent magnet (IPM) motors have advantages over surface permanent magnet (SPM) motors in terms of higher rotation speed and power output and are widely used, for example, in compressors and vehicle traction. To improve performance of these motors, it is important to optimize the rotor structure to maximize the motor characteristics.

The parameter optimization (PO) using the finite element method (FEM) is frequently used to design electrical equipment efficiently. The PO for IPM motors sometimes involves dozens of parameters simultaneously. In this situation, the number of shape combinations increases, so that random generation of the shape is likely to lead to overlapping of materials, which is a shape collapse. This deteriorates the search performance and increases the calculation time of the optimization with the stochastic algorithm such as genetic algorithm and CMA-ES.

In this paper, we propose the novel PO algorithm preventing shape collapse during the optimization. The proposed method generates the new shapes with reduced rate of shape collapse. This method is used in PO in which the function is evaluated by the machine learning [1]–[6] to reduce computational costs.

II. PROPOSED METHOD

To avoid the shape collapse in the optimization process, a checking algorithm is introduced before the objective function evaluation. When the shape collapse is detected, a new individual is generated with reduced rate of shape collapse. The overview of the proposed method is shown in Fig. 1, in which (A), (B) and (C) show the flowchart of genetic algorithm process, collapse checking process and generation of a new individual by perturbation of a non-collapsed individual, respectively. The proposed method aims to avoid shape collapse after the crossover and mutation of genetic algorithm. To detect the overlapping, the edges of the magnets and flux barriers are represented by equations of a straight line and judge whether there are intersections between the lines. This process avoids the process of starting and closing CAD software and sending data, thereby speeding up the process. If the individual shape

obtained by crossover or mutation is collapse, a new individual is generated as shown in Fig. 1(C). By perturbing the geometry of an existing individual without overlapping, the rate of shape collapse can be reduced compared to generating the new individual with uniform random numbers for the geometric parameters. However, if the number of detected shape collapses is greater than a threshold, new individuals are generated using uniform random numbers to prevent shape bias.

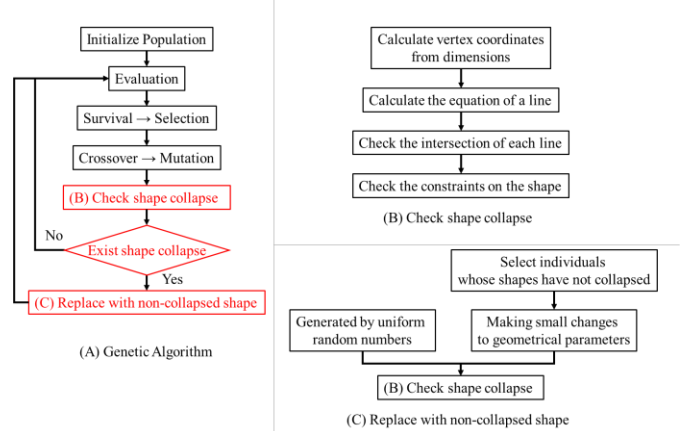


Fig. 1. Flow of the proposed method

III. OPTIMIZATION PROBLEM

The target IPM motor is shown in Fig. 2. The IPM motor is represented by 19 geometrical parameters $\mathbf{p}$ expressing the magnet and airgap shapes. The optimization problem is defined as follow:

$$\begin{aligned}
 \min. \quad & F = -1.3 \frac{T_{ave}}{T_{ave}^0} + 0.3 \frac{T_{pp}}{T_{pp}^0} \\
 \text{s.t.} \quad & T_{ave_max} \geq 175.0 \\
 & P_{max} \geq 100.0
 \end{aligned} \tag{1}$$

where T_{ave} , T_{pp} , T_{ave_max} and P_{max} are the average torque, the torque amplitude, the maximum average torque and the maximum mechanical power, respectively. $T_{ave}^0 = 175$ Nm and $T_{pp}^0 = 35$ Nm are the average torque and torque amplitude of

reference model, respectively. The evaluation value is calculated under rotating speed at 8500 rpm.

In addition, for fast optimization, the motor performance is evaluated by multilayer perceptron (MLP). The prediction model is constructed for each characteristic, T_{ave} , T_{pp} , d- and q-flux linkages, respectively. The input of MLP are $\mathbf{p}$ and the d- and q-axis currents amplitude, i_d and i_q [7]. To build the regression model, 21,996 different shape patterns were generated avoiding shape collapse by uniform random numbers. In addition, 20 patterns with uniform random numbers were generated per shape pattern with different current command values, and a total of 439,920 motor characteristic data were computed in advance by finite element method (FEM). The hyperparameters of MLP were adjusted by Bayesian optimization. The coefficient of determination (R^2) and root mean square error (RMSE) of the obtained regression model are shown in Table I.

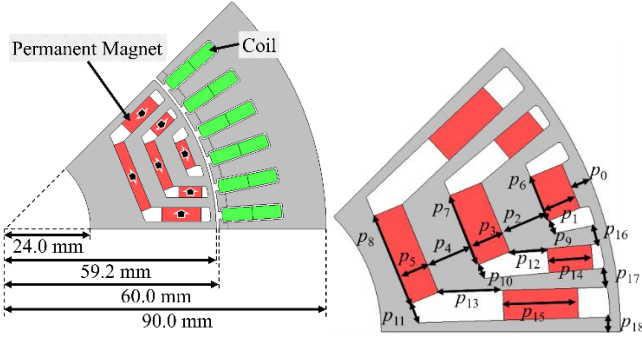


Fig. 2. Target IPM motor

TABLE I
THE RESULTS OF PREDICTION

Prediction	R^2	RMSE
Average Torque (T_{ave}) [Nm]	0.999	2.250
Amplitude Torque (T_{pp}) [Nm _{p-p}]	0.978	4.110
d-axis Flux Linkage (ψ_d) [Wb]	0.999	3.600×10^{-4}
q-axis Flux Linkage (ψ_q) [Wb]	0.999	3.500×10^{-4}

IV. RESULTS AND CONCLUSION

The results of shape optimization are summarized in Table III and Fig. 3. The machine specs for PO is Intel® Xeon® Gold 6234 (2 CPUs) 3.30 GHz/32 Threads. Since the conventional method generates individuals by random numbers, many re-generations were required due to the high rate of shape collapse. We can see that the optimization time of the proposed method is 21 times faster while maintaining the optimization quality. Fig. 4 shows the transition of the minimum value of the objective function for each generation. In conventional optimization, valid individuals that do not collapse and satisfy the constraints were not obtained until the 23rd generation. On the other hand, in the proposed method, valid individuals were obtained from the early generations, and shape optimization progressed appropriately.

The above numerical results suggest that the proposed method can reduce the computational cost by effectively preventing shape collapse without degrading the optimization quality.

TABLE II
THE RESULTS OF OPTIMIZATION

Result		Conventional	Proposed
MLP	T_{ave} [Nm]	234.9	258.8
	T_{pp} [Nm _{p-p}]	11.7	13.8
	F [-]	-1.64	-1.80
FEM (Recalculation)	T_{ave} [Nm]	233.2	254.4
	T_{pp} [Nm _{p-p}]	15.1	15.9
	F [-]	-1.60	-1.75
Elapsed time	[hour]	19.45	0.90

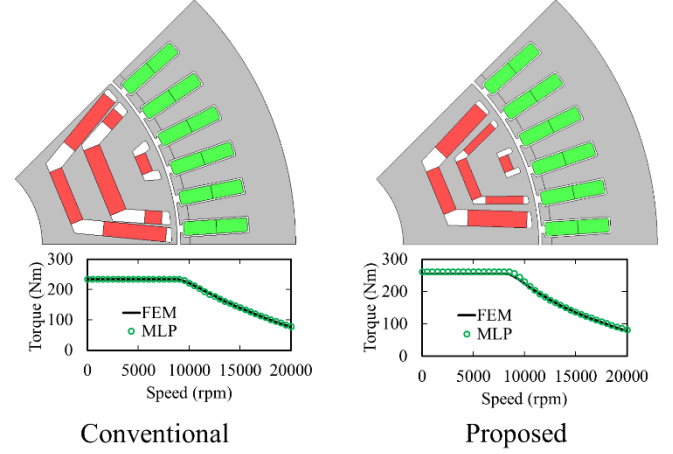


Fig. 3. Motor shape and T-N curve after optimization

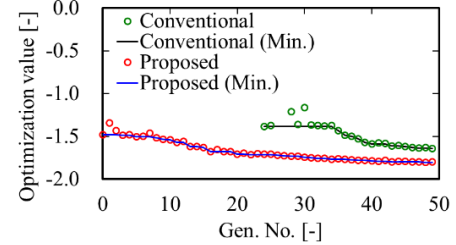


Fig. 4. Transition of optimization value

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