J Electr Eng Technol.2018; 13(6): 2262-2267
http://doi.org/10.5370/JEET.2018.13.6.2262

ISSN(Print) 1975-0102
ISSN(Online) 2093-7423

Robust Optimization with Static Analysis Assisted Technique for Design of Electric Machine

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Abstract – In electric machine design, there is a large computation cost for finite element analyses (FEA) when analyzing nonlinear characteristics in the machine Therefore, for the optimal design of an electric machine, designers commonly use an optimization algorithm capable of excellent convergence performance. However, robustness consideration, as this factor can guarantee machine performances capabilities within design uncertainties such as the manufacturing tolerance or external perturbations, is essential during the machine design process. Moreover, additional FEA is required to search robust optimum. To address this issue, this paper proposes a computationally efficient robust optimization algorithm. To reduce the computational burden of the FEA, the proposed algorithm employs a useful technique which termed static analysis assisted technique (SAAT). The proposed method is verified via the effective robust optimal design of electric machine to reduce cogging torque at a reasonable computational cost.

Keywords: Cogging torque reduction, Electric machine, Optimal design, Robust optimization.

1. Introduction

Robustness of a design solution is an important issue in optimization problems that should be considered in electric machine design so as to guarantee machine performance.

There are several uncertainties which cause mismatches between the intended performance outcomes of an electric machine design and that of a prototype. First, the manufacturing tolerance which depends on the manufacturing cost, is a production limitation. The manufacturing tolerance may not allow design values to correspond completely to their established values, as the optimal solution is usually a set of numerical values. Secondly, unpredictable perturbations such as those related to the characteristics of the materials used can have a severe effect on target performance outcomes. Especially in mass production, possible uncertainties during the manufacturing process can increase in a manner inversely proportional to the cost with a decrease in the production yield. With regard to robustness, the optimal solution should be less sensitive to minute variations of design parameters [1-3].

In electric machine design, finite element analysis (FEA) is required to analyze nonlinear electromagnetic characteristics, though this increases the computational time due to the inevitable trial and error process. From this point of view, stochastic optimization algorithms with excellent convergence performance such as genetic algorithm (GA), particle swarm algorithm (PSO), and evolutionary strategy (ES) are widely used to obtain the optimal solution at a reasonable computation cost. Moreover, with regard to robust optimization problems of electric machines, many researchers have studied various methods such as sensitivity analysis (SA), gradient index (GI) approach, approaches based on the worst target function value, and six sigma quality (SSQ) [1-10]. However, even these methods incur additional computation burdens when searching for robust optimum [2-4].

Recently, the interior permanent magnet synchronous motor (IPMSM) has been widely used in many applications due to its high torque density. However, the complex structure of the IPMSM also generates high cogging torque and torque ripple, both of which should be reduced to ensure smooth operation. Many researchers have investigated various techniques to reduce cogging torque and torque ripple such as skew or notch in the stator or rotor [11]. Cogging torque in permanent magnet (PM) machine is much sensitive to manufacturing and assembly tolerance, even magnetization quality [12, 13]. Several researches had efforts to predict the parasitic effects with manufacturing tolerance or implemented robust design using Taguchi's method and sensitivity analysis [14-16]. Though these methods made a lot of contributions, we focused on a much effective and simpler technique in dimensional aspect to decrease cogging torque in PM machine which is the optimized notch design on rotor surface with robustness.

In this paper, we develop a computationally efficient method for robust optimization problems to reduce cogging torque in an electric machine. By combining the worst function value (WFV) approach and immune algorithm (IA) [17, 18], the WFV based IA (WFV-IA) was developed. However, before the WFV-IA is directly applied to

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Received: December 11, 2017; Accepted: May 26, 2018

optimization problems, the computational cost requires to a further reduction due to the 2^n fold increase in the function evaluations, where n represents the parameter dimension. To solve this problem, we propose an effective strategy, static analysis assisted technique (SAAT), which could significantly reduce the large amount computation required by the FEA. This reduction makes the proposed algorithm particularly suitable for the robust optimization problem of the IPMSM. The usefulness of the proposed method was validated by an IPMSM design example.

2. Robust optimization

In Fig. 1, the design parameter A is regarded as the global optimum. However, due to the uncertainty of this parameter, it can be any value within the uncertainty band. If the uncertainty of the design parameter is considered, shape of the objective function can be distorted as an unwanted one.

The design parameter B is considered as the local optimum. However, although design parameter B became

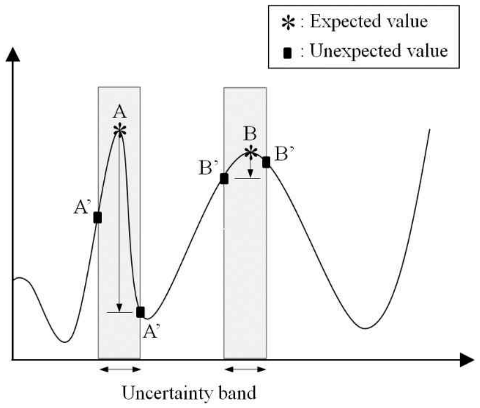

Fig. 1. Curves in the problem with uncertainty

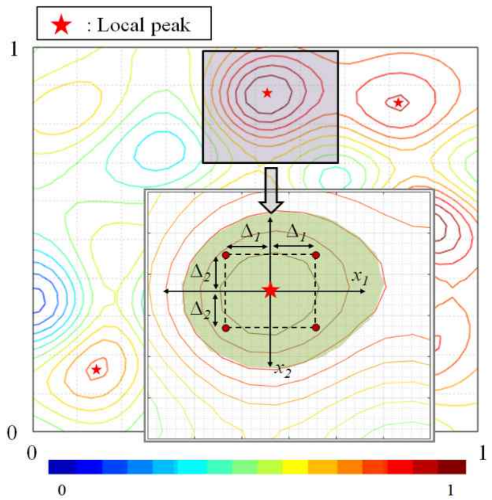

Fig. 2. Rectangular uncertainty band

to the design parameter B' within the uncertainty band, it remains still a qualified as the local optimum due to very minor difference from nominal point B. Therefore, design parameter B will be considered as a robust optimal solution against the uncertainty of the design parameters.

In order to measure the robustness of the optimum, the uncertainty band of design parameters should be defined beforehand. Then, with the WFV in the uncertainty band, a robustness of the optimum can be evaluated.

$$\min\left\{\max_{\xi\in U(x)}\{f(\xi)\}\right\} \tag{1}$$

$$\max_{\xi\in U(x)}\{g_i(\xi)\}\le 0,\quad i=1,\dots,m \tag{2}$$

$$U(x_n)=\left\{\xi\in R^n : x_n-\Delta\le\xi\le x_n+\Delta\right\} \tag{3}$$

Eq. (1) represents the objective of problem in the uncertainty problem area replaced from original problem. Eq. (2) represents the replaced constraint conditions considering uncertainties. Here, possible uncertainty is defined as Eq. (3) which was assumed that uncertainty could arise with equal probability in each design parameter and the uncertainty band is modeled with a rectangular shape. In Fig. 2, the uncertainty bands, Δ_1 and Δ_2 are represented from (1) to (3) [2]. This approach assumes that one of the vertices in the uncertainty band is likely to have the worst values in that region.

3. Proposed algorithm: WFV-IA

The proposed algorithm is based on the IA, which is inspired from defense systems against bacteria or viruses in the human body [17, 18]. When implementing it, the algorithm imitates the affinity between an antigen and an antibody in the immune system of the human. The conventional IA can rapidly and efficiently find the optimum in an optimization problem. However, it has a defect in that it cannot guarantee the robustness of the optimum [17]. Therefore, in this paper, the WFV approach was combined with the IA. In the calculation of the affinity between the antibody and the antigen, the WFV concept was applied.

The WFV-IA was applied to the optimization of the mathematical function. The formula for the test function is shown blow (4).

$$f(x)=\sum_{i=1}^{m}\alpha_i\exp\left(-\sum_{j=1}^{n}\left(x_j-x_{ij}\right)^2\Big/2\sigma_i^2\right) \tag{4}$$

where, $0 < x_1, x_2 < 5$. Fig. 3 shows the shape of the test function developed by parameters shown in Table 1, where α and σ^2 are related to the magnitude and the steepness of the local peaks respectively.

In Fig. 3, there are several local peaks. However, point A is considered as global optimum. On the other hand, the

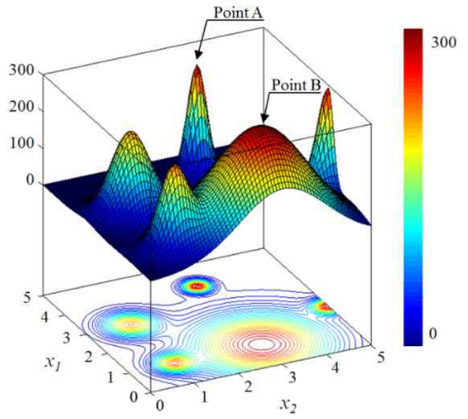

Fig. 3. Shape of the mathematical test function

Table 1. Test function information

Peak point	α	σ^2
(1, 1)	200	0.09
(3, 1)	220	0.16
(1, 3)	290	1
(2, 5)	270	0.05
(4, 3)	300	0.04

Table 2. Comparison of results

	IA	WFV-IA
Function calls	2640	9887
Optimum value	296.7	289.6
Position	(3.99, 2.99)	(1.01, 2.99)
WFV	284.7	288.5
Variation	-8.0	-1.1

point B will be considered as a robust optimal solution. Table 2 shows the results of a comparison between the proposed method and conventional optimization method, when applied on the test function. Each simulation was repeated ten times with the same terminal criterion. In proposed algorithm, WFV-IA, variation sizes of parameters are assumed 0.05 which is 1[%] of dimension length. Thus, WFV in Table 2 for IA means the worst value of points which are that extent far from the converged global optimum. From Table 2, the conventional IA found the global optimum with much possible function variation, -8.0, in uncertainty while the WFV-IA converged to the robust optimum with respectfully minute function variation, -1.1. However there exist difference of a large number of function calls, 2640 versus 9887.

4. Proposed Algorithm: SAAT

Because the WFV-IA simultaneously considers the uncertainties of the design parameters, it inherently requires a large number of function evaluations. Specifically, in an n-dimensional problem, it requires 2^n times of function calls for the WFV evaluation. The large number of function calls could be a major problem when the WFV-IA is applied to the design of a practical electric machine my means of a FEA. Therefore, the computational cost requires a further reduction. In this point of view, we propose static analysis assisted technique (SAAT) in order to evaluate robustness of design points even with small computational effort. In the design of an electric machine, one of the main goal is commonly related to the generating torque or power. This paper is specifically concentrated on the minimization of the cogging torque. Consideration of cogging torque is one of the important part in the design process because cogging torque can induce noise and vibration, thus hindering the smooth operation of the electric machine. For cogging torque minimization design, there can exist a huge number of combinations for design parameters which require FEAs. For measuring robustness by WFV, it is very challenging computational burden.

In this point of view, we approximately compress the required analysis into a static analysis (SA). It is possible because the practical uncertainty scale has little influence on the rotor position that generates peak value of torque in the uncertainty set. From this point, we firstly evaluate a function value of nominal design point for dozens of analyses. After that, we extract the information of rotor position with peak torque value and utilize it to evaluate WFV only by SAs of corners of uncertainty set.

In this respect, the proposed SAAT can serve as an effective way to dramatically reduce the calculation burden during WFV evaluations. The detailed process of the proposed method is as follows:

4.1 Step 1: Uncertainty range determination

In the initial stage, we define the uncertainty band, which refers to how much the design parameters can vary to uncertainties. In view point of electric machine design, it can be a scale of tolerance depending on the degree of precision in the manufacturing process.

4.2 Step 2: Evaluation of the nominal point

At this stage, the objective function value of the nominal point which does not consider any parameter variation is evaluated. In other words, the torque ripple or cogging torque is analyzed by means of FEA with accurate design parameters. This process is identical to any typical optimization process.

4.3 Step 3: Information extraction for the static SAs

As in the previous WFV concept, the vertex values of the uncertainty set should be evaluated. However, evaluating function values of vertex points straightforwardly in every set of parameter combinations is computationally expensive. Thus we extract the necessary information which is the rotor position generating the peak value of torque in order to utilize it to next SAs.

4.4 Step 4: Uncertainty set evaluation by the SA

For the uncertainty set evaluations, SA at the vertex points using the information from step 3 in place of calculating the entire period of the torque waveform which commonly needs dozens of times computational cost are conducted. The field distribution at a specific rotor position can be obtained by means of the SAs and torque can be calculated by Maxwell stress tensor. In an n-dimensional problem, 2^n times of SAs are required, but it is still much efficient compared to direct verification.

4.5 Step 5: WFV verification

As results of step 4, the WFV of the uncertainty set corresponding to the nominal point can be obtained in every parameter combinations. In main optimization algorithm, this value is dealt with as a changed objective as the function value instead of function value of the nominal point.

5. Optimal design of IPMSM

5.1 Target design

In this section, as a practical application, cogging torque minimization of IPMSM for electric power steering (EPS) was implemented.

Due to the recent requirement of high torque density, IPMSM with rare earth magnet is widely used because the IPMSM can utilize not only magnetic torque but also reluctance torque. However, due to the partial saturation and magnetic air gap, IPMSM generates large torque fluctuation and cogging torque.

In addition, cogging torque is a very critical issue in the EPS system because it has direct effect on noise, vibration, and control stability which can influence on driver's safety. In this viewpoint, the cogging torque in EPS application should be minimized. In order to conduct cogging torque optimization and verify the validity of the developed robust optimization algorithm simultaneously, much sensitive design parameters to the objective function should be selected. The configuration and specifications of a reference motor are shown in Fig. 4 and Table 3.

5.2 Problem setting

For the optimal design, the objective function was set to the cogging torque minimization. The design parameters were determined as two variables, notch depth x_1 and angular notch length x_2 to form the shape of notch on the rotor surface. Because these variables are much sensitive to the cogging torque and minute variation with uncertainty like manufacturing tolerance, it is proper to them as the design parameters use to verify the proposed WFV-IA with SAAT. The design parameters are represented in Fig. 5. In order to compare optimization performances, the optimization is individually implemented by conventional IA and proposed WFV-IA with SAAT. The terminal criteria was set as when the best antibody is improved less than 1[%] for five iterations. And the possible variation size was set as 0.05[mm] in both design parameters which was determined considering manufacturing tolerance. The number of initial antibodies, crossover rate, mutation rate, and Gaussian mutation parameter were set to 30, 0.7, 0.3, and 0.1, respectively.

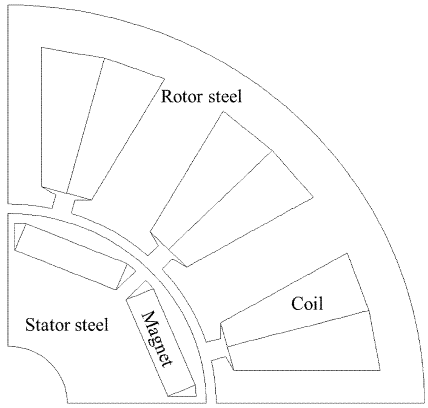

Fig. 4. Configuration of the reference IPMSM

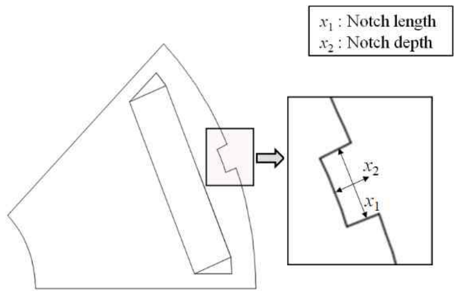

Fig. 5. Design variables

Table 3. Specifications of the reference IPMSM

Item	Value
Number of poles	8
Number of slots	12
Stator outer diameter [mm]	84
Stack length [mm]	30
Remanence of permanent magnet [T]	1.2
Core material	35H230

Table 4. Comparison of results

	Reference	IA	Proposed
Avg.func. calls	-	563	488+1952(static)
Optimum	-	(0.38, 1.62)	(0.25, 1.29)
Cog. torque (WFV) [mNm]	-	7.55	4.80
Cog. torque (nominal)[mNm]	33.6	1.47	3.78
Variation [mNm]	-	6.08	1.02

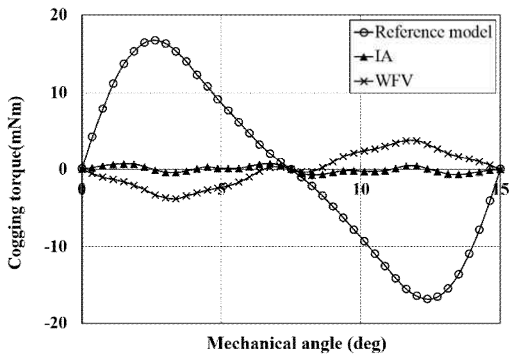

Fig. 6. Cogging torque result of conventional optimization.

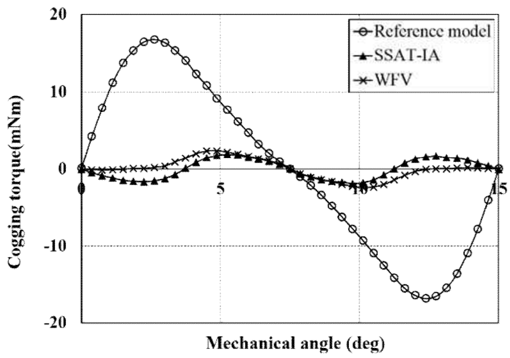

Fig. 7. Cogging torque result of robust optimization

5.3 Result

In Table 4, the optimization results from conventional IA and WFV–IA with SAAT are compared with reference model. As shown in Table III, the optimal cogging torque value from conventional IA was much better than that of WFV-IA with SAAT as 1.47[mNm], and 3.78[mNm] respectively. However, the WFV in uncertainty set of optimum from conventional IA was significantly increased to 7.55[mNm], while the result from WFV-IA increased only to 4.80[mNm]. Consequently, the variation of objective functions are 6.08[mNm] and 1.02[mNm], respectively, which shows the proposed method obtains a robust optimum. The number function calls was 563 versus 488+1952, but the leading time was almost similar because 1952 times in WFV-IA were SAs. Each result of cogging torque waveform is compared with that of reference model in Fig. 6, and Fig. 7, respectively.

6. Conclusion

In this paper, a new robust optimization algorithm was proposed. The main contribution of the proposed method is the point to obtain robust optimum with less computation cost. First, robustness of the objective function could be considered by developed WFV-IA. Moreover, a dramatic reduction in the computational cost could obtained by using proposed SAAT. This reduction makes the proposed algorithm particularly suitable for the robust optimal design of electric machine. In the future work, the additional attempts for torque and torque ripple will be also required as well as cogging torque.

Acknowledgements

This work was supported by the Engineering Development Research Center through the Ministry of Trade, Industry and Energy under Grant N0000990 and the 2017 Yeungnam University Research Grant.

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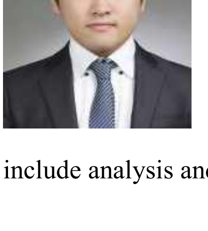

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