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Improved Method for Inverse Shape Optimization Using Constrained Condition Gradients and Genetic Algorithms

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Abstract. For optimization of various electromagnetic devices an optimization method which efficiently optimizes working parameters, design and shape of the device is necessary. Recently, for this purpose various deterministic and stochastic searching methods have been used, among which the genetic algorithm searching procedure appears to be very promising, especially for multivariable optimization. However, the genetic algorithms have also several demerits, among them their long computation time is usually considered as being the most important. In this paper, an improved optimization procedure based on the genetic algorithm (GA) searching procedure and the gradient of the constrained condition is proposed. With this method an optimal solution of a problem is searched by using the gradient of the user-defined constrained condition after quasi-optimal solution is initially obtained by means of the genetic algorithm searching procedure. The usefulness of the proposed method is verified by its application for optimization of a power transformer's tank shield model for which very good results are obtained.

1. Introduction

Recently, mainly as a result of increasing performances of modern digital computers, vigorous research has been observed in the fields of direct and inverse optimizations of various electromagnetic devices. Therefore, some complex and mainly multivariable optimization problems, which were very difficult for solution with the physically reasonable time frames, become possible tasks. Additionally, with the emergence and application of the so–called stochastic searching algorithms, such as the genetic algorithms (GA), immune algorithms (IA) or evolutionary strategies, optimization of multivariable problems becomes easy for computer handling. However, although computationally possible, solution of complex and usually multivariable problems is still a time consuming process. Therefore, decreasing of the computation time and improving the accuracy of the obtained results are still of paramount importance.

In this paper, we present a new algorithm for improved inverse optimization of electromagnetic devices. The proposed algorithm is based on stochastic searching using genetic algorithms, and for the improvement of the accuracy of the results and the computation speed, the gradient function of the constrained condition is utilized. With the proposed method, first the objective function is defined and its minimization is performed according to the ordinary genetic searching algorithm [1]. When the speed of the minimization process becomes rather slow, the genetic searching algorithm is stopped at this quasi-optimal solution. From this point on, the stochastic optimization process is replaced with the deterministic minimization algorithm using the steepest descent method, which is based on computation of the gradient function of the constrained condition. Because the convergence of the steepest decent method strongly depends on its starting point, setting the quasi-optimal solution obtained from the genetic algorithm searching process as a starting point largely improves the accuracy of the results and the convergence rate of the entire optimization process [2].

The proposed optimization method was successfully applied for inverse shape optimization of a power transformer's tank shield in order to decrease the eddy-current loss [3]. First, the proposed optimization process is discussed in details, followed by the definition of the problem model, its objective function and the numerically obtained results. Conclusions and some final remarks are also given.

2. Proposed Optimization Procedure

The Genetic Algorithms (GAs) have recently emerged as a very promising searching procedure, especially for multivariable optimization processes. They are very robust and easy applicable to various problems. Additionally, the GAs work with coded values rather than directly with real values of the optimization variable, enabling development of a single program that will successfully deal with various optimization problems. On the other side, the GAs are quite slow procedures because they converge rather slow, especially in the neighborhood of the global optimum. To aid in this problem, several improved procedures have already been proposed [1], [4]. Some authors also proposed to use mixed approaches such as stochastic and deterministic in order to improve the convergence rate of the optimization process and decrease the computation time [2]. For that purpose, usually the GAs are linked with some deterministic method such as *the Newton* or *the quasi-Newton methods*. The deterministic methods usually require computation of the gradient vector of the objective function that can sometimes be difficult or even impossible. Even more, in some cases, the gradient vector might be constant resulting in slow and not adequately accurate optimization results.

We want to optimize a model of a power transformer tank shield where the above problem occurs. The value of the gradient vector for this model is constant, therefore not adequately accurate solution can be obtained. To solve this problem, we propose using a gradient vector of the additionally defined constrained function, e.g. value of the eddy-currents flowing inside the tank shield, rather than using directly the gradient vector of the optimization function itself. The main algorithm of the proposed optimization procedure can be summarized as follows:

Step #1: Perform optimization using the ordinary GA searching algorithms. The user can define the final number of iterations freely. After this optimization process is finished, a quasi-optimal solution is obtained. Next, set the counter $k = 0$.

Step #2: Compute the searching vector $\mathbf{d}^{(k)} = -1/\nabla J_{\max}\left(\mathbf{L}^{(k)}\right)$, where $\mathbf{L}$ is the vector of the design variable, and $J_{\max}$ is the maximum value of the eddy-current that flows inside the transformer's tank. For finite elements with various values of the searching vector, only the finite element with the largest negative value is taken into account, and for all other elements the searching vector becomes equal to zero. Additionally, for elements where the searching vector does not physically exists, the zero value for the searching vector is used.

Step #3: Compute the length of the improving step $t^{(k)}\sum_{i=1}^{4}\mathbf{d}_i^{(k)} = -0.02$, and find a new improved optimization value according such as: $\mathbf{L}^{(k+1)} = \mathbf{L}^{(k)} + t^{(k)}\cdot\mathbf{d}^{(k)}$. Remesh the analysis domain and again perform eddy-current finite element analysis in order to compute the values of the eddy-currents inside the tank shield.

Step #4: If the computed values for eddy-currents are larger than those desired, than the values obtained at previous optimization step are used as optimal. Otherwise, change the counter $k = k + 1$, and continue with *Step #2*.

3. Optimization Problem

3.1. Analysis Model

A power transformer's tank shield model used for optimization with the proposed optimization method is presented in Figure 1. It consists of two coils and a tank with constant sizes. The optimized size of the shields is numerically defined with the distances L_1, L_2, L_3, L_4 as shown in the same figure. The optimization goal is to define minimum values for the lengths L_1, L_2, L_3, L_4 so that the eddy-current density that flows inside the transformer's tanks is less or equal to 0.4 [A/mm^2]. The following objective function that actually corresponds to the volume of the shielded area is considered:

$$W = \frac{1}{2}\frac{200}{3}\left(L_1 + 2\cdot L_2 + 2\cdot L_3 + L_4\right) \quad . \tag{1}$$

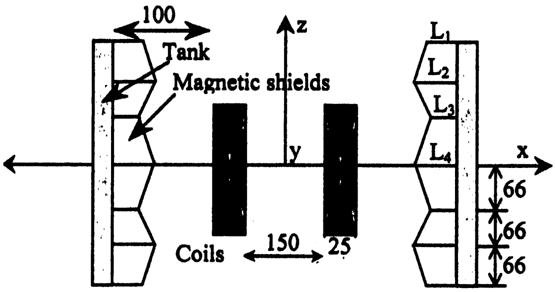


Figure 1 Analyzed model of power transformer.

3.2. Numerical Analysis

For each of the computed intermediate optimization results, a finite element analysis was performed. The finite element mesh for each model was automatically generated using dynamic bubble mesh generation system [5]. The analysis was performed using 2D eddy-current finite element $\mathbf{A}-\phi$ method:

$$\nabla \times \nu\ \nabla \times\ \mathbf{A} = \mathbf{J}_0\ - \sigma\left(\partial \mathbf{A}/_{\partial t} + \nabla\phi\right)\ , \tag{2}$$

where, **A** is the magnetic vector potential, $\mathbf{J}_0$ is the source density vector, σ and ν are the electric conductivity and the magnetic permeability coefficients and ϕ is the scalar potential.

3.3. Optimization Results

As already mentioned above, in the proposed optimization procedure, first a quasi-optimal solution is obtained using the ordinary GA. For this part of the optimization process, three cases were investigated:

Case #1: Constant width of the searching space $l = 10\,[mm]$, defined by the model.

Case #2: Variable searching space; Starting from initial space $l = 10\,[mm]$, at 100^{th} generation, the searching space is reduced to $l/2$.

Case #3: Variable searching space; Searching space is reduced two times: after 70^{th} and after 140^{th} generation, each time to one half of the previous value, i.e. $l, l/2$ and $l/4$.

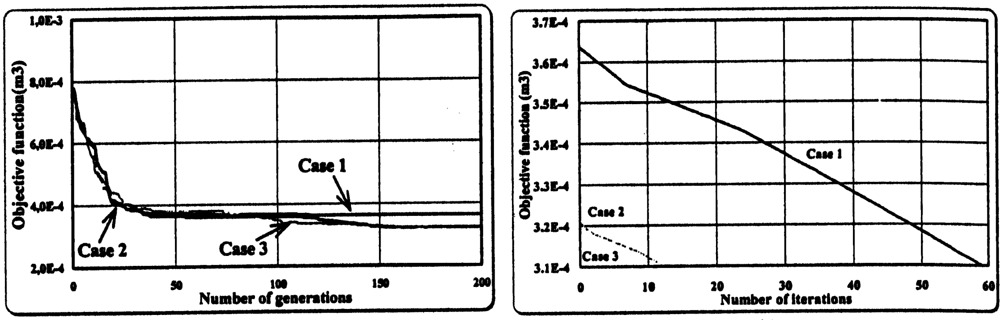
As GA parameters, 20 five–bit strings with 10 elite strings, crossover rate of 60 % and mutation rate of 10 % were used. The obtained results for all three cases after generation of 200 populations are given in Table I and Figure 2(a). As can be seen, for all three cases the optimization process is smooth, with better results obtained for *Case #2* and *Case #3*. For all three cases the convergence speed of the optimization process decreases with its approach towards the optimal solution.

After the initial optimization process using GA is finished, the quasi-optimal solution was used as an initial solution for next optimization step, performed using steepest descent method with gradients of the constrained function as described above. Optimal solutions for all three cases are given in Table II. As can be seen, the final values for each of the four optimization parameters L_1, L_2, L_3, L_4 are very similar, however, the number of iterations is different and it is the smallest for the *Case #3* as expected. The final optimal value of the objective function is the same for all three cases. The convergence of the optimization process based on steepest decent method is given in Figure 2(b). Convergence rates for all three cases are fast and similar, however, for *Case #1* the number of iterations is much larger because it has the worst initial solution.

Finally, Figure 3 shows the distribution of the magnetic flux lines for a model without shields and for a model with optimized size of the magnetic shields. It is obvious that for the optimized model the amount of eddy-currents that flow inside the tank is negligible small.

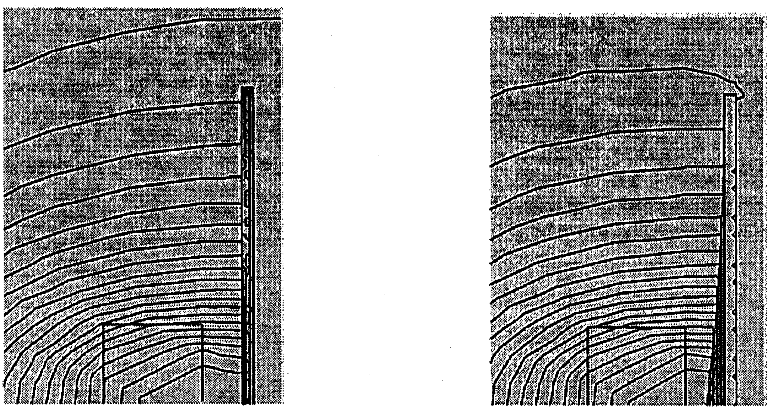
4. Conclusions

A new optimization procedure based on mixed stochastic and deterministic optimization methods is presented. As a stochastic method an ordinary GA searching algorithm was employed, and to improve the accuracy of the optimized results, a deterministic optimization method based on the steepest descent method using gradients of the constrained function is used. The proposed method was successfully utilized for shape optimization of tank shields of a power transformer in order to decrease the amount of the eddy-currents that flow inside the tank.



(a) (b)

Figure 2 Changes of the objective function, (a) for GA optimization process, (b) for steepest decent optimization process.



(a) Initial model (no shields) (b) Model with optimized shields

Figure 3 Magnetic flux lines and the eddy-current distribution inside the tank and shields.

Table I GA quasi-optimal solutions

	Case #1	Case #2	Case #3
L_1 [mm]	4.545	4.621	4.735
L_2 [mm]	2.121	1.970	1.856
L_3 [mm]	0.606	0.455	0.455
L_4 [mm]	0.303	0.152	0.152
Iterations	18	131	174
W [10^{-3} m^3]	0.343	0.321	0.317

Table II Steepest descent optimal results

	Case #1	Case #2	Case #3
L_1 [mm]	4.676	4.585	4.640
L_2 [mm]	1.891	1.949	1.919
L_3 [mm]	0.408	0.408	0.403
L_4 [mm]	0.027	0.015	0.019
Iterations	50	12	6
W [10^{-3} m^3]	0.310	0.310	0.310

References

[1] V. Cingoski, N. Kowata, K. Kaneda, and H. Yamashita, "Inverse Shape Optimization Using Dynamically Adjustable Genetic Algorithms," *in press, IEEE Transaction on Energy Conversion*, 1999.

[2] J. Kim, H. Lee, H. Jung, and S. Hahn, "Optimal Design Technique for Waveguide Device," *IEEE Transaction on Magnetics*, Vol. 32, No. 3, pp. 1250-1253, 1996.

[3] N. Takahashi and T. Kitamura, "Optimal Design of Tank Shield Model of Transformer," *Proceedings of the Conference on Computational Engineering and Science*, Vol. 3, pp. 327-330, 1998.

[4] Y. Yokose, V. Cingoski, K. Kaneda, and H. Yamashita, "Shape Optimization of Magnetic Devices Using Genetic Algorithms with Dynamically Adjustable Parameters," *in press, IEEE Transaction on Magnetics*, May 1999.

[5] V. Cingoski, R. Murakawa, K. Kaneda and H. Yamashita, "Automatic mesh generation in finite element analysis using dynamic bubble system," *Journal of Applied Physics*, Vol. 81, No. 8, Part 2, pp. 4085 – 4087, 1997.