Shape Optimization of Magnetic Devices Using Genetic Algorithms with Dynamically Adjustable Parameters

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***Abstract*—An improved method for inverse shape optimization of magnetic devices using the Genetic Algorithms(GAs) with dynamically adjustable parameters is presented. The proposed method starts from an initial population using large number of bits per chromosome enabling searching for the optimal solution in a wider region without aggravating the computational speed. Later, as the optimization process evolves, the searching space is gradually decreased by restriction of the number of bits and by translation and reduction of the searching space according to the values of the objective function, therefore, dynamically adjusting to the best fit solution decreasing the computation resources to a minimum. The obtained results exhibit acceleration of the optimization process and increase of the solution accuracy.**

***Index terms*—Genetic algorithms, optimization methods, finite element methods, magnetic materials/devices, magnetization processes.**

I. Introduction

In general, searching techniques can be divided into two distinctive groups: deterministic and stochastic techniques. The deterministic searching techniques are usually based on the calculation of the gradient of the objective function, therefore, they are not generally applicable to any problem because they require gradient computation which for some problems with large number of parameters is difficult or even impossible to evaluate. Searching for only one function at time, they could very easy trap themselves into local optimum instead of the global optimum which is desired. On the other hand, for stochastic methods, such as the Genetic Algorithms, Evolutionary Strategies or Artificial Life, computation of gradients is not necessary. Therefore, recently stochastic methods have been widely applied for multivariable inverse shape optimization, mainly due to their ability to avoid being trapped in a local optimum of the objective function. They usually work with coded information rather than directly with the optimized functions, thus, they can be adjusted to a particular problem easily. However, since they provide a searching algorithm for the solution which exists in the multidimensional space, they are usually computationally expensive.

GAs as a stochastic searching technique have the same advantages and disadvantages that are shared by all stochastic methods [1], [2]. They work fine with multidimensional searching space, do not need any gradient computation and could successfully avoid any local optimum. However, they usually required a long computation time. It is commonly known that at the beginning of the searching process GAs exhibits fast and good convergence rate, however, as the searching procedure evolves with time, the convergence rate becomes extremely slow.

Recently, we proposed a new method for improving the convergence rate using a flexible and contracting searching space [3]. However, since we usually do not know where is the optimum of the objective function, it is usually very difficult to choose the appropriate initial searching space. Additionally, since the searching space is gradually reduced, there is a possibility that the optimal point can become excluded from the searching space, In that case, instead of obtaining a global optimum our searching procedure would result only with a local optimum. Therefore, the reduction of the searching space must be done in correlation with the values of the objective function and its changes from generation to generation. Even more, this correlation should not be limited only to the best value of the objective function, but rather it should be established with several top values of the objective function at each generation.

The main objective of this paper is to improve the previously proposed method for inverse shape optimization based on the GAs as a searching technique by using directly the information from the objective function and by dynamically changing and adjusting the parameters of the searching algorithm, such as the number of bits and the width of the searching space. First, we present the procedure for improving the characteristic of the searching properties of the GA by means of dynamically adjusting its working parameters. Next, to verify the usefulness of our method a comparison between three various searching procedures using GAs is given for a model of a die press mold. Finally, we conclude our paper with some final remarks and points for future research.

II. Proposed Method

As mentioned above, we have already proved in our recent paper [3], that changing of the width of the search-

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ing space could be very advantageous for increasing the speed and accuracy of the optimization process. However, since the user usually does not know if or where inside the searching space is the global optimum of the objective function, the decision of the position and width of the searching space must be considered very carefully. Naturally, it seems beneficial to choose a wider initial searching space ensuring that the optimal value will be always included inside it. However, even a small increase of the searching space almost always results in large increase of the computation time. However, because the searching procedure is discontinuous with jumps between available solutions inside the searching space which best fit our objective function from generation to generation, the large number of bits, therefore, the larger number of possible solutions must be considered. Thus, if we choose a wider searching space and if we want accurate results, we must increase the number of bits. Consequently, the computation time again will be prolongated.

The main idea of our proposed methodology is to start with a wider searching space and larger number of bits, and as the optimization process evolves by monitoring of the value of the objective function and its changes, gradually narrow the searching space and decrease the number of bits. This procedure has the following features:

- Wider initial searching space will ensure that the global optimal solution is always included inside that space, if such a solution exists.
- Larger initial number of bits will provide a smoother optimization procedure for such wide searching space. It will provide solutions with less discontinuity between populations, increase the accuracy of the results and decrease the computational time.
- Reduction of the searching space using the values of the objective function will ensure that at any time several solutions with best fitness values of the objective function will be included inside the searching space, thus, the possibility that the global optimal solution does not exist inside the searching space is excluded.
- Decreasing the number of bits, according to the values of the objective function will ensure a stable and fast convergence rate for the entire searching process. This procedure also acts as a kind of mutation factor which helps that the searching process does not get trapped by any local optimum.
- Overall performance of the searching process is improved and the computation time is decreased up to fifty percent in comparison with the original GA procedures.

A practical example of the proposed method is given in Fig. 1. We start our optimization with three bits chromosome generation, therefore inside the searching space we have eight possible solutions with inter-solution interval ΔL_1. Then, lets have two solutions, one with the best

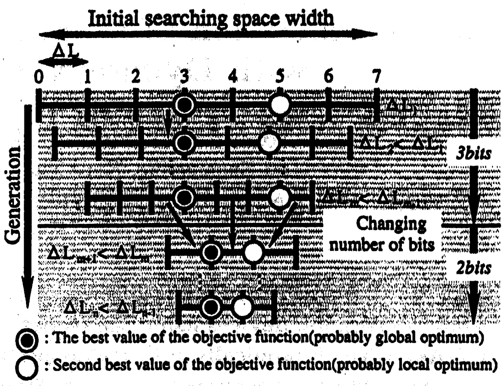
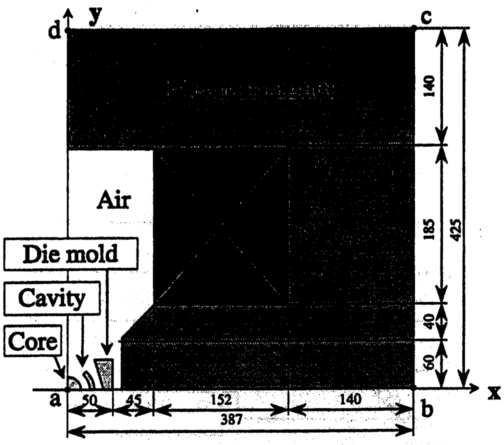


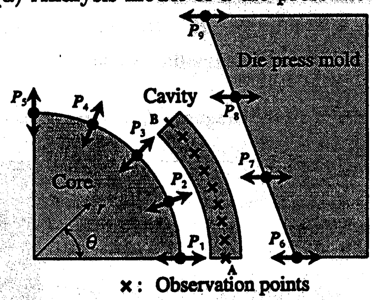
Fig. 1. Transition and contraction of the searching space.

and the other with the second best value of the objective function among these eight solutions as show in the figure. In the next population we reduce the searching space in that manner that the both above computed solutions are included inside this new searching space. Now, the inter-solution interval became $\Delta L_2 < \Delta L_1$, while the number of possible solutions is still eight. What we gained with this is that we have smaller inter-solution interval which will insure smoother approach towards the global optimum. Also, since we included both, the best and the second best solution from which one is probably local but the other is probably the global optimum, the possibility to avoid the global solution from the searching space is minimized or totally excluded. If we continued with this procedure, after several generations we will have new much narrower searching space, with eight possible solutions and with very small inter-solution interval $\Delta L_m < \Delta L_{m-1}$. However, the first thing that we will notice is that since this inter-solution interval became very small, the convergence of the optimization process decreases. At that point, we perform the second improvement, we decrease the number of bits from three to two. What we have now is narrower searching space with only four possible solutions and with inter-solution interval ΔL_{m+1} larger than that of the previous three bits generation ΔL_m. This procedure will increase the convergence speed of the iteration process without any aggravation of the accuracy of the results. Later, we proceed with the reduction of the searching space in order to further improve the accuracy of the solution. These procedures are executed until the desired accuracy of the objective function is achieved.

Finally, we would like to point out the followings: (1) any optimum which lies inside that searching space can be found, even if its position is between two discrete possible solutions (a very common case) as a result of the contraction of the searching space and decreasing the number of bits; (2) due to non-uniform changes of the objective function it is impossible to define the exact timing when the number of bits should be reduced. Therefore, in our approach the reduction of bits is done according to user's experience and the analyzed model; (3) the number of significant solutions of the objective function which are monitored for the reduction of the searching space (in the



(a) Analysis model of a die press mold



(b) Enlarged view of die mold and cavity area

Fig. 2. A model of a die press mold.

above example two), can be defined by the user.

III. Application

A. Analyzed Model and Optimization Goals

A die press mold model [3] which was used for optimization by the proposed method is given in Fig. 2a. The optimization goal is to optimize the shape of the central spherical core and the die press mold which will result in the desired intensity and direction of the magnetic flux density vector **B** at several observation points along the line A–B inside the mold's cavity as shown in Fig. 2b. Five control points P_1 to P_5 along the surface of the central core, and four control points P_6 to P_9 along the die mold are established and they define the shape of the model. The objective function is defined as the minimum square error between the desired magnetic flux density distributions in the x and y directions, respectively, B_{0x} and B_{0y} and their computed values B_x and B_y:

$$Obj = \frac{1}{N}\sum_{n=1}^{N}\left[(B_{ox}-B_x)^2+(B_{oy}-B_y)^2\right] \quad , \qquad (1)$$

where N is the number of observation points along central cavity line A–B as shown in Fig. 2b.

Three different searching procedures using GAs were compared: (1) GA with fixed searching space and fixed number of bits per population, (2) fixed number of bits with reducing searching space [3], and (3) the proposed method with dynamically adjustable parameters such as reducing searching space and number of bits per generation. The GA parameters, the initial and the final width of the searching space as well as the number of bits for all three methods are given in Table I. To make comparison among all three searching procedures accurate, for each of them we used the same elite strategy, the same number of chromosomes per population and the same crossover and mutation rate coefficients as given in Table II.

TABLE I
Comparison between initial and final GA parameters

Method	(1)	(2)	(3)
Initial width of the searching space [mm]	12.6	12.6	12.6
Final width of the searching space [mm]	12.6	0.64	0.15
Initial number of bits	6	6	6
Final number of bits	6	6	4

TABLE II
GA parameters

Number of chromosomes	14
Number of elite chromosomes	4
Number of control points	9
Crossover rate [%]	40
Mutation rate [%]	10

B. Obtained Results and Comparison

The average inverse values of the objective function Obj for all three different procedures explained above and computed according to equation (1) are presented in Fig. 3. As can be seen, the searching procedure (3) exhibits a better convergence rate than both procedures (1), and (2) for the entire optimization process. Additionally, while procedure (2) which employs only reduction of the searching space converges faster than the original GA procedure (1), this procedure becomes slowly convergent as the fitness of the objective functions improves. On the other side, the proposed procedure (3) not only has a

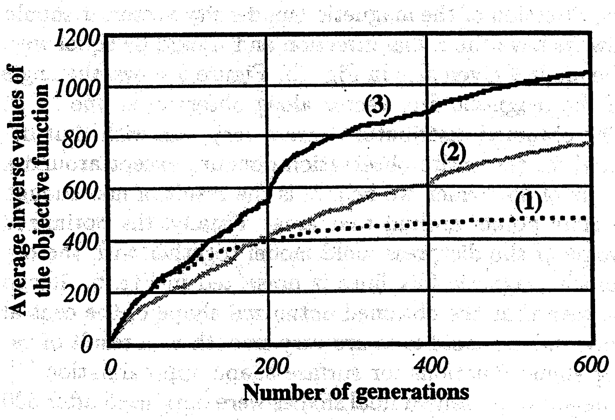


Fig. 3. Average inverse values of the objective function.

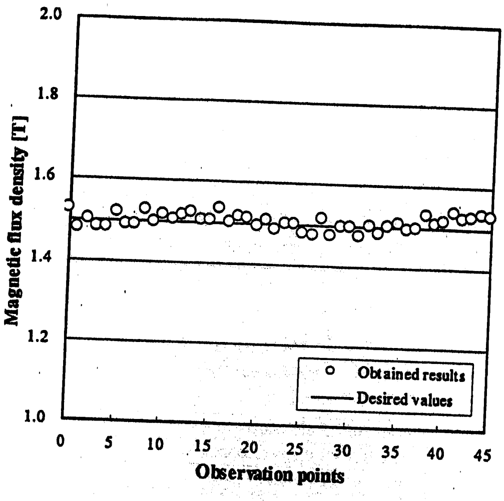


Fig. 4. Intensity of the magnetic flux density vector.

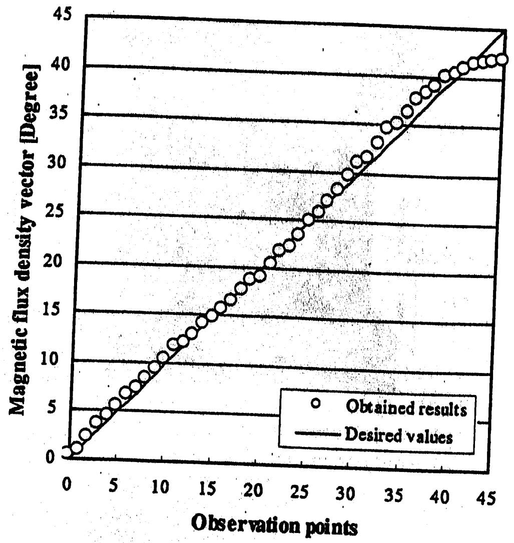


Fig. 5. Angle of the magnetic flux density vector.

faster convergence rate but also keeps that good convergence rate for the entire optimization process.

From Fig. 3 one can easily notice that at 200 and 400 generations when the number of bits from 6 was decreased to 5 and from 5 to 4, respectively, the convergence rate was greatly improved. The decrease of the number of bits keeps the convergence rate high and protects it from decreasing with the evolution of the optimization process as can be seen for procedure (2). Therefore, the proposed procedure, not only decreases the computation time by improving the convergence rate of the optimization process, but also improves the accuracy of the results. As can be seen, almost half iterations were needed for achieving the same accuracy of the optimization process for the proposed method (3) in comparison with method (2). This rate was even larger in favor of the proposed method (3) in comparison with the traditional method (1).

Figure 4 shows the computed results for the intensity of the magnetic flux density vector **B** along the observation line *A–B* shown in Fig. 2b using the proposed GA procedure. As can be seen the obtained results are in very good agreement with the desired value of 1.5 T. Regarding direction of the magnetic flux density vector, it should always have the radial direction and should be equal with the angle θ given also in Fig. 2b. Figure 5 shows the angle of the magnetic flux vector along observation line *A–B*. The obtained distribution agrees very well with that desired for the entire observation domain, except around a angle of 45° which we believe is the result of non enough control points around that area. Finally, the optimized shape of the die press mold model together with the obtained magnetic flux lines is presented in Fig. 6. It can be seen that the obtained optimized shape of the central core and die mold area are very smooth as a result of using spline functions for surface shape approximation [3]. The above presented final shapes were optimized after 600 generations and for total computation time of 185 minutes on SGI Indigo2 Workstation.

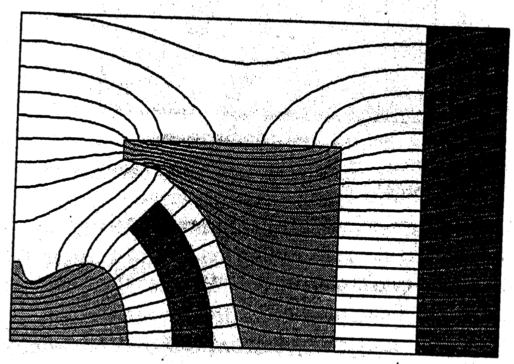


Fig. 6. Optimized shape using proposed method and magnetic flux lines.

IV. Conclusions

A new method for inverse shape optimization using GA searching procedure was proposed. The method introduces dynamic changes of the searching parameters such as searching space and the number of bits according to the information gathered directly from the objective function. The improved convergence rate of the optimization process was achieved with better accuracy of the obtained results in almost half the iteration steps of the currently available procedures. The proposed method is robust and easy applicable to various inverse shape optimization problems.

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