Genetic Algorithms with Assistant Chromosomes for Inverse Shape Optimization of Electromagnetic Devices

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***Abstract*—Stochastic searching algorithms such as the Genetic Algorithms (GA's) are commonly used for shape optimization of electromagnetic devices. Although very robust and easy applicable, the GA's are usually time consuming. In this paper, we present a new improved method for optimization of electromagnetic devices that utilizes the ordinary GA with enriched searching population of so called assistant chromosomes. These new assistant chromosomes are generated in accordance with the values of the objective function. The proposed procedure is highly flexible and exhibits improvements of the searching speed and accuracy of the computed results.**

***Index Terms*—Finite element method, genetic algorithms, optimization methods, magnetostatics.**

I. INTRODUCTION

RECENTLY, the genetic algorithms (GA's) [1] have been widely used mainly in connection with the finite element method for inverse shape optimizations [2]–[4]. The main advantages of the GA's are: 1) they can search effectively in multivariable searching space, and 2) they are able to pass the optimizing information from one population to the following one, i.e. new chromosomes (children) inherit important optimizing information from their parents (two chromosomes from the previous population).

On the other side, the GA's are usually time consuming optimization procedures. Because they usually work in a multivariable region with a set of possible solutions (chromosomes), the fitness values must be computed for each possible solution, separately. The obtained fitness values determine which solutions could mate and leave offsprings and which solution drops from the searching procedure. Therefore, for each possible solution the fitness function must be computed, which means that for each possible solution a finite element analysis must be performed and computed the objective function at several points which are usually called control points. Since the mutation and crossover as GA's operations have random characters, it seems advantageous to assist in some way to the searching process by producing some additional possible solutions (chromosomes) in accordance with the objective function. It is very rational to think that the generation of additional solutions in the neighborhood of the currently best solution could lead to faster convergence of the entire optimization process. This reasoning was employed in this paper resulting in an improved searching procedure based on the ordinary GA's with assistant chromosomes.

II. PROPOSED METHOD

The searching procedure based on the genetic algorithms is a stochastic process based on the following three main operations: 1) *reproduction*—mating pairs of chromosomes called parents and producing a new pair of chromosomes called offsprings or children, 2) *crossover*—exchanging information data between parent and offspring chromosomes, and 3) *mutation*—changing randomly the information data of a single chromosome. As a results, the GA's provide possibilities for knowledge inheritance and transformation between successive populations. That means that the chromosomes with good properties regarding the user-defined objective function have higher probability to pass their data (knowledge) to their offsprings. However, as the searching process evolves, the convergence of the optimization decrease because all chromosomes with higher fitness values have very similar data and any data interchange (crossover) improves the searching process very slowly. Therefore, it is advantageous along with the ordinary GA, to find additional ways to enrich the information data by adding new chromosomes in the searching procedure. These new chromosomes we called *assistant chromosomes*.

Fig. 1 shows a simple two-dimensional searching space, where a GA based searching procedure is initiated. Two design variables X_1 and X_2 are varied and the optimal solution according to an objective function is sought. The isolines in Fig. 1 represent the objective function and darker values corresponding to better values. Let us have two temporary optimal solutions: solution A which has the best fitness value according to the objective function, and solution B which has the second best fitness value. The probability that better solutions than A and B exists in their neighborhood, especially along the straight line that connects these two points inside the searching space is obviously high. Therefore, instead of generation the entire new population according to the above mentioned GA operations, we generate only a part of it. The rest of the needed population is generated according to the fitness values of already generated chromosomes, such as A and B. An example

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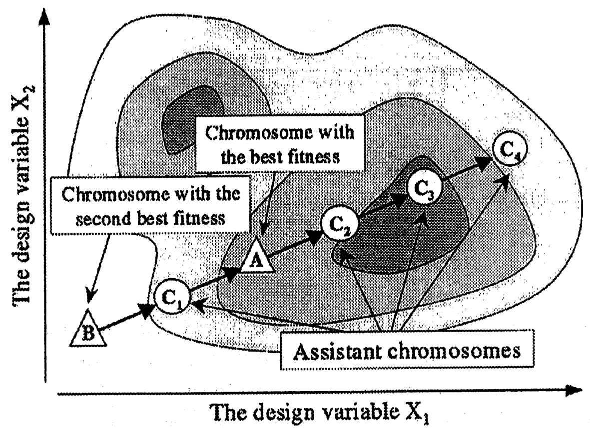

Fig. 1. The method of making assistant chromosomes.

TABLE I
TYPICAL TABLE FOR GENERATION OF ASSISTANT CHROMOSOMES

Assistant chromosomes	$\overline{AB}$	$\overline{AC}$	$\overline{AD}$	$\overline{AE}$
C_1	0.5	0.5	0.5	0.5
C_2	1.5	1.5	1.5	1.5
C_3	2.0	2.0	2.0	2.0
C_4	3.0	3.0	3.0	-
C_5	4.0	4.0	-	-
C_6	5.0	5.0	-	-
C_7	6.0	-	-	-

of a typical assistant chromosomes generation scheme is given in Table I. As can be seen from Table I, in this case we use the first five chromosomes with best fitness values A, B, $\cdots$, E and generate additional twenty chromosomes at positions: $\{0.5, 1.5, 2.0, \cdots\} \times \overline{AB}$, $\{0.5, 1.5, 2.0, \cdots\} \times \overline{AC}$, etc. These newly generated chromosomes C_j ($j = 1, \cdots, 7$) (see Fig. 1) together with the ordinary generated chromosomes made new searching population for the GA optimizations.

III. VERIFICATION MODELS

To verify the efficiency of the proposed searching procedure, we used two optimization models: a rotating machine pole face model, and a model of die press machine for making permanent magnets. For obtaining the fitness of each shape configuration we used a numerical method for computation of the magnetic flux density values based on 2D finite element method. The computation of the objective function, the arrangements of the control points and the moving points that decides the shape of the device are given next for each model, separately.

A. Pole Face Model

For inverse shape optimization of a rotating machine pole face we used a model given in Fig. 2. Enlarged view of the pole face area, control points and the searching space are given in Fig. 3. The model has 5 control points, P_1 to P_5 placed along, the pole face. The optimization variable is the intensity and direction of

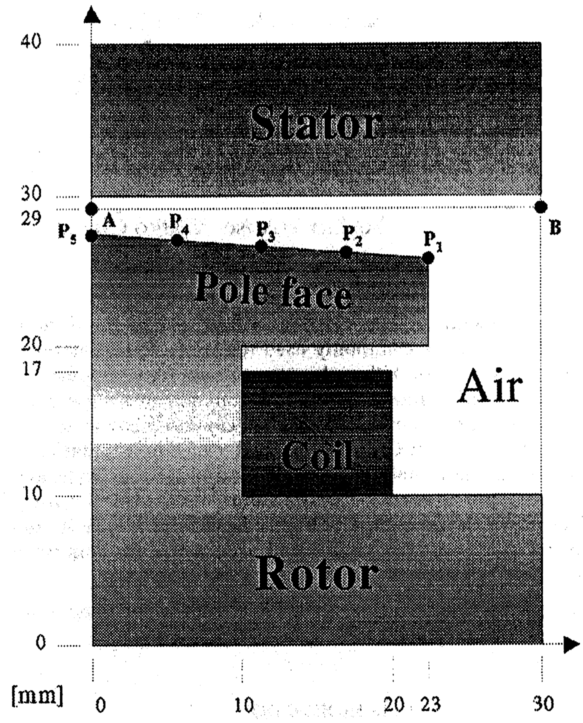

Fig. 2. Analyzed model of a pole fare.

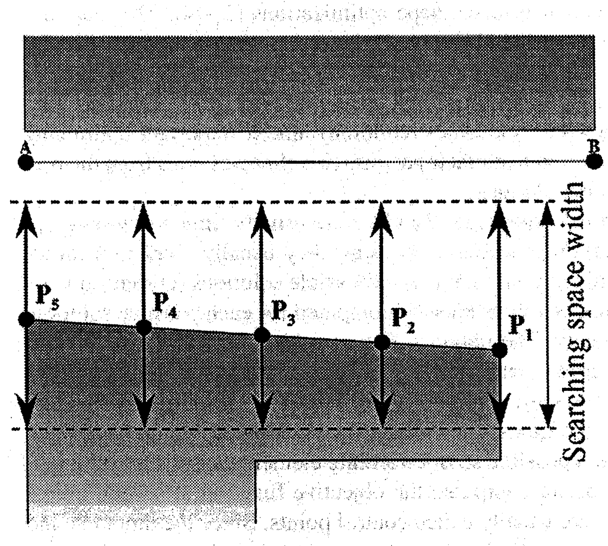

Fig. 3. Enlarged view of a pole face area, control points and searching space.

the magnetic flux density vector. The objective function is defined as the minimum error between the desired magnetic flux density values, $B_{0,i}$ and their corresponding computed values B_i, respectively.

$$f_{pf} = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{(B_{0,i} - B_i) \times 100}{B_{0,i}} \right|, \tag{1}$$

where $N = 17$ is the total number of observation points. The shape of the pole face surface was decided using spline function [3].

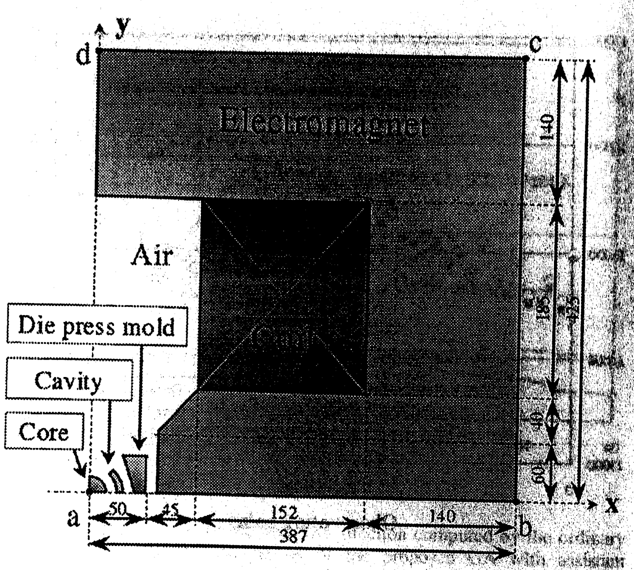

Fig. 4. Analyzed model of a die press mold.

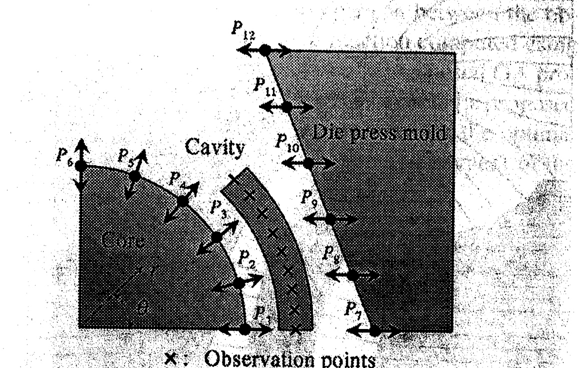

Fig. 5. Enlarged view of a die press mold, control points and searching space.

B. Die Press Mold Model

The proposed searching algorithms was also applied for inverse shape optimization of a die press mold model shown in Fig. 4. The enlarged view of the optimized area is given in Fig. 5. This model has 12 control points, P_1 to P_6 along the core surface, and P_7 to P_{12} along the die press mold surface. The optimization variable is the intensity and direction of the magnetic flux vector along the central cavity line (see Fig. 5). The objective function is defined as the minimum square error between the desired magnetic flux density values in the x and y directions, B_{0x} and B_{0y}, and their corresponding computed values B_x and B_y, respectively.

$$f_{press} = \sum_{i=1}^{N} \left\{ (B_{0x,i} - B_{x,i})^2 + (B_{0y,i} - B_{y,i})^2 \right\}, \quad (2)$$

where N is the total number of observation points. The shape of the core and the die press mold surface for this model too were decided using a spline function.

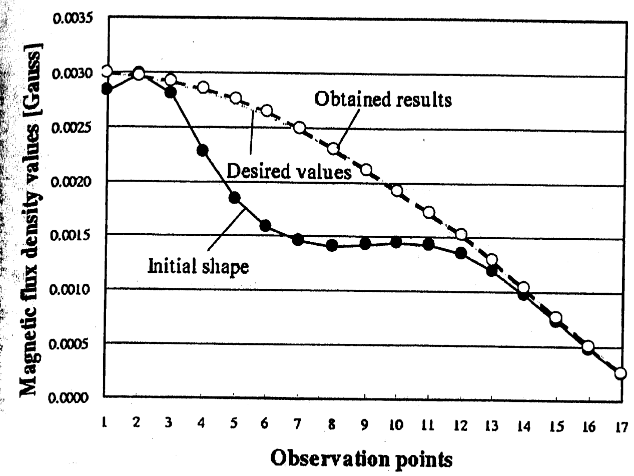

Fig. 6. Comparison between desired and computed magnetic flux density distributions.

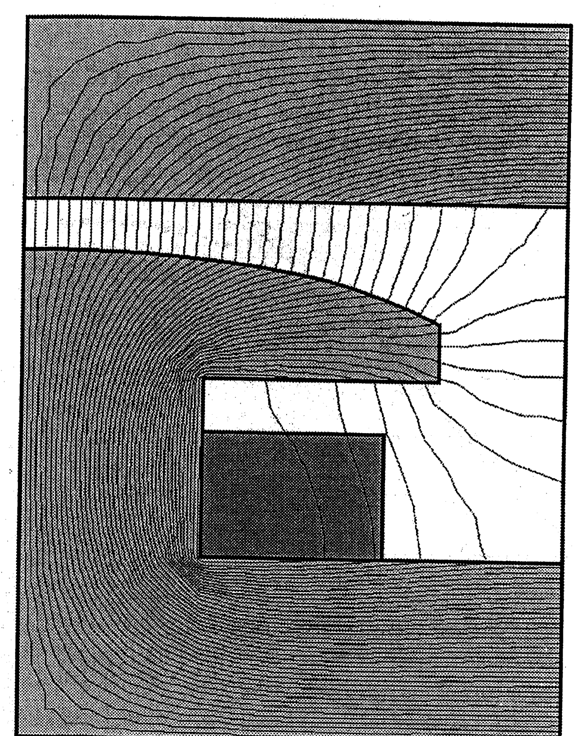

Fig. 7. Final shape of a pole face and magnetic flux line distribution.

IV. Optimization Results

The proposed GA searching procedure using assistant chromosomes was compared with the ordinary GA searching procedure. Random initial population with 30 chromosomes was generated in both cases. The crossover and mutation rates were also the same for both searching procedures, 50%, and 5%, respectively. The number of assistant chromosomes was 20 and they were generated using the table shown in Table I, while the

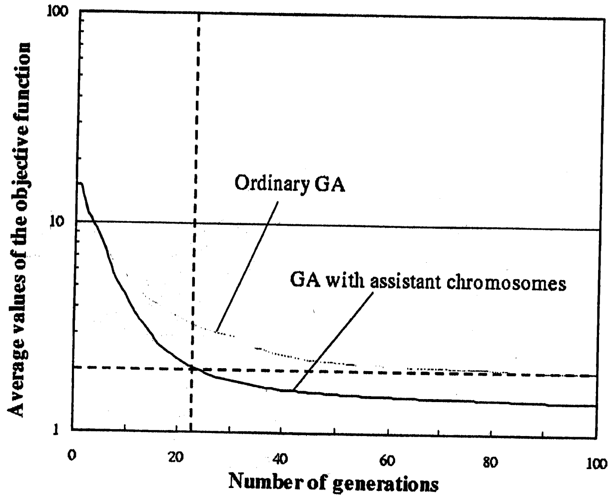

Fig. 8. Average values of the objective function using the ordinary GA and the proposed GA method with assistant chromosomes.

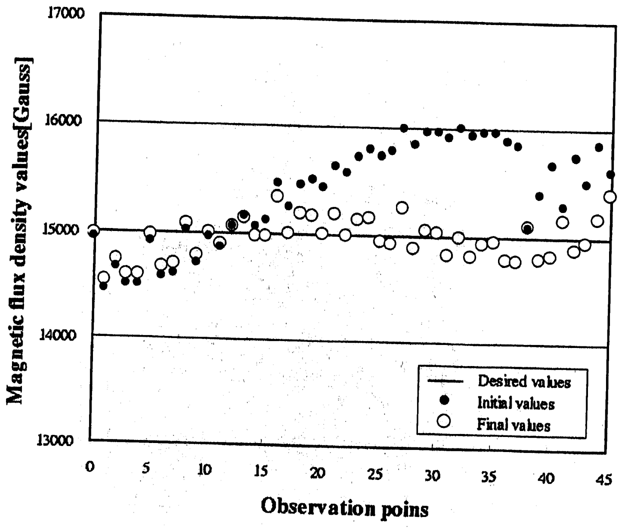

Fig. 10. Comparison between desired and computed magnetic flux density distributions.

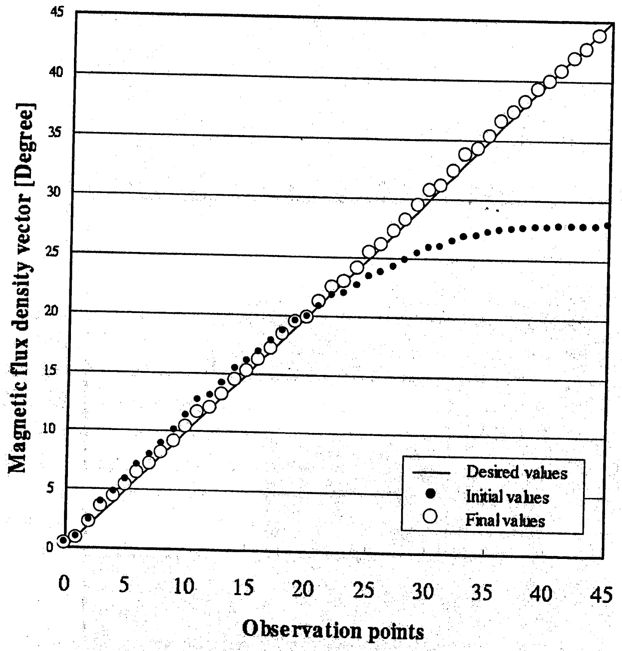

Fig. 9. Angle of the magnetic flux density vector.

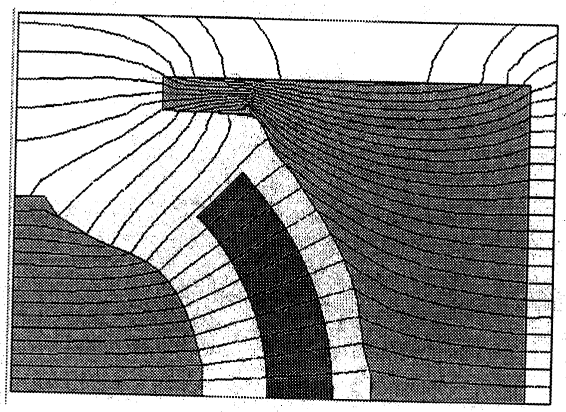

Fig. 11. Final shape of a die press mold model and magnetic flux lines.

other 10 chromosomes were elite chromosomes of last generation.

The results of the optimization processes are described next separately for both analyzed models. For each model we compared results obtained by the ordinary GA and results obtained by the proposed method. Because, the GA searching procedure is stochastic and has a strong random characters, for comparison we used an average values for the magnetic flux density obtained by repeating the searching process 100 times.

A. *Pole Face Model*

A comparison between the magnetic flux density values for the initial and the final (optimized) pole shape at each observation point is shown in Fig. 6. The magnetic flux density distribution after the optimize is better than for the initial shape, and corresponds well to the desired one. The optimal pole shape with the obtained magnetic flux lines is presented in Fig. 7. As a result of using spline surface approximation, the generated surface defined by such a small number of control points (five) is very smooth. Additionally, in Fig. 8 the comparison between the obtained average values of the objective function using the ordinary GA and the proposed GA with assistant chromosome is given.

B. *Die Press Mold Model*

Similar as for the pole face model, a comparison between values for the magnetic flux density obtained for the initial shape and for the optimized shape of a die press model is shown in Fig. 9. The magnetic flux density vectors for the final shape and the initial shape at each observation points are shown in Fig. 10. It is obvious that the magnetic flux density distribution obtained after the optimization is better than that for initial shape, and corresponds very well to desired one. The optimal shape of the die

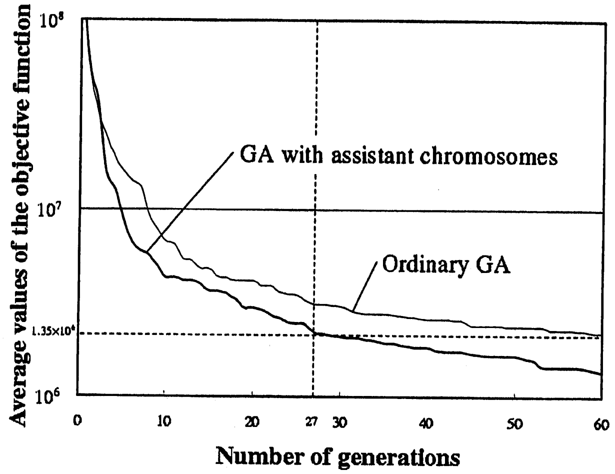

Fig. 12. Average values of the objective function computed by the ordinary GA and those computed by means of the proposed GA with assistant chromosomes.

press model with the obtained magnetic flux lines is presented in Fig. 11. Fig. 12 represents the comparison between the obtained average values of the objective function computed using the ordinary GA and those computed by the proposed GA procedure with assistant chromosome. As can be seen the proposed GA procedure provides faster convergence toward the optimal solution which was the main objective for development of the proposed optimization method.

V. Conclusions

An improved method for inverse shape optimization using GA searching procedure was proposed. The proposed method introduces the generation of assistant chromosomes according to the information gathered directly from the values of the objective function. The improved convergence rate of the optimization process was achieved with better accuracy of the obtained results with less iteration steps than the currently available GA searching procedures. This can be summarize in two main conclusions: 1) the convergence rate of the proposed GA procedure with assistant chromosomes is better than that of the ordinary GA, and 2) the proposed procedure exhibits good convergence rate for the entire optimization process, providing optimization results with the same accuracy as the ordinary GA for less number of iteration steps (see Figs. 8 and 12). Finally, the proposed method is robust and easy applicable to various inverse shape optimization problems.

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