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Inverse Shape Optimization Using Dynamically Adjustable Genetic Algorithms

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Abstract— **In this paper, a new dynamically adjustable genetic algorithm for inverse shape optimization of electrical devices is proposed. The algorithm starts with initial population which is not entirely randomly defined and dynamically changes the position and the width of the searching space as the searching procedure evolves with time and the objective function approaches its optimum. The proposed algorithm is successfully applied for inverse shape optimization of a die mold press machine and for pole shape optimization of a rotating machine. To achieve smooth pole face the optimized shape is defined using several control points and ordinary spline functions.**

Keywords— **Inverse optimization, genetic algorithm, rotation machines, design of pole face, die mold, spline functions.**

I. Introduction

For optimization and design of shapes and parameters of various electromagnetic devices, in general, two classes of optimization methods can be utilized: direct optimization methods and inverse optimization methods. Direct methods are usually very time consuming and require treatment of one variable as a parameter while other variables are changeable. On the other hand, inverse optimization methods although faster than direct methods, they are very case sensitive and problem dependable.

Recently, various deterministic and probabilistic searching methods, such as simulated annealing, neural networks, genetic algorithms, artificial life (A-life), evolutionary strategies, etc., have been widely employed in various scientific fields for identifying optimal solutions. Among them, the genetic algorithms (GAs) have emerged as very practical and robust optimization tools and searching methods [1].

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Genetic algorithms belong to the group of probabilistic searching methods and they have a high probability of locating the global optimum in the multidimensional searching space discarding all existing local optima. The implementation of GAs for inverse optimization of electromagnetic devices has been recently proposed [2], [3]. The robustness of the method, its ability to deal directly with optimization variables without any derivatives and usage of an encoded binary representation of the optimization variables rather than the variable itself, are very promising and advantageous.

In this paper, a novel searching procedure for inverse shape optimization using dynamically adjustable GAs is introduced. The main features of the proposed method are:

- The solution space for the optimization variables changes dynamically as the optimization process evolves;
- The interval of the searching space is flexible; as the optimization process evolves with time the solution space becomes smaller and narrower increasing the sensitivity of the searching algorithm;
- To achieve smoothness of the optimized surface, several control points are established inside the solution space and a third order spline functions are used for surface modeling.
- The initial population of chromosomes (strings) is not defined entirely randomly, but according to user defined rules;

In what follows, the proposed dynamically adjustable GA is presented in detail. Each of its features is described entirely and its influence on the searching procedure and obtained solutions is discussed. Finally, two successful applications of the proposed dynamically adjustable GA is presented: for inverse shape optimization of a die mold press machine for production of oriented magnetic materials, and for shape optimization of a pole face of rotating machine which model was previously presented in [2].

II. Dynamically Adjustable GAs

A. Dynamic adjustment of the searching space

The main feature of the proposed method is its ability to adjust its searching space dynamically, i.e. as the opti-

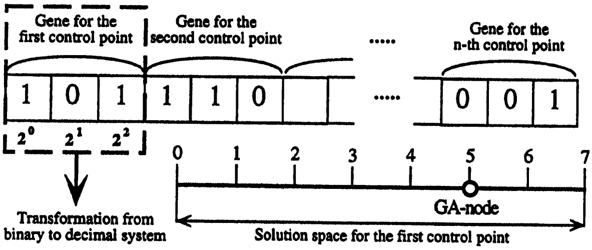


Fig. 1. Encoding procedure.

mization process evolves with time. Before we describe this property in detail, let us first define simply the encoding procedure employed.

For encoding the coordinates of each control point in the two-dimensional space where we search for the optimum, a simple binary encoding procedure is used (see Fig. 1). Therefore, for each control point several discrete values in the entire searching space are allowed. For example, in Fig. 1 a three-bits encoding procedure is shown. For the initial value of a gene that represents encoded value of the first control point we have binary string 101, which back to the decimal space results with control point at position 5. The same procedure applies for all other genes i.e. other control points.

Now, let us examine how the proposed GA can dynamically adjust itself to the searching space. As an example, let's have an optimal solution of the inverse optimization problem for the $n-th$ generation given with gray dashed line in Fig. 2. In the same figure, the global optimum of the treated problem is given with black continuous line. The gray dashed line of this temporary solution is obtained using spline approximation and utilizing coordinates of each control point obtained from the string with the largest fitness value among all strings at $n-th$ generation. The solution of one particular control point is given with a circle in Fig. 2. If this optimal solution lies at the one of both terminal nodes of the searching interval, as in Fig. 2, better solution can not be obtained using this searching space. Therefore, since this temporary solution is not yet an optimum, the searching procedure must continue, however, over a new searching space. The new searching space is established in the manner that the previously obtained solution (circle in Fig. 2) is placed at the center of a new searching space for the next generation $n+1$. Because, in fact the searching procedure has discrete character, this method enables faster convergence rate of the searching process.

B. Contraction of the searching space

In addition to dynamically adjusting its searching space from generation to generation, the proposed algorithm also dynamically changes the width of this searching space. For each or for several consequently searching steps the interval of the searching space becomes smaller and narrower as shown in Fig. 3. This further improves searching charac-

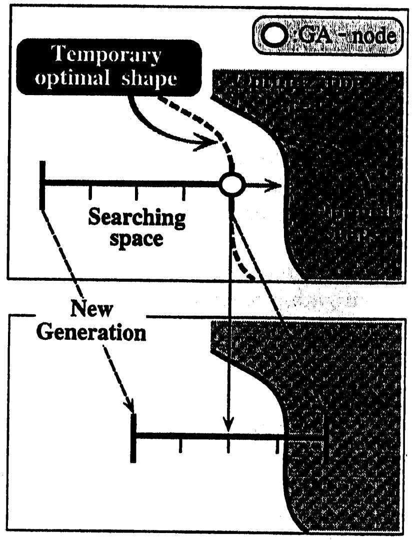


Fig. 2. Dynamically adjustable searching space.

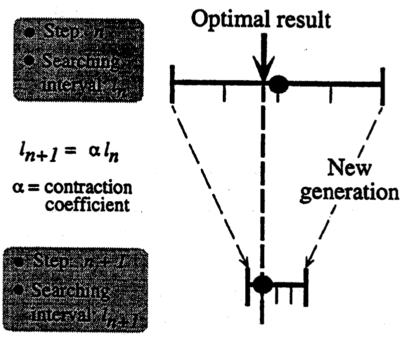


Fig. 3. Contraction of the searching space.

teristic of the proposed GA making it more sensitive. The amount of contraction of the searching space can be defined by the user.

C. Definition of the initial population

As mentioned in the introduction, the initial population for the proposed GA is not entirely randomly defined; rather, for each control point, it must satisfy the following criteria:

- It must contain two initial strings with encoded information for the largest and smallest value of optimization variable from the entire searching interval;
- It must contain one initial string with encoded information for the value of the optimization variable at the center of the searching interval;
- All other strings can be defined randomly.

Using this procedure the initial population becomes "richer " with good optimization properties and localizing of the global optimum becomes easier.

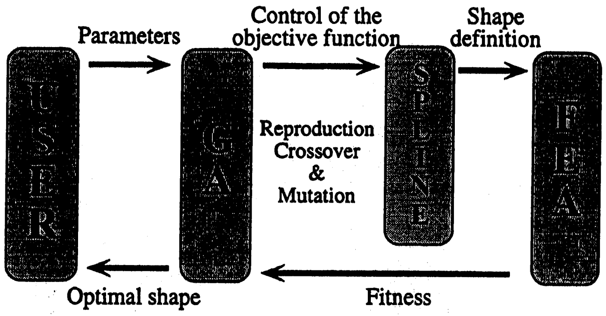
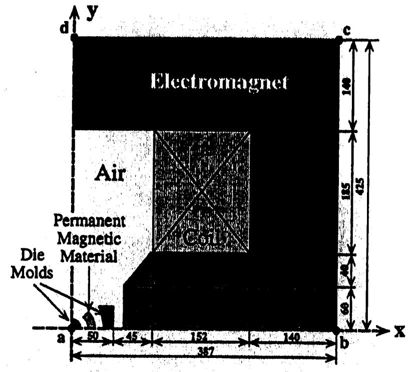
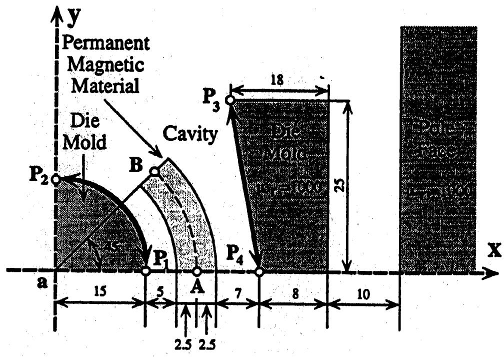


Fig. 4. Data flow of the proposed inverse optimization method.



a) analysis model of a die mold press



b) zoom-in view of a die molds and cavity area

Fig. 5. Model of a die mold press machine.

D. Data flow

Simplified data flow of the proposed inverse optimization method using dynamically adjustable GA is presented in Fig. 4. Initially, the user defines the optimization parameters and the objective function. Then, the searching process is executed using the proposed dynamically adjustable GA according to some predefined rules and the three common operators of the GA itself: reproduction, crossover and mutation. The probability for occurrence of the crossover and mutation operations must be defined by the user. After obtaining a set of temporary optimal solutions for each control point, the shape of the model that has to be optimized can be obtained using ordinary spline functions. Next, the finite element analysis (FEA) is performed in order to verify the obtained solution, i.e. to compute the fitness of the obtained population and the value of the objective function. If the fitness and the value of the objective function satisfy the previously defined stopping criterion, the optimal shape of the device is obtained and the searching process is finished. Otherwise, a new searching procedure is establish utilizing new generation of strings.

III. Applications

A. Inverse Optimization of a Die Mold Press

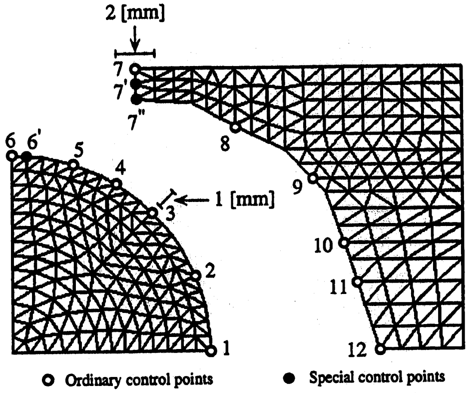
The usage of oriented magnetic materials have been increased recently, especially in production of anisotropic permanent magnets. For inverse shape optimization of a model of a die press machine shown in Fig. 5a which can be used for production of oriented magnetic materials, we applied the proposed dynamically adjustable GA. The die molds in the model shown in Fig. 5b are set in order to generate the radial flux distribution inside the press cavity. As can be seen from Fig. 5b that shows the enlarged area around the cavity and die molds, the optimization goal was to obtain an optimal shape of die molds along lines $P_1 - P_2$, and $P_3 - P_4$, and to generate desired radial magnetic flux density distribution along the cord $\widehat{AB}$ given as:

$$\begin{aligned} B_x &= 1.5\cos(\theta) \quad (T) \\ B_y &= 1.5\sin(\theta) \quad (T) \end{aligned} \tag{1}$$

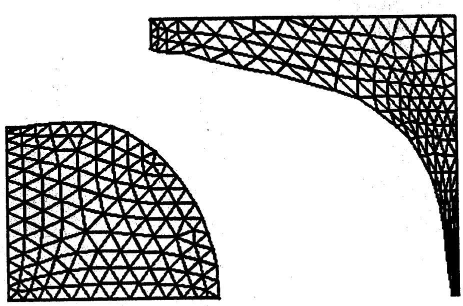
where, θ is the position angle for each observation point along cord $\widehat{AB}$ measured from the x-axis. For optimization purposes, a several control points were set along these two lines. The initial finite element mesh around die molds and the cavity area together with several control optimization points marked with $\circ$ are shown in Fig. 6a. Additionally, special control points with reduced movement abilities and marked with sign $\bullet$ are also introduced and can be seen in Fig. 6a too. Point $6'$ can move only in x-direction and always has the same y-coordinate with point 6, while points $7'$ and $7''$ can move only in y-direction and have always the same x-coordinate with control point 7. For minimization we considered the following objective function

$$O = \sum_{i=1}^{NCP} \left| \frac{B_0(i) - B(i)}{B_0(i)} \right| , \tag{2}$$

where $B_0(i)$ and $B(i)$ are the desired and the numerically obtained values of magnetic flux density B at control point i, and NCP is the total number of control points. The parameters of the GA optimization process are given in Table I. For evaluation of the string fitness and the objective function 2-D FEA was executed. To decrease the total computation time, the finite element mesh was only rearranged around each control point without remeshing the entire analysis domain. The optimized shape of the die mold area with the generated finite element mesh is pre-



a) initial FEM mesh and control optimization points



b) final FEM mesh

Fig. 6. Finite element meshes before and after optimization.

sented in Fig. 6b. Figure 7 shows the obtained magnetic flux lines for the optimal shape of die molds and cavity area. Additionally, the comparison between computed and the desired values for the magnetic flux density vector and its direction for the initial shape and for the final (optimal) shape of the die mold area are presented in Figs. 8a and 8b, respectively. It can be seen that the obtained distribution of magnetic flux density vector for the final shape of the die molds is almost identical with the desired. The maximum and the average error for the initial and for the final shape of the analyzed die mold area, and for the intensity and direction of magnetic flux vector, are given separately in Table II.

B. Inverse Optimization of a Pole Face

The proposed dynamically adjustable GA was also applied for inverse shape optimization of a pole face of rotating machine. The analyzed model was the same as previously treated in [2] and is represented in Fig. 9. The stator and rotor magnetic materials were linear with relative magnetic permeability $\mu_r = 2000$ $[Vs/Am]$ and constant source current density $J = 10$ $[A/m^2]$. The optimization goal was to achieve sinusoidal magnetic flux density distribution $B(x) = 0.003\ \cos(\pi/2 \cdot x/30)$ $[Gauss]$, along line $A - B$ one millimeter below the stator line, with $B_A = 0.003$ $[Gauss]$ and $B_B = 0.0$ $[Gauss]$. As an objective function,

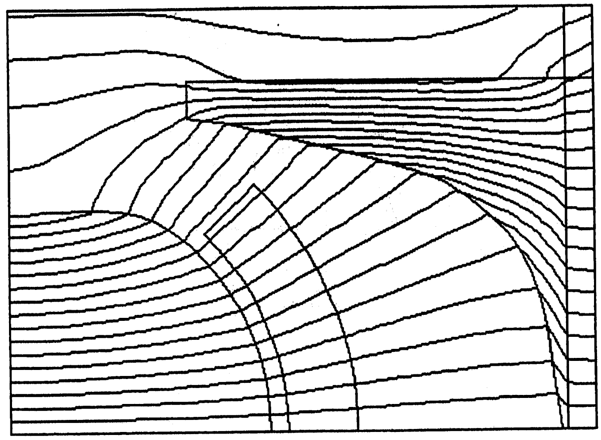
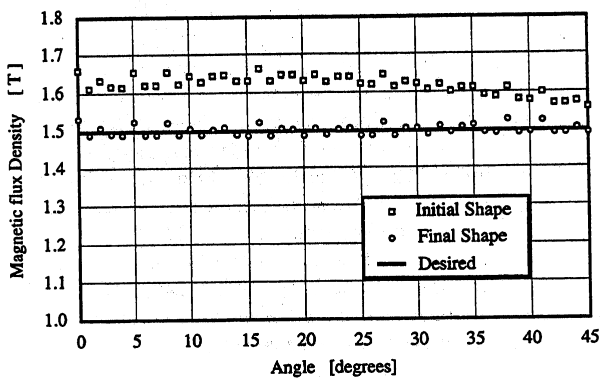
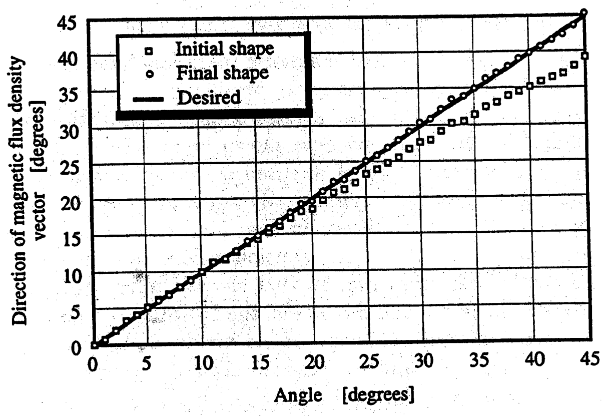


Fig. 7. Magnetic flux lines for optimized shape of die mold press.



a) intensity of magnetic flux density vector



a) direction of magnetic flux density vector

Fig. 8. Computed vs. desired distributions.

TABLE I

PARAMETERS OF THE GA OPTIMIZATION PROCESS.

Four-bits binary encoding procedure	
Total number of generations:	300
Crossover rate:	0.3
Mutation rate:	0.1
Number of strings:	10
Initial searching space:	1 [mm] (P_1 - P_2) 2 [mm] (P_3 - P_4)
Contraction of the searching space:	
• Starts after 125 − th generations	
• Occurs after every 8 generations	
• With the contraction coefficient $\alpha = 0.95$	

TABLE II

MAXIMUM AND AVERAGE ERROR FOR DIE MOLD PRESS MODEL.

Intensity of magnetic flux density vector [%]		
	initial shape	final shape
Maximum error:	10.9	2.10
Average error:	8.03	0.75
Direction of magnetic flux density vector [*degrees*]		
	initial shape	final shape
Maximum error:	5.98	0.60
Average error:	1.98	0.20

the same function given in Eq. 2 was used. The parameters of the GA are given in Table III.

For fitness and objective function evaluation again 2-D FEA was employed. Figure 10 shows the initial and final mesh division for FEA. The finite element mesh division was only rearranged around the control points after the generation of each population without remeshing of the entire analysis region which decreases the overall computation time. The obtained results for magnetic flux density distribution and those for magnetic flux lines for both initial and optimal shape of a pole face are given in Fig. 11. Finally, the calculated magnetic flux density vs.

TABLE III

PARAMETERS OF THE GA OPTIMIZATION PROCESS.

Four-bits binary encoding procedure	
Total number of generations:	300
Crossover rate:	0.3
Mutation rate:	0.1
Number of strings:	10
Initial searching space:	1 [mm]
Contraction of the searching space:	
• Starts after 75 − th generations	
• Occurs after every 5 generations	
• With the contraction coefficient $\alpha = 0.95$	

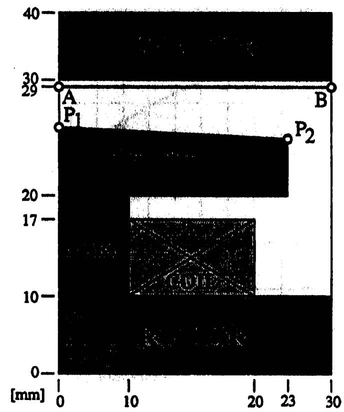
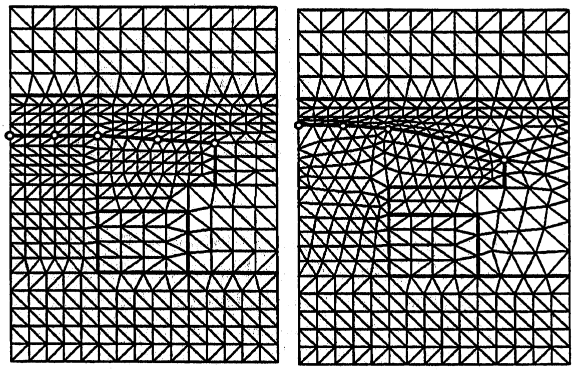
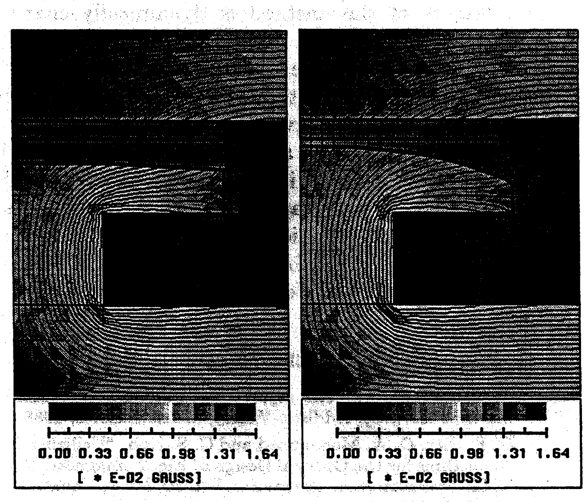


Fig. 9. Initial pole shape to be optimized.



a) initial mesh b) final mesh

Fig. 10. Finite element mesh divisions.



a) initial shape b) final shape

Fig. 11. Obtained results for magnetic flux density B and magnetic flux lines.

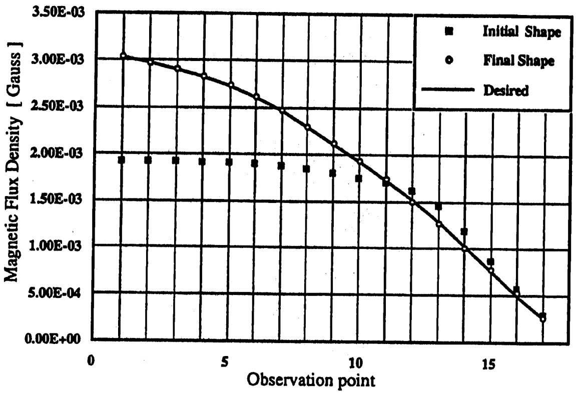


Fig. 12. Computed vs. desired distribution of magnetic flux density.

TABLE IV

MAXIMUM AND AVERAGE ERROR FOR POLE FACE MODEL.

Intensity of magnetic flux density vector [%]		
	initial shape	final shape
Maximum error:	35.8	5.30
Average error:	19.4	0.99

desired magnetic flux density is given in Fig. 12. It can be seen that the obtained and desired distributions of magnetic flux density are almost identical. The maximum and average error for initial and for final shape of the analyzed pole face are given in Table IV, respectively.

IV. CONCLUSION

A new dynamically adjustable GA was introduced. The main feature of this method is dynamically changeable searching space which is constantly contracted enabling faster convergence of the searching procedure and more sensitive searching algorithm. The proposed method was successfully applied for inverse shape optimization of a die mold press machine and a pole face of rotating machine. The obtained results are in very good agreement with desired and the obtained shape of the pole is very smooth due to the spline approximation of its surface. The proposed dynamically adjustable GA could be useful tool for inverse optimization of various electromagnetic devices.

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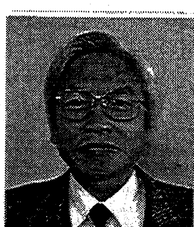

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