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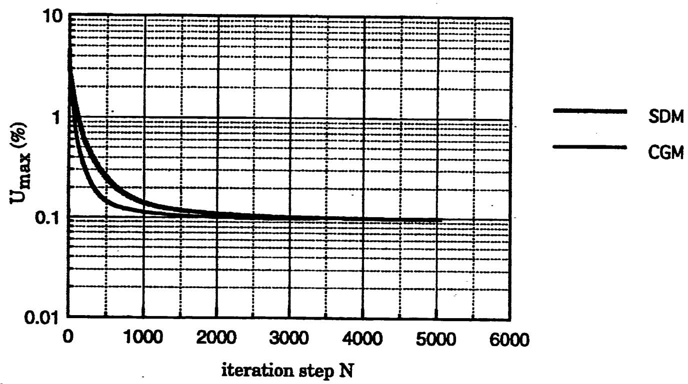


**Figure 2.** Convergence characteristic of $U_{max}$ for the optimization of uniform field by SDM and CGM.

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# Performance Comparison Between Gray Coded and Binary Coded Genetic Algorithms for Inverse Shape Optimization of Magnetic Devices


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Abstract -- Genetic Algorithms (GAs) work with coded information rather than directly with the physical values of the optimized variables, therefore, they are very robust and easy applicable as searching and optimization tools. The coding method, however, is usually not general and mainly depends of the analysis problem. In this paper, we show that the coding method has additionally large influence on the computation speed and the accuracy of the obtained results. We present a comparison between Gray coded and binary coded GAs for inverse shape optimization of a rotating machine pole face. We show that the Gray coded GA is better suited for inverse optimization and could provide more accurate results for shorter computation time.


## 1. Introduction

For optimal performance of electromagnetic devices, it is necessary to perform design optimization of the shape and parameters of their magnetic circuit, size and positions of the current windings, magnetic properties of the used magnetic materials, etc. The traditional optimization methods based on try-and-error procedures are not very suitable, especially for highly complex and multivariable optimization problems because they are very laborious, time consuming and not enough accurate. Therefore, the development of a new and more efficient methods for inverse optimization and automation of the entire optimization process are always desired. In general, the optimization methods can be divided into two large categories: the gradient-based (deterministic) searching methods and nongradient-based (stochastic) searching methods. While the former ones need computation of the gradient function of the objective function, the later ones work directly with the values of the objective function, and are more convenient in cases where it is very difficult or even impossible to compute exactly the gradient of the objective function.

In electromagnetic device optimization, the problem of obtaining such a device which will result with desired values of the magnetic flux density vector and its direction at several specific points, is a very common problem. However, since the exact expression of the magnetic properties and the dependences of the magnetic field distribution on the geometry and the shape of a device are mathematically unknown, the computation of the gradient function is impossible, therefore, usage of the deterministic optimization methods is excluded. Consequently, for such optimization problems, designers usually utilize stochastic methods, among which the Genetic Algorithms (GAs), recently, attract wide popularity. Various searching techniques based on the GAs has already been applied for inverse shape optimization of electromagnetic devices, mainly due to their ability to avoid trapping into local optimum of the objective function [1] [2]. GAs work with coded information rather than directly with the optimized functions, therefore, they can be adjusted to particular problem easily. However, since they search for the solution in the multidimensional space, they are usually very computationally expensive. Consequently, it is necessary to apply additional techniques to reduce the computation time and to increase the effectiveness of the searching process. One of these techniques is to use better coding methods, to provide fast computation and high accuracy.

To express real value of the optimization variable for GA, such as position coordinates, it is necessary to use a coding technique. Due to its simple appearance, the binary coding is the most attractive; that is each real value is represented into an unique string of 0 and 1. However, as we can see later in this paper, the coding can be done in different ways, and the results will be always different. In this paper, we present our investigation about the differences in the efficiency that the GA searching procedure exhibits in case of two different coding techniques: the ordinary binary coding and the Gray coding. We show that the Gray Code is superior and should be preferable as a coding technique in connection with GA searching procedure. Additionally, we discuss some problems that occurs with binary coding, the most important being the bias in the searching direction which occurs as a result of the different number of bit swaps for the same distance between genes. The comparison is performed using a model of rotating machine pole face, which is optimized in order to satisfy the user's prescribed objective function.

## 2. Optimization using GA searching technique

To develop our idea, first, let us briefly describe a method for inverse shape optimization based on the GA searching technique employed in our approach. First, we have to define the searching space, and established several control points along the outline of the device which shape optimization is desired as shown in Fig. 1. We can see that in this simple example, we have to define an optimal shape of the iron core, and for that purpose, we set a set of four control points. Each point can move freely inside the searching space width (see Figs.1 and 2), according to the GA operations such as reproduction, crossover and mutation, and according to the values of the objective function which also must be defined by the user before the optimization process is executed. Because we have a discrete number of control points (four), the shape of the device between these four points will be undefined. In order to overcome this problem and to obtain shape of the device with highly smooth surface, we use a spline approximation for the shape between control points [3].

### *2.1. Definition of search spaces and gene settings*

The most important task is to set appropriately the width of the searching space for each control point. If this space is set too narrow, the possibility that the optimal solution is excluded from the searching area is high. On the other side, if the searching space is set too wide, then the optimization process goes slowly and the large computation time is necessary.

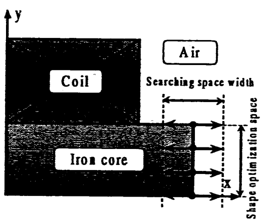


Figure 1: Initial position of GA points.

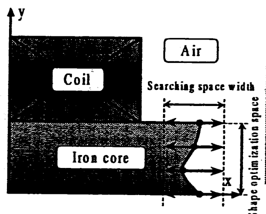


Figure 2: Position of GA points during searching.

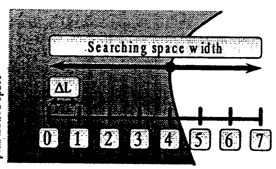


Figure 3: P-type for GA control point.

Additionally, since we use a coded representation of the searching space, we always obtain only a discrete solution, not continuous one, therefore, if the searching space is wide and the number of bits too small, the optimization process will be trapped somewhere on the way towards optimal solution. Figure 3 shows one example, where the entire searching space is coded using 3-bit genes, which as can be seen results in $2^3 = 8$ possible solutions, and the distance between to adjoin solutions is $\Delta L$. Each solution (position of the GA control point along the searching space), is represented by its phenotype (P-type). For each control point there are $2^M$ number of solutions, where $M$ is the number of bits (length of the gene). In our simple example shown in Fig. 3 the current P-type of the GA for this particular control point is 4.

## 3. Gray Coding vs. Binary Coding

GAs work with coded information represented into a compact form such as chromosomes and/or genes. It is very advantageous to use binary representation with only two bits information data 0 and 1. Therefore, most of the coding method for GA searching is usually done using binary coding and decoding techniques. Table 1 shows the binary coding where each decimal number is encoded into a binary number, which is very easy computer task. For example, as shown on the left side of Fig. 4, decimal numbers 7 and 8 can be easily encoded into binary numbers $B(7)$=0111 and $B(8)$=1000 using binary coding technique [3]. However, if we want to move from P-type 7 into P-type 8 one must necessary change all four bits in order to come from $B(7)$=0111 to $B(8)$=1000. In order words, during GA optimization we need four separate GA operations to move from solution 7 to solution 8, which is time consuming. On the other hand, if we want to move from solution $B(0)$=0000 to solution $B(1)$=0001 we need only one GA swapping operation. Therefore, we may conclude that using ordinary binary coding some searching directions are preferred to the others, i.e. we have bias. It will be ideal, if we could move from one to another neighboring solution with only one swap. Fortunately, the Gray Code provides exactly that; generation of P-type with the same swap distance of only one. The Gray coding can be executed by encoding the binary codes into the Gray codes using the logical circuits shown in Fig. 4. This binary transformation function $G(B(i))$ encodes any binary code into another code with better GA properties than the original one [4]:

$$\text{encoding} \quad G_3 = B_3 \quad G_2 = B_3 \otimes B_2 \quad G_1 = B_2 \otimes B_1 \quad G_0 = B_1 \otimes B_0 \quad , \tag{1}$$

$$\text{decoding} \quad B_3 = G_3 \quad B_2 = B_3 \otimes G_2 \quad B_1 = B_2 \otimes G_1 \quad B_0 = B_1 \otimes G_0 \quad . \tag{2}$$

This transformation function $G(B(\text{i}))$ encodes and decodes any integer number of $i$ ($0 \leq i < 2^M-1$), where $M$ is integer number ($M \geq 0$). This Gray code, has this very good property: codes for two adjacent values of the coding variable $i$ and $i$+1 always differ in exactly one bit information, e.g. $G(B(7))$ = 0100 and $G(B(8))$ = 1100 (see the right side of Fig. 5). As can be seen, this is very important for GA searching technique, where instead of exchanging four bits to reach from 7 to 8 for binary coding, using the Gray coding we need only one bit exchange. This property, as can be seen later, has large influence on the computation time and the accuracy of the obtained results.

## 4. Definition of the Analysis Model and the Objective Function

A model of a rotating machine pole face, which was used for inverse shape optimization using GA and the Finite Element Method (FEM) is given in Fig. 6. Fig. 7 shows the enlarged view of the pole face that was optimized. Five control points along the pole face $P_1$ - $P_5$ were established. They define the shape of the pole and during the optimization process these

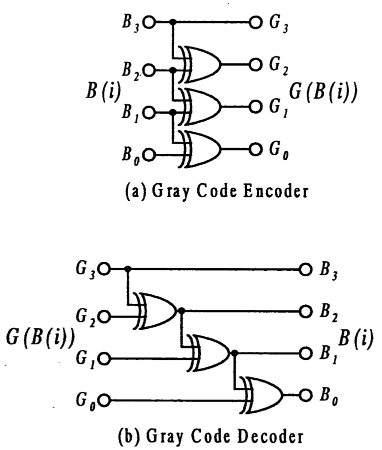


Figure 4: Gray code coding.

Table 1: P-type encoded into the binary code and the Gray code.

| P-Type | Binary code | Gray code |
|---|---|---|
| 0 | 0000 | 0000 |
| 1 | 0001 | 0001 |
| 2 | 0010 | 0011 |
| 3 | 0011 | 0010 |
| 4 | 0100 | 0110 |
| 5 | 0101 | 0111 |
| 6 | 0110 | 0101 |
| 7 | 0111 | 0100 |
| 8 | 1000 | 1100 |
| 9 | 1001 | 1101 |
| 10 | 1010 | 1111 |
| 11 | 1011 | 1110 |
| 12 | 1100 | 1010 |
| 13 | 1101 | 1011 |
| 14 | 1110 | 1001 |
| 15 | 1111 | 1000 |

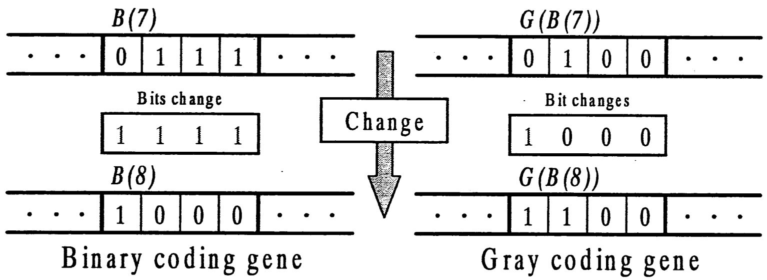


Figure 5: P-type binary and Gray code changes.

points could move only in the vertical direction as shown in Fig. 7. The optimization goal was to obtained a kind of pole face shape which will result in the desired sinusoidal distribution of the magnetic flux density $B_{0,n}$ at several observation points along the line *A-B* also shown in Fig. 7. The objective function was defined as the minimum error between the desired magnetic flux density values $B_0$ and their computed values $B$ at each observation point:

$$Obj = \frac{1}{N}\sum_{n=1}^{N}\left|\frac{B_{0,n} - B_n}{B_{o,n}}\right| \quad , \tag{3}$$

where $N$=17 was the total number of observation points along line *A-B* as shown in Figs. 6, and 7.

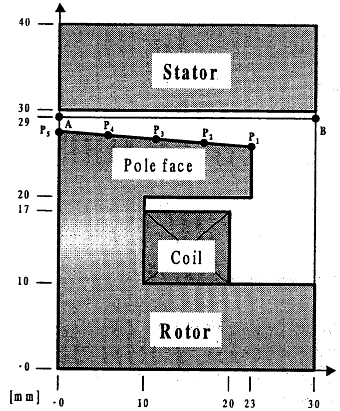


Figure 6: Analysis model of a pole face.

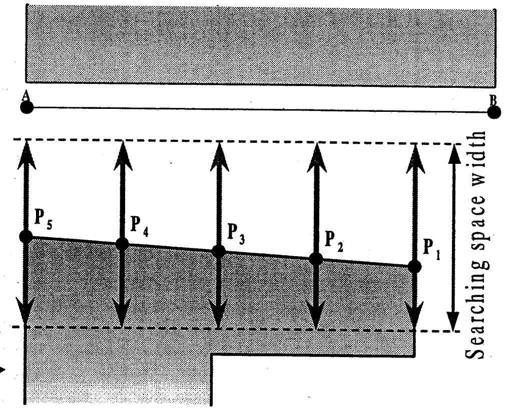


Figure 7: Enlarged view of pole face area, control points and searching space.

## 5. Optimization Results

Figure 8 shows the changes of the objective function as the optimization process evolves for binary and Gray coding GAs, separately. Two conclusions are readily visible:

1. The Gray coded GA exhibits accelerated convergence rate of the objective function over the ordinary binary coded GA;
2. Using Gray coding the accuracy of the results strongly improves.

From Fig. 8, one can easily see that the accuracy of the results achieved after 600 generations of a binary coded GA can be achieved only after 80 generations of a Gray coded GA. Additionally, the accuracy achieved after 600 Gray coded GA generation is almost four times better than that of the binary coded GA. Figure 9 shows the comparison between desired and obtained magnetic flux density distribution along observation points, for initial and final pole shapes. As can be seen the final shape of a pole face provides almost exact magnetic field distribution with the desired one. The initial and the optimal pole shapes together with the obtained magnetic flux lines are presented in Figs. 10 and 11, respectively. As a result of using spline surface approximation, the generated surface defined by such a small number of control points (five) is very smooth.

## 6. Conclusion

A comparison between the binary coded and the Gray coded GAs for inverse shape optimization of electromagnetic devices is presented. For computation of the fitness of the solution we used the 2D finite element electromagnetic field analysis. It was shown that the Gray coded GA are better suited for inverse shape optimization and that they are superior than the ordinary binary coded GA, mainly because they do not bias the searching direction. The Gray coded GA provided faster convergence, and better accuracy than the binary coded GA. The comparison was performed using a model of a rotating machine pole face optimized to provide almost sinusoidal magnetic flux density distribution in the air-gap region.

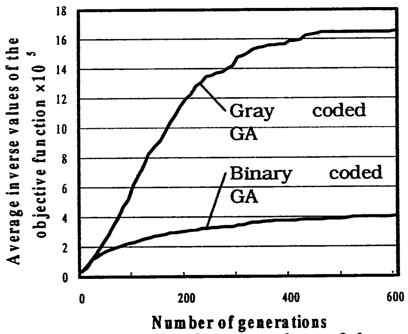


Figure 8: Average inverse values of the objective function using Gray coded and binary coded GAs, respectively.

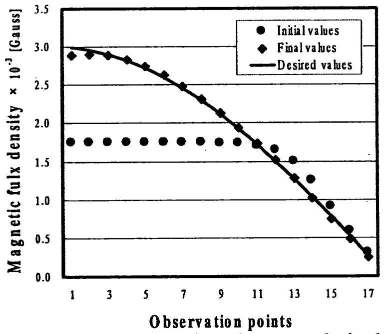


Figure 9: Comparison between desired and computed magnetic flux density distributions.

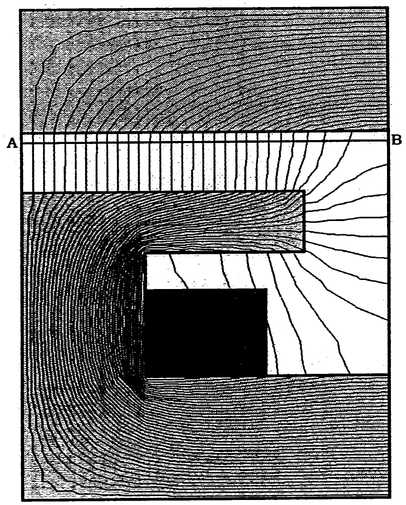


Figure 10: Initial shape of pole face and magnetic flux line distribution.

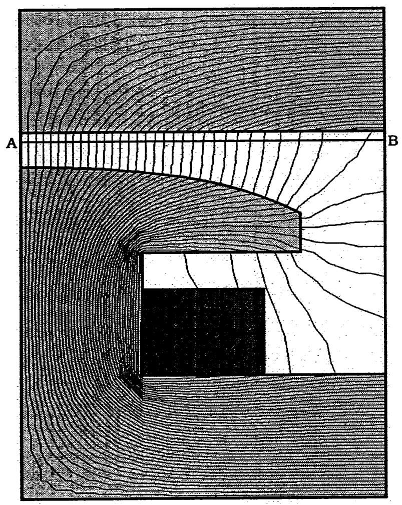


Figure 11: Final shape of pole face and magnetic flux line distribution.

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# Neural Networks for Inverse Electromagnetic Problems


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**Abstract.** An inverse multilayered artificial neural network (ANN) has been proposed to solve inverse problem of field source searching in inaccessible region by local field data. The ANN has been trained using magnetic field data obtained from numerical simulation of the forward problem. The location and magnitude of current sources in target distribution pattern are controlled since the results obtained depend on the initial state. The application of the proposed method for inverse problem of source distribution is presented. The effectiveness of proposed method is proved by computational simulation.


## 1. Introduction

Identification of electromagnetic activity within a closed system to which the instrumentation has no access is of great importance when dealing with inverse problems of electromagnetics (optimal field synthesis, optimal device design, identification problems, etc.). Determining the current source distribution in order to obtain prescribed external or internal magnetic field densities is of main interest considering nondestructive testing (NDT) or electromagnetic compatibility (EMC) problems. The current source distribution in conducting media is one of the most important properties that determines the quality and performance of the electromagnetic devices (transformers, reactors, inductors, converters, AC transmission lines etc.). Reconstruction of current source distribution in the human body from the measured magnetic field distribution is basically used for medical diagnosis and therapy. In either problem, as much as in many others from other branches of engineering, the exterior field activity that we can measure must be used to identify the interior system. There is significant number of publications in this field [1-4].

Many electromagnetic devices are designed with respect to the spatial distribution of the magnetic field as well as the electric field. Designing of a device as well as determine its location in order to obtain prescribed external magnetic and electric fields is a main inverse problem.

In this paper an inverse multilayered artificial neural network (ANN) has been proposed to solve inverse problem of source searching in inaccessible region by given field data. The ANN has been trained using magnetic field data obtained from numerical simulation of the forward problem. An inverse source problem is transformed into a discrete problem through the division of the entire target region into disks with constant current density. A uniform pattern is applied to the input units in the first step, whose activation level depends upon the variable input pattern. This pattern is propagated through the net and generates the initial output. The difference between this output vector and the target output vector is propagated backwards through the net as error signals. When the error signals reach the input layer, they represent a gradient in input space, which gives the direction for the gradient decent. This procedure is repeated with the new input vector until the distance between the generated