



Title	Meander Line Antenna Design Using an Adaptive Genetic Algorithm
Author(s)	Sato, Yuki; Campelo, Felipe; Igarashi, Hajime
Citation	IEEE Transactions on Magnetics, 49(5), 1889-1892 <a href="https://doi.org/10.1109/TMAG.2013.2239979">https://doi.org/10.1109/TMAG.2013.2239979</a>
Issue Date	2013-05
Doc URL	<a href="http://hdl.handle.net/2115/53102">http://hdl.handle.net/2115/53102</a>
Rights	© 2013 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works.
Type	article (author version)
File Information	Meander Line Antenna Design Using an Adaptive Genetic Algorithm.pdf



[Instructions for use](#)

# Meander Line Antenna Design Using an Adaptive Genetic Algorithm

Yuki Sato<sup>1</sup>, Felipe Campelo<sup>2</sup> and Hajime Igarashi<sup>1</sup>

<sup>1</sup>Graduate School of Information Science and Technology, Hokkaido University, 060-0814 Sapporo, Japan

<sup>2</sup>Universidade Federal de Minas Gerais, Departamento de Engenharia Eletrica, Belo Horizonte 31270-901, Brazil.

This paper presents the optimization of a meander line antenna (MLA) finite element model by means of an adaptive genetic algorithm (GA). To search for optimal antenna configurations, the present method employs a genetic algorithm with an adaptive method that adjusts the characteristics of its selection, crossover and mutation operators in order to maintain a diverse set of high-quality candidate solutions during its execution. It is shown that the present method can find optimal solution faster than the conventional GA. Moreover, the fitness value of the optimal solutions obtained by the present method are better than these obtained by conventional GA.

*Index Terms*— Meander line antenna, optimization, adaptive genetic algorithm, moment method.

## I. INTRODUCTION

MEANDER LINE ANTENNAS (MLAs) are widely used in a variety of applications of radio frequency identification (RFID), such as contactless rechargeable devices, security and medical systems [1-5]. Due to its intended applications, certain characteristics of RFID devices, such as antenna size and impedance matching, are critical to its efficiency and working autonomy. The first characteristic influences the overall size and manufacturing costs of the device; the second defines limits on the power transfer efficiency between the antenna and the IC tag to which it is attached. Ideally, antennas should be as small and as impedance-matched as possible. These characteristics are usually defined in the optimization step in the design cycle of an RFID device, which relies on computational models of the antenna in order to simulate its characteristics. However, most models do not take into account the effects of the dielectric layer on which the antennas are built, mostly because of tends to increase the computational cost of the antenna simulation. By ignoring these effects, however, one increases the simulation error, which can subsequently compromise the accuracy of the results obtained.

In this paper, we present an MLA optimization model that takes into account the effects of this dielectric layer [4]. The genetic algorithm (GA) has been successfully applied to RFID antenna optimization [1], [4-5]. Because of high computational burden in the antenna analysis, speed-up of the GA process has been required. In this study, a genetic algorithm known as ACROMUSE [6] will be employed for this purpose. This method iteratively changes its selection, crossover and mutation characteristics in order to maintain a diverse population of high-performance candidate solutions. This means that we do not need to pre-determine these GA parameters unlike the conventional GA. ACROMUSE has been shown very effective for mathematical problems in [6]. However, this method has not been applied to engineering problems. In this paper, an adaptation of the ACROMUSE for discrete optimization is proposed, and the performance of

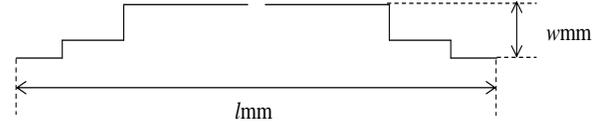


Fig. 1. Geometry of meander line antenna

ACROMUSE is compared with that of GA.

## II. ANTENNA MODEL

### A. Moment Method

For the antenna analysis, the moment method [4], [7] is employed in this work. The line antenna, shown in Fig.1, is divided into segments and the unknown currents along the segments are obtained by solving

$$\mathbf{v} = \mathbf{Z}\mathbf{i} \quad (1)$$

where  $\mathbf{v}$  and  $\mathbf{i}$  are the voltage and current vectors and  $\mathbf{Z}$  is impedance matrix. The entities of  $\mathbf{Z}$  is given by

$$Z_{mn} = j\omega\mu\varphi_{mn}^f \Delta\mathbf{l}_m \cdot \Delta\mathbf{l}_n + \frac{1}{j\omega\epsilon\Delta\mathbf{l}_m} \times \left\{ \varphi_{m-n}^c + \varphi_{m+n}^c - \varphi_{m+n}^c - \varphi_{m-n}^c \right\} \quad (2)$$

where  $\Delta\mathbf{l}$  denotes the tangential vector of the segment, the subscripts  $f$  and  $c$  represent Faraday and Coulomb potentials and the potential  $\varphi$  is expressed as

$$\varphi_{mn} = \frac{1}{\Delta\mathbf{l}_n \Delta\mathbf{l}_m} \int \frac{e^{-jkR_{mn}}}{4\pi R_{mn}} d\mathbf{l} \quad (3)$$

where  $R_{mn}$  is the distance between  $m$ th and  $n$ th segments and  $k$  is wave number.

### B. Meander Line Antenna

Figure 1 shows a meander line antenna with total area given by  $a = wl$ . The input impedance  $Z$  of an MLA is defined by Ohm's law: if  $V_0$  and  $I_0$  are the induced voltage and current at

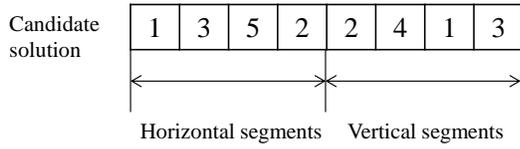


Fig. 2. Variable vector structure

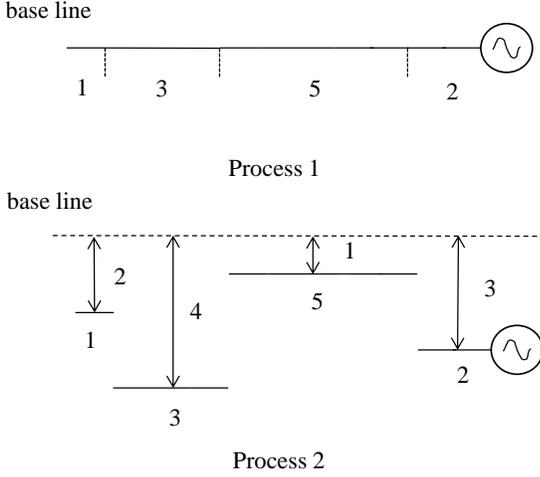


Fig. 3. Generation processes of MLA

the feeding point of MLA, then

$$Z = \frac{V_0}{I_0} \quad (4)$$

is its input impedance. In this work,  $Z$  is obtained by computing  $I_0$  for given  $V_0$  using Moment Method.

### C. Design of Antenna Shape

In this work, the antenna shape is expressed [1], [4] in terms of a vector of  $2k$  integer-valued variables, as shown in Fig. 2. The number of folds in the MLA increases with  $k$ . The first half of the variables represents the transverse structure of the antenna while the second half represents the longitudinal structure. The MLA shape is decoded from this vector as shown in Fig. 3: a straight antenna is divided into the line segments with length  $H_i$  determined from the horizontal genes, then each part of the line segment is moved  $V_i$  determined from the vertical genes downward from base line. Next each neighboring part is connected. And finally, the other half of the antenna is formed to have a right-left symmetric shape. The antenna sizes are computed as follows:  $l = 3\text{mm} \times \sum_i H_i$ ,  $w = 3\text{mm} \times \max_i(V_i)$ .

## III. OPTIMIZATION ALGORITHM

In order to search for optimal antenna configurations, an adaptive genetic algorithm known as ACROMUSE [6] is employed. This method was originally introduced in late 2011, and seeks to address the problem of maintaining a diverse set of candidate solutions with a reasonably high performance, in order to promote global exploration of the design space without spending too many function evaluations in low-

performance regions. In this section, an alternative description of the ACROMUSE genetic algorithm is presented. This presentation includes a discussion of some aspects of this algorithm that were neglected in [6], as well as some corrections of the formulation given in the original reference.

Before proceeding to the description of the algorithm, a few definitions must be given. Let a general optimization problem be defined as:

$$\text{Find } \mathbf{x}^* = \underset{\mathbf{x}}{\operatorname{argmin}} f(\mathbf{x}) \quad \text{Subj. to } \mathbf{x} \in \Omega \quad (5)$$

where  $\mathbf{x}$  is a vector of design variables (e.g., segment lengths describing a meander line antenna) usually referred to as a *candidate solution*,  $f(\mathbf{x})$  is a function that attributes a performance value to its argument, and  $\Omega$  is a subspace (usually of  $R^n$  or another  $n$ -dimensional set, where  $n$  is the number of variables in the optimization problem) within which the solutions to the problem can exist.  $\Omega$  is also usually called the *design space* of the problem.

A genetic algorithm (GA) is a procedure in which a population of candidate solutions iteratively samples the design space. New candidate solutions are generated by means of a number of operators usually called *genetic operators*: crossover (or recombination), mutation, and selection. By generating new samples of the design space using characteristics of the best-performing candidate solutions from the preceding iterations, a GA is capable of implicitly adapting the sampling function, and iteratively concentrates on the exploration of the most promising regions of the design space.

The ACROMUSE GA used in this work employs a few strategies to prevent a critical drawback of usual genetic algorithms, namely the inability to maintain a diverse population of candidate solutions with high performance. Traditional approaches for the preservation of diversity in GAs [8], [9] usually do so regardless of relative performance values, which tends to result in a waste of function evaluations spent in the exploration of low-performance regions. The ACROMUSE, on the other hand, takes into account the contribution of a given candidate solution both to the diversity and the average performance of the population, and uses this information to foster the preservation of potentially interesting solutions that represent viable design alternatives for a given problem.

Two concepts play a main role in the operation of this method. The first is the *standard population diversity* (SPD), which is a measure of the spread of the candidate solutions within the design space. More formally, the SPD is calculated as the average of the variable-wise *coefficients of variation* [10]:

$$SPD = \frac{1}{n} \sum_{i=1}^n \frac{s_i}{|\bar{\mathbf{x}}_i|} \quad (6)$$

that is, the mean of the ratios between the sample standard deviation and absolute sample mean of the variables in the

1. **Generate random initial population  $P$ ;**
2. **Evaluate population  $P$ ;**
3. **While (stop condition not met) do**
  - a. **Calculate algorithm parameters;**
  - b. **Perform selection for crossover;**
  - c. **Perform crossover and exploitative mutation;**
  - d. **Perform exploratory mutation;**
  - e. **Evaluate newly generated points;**
4. **Return final population;**

Fig. 4. Pseudocode for the ACROMUSE GA.

population of points at a given iteration. Here the absolute value of the sample mean is used instead of the pure value described in [6], in order to avoid negative SPD values in spaces where the variables can assume negative values.

The second concept is the *healthy population diversity* (HPD), which incorporates the performance information of each point as in the calculation of a weighted average point, and then computes a metric that quantifies not only the spread of points, but also the quality of the points in a population.

The calculation of the HPD is performed as follows. First, a vector of weights is calculated based on the relative performance values of each candidate solution,  $w = f^*/|f^*|$ , where  $f^* = f - \min(f)$  is a vector containing the shifted performance values of each candidate solution in the population, and  $|f^*|$  is the 1-norm of this vector. The shifted performance value is used instead of the pure performance value used in [6] in order to avoid negative weights. A weighted mean vector of the population is then calculated as:

$$\bar{x}_w = \frac{1}{n} \sum_{j=1}^N D(w) x_j \quad (7)$$

where  $D(w)$  represents a diagonal matrix with the elements of the weight vector as the main diagonal, and  $x_j$  is the  $j^{\text{th}}$  candidate solution. Each element of the resulting vector therefore contains the weighted mean of the corresponding variable.

The calculation of the HPD is similar to that of the SPD, consisting of the simple average of a variable-wise ratio between a measure of deviation and one of location:

$$HPD = \frac{1}{n} \sum_{i=1}^n \frac{s_i^w}{|\bar{x}_i|} \quad (8)$$

where the simple standard deviation of the SPD is replaced by its weighted counterpart, calculated using the  $x_w$  value from (7). Here again the absolute value of the mean is used to avoid the problem of negativity of HPD values. The individual contributions of each candidate solution to the HPD are calculated as the product of the weight  $w_j$  by the Euclidean distance between the  $j^{\text{th}}$  candidate solution and the mean point of the population.

The ACROMUSE employs these two quantities (SPD and HPD) for the adaptation of its genetic operators. The general

sequence of the algorithm is given in Fig. 4. The SPD and HPD values are used to dynamically adapt the parameters used for the crossover, mutation and selection<sup>1</sup>, as detailed below. For the sake of brevity, all constant values employed in this work (e.g., constant multiplier for tournament size, etc.) are already included in these calculations. For further details, see [6].

1. **Selection:** Adaptive tournament selection is employed, with  $T_{size} = HPD / HPD_{max} \times P / 6$ , where  $P = 30$  is the population size. The tournament compares the individual HPD values and selects the candidate solution with the highest contribution.
2. **Crossover:** Uniform crossover is performed with probability  $P_c = 0.4 \times (SPD / SPD_{max} + 1)$ .
3. **Exploitative Mutation:** Solutions that have undergone crossover are subject afterwards to small grade mutation with low probability ( $P_m = 0.01$ , variable-wise) and low intensity ( $\pm 1$  in our discrete implementation).
4. **Exploratory Mutation:** Candidate solutions that did not undergo crossover are mutated at higher intensities, with individual mutation rates given by  $P_m^j = 0.5 \times [(SPD_{max} - SPD) / SPD_{max} + (f_{max} - f(x_j)) / (f_{max} - f_{min})] / 2$ , where  $f_{max}$  and  $f_{min}$  are the largest and smallest performance values in the population at a given iteration.

#### IV. RESULTS

The MLA optimization problem was set as the minimization of the antenna area, subject to an equality constraint concerning the antenna input impedance. In order to employ the ACROMUSE for the solution of this problem, a penalized objective function was defined as:

$$f(x) = a(x) + w|Z(x) - Z_0| \quad (9)$$

where  $x$  is a vector representing a given antenna configuration (see Fig. 2),  $a(x)$  is the antenna area,  $Z(x)$  is the complex input impedance of the antenna. Moreover,  $w$  and  $Z_0$  are the weight and target impedance, which are set to 100 and 50  $\Omega$ , respectively, where we determine the value of  $w$  to have a good balance between the first and second term of (9). The purpose of this optimization is that we realize the impedance matching between the antenna and circuit and minimize the antenna area. In this study, we use the moment method to compute  $Z$ . To take the effect of the dielectric layer with permittivity  $\epsilon_r$ , the effect of image charges due to the dielectric layer is included in the Green function [4].

In this paper, optimization results obtained by adaptive GA are compared to those obtained by the conventional GA. Two trials are performed for each method by changing random seeds. In the conventional GA, the uniform crossover and exploitative mutation are employed and their probabilities are set to  $P_c = 1.0$  and  $P_m = 0.05$ , respectively. Moreover, we use the tournament selection with  $T_{size} = P / 6$ . In both methods,

<sup>1</sup> In the determination of the probabilities of mutation and crossover, the calculated values were forced to remain within the interval (0,1) by means of truncation operators, which are omitted in the original reference [6].

the population number  $P$  is 30, the number of generations is 250 and the best individual in the generation is preserved. The changes in the fitness values of the elite individuals during the optimization processes are plotted in Fig. 5. It is found that the final fitness values obtained by the present method are better than those obtained by the conventional GA. In Table I, we summarize fitness, input impedance  $Z$  and antenna area  $a(x)$  at the last generation. It can be seen in this result that  $a(x)$  converges to about  $0.020\text{m}^2$  in all the optimizations. The variance in  $Z$  values obtained by the present method is clearly smaller than those obtained by the conventional GA. Figure 6 shows the changes in  $P_c$  and  $P_m$  during the optimization processes. It is found that both probabilities dynamically change during the optimization process and there is a reciprocal relationship between  $P_c$  and  $P_m$ :  $P_m$  decreases when  $P_c$  increases and vice versa. This dynamic change in  $P_c$  and  $P_m$  keeps healthy diversity in the population to improve the searching ability. Figure 7 shows the antenna shapes optimized by the present and conventional GA.

## V. CONCLUSION

In this paper, an adaptive genetic algorithm known as ACROMUSE was employed for the optimization of a meander line antenna model. The operators of the algorithm designed in such a way so as to maintain a healthy diversity in the population. It is shown that the present method gives better optimization results in comparison with the conventional GA. The present method would be advantageous for optimization problems in which fitness evaluation is time consuming because of its fast convergence to high-quality solutions. The present method is, therefore, effective for optimization of electromagnetic devices and machines.

Future works include the hybridization of this approach with meta-modeling methods such as local quadratic approximations or neural networks, in order to enable a better search through the use of surrogate models.

## ACKNOWLEDGMENT

This work was partially supported by the National Council for Scientific and Technological Development (CNPq/Brazil, grant 472446/2010-0).

## REFERENCES

- [1] Y. Watanabe, K. Watanabe and H. Igarashi, "Optimization meander line antenna considering coupling between non-linear circuit and electromagnetic waves for UHF-band RFID," *IEEE Trans. Magn.*, vol. 47, no.5, pp 1506-1509, May 2011.
- [2] R. Want, "An introduction to RFID technology", *IEEE Pervasive Computing*, vol. 5, no. 1, pp. 25-33, 2006.
- [3] H. Yu, C.M. Tang, and R. Bashirullah, "An asymmetric RF tagging IC for ingestible medication compliance capsules", in *Proc. IEEE Radio Frequency Integrated Circuits Symp. (RFIC)*, pp. 101-104, 2009.
- [4] H. Makimura, Y. Watanabe, K. Watanabe, and H. Igarashi, "Evolutional design of small antennas for passive UHF-band RFID," *IEEE Trans. Magn.*, vol. 47, no. 5, pp. 1510-1513, May 2011.
- [5] G. Marrocco, "Optimized Self-Resonant Meander Line Antennas for RFID Applications," *IEEE Antennas Wireless Propag. Lett.*, vol. 2, pp. 302-305, 2003.

- [6] B. McGinley, J. Maher, C. O'Riordan, and F. Morganh, "Maintaining healthy population diversity using adaptive crossover, mutation, and selection", *IEEE Trans. Evol. Comp.*, Vol. 15 No. 5, pp. 692-714, 2011.
- [7] R. F. Harrington, *Field Computation by Moment Methods*. New York:Wiley, 1993, pp. 62-71.
- [8] A. Cioppa, C. de Stefano, and A. Marcelli, "Where are the niches? Dynamic fitness sharing," *IEEE Trans. Evol. Comp.*, Vol. 11 No. 4, pp. 453-465, 2007.
- [9] S. Mahfoud, "Crowding and preselection revisited", in *Proc. Parallel Problem Solving From Nature (PPSN)*, pp. 27-36, 1992.
- [10] W.A. Hendricks, and K.W. Robey, "The Sampling Distribution of the Coefficient of Variation", *The Annals of Mathematical Statistics*, Vol. 7 No. 3, pp. 129-132, 1936.

TABLE I  
OPTIMIZATION RESULTS

method (permittivity)	$f(x)$	$\text{Re}[Z]$ ( $\Omega$ )	$\text{Im}[Z]$ ( $\Omega$ )	$a(x)$ ( $\text{m}^2$ )
Conventional #1 ( $\epsilon_r=1.0$ )	484.7	54.0	-2.7	0.018
Conventional #2 ( $\epsilon_r=2.2$ )	307.1	49.0	-2.9	0.016
Present #1 ( $\epsilon_r=1.0$ )	95.5	50.2	-0.9	0.021
Present #2 ( $\epsilon_r=2.2$ )	44.3	50.0	0.4	0.021

Two trials are performed for each method by changing seeds.

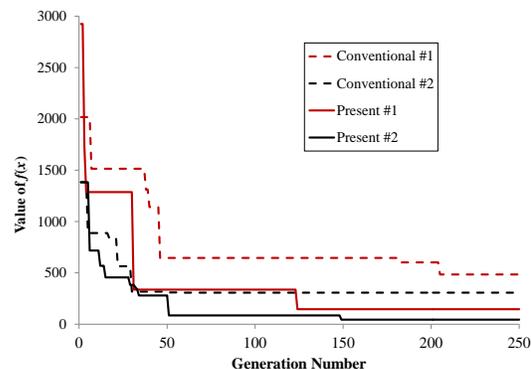


Fig. 5. Change in the fitness values during optimization process.

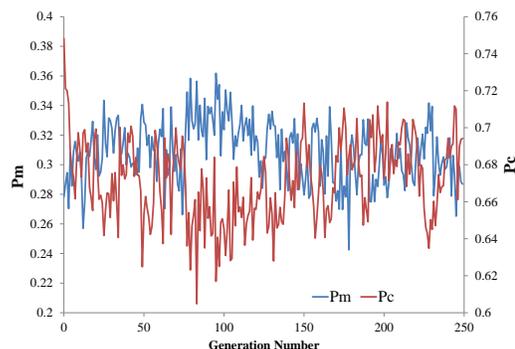
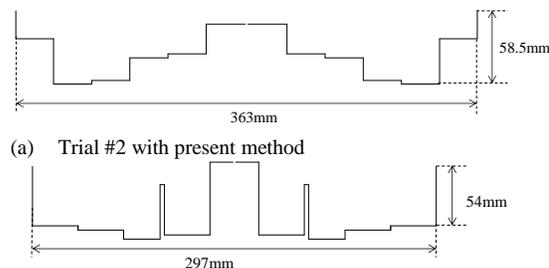


Fig. 6. Changes in  $P_c$  and  $P_m$  during optimization process.



(a) Trial #2 with present method  
(b) Trial #2 with conventional method  
Fig. 7. Optimized meander line antenna