GENETIC OPTIMIZATION OF WIRE ANTENNAS

Erik GOVEN, Luc VERHEYEN
Katholieke Hogeschool Limburg
Dept. of Industrial Science and Technology
Universitaire Campus, 3590 Diepenbeek
Belgium
E-mail: erikg@dma.be, parallax@dma.be

Zbyněk RAIDA
Technical University of Brno
Dept. of Radio Electronics
Purkyòova 118, 612 00 Brno
Czech Republic
E-mail: raida@urel.fee.vutbr.cz

Abstract

The presented submission describes how genetic algorithms can be applied to the optimization and design of wire antennas. The proposed optimization method is easily programmable and well understandable on one hand, but relatively slowly converging and depending on the parameters of the genetic algorithms on the other hand. The disadvantages of the method are deeply discussed and their elimination is discussed in the paper.

Keywords

Genetic Algorithms, Wire Antennas, Method of Moments.

1. Introduction

In the today's society, communication systems play more and more an important role. Some of those systems, e.g. mobile telephone or radio broadcasting devices, are based on the propagation of electromagnetic waves in the free space (radio communication systems). And antennas are one of the most important parts in those systems. Therefore, an extreme care has to be taken for them.

There are many types of antennas which are used in radio communications. Among them, wire antennas (antennas which consist of elementary linear radiators) play an important role: they can be used in the form of monopoles as antennas for mobile telephones, they can serve in the form of dipoles as primary radiators in reflector antennas etc. Therefore, the analysis and the design of wire antennas are of extreme importance in the today's applications which corresponds with an attention paid to these topics in the literature [1] - [5].

Dealing with the analysis of wire antennas, there is no analytical solution for the problem, and therefore, numerical methods have to be explored [6].

Dealing with the optimization and design of wire antennas, classical optimization techniques fail here because of the unknown explicit mathematical model of antennas on one hand and because of the optimization surface exhibiting many local minims on the other hand. Therefore, the use of non-traditional optimization techniques based on artificial neural networks [7] and genetic algorithms [8] was proposed in the literature.

In the presented paper, problems of the design of wire antennas are discussed on a folded dipole representing wire antennas. Section II describes a simple and computationally efficient numerical model of the folded dipole based on the combination of the method of moments [9] and the Howe's method [10]. In section III, an application of the genetic algorithm to the optimization of the folded dipole is described. In section IV, the final algorithm is discussed, and in V, numerical examples are given

2. Numerical model of folded dipole

In the presented paper, the folded dipole (Fig. 1) is assumed to consist of wires with the radius a which is very small with respect to the wavelength λ and with respect to the length of the dipole l. The distance between horizontal wire of the dipole d is small with respect to l which conditions the proper work of the antenna.

As shown in [6], the folded dipole is flown by a symmetric current I_s and by an asymmetric one I_{as} (Fig. 1). Whereas the asymmetric current is dominant in the radiation of the antenna, the symmetric current influences the input impedance of the folded dipole only (radiation of nearly placed currents with opposite orientation mutually eliminates).

The contribution of the symmetric current to the input impedance of the folded dipole is computed using the Howe's method [10]. The characteristic impedance of one arm of the folded dipole (which is formed by the transmission line with the short end) is given by the formula [10]

$$Z_0 = 120 \ln(d/a) \qquad (1)$$

and the input impedance of one arm can be evaluated then using [10]

$$Z_s = j\, Z_0 \tan(kl/2) \tag{2}$$

where k is wavenumber and the rest of symbols represents sizes of the antenna depicted in Fig. 1.

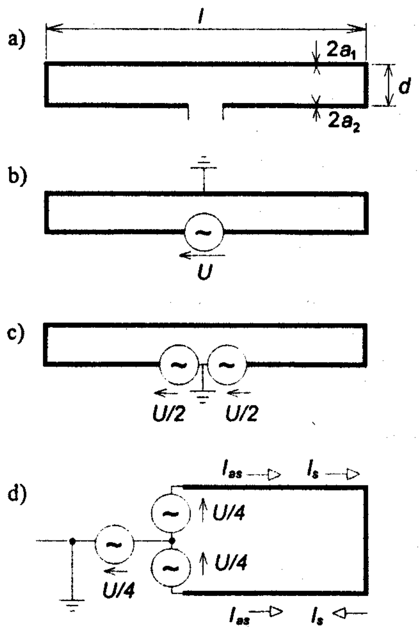

Fig. 1 Folded dipole and its supplying causing the presence of symmetric and asymmetric currents

The contribution of the asymmetric current to the input impedance of the folded dipole is computed using the method of moments [9] applied to the symmetric dipole with the equivalent radius [10]

$$a_{ekv} = \sqrt{a\,d} \tag{3}$$

Electric intensity of the radiated electromagnetic wave in the point $\mathbf{r}$ is computed on the basis of the vectorial potential $\mathbf{A}(\mathbf{r})$ and the scalar one $\phi(\mathbf{r})$ [6]

$$\mathbf{E}^s(\mathbf{r}) = -j\omega\,\mathbf{A}(\mathbf{r}) - \nabla\phi(\mathbf{r}) \tag{4}$$

where ω denotes angular frequency.

The vectorial potential in $\mathbf{r}$ is computed integrating contributions of the current density $\mathbf{J}$ on the antenna surface S [6]

$$\mathbf{A}(\mathbf{r}) = \mu \int_S \mathbf{J}(\mathbf{r}') \frac{e^{-jkR(\mathbf{r},\mathbf{r}')}}{4\pi R(\mathbf{r},\mathbf{r}')}\, dS \tag{5}$$

(R denotes the distance between the source of the potential $\mathbf{r}'$ and between the point in which the potential is computed) whereas the scalar potential is obtained integrating contributions of the charge density on the antenna [6]

$$\phi(\mathbf{r}) = \frac{1}{\varepsilon} \int_S \sigma(\mathbf{r}') \frac{e^{-jkR(\mathbf{r},\mathbf{r}')}}{4\pi R(\mathbf{r},\mathbf{r}')}\, dS \tag{6}$$

(ε denotes permittivity of the antenna surroundings). Both the current density and the charge density are bounded together by the theorem of continuity [6]

$$\sigma = \frac{-1}{j\omega} \nabla\cdot\mathbf{J} \tag{7}$$

Moreover, the tangential component of the electric intensity vector (consists of the intensity of the incident wave $\mathbf{E}^i$ and of the scattered one $\mathbf{E}^s$) on the perfectly conducting surface of the antenna is enforced to be zero [6]

$$\mathbf{n}\times\mathbf{E}^s = -\mathbf{n}\times\mathbf{E}^i \tag{8}$$

Assuming that both the current density and the charge density are placed into the axes of antenna wires [9], approximating the current distribution by a piece-wise constant function and exploring the method of weighted residua [9] with Dirac pulses as weighting function yields the contribution of asymmetric currents to the input impedance of the folded dipole Z_{as}.

Afterwards, bringing the contributions of symmetric and asymmetric currents to the input impedance together gives us the input admittance of the folded dipole [6]

$$Y_{inp} = Y_{as} + \tfrac{1}{2} Y_s \tag{9}$$

By the above described way, a relatively accurate and computationally efficient numerical model of the folded dipole was developed. This numerical model is used in the following chapter for the genetic optimization of the folded dipole.

3. Genetic optimization

Genetic optimization algorithms are inspired by the biological principle of natural selection. Therefore, every folded dipole is called an *individual*. All the parameters of the *individual*, which are changed during the optimization process, are encapsulated in a *chromosome*. The single parameter is called a *gene*. In a computer algorithm, *chromosomes* can be understood as arrays of *genes*. Further, a *gene* is a binary encoding of a parameter [11] - [17].

At first, a number of *individuals*, representing the optimised antenna, is created. Properties of those *individuals* are randomly chosen from a certain, previously defined interval. Then, the *individuals* are sorted with respect to their ability to meet requirements to them, which are described by the cost function. In the next step, the *breeding* of new generation is performed combining *chromosomes* of individuals, and moreover, some *mutation* (random change of a few bits in the *gene*) can be done. Quality of new generation is then again tested by evaluating the cost function. If the cost function produces small error for the new generation then the algorithm stops. Otherwise, new *breeding* is performed [11] - [17].

Concentrating on the folded dipole from Fig. 1, every *individual* is described by a chromosome consisting of two genes - two parameters which can be changed during the optimisation process. Therefore, the *gene 1* can correspond with the horizontal size of the dipole *l* and the *gene 2* can represent the vertical size of the dipole *d*. In our optimization, the diameter of the wire is assumed being constant.

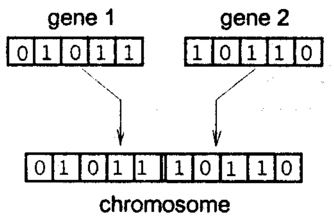

Fig. 2 **Structure of chromosome**

In the genetic algorithms, *chromosomes* represent every *individual*. In order to evaluate the quality of the *individual*, each *chromosome* is associated with a cost function, assigning a relative merit to that *chromosome*. This means that after the random generation of the *chromosomes*, cost functions are evaluated for each *chromosome* and the corresponding individuals are ranked from the most-fit to the least-fit, according to their respective cost functions. Unacceptable individuals are discarded, leaving a superior species-subset to the original list.

In the next step, the parents, which may create *offspring*, are chosen. In the presented algorithm, a very simple function creating *offspring* is used: two randomly chosen *parents* are compared and the best one of them is used. This is repeated until the number of *parents* is the same as the number of *individuals* in the present *generation*. In this way, a matrix with a relatively high chance of the presence of the best *parents* is developed.

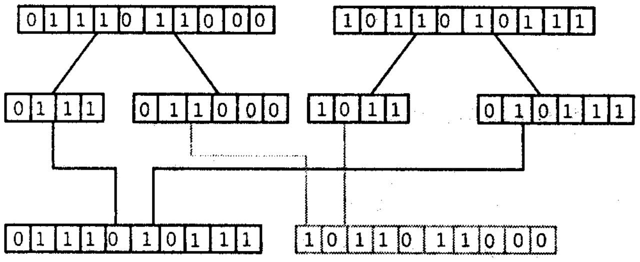

Fig. 3 Cross over

All the *parents* produce two new *offspring* by swapping some of their genetic material (Fig 3). The point of the *crossover* is randomly chosen by the algorithm and it defines where the *chromosome* is broken.

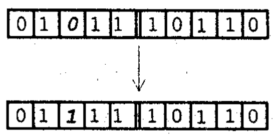

Fig. 4 Mutation

The both parts of the *chromosome* are used to combine two new *individuals*, which both possess a part of the genetic information from both *parents*. By this way of *breeding*, the number of *individuals* is remained constant during all the different *generations*.

In the next section, the problems, which might appear in implementation of genetic algorithms, are described and their possible solution is suggested.

4. Problems of genetic algorithms

One of the common problems occurs when the algorithm chooses often the same parents in the auxiliary matrix. In this case, the parents are possible to be the same, and thus, the children will be the exact copies of their parents (no offspring with different genetic information is obtained).

The problem can be solved by introducing a *mutation* into the algorithm which means that random changes are done in the binary code of the chromosome. In the example in Fig. 4, the mutation was done by changing the third bit of the first gene. Most of the papers about the use of genetic algorithms mention a value for the chance that a bit changes due to mutation between 1 and 10 percent [13], [15].

After the breeding and the mutation, cost functions are again evaluated for the offspring and the mutated chromosome, and the process is repeated.

Next of the most common problems is that there is no rule for electing such a probability of the mutation which is the best for obtaining the best result as fast as possible.

If the probability of the mutation is very high (about 10 percent), then the algorithm risks to destroy a good obtained individual by destroying his genetic information. On the other hand, if the probability of mutation is very small (1 percent or less), the algorithm exhibits very fast convergence to some solution, but the result will only improve after a very long time.

The problem of the number of mutations can be solved by increasing the chance of mutation in the case of significant number of individuals in the generation (one half of the generation, e.g.) being the same. Since this problem appears after a larger amount of generations, there is no need to reduce again the number of mutations.

If the number of mutations is quite big, and therefore, the good results of the previous generations are deleted, it might be a good idea to keep the previous two generations in some auxiliary matrix, and if the algorithm is found out to produce only bad results, the better result of these saved two generations can be called back.

The third problem is that convergence of the algorithm to the global minimum is dominantly influenced by the randomly chosen first generation and by the randomly chosen breeding in every generation. Therefore, the algorithm should be stopped between every generation and all the individuals of the present generation and of the previous one should be checked. Is this way, this population can decided whether it has some good „future“ or whether the algorithm should be stopped and started all over again. If more or less good solution is at the disposal, then the chance of mutation should be increased to obtain faster some result (either better or worse, you are not sure).

In most of the cases where genetic algorithms are used, there is a problem with long computation time: the model should be evaluated in every generation as many times as there are individuals. Sometimes, the computation of a generation takes more than 30 minutes (if the number of individuals is very large and the model is sophisticated), and this makes it impossible to check every generation manually.

The final problem is that the user of the algorithm should be experienced, because otherwise, he cannot understand the meaning of the data totally and is not able to take decision how to influence the parameters of the process which is going on. Therefore, the users are encouraged to hardly study the nature of optimized systems.

Another possibility is to make the genetic algorithm more intelligent, and make it possible to anticipate itself on the progress of the process.

5. Examples

At this moment, the attention is turned to the numerical examples of the work of the genetic optimization of the folded dipole. The task, which the genetic algorithm was asked to solve, was finding the optimal length of the folded dipole l and the optimal distance between horizontal wires of the dipole d so that the input impedance of the folded dipole could be Z_{inp} = 300 Ω on the frequency f = 71.7 MHz. The radius of all the antenna wires was fixed to a = 2.5 mm.

Observing Fig. 5 and Fig. 6, which show the learning curves of the same algorithm running twice with the different chance of mutation and different number of individuals, the results of the algorithm are obvious to work in an unique way in each case.

In Fig. 5, we see that after the 6th generation no other results are given due to the fact that most of the parents have the same chromosome. Only in the 15th generation, there is a very big progression due to the mutation. Optimal sizes of the folded dipole were l = 1.9490 m and d = 0.1473 m.

In fig. 6, there is shown the danger of mutation: the rather small squared error (36 Ω) of the generation one is immediately destroyed by mutation and even after 36 generations, the result isn't better then 64 Ω. Therefore, we can conclude that mutations are useful, but have to be handled with care.

Dealing with the number of individuals in one generation, higher number of individuals decreases number of generations, which are necessary to obtain optimal results, but the computational requirements of the algorithm are increased.

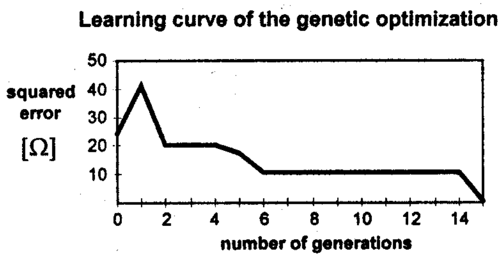

Fig. 5 Learning curve of a genetic algorithm, with 18 individuals, 15 generations, and 2% chance of mutation.

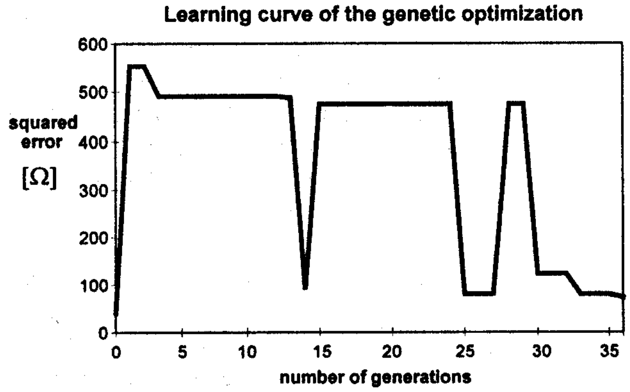

Fig. 6 Learning curve of a genetic algorithm, with 12 individuals, 36 generations, and 5% chance of mutation.

6. Conclusions

The presented paper is concerned in the design of wire antennas by genetic algorithms.

In the paper, the folded dipole was chosen to represent wire antennas and its numerical model was developed. The model was based on the combination of the method of moments and Howe's method.

Dealing with the optimization technique, genetic algorithms were found to be suitable for the purpose of the optimization of wire antennas because they are very general (and therefore, they can serve for the optimization of an arbitrary wire antenna in our case), they are very understandable and easily programmable.

Dealing with the properties of genetic algorithms, low convergence rate is their main, and at the same time only, disadvantage. On the other hand, the genetic optimization belongs to the global methods, and therefore, it does not have so serious problems with local minima of the cost function as the classical methods.

7. Acknowledgements

Authors are grateful to Prof. Černohorský for his practical advises about software implementation of the genetic algorithms.

The research described in this paper was supported by the Grant Agency of the Czech Republic under the grant No. 102/97/1224: „*Design, analysis and optimization of special microwave structures*“.

The paper is the result of the co-operation between KH Limburg and TU Brno in accordance with TEMPUS.

References

[1] WERNER, P. L., WERNWER, D. H.: "Approximations for the Cylindrical Wire Kernel". *Electronics Lett.*, vol. 32, no. 23, pp. 2108 - 2109, November 1996.

[2] MACPHIE, R. H., DARBHA, S. K.: "The Input Impedance of a Thin Dipole with Sinusoidal Surface Current Distribution by the Pointing Vector Method". *IEEE Trans. on Antennas and Propag.*, vol. 43, no. 11, pp. 1336 - 1339, November 1995.

[3] PARK, S. O., BALANIS, C. A.: "Efficient Kernel Calculation of Cylindrical Antennas". *IEEE Trans. on Antennas and Propag.*, vol. 43, no. 11, pp. 1328 - 1331, November 1995.

[4] AMARI, S., BORNEMAN, J.: "Efficient Numerical Computation of Singular Integrals with Applications to Electromagnetics". *IEEE Trans. on Antennas and Propag.*, vol. 43, no. 11, pp. 1343 - 1348, November 1995.

[5] WERNER, D. H.: "An Exact Formulation for the Vector Potential of a Cylindrical Antenna with Uniformly Distributed Current and Arbitrary Radius". *IEEE Trans. on Antennas and Propag.*, vol. 41, no. 8, pp. 1009 - 1018, August 1993.

[6] JORDAN, E. C., BALMAIN, K. G.: "*Electromagnetic Waves and Radiating Systems*". 2/E, Prentice-Hall, Englewood Cliffs 1968.

[7] SAGIROGLU, S., GUNEY, K.: "Calculation of Resonant Frequency for an Equilateral Triangular Microstrip Antenna with the Use of Artificial Neural Networks". *Microwave and Optical Technology Lett.*, vol. 14, no. 2, pp.89 - 93, February 1997.

[8] JONES, E. A.: "Design of Yagi-Uda Antennas Using Genetic Algorithms". *IEEE Trans. on Antennas and Propag.*, vol. 45, no. 9, pp. 1386 - 1392, September 1997.

[9] HARRINGTON, R. F.: "*Field Computation by Moment Methods*". 2/E, IEEE PRESS, Piscataway, 1994

[10] HOWE, G. W. O.: "On the Capacity of Radio-Telegraphic Antennae". *The Electrician*, pp. 829, August 1914.

[11] BOAG, A., BOAG, A., MICHIELSSEN E., MITTRA, R.: "Design of Electrically Loaded Wire Antennas Using Genetic Algorithms". *IEEE Trans. on Antennas and Propag.*, vol. 44, no. 5, pp. 687 - 695, May 1996.

[12] HAUPT, R. L.: "An Introduction to Genetic Algorithms for Electromagnetics". *IEEE Antennas and Propag. Magazine*, vol. 37, no. 2, pp. 7 - 15, April 1995.

[13] JOHNSON, J. M., RAHMAT-SAMAII, Y.: "Genetic Algorithms in Engineering Electromagnetics". *IEEE Antennas and Propag. Magazine*, vol. 39, no. 4, pp. 7 - 25, August 1997.

[14] LI, Q., ROTHWELL, E. J., CHEN, K. M., NYQUIST, D. P.: "Scattering Center Analysis of Radar Targets Using Fitting Scheme and Genetic Algorithm". *IEEE Trans. on Antennas and Propag.*, vol. 44, no. 2, pp. 198 - 206, February 1996.

[15] WEILE, D. S., MICHIELSSEN, E.: "Genetic Algorithm Optimisation Applied to Electromagnetics: A Review". *IEEE Trans. on Antennas and Prop.*, vol. 45, no. 3, pp. 343 - 353, March 1997.

[16] WEILE, D. S., MICHIELSSEN, E., GOLDBERG, D. E.: "Genetic Algorithm Design of Pareto Optimal Broadband Microwave Absorbers". *IEEE Trans. on EMC*, vol. 38, no. 3, pp. 518 - 525, August 1996.

[17] YAN, K. K., LU, Y.: "Sidelobe Reduction in Array-Pattern Synthesis Using Genetic Algorithm". *IEEE Trans. on Antennas and Propag.*, vol. 45, no. 7, pp. 1117 - 1121, July 1997.

About authors...

Erik Goven was born in 1974 in Maaseik. He studies electronics with the option of telecommunication on the KH Limburg (Belgium) and will finish this in the end of June 1998. From March 1998 till July 1998 he worked at the Technical University of Brno with the Institute of Radio Electronics in the frame of TEMPUS. His major interest is the design and building of antennas and the study of wave propagation on long distances.

Luc VERHEYEN was born in 1974 in Genk. He studies telecommunication at KH Limburg (Belgium) and will finish his studies at the end of June 1998. From March 1998 till Juli.1998 he worked at the Technical University of Brno at the Institute of Radio Electronics with the help of the TEMPUS program. His main interests are computers and geology.

Zbyněk RAIDA was born in 1967 in Opava. He received Ing. (M.S.) degree in Radio Electronics in 1991 and Dr. (PhD.) degree in Electronics in 1994, both at the Technical University of Brno. Since 1993, he is with the Institute of Radio Electronics TU Brno where he works as an assistant professor. In 1996, he spent 6 months on leave at the Université Catholique de Louvain, Laboratoire de Hyperfrequences, Louvain-la-Neuve in Belgium. His teaching and research interest include adaptive filtering and artificial intelligence, numerical modelling of microwave circuits and antennas, object oriented programming and related topics.