Multi-Objective Optimization of Wire Antennas: Genetic Algorithms Versus Particle Swarm Optimization

Zbyněk LUKEŠ, Zbyněk RAIDA

Dept. of Radio Electronics, Brno University of Technology, Purkyňova 118, 612 00 Brno, Czech Republic

lukes@feec.vutbr.cz, raida@feec.vutbr.cz

Abstract. *The paper is aimed to the multi-objective optimization of wire multi-band antennas. Antennas are numerically modeled using time-domain integral-equation method. That way, the designed antennas can be characterized in a wide band of frequencies within a single run of the analysis. Antennas are optimized to reach the prescribed matching, to exhibit the omni-directional constant gain and to have the satisfactory polarization purity. Results of the design are experimentally verified.*

The multi-objective cost function is minimized by the genetic algorithm and by the particle swarm optimization. Results of the optimization by both the multi-objective methods are in detail compared.

The combination of the time domain analysis and global optimization methods for the broadband antenna design and the detailed comparison of the multi-objective particle swarm optimization with the multi-objective genetic algorithm are the original contributions of the paper.

Keywords

Wire antennas, multi-band antennas, multi-objective optimization, time-domain integral-equation method, genetic algorithms, particle swarm optimization.

1. Introduction

In today's radio communication systems, broad- and multi-band antennas play more and more important role. In order to make the design of such antennas as efficient as possible, we propose to combine the time-domain integral-equation (TDIE) method for the antenna analysis, and global optimization techniques for improving parameters of the analyzed antenna model.

If TDIE is used for the antenna analysis, the investigated antenna structure can be characterized within a single run of the analysis when excited by a very short pulse, which spectrum covers the whole frequency band of the interest [1]. Nevertheless, the TDIE suffers from stability problems in certain situations [2]–[5], and hence, its popularity is lower compared to other numerical techniques.

Genetic algorithms (GA) were introduced to the computational electromagnetics like the efficient global optimization tool in the middle of nineties [6]–[8]. For the design of broad- and multi-band antennas, GA were applied in [9], [10] in conjunction with frequency domain method of moments – the analysis was run thousands times. In order to overcome this difficulty, a technique of the optimal selection of frequency points in the wide band of the design was developed [11]. Also, the first attempt to move the analysis into the time domain was published in [12] – as a computational tool, the finite-difference time-domain (FDTD) method was used.

An intensive activity has been focused also on the development of multi-objective genetic optimization. In [13] and [14], the multi-objective genetic algorithm is applied to the design of broadband wire antennas using the frequency domain moment method as the computational tool. In [15], the moment method was replaced by the frequency domain finite element method combined with boundary integral equation method to design absorbers. Obviously, no so-far published approach combines TDIE and GA for multi-objective optimization of antennas.

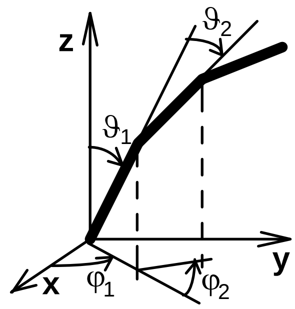

Fig. 1. The optimized wire antenna consists of N linear segments of the length dl. During the optimization, orientation of segments φ_n and ϑ_n can be changed.

Particle swarm optimization (PSO) appeared in the computational electromagnetics community recently [16]. By now, the PSO of a multi-band CPW-fed monopole antenna was published [17] with the frequency domain moment method in the role of the computational tool. The multi-objective version of PSO has not appeared in the open literature yet.

The single-objective versions of GA and PSO were confronted in [18] when applied to the phased array synthesis. The comparison of multi-objective algorithms is published first here.

The paper is organized as follows. In Section 2, the antenna to be synthesized is described. In Section 3, the techniques used (TDIE, GA, PSO) are briefly reviewed. Section 4 describes results obtained by computations, and confronts them with measurements. And finally, Section 5 concludes the paper.

2. Synthesized Antenna

Abilities of the design technique combining the TDIE and multi-objective global optimization algorithms will be demonstrated on the synthesis of the double-band GPS antenna. The antenna consists of the arbitrarily shaped wire monopole, which is completed by the planar reflector. Both the monopole and the reflector are assumed to be perfectly electrically conductive. The antenna is surrounded by the free space with the parameters of vacuum.

The antenna will operate in the frequency bands L1 (the central frequency f_{L1} = 1575.42 MHz) and L2 (the central frequency f_{L2} = 1227.6 MHz). The antenna is required to exhibit the omni-directional constant gain for the elevation from 5° to 90°. The antenna has to be designed for the right-hand circular polarization.

The monopole is assumed to consist of N linear segments of lengths dl_n and the radius a (dl_n are much longer than a, and therefore, the thin-wire approximation can be applied in the TDIE). When synthesizing the shape of the antenna, we change local spherical coordinates φ_n, ϑ_n and lengths dl_n of all antenna segments. The origin of the local spherical coordinate system of the n-th antenna segment is located at the end of the (n–1) segment as depicted in Fig. 1. Hence, N triplets [φ_n, ϑ_n, dl_n] are the result of the design.

For the antenna optimization, three partial objective functions are formulated. The first one

$$F_f = \frac{1}{2}\sum_{i=1}^{2}\sqrt{\left[\mathrm{Re}\{Z_i\}-100\right]^2+\left[\mathrm{Im}\{Z_i\}-0\right]^2} \tag{1}$$

is zero if the real part of input impedance Re{Z_i} = 100 Ω and the imaginary part Im{X_i} = 0 Ω on central frequencies of both the frequency bands i = 1, 2.

The second partial objective function

$$F_g = \sum_{i=1}^{2}\left[G_{max,i} - G_{min,i}\right] \tag{2}$$

is zero in case if the maximum gain $G_{max,\,i}$ in any direction of elevation ϑ = <5°, 90°> and azimuth φ = <0°, 360°> equals to the minimum gain $G_{min,\,i}$ on central frequencies of both the frequency bands i = 1, 2. Hence, the omni-directional constant value of the antenna gain is reached.

The third partial objective function formulates the criteria of the polarization purity: the ratio (E_φ / E_ϑ) has to equal one, and the phase shift between E_φ and E_ϑ has to be the odd multiple of π/2. If both the conditions are met on central frequencies of both the frequency bands, then the polarization purity objective function F_p is zero.

The partial objective functions can be joined into the global objective function

$$F = \sqrt{F_f^2 + F_g^2 + F_p^2}\ . \tag{3}$$

Triplets [φ_n, ϑ_n, dl_n] are changed during the optimization to reach the minimum of the global objective function F.

3. Techniques Used

In this Section, we briefly review the time-domain integral-equation (TDIE) method we use for evaluating the objective functions in the optimization procedure. The genetic algorithm (GA) and the particle swarm optimization (PSO) we use for minimizing objective functions are also briefly described here.

3.1 Time Domain Integral Equations

The method uses electric field integral equations [23] for the description of the analyzed structure. The equations are formulated for an arbitrary time response. Formulations are based on the retarded vector potential [22]

$$\mathbf{A}(\mathbf{r},t) = \mathbf{A}\left[\mathbf{J}\left(\mathbf{r}',t-|\mathbf{r}-\mathbf{r}'|/c\right)\right], \tag{4}$$

and the retarded scalar one [22]

$$V(\mathbf{r},t) = V\left[q\left(\mathbf{r}',t-|\mathbf{r}-\mathbf{r}'|/c\right)\right]. \tag{5}$$

Here, **r** gives the observation point (potentials are computed here) and **r**' is the source point (points out to current and charge sources contributing to potentials), |**r** – **r**'| is the distance between the observation point and the source one, and c is the velocity of light in a free space. The **J** represents the current density vector and q is the charge density. Currents and charges are joined by the continuity theorem, and the vector potential **A** and the scalar one V are used to evaluate the intensity of the scattered electric field [23].

In case of thin wire antennas, a so-called thin-wire approximation[1] can be introduced, which decreases the dimension of the problem. Then, the antenna segments can be represented by their axes, the axes of segments can be

[1] If the length of the antenna segment is much smaller than the radius of the antenna wire and much smaller than the wavelength, all the currents and charges on the antenna wire can be assumed to be concentrated on the axes of antenna segments. This assumption does not agree with the reality (due to the skin effect) but provides results, which are close to measurements.

broken into one-dimensional (1D) discretization cells, and the current distribution can be approximated over discretization cells using piecewise constant basis functions (on the discretization cell, the current is the same for all the points of the cell, but it can change in time).

Performing several mathematical operations, an explicit formula for the current on the m-th discretization cell in the k-th time step can be obtained [22]

$$\begin{aligned} I(m,k)\kappa(m,\ m) = & \qquad (6)\\ & - A_1(m,k) + 2A_0(m,k-1) - A_0(m,k-2) + \\ & + \left[\frac{c\,\Delta t}{\Delta}\right]^2 \left[A_0(m+1,k) - 2A_0(m,k) + A_0(m-1,k)\right] + \\ & + (c\,\Delta t)^2\ F(m,k-1)\,, \end{aligned}$$

where $\kappa(\ m,\ n)$ denotes the integral of the time-domain Green function over the n-th discretization cell for the m-th observation point [22], $A_t(\ m,\ k)$ is the contribution of the upcoming current samples (the moment k) to the vector potential in the centre of the m-th discretization cell, and $A_1(\ m,\ k)$ is the contribution of former current samples (the moments k–1, k–2, ...) to the vector potential in the centre of the m-th discretization cell, and $A_0(\ m,\ k) = A_1(\ m,\ k-1) - A_t(\ m,\ k-1)$ [22]. Next, c denotes velocity of light, Δt is the time step (the discretization segment in time), and Δ denotes the length of the spatial discretization segment [22]. Finally, the term

$$F(m,k) = \frac{1}{c^2}\,\frac{\partial E^I(m,k)}{\partial t} \qquad (7)$$

describes the excitation (E^I is the electric field intensity of the incident wave). In our computations, antennas are excited by Gaussian pulse of the width 0.25 LM[2]. Then, antenna parameters in both the frequency bands L1 and L2 can be obtained within a single analysis.

The explicit formula is stable for the time step shorter than $\Delta t \leq R_{min} / c$ (the minimum distance between the centers of the discretization cells R_{min} is longer than the distance covered by light within one time step of the algorithm Δt). Meeting this condition, TDIE becomes an efficient and accurate computational tool for evaluating cost functions in our optimization.

3.2 Genetic Algorithms

Genetic algorithms (GA) understand the optimized antenna like an individual, which properties are described by a gene [8]. Therefore, all the state variables of the antenna, which are changed during the optimization, are binary encoded and sequentially put into a binary array – gene.

[2] The light meter (LM) equals to the time needed for covering one meter by an electromagnetic wave in free space.

In order to improve the antenna parameters, a population of individuals (antennas) is randomly generated (i.e., a set of optimized antennas differing in the setting of their state variables is created). Then, each individual in the population is evaluated (the objective function is computed for each antenna) and the best ones are selected to become parents. Couples of parents are then randomly selected [8].

The cross-over operation randomly divides genes of parents (a sequence of binary encoded state variables), and forms two children (the gene of the first child contains the first part of the first parent gene and the second part of the second parent gene and vice versa). That way, the population of parents is replaced by a population of children, which should exhibit better properties [8].

In case of our antenna, the gene is composed of three parts: the first one contains the binary-coded elevation angles ϑ_n (10 bits), the second one the binary coded azimuth angles φ_n (10 bits), and the third one the binary coded number of the discretization elements Δ (3 to 6) forming antenna segments dl_n. The antenna consists of 7 segments.

Initially, 32 binary genes were randomly generated to form the population, 32 antennas were analyzed using TDIE, and the best of them (the lowest value of the global objective function) were selected to become parents.

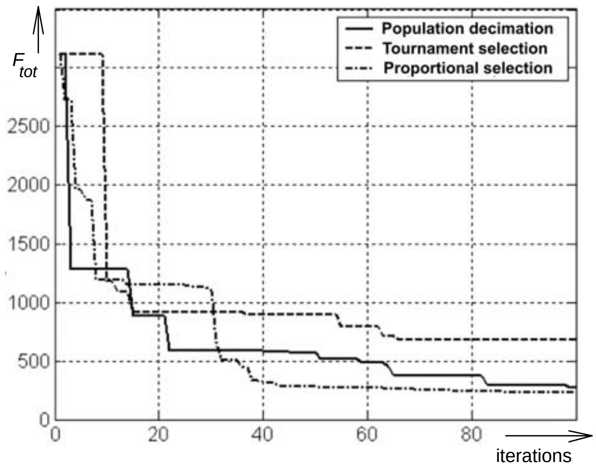

Fig. 2. Genetic optimization of the antenna. Comparison of different selection strategies: population decimation (solid), tournament selection (dashed), proportional selection (dash-dotted).

In our experiments, 3 selection strategies were tested. Population decimation selects 50 % of the best individuals to be parents (therefore, 64 individuals form the initial population in that case), and in the following steps, the better half generation overwrites the worse one. Tournament selection randomly selects couples, and the better individual in the couple is allowed to be a parent. In case of proportional selection, probability of the individual to become a parent is related to the value of its objective function (lower the objective function is, higher the probability is) [8].

We also applied 10 % mutation (10 % probability that one bit randomly selected in a gene will be inverted).

Fig. 2 compares convergence properties of all the 3 selection strategies. The convergence curves were averaged over 5 realizations of the optimization. The optimization was stopped in the 100th iteration. Since the tournament selection exhibited the best properties, we used it in the following computations.

3.3 Particle Swarm Optimization

The particle swarm optimization (PSO) is a stochastic evolutionary computation technique based on the movement and intelligence of swarms [16]. Speaking about the swarm of bees, its intention is to find the best flowers in a given (feasible) space. Applying this concept to the optimization of the GPS antenna, the bees (agents) move in a space formed by N triplets [φ_n, ϑ_n, dl_n], each bee is described by its coordinates, its velocity of movement to the best flowers, and its value of the objective function. Each bee remembers the position of the lowest value of the objective function (so called local minim) it reached during its fly. The lowest local minim (through the whole swarm) is called the global minim. The position of the global minim and the local one are used to determine an optimal velocity vector (direction and speed of flight) of the bee to the area of best flowers [16]

$$\mathbf{v}_{n+1} = w\,\mathbf{v}_n + w_1\, r_1 \left(\mathbf{L}_{best} - \mathbf{x}_n\right) + w_2\, r_2 \,\left(\mathbf{G}_{best} - \mathbf{x}_n\right). \quad (8)$$

The velocity in the (n+1) iteration step $\mathbf{v}_{n+1}$ equals to the velocity in the previous iteration multiplied by a weighting factor w (how quickly is the speed $\mathbf{v}_n$ forgotten), $\mathbf{L}_{best}$ is the position of the local minim and $\mathbf{G}_{best}$ of the global one, $\mathbf{x}_n$ denotes the position of the bee in the n-th iteration step, w_1 and w_2 are again weighting factors, r_1 and r_2 are random numbers from 0 to 1.

When a new velocity vector of a bee is known, its new position can be computed [16]

$$\mathbf{x}_{n+1} = \mathbf{x}_n + \Delta t\;\mathbf{v}_{n+1}\;, \quad (9)$$

where Δt is the time period the bee flies by the velocity $\mathbf{v}_{n+1}$ (usually 1 second).

In case the bee reaches the border of the feasible space, the velocity vector can be *reflected* (orientation of the velocity vector is reverted, and the bee returns to the feasible space), *absorbed* (magnitude of the velocity vector is set to zero, and the position of the bee does not change), or *ignored* (the bee stays out of the feasible space, its objective function is not evaluated, and the bee is expected to come back to the feasible space within a few iteration steps).

At the beginning of the optimization, 50 agents were randomly generated. Each agent was described by N (seven) triplets of rational coordinates: φ_n is azimuth, ϑ_n is elevation, and dl_n is the length of the antenna element expressed in the number of antenna segments. For each agent, objective function was evaluated, $\mathbf{L}_{best}$ and $\mathbf{G}_{best}$ were computed, and its velocity was randomly given. Then, a new velocity could be determined using (8), and a new position could be evaluated using (9). This procedure was repeated 100 times in our case.

4. Results

In this Section, we are going to present results of the synthesis of the GPS antenna described in Section 2. The antenna consists of a monopole, which is composed of 7 elements. Each element is described by the azimuth angle φ_n, the elevation angle ϑ_n, and the length given by the number of discretization segments $dl_n = p\,\Delta$, where p = 3 to 6. The monopole is completed by the infinite planar reflector. The radius of the antenna wire is fixed to a = 1 mm.

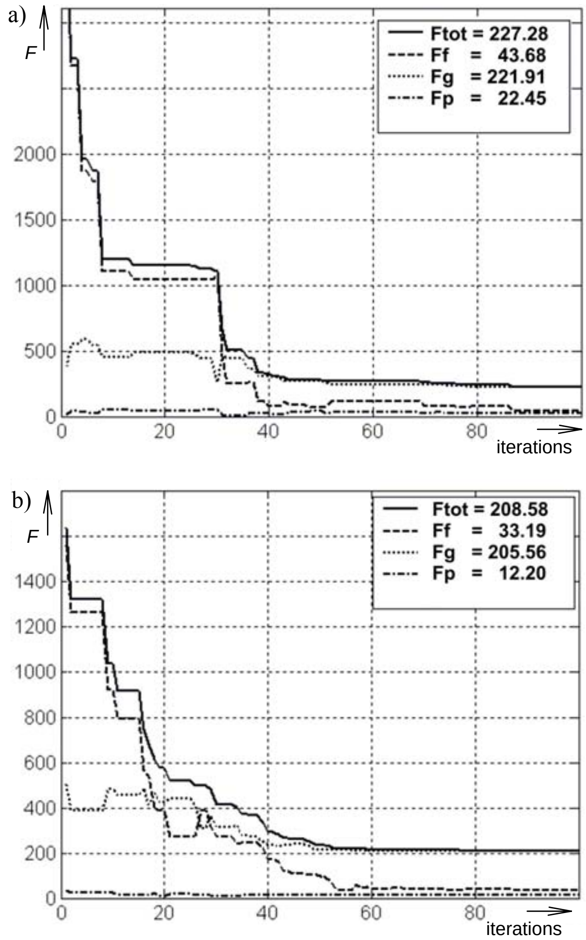

Fig. 3. Time responses of partial objective functions F_f (matching), F_g (gain), F_p (polarization), and the global one F_{tot} during the multi-objective optimization of the GPS antenna: a) genetic algorithm, b) particle swarm optimization.

The described antenna is numerically analyzed by TDIE. Computed time responses of currents on discretization segments of the antenna are converted to frequency domain using fast Fourier transform. In frequency domain, criteria on matching, gain and polarization purity are formulated.

The global objective function (3) is minimized using GA and PSO. Both the algorithms are allowed to perform 100 iteration steps. Both the algorithms are run five times, and the best realization is considered in comparisons.

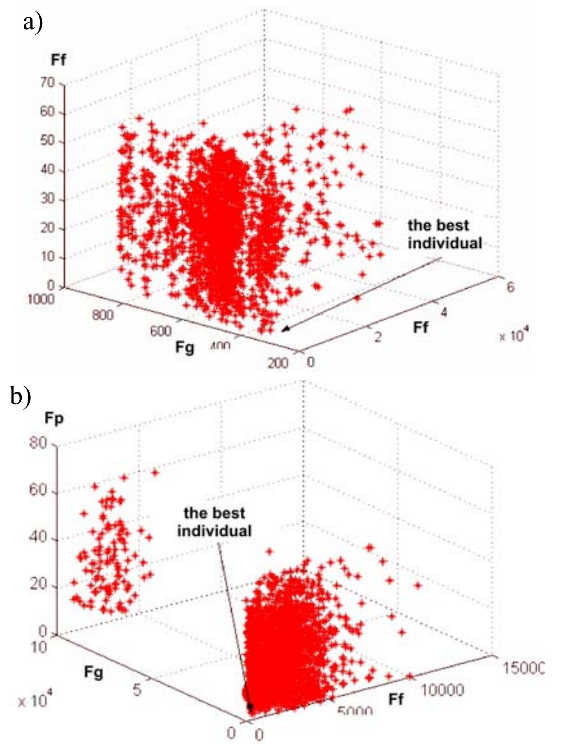

Fig. 4. The movement of individuals (agents) to the global optimum $[F_f, F_g, F_p] = [0, 0, 0]$: a) genetic algorithms, b) particle swarm optimization.

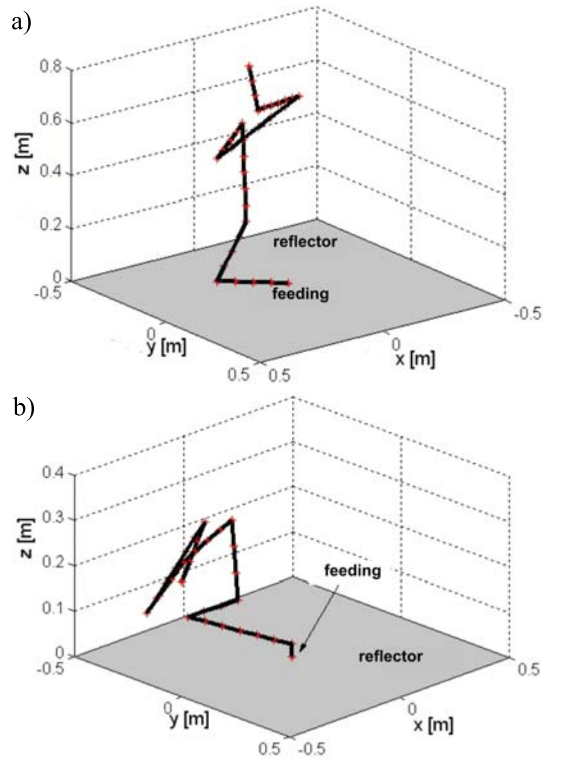

Fig. 5. Shape of the synthesized GPS antennas: a) the best individual by genetic algorithm, b) the best agent by particle swarm optimization.

In Fig. 3, time responses of partial objective functions and the global one during the optimization of GPS antenna are depicted. Time response of PSO is smoother and reaches a deeper global minim (208.58 versus 227.28) compared to GA. Whereas the global objective function decreases monotonously, partial objective functions can both decrease and increase during the optimization. Partial objective functions should be of similar values to optimize successfully – hence the gain function F_g and the polarization function F_p should be enhanced by weighting coefficients up to the level of the matching function F_f.

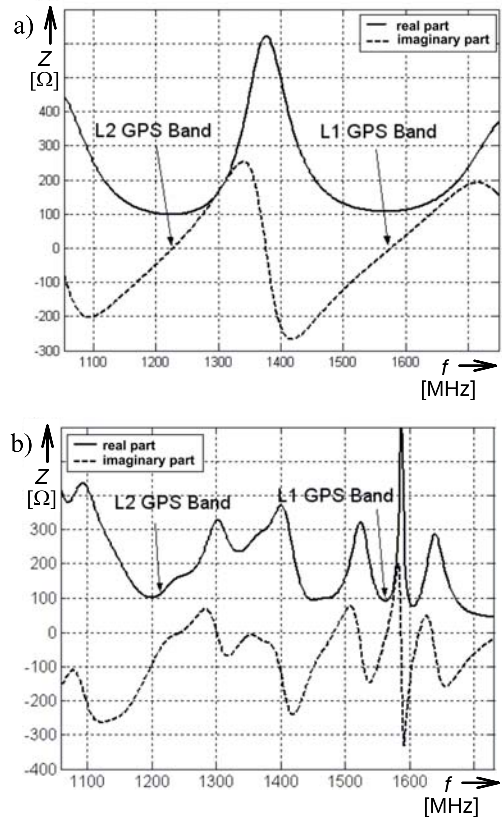

Fig. 6. Impedance characteristics of the synthesized GPS antennas: a) genetic algorithm, b) particle swarm optimization.

Fig. 4 shows the position of individuals (agents) in the coordinate system composed of partial objective functions F_f, F_g and F_p. The global optimum is identical with the point [0, 0, 0] in this coordinate system (the antenna perfectly meets requirements on matching, gain, and polarization purity). Agents of PSO are highly concentrated close to the global optimum; individuals of GA are more spread in the feasible space. Agents of PSO are closer to the global optimum compared to the individuals of GA.

In Fig. 5, the synthesized monopoles (the best individual by GA and the best agent by PSO) are depicted.

Impedance characteristic of the antennas are shown in Fig. 6. The GA antenna is accurately matched in both the bands, and moreover, the impedance characteristics are smooth without parasitic resonances. On the contrary, the PSO antenna is matched on slightly lower frequency in the lower band, and moreover, the frequency response of input impedance is corrupted by several resonances in between bands L2 and L1.

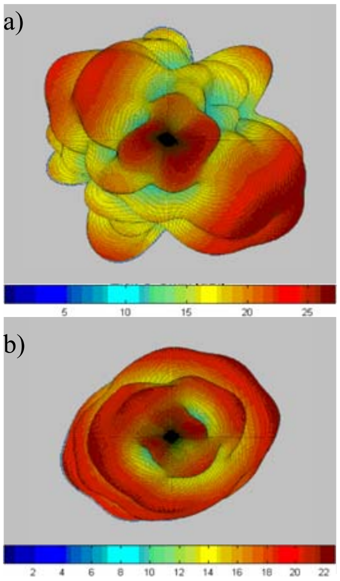

Fig. 7. Directivity pattern of the designed antenna in the band L1: a) genetic algorithm, b) particle swarm optimization.

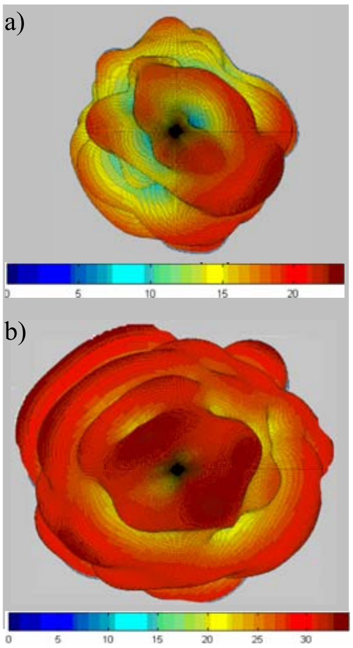

Fig. 8. Directivity pattern of the designed antenna in the band L2: a) genetic algorithm, b) particle swarm optimization.

Directivity patterns of the synthesized GPS antennas are depicted in Fig. 7 for the L1 band and in Fig 8 for the L2 band. In both bands, the PSO antenna meets better the requirement on the constant gain for all directions.

The matching criteria were also verified experimentally (see Fig. 9). The GA antenna exhibits the first minim of the reflection coefficient on 1248.5 MHz (the declination +2 %) and the second minim on 1521.5 MHz (the declination –4 %). Both minims are about –10 dB.

The PSO antenna exhibits the first minim of the reflection coefficient on 1240.4 MHz (the declination +1 %) and the second minim on 1520.9 MHz (the declination –4 per cent). Both minims are about –10 dB.

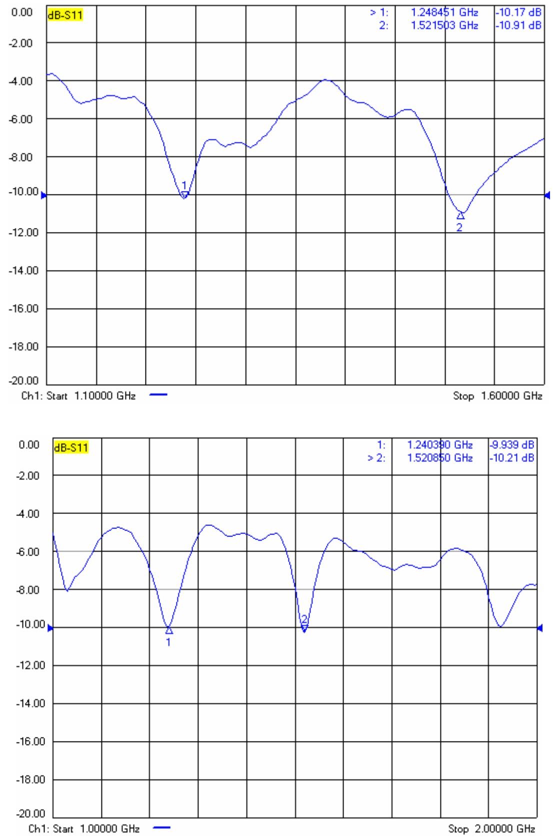

Fig. 9. Measured frequency response of the reflection coefficient of the designed antennas: genetic algorithm (top), particle swarm optimization (bottom).

Measurements did not show any differences between the GA antenna and the PSO one from the viewpoint of impedance matching.

5. Conclusions

Our experience with the synthesis of wire antennas combining TDIE in the role of the computational tool plus GA and PSO as global optimizers can be concentrated into the following statements:

- Both GA and PSO provide similar results of the synthesis. The synthesized antennas meet quite well the requirements. Weaknesses and advantages of solutions are both on the side of GA (better impedance characteristics, worse patterns) and PSO (better directivity patterns, worse characteristics).
- Software implementation of PSO is simpler compared to GA: no coding and decoding of state variables is needed in case of PSO.
- CPU-time demands of both PSO and GA are similar. The biggest portion of CPU time is consumed by evaluating directivity patterns (92 %). TDIE analysis is quite efficient (6 % of the total CPU time).

The further development should be focused in the post-processing of the TDIE results to reduce the 92 per cent portion of the total CPU time consumed to the lower value. Formulating objective functions directly in the time domain might be one of possible solutions.

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About Authors...

Zbyněk LUKEŠ graduated at the Faculty of Electrical Engineering and Communication (FEEC), Brno University of Technology (BUT), in 2002. Now, he has finished his dissertation at the Dept. of Radio Electronics, FEEC BUT. He is interested in the time-domain design of broadband planar and wire antennas.

Zbyněk RAIDA – for biography, see p. 20 in this issue of the Radioengineering journal.