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Location Optimization of WLAN Access Points Based on a Neural Network Model and Evolutionary Algorithms

In this article we intend to show the use of well-known evolutionary computation techniques - Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) - in an indoor propagation problem. Although these algorithms employ different strategies and computational efforts, they also share certain similarities. Their performance is compared with a genetic algorithm (GA), which is used as reference in this case. The ability of these algorithms to optimize access point locations using data derived from the neural network model of a particular Wireless Local Area Network (WLAN) is demonstrated. Better results are obtained by the PSO algorithm compared to the ACO algorithm. Although the ACO algorithm requires further work to optimize its parameters, improve the analysis of pheromone data and reduce computation time, the ant colony-based approach is useful for solving propagation problems.

Key words: Indoor propagation, Complex indoor environment, Signal strength prediction, WLAN, Neural network modelling, Access point optimization, Particle swarm optimization, Ant colony optimization

Optimizacija položaja pristupnih točaka lokalne bežične mreže zasnovana na neuronskom modelu i evolucijskim algoritmima. U članku se nastoji pokazati uporaba dobro poznatih evolucijskih računarskih tehnika - Optimizacija rojem čestica (PSO) i Optimizacija mravljom kolonijom (ACO) – u rješavanju propagacijskog problema zatvorenog prostora. Spomenuti algoritmi imaju različite strategije i računarske zahtjevanosti, a istovremeno i niz sličnosti. Ponašanje ovih alogoritama se uspoređuje s Genetskim algoritmom (GA), koji se koristi kao referenca. Pokazana je sposobnost navedenih algoritama za optimiziranje pristupne točke bežične lokalne mreže korištenjem podataka dobivenih od modela neuronske mreže. Algoritam roja čestica pokazao je bolje rezultate od algoritma mravlje kolonije. Algoritam mravlje kolonije se pokazao korisnim, iako je potrebno dodatno optimizirati njegove parametre, poboljšati analizu feromonskih podataka i smanjiti vrijeme rada računala.

Ključne riječi: širenje u zatvorenom prostoru, složeni prostor, predviđanje snage signala, bežična lokalna mreža, modeliranje neuronskom mrežom, optimizacija pristupne točke, optimizacija rojem čestica, optimizacija mravljom kolonijom

1 INTRODUCTION

Indoor wireless communication systems - phones, hand-held terminals, various PDA devices - are used extensively in modern society. These portable devices tend to be mobile and in principle can be located anywhere, with access points potentially providing a good link to the backbone of the communication system. Access points must be positioned carefully so that they cover entire buildings at an appropriate signal level. In general, the problem can be reduced to the needs of the given building, from which point questions such as how many access points will be needed,and where do they need to be placed in order to cover the building at minimum power level, can be answered. The main environmental impact on propagation

occurs in terms of path loss, an accurate estimation of which is extremely important for the proper determination of access point locations. Knowledge of path loss enables the determination of field signal strength, which in turn leads to the effective positioning of access point locations.

Prediction of signal strength for indoor propagation environments must take into account the problems associated with multipath propagation, such as signal attenuation, reflection, diffraction and interference caused by the diversity of building geometrical and construction characteristics. All of these factors combine to result in extreme computational complexity. In the case of architecturally-complex buildings, there is no truly accurate method of signal strength prediction and thus neural network mod-

els potentially offer an easy solution (less computing complex) for propagation problem in indoor environments [1]. The neural modelling process includes both theoretical and experimental investigations that result in a model based on a multi-layer perceptron (MLP) [2]. Model inputs are the positions (coordinates) of the base stations and of the receiving point, while the output consists of one neuron to obtain the relevant signal strength level. As a training rule we selected an algorithm that updates weight and bias values according to the Levenberg-Marquardt optimization method [3]. This choice was the result of extensive investigation involving analysis of two neural network architectures (multi-layer perceptron (MLP) and generalized radial basis function (RBF) neural networks) and a number of different learning algorithms. The selected model was tested in a particular building environment of such geometrical and construction complexity that makes the application of any analytical method very difficult. The neural network was trained and tested by measuring the field strength at various receiving points. The results were very promising [4]. Such a trained neural network can be used to predict both field strength distribution and optimum access point position. We will try to show how this model can be useful in the optimization of access point location.

The problem presented here is our attempt to optimally locate a transmitter covering a specified coverage region, so that the signal at every receiving point has sufficient strength for quality communication. The results obtained via neural network modelling were used in an optimization process comprising two methods of biological origin: Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) algorithms. It has already been shown how PSO can be effective in optimizing a variety of electromagnetic problems, especially regarding antenna design [5]. In some instances this type of algorithm has outperformed other popular optimization methods such as genetic algorithms (GA) [6], with this particular algorithm initially developed in 1995 by Kennedy and Eberhart [7] and subsequently applied in a variety of fields. The second optimization algorithm used here was the ACO algorithm, although this is less popularly applied in electromagnetics. First derived by Dorigo in 1991 [8], the ACO algorithm is based on the behaviour of ant colonies in obtaining food and carrying it back to the nest. Ants select paths according to the pheromone level they give off on the ground, with the shortest path the one with the highest level of pheromones. Although this technique is well-suited for discrete problems such as the travelling salesman problem, there are instances of its application in antenna design [9]. We developed a numerical representation (cost function) system in which the quality of signal coverage over the given space can be expressed as a function of transmitter location. Extreme values (minimum or maximum) of this cost function

represent an optimal location of an access point that satisfies given constraints. The trained neural network can then be used to determine the signal level at an arbitrary point wherever the access point is located. The presented model ensures that signal strength is above the specified threshold at any arbitrary point in the space under consideration.

2 THE NEURAL NETWORK MODEL AND COST FUNCTION

The neural network model used is represented by the network shown in Fig. 1 [10]. This model enables a practically unlimited number of access and receiving points to be represented as inputs in the network, which in turn produces signal strength as output for the appropriate locations of these access and receiving points. The training of the network was carried out by measuring signal strength at these locations as described in [10]. The neural model was applied to two different indoor environments for the determination of the optimum location of access points: simple and complex, as illustrated in Fig. 2 and Fig. 3, respectively [10].

The neural network model is designed to obtain signal strength at any particular location within a given environment in a very short time, while the indoor environment itself can also be searched rapidly for any particular location of an access point. In this way the optimum access point location, i.e. one that ensures sufficient signal strength at any arbitrary point, can be determined thanks to the functional dependence between quality signal coverage and access point location. In this case the arguments of the function are the coordinates of access point location, while the value of the function is that of space coverage with adequate signal strength, which depends on the environmental characteristics that influence signal propagation. All possible access point locations must be determined for the entire environment, with the accuracy of the obtained results depending on the density of the possible access point and receiver locations. The inputs to the model are the coordinates of the access point locations (more than one) and of the receiver locations that can be randomly distributed across the particular environment. Thus the cost function can be defined as the sum of the signal strengths weighted by the values that represent deviation from the given signal threshold at the receiving point (-76 dBm in our case). The cost function can be expressed as

$$f_c = -\sum_{i=1}^{N} \sum_{j=1}^{M} S_i\left(x_j, y_j, z_j\right) w_j\left(S_i(x_j, y_j, z_j)\right), \quad (1)$$

where N is the number of access point locations, M is the number of potential receiving points, S_i is the signal
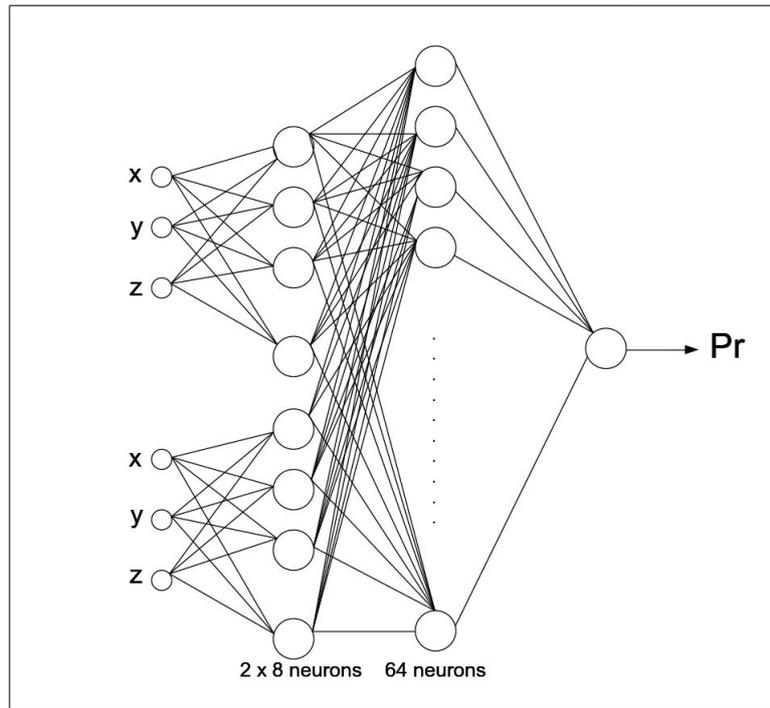
Fig. 1. The neural network model
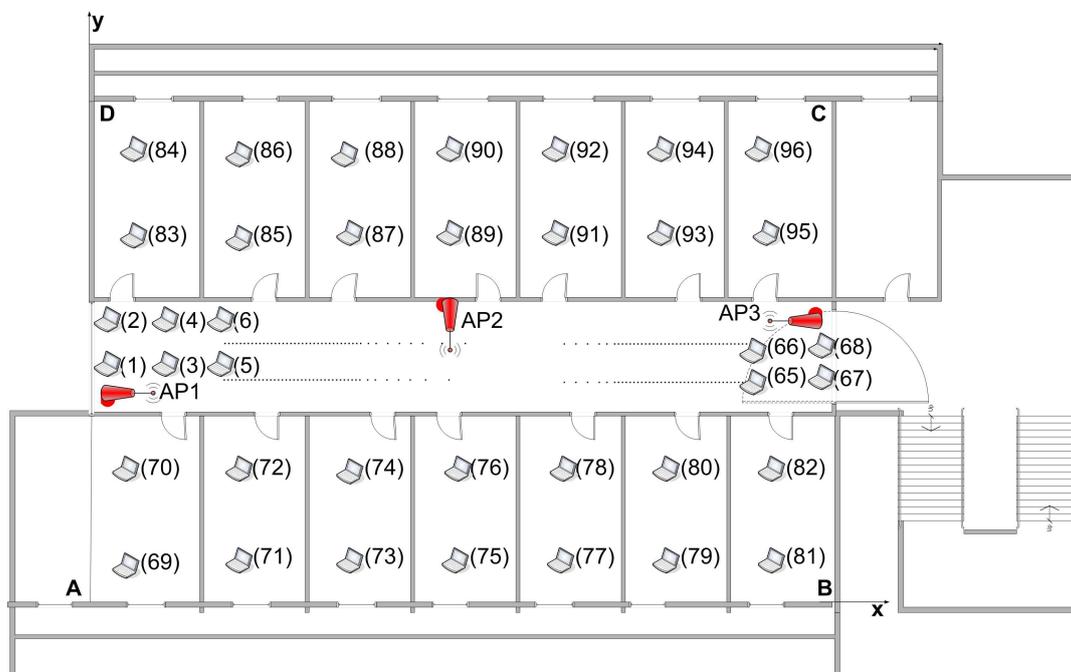
Fig. 2. Second-floor plan of the Dubrovnik University building showing the grid of measurement points and possible locations of access points – simplex environment
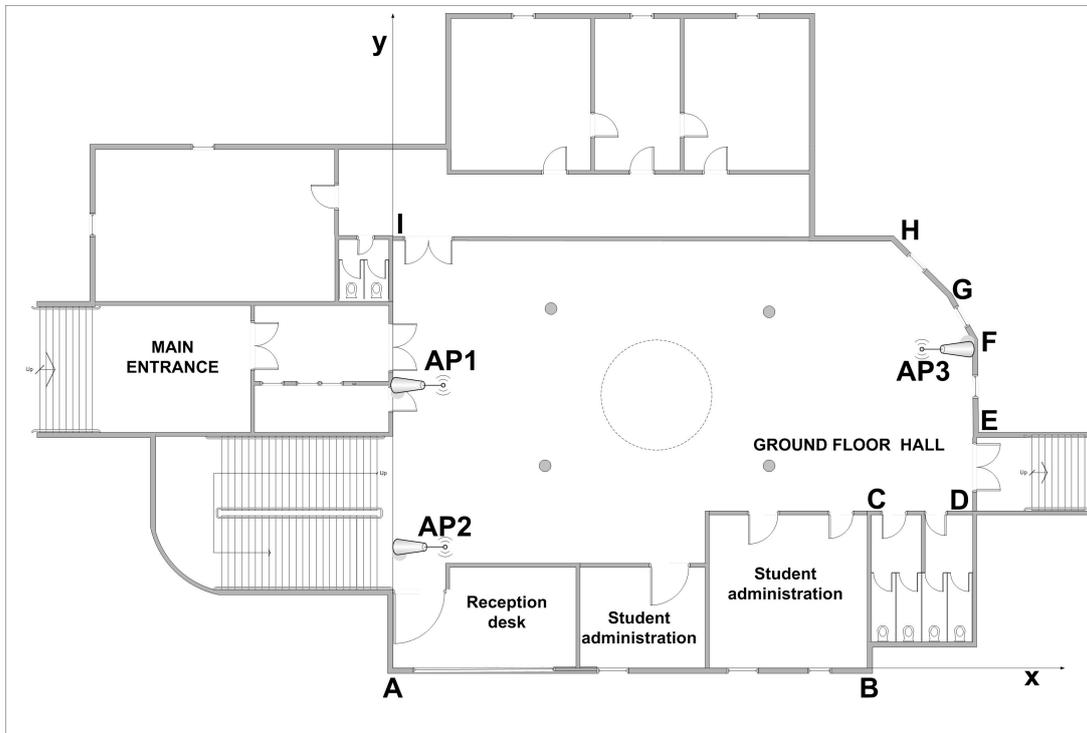
Fig. 3. Plan of the lobby at Dubrovnik University - complex environment
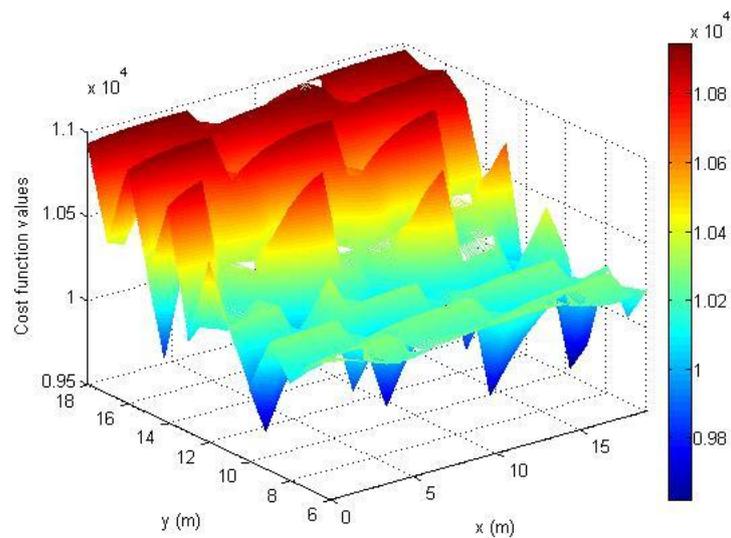
Fig. 4. Cost function for the assumed location of access point AP1

strength (dBm) received from access point i that is located at coordinates (x_i, y_i, z_i) and w_j is the weighted value of receiving point j. The weighted values can be expressed as follows:

$$
\begin{aligned}
S_i\left(x_j, y_j, z_j\right) &> -60 dBm &\rightarrow&\quad w_j = 1 \\
-60 \geq S_i\left(x_j, y_j, z_j\right) &\geq -76 dBm &\rightarrow&\quad w_j = 10 \quad (2)\\
S_i\left(x_j, y_j, z_j\right) &< -76 dBm &\rightarrow&\quad w_j = 100
\end{aligned}
$$

The above equations are used for calculation of the cost function, while the signal strength for every receiving point is obtained via the neural model. It is also necessary to determine the coordinates of the access point for which the cost function has minimal value. Signal coverage is neither smooth nor a derivable function of access point location. Very small changes in the receiver positions can cause great variation in signal strength, which in turn may result in the formation of many discontinuity points in signal strength across the space under consideration. These signal strength discontinuity points are distributed in an unpredictable manner and thus the classic optimization method cannot be applied. The cost function has many local minima, as can be seen in Fig. 4, which presents the scenario for the assumed location of an access point (AP1) and a limited number of receiving points (233) a distance of 1 m from each other, applied for the complex environment (Fig. 3). Signal strength was obtained by applying the neural model (Fig. 1) to the complex environment (Fig. 3). Analysis of Fig. 4 reveals the presence of many discontinuities and local minima that influence the optimization process significantly. According to these results, the optimization algorithm is very sensitive regarding starting conditions and thus the use of evolutionary algorithms is required.

3 EVOLUTIONARY OPTIMIZATION ALGORITHMS

3.1 Particle Swarm Optimization (PSO)

The PSO algorithm has already shown low sensitivity for local minima [7], while good results have also been obtained when applying the algorithm to certain electromagnetic problems [5]. Contrary to genetic algorithms, which are based on Darwin's theory of natural selection and competition among chromosomes, the model of swarm intelligent behaviour with change of position and velocity can be founded upon swarm behaviour (like bees) [10].

As with genetic algorithms, the system is populated by a specific number of particles (bees) which are randomly distributed across a solution space. Particle movement is determined by the random velocity associated with each particle. Moving across the solution space, each particle
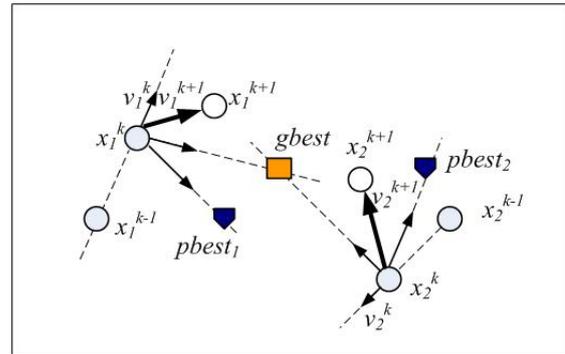
Fig. 5. The two particles searching solution space

not only 'records' its own best solution achieved so far (*pbest*), but also knows the best result achieved by the entire swarm (*gbest*). The behaviour of two particles is illustrated in Fig. 5. Particle *x1*, searching solution space at velocity v_1, changes position by moving from location k to location $k+1$. At the same time the particle changes the magnitude and direction of its velocity from v_1^k to v_1^{k+1}. The behaviour of the second particle x_2 is identical to that of the first. The personal best achieved result of particle x_1 is *pbest1* and that of particle x_2 is *pbest2*, while the best result of the entire swarm is *gbest*. These changes in location and velocity ultimately lead the particles toward the best solution.

The algorithm is generally applicable to n-dimensional space, so for particle movement of $k+1$ and the j-th coordinate component of the velocity of the i-th particle, particle velocity can be written

$$
v_{ij}^{k+1} = c_0 v_{ij}^k + c_1 r_{n1}\left(pbest_{ij} - x_{ij}^k\right) + c_2 r_{n2}\left(gbest_{ij} - x_{ij}^k\right) \tag{3}
$$

In (3) $i = 1, 2, ..., m$, where m is the size of the swarm, and $j = 1, 2, ..., n$, where n is the dimension of the space. As behaviour in nature is not completely predictable, some kind of randomness must be included in these quantitative considerations. To this end the adaptability of the swarm to various environments is quantified by multiplying constants c_1 and c_2 by the random numbers r_{n1} and r_{n2}. These random numbers need to be uniformly distributed between 0 and 1, while for the purpose of better convergence, values of 2 are recommended for constants c_1 and c_2 [7]. The random numbers (r_{n1} and r_{n2}) are vectors that ensure the randomness of the magnitude and direction of particle movement. The convergence of the swarm progresses more rapidly by including a so-called inertial weight, c_0. This inertial weight determines whether a particle stays on its current trajectory or is strongly pulled toward gbest (for higher values) or pbest (for lower values). It is also recommended for acceleration of convergence that the value of the inertial weight is linearly changed from 0.9 to 0.2 [5]. Another problem arises when a searching particle leaves
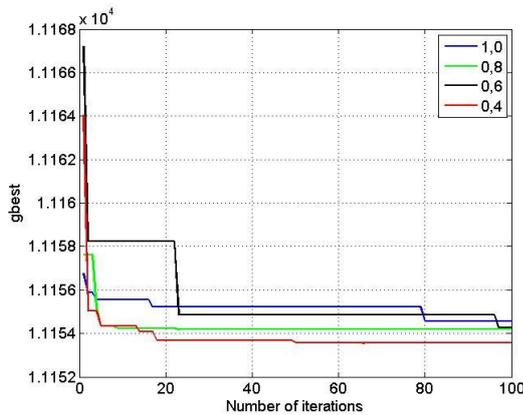
Fig. 6. Global optima for different values of time step
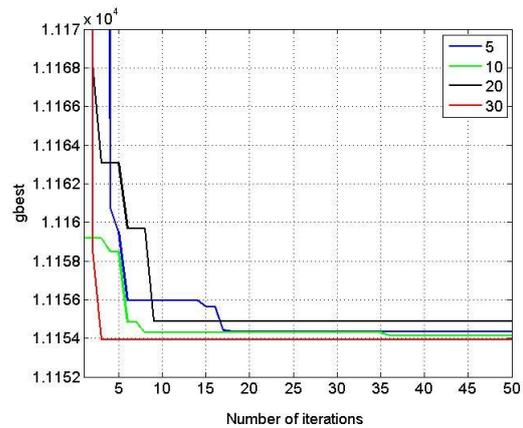
Fig. 7. Global optima for different populatin sizes

the solution space. One of the solution is to limit the maximum velocity. In our case it was set at 20% of the dynamic range of each particle dimension. The respective influences of inertial weight and maximum velocity on the optimization process were investigated separately, with the best results obtained by linearly decreasing inertial weight with limited maximum velocity.

The new particle location is given by

$$x_{ij}^{k+1} = x_{ij}^k + \Delta t \cdot v_{ij}^{k+1}, \qquad (4)$$

where Δt is the time step that is usually set at 1. In our case the cost function exhibited a lot of local minima (Fig. 4) and thus the solution space had to be searched in very short steps. Such a shortening of the time step results in a higher density of search points. Fig. 6 shows the influence of time step on the global optimum (*gbest*). The present investigation included four different values of the time step (1, 0.8, 0.6 and 0.4), with the best results obtained using the lowest value, since it resulted in the densest grid of solution points.

Population size had to be carefully determined, since too large a number of particles would increase computation time and would not contribute significantly to the results. Fig. 7 presents the results for four different population sizes (5, 10, 20 and 30). Convergence is achieved relatively rapidly for all populations, although the largest population resulted in faster convergence and thus a population size of 30 particles was chosen for the present study.

Further consideration is also required regarding the arrival of a particle at the solution space boundary, or even its complete exit from the space. Boundary conditions are commonly treated in one of three ways (Fig. 8): *absorbing wall*, *reflecting wall* and *invisible wall* [5]. An absorbing wall absorbs particle energy so that the latter's velocity in the dimension on the boundary becomes zero. The particle
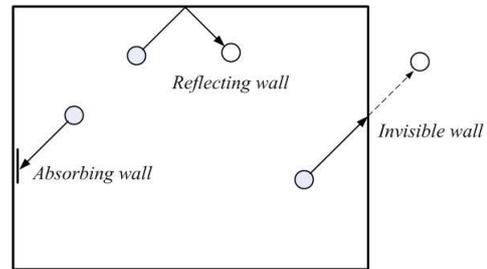
Fig. 8. Boundary conditions

then changes position in the other dimensions and is pulled back into the solution space by the next iteration. A reflecting wall reflects the particle from the boundary, changing the sign of the dimension of the particle on the boundary and bringing the particle back into the solution space. An invisible wall enables particles to leave the solution space; in this case the cost function is not calculated. There is the possibility that the particle may be either returned to the solution space or lost, but it is generally pulled back as pbest and gbest are located inside solution space. In the present study, boundary conditions were analysed experimentally, with the global best results considered for the three different boundary conditions mentioned above. For each application of the specific boundary condition, the optimization process was independently repeated 10 times. These results are presented as average values in Fig. 9. As can be seen from this figure, there were no significant differences between the three cases. The application of reflecting wall boundary conditions resulted in the lowest values of the cost function. Using this method, all particles are preserved and thus the search of the solution space is made in more detail, leading to a more accurate final result.
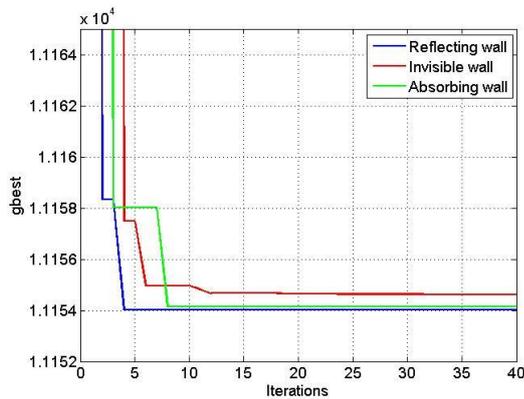
Fig. 9. The best global result for different boundary conditions

3.2   Ant Colony Optimization (ACO)

The ACO method is based on ant food searching behaviour. Travelling to a food area, ants select paths according to the pheromone level they give off on the ground, with the shortest path ultimately the one with the highest level of pheromones. In an artificial ant colony, each ant has the ability to choose its path according to transition probability, which is a function of path pheromone concentration and a parameter connected with cost function. The path along which an individual ant can move must be one it has never passed through within a particular iteration. A certain amount of pheromone is left on the path along which the ant travelled, the level of which gradually attenuates with time [8].

In the present case study, the classical ant algorithm had to be modified in order to solve the continuous optimization problem of base station positioning. As a solution space, a pheromone matrix is generated in which the matrix elements represent potential locations for ant movement. These matrix elements are also possible receiver locations. The ant population is randomly generated, with each ant associated with one matrix element. Each ant can then move to any other location according to the transition probability defined by

$$p_{ij}^k = \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{l \in N_i^k} [\tau_{il}]^\alpha [\eta_{il}]^\beta}, \qquad (5)$$

where τ_{ij} is the pheromone intensity of an individual ant at position j, and N_i^k all neighbouring positions of ant k at position i which cannot be visited by ant k. The value of the propitiatory of the new position is expressed by η_{il}, which corresponds to the cost function. The influence of pheromone concentration is expressed by parameter α, and cost function by parameter β, both of which are empirically determined. In the present case study we granted

Table 1. Parameters of the ACO algorithm

Parameter	Label	Value
Number of ants	m	30
Pheromone exponent	α	1
Heuristic exponent	β	10
Pheromone decay	ρ	0.02

more influence to the cost function. All of these parameters are presented in Table 1. After each change of ant position, pheromone concentration alters according to the expression

$$\tau_j^{new} = \tau_j^{current} + \Delta\tau_j^k, \qquad (6)$$

where $\Delta\tau_j^k$ is the pheromone quantity left by ant k at position j during its transition from position i to J. The result of ant movement is pheromone update, expressed as

$$\Delta\tau_j^k = \frac{1}{f_{cj}}, \qquad (7)$$

where f_{cj} is the value of the cost function at position j. The ultimate goal of the algorithm is to find the minimum value of the cost function. However, the pheromone levels decay over time if there are no new updates. The influence of such pheromone decay must therefore be introduced:

$$\tau_j^{new} = \rho\tau_j^{current} + \Delta\tau_j^k. \qquad (8)$$

The value of parameter ρ can be empirically obtained, and falls within the interval from 0 to 1 (Table 1).

The ACO algorithm converges more slowly than the PSO algorithm, as can be seen in Fig. 10.

4   WLAN ACCESS POINT LOCATION OPTIMIZATION

4.1   Simple environment

The parameters of the PSO algorithm for the studied environment (Fig. 2), as calculated according to the method outlined in section 3.1, are given in Table 2. The final value of the cost function is 11153.96, obtained after 15 iterations, while ACO algorithm converged after 25 iterations with higher value of cost function of 1.11567 (Fig. 11).

The coordinates of the optimum access point position obtained via the PSO algorithm are [12.91, 7.56, 2.4], as presented in Fig. 12. Detailed investigation of cost function values revealed several more local minima that were
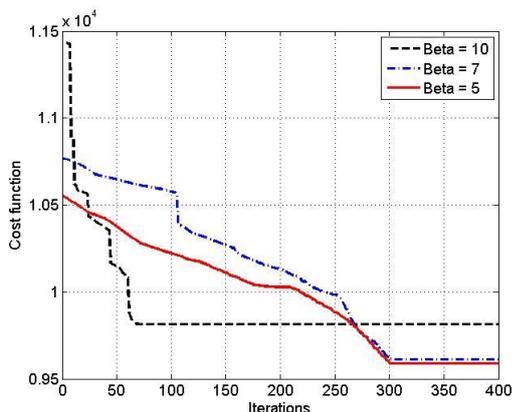
Fig. 10. Best values of the cost function during algorithm evolution
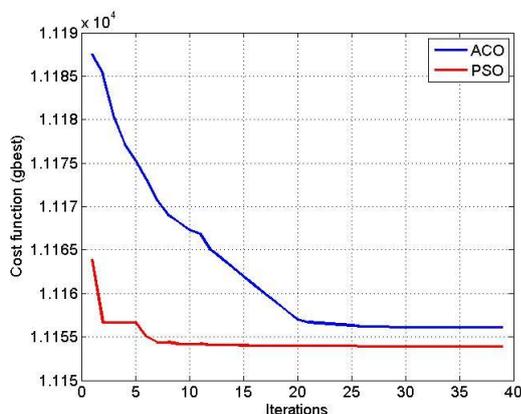
Fig. 11. The best global value after each iteration

Table 2. PSO parameters for the simple environment

Parameter	Value
Number of particles	30
Max. number of iterations	100
c_1	2
c_1	2
Inertial weight $c0$	Changes linearly $[0.9, 0.2]$
Time step	0.4
Boundary condition	*Reflecting wall*
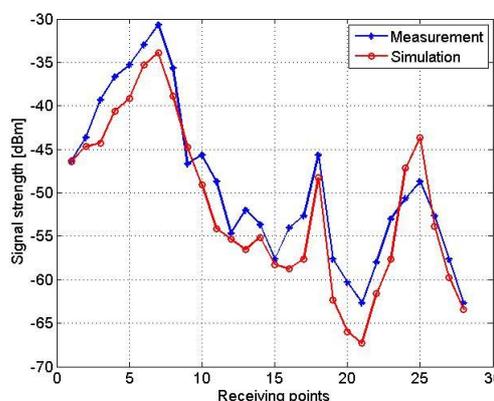
Fig. 13. Comparison of measured and simulated signal strength values for an optimally positioned access point

equal to six decimal places, with propagation prerequisites satisfied for all of these receiving points. Accordingly, the access point could be located at several other points along the corridor with the same result, as it is illustrated in Fig. 12, where red colour denotes optimal position of access point obtained by PSO algorithm, that is also valid for ACO algorithm because small difference between them.

The coordinates of the optimum access point position obtained via the PSO algorithm are $[12.91, 7.56, 2.4]$, as presented in Fig. 12. Detailed investigation of cost function values revealed several more local minima that were equal to six decimal places, with propagation prerequisites satisfied for all of these receiving points. Accordingly, the access point could be located at several other points along the corridor with the same result (Fig. 12).

Neural model simulation was performed for 28 randomly chosen receiving points that haven't been used in training process. The numerical results of these simulations give average absolute error of 3.166 dB, standard de-

viation of 1.6868 dB and mse of 3.587 dB. The graphical comparison of measured and simulated data regarding optimum access point position is illustrated in Fig. 13. The good correlation between the two is obvious; the mean squared error is 3.59 dB. The levels of the signal strength are much lower for the receiving points without line of sight, as it can be seen for the points from 18 to 22 and 27 to 28.

4.2   Complex environment

4.2.1   PSO algorithm

Although the studied complex environment (Fig. 3) is significantly larger than its simple counterpart, the determined PSO parameters were the same (Table 2). Variation in global optimum values during the optimization process is presented in Fig. 14. The cost function converges extremely rapidly (less than 40 iterations) and with very short computing time (less than 2 minutes).

The signal strength at 33 receiving points was simulated by the neural model according to Fig. 3. Deviation

Optimal position:
PSO: (12.91; 7.56; 2.4)
ACO: (12.03; 6.27; 2.4)
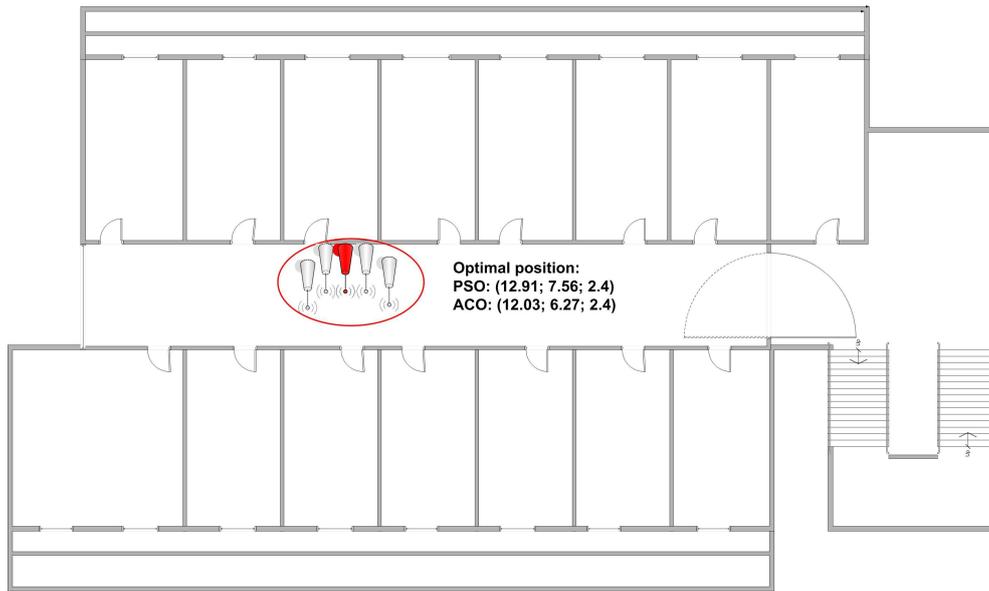
Fig. 12. *The optimum position of the access point for PSO and ACO algorithms*
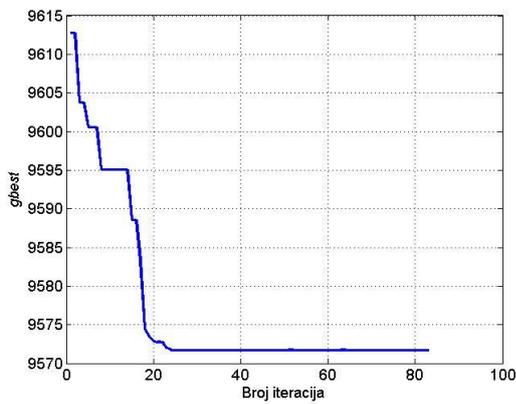
Fig. 14. *Change in the best global result during the optimization process*
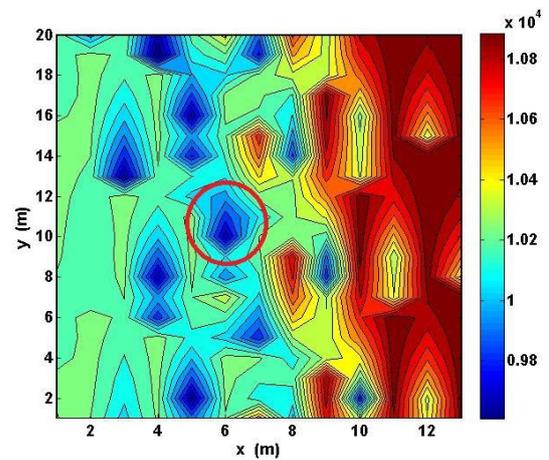
Fig. 15. *Contour diagram of cost function with denoted global minimum (red circle)*

from the measured values is as follows: average absolute error is 2.5223 dB, standard deviation is 1.5869 dB and mse is 2.98 dB. A graphical comparison of these values is presented in Fig. 17 for all 33 receiving points.

The determined optimum position ensures sufficient signal strength for every part of the environment, at a level significantly above the threshold (receiver sensitivity -76 dBm). This is confirmed by the contour diagram presented in Fig. 18, which shows measured signal strength values for the optimum position of the access point. The white area was not included in considerations since its usage does not require WLAN coverage (lavatory area).

The quality of signal coverage is presented by the bar diagram shown in Fig. 19, which includes data regarding all access points and associated coverage (Fig. 3). Environment signal strength for each access point position is associated with the receiving points covered. The optimally-positioned access point covers more than 92% of the total space with a signal strength of between -50 and -30 dBm, and more than 51% of the total space with a signal strength of between -50 and -40 dBm. It can therefore be concluded that the entire space is best covered in terms of signal strength by an access point located at the optimum position, with a slightly worse situation obtained by the other access point positions.

4.2.2 ACO algorithm

The ACO algorithm converges more slowly than the other two algorithms, PSO and GA (Fig. 20), and as a result the computer time required for program running is significantly longer. Coordinates of optimum position of the access point are $(5.10; 8.50; 2.75)$ and corresponding value of the cost function is 9589. Although the minimum value of the cost function does not deviate significantly from that obtained via the PSO algorithm, the coordinates of the optimum access point position differ by around 1 m. This difference can be expected given the existence of a great number of local minima.

In the case of the complex environment presented here, coverage with sufficient quality signal strength is obtained in spite of the aforementioned differences from the PSO-derived results. This is confirmed by the bar diagram shown in Fig. 21, with the use of the ACO algorithm resulting in fewer receiving points receiving a signal strength of between -40 dBm and -30 dBm (81.4%), but a larger number receiving a signal strength of between $\check{\ }60$ dBm and -50 dBm (14.29%)

4.2.3 Comparison of the results obtained by the different optimization algorithms

An effective comparison of the two different methods employed in the present paper requires the use of a third
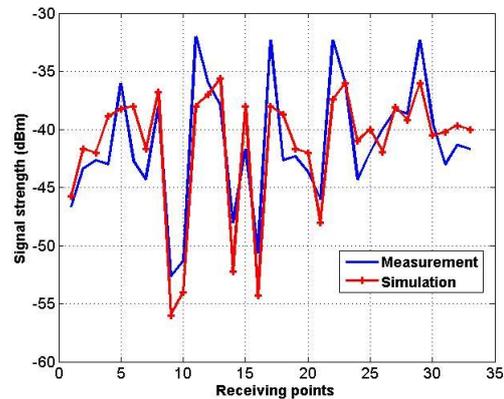
Fig. 17. Comparison between measured and simulated signal strength values for optimally positioned access point
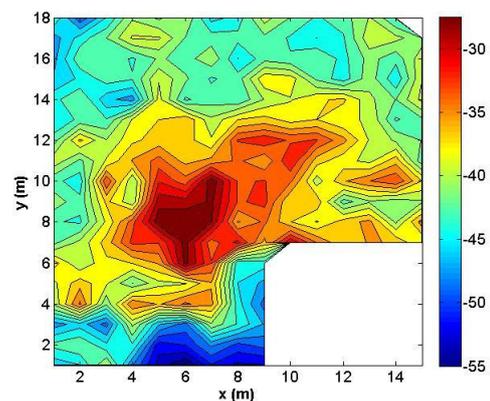
Fig. 18. Contour signal strength distribution diagram for optimum position of the access point
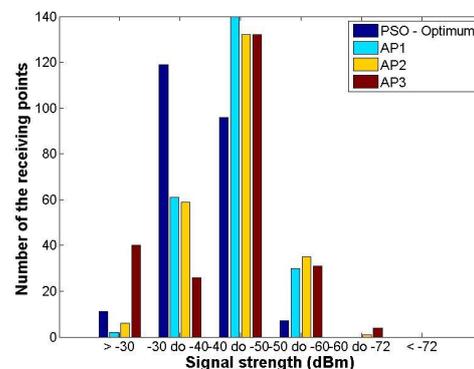
Fig. 19. Distribution of signal coverage for several access points, including that optimally positioned (PSO)
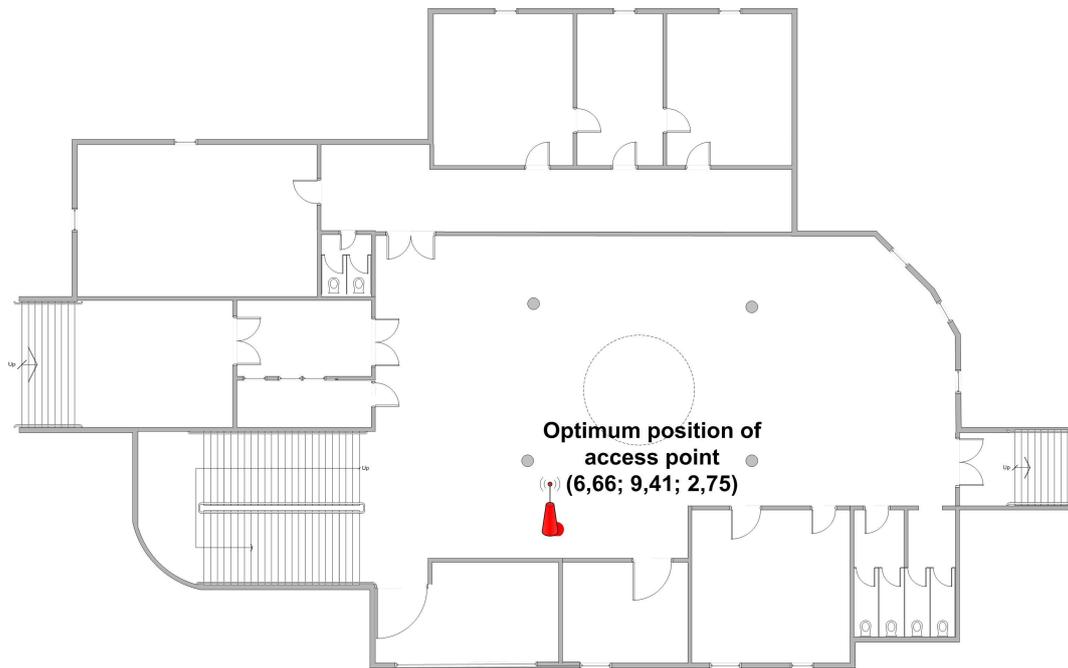
Fig. 16. Optimum position of the access point
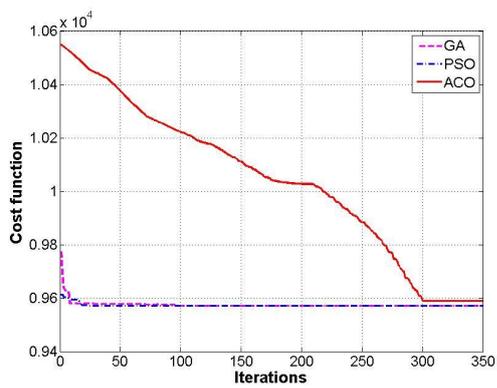
Fig. 20. Comparison of the best values of the cost function for the three optimization methods
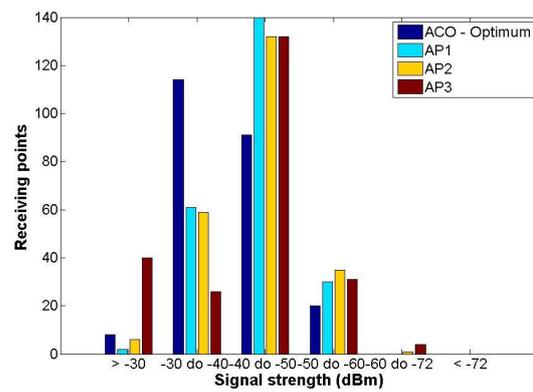
Fig. 21. Distribution of signal coverage for several access points including that optimally positioned (ACO)
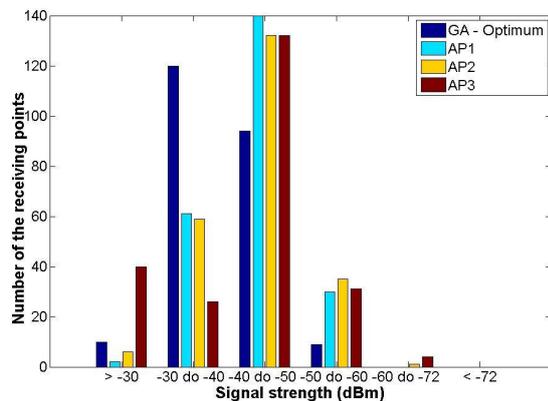
Fig. 22. Distribution of signal coverage for several access points, including that optimally positioned (GA)
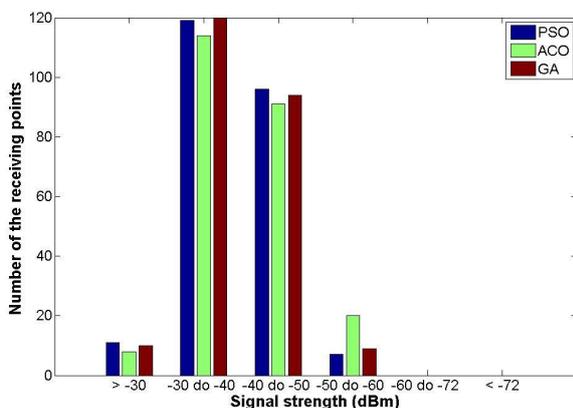
Fig. 23. Distribution of signal coverage for an access point optimally positioned via the three different optimization algorithms

as reference - in this case the genetic algorithm (GA). The latter was selected given its successful use in a number of applications, as well as its inclusion in available software (Matlab [11]). The distribution of signal coverage for an access point optimally positioned via GA is presented in Fig. 22. As can be seen from this figure, the results are nearly identical to those obtained by the PSO algorithm.

The distribution of signal coverage for an access point optimally positioned via the three different optimizing algorithms is presented in Fig. 23. Analysis of this figure reveals no significant difference between the PSO and genetic algorithm. Some discrepancies are apparent with respect to the ACO algorithm, but the results are acceptable.

A comparison of the three algorithms is summarized in Table 3. Besides the coordinates of optimum access point location and corresponding values of the cost func-

Table 3. Comparison of optimization results

Algorithm	Optimal position (x, y, z)	*gbest*	CPU time (sec)
PSO	$(6.6, 9.4, 2.75)$	$9.572 \cdot 10^3$	184.47
ACO	$(5.1, 8.5, 2.75)$	$9.589 \cdot 10^3$	814.44
GA	$(5.92, 8.96, 2.75)$	$9.573 \cdot 10^3$	189.25

tion, computing time is also included. As can be observed from this table, the main difference takes the form of a much longer computing time for the ACO algorithm.

5   CONCLUSION

The research presented in this paper reveals that analysis of propagation phenomena and optimization of base station position can be carried out without the need for complex and lengthy computations, as well as with a practically equal level of accuracy as that achieved by more deterministic methods. The most significant contribution made by this paper is the application of a relatively new algorithm in solving a propagation optimization problem. The main advantage of the ACO algorithm is its simplicity, providing both an easily obtainable and sufficiently accurate result. Although it is not as fast as either the PSO or genetic algorithm, its accuracy is certainly comparable. The selection of the main user-defined parameters for this type of problem was described here using an experimental method, a technique which could also potentially be helpful in other scenarios and fields.

The introduced method can be used to improve the performance of existing indoor wireless networks, as well as serving as a useful tool for wireless network planning in general.

REFERENCES

[1] G. Wolfe, F.M. Landstorfer, "Field Strength Prediction with Neural Networks for Indoor Mobile Communication", 47th *IEEE International Conference on Vehicular Technology,* pp. 82-86, May 1997.

[2] S. Hykin, *Neural Networks – A Comprehensive Foundation*, Prentice Hall, USA, 1999.

[3] F.M. Ham, I. Kostanic, *Principles of Neurocomputing for Science and Engineering*, McGraw Hill, New York, 2001.

[4] I. Vilovic, Z. Sipus, N. Burum, "Design of an Indoor Wireless Network with Neural Prediction Model", *Proc. of the 2ndEuropean Conference on Antennas and Propagation*, Edinburgh, UK, pp361-264, 2007.

[5] J. Robinson, Y. Rahmat-Sammii, "Particle Swam Optimization in Electromagnetics", *IEEE Trans. on Antennas and Propagation,* vol. 52, No. 2, Feb. 2004.

[6] D.E. Goldberg, *Genetic Algorithms in Search Optimization, and Machine Learning*, Addison-Wesley, Reading MA, 1989.

[7] R.C. Eberhart, Y. Shi, "Particle Swarm Optimization: developments, applications, and resources", *Proc. 2001 Congr. Evolutionary Computation*, vol. 1, 2001.

[8] M. Dorigo, V. Maniezzo, A. Coloni, "Ant system: Optimization by a colony of cooperative agents", *IEEE Trans. on System, Man, and Cybernetics-Part B*, vol. 26, pp. 29-41, Feb. 1996.

[9] E. Rajo-Iglesias, O. Quevedo-Tenel, "Linear Array Synthesis using an Ant Colony Optimization Base Algorithm", *IEEE Antennas and Propagation Magazine,* vol. 49, No. 2, pp. 70-79, 2007.

[10] I. Vilovic, "Predviđanje jakosti elektromagnetskog polja u lokalnim bežičnim mrežama zasnovano na neuronskom modelu I optimizaciji rojem čestica", Doctoral thesis, 2008, (in Croatian).

[11] www.mathworks.com/products/matlab

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