IZVORNI ZNANSTVENI ČLANAK / *ORIGINAL SCIENTIFIC PAPER*

SIGNAL STRENGTH PREDICTION IN INDOOR ENVIRONMENTS BASED ON NEURAL NETWORK MODEL AND PARTICLE SWARM OPTIMIZATION

Predviđanje snage signala u zatvorenim prostorima zasnovano na modelu neuronske mreže i optimizaciji rojem čestica

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Abstract

This paper deals with an indoor propagation problem where it is difficult to rigorously obtain the field strength distribution. We have developed a propagation model based on a neural network, which has advantages of deterministic (high accuracy) and empirical (short computation time) approaches. The neural network architecture, based on the multilayer perception, is used to absorb the knowledge about the given environment through training based on measurements. Such network then becomes capable to predict signal strength that includes absorption and reflection effects without additional computation and measurement efforts. The neural network model is used as a cost function in the optimization of the base station location. As optimization algorithm we have applied the particle swarm optimization (PSO) algorithm, i.e. a global optimization routine based on the movement of particles and their intelligence. Appropriate PSO parameters are discussed in the paper, and the results of PSO are compared with results obtained with two standard algorithms such as simplex optimization method and Powell's conjugate direction method.

Keywords: Indoor propagation, Neural network, Particle Swarm Optimization.

Sažetak

Ovaj se članak bavi problemom rasprostiranja elektromagnetskih valova u zatvorenom prostoru, gdje je teško potpuno točno dobiti razdiobu polja. Razvili smo model rasprostiranja zasnovan na neuronskoj mreži, koja ima prednosti pred determinističkim (točnost) empirijskim (vremenski kraća) pristupima. Odabran je višeslojni perceptron za apsorbiranje znanja o danom prostoru preko učenja zasnovanoga na mjerenjima. Tako naučena mreža sposobna je predvidjeti snagu signala, uključujući efekte refleksije i apsorpcije bez dodatnih računanja i mjerenja. Neuronska mreža je upotrijebljena kao ciljna funkcija u postupku optimizacije položaja bazne stanice. Kao optimizacijski algoritam primijenili smo algoritam roja čestica (PSO), što je globalna optimizacijska rutina zasnovana na gibanju čestica i njihovoj inteligenciji. Razmatrani su pojedini PSO parametri, pa su rezultati PSO algoritma uspoređeni s rezultatima dobivenima s dva standardna optimizacijska algoritma, kao što su simpleksna metoda i Powellov algoritam.

Ključne riječi: rasprostiranje u zatvorenom prostoru, neuronska mreža, optimizacija rojem čestica.

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INTRODUCTION / *Uvod*

The popularity of indoor wireless communication systems - phones, hand-held terminals, various PDA devices - are constantly increasing. These portable devices tend to be mobile and in principle can be located anywhere, while base stations need to provide good link to the communications backbone of the system. The base stations need to be positioned carefully so that they cover the building with appropriate signal level. In general, problem can be reduced to given building, where we need to answer the questions like: how many base stations will be needed, on which positions will they be placed to cover the building with minimum power level?

Absence of real accurate method for the signal strength prediction in indoor environment [1] enables usage of the neural network methods in this area. The usage of neural networks for signal strength estimation in indoor communication is not new, and there are a number of articles referring about applying different neural network models for propagation parameters estimation with different results. Some authors introduced the dominant paths [2], [3], [4], [5] to simplify the propagation problem, especially for eliminating the time-variant effects. The information about reflection and diffraction points is not included in dominant paths, just the direction of the path. The deficiency of this approach is in the need of determination of a dominant path for each prediction point. In other words, a rather accurate data base of building geometry is needed to achieve good results. The multilayer perception with standard back propagation algorithm is used for field strength estimation along dominant paths. Inputs to neural network include (besides geometrical position data) data of visibility among the transmitter and receiving point and shape of room, as well as number of walls through which electromagnetic ray passes. The results show acceptable accuracy, with prediction mean error of about 8dB [4].

Two different neural network models for prediction of propagation loss were compared in [6]. The comparison of multilayer perception and radial basis function network showed something better performance of the first one.

In ref. [7], the algorithm for field strength prediction of wireless signal propagation, based on neural network approach, is presented. Two propagation model are proposed, the first based on the ray tracing technique and the second assumes that all received power can be weighted sum of coherent power blocks. The convergence of the neural network is not achieved in the case of the first propagation model, while in the second case the results are not worse than empirical ones.

In our approach we try to predict signal strength in indoor wireless communication in given environment without any detail knowledge about building geometry and construction characteristics.

Our indoor environment is rather difficult for ray-tracing calculation because of its irregular shape and a lot of different objects inside (different information tables, boat with sail, pots with palms…). The relevant network architecture is trained for determining receiving signal on randomly distributed locations from three base stations located on different places. As this neural network model showed very good generalization characteristics, it is used to produce relevant values of cost (objective) function for coverage and interference limited environments. We utilize the penalty function approach. The accuracy of the cost function is critical for usefulness of our approach, so the propagation and fading environment need to be correctly modeled.

Such trained neural network is used for predicting the field strength distribution as well as for prediction of the optimum base station position. Different optimization methods are used for determining the optimum locations for the base stations that must meet a given performance criterion. The unconstrained optimization techniques are selected according to the penalty function approach. The Particle Swarm Optimization (PSO) algorithm [9] (representative of global optimization algorithms) is compared with results of the downhill simplex method and Powell's conjugate direction method [8]. PSO has been presented as effective method in optimizing complex multidimensional problems. In particular, successful application of this method to antenna design has been shown [9], [10]. In our case, we were faced with multiple local optima. The problem is overcome by fine tuning the parameters of the each optimization algorithm.

NEURAL PROPAGATION MODEL AND MEASUREMENT SETUP / *Neuronski model rasprostiranja i mjerni postav*

The ground floor of Dubrovnik University building is chosen for simulation environment. The part of the floor under consideration is bordered by points ABCDEFGHI, Fig. 1, which area is 323 m^2 and height is 3 m. The origin of the coordinate system is located in the left lower corner as it is shown in the Fig. 1. The locations of base stations are denoted by AP1, AP2 and AP3. The height of the base stations was fixed on 2.75 m above the floor, so there is no need for this coordinate in the calculations. The base stations are Cisco Aironet 1100 that supports 802.11g standard with data rates up to 54 Mbps. Locations (coordinates) of base stations are shown in the Table 1. The walls are made of the bricks with large windows in aluminum frames. The doors of side rooms are made of

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wood, while the ceiling is covered with metal plasters and floor are made of the stone blocks.

Measurements of the received signal strength for the various locations of the receiver and each base station (Fig.1) have been made in the first step. The each WLAN access point was operating on the 4th channel at 2.427 GHz (100mW). The signal strength measurements were made by a laptop computer with PCMCIA wireless card positioned 1.2 m above the floor. The measurements were performed for 233 receiving points (locations) that were 1 m apart from each other. Three measurements were made for each location and mean value was saved with location coordinates. These values were used in the training and testing of the neural network.

Table 1. The coordinates of base stations
Tablica 1. Koordinate baznih stanica

Base station	x	y
AP1	0.0	12.0
AP2	0.0	4.0
AP3	19.2	16.0

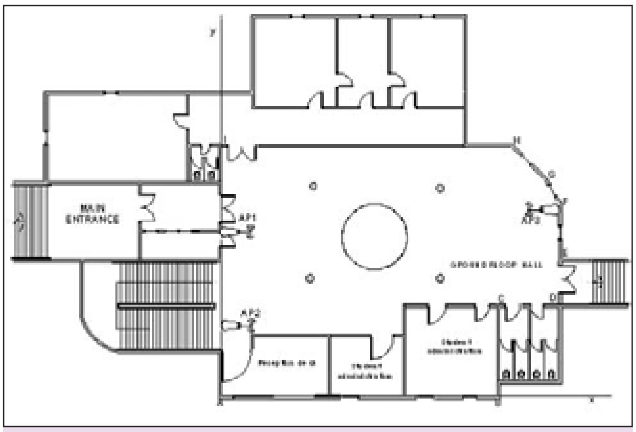

Fig. 1. Plan of the university building ground floor
Slika 1. Skica tlocrta prizemlja sveučilišne zgrade

According to the recommendations from [10] we have chosen the multilayer perception (MLP) for the neural model, shown in the Fig. 2 with two input layers and two hidden layers. The number of neurons in hidden layers is obtained by searching the best convergence of the network during training process. The input layers have location coordinates of base stations (AP1, AP2, and AP3) and receiving points as inputs. The network has one neuron in output layer for obtaining relevant signal strength value. The activation function in hidden layers is sigmoidal type, while simple linear function is used in the output layer.

Such neural network architecture is trained by Levenberg-Marquardt and Bayesian algorithm, and the latter one showed better generalization. In more details, a regularization approach is selected to modify the network performance function, and it is defined as the mean sum of squares of errors on the training set [12]. If the network performance function *mse* is defined as

$$mse = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \qquad (1)$$

where t_i and a_i are target and actual output value of *i-th* neuron, it can be modified by adding a term that consists of the mean of the sum of squares of the network weights and biases (*msw*):

$$mse_{reg} = \rho \cdot mse + (1-\rho)\cdot msw \qquad (2)$$

where ρ is performance ratio $(\rho \in [0,1])$, and

$$msw = \frac{1}{M}\sum_{j=1}^{M} w_j^2 \qquad (3)$$

Here w_j is the *j-th* weight of *M* synaptic connections. The optimum value of performance ratio parameter is difficult to determine, and proper regularization depends on it. The overfitting may be the result for too large values of this parameter, and for too small performance ratio the network will not converge. The Bayesian regularization solves this problem [13]. The activation function in hidden layers is sigmoidal type, while simple linear function is used in the output layer. For training purpose, 200 receiving locations are randomly chosen, and additional 33 locations are selected for network testing.

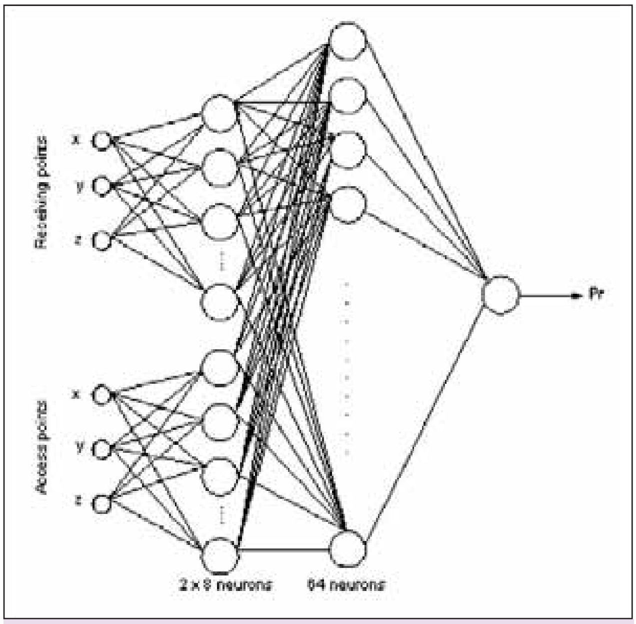

Fig. 2. Neural network architecture
Slika 2. Neuronska mreža

Neural network simulation results for base stations AP1, AP2 and AP3 are shown in Figures. 3, 4 and 5.

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Simulated curve follows measured one rather well. The measure of quality of obtained results is shown by mean squared error (*mse*) and cumulative error. The cumulative error is defined as

$$ce = \frac{|T(x,y) - A(x,y)|}{T(x,y)} \qquad (4)$$

where T(*x,y,z*) are target values, and A(*x,y,z*) are actual values of signal strength as function of receiver location. The mean squared errors and cumulative errors for three cases are given in the Table 2. The results obtained for base stations AP1and AP2 enable satisfied signal strength prediction at any point. The simulation results for base station AP3 shows the highest errors, but even with these results is possible to satisfactory predict signal strength.

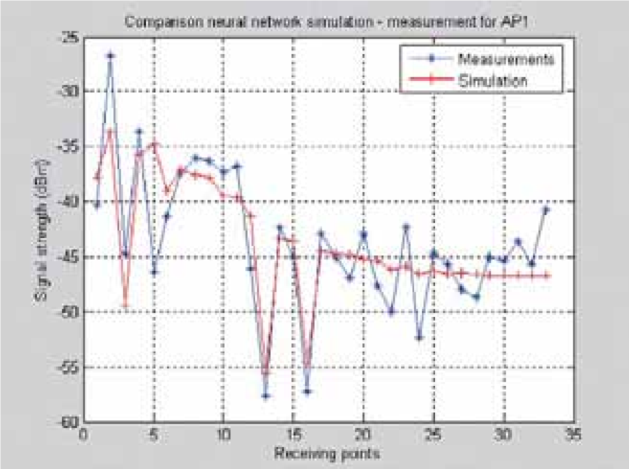

Fig. 3. Comparison of neural network simulation and measurement for base station AP1
Slika 3. Usporedba rezultata dobivenih neuronskom mrežom i mjerenjem za AP1

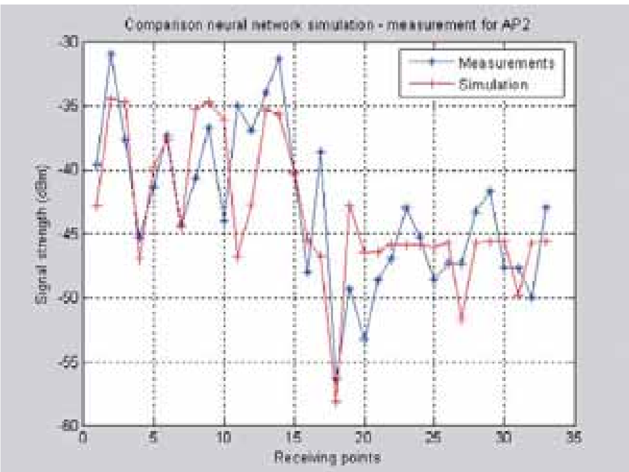

Fig. 4. Comparison of neural network simulation and measurement for base station AP2
Slika 4. Usporedba rezultata dobivenih neuronskom mrežom i mjerenjem za AP2

Table 2. *mse* and cumulative simulation errors for various base stations
Tablica 2. Srednja kvadratna i kumulativna pogreška

Base station	*mse*	*ce*
AP1	3.55	0.0592
AP2	4.07	0.0708
AP3	6.27	0.1059

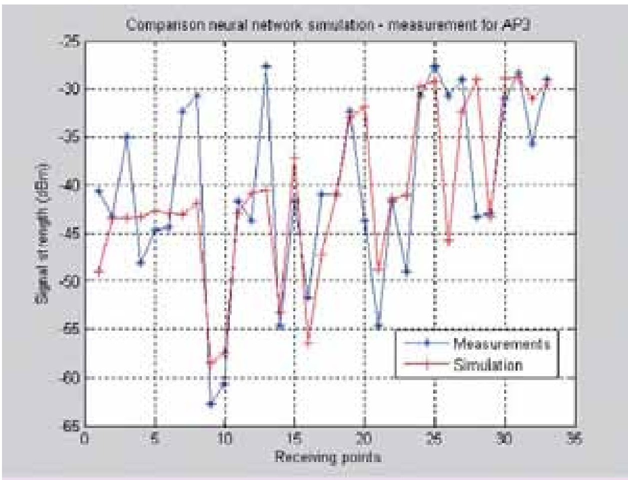

Fig. 5. Comparison of neural network simulation and measurement for base station AP3
Slika 5. Usporedba rezultata dobivenih neuronskom mrežom i mjerenjem za AP3

BASE STATION OPTIMIZATION / *Optimizacija bazne stanice*

A cost function based on neural network model / *Ciljna funkcija zasnovana na neuronskom modelu*

In order to find optimal location of a single transmitter for a given distribution of receivers, we need to develop a numerical representation for the quality of signal coverage over the given space as a function of the transmitter location. To obtain such function we need to divide given space into grid of possible receiver and transmitter locations. The density of the grid is determined by the desired accuracy. The trained neural network is used to determine signal level on any receiver location wherever base station was located. According to such approach cost function is presented as sum of all weighted relative signal level predictions (dBm) along with a penalty value that represents a violation in a maximum tolerated path loss threshold at receiver location, what in our case was receiver threshold (-72 dBm for 54 Mbps). The cost function, then, can be expressed as

$$f_i = -\sum_{i=1}^{N} \sum_{j=1}^{M} S_i(x_j, y_j) w(S_i(x_j, y_j)) \qquad (5)$$

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where N and M are the number of possible locations of base stations and receiving points respectively. S_i is relative signal level (dBm) received from base station i at location with coordinates (x_j, y_j) while w_j is relevant priority weight ascribed to the jth receiver location, and it makes constraints in cost function. This constraint requires that the quality of signal coverage at each receiver location over a given space must be above a given threshold value (-72 dBm). In our case the value of weight w_j is obtained as

$$w_j = \begin{cases} S_i(x_j, y_j) > -60dBm & w = 1 \\ -60 \geq S_i(x_j, y_j) \geq -72dBm & w = 10 \\ S_i(x_j, y_j) < -72dBm & w = 100 \end{cases}$$

The cost function as a function of two variables (x, y), that represent location of base station, is calculated according above rules where relevant signal levels are obtained from neural network trained model. The coverage is not smooth or differentiable function of the base station locations, so received signal strength may exhibit discontinuities because very little change in base station location can cause great change in received signal strength that is caused by completely different pattern of reflected, transmitted and diffracted rays. We need to expect a lot of such discontinuities in the case of real indoor environment.

The mentioned reasons make such cost function extremely limited in accuracy when it is calculated for limited number of grid points. As in our method the cost function is calculated from neural network propagation model, there are no limits in grid points i.e. the received signal strength can be calculated for any number of points in the given space in the optimization process. The optimization process is performed through the searching for the minimum of cost function. We have used three different methods in optimization process that will be described in next sections.

Direct Search Methods / *Metode izravnog pretraživanja*

As presented cost function incorporates constraints, unconstrained optimization technique will be used. The described properties of cost function determine which optimization procedure will be the most appropriate, and according to that we should use an optimization method that is not gradient based. Such algorithms are known as direct search methods. Here we consider two of them the Simplex Search method [8] and Powell's conjugate direction method [8]. Actually, we used the results of these two methods for comparison with the result of the Particle Swarm Optimization (PSO) algorithm [9].

The Simplex Search method is an evolutionary optimization approach that starts with initial simplex which is a polyhedron of $n+1$ vertices where n is the dimension of the problem [8]. Powell's conjugate direction method provides optimization of a general n-dimensional quadratic objective function through n searches [8]. The important aspect of optimization algorithms is how well they can handle multiple local minima, because we expect many local minima in our cost function as consequence of the propagation environment. The technique of Simplex Search method is less susceptible to the local minima problem than Powell's conjugate method. It is impossible to overcome this problem completely. There is possibility to restart optimization procedure with an alternative initial position and run algorithm again to verify are the same optimum values achieved.

Particle swarm optimization (PSO) algorithm / *Optimizacijski algoritam roja čestica*

The PSO, although originally invented for research on simulating the movement of the swarm in 2-dimensional space, as an optimization method can be applied in n-dimensional space [10]. The particles are defined with its own position x and velocity v, and with personal best result so far (*pbest*). The key element of the entire optimization is the changing of particle's velocity [9]. For the $k+1$ particle movement, the j-th coordinate component of velocity i-th particle, we can write for the particle velocity

$$v_{ij}^{k+1} = c_0 v_{ij}^{k} + c_1 rand_1 (pbest_{ij} - x_{ij}^{k}) + \\ + c_2 rand_2 (gbest_{ij} - x_{ij}^{k}) \quad (6)$$

In above equation $i = 1,2,\ldots.m$, where m is the size of the swarm; $j = 1,2,\ldots.n$, where n is dimension of the space; c_0, c_1, and c_2 are positive constants that scale the old velocity and increase new velocity toward *pbest* (local best result) or *gbest* (global best result), respectively. $rand_1$ and $rand_2$ represent random number that is uniformly distributed in interval [0,1]. The parameter c_0 is called "inertial weight" and it determines does the particle will stay on its current trajectory or it will be strongly pulled toward *pbest* or *gbest*. Its value is between 0 and 1. The new particle location is given by

$$x_{ij}^{k+1} = x_{ij}^{k} + \Delta t v_{ij}^{k+1} \quad (7)$$

The new velocity is applied after some time-step Δt, which is usually one. In other words, particles exchange information about results they obtained, so they know

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the best of all results so far. According to this information they accelerate in the direction of the global best result (*gbest*) and in the same time toward its own best result (*pbest*), so their trajectory is altering between these two goals depending on what direction prevails.

A proper selection of parameter values is very important to obtain qualitative result. We can find different proposals for inertial weights and other constants in articles of various authors. Considering suggestions of several authors and experimenting PSO algorithm with different parameters we got best result when inertial weight c_0 was changed linearly from 0.9 to 0.2 during the run of algorithm. In this way we got that in the beginning of the algorithm run particle is less pulled toward *pbest* and *gbest*, but after a number of iterations they are more rapidly pulled toward these values, what illustrates Fig. 6 for three different values of c_0. Higher value of c_0 means faster move toward *gbest*, faster convergence, but less accuracy.

For the constants c_1 and c_2, value of 2 is used, but in our case where very little change in coordinates may result in great change in cost function value, the time step needs to be chosen carefully. Considering chosen values for c_0, c_1, c_2 and examining equations (7) and (8), we have chosen 0.4 for the time step value.

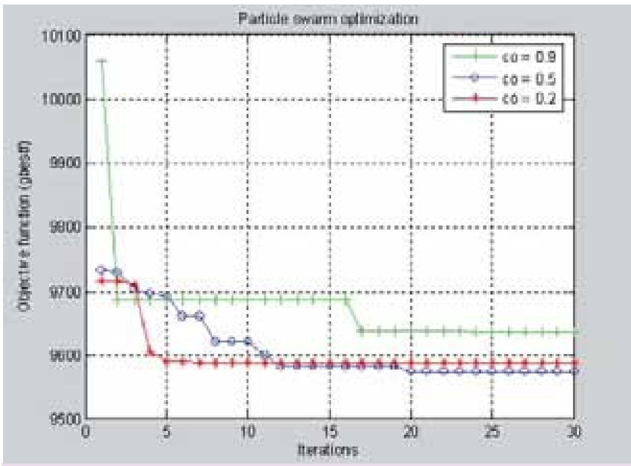

Fig. 6. Cost function for different inertial weights
Slika 6. Ciljna funkcija za različite inertne težine

We carefully selected population size among large populations with a lot cost function evaluations and longer computation time, and smaller populations that give the result much faster. It was determined by many parametric studies [10] that relatively small populations can efficiently explore the space under consideration, so population of 30 particles is used in our algorithm. This result is outcome of our investigation for different populations as it can be seen in the Fig. 7. In the Fig. 8 the three common known boundary conditions are analyzed. Among the suggested boundary conditions, introduced by various authors, we have selected so-called “reflecting wall” to avoid moving the particle out from the given space [10].

Optimization results / *Rezultati optimizacije*

The computer programs for considered three optimization methods and cost function evaluation have been developed. It is necessary to emphasize that the accuracy of final results depends on accuracy of the signal strength estimation obtained by described neural model. The results are presented in the Table 3.

The *n* in Table 3 denotes number of evaluations of the cost function during algorithms run, while other data are relevant locations of base stations (*Result*) and the values of cost function (*f*) at the optimum locations. As a *simplex* is the geometrical figure consisting of four points (number of dimensions +1) [8] it is a need to have four starting points that can be obtained as $P_i = P_0 + \lambda e_i$, where P_0 is initial starting point (0, 4.85), e_i's are unit vectors, and λ is a constant that defines length scale (16 in our case). The initial point in the Powell's method is located at the left boundary of the given space.

All three methods give very similar results. The PSO algorithm shows better performance than two others, which is manifesting in less iterations, and the lowest value of cost function. Note that all three methods satisfy the coverage requirements (i.e. that the field strength is larger than -72 dBm).

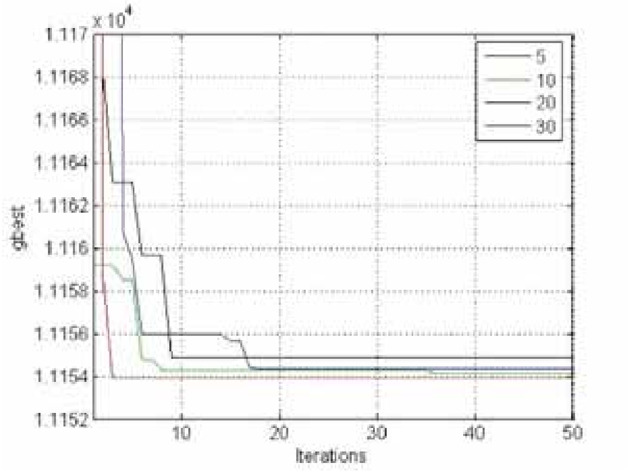

Fig. 7. The best global result for different populations
Slika 7. Najbolji globalni rezultat za različite brojeve čestica

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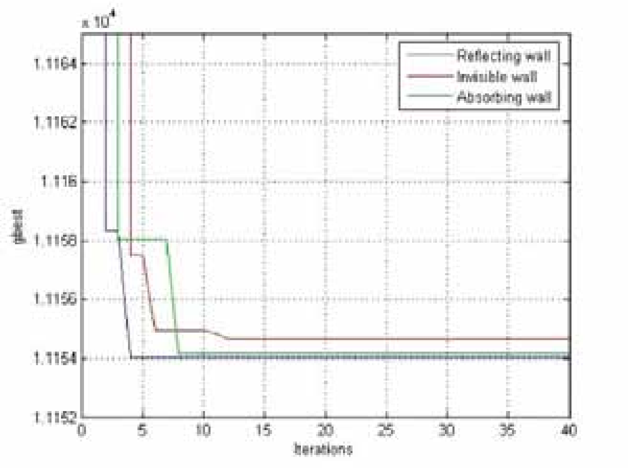

Fig. 8. The best global results for three different boundary conditions

Slika 8. Najbolji globalni rezultati za tri rubna stanja

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Table 3. Optimization results obtained by three methods

Tablica 3. Rezultati optimizacijskih postupaka

Simplex method			Powell's method			PSO		
n	*Result*	*f*	*n*	*Result*	*f*	*n*	*Result*	*f*
595	(7.48, 10.37)	$9.66 \cdot 10^3$	59	(6.62, 9.40)	$9.63 \cdot 10^3$	30	(6.66, 9.43)	$9.60 \cdot 10^3$

CONCLUSION / *Zaključak*

In this paper the field strength prediction in the indoor environment and optimization of the base station location are studied without introducing complex and lengthy computations. The analysis method is based on the neural network (as a propagation model) and Particle Swarm Optimization (PSO) algorithm (as an optimization algorithm for determining the base station location). The advantage of neural network model is that there is no need for a large database with detailed construction and electromagnetic parameters of the building. The algorithm itself is quite fast, and even the training process is relatively short (10 - 15 min). It is important to emphasize that the accuracy of the neural network model is comparable to the accuracy of the deterministic and empirical propagation models. The advantages of PSO algorithm are the robustness in overcoming local minima problem and its simplicity, i.e. in comparison with Simplex Search and Powell's method, PSO is faster and more accurate. The introduced model can be used for improving the performances of existing indoor wireless networks, and it can serve as a good tool for wireless network planning in general.

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