

Indoor Field Strength Prediction Based on Neural Network Model and Particle Swarm Optimization

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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, optimization, particle swarm.

1. Introduction

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 should provide a good link to the backbone of the communication 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 on questions like how many base stations will be needed, on which positions they will 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. Information about reflection and diffraction points is not included in dominant paths, just the direction of the path. This approach has a drawback and there is a need for determining the 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 backpropagation algorithm is used for field strength estimation along dominant paths. Inputs to the 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 electromagnetic field strength prediction, based on neural network approach, is presented. Two propagation model are proposed, first based on the ray tracing technique and second assumes that all received power can be expressed as 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 using the measured field strength from three base stations at randomly distributed locations. Such trained neural network is used for predicting the field strength distribution as well as for prediction of the optimum base station position. 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.

2. Neural Propagation Model and Measurement setup

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 m² 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, and the height of the base stations was fixed on 2.75 m above the floor. 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 wood, while the ceiling is covered by metal plasters and the floor is 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. There were made three measurements for each location and mean value was used as the field strength at the considered locations. These values were used in the training and testing of the neural network.

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 level. 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

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

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 (m_{sw}):

$$m_{se}_{reg} = \rho \cdot m_{se} + (1 - \rho) \cdot m_{sw} \quad (2)$$

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

$$m_{sw} = \frac{1}{M} \sum_{j=1}^M w_j^2 \quad (3)$$

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.

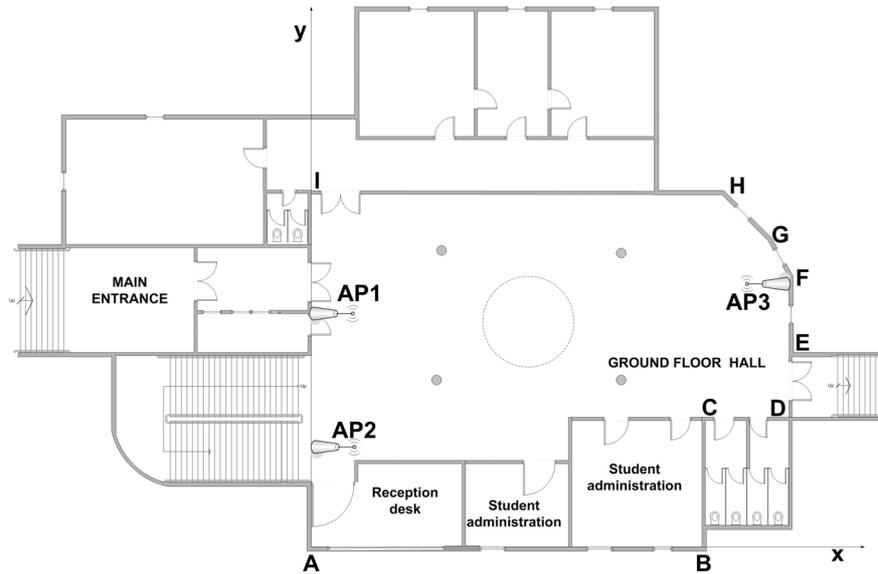


Fig. 1. Plan of the university building ground floor

Table 1. The Coordinates of base stations

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

Neural network simulation results for base stations AP1, AP2 and AP3 are shown in Fig. 3. Simulated curves follow the measured ones rather well. The measure of quality of obtained results is shown by mean squared error (m_{se}) and cumulative error. The cumulative error is defined as

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

where $T(x,y,z)$ are target values, and $A(x,y,z)$ are actual values of signal strength as function of receiver location.

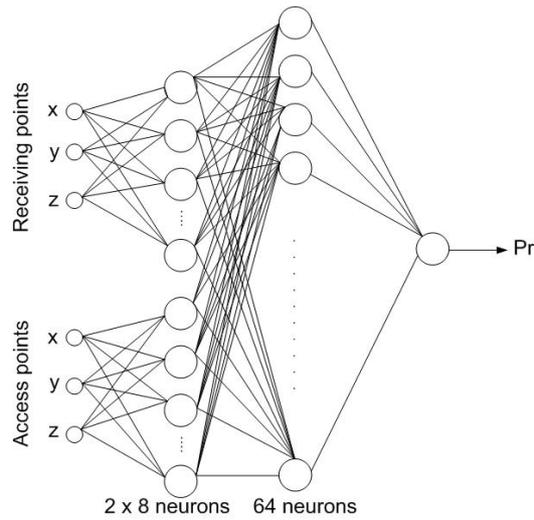
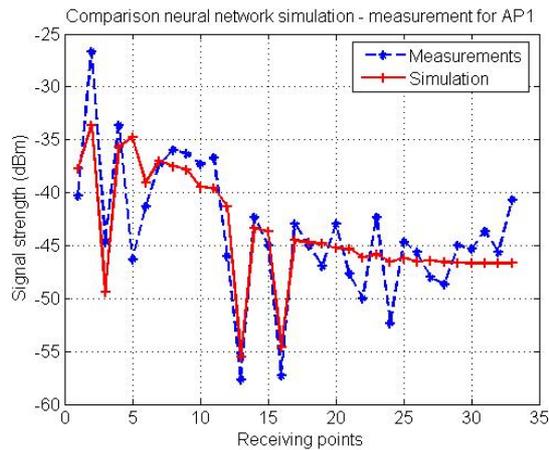
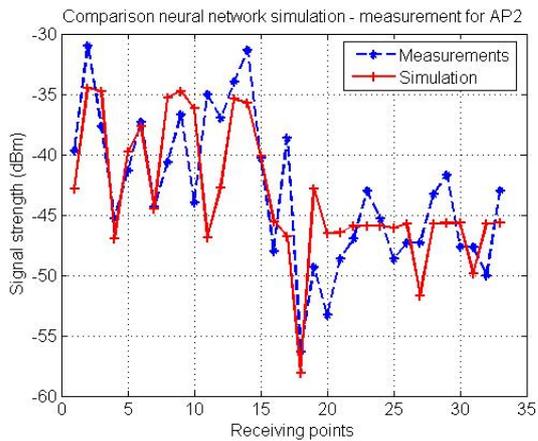


Fig. 2. Neural network architecture

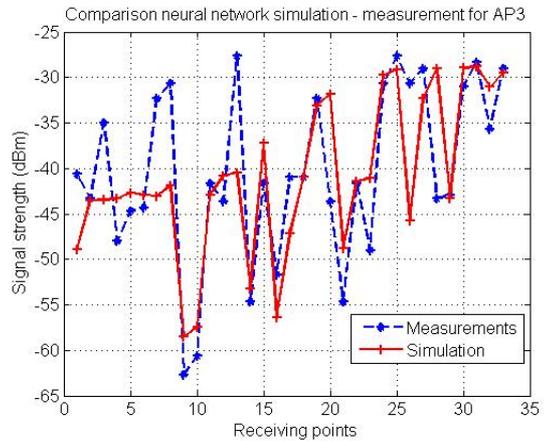
The mean squared errors and cumulative errors for three cases are given in the Table 2. The results obtained for base stations AP1 and AP2 show good signal strength prediction at all testing points. The simulation results for base station AP3 shows the highest errors, but even with these results is possible to satisfactory predict signal strength.



(a)



(b)



(c)

Fig. 3. Comparison of neural network simulation and measurement for base station AP1 (a), AP2(b), and AP3 (c)

Table 2. *mse* and cumulative simulation errors for various base stations

Base station	<i>mse</i>	<i>ce</i>
AP1	3.55	0.0592
AP2	4.07	0.0708
AP3	6.27	0.1059

3. Base Station Optimization

3.1 A Cost Function Based on Neural Network Model

In order to find the 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 the signal level at arbitrary point wherever the base station is located. According to such approach cost function is presented as sum of all weighted relative signal level predictions (in dBm) along with a penalty value that represents a violation of a maximum tolerated path loss threshold at receiver location, which in our case was the receiver threshold (-72dBm for 54 Mbps). The cost function, then, can be expressed as

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

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 j th 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

$$w_j = \begin{cases} S_i(x_j, y_j) > -60dBm & w = 1 \\ -60 \geq S_i(x_j, y_j) \geq -72dBm & w = 10 \\ S_i(x_j, y_j) < -72dBm & w = 100 \end{cases} \quad (6)$$

The cost function as a function of two variables (x, y) , that represent location of base station, is calculated according the equations (5) and (6) where the needed signal levels are obtained from neural network trained model. The coverage is not a differentiable function of the base station locations, so small changes in the base station location can cause great changes in received signal strength, which is caused by completely different pattern of reflected, transmitted and diffracted rays. We may expect a lot of such rapid changes in the case of real indoor environment.

The mentioned reasons make such cost function extremely limited in accuracy when it is evaluated 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 the number of grid points.

3.2 Direct Search Methods

As presented cost function incorporates constraints, unconstrained optimization technique will be used. The described properties of cost function determine which optimization procedure is 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 Simplex Search method is less susceptible to the local minima problem than the Powell's conjugate method since it is impossible to completely overcome this problem. In more details, there is possibility to restart optimization procedure with an alternative initial position and run algorithm again to verify the achieved optimum values.

3.3 Particle Swarm Optimization (PSO) Algorithm

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 , velocity v , and 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

$$v_{ij}^{k+1} = c_0 v_{ij}^k + c_1 rand_1 (pbest_{ij} - x_{ij}^k) + c_2 rand_2 (gbest_{ij} - x_{ij}^k) \quad (7)$$

In the above equation $i = 1, 2, \dots, m$, where m is the size of the swarm; $j = 1, 2, \dots, n$, 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 numbers that are uniformly distributed in the interval $[0,1]$. The parameter c_0 is called "inertial weight" and it determines if the particle will stay on its current trajectory or if it will be strongly pulled toward $pbest$ or $gbest$. Its value is between 0 and 1. The new particle location is given by

$$x_{ij}^{k+1} = x_{ij}^k + \Delta t v_{ij}^{k+1} \quad (8)$$

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 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 which direction prevails.

A proper selection of parameter values is very important to obtain qualitative result. Various authors have proposed different inertial weights and other constants. After running PSO algorithm with different parameters we got the best result when inertial weight c_0 was changed linearly from 0.9 to 0.2 during the run of algorithm. In this way, particles in the beginning are less pulled toward $pbest$ and $gbest$, but after a number of iterations they are more rapidly pulled toward these values, which are illustrated in Fig. 4 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.

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 sufficiently explore the space under consideration, so population of 30 particles is used in our algorithm. Among the suggested boundary conditions, introduced by various authors, we have selected so-called "reflecting walls" to avoid moving the particle out from the given space [10].

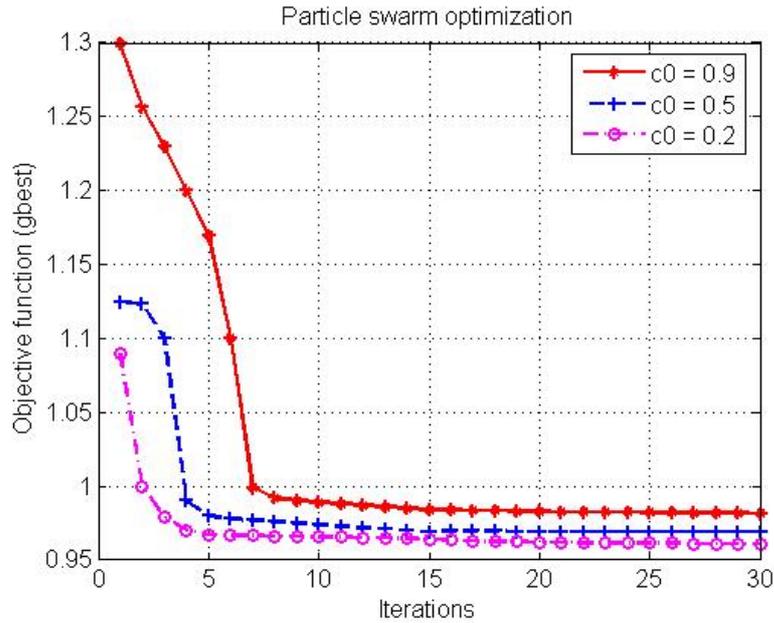


Fig. 4 Cost function for different inertial weights

3.4 Optimization Results

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.

Table 3. Optimization results obtained by three methods

Simplex method			Powell's method			PSO		
n	<i>Result</i>	f	n	<i>Result</i>	f	n	<i>Result</i>	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)	$9.60 \cdot 10^3$

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 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).

4. Conclusion

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. PSO is faster and more accurate in comparison with Simplex Search and Powell's method. 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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