

# Neural Network Prediction of Signal Strength for Irregular Indoor Environments

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Original scientific paper

A neural-network based approach for modelling propagation inside complex indoor environments is presented. Selection of the neural network model, initialization, and training and performance evaluation are studied in details. Furthermore, in order to determine optimal access point arrangement the neural network propagation model is merged with the particle swarm optimization method. In the case of simple indoor environments the developed propagation model is equally accurate as the deterministic methods, while in the case of complex environments the proposed method shows superior properties. Finally, the calculated results were tested in direct comparison with the measurements for both simple and complex indoor environments.

**Key words:** Indoor propagation, Complex indoor environment, Signal strength prediction, Neural network modelling, Ray tracing, Motley-Keenan method, Optimal position

**Predviđanje snage signala neuronskim mrežama za nepravilne zatvorene prostore.** Predviđanje snage signala neuronskim mrežama za nepravilne zatvorene prostore. U članku je prikazano modeliranje širenja signala u složenim zatvorenim prostorima temeljeno na neuronskim mrežama. Detaljno su razmotreni postupci odabira modela mreže, inicijalizacija i učenje mreže, kao i proces testiranja neuronskog modela. Optimalna pozicija pristupne točke određena je neuronskim modelom i optimizacijskim postupkom na osnovi roja čestica. Kod zatvorenih prostora jednostavne konstrukcije i jednostavnog geometrijskog oblika metoda neuronskom mrežom daje jednako točne rezultate, kao i poznate determinističke metode, ali u slučaju složenijih prostora predložena metoda pokazuje znatno bolje rezultate. Izračunate vrijednosti snage signala su uspoređene s mjerenjima za jednostavne i složene prostore.

**Ključne riječi:** Širenje u zatvorenom prostoru, složeni prostor, predviđanje snage signala, modeliranje neuronskom mrežom, slijeđenje zrake, Motley-Keenan-ova metoda, optimalna pozicija

## 1 INTRODUCTION

Rapid development of radio communication systems in a few past decades demands its careful planning and design. The increase popularity of indoor communication systems gives a significant rise in application of various mobile devices. These devices can be located anywhere, while base stations should provide good link to the backbone of the communication system. The first step in the process of WLAN (Wireless Local Area Network) design is to determine access point locations and frequency plan, what is mainly dependent on environmental characteristics.

The main environmental impact on electromagnetic wave propagation results in path loss. An accurate estimation of the path loss is therefore extremely important for proper determination of access point locations. A full-wave analysis method for the field strength prediction is extremely complex and very difficult task. The complexity

and diversity of propagation mechanisms in indoor environments arises from many different factors like diffraction, scattering, transmission, refraction, reflection etc. In the most cases there is no line of sight between receiver and transmitter, so the received signal is the sum

of the components that have been propagated by the mentioned mechanisms. Consequently the received signal varies in time and with respect to the receiver and transmitter locations. There are large fluctuations in the received signal for the case of mobile receiver. Very small displacement (even a fraction of the wavelength) of the receiver (or transmitter) can cause signal level to change by few tens of decibels.

Up to date, several groups of methods for field strength prediction have been proposed. The empirical methods [1] have been preferred for wireless communication, equally for outdoor and indoor environments. These methods are based on fitting the statistical data (in the sense of av-

erages). In outdoor environments empirical models give reasonably good predictions, but in indoor environments, where the receiver can be shadowed with larger number of different obstacles, empirical results have not such accuracy. The better accuracy is achieved when the environment under consideration is similar to the environment where the measurements are carried out, but it is not always the case.

The deterministic models based on the principles of electromagnetic wave propagation can be applied to different indoor environments with equal accuracy. Well known ray tracing method may be the choice. It results in computations based on realistic geometrical and electrical parameters. Commonly, electrical parameters of the obstacles are unknown, so sophisticated measurement methods need to be applied and performed in real environment (*in situ*) [2]-[4]. The electrical parameters estimated in such a way are more or less approximated values. Therefore, deterministic models can be applied in regular geometrical environments with straight walls made of known materials.

The computation becomes extremely complex when the indoor environment has irregular shape with a lot of diverse obstacles in it. In such cases both empirical and deterministic methods are became inapplicable and there is a need for another analysis approaches which will be less complex and at least equally accurate as deterministic methods. Several authors applied neural network model in the field strength prediction. In [5]-[7] dominant paths are introduced for eliminating the time-variant effects, which leads to additional simplification and less accuracy. The main deficiency of this method is in the requirement for accurate data base of the building geometry, as the dominant path needs to be determined for each prediction point. The achieved mean error is not better than 8 dB [6]. The multilayer perception and the radial basis function network models are compared in [10], showing that the first approach is more accurate in propagation loss prediction. In [11] two propagation models are presented, first based on the ray tracing technique and second based on the assumption that all received power can be represented as weighted sum of coherent power blocks. The obtained results are not worse than empirical ones.

In the proposed approach geometrical and constructional simple and complex environments are distinguished. In the case of the simple environments deterministic and even empirical methods can be applied with satisfactory accuracy. On the other hand, there is no proper analytical method to compute the field strength distribution in the complex environment. The complex environments require a method that is not dependent on detailed knowledge about building constructional characteristics, and that is achieved by applying the neural network model trained by simple field-strength measurements.

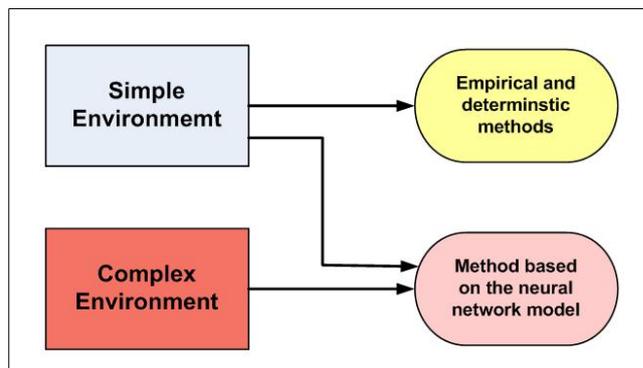


Fig. 1. Proposed approach to the propagation problem in indoor environments

## 2 SIMPLE AND COMPLEX ENVIRONMENTS

Indoor environment has much stronger influence on field strength dynamics than it is in outdoor environments, where the field strength nearly uniformly decreases with distance. Contrary to outdoor environment indoor environment is usually full of objects that are in proximity of each other. According to the geometrical and constructional characteristics each environment is unique, and generalization is hardly possible. We have divided indoor environments into two main groups: simple and complex environments (Fig.1). The simple environment allows the application of empirical and deterministic methods as Motley-Keenan or ray tracing method [8]-[9] and there is no need for measurements if the electromagnetic parameters of the materials are known. Unfortunately these simple methods can not be applied to the complex environments so neural network model is developed for this case.

The proposed models are verified by measurements. The measurement setup consisted of WLAN access point operating at 2.427 GHz and laptop computer provided with appropriate wireless card. The transmitting power of the access point was 100mW. The gain of antennas was 8 dBi. Three measurements were made for each receiving point, and the average value is recorded in computer. The height of the transmitting antenna was 2.4 m above floor, while the receiving antenna was 1.5 m above floor.

### 2.1 Simple Environment

As a reference case of the geometrical and constructional simple environment we have considered the second floor of the B building of the University of Dubrovnik (Fig. 2). The length of the corridor is 34m and the dimensions of each side offices are 4.5x5m. The floor is covered by stone blocks. The ceiling is made by concrete and it is 3m above the floor. We measured field distribution from three access points denoted by AP1, AP2 and AP3, which coordinates

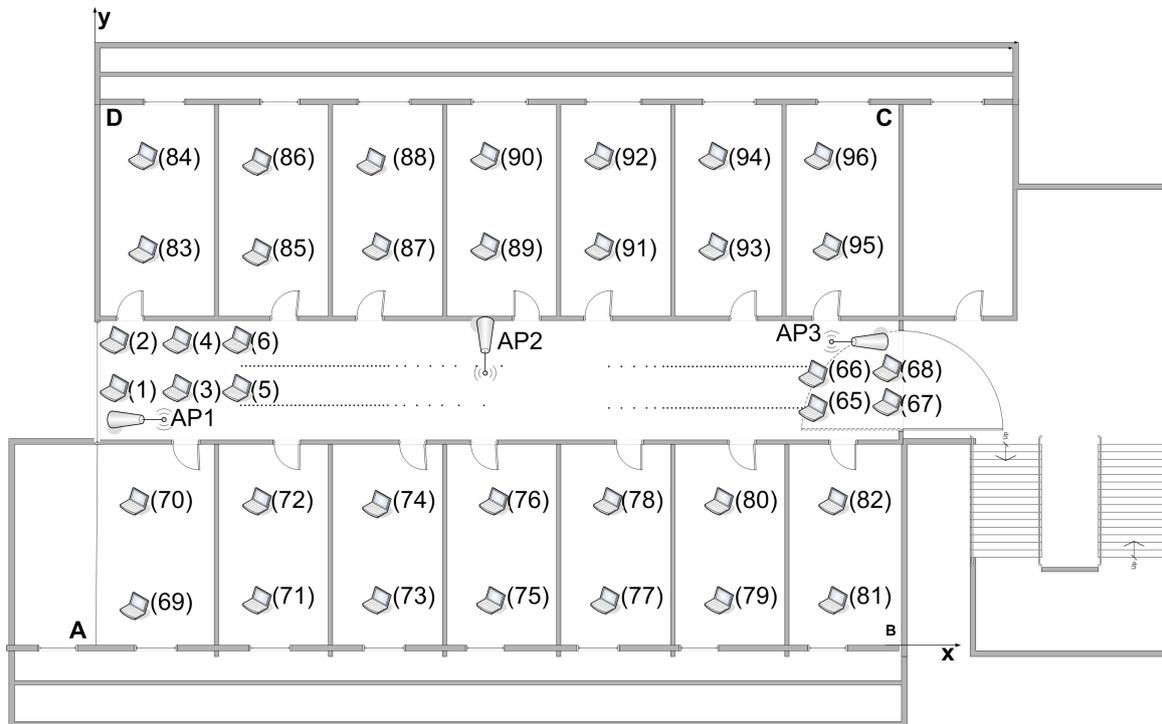


Fig. 2. The second floor plan of the B university building with the grid of measurement points and locations of access points

are given in the Table 1 (the origin of the coordinate system is located at the point A). The receiving points were uniformly distributed along the corridor and inside the offices denoted by numbers. There were 96 receiving points from which 68 were located in the corridor, and the distance between neighbouring points was 1 m.

Table 1. The coordinates of the access points in the simple environment

Access points	x	y	z
AP1	0.0	5.15	2.4
AP2	17.0	7.85	2.4
AP3	33.0	7.85	2.4

The measured field strength in the presented simple indoor environment is illustrated in the Fig. 3, for access point AP1 as transmitter. The first 68 receiving points were located in the corridor with existence of the line of sight (LOS). The receiving points from 69 to 96 were located in the rooms and there is no LOS, so the signal level is smaller and dynamics of the signal strength variation was larger.

### 2.2 Complex environment

Indoor environments with significant architectural complexity and irregular shape, constructed from a number

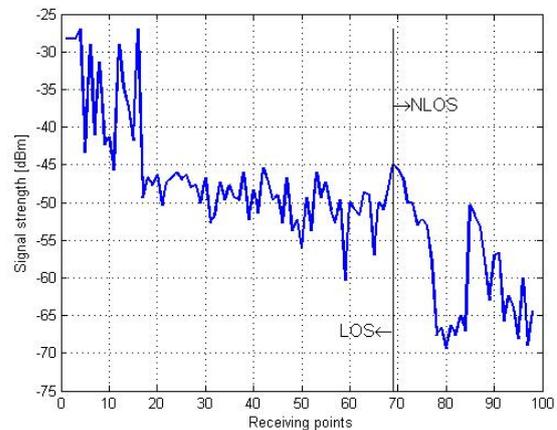


Fig. 3. Signal strength for AP1 and receiving points according to the Fig. 2.

of different and composite materials, need to be classified as complex ones. The lobby of the Dubrovnik’s University building is an example of such environments. Besides the geometrical irregularity, this environment is filled with various objects like pots with plants, tables, benches and variety of panels. The complexity of this environment is

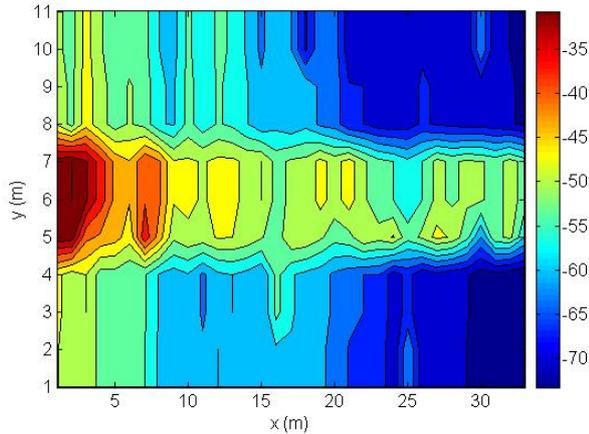


Fig. 4. Contour diagram of the signal strength coverage for simple indoor environment (transmitter AP1)

shown in the Fig. 5.



Fig. 5. Real complex environment the lobby of Dubrovnik's University building

Fig. 6 gives the ground plan of this complex environment, where the area under consideration is bordered by the points from A to I. The total area is 323 m<sup>2</sup> and height is 3 m. The origin of the coordinate system is located in the left lower corner (point A). The locations of the access points, denoted by AP1, AP2 and AP3, are given in the Table 2. The construction materials are very similar as in the simple indoor environment described above.

The signal strength was measured at 233 receiving points for each of three access points. The receiving points were located in the same way as in the simple environment case. The Fig. 6 shows the field strength for all receiving points uniquely distributed along the area of interest. In

Table 2. The coordinates of the access points in the complex environment

Access point	<i>x</i>	<i>y</i>	<i>z</i>
AP1	0,0	12,0	2,75
AP2	0,0	4,0	2,75
AP3	15,0	16,0	2,75

this case the field strength changes are so fast that it is difficult to distinguish LOS receiving points from NLOS ones. The signal strength at each receiving point is influenced by large number of different factors that deterministic analysis approach makes extremely difficult.

The fast fluctuations are additionally described by a contour diagram in the Fig. 8, for the same access point as in the Fig. 7. Here is easier to realize the locations of the various objects and its influence on the signal propagation inside the environment. The white area is the part of the environment that was not taken in considerations.

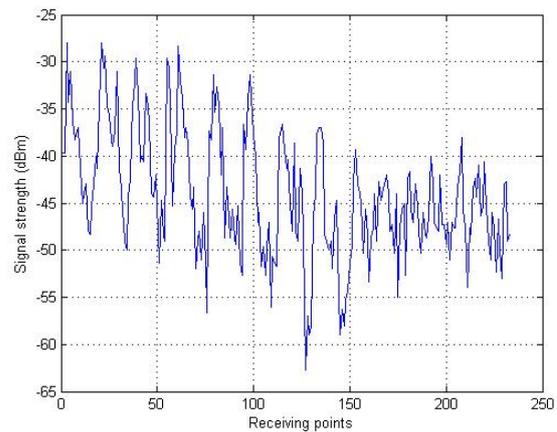


Fig. 7. Signal strength for receiving points inside complex indoor environments (Fig. 5) for access point AP2

### 3 DETERMINISTIC PROPAGATION MODELS FOR SIMPLE ENVIRONMENT

The simple environment allows us to apply some of the well known deterministic methods. These methods we will compare with less conventional model based on the application of neural networks. As neural network model described hereafter requires measured receiving signal for training purposes, we have used reduced number of receiving points (28) for testing propagation models (i.e. these measurement points were not used for training the neural network). In the Fig. 9 these receiving points are indicated for the case of simple environment.

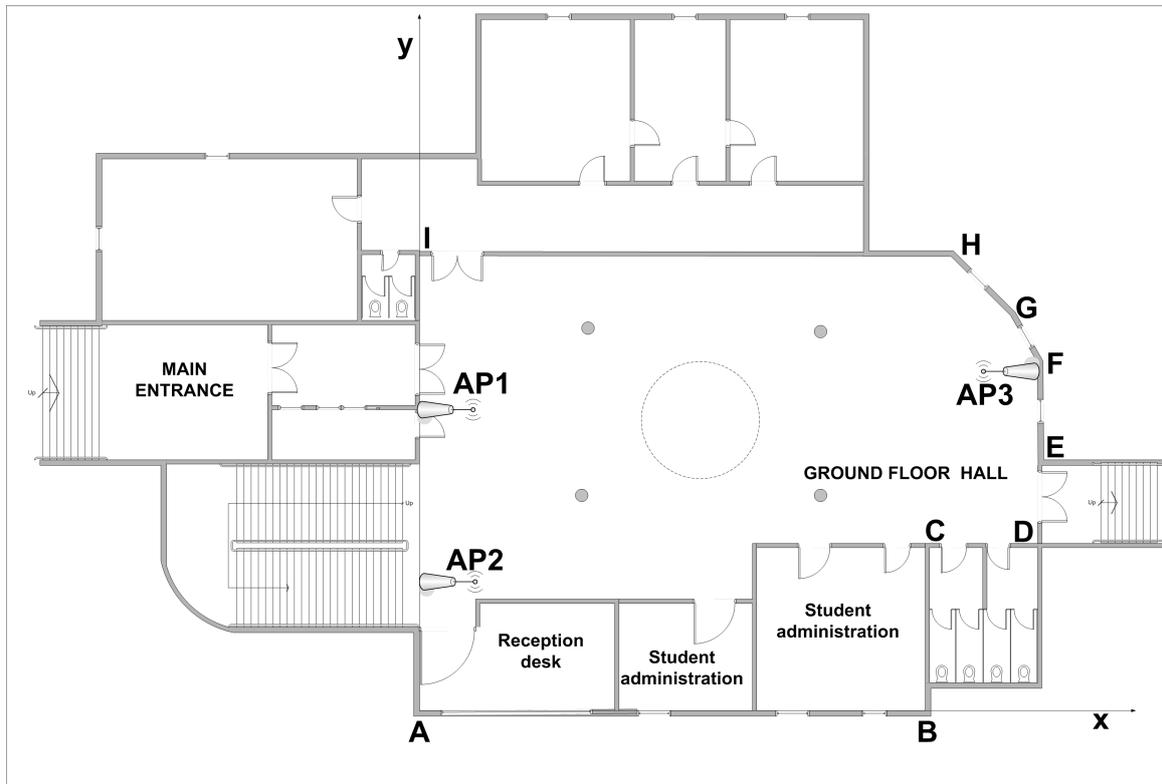


Fig. 6. Ground plan of the Dubrovnik's University lobby

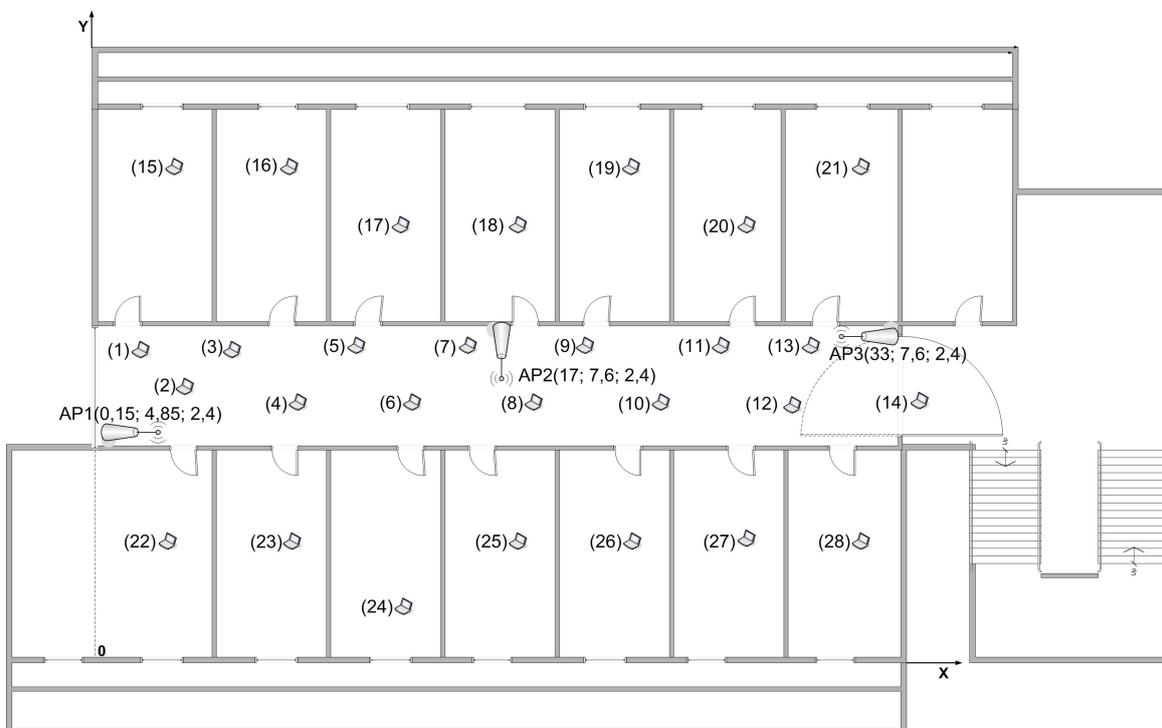


Fig. 9. The sample of the simple environment with denoted receiving points considered in simulation

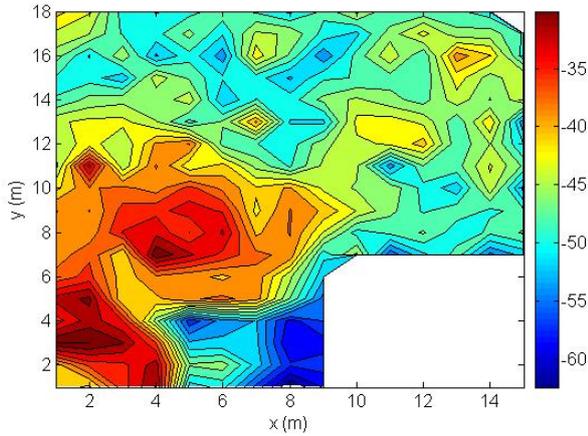


Fig. 8. Contour diagram for signal strength coverage for complex indoor environment (AP2)

### 3.1 Motley-Keenan Model

The Motley-Keenan method requires knowledge of the field attenuation caused by the walls. According to this method [8] the signal strength can be generally expressed as

$$P_r = P_t + G_r + G_t - L_{fs} - \sum_{i=1}^N k_{wi} L_{wi} - \sum_{j=1}^M k_{fj} L_{fj}, \quad (1)$$

where the  $kL$  products represent values of the attenuation in the walls and the floors ( $N$  is the number of walls with different electromagnetic characteristics, while  $M$  is the same for the floors). The factor  $k$  represents the number of the walls (floors) with the same electromagnetic parameters. The operand  $L_{fs}$  is the value in the free space attenuation (line of sight). The typical wall (floor) attenuation factors are given in the Table 3.

Table 3. Empirical values of power loss for different obstacles

Type of the wall(floor)	Width of the obstacle (cm)	Power loss (dB)
Concrete	20	13
Brick + mortar	20	8
Wood	6	1
Metallic frames	4,5	47

The accuracy obtained by Motley-Keenan model is presented in Fig. 10 and Table 4. There are differences in accuracy between considered access points, which are caused by different environmental impact that can't be embraced by simple empirical equation (1) and assumed material's parameters (Table 3).

Table 4. Error values obtained by Motley-Keenan model

Access point	Average absolute error (dB)	Standard deviation (dB)	MSE (dB)
AP1	3.6927	2.641	4.7352
AP2	5.0261	3.5186	6.1353
AP3	3.5416	2.0273	4.0808

### 3.2 Ray-tracing Model

The ray tracing method [9] requires knowledge of conductivity, permittivity and permeability of the constructing materials. As the building under consideration is relatively new one, these values were mostly known, with the exception of side walls. Therefore, we needed to measure permittivity values, so appropriate measurement method ([12], [13]) has been established.

We used multi-ray model where rays with single and double reflections are used. The numerical check demonstrated that the contribution of higher order reflections to the total field strength were negligible. The description of the reflection geometry is presented in the Fig. 11.

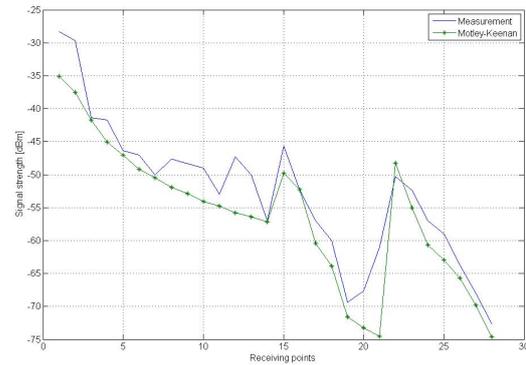


Fig. 10. Signal strength AP1 obtained by Motley-Keenan model

According to Fig. 11 the total signal strength at receiving point for direct ray,  $N$  rays with one reflection, and  $M$  rays with two reflections can be expressed as

$$P_r = P_t G_t G_r \left( \frac{\lambda}{4\pi} \right)^2 \left| \frac{1}{d_0} + \sum_{i=1}^N \frac{\Gamma_i}{d_i} e^{-j\Delta\phi_i} + \sum_{j=1}^M \frac{\Gamma_{1j}\Gamma_{2j}}{d_j} e^{-j\Delta\phi_j} \right|^2, \quad (2)$$

where  $P_t$  is the signal strength at the output of the transmitter,  $G_t$  and  $G_r$  are transmitter and receiver antenna gains respectively,  $\Gamma_i$  is the reflection coefficient,  $d_0$

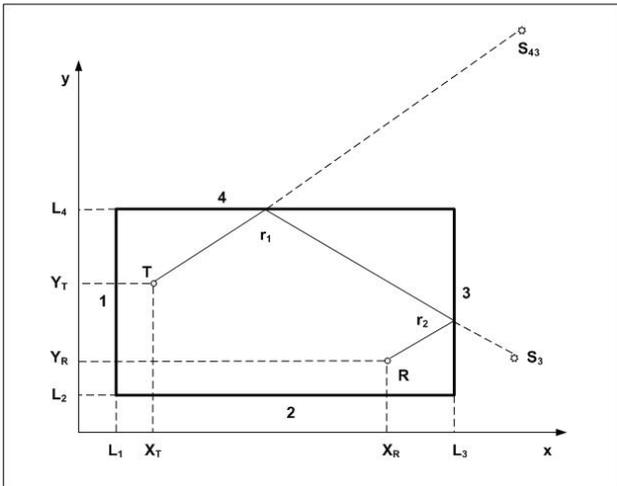


Fig. 11. Ray tracing methodology

is the length of the direct ray,  $d_i$  and  $d_j$  are the lengths of rays with one and two reflections respectively. The phase differences between direct and the reflected rays can be expressed as  $\Delta\phi_i = (2\pi/\lambda) \Delta l_i$ ,  $\Delta\phi_j = (2\pi/\lambda) \Delta l_j$ , where  $\Delta l_i$  and  $\Delta l_j$  are differences in path lengths between direct and the single  $i$  and the double  $j$  reflected rays.

The presented model is applied to the simple indoor environment presented in the Fig. 9. We assumed the vertical polarization so the perpendicular reflection coefficient is used for the reflections from vertical walls and parallel reflection coefficient is used for the reflections from ceiling and floor.

The obtained results are compared to measurement values and they are expressed in terms of absolute and MSE data as it is presented in Fig. 3 and Table 5. These results are, obviously, better than those obtained by the Motley-Keenan method, since more propagation mechanisms are included in the calculation. The divergence from the measurement values is greater for the receiving points located in the area with no line of sight, which is understandable.

Table 5. Error values obtained by ray-tracing model

Access point	Average absolute error (dB)	Standard deviation (dB)	MSE (dB)
AP1	3.1867	1.7741	3.6472
AP2	4.4220	3.0541	5.3741
AP3	2.6667	1.8703	3.2572

#### 4 NEURAL NETWORK MODELLING

The capability of learning by examples, adaptability and ability to generalize are main properties of artificial

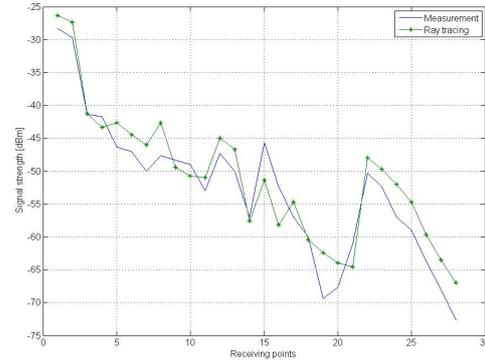


Fig. 12. Comparison between measurement and ray tracing results

neural networks [14]. These properties make neural networks applicable to electromagnetic field prediction in indoor environments where known empirical and deterministic models can't obtain enough accurate results or can't be applied because of the complexity of an environment.

Neural networks are constructed from number of individual neurons interconnected by the links called synapses. The first step in neural networks application is to determine network architecture (topology). We have selected Multilayer Perceptron (MLP) due to its robustness in various types of problems [15]. The number of input and output values determines number of neurons in input and output layers, while the number of neurons in hidden layer as well as number of hidden layers is not so easy to determine. For some authors the neural network with one hidden layer can be considered as universal neural network model for input-output mapping [14]. In our case, the final neural network configuration was determined after testing different network models. Finally, the network architecture presented in the Fig. 13 was selected. It consists of four layers: input layer (no neurons), two hidden layers and output layer with just one neuron. The inputs are the coordinates of the access points (transmitters) and receiving points. The output is signal strength at appropriate receiving point ( $P_r$ ). Input values are directly connected via synaptic weights to the neurons of the first hidden layer (16 neurons). The second hidden layer with 64 neurons has inputs from the first hidden layer and all its neurons are connected to the neuron in the output layer. The output of the neural network is described by the following equation

$$P_r = \phi_o \sum_{k=1}^K w_{ok} \left( \phi_{h2} \left( \sum_{j=1}^M w_{kj} v_j \left( \phi_{h1} \left( \sum_{i=1}^N w_{ji} u_i \right) \right) \right) \right) \quad (3)$$

where the following notations are used:

- $K, M, N$  - number of neurons in second hidden layer, first hidden layer, and output layer respectively,
- $w_{ok}$  - synaptic weights from neuron  $k$  in the hidden layer to the single output neuron,
- $v_j$  -  $j$ -th element of the vector that inputs to the second hidden layer,
- $w_{kj}$  - connection weights between neurons in the two hidden layers,
- $u_i$  -  $i$ -th element of the vector that inputs to the second hidden layer, that consists of the appropriate coordinates  $(x, y, z)$ ,
- $v_{ji}$  - connection weights between inputs and the first hidden layer,
- $\varphi_{h1}, \varphi_{h2}$  and  $\varphi_o$  - activation functions in the first, second and output layers respectively.

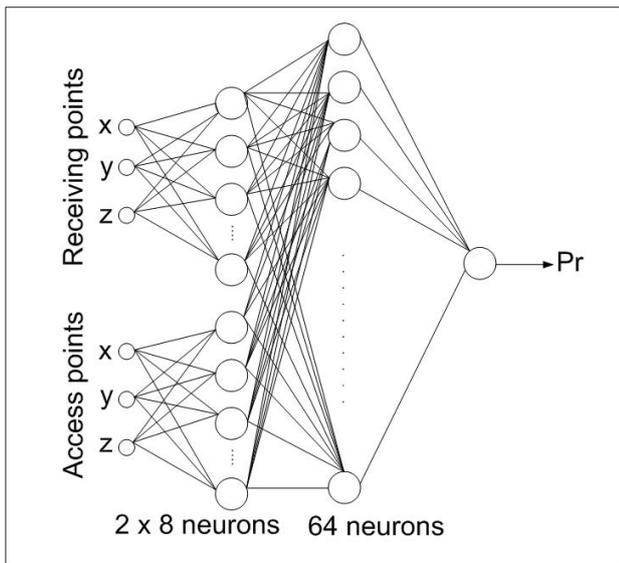


Fig. 13. Neural network architecture

The activation function of the output layer is linear function, while the activation function of the hidden layers is sigmoid type, according to the equation

$$\phi(a, v) = \frac{1 - e^{-av}}{1 + e^{-av}}, \quad (4)$$

where  $a$  represents a slope of the activation function. The duration of the network training is determined by the activation function, so by changing the parameter  $a$  speed of the training process can be tuned. It is impossible to determine the appropriate slope of the activation function for every neuron in neural model, so their estimation is made in adaptive way during the process of training.

#### 4.1 Neural network training and testing

The network was trained by the known values of the signal strength at known locations, which were obtained by the measurements. The selection of the receiving points for the network training was made in random way considering its uniform distribution across entire environment. In the case of simple environment 68 such locations were chosen (from totally 96 points), and in the case of the complex environment 200 receiving points (from totally 233 points) were used in training procedure. The training process was made for the access points AP1 and AP3 in both cases (Figures 2 and 6).

The learning process applied to the network adaptively adjusts the free parameters (weights and biases) of the network model based on the mean squared error that is commonly expressed as

$$E = \frac{1}{2} \sum_{i=1}^N (y_i - d_i)^2, \quad (5)$$

where  $y_i$  is the output value calculated by the network and  $d_i$  is the expected output [14]. When the error between network output and expected output is minimized, the learning process is terminated. After extensive experimental work on the various different training algorithms the Levenberg-Marquardt algorithm with Bayesian regularization was chosen [16]. This algorithm showed good generalization with relative fast training process (not more than 1000 epochs). Table 6 shows the sums of the squared errors for three different training algorithms.

##### 4.1.1 Simple environment case

The rest of the 28 receiving points for the simple indoor environment (Fig. 9) that were not used in the training process were used for the testing the neural network. The coordinates of these receiving points together with coordinates of access points were applied to the input of the network and the network gave the signal strength prediction at each of these points.

Table 6. Sums of squared errors for different training processes

Type of environment	Training algorithm		
	Scaled conjugate gradient	Levenberg - Marquardt	Levenberg -Marquardt with Bayesian regularization
simple	0.22501	0.09042	0.08519
complex	0.27906	0.16932	0.15393

The testing results are presented in the Figs. 14.a and 14.b for the access points AP1 and AP3 respectively. First

14 receiving points were in the line of the site, while the others were located in the side rooms. Neural network model showed good covering with the data obtained by the measurements. Larger variation in the signal strength (comparing to the measured ones) was obtained for receiving points located out of the line of site, what is the influence of the building construction characteristics and different furniture inside the rooms. By comparing the results obtained by all considered methods we can conclude that the worst results were obtained by Motley-Keenan empirical method, what can be expected, because the main parameters were assumed in this particular case? Furthermore, there is no significant difference between neural network results and those obtained by ray tracing method.

Table 7. Results of the testing process for AP1 and AP3

Access point	Average absolute error (dB)	Standard deviation (dB)	MSE (dB)
AP1	2.2857	1.4336	2.6981
AP3	2.8810	2.6047	3.2610

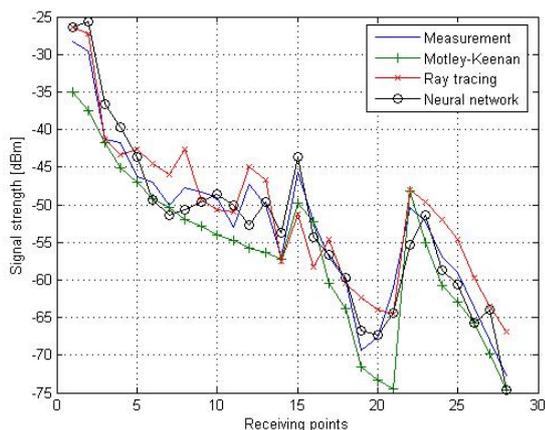
4.1.2 Complex environment case

The Fig. 15 shows locations of 33 receiving points used only in testing process for complex indoor environment. As in the case of the simple environment the access points

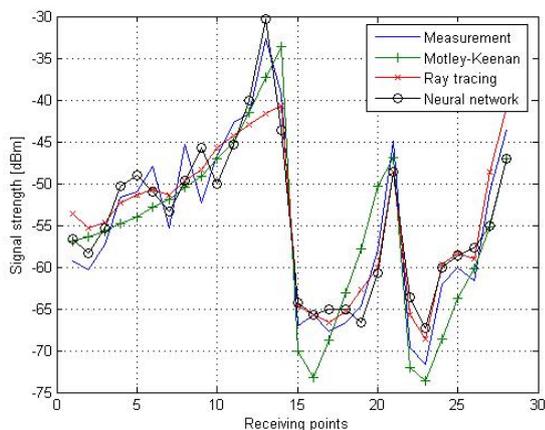
AP1 and AP3 were tested separately. As it has already been explained above in this article, this indoor environment is highly irregular according to its constructional and geometrical characteristics, so it is extremely difficult to apply such methods as Motley-Keenan or ray tracing. The comparison of the results obtained by conventional methods and neural network method approve usefulness of latter one. Therefore, the neural network model was only choice.

The results are graphically presented in the Figs. 16.a and 16.b for AP1 and AP3 access points respectively. The differences between the results obtained by measurement and neural network model were in satisfactory limits. In the case of the access point AP1 (Fig. 16.a) the worst results are obtained for the receiving point 2 and 5, where the receiver has been in proximity of the transmitter, but signal propagation was effected by the factors that couldn't be detected by the training of the neural network. It is significant to emphasise very good covering for the receiving points 14 and 16 where there was no line of sight (Fig. 15). The signal strengths for the receiving points from 25 to 33 were higher than measured ones because multipath propagation was not completely resolved by neural model. The something worse results were obtained for the access point AP3 (Fig.16.b). The main reason was in the distribution of the receiving points for neural network testing (Fig. 15). The most of the receiving points were located in the proximity of the access point and show good covering with measured results, but the minority of the receiving points were scattered across the environment (Fig. 15), where agreement with measured values was not so good.

The numerically expressed results in terms of absolute mean error, standard deviation and mean squared error are presented in the Table 8. The minimal mean squared error is obtained in the case of access point AP1 as transmitter (2.8826 dB). The contour diagrams of the signal strengths obtained by measurements and by neural model are presented in the Figs. 17 and 18 for the AP1 and AP3 access points. Comparing these two pairs of figures it can be seen how much of details in signal propagation couldn't be re-



(a) AP1 access point



(b) AP3 access point

Fig. 14. The results comparison for two access points

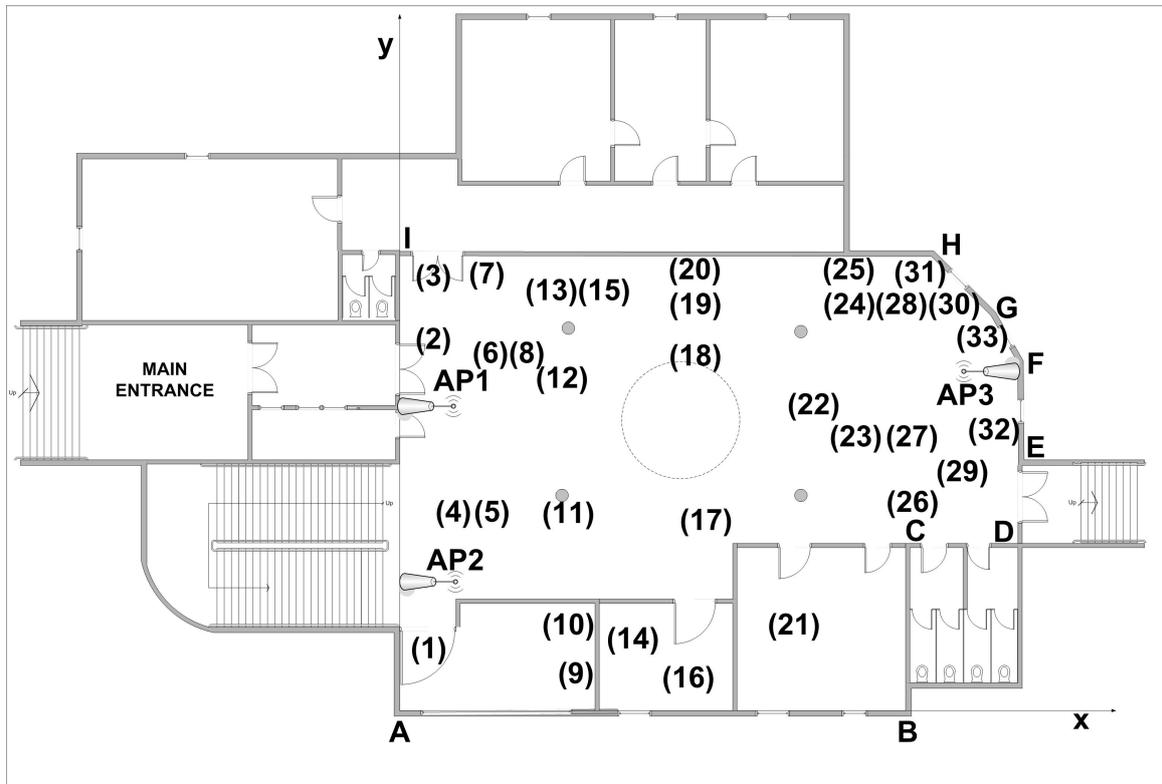


Fig. 15. The ground plan of the complex indoor environment (The receiving points used in testing and simulation are denoted by numbers).

solved by neural network model. In the spite of these differences good qualitative matching between these contour diagrams is obtained.

Table 8. Results of the testing process for AP1 and AP3

Access point	Average absolute error (dB)	Standard deviation (dB)	MSE (dB)
AP1	2.2918	1.7485	2.8826
AP3	3.1091	2.2892	3.8610

#### 4.2 Network Modelling

The neural network model was tested for the access point AP2 as it is sketched in the Fig. 16. The values of the received signal strengths from this access point didn't participate in the training process (neither in the testing process). Therefore, this case presents a real-life test case of the accuracy of the proposed propagation model.

Comparison of signal strength values obtained by neural model and measurements for the complex environment is presented in Table 9 and Fig. 19. According to the obtained results it is clear that the neural network model represents an accurate method for calculating field strength in complex environments.

resents an accurate method for calculating field strength in complex environments.

Table 9. Results of the testing process for AP2

Access point	Average absolute error (dB)	Standard deviation (dB)	MSE (dB)
AP2	2.6067	1.3952	2.9566

We have studied what is the minimal number of the measured receiving points, needed for training the network, for accurate generalization of the neural network. After careful investigation of the training process with different numbers of the measured values we found that the number of the training values can be considerably reduced and still achieving accurate results. Dependence of the MSE and the number of the training values for three access points of the interest (AP1, AP2 and AP3) is presented in the Fig. 20. It can be seen that 110 receiving points (measurement data) are enough to obtain the MSE of 3.7 dB in the case of AP1 and AP3, and 6.5 dB in the case of AP2. For smaller number of training values the MSE for AP2 (not used in training process) was significantly higher.

Comparison of the measured data and results obtained

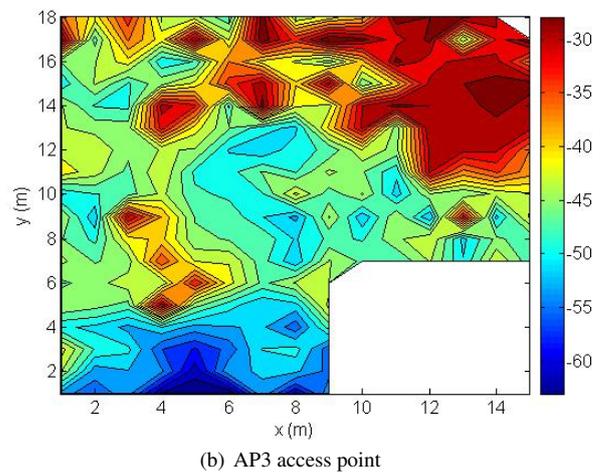
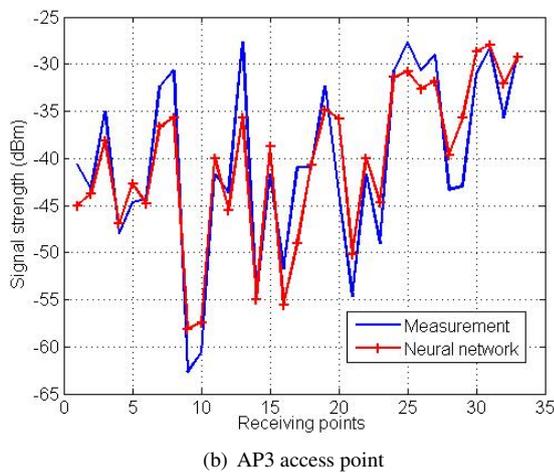
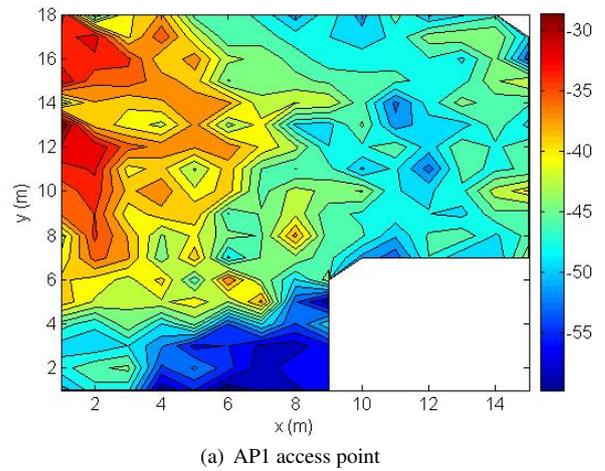
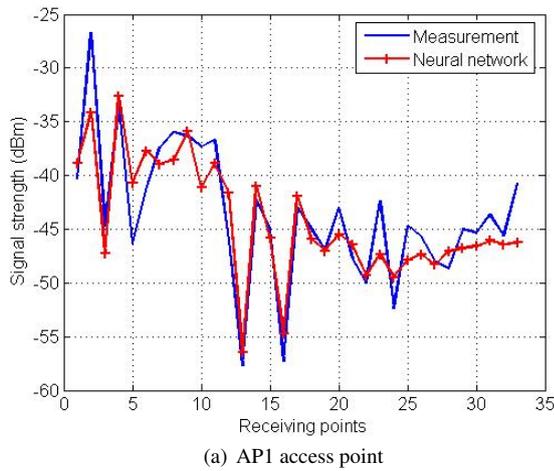


Fig. 16. Comparison of the results obtained by neural network model and measurements in complex environment

Fig. 17. Contour diagram for signal strength coverage obtained by measurement

by the neural model trained with 200 and 110 input values is presented in the Fig.21. The good covering of the two curves obtained by neural network model is obvious. Number of needed measurement points depends of the environment configuration; some less complex environment requires smaller number of the neural network input values, while, in present case study, the environment was highly irregular, so less than 80 measurement values lead to unacceptable results.

One of the important questions when designing wireless network is the needed number and position of access points. The neural network model can be used for optimization of the position of access points. For that purpose the presented neural-network based algorithm was merged with optimization routine. We have tested several optimization routines [17]-[18], and concluded that the particle swarm optimization (PSO) represents a fast and accurate

optimization method that is immune to presence of local minima (characteristic for this type of optimization problems). The optimization process was tested in complex environment. The results for optimally-positioned access point are presented in Fig. 22. We obtained comparable numerical results in terms of the MSEs, as it can be seen in the Table 10. Our results are comparable with results obtained by genetic and simulated annealing algorithms described in [19]. Therefore, the proposed combination presents good analysis tool for WLAN planning.

Table 10. Results obtained by the optimization process

Access point	Average absolute error (dB)	Standard deviation (dB)	MSE (dB)
Optimized position	2.5223	1.5869	2.9800

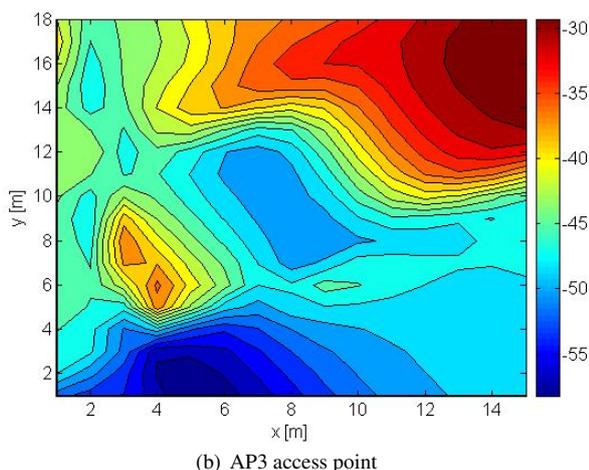
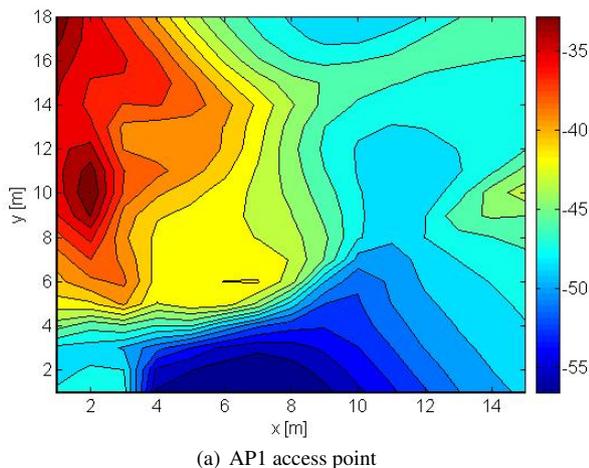


Fig. 18. Contour diagram for signal strength coverage obtained by neural model

### 5 CONCLUSION

Field strength prediction in indoor environments was studied without introducing complex and long lasting computations. The proposed analysis method, based on the neural network as propagation model, presents a simple and fast way to obtain signal strength distribution in the considered indoor environment. The results obtained by conventional deterministic methods are comparable in accuracy to those obtained by neural network model in the case of simple indoor environments. However, for highly-irregular (complex) environments the neural-network based model is advantageous both in simplicity and in needed CPU time. The main advantage of the proposed neural network model is that there is no need for a large database with detailed construction and electromagnetic parameters of the considered building. The algorithm itself is quite fast with the training process lasting only sev-

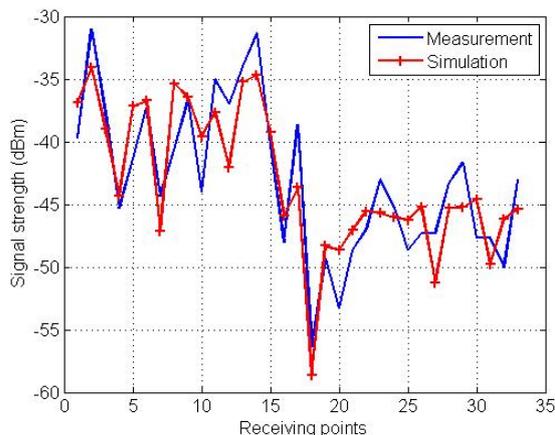


Fig. 19. Comparison between results obtained by neural network model and measurements for AP2 in complex environment

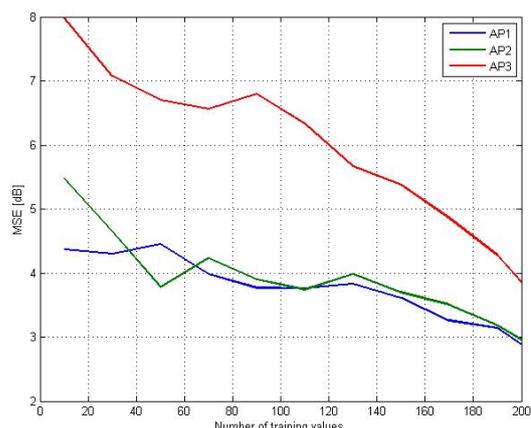


Fig. 20. MSE versus the number of the training values

eral minutes; however one has to keep in mind that prior to the calculations it is necessary to perform actual measurements at the selected receiving points for the training purpose.

The developed algorithm was also merged with a suitable optimization routine to determine the optimum positions for the access points in order to achieve best signal coverage.

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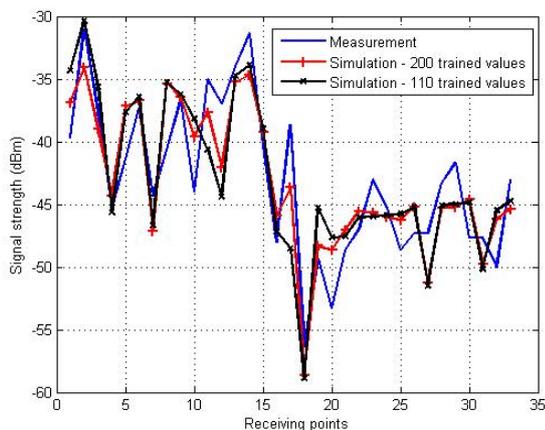


Fig. 21. Comparison of measurements and results obtained by the neural model with 200 and 110 trained input values for AP2 in complex environment

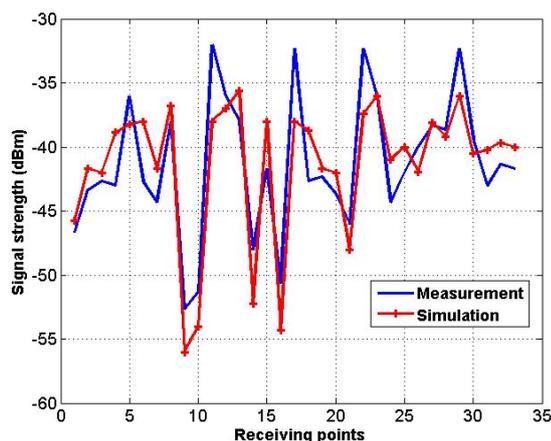


Fig. 22. Comparison of measurements and results obtained by neural network model for optimally positioned access point

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**Ivan Vilović** was born in Dubrovnik, Croatia. He received the B.Sc. , the M.Sc. and the Ph.D. degrees in electrical engineering from the University of Zagreb, in 1974 , 1983 and 2008 respectively.

From 1974 to 2004, he worked in IT industry as a research engineer and IT manager in different business environments. He worked as team leader in development of various information and communication systems. He joined the Department of Electrical Engineering and Computing,

University of Dubrovnik, Croatia, 2004 as an Assistant Professor. He is currently Head of the Department of Electrical Engineering and Computing. His main research interests are: propagation of electromagnetic signals, antenna design and wireless communications.



**Nikša Burum** was born in Dubrovnik, Croatia. He received the M.Sc. and the Ph.D. degrees in electrical engineering from University of Zagreb, in 1999 and 2004, respectively.

From 1990 to 2003, he worked at ITI Computers, Dubrovnik, Croatia, as a Research Engineer. He participated in the development of communication software and design of computer networks. His main research interest was embedded communication systems. Since 2003, he has been at the Department of Electrical Engineering and

Computing, University of Dubrovnik, Croatia, as an Assistant Professor. Currently, he is Full Professor. His main research interests are: antenna, design, numerical techniques in electromagnetic and embedded telemetry systems.

#### **AUTHORS' ADDRESSES**

**Asst. Prof. Ivan Vilović, Ph.D.**

**Prof. Nikša Burum, Ph.D.**

**Department of Electrical Engineering and Computing,**

**University of Dubrovnik,**

**Dubrovnik, Croatia**

**email: [ivan.vilovic@unidu.hr](mailto:ivan.vilovic@unidu.hr), [niksa.burum@unidu.hr](mailto:niksa.burum@unidu.hr)**

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