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Wireless LAN Electromagnetic Field Prediction for Indoor Environment Using Artificial Neural Network

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Original scientific paper

A simple neural model for electromagnetic field prediction in indoor environment was created based on field strength measurements at 2.4 GHz, conducted at University of Split, Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture (FESB Split). Vertical rod antenna (omnidirectional in the horizontal plane) was placed in a faculty hallway and used as the electromagnetic field source. Electromagnetic field distribution was defined by commonly used rectangular grid of uniformly distributed measurement points. However, instead of commonly used Cartesian coordinates for measurement points location description, we used polar coordinates of distance and azimuth angle measured from the field source. These coordinates are found to be more suitable for the organization of input data, as the physical distribution of the field strength around the antenna depends on the same variables. This resulted with predictive ability improvement of the neural model, as confirmed by simulation results. Three-Layer Perceptron, trained with Levenberg-Marquardt (LM) algorithm, produced the best results.

Key words: Electromagnetic field prediction, Indoor propagation, Artificial neural network (ANN), Multilayer perceptron (MLP), MATLAB

Predviđanje elektromagnetskog polja bežičnog LAN-a u zatvorenom prostoru korištenjem umjetne neuronske mreže. Na temelju rezultata mjerenja jakosti polja provedenih na Fakultetu elektrotehnike, strojarstva i brodogradnje Sveučilišta u Splitu (FESB Split), izrađen je jednostavni neuronski model za predviđanje elektromagnetskog polja u zatvorenom prostoru. Kao izvor elektromagnetskog vala korištena je vertikalna štap antena (neusmjerena u horizontalnoj ravnini), postavljena u fakultetskom hodniku. Mjerenje je provedeno na frekvenciji od 2.4 GHz. Raspodjela polja u prostoru definirana je uobičajenom pravokutnom mrežom jednoliko raspoređenih mjernih točaka. Međutim, pozicije mjernih točaka opisane su polarnim koordinatama udaljenosti i azimuta u odnosu na izvor vala, za razliku od uobičajeno korištenih Kartezijevih koordinata. Pokazalo se da su polarne koordinate pogodnije za organizaciju ulaznih podataka, s obzirom da fizikalna funkcija raspodjele jakosti polja u okolišu izvora ovisi o istim varijablama. Ovakav pristup rezultirao je poboljšanjem mogućnosti predviđanja polja, što je potvrđeno i rezultatima simulacije. Najbolje rezultate dao je troslojni perceptron treniran pomoću Levenberg-Marquardt-ovog algoritma.

Ključne riječi: elektromagnetsko polje, predviđanje, zatvoreni prostor, umjetna neuronska mreža, višeslojni perceptron, MATLAB

1 INTRODUCTION

Electromagnetic field (EMF) prediction for WLAN or other wireless devices in indoor environment is a very complex and difficult task because of geometric and structural complexity of the environment. In addition, the environment can change radically by simple movement of people and/or objects.

The prediction models can be either statistical (based on empirical data), or deterministic, environment-specific [1]. Deterministic models are commonly more accurate, because they rely on physical principles. However, they require a large environmental database which is sometimes impossible to obtain. Furthermore, they use very complex algorithms which make them computationally inefficient. Still, the main property that limits the application of deterministic models is a large scale of environmental changes. For these reasons deterministic models are not often used for an indoor field prediction [2]. In statistical models, all environmental influences are implicitly taken into account; however they suffer from accuracy problems.

Results from [1] and [3-4], show that significant improvements of EMF prediction for indoor environment can be made using neural networks. Because of the constructive and destructive interference effect, EMF distribution for indoor environment is highly nonlinear. Multilayer Perceptron trained with back-propagation algorithm may be viewed as a practical vehicle for performing a nonlinear input-output mapping of a general nature [5]. Because of the generalization property, neural network can produce good predictions, even for unknown environment [3]. However, the neural network used in this case was rather complex and also needed a large environmental data base. Furthermore, extensive measurements, as well as training data processing had to be conducted to achieve good results. Different, simpler type of study was reported in [6] and [7], where no environmental data base was needed. Results from these papers suggest that it is possible to predict an EMF distribution for indoor environment using neural network trained only with field measurements.

The main objective of this work was to create a simple neural model that can give accurate predictions of EMF distribution for indoor environment based only on field measurements. To achieve that goal, a specific organization of training data was used. The procedure of creating such a model is described in Section 2 of this paper. Underlying physical principles of indoor propagation are given in Section 3. Prediction abilities of created neural model are tested on a specific prediction problem through an experiment described in Section 4. Simulation results of five case studies are presented in Section 5, and the conclusion is reported in Section 6.

2 ANN FOR EMF PREDICTION

Artificial neural networks (ANN), in general, represent a set of highly interconnected artificial neurons, which work in unified manner to solve given problems. Every neuron calculates the output value o_j, based on the input values i_n, weight factors w_n, bias value b and transfer function f, according to (1):

$$o_j = f\left(\sum_{n=1} w_n i_n + b\right). \tag{1}$$

ANNs are supposed to solve problems more efficiently than conventional computer techniques. In order to create a neural model for EMF prediction, it is necessary to determine the type of network, number of layers and neurons, training algorithm and training conditions.

Multi-Layer Perceptrons (MLPs), with sigmoid transfer functions in the hidden layer and linear transfer functions in the output layer are universal approximators [8].

During the training process, weights w_i and biases b are being adjusted according to the training algorithm in order to produce minimal MSE (mean square error) i.e. network performance function, given by (2), where Q denotes total number of training samples k in one epoch.

$$MSE = \frac{1}{Q}\sum_{k=1}^{Q}\left[d(k) - y(k)\right]^2. \tag{2}$$

MLP neural networks are usually trained with back-propagation training algorithm, described in [5] and [9]. The basic algorithm, given by (3), calculates the adjustable network parameter updates for each calculation step m:

$$\chi(m+1) = \chi(m) - \eta \cdot \frac{\partial MSE}{\partial \chi(m)} \tag{3}$$

where χ represents a vector of current weights and biases, partial derivation of MSE is the current gradient and η is the learning rate. There are a number of variations of the basic algorithm (3) that are based on other standard optimization techniques, such as conjugate gradient and Newton methods [9]. Currently, the most commonly used algorithm, which produces best results, is Levenberg-Marquardt (LM) algorithm, described in [9] and [10].

In order to train the network for function approximation, the training process requires a set of examples of proper network behaviour, network inputs (P) and target outputs (T). Therefore, the values of EMF strength were measured at certain points of considered indoor environment.

During the training process, ANN learns the relationship between locations of measurement points and EMF strength at these points, i.e. it learns, from measured data, the functional link between input (P) and target vector (T), for given indoor environment. The knowledge collected through the training process is stored in terms of adjustable network parameter values (weights and biases).

The number of layers and neurons for proposed neural model was determined experimentally. MLP-12-64-1 neural network, with 12 neurons of first, 64 neurons of second hidden layer and 1 output neuron, trained with LM algorithm, produced the best results. It is important to notice that the total number of points in the training set is limited and not larger than the number of network parameters. One of the problems that can occur during neural network training in situations like this is overfitting, that reduces ANN's ability to generalize and thus make an accurate prediction. The two methods for improving generalization used here are regularization and early stopping, described in [9].

3 PROPAGATION CONDITIONS AND CHOICE OF COORDINATE SYSTEM

In order to best cover the whole extent of the analyzed area, the measurement points were organized into a rectangular grid with uniform spacing (Fig. 1). Normally, each point could be characterized by its Cartesian $(x - y)$ coordinates. On the other hand, there is possibly a better option, explained hereafter.

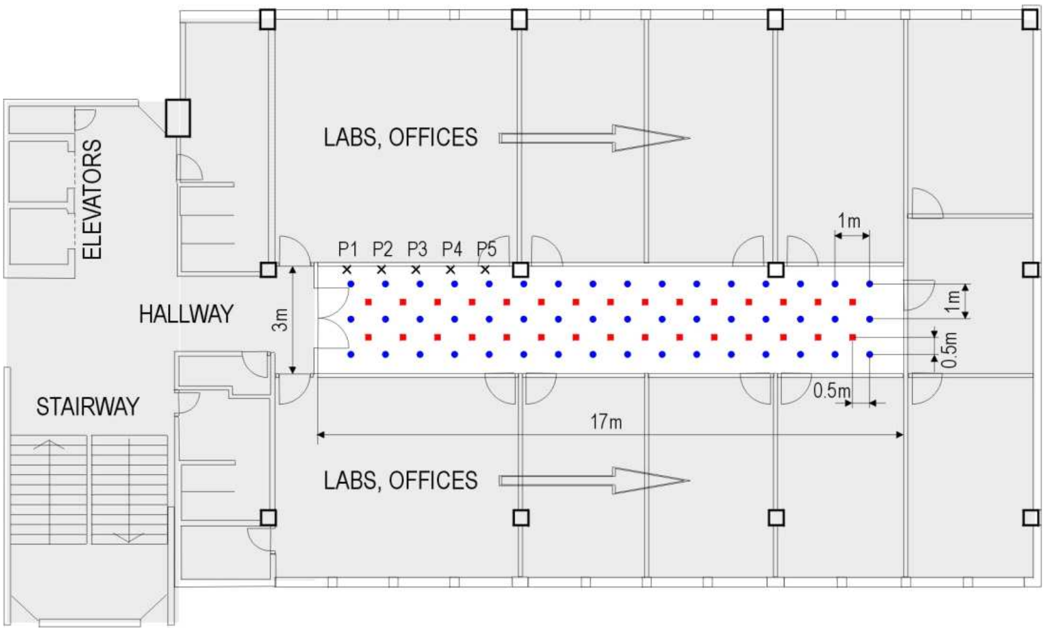

Fig. 1. Grid of measurement points in the closed part of the hallway (ground plan).

EM wave propagates radially from the source, thus decreasing its field strength as the distance from the source increases. WLAN access points commonly use vertically polarized antennas such as half-wave sleeve dipoles (looking like a rubber whip). The electric far field of such vertically polarized antenna in free space has only the elevation θ component and is given by:

$$E_\theta = \mathrm{j}\eta \frac{I}{2\pi r} \mathrm{e}^{-\mathrm{j}kr} \frac{\cos\left(\frac{\pi}{2}\cos\theta\right)}{\sin\theta} \tag{4}$$

where η is the wave impedance of the propagation medium and for free space equals $\eta_0 = 120\pi\Omega$, I is the current fed to the antenna, r is the distance from the transmitting antenna, k is the phase constant and equals $2\pi/\lambda$, and θ is the elevation angle (antenna being the origin of the coordinate system). The field strength dependence on the distance r is obvious.

This equation contains the trigonometric functions that define the radiation pattern; it is omnidirectional in the horizontal plane and directional (eight-shaped) in the vertical plane. If we are interested in a receiving point at the same height as the transmitting antenna (two-dimensional problem), the field strength of the direct line-of-sight (LOS) wave is given by entering $\theta = \pi/2$ into (4) yielding:

$$E_{\mathrm{LOS}} = \mathrm{j}\eta \frac{I}{2\pi r} \mathrm{e}^{-\mathrm{j}kr}. \tag{5}$$

The electric field magnitude is a complex number; its phase depending on the traveled distance, according to the term e^{-jkr}.

In order to cover the indoor area with a WLAN signal, an antenna is placed in a closed volume, e.g. a room or a hallway. The boundaries of the volume (walls, floor and ceiling), as well as objects inside it, create multiple reflected waves that propagate inside the volume. The field strength in any point is a complex sum of all waves that reached that point.

As shown in Fig. 2, receive point in space is reached by the direct LOS wave and by the reflections arriving from different angles.

The original wave can be observed as a large number of rays. Only one of them, the LOS ray, can arrive to a

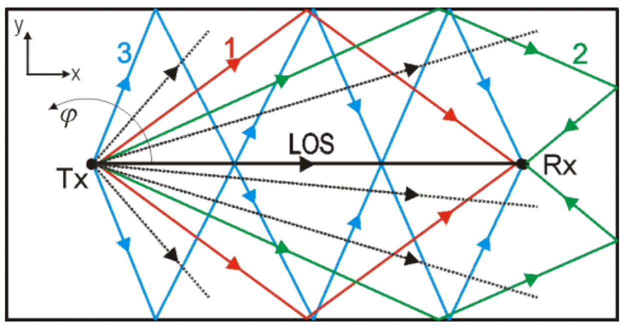

Fig. 2. Example of indoor propagation (room ground plan) with several illustrative rays. Numbers designate the number of reflections for each contributing ray. Dotted lines are examples of rays not likely to contribute significantly to the field at Rx point.

receiving point without reflections. Of all other rays, some will arrive after one reflection, other after two, three, and so on. Each will travel a different distance, thus arriving with a different phase, generating constructive and destructive interference at a point of interest. However, as the number of reflections rises, so does the distance traveled from the transmitting antenna, causing a decrease of amplitude of such rays. Furthermore, a wave (ray) looses some of its energy every time it reflects from a wall, according to the expression:

$$|E_{\mathrm{r}}| = |R|\,|E_{\mathrm{i}}| \tag{6}$$

where E_r is the reflected field strength, E_i is the reflected field strength, R is the reflection coefficient and $|R| < 1$.

Consequently, rays with multiple reflections do not contribute much to the total field. This especially applies to the area closer to the antenna, where the LOS wave travels much smaller distance than the reflected ones.

Those reflected rays that reach the receiving point with significant amplitude, contribute to the total electric field with their amplitude and phase. Since the electric field is a vector quantity, the total field at any point would generally be a vector sum of all incident field vectors. Considering that the interest of this analysis is WLAN, both Tx and Rx antennas are vertically polarized and only the resulting z component of the electric field is relevant.

When a ray is reflected from the side walls, the incident polarization of the incident wave is TE (transverse electric field), electric field is perpendicular to the reflection plane and the reflection coefficient R is given as:

$$R_{\perp} = \frac{\eta_1 \cos\phi_{\mathrm{i}} - \eta_0 \cos\phi_{\mathrm{t}}}{\eta_1 \cos\phi_{\mathrm{i}} + \eta_0 \cos\phi_{\mathrm{t}}} \tag{7}$$

where η_0 is the wave impedance of the free space, η_1 is the wave impedance of the boundary medium, φ_i is the incidence angle and φ_t is the refraction angle. Both angles are in the azimuth plane, thus designated as φ. For both Tx and Rx antennas at the same height, only z component exists.

When a ray is reflected from the floor or ceiling, the incident polarization of the incident wave is TM (transverse magnetic field), electric field is parallel to the reflection plane and the reflection coefficient R is given as:

$$R_{\,||} = \frac{\eta_1 \cos\theta_{\mathrm{t}} - \eta_0 \cos\theta_{\mathrm{i}}}{\eta_1 \cos\theta_{\mathrm{t}} + \eta_0 \cos\theta_{\mathrm{i}}}. \tag{8}$$

Both angles are in the elevation plane, thus designated as θ. The wave impedance of the boundary medium is generally a complex number, dependent on the dielectric properties of the material, given by:

$$\eta_1 = \sqrt{\frac{\mathrm{j}\omega\mu_1}{\sigma_1 + \mathrm{j}\omega\varepsilon_1}} \tag{9}$$

where μ_1, σ_1 and ϵ_1 are magnetic permeability, electrical conductivity and dielectric permittivity of the material, respectively.

Concerning the vertical radiation pattern shown in red color in Fig.3, the radiation towards the floor or ceiling directly above or beneath the Tx antenna (blue ray) is low, so reflections from floor or ceiling are not relevant close to Tx antenna. Furthermore, the z component of the E field is also low in those directions, as shown by vector magnitudes in Fig. 3. As the Rx antenna moves away from the Tx, the reflections from floor or ceiling are more relevant in both ways. Also, consequent reflections from floor/ceiling and back wall are possible.

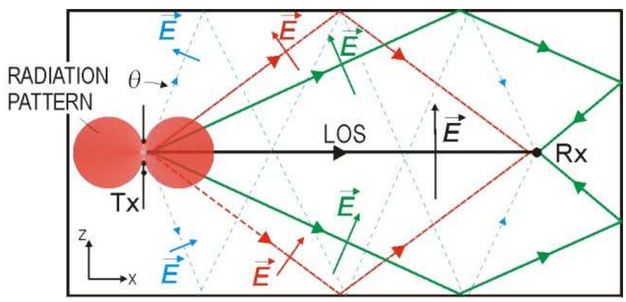

Fig. 3. Room side elevation with several illustrative rays. The amplitude and polarization of electric field vector is shown for each ray

Finally, the total field will be a complex sum of all contributions:

$$|E_{\mathrm{total}}| = \left| E_{\mathrm{LOS}} + \sum_i E_{\perp,i} + \sum_j E_{||,j} + \sum_k E_{\perp,||,k} \right| \tag{10}$$

where the first term refers to the LOS wave, second term refers to the rays reflected from the side walls (once or multiple times), third term refers to the rays reflected from the floor or ceiling (once or multiple times), fourth term refers to the rays reflected both from the side walls and ceiling or floor. In this brief explanation, other complications, such as existence of other rooms, furniture etc. were not taken into account, for the sake of simplification. However, the field distribution is in fact even more complex than presented herein.

The purpose of this analysis was to show that, if a problem is reduced to the horizontal plane (two dimensions), the received field strength in any point will depend strongly on its distance from the transmitting antenna and the azimuth angle in the horizontal plane.

The dependence on the distance is incorporated in the fundamental expressions (4) and (5), for the free space propagation. Moreover, we explained another distance dependence, for the indoor propagation: the relevance of reflected rays amplitude with respect to the LOS ray amplitude will depend on the distance. Close to the transmitter, the LOS ray is more dominant and the reflected rays are less significant. Also, just moving a receiving point along the LOS (changing its distance for the transmitter) changes the reflection angles of arriving reflected rays. This changes their reflection coefficient (7), as well as their amplitude, according to (6).

The azimuth angle dependence was also shown by previous analysis. As the receiver is moved along the azimuth angle, while keeping the constant distance from the transmitter, the phases of arriving reflected rays change and therefore the interference of all rays arriving to the receiver moves periodically from constructive to destructive. Thus the field strength varies with the azimuth coordinate of the receiver.

Field strength at a receiving point would depend on azimuth even more if the transmitting antenna were not omnidirectional. However, when omnidirectional antennas are placed close to a wall or other object (common case), their radiation pattern is surely deformed from the omnidirectional to directional, yielding further azimuth angle dependence.

If the space consists of complex geometry and different objects with different reflective properties, as in Fig.1, the field strength varies even more. Some rays get lost in other rooms and decay through reflections, never reaching certain receiving points. The amplitude of reflected rays also varies with the reflective properties of different objects. These two effects transform into complex dependence on both the distance and azimuth.

Consequently, the field strength distribution across various points in indoor area depends on the distance from the Tx antenna and the azimuth of the direction from the Tx antenna to the point of interest. However, this function is very complex and surely not linear.

Therefore, we chose to describe the locations of measurement points as a function of distance (r) and azimuth angle (φ), as measured from EMF source. Instead of Cartesian $(x-y)$ coordinates, used in [6] and [7], we chose polar coordinates to come as close as possible to the physical law of EMF distribution, and thus make an improvement in EMF prediction. Furthermore, input-target pairs were sorted by the distance from EMF source to alleviate the process of learning.

4 FIELD STRENGTH MEASUREMENTS

The measurements were conducted at University of Split, Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture, as shown in Fig. 1.

EMF was generated by a vertically polarized rod antenna, omnidirectional in horizontal plane, fed from Rohde&Schwarz SM300 signal generator having output power of 13 dBm, working at 2.4 GHz.

The signal was received by vertically polarized ARC Seibersdorf PCD8250 biconical antenna, and the received power P_{rec} (proportional to EMF strength) was measured by Anritsu MS2663C spectrum analyser, using averaging over 20 measurements for each point. Both the transmitting and the receiving antenna were placed at the same height of 1.5 m above the floor, making this a two-dimensional problem. Measured distributions are shown in Fig. 4.

5 SIMULATION RESULTS AND DISCUSSION

ANN for indoor EMF prediction was created in MATLAB, using *newff* function from Neural Network Toolbox. The network was trained with LM training algorithm that used MSE as a performance function, early stopping and random division of training data. MSE converged towards a training goal (set to zero) after approximately 60 training epochs. The input vector was created with data gained from 48 measurement points (blue circles in Fig. 1), repeated 6 times in 1 training epoch. The network was first trained with EMF measured data at 48 points (blue circles) described as function of polar (r and φ) coordinates to create "ANN-12-64-1_fi-d" neural model. ANN of the same structure was then trained in the same conditions, but with the location of measurement points described with Cartesian $(x-y)$ coordinates. In this way the "ANN-12-64-1_x-y" neural model was created. The remaining 30 points (red squares in Fig. 1) were predicted using these two models, and then compared to the actual measured values (Fig. 5).

Neural models responses shown in Fig. 5 and RMSE (root mean square error, calculated as the square root of MSE defined by (2)) values in Table 1 confirm the advantage of using polar instead of Cartesian parameters.

It is important to notice, that ANNs are trained equally well, in both cases. The process of forming neural models with the specific organization of input data was then repeated for the case of training the network with Bayesian Regularization (BR). One feature of this algorithm is that it provides a measure of how many network parameters (weights and biases) are being effectively used by the network. This eliminates the guesswork required in determining the optimum network size [9]. Since LM training algorithm and early stopping produced equally good results as

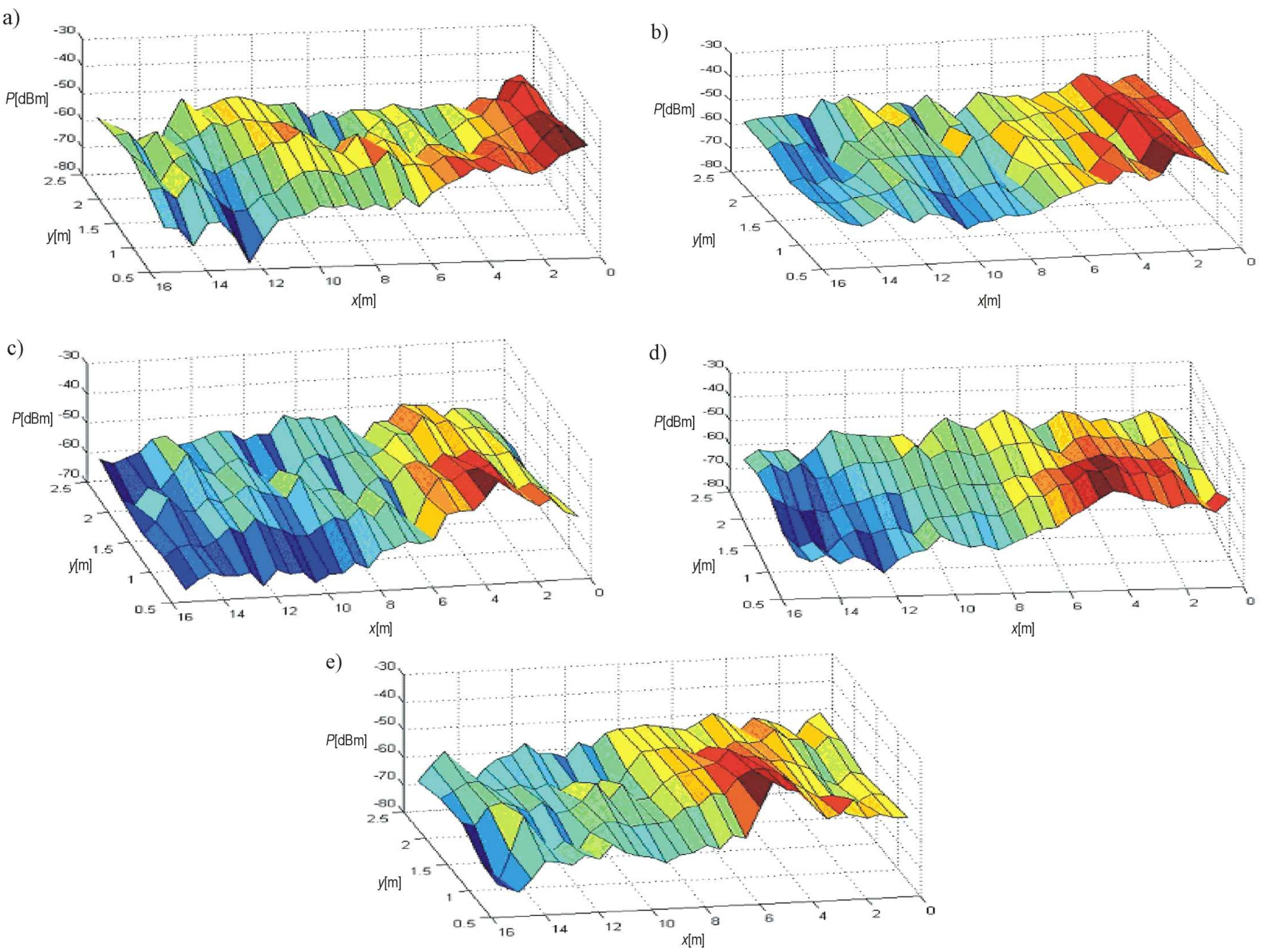

Fig. 4. Measured EMF distributions in terms of received power P_{rec} in dBm, for transmitter positioned at: a) P1, b) P2, c) P3, d) P4, e) P5

BR training algorithm, but insure an easier training procedure, LM algorithm was used to obtain neural models. BR was used only to verify selected network structure, i.e. the number of network parameters.

6 CONCLUSION

This work represents a report on conducted research of the improvement possibilities in indoor WLAN signal strength prediction using neural network trained with measurement data. Due to radial propagation of the signal from a WLAN antenna, polar coordinates were the right choice for the description of the real physical distribution of EMF strength that needed to be simulated. The simulation results confirmed improvement of the neural model's predictive ability when points in space were described by polar coordinates measured as distance and azimuth from the EMF source, instead of using Cartesian coordinates. ANN trained with measured values of EMF at points described by their polar coordinates made the training process easier, faster and more efficient.

ANN for indoor EMF prediction used LM training algorithm and early stopping as a measure against overfitting problem. BR algorithm was also used, but only to verify the selected network structure. Simulation studies suggested the possibility of achieving smaller prediction errors if the network training goal would be less strict (not equal to zero). Determination of the optimally trained network, i.e. determination of the optimal objective function minimum, might be the next step towards further improvement of indoor EMF prediction using neural network.

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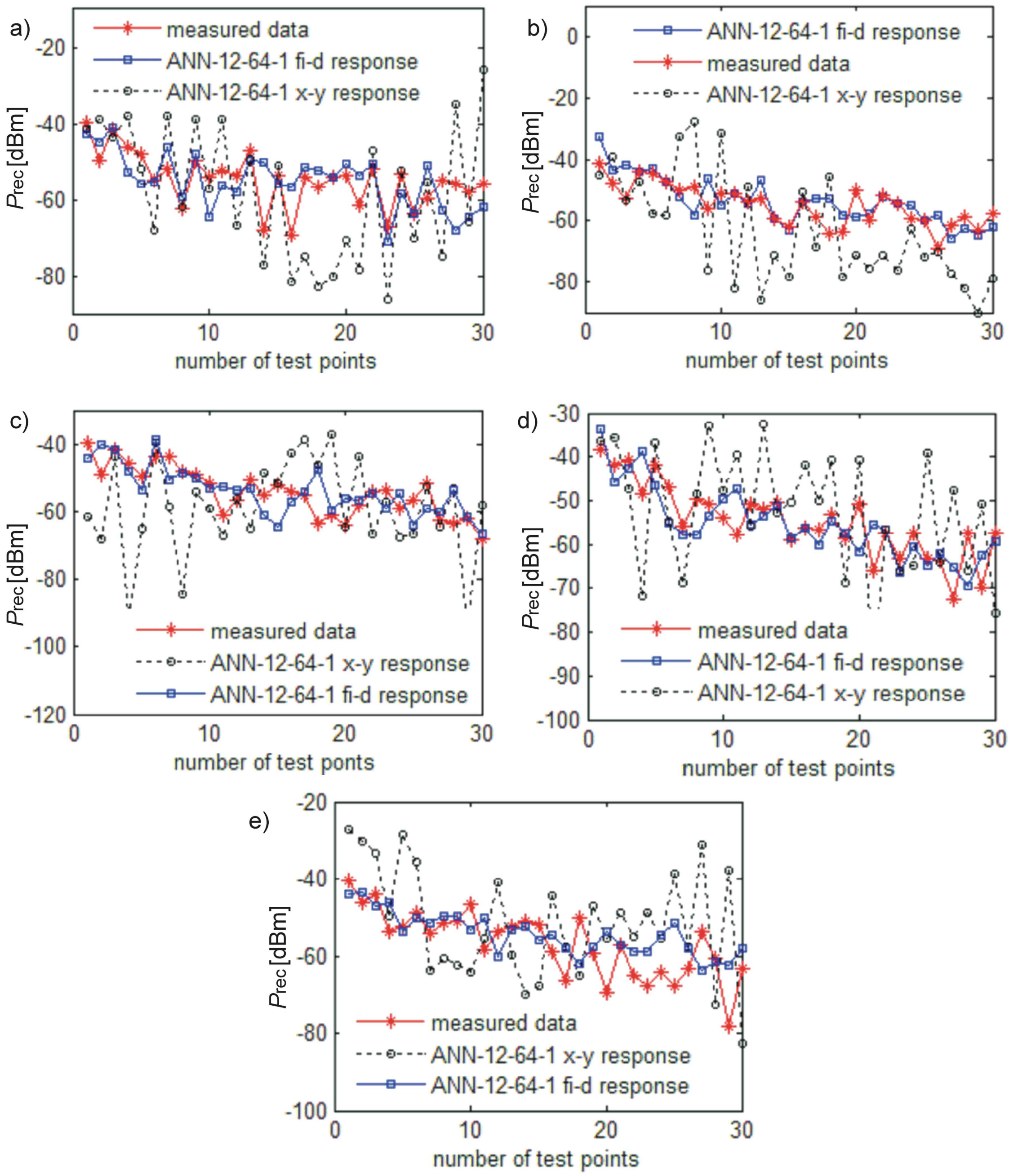

Fig. 5. Predicted and measured values of EMF in terms of received power P_{rec} in dBm, for transmitter positioned at: a) P1, b) P2, c) P3, d) P4, e) P5

Table 1. RMSE values in dB

Transmitter position	ANN-12-64-1_x-y	ANN-12-64-1_fi-d
P1	14,07	6,67
P2	17,15	5,61
P3	16,42	5,99
P4	13,26	5,72
P5	16,09	7,38

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