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FIELD STRENGTH PREDICTION IN INDOOR ENVIROMENT WITH A NEURAL MODEL

Ileana Popescu, Ioan Naforni, Gheorghe Gavriloaia, Philip Constantinou and Cornelia Gordan

Abstract: This paper presents the results of our studies concerning the application of the neural networks to the field strength prediction in indoor environment. The proposed model consists of a multilayer perceptron trained with measurements. The results of the prediction show a good agreement with the measurements

Key words: Artificial neural networks, neural model, indoor environment, propagation models.

1. Introduction

The basis for a propagation model may be either theoretical or empirical, or a combination of these two. Theoretical propagation models allow recognition of the fundamental relationships that apply over a broad range of circumstances. They also allow definition of relationships that exist among any combination of input parameters. Empirical models are derived from measurements and observations and offer a major advantage in that all environmental influences are implicit in the result regardless of whether or

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I. Popescu is with the University of Oradea, Romania and is a visitor researcher at the Mobile Radiocommunications Laboratory, National Technical University of Athens, 9 Heroon Polytechniou Str., GR-15773, Zografou, Athens, Greece (e-mail: `ipopes@cc.ece.ntua.gr`). I. Nafornita is with the Telecommunications Department, "Politechnica" University of Timisoara, 2 Vasile Parvan Str., Timisoara, Romania. Gh. Gavriloaia is with the Radar Department, Military Technical Academy, Bucharest, 81-83 George Cosbuc Av. 7525, Bucharest, Romania. P. Constantinou is with the Mobile Radiocommunications Laboratory, National Technical University of Athens, 9 Heroon Polytechniou Str., GR-15773, Zografou, Athens, Greece. C. Gordan, associate professor, is with the University of Oradea, 5 Armatei Romane Str., Oradea, Romania.

not they can be separately recognized and theoretically studied. Empirical models offer the opportunity to provide probabilistic descriptions of the propagation phenomena. The validity of empirical models is limited only by the accuracy with which individual measurements are made and by the extent to which the environment of the measurements adequately represents the physical environment in which the model is to be applied [1].

Indoor radio propagation is a very complex and difficult radio propagation environment because the shortest direct path between transmit and receive locations is usually blocked by walls, ceilings or other objects. Signals propagate along the corridors and other open areas, depending on the structure of the building.

In modeling indoor propagation the following parameters must be considered: the location of the transmitter and the receiver antennas, the locations within a building, the types of interiors (rooms, corridors, etc) and the construction materials [1].

An alternative approach to the field strength prediction in indoor environment is given by prediction models based on artificial neural networks [6]. The advantages of these models are given by the flexibility to adapt to different environments, the high speed processing and the ability to process a large amount of data. The problem of field strength prediction is viewed as a function approximation problem consisting of a nonlinear mapping from a set of input variables containing information about the potential receiver onto a single output variable representing the predicted field strength.

2. Neural Network Overview

In our studies we have used multilayer feedforward networks, commonly referred to as multilayer perceptrons (MLP). The basic component of a neural network is the neuron. Figure 1 shows the configuration of a multilayer perceptron with one hidden layer and one output layer. The network shown here is fully interconnected. This means that each neuron of a layer is connected to each neuron of the next layer so that only forward transmission through the network is possible, from the input layer to the output layer through the hidden layers. Two kind of signals are identified in this network:

- The function signals also called input signals that come in at the input of the network, propagate forward (neuron by neuron) through the network and reach the output end of the network as output signals;
- The error signals that originate at the output neuron of the network

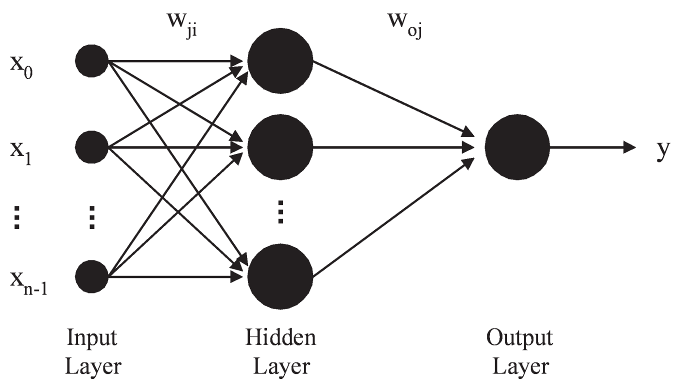

Fig. 1. The configuration of the multilayer perceptron.

and propagate backward (layer by layer) through the network.

The output of the neural network is described by the following equation

$$y = F_0\left\{\sum_{j=0}^{M} w_{0j}\left[F_h\left(\sum_{i=0}^{N} w_{ij}x_{ij}\right)\right]\right\} \tag{1}$$

where N represents the number neurons in the input layer and M represents the number of neurons in the hidden layer, w_{0j} represents the synaptic weights from neuron j in the hidden layer to the single output neuron, x_i represents the i^{th} element of the input vector, F_h and F_0 are the activation function of the neurons from the hidden layer and output layer, respectively, w_{ji} are the connection weights between the neurons of the hidden layer and the inputs.

The learning phase of the network proceeds by adaptively adjusting the free parameters of the system based on the mean squared error E, described by Eq. (2), between predicted and measured path loss for a set of appropriately selected training examples

$$E = \frac{1}{2}\sum_{i=1}^{m}(y_i - d_i)^2 \tag{2}$$

where y_i is the output value calculated by the network and d_i represents the expected output.

When the error between network output and the desired output is minimized, the learning process is terminated and the network can be used in a testing phase with test vectors. At this stage, the neural network is described by the optimal weight configuration, which means that theoretically ensures the output error minimization.

The goal of the prediction is not only to produce small errors for the set of training examples but also to be able to perform well with examples not used in the training process. This generalization property is very important in practical prediction situation where the intention is to use the propagation prediction model to determine the coverage area of potential transmitter locations for which no or limited measured data are available.

The selection of the set of training examples is very important in order to achieve good generalization properties [2]. The set of all available data is separated in two disjoint sets that are training set and test set. The test set is not involved in the learning phase of the networks and it is used to evaluate the performance of the neural model.

In our application the neural network is trained with the Resilient Backpropagation algorithm. In order to determine the direction of the weight update only the sign of the derivative is used. The magnitude of the derivative has no effect on the weight update. The size of the weight change is determined by a separate update value. The update value for each weight and bias is increased whenever the derivative of the performance function with respect to that weight has the same sign for two successive iterations. If the derivative with respect to that weight changes sign from the previous iteration, the update value is decreased. If the derivative is zero, there are no changes in the update value. Whenever the weights are oscillating the weight change will be reduced. If the weights continue to change in the same direction for several iterations, then the magnitude of the weight change will be decreased. A more detailed description of this algorithm can be found in [5].

3. The Measurements

The measurements were conducted in the 1890 MHz frequency band, at the Hellenic Telecommunication Organization premises following different scenarios. A detailed description of the measurement procedure can be found in [4]. Each floor of the building consists of a circular sector of 60m in circumference located at the center of each floor and 3 branches departing from the circular sector, where at each branch there are one main long corridor and two short back corridors with offices flanked on both sides of corridors, as shown in Fig 2.

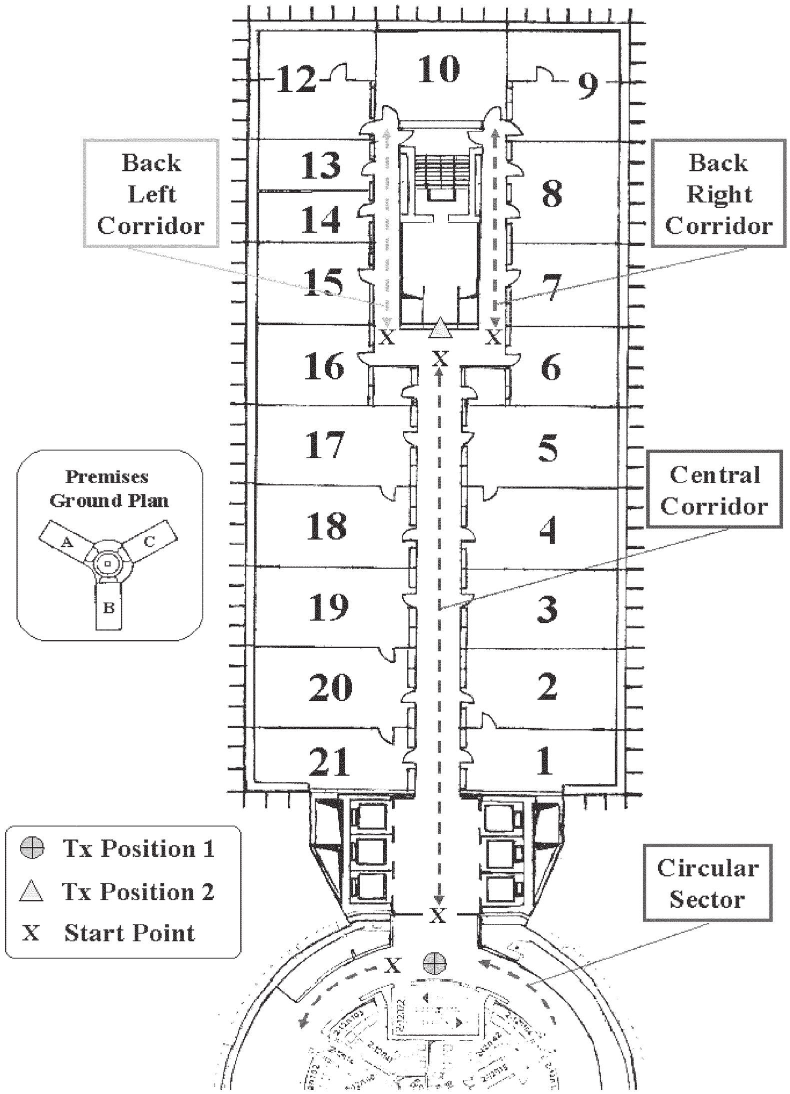

Fig. 2. The building topology and the transmitter positions.

Offices are in consecutive order and are separated by soft partitions. Measurements were done along the corridors and inside the offices, in all three branches. In every position of the receiver inside the offices about 10000 samples of the received power were recorded while the receiving antenna was rotating. The transmitting antenna was located always in the same sector of the eleventh floor in two different sites (position: 1 or 2 in Fig. 1). The base station antenna heights used were 2.2m, 2.6m and 2.7m. The measurements were performed using two different types of transmitting antenna: OMNI and directional. The receiving antenna was always an OMNI antenna. Our study includes the single floor scenario and the procedure used to select the measurement data is described below.

In order to train the neural network we have used the measurements collected from two branches, denoted sector B, where the transmitter was always located, and sector A. The fast fading was eliminated, in the case of longitudinal measurements (along the corridors), by averaging the measured received power using a 2? windowing technique [3]. In the case of static measurements the average values of the recorded samples in every position of the receiver inside the offices were computed. In this way we have obtained two values for the received power in each office (with closed doors respectively with open doors) for each combination of the position, height and gain of the transmitter antenna.

Following the filtering process of the measured data we obtained more than 1400 measurement locations corresponding to the non-line-of-sight (NLOS) case.

The performance of the neural network model is evaluated by making a comparison between predicted and measured values based on the absolute mean error, standard deviation and root mean squared error. The absolute error between the measured and predicted path loss is computed with

$$E_i = \left| PL_i^{measured} - PL_i^{predicted} \right| \tag{3}$$

where i represents the number of the measured sample. The absolute mean error is computed by

$$\mu = \frac{1}{N} \sum_{i=1}^{N} E_i \tag{4}$$

where N is the total number of measured samples. The standard deviation is determined from the absolute error and the mean absolute error

$$\sigma = \sqrt{\frac{1}{N-1} \Big(\sum_{i=1}^{N} E_i^2 - N\mu^2 \Big)} \tag{5}$$

The RMS error is given by

$$RMS = \sqrt{\mu^2 + \sigma^2} \tag{6}$$

4. Results

In our study we consider the feed-forward multilayer perceptron trained with the Resilient Backpropagation algorithm. The inputs of the neural network are the following:

- three inputs for the transmitter site: position, gain and height of the
- antenna,
- two inputs for the distance between transmitter and the staring point of the measurements and the distance covered by the mobile unit,
- two inputs describing the receiver site; three inputs for the smallest number of walls and
- windows penetrated by the ray between transmitter and receiver and their accumulated losses.

The input parameters that describe the transmitter and receiver location are quantized so the effect of each parameter is more obvious for the neural network [6]. For example, the parameters like size of the corridors where the receiver is located are quantized as follows: 1 for the large corridor and 0.3 for the medium corridor. All parameters are normalized to the range [-1, +1].

The output layer consists of one neuron that provides the normalized received power. Two hidden layers of 18 neurons have been used in the architecture of the network.

A data set of 289 patterns (input/desired output pairs) was divided in 2 different sets: 271 patterns used for training and 18 patterns used for validation. A set of 1155 training patterns was used to test the model. In Table 1 are represented the absolute mean error, the standard deviation and the root mean squared error obtained for the training set, the test set and in case of one particular route of the receiver.

Table 1. Results of the prediction.

	Training patterns	Test patterns	Particular route
Mean Error [dB]	2.77	3.05	2.33
Std. Dev. [dB]	2.31	3.15	1.79
RMS [dB]	3.61	4.38	2.94

In Fig. 3 is represented a comparison between predicted and measured values when the transmitter is in position 1 and the receiver is located along the main corridor in sector A. For this particular route, the values for the

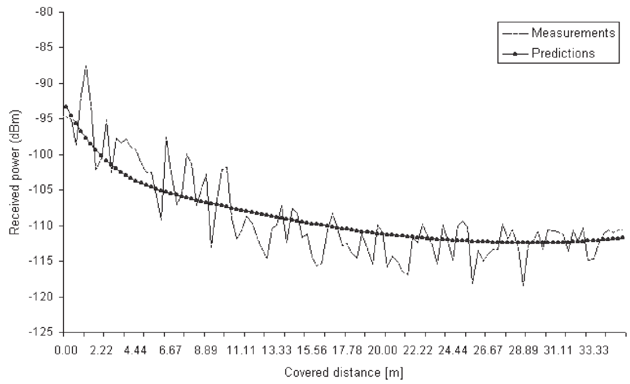

Fig. 3. Comparison between predictions and measurements with the transmitter in position 2 and the receiver located in sector A, along the main corridor.

absolute mean error, standard deviation and RMS are presented in Table 1. The percentage of the predicted values with a mean error below 5 dB is 81.55 % in the case of the entire test set respectively 90.17 % in the case of the particular route.

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