Prediction Models of an Indoor Smart Antenna System using Artificial Neural Networks

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Abstract. This study presents the prediction propagation paths of angle of arrivals (AoAs) of a Smart Antenna System in an indoor environment utilizing Artificial Neural Networks (ANN). The proposed models consist of a Multilayer Perceptron and a Generalized Regression Neural Network trained with measurements. For comparison purposes the theoretical Gaussian scatter density model was investigated for the derivation of the power angle profile. The antenna system consisted of a Single Input Multiple Output (SIMO) system with two or four antenna elements at the receiver site and the realized antenna configuration comprised of Uniform Linear Arrays (ULAs). The proposed models utilize the characteristics of the environment, the antenna elements and their spacing for prediction of the angle of arrivals of each one of the propagation paths. The results are presented towards the average error, standard deviation and mean square error compared with the measurements and they are capable for the derivation of accurate prediction models for the case of AoA in an indoor millimeter wave propagation environment.

Keywords. ANN, SIMO, Millimeter band, Smart Antenna

Introduction

Smart Antenna Systems [1] and especially MISO (Multiple Input Single Output) [2] or SIMO (Single Input Multiple Output) [3] systems have already been evaluated for the optimization of wireless system performance. In millimeter wave frequencies the propagation modeling, apart from the known empirical models, can be realized based on geometrical optics using ray-tracing theory. In the 60 GHz region the diffraction phenomenon can be neglected, and the sum of the direct ray and the reflected rays is enough to describe the behavior of the propagation channel with great accuracy. The prediction of the field strength is a very complex and difficult task. In most cases, there are no clear line-of-sight (LOS) conditions between the transmitter and the receiver. Generally, the prediction models are classified as empirical [4] or theoretical [5], or a combination of
these two [6]. However, the main problem of the classical empirical models is the unsatisfactory accuracy, while the theoretical models lack in computational efficiency.

During last years, Artificial Neural Networks (ANN) have experienced a great development. ANN applications are already very numerous. Classificators, signal processors, optimizers and controllers have already been realized. Although there are several types of ANN’s all of them share the following features [7]: exact analytical formula impossible; required accuracy around some percent; medium quantity of data to process; environment adaptation that allows them to learn from a changing environment and parallel structure that allows them to achieve high computation speed. All these characteristics of ANN’s make them suitable for predicting field strength in different environments and furthermore angle of arrivals (AoA).

The prediction of field strength and AoA can be described as the transformation of an input vector containing topographical and morphographical information (e.g. path profile) to the desired output value. The unknown transformation is a scalar function of many variables (several inputs and a single output), because a huge amount of input data has to be processed. The inputs contain information about the transmitter and receiver locations, surrounding buildings, frequency, etc while the output gives the propagation loss for those inputs. From this point of view, research in propagation loss modeling consists in finding both the inputs and the function that best approximate the propagation loss. Given that ANN’s are capable of function approximation, they are useful for the propagation loss and angle of arrival modeling. The feedforward neural networks are very well suited for prediction purposes because do not allow any feedback from the output (field strength or path loss) to the input (topographical and morphographical data).

In this paper, the presented studies develop a number of Multilayer Perceptron Neural Networks (MLP-NN) and Generalized Radial Basis Function Neural Networks (RBF-NN) based models trained on extended data set of propagation path loss measurements taken in an indoor environment. The smart antenna measurement system was a SIMO one where a continuous wave (CW) signal at 60 GHz was transmitted from a fixed base station to a fixed receiver, comprised of two or four antenna elements. The signal envelope as a function of time was recorded. The performance of the neural network based models is evaluated by comparing their prediction, standard deviation and mean square error (MSE) between their predicted values and measurements data. Also, a comparison with the results is obtained by applying the Gaussian model.

The remainder of this paper is organized as follows. Section 1 deals with the ANN overview describing and explaining the behavior of the two NN utilized models. In Section 2, an analytically description of the geometry of the measurement environment under consideration is presented along with the measurement procedure. In Section 3, the NN prediction models are implemented analytically describing the implementation method and the prediction results are presented in terms of measured Power Angle Profile (PAP), taking also into consideration the Gaussian model. Finally, Section 4 is devoted to conclusions derived by the prediction procedure.
1. The ANN Overview

1.1. Multilayer Perceptron Neural Network (MLP-NN)

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

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

\[
y = F_o \left( \sum_{j=0}^{M} w_{oj} \left( F_h \left( \sum_{i=0}^{N} w_{ji} x_i \right) \right) \right)
\]

where

- \( w_{oj} \) 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 \( F_o \) 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 square error $E$, described by Eq. (2), between predicted and measured path loss for a set of appropriately selected training examples:

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

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.

1.2. Generalized Radial Basis Function Neural Network (RBF-NN)

The Generalized Radial Basis Function Neural Network (RBF-NN) is a neural network architecture that can solve any function approximation problem. The learning process is equivalent to finding a surface in a multidimensional space that provides a best fit to the training data, with the criterion for the “best fit” being measured in some statistical sense. The generalization is equivalent to the use of this multidimensional surface to interpolate the test data.

As it can be seen from Figure 2, the Generalized Radial Basis Function Neural Network (RBF-NN) consists of three layers of nodes with entirely different roles:

- The input layer, where the inputs are applied,
- The hidden layer, where a nonlinear transformation is applied on the data from the input space to the hidden space; in most applications the hidden space is of high dimensionality.
The linear output layer, where the outputs are produced. The most popular choice for the function $\phi$ is a multivariate Gaussian function with an appropriate mean and autocovariance matrix. The outputs of the hidden layer units are of the form:

$$\phi_i \left[ x \right] = \exp \left[ -\frac{\left( x - v_i^* \right)^T \left( x - v_i^* \right)}{2\sigma^2} \right]$$  \hspace{1cm} (3)

when $v_i^*$ are the corresponding clusters for the inputs and $v_i^*$ are the corresponding clusters for the outputs obtained by applying a clustering technique of the input/output data that produces $K$ cluster centers [8]. $v_i^*$ and $v_i^*$ are defined as:

$$v_i^* = \sum_{x(p) \in \text{cluster } k} x(p)$$  \hspace{1cm} (4)

$$v_i^* = \sum_{y(p) \in \text{cluster } k} y(p)$$  \hspace{1cm} (5)

The outputs of the hidden layer nodes are multiplied with appropriate interconnection weights to produce the output of the GRNN. The weight for the hidden node $k$ (i.e., $w_k$) is equal to:

$$w_k = \frac{v_i^*}{\sum_{i \in k} N_i \exp \left[ -\frac{d \left( x, v_i^* \right)^T \left( x - v_i^* \right)}{2\sigma^2} \right]}$$  \hspace{1cm} (6)

where $N_i$ is the number of input data in the cluster centre $k$, and

$$d \left( x, v_i^* \right) = \left( x - v_i^* \right)^T \left( x - v_i^* \right)$$  \hspace{1cm} (7)

2. Measurement Environment and Procedure

The measurement took place in a typical office environment as indicated in Figure 3. As it is evident, with dark shaded colours are presented the furniture (wooden or metal closets...
and workbenches) that are above the direct path between the transmitter (height 1.6 m) and receiver (height 1.6 m) and would potentially block the signal propagation (apart from the partitions). With lighter colours are depicted furniture surfaces (e.g., desks) that do not obstruct the direct signal propagation. The closets have a height of 2 m, the workbenches 1.4 m and the desks (including the computers) 1.15 m.

Surface A is an external wall with windows in consecutive order separated by concrete pillars. Each window has 5 mm glass with aluminium frame. The windows have metallic window shades in front which during the measurements were down. Surface B is an internal thick wall made of brick and covered with plaster and paint on both sides. The total wall thickness is 23 cm.

Figure 3. Measurement environment and superimposed the derived Power Angle Profile.

The floor is made of concrete and covered with marble and a thin antistatic plastic layer. The ceiling is made of concrete with a total height of 3.4 m. Approximately 60 cm below the ceiling a metal frame structure suspends, holding the fluorescent light tubes. The Partition is made of 5 mm glass with aluminium studs every 1.5 m. The internal doors consist of 5 mm glass with aluminium frame. The internal doors during the measurements were closed. The wooden closets have a thickness of 42 cm and made of 1.5 cm wooden chipboard covered with melamine and 5 mm glass as a front cover. Similarly the metal closets are 36 cm thick and consist of 3 mm galvanized steel with 5 mm glass as a front cover. We should mention though, that the total true material thickness, which the signal penetrates, is 2 cm for the wooden and 8 mm for the metal closet.

The measurement was accomplished by transmitting a continuous wave (CW) signal at 60 GHz, from a fixed base station to a fixed receiver, and recording the signal envelope as a
function of time. Details for the measurement setup can be found in [9]. The transmitter was fixed at 1.6 m above the floor, at position Tx shown in Figure 3, whereas the output power was +10 dBm. The receiver hardware is located on a trolley, which was stationary at the measurement position. The distance between the transmitter and receiver was 6 m. After amplification, the received signal is down-converted to 300 MHz IF and fed to a commercial receiver. The input to the automatic gain control (AGC) of the receiver is then sampled at 2 kHz and the data values were stored to a portable PC. The receiver had a noise floor of -90 dBm. For this measurement, an omnidirectional with 0 dBi gain was used as the transmitter antenna, and a horn antenna with 35 dBi gain was used as the receiver antenna. Both antennas are vertically polarized. The half power beamwidth of the horn antenna was 4° in azimuth and 3° in elevation. The directional receive antenna was fixed at 1.6 m above the floor. When a highly directional antenna is used, the system provides high spatial resolution to resolve multipath components with different AoAs.

During the measurements, a mechanically steered directional antenna was used to resolve multipath components. An automated system was used to precisely position the receiver antenna along a linear track and then rotate the antenna in the azimuthal direction. At each position, the receiver antenna is rotated in azimuth from 0 to 360° with a step size of 5° and power was recorded at each of the 72 angular steps. Then, a local average is calculated from the measurement results at four different positions along the linear track being $\lambda/2$ apart. The local average helps to remove any residual small-scale or time-varying fading that may occur at individual positions. The precisions of the track and spin positions are better than 1 mm and 1°, respectively.

From the aforementioned measurement procedure, the PAP of a SISO channel can be derived. Consequently, if we know the Power Angle Profile (PAP) of a SISO channel, we can calculate the channel matrix of a SIMO channel multiplying the array response vector at the receiver. The PAP of a SISO channel can be yielded by either PAP measurements between fixed transmit and receive terminals, a properly trained NN model and, a theoretical model (e.g. Gaussian model). Furthermore, the aforementioned PAP extraction methods can be used in order to calculate the channel matrix for the antenna element configuration (ULA) and then we can easily estimate the channel capacity of the system.

3. Prediction Models’ Implementation

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 angle of arrival 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 [7], [10]. 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. An important problem that occurs during the neural network training is the overadaptation that is the
network memorizes the training examples and it does not learn to generalize the new situations. In order to avoid overadaptation and to achieve good generalization performances, the training set is separated in the actual training subset and the validation subset, typically 10-20% of the full training set [7]. In order to make the neural network training process more efficient, the input and desired output values are normalized so that they will have zero mean and unity standard deviation. With the intention of establishing the optimum configuration of the MLP neural network, networks with different architectures and different training algorithms were investigated. The results presented here refer to the optimum MLP-NN for each prediction case.

Since the purpose is to train the neural networks to perform well for all the routes, we should build the training set including points from the entire set of measurements data. For training and test purpose we have used the same number of patterns as in the prediction models for the indoor environment. Various inputs for the neural network were taken into consideration, consisting of position, gain and height of the transmitter site, the sector where the receiver antenna is located, the type of interior where the receiver is located, distances between the transmitter and receiver, received multipaths rays and penetration parameters such as number of penetrated walls and windows and accumulated losses.

The input parameters that describe the transmitter and receiver site are quantized so the effect of each parameter is more obvious for the neural network. For example, in order to describe the type of interior where the receiver is located, parameters like size of the corridors are quantized as follows: 1 for the large corridor and 0.3 for the medium corridor. The attenuation factors for different types of walls intervening between transmitter and receiver, as well as the loss for glasses were used as reported in [11] for this particular type of building. All parameters are normalized to the range [-1, +1]. The output layer of the Artificial Neural Network consists of one neuron that provides the received power.

A data set of 298 patterns, that represents 20% from all available patterns, was used for training purpose. A set of 1186 patterns was used to test the model. In order to train the NN model the measured PAP was used. In Table 1, the average error, the standard deviation and the mean square error are presented, obtained from the training set by the proposed Multilayer Perceptron Neural Network and the Generalized Regression Neural Network. Figure 4 presents the measured Power Angle Profile (PAP) together with the results derived by the MLP-NN and the RBF-NN predictions. As it is evident the results between the measured and the predicted PAP are very good with the Mean Square Error (MSE) equals to 6.5 dB for the MLP-NN model and 4.3 dB for the RBF-NN model. Furthermore, the theoretical Gaussian model for angular profile prediction is utilized for comparison reasons and presented also in Table 1 and Figure 4. The Gaussian model is given by [12]:

\[
PAP(\phi) = \frac{1}{2\pi\sigma_{\phi}^2} \exp \left[-\frac{\phi^2}{2\sigma_{\phi}^2}\right]
\]  

(11)

The measured angular spread \(\sigma_{\phi}\) was calculated 24° hence the same value will be used in Eq. (11). The measured angular spread is calculated by [13]:

...
\[
\sigma_p = \sqrt{1 - \left(\frac{F_1}{F_2}\right)^2}, \quad F_n = \int_0^{2\pi} p(\theta) \exp(jn\theta) d\theta
\]  

where \( F_n \) \((n = 1 \text{ or } 2)\) is given by [13], and \( p(\theta) \) is the measured PAP. The MSE between the measured PAP and the Gaussian model was found equal to 8.1 dB. All the results are summarized in Table 1.

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<td>Gaussian Model</td>
<td>6.4</td>
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![Figure 4](image)

**Figure 4.** Comparison between the measured PAP, RBF-NN, MLP-NN prediction, and theoretical Gaussian model.

From Figure 4 it is clear that the prediction of the trained NN models is very good, whereas the best results are yielded by the RBF-NN model. On the other hand the Gaussian model provides greater errors than the other two cases because it is not so accurate, and takes into account a smaller range of azimuth angle.
4. Conclusions

This study examined the applicability of the neural networks for the prediction of angle of arrivals in an indoor smart antenna system. The data measurement of an indoor environment using multiple element antennas comprising of linear and uniform array antennas at the millimeter wave band of 60 GHz, were taken into consideration for training purposes of the NN. Two NN models (RBF and MLP) were considered for the derivation of the prediction models as well as the Gaussian theoretical model is evaluated for comparison purposes. The main advantage of the proposed NN models is that the models should be easily adjusted to some specific environments and complex propagation conditions. The results are depicted in terms of average error, standard deviation and mean square error compared with the measurements and showed very good accuracy. The MSE between the measurements and the NN-models was found 6.5 dB for the MLP-NN model and 4.3 dB for the RBG-NN model. The Gaussian model provides greater errors because it takes into account a smaller range of azimuth angle. High accuracy can be obtained, because the NNs are trained with measurements inside buildings and thus include realistic propagation effects considering parameters which are difficult to include in analytic equations. In more specific local cases, the accuracy can be improved by using additional NNs training. Results are always connected with some uncertainty but accuracy is sufficient for prediction purposes.

References