A Neural Network Approach to the Prediction of the Propagation Path-loss for Mobile Communications Systems in Urban Environments

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Abstract — This paper presents an alternative procedure for the prediction of propagation path loss in urban environments. It is based on Neural Network (NN) algorithms and uses the detailed environment profile instead of the mean values of its structural parameters. The general performance of the NN shows its effectiveness to yield results with satisfactory accuracy in short time. The received results are compared to the respective ones yielded by the Ray-Tracing model and exhibit satisfactory accuracy either for uniform or for non-uniform distribution of the manmade structured environment.

1. INTRODUCTION

The prediction of electromagnetic wave propagation is of great importance in the design and planning of a cellular-network both for mobile and fixed wireless-access systems. A prediction, based on theoretical models, is really valuable since it offers the capability of determining optimum base locations, in order to obtain suitable data rates, to estimate their coverage and evaluate the quality of the wireless network without the need of expensive and time consuming measurements.

The theoretical models used for the estimation of the path-loss in various urban or suburban areas, even within buildings, are grouped in two categories [1]: the empirical or statistical models (e.g., the COST-231-Walfisch-Ikegami model, the Hata model, etc.) and the site-specific or deterministic ones (e.g., the Ray Tracing technique, the Image Method, the FDTD or the Moment Method, etc.). The models of the former category are easier to implement and require less computational effort but are less sensitive to the environment’s physical and geometrical structure. Those of the latter category have a certain physical basis and are more accurate but at the cost of more computations and at the necessity of more detailed information about the coverage area.

In the present work, a prediction model based on Neural Network (NN)-architectures is proposed. Published works have introduced the NN-methodologies as efficient techniques for indoor and outdoor estimation of path-loss propagation. They have given solutions, using measured or theoretically produced data and feeding the input of the NN by the values of some of the geometry parameters of the environment, e.g., the mean height and mean dimensions of the buildings and the mean width of the roads [2–6]. In the work at hand a Multiple Layer Perceptron (MLP) neural network was composed, and the collections of data, by which it was trained, include the detailed environment profile. These data were produced using the Ray Tracing technique. Although the calculation for the training collections were made for simple and uniform distribution of the manmade structures, the appropriate grid modeling of the built-up area as well as the way by which the input data were presented to the NN made it efficient to give, in the generalization phase, results for arbitrary environments, if their profile is provided.

2. FORMULATION

The propagation of radio waves in built-up areas is strongly influenced by the nature of the environment, in particular by the size and the density of the buildings. Urban areas are dominated by tall building blocks with high density and non uniform distribution. Empirical prediction models use mean values for the parameters of the manmade terrain (mealy the mean values of the roads’ widths or of the buildings’ height). Many proposed NN models use also these parameters as information for the NN. The present work suggests an alternative approach for the prediction of path loss based on a NN-methodology which uses detailed description of the entire coverage area. The used Neural Network was composed via a Multiple Layer Perceptron (MLP) architecture. The input layer consists of a large number of nodes that accept analytical information for the structure
of the built-up environment as well as for the coordinates of the position at which the path-loss is going to be estimated. A single node output layer gives the value of this path loss.

A virtual grid of a $N \times N$ cell that covers the area under investigation is supposed (Fig. 1). The center of each cell may lay on a built block of the area or on a street, depending on the specific distribution of the buildings, and it is described via three numbers. If the point lays on a block, then the numbers are the values of $W$ and $L$ (Fig. 1(a)) as well the height of the block. If the center point is on a street two of the numbers are set equal to zero and the third one is set equal to the value of the street’s width. Therefore the terrain of the area under consideration is described via $3N^2$ numbers. All this information must be presented to the network during the training, testing and generalization phases.

![Figure 1: The scheme of the urban environment with (a) uniform and (b) non-uniform built-up profile.](image)

The general form of an MLP-NN is depicted in Fig. 2. The input layer consists of $I$ nodes, $M$ hidden layers exist each one having $m_i$ nodes and the output is a layer of $N_{out}$ nodes. In this work the input layer has $I = 3N^2 + 2$ nodes. The first $3N^2$ nodes accept the above mentioned information about the area under study and the last two ones accept the coordinates of the point at which the path loss is predicted. The output is a single node layer ($N_{out} = 1$) and exhibits the path loss value. The number of hidden layers is collected under the criterion of the best convergence of the results.

![Figure 2: The composed MLP neural network.](image)

For the training of the NN, a collection of $N_{tr}$ input-output data sets is used. These data would come from measurements or calculations via one of the theoretical path loss prediction techniques. For the test of the NN a set of input patterns and the respective output set containing the a priori calculated path loss values is created. The results, yielded from the phase of NN testing, show if the NN is efficiently trained. If so, it is ready to accept at its input the terrain information of the area of interest as well as the coordinates of the point at which the estimation of the path loss is needed and to exhibit at its output this path loss value. Fig. 2 shows the configuration of the
MLP-NN. The NN’s output is described by the following equation

$$y_o(p) = F_o \left[ \sum_{\ell=1}^{m_3} w_3^\ell \left( F_3^h \left( \sum_{k=1}^{m_2} w_2^{k\ell} \left( F_2^h \left( \sum_{j=1}^{m_1} w_1^{j\ell} \left( F_1^h \sum_{i=1}^{I} w_{1n}^{i\ell} x_i \right) \right) \right) \right) \right] \right]$$  \hspace{1cm} (1)

where $w_3^{\ell}$ represents the synaptic weight from $n$th neuron of the $q$th layer towards the $t$th neuron of the next layer, $x_i^p$ represents the $i$th element of the $p$th input pattern and $F_m^h$ is the activation function of the $m$th layer. The error function, used for the control of NN’S convergence, is $E(p) = (1/2)[d(p) - y_o(p)]^2$ where $d(p)$ is the desired value of the $p$th output pattern and $y_o(p)$ is the output of the NN when the $p$th input pattern is presented to its input. During the training phase the network changes its weights so that the above function is minimized. It is realized by the gradient descent procedure [7] via which the weights change by an amount proportional to the negative gradient of the error function, that is $\Delta w(p) = -\eta \nabla E_p(w) + \alpha \Delta w(p-1)$. The constant of proportionality, $\eta$, is the learning rate and $\alpha$ is the momentum constant. When the error function is minimized the learning process is terminated and the network can be tested by the test data set.

3. RESULTS

The target of the total procedure was to make the composed NN capable to yield accurate path loss prediction for a non uniformly built-up area. Two issues that condition the successfulness of the procedure are the proper selection of the training set and the appropriate configuration of the MLP-NN. A collection of $N_{tr} = 7700$ training patterns (Train 1) was prepared. Their calculation was made via the Ray-tracing prediction model for a large number of uniformly manmade surroundings (Fig. 1(a)). The heights of the built blocks were ranging between 12 m and 27 m, the size of coverage areas was ranging from 500 m $\times$ 500 m to 1300 m $\times$ 1300 m and various sizes were considered for the blocks’ sectoral plans and the widths of the roads. Two test sets were prepared using the Ray Tracing model: A test set (Test$^{\text{unif}}$) of 1200 patterns coming from uniformly structured areas and a second set (Test$^{\text{non-unif}}$) of 580 patterns calculated for non uniformly built-up environments.

The optimum configuration of the MLP-NN was obtained with $M = 3$ hidden layers (see Fig. 2). The learning rates were 0.3 and 0.15 for the hidden and output layers respectively, the values of the momentums were 0.1 for the hidden and 0.2 for the output layer. The activation function for the hidden layers was the hyperbolic tangent function and for the output layer was the linear one. At first it was trained with the Train 1 set and was tested with the Test$^{\text{unif}}$ set. In this case the best satisfactory convergence was achieved using 8 epochs. The convergence process as a function of the number of iterations, is presented in Fig. 3. For each number of iterations the NN was tested with the Test$^{\text{unif}}$ set and the absolute value of the difference $D$, between the expected and the received path-loss values for all the 1200 data, was calculated. The statistical manipulation of these differences yielded an absolute mean value that is depicted in Fig. 3(a), as a function of the number of iterations. It is observed that the mean value of the difference $D$ is reducing by the increase of the number of iterations converging to the value of 2.46 dB, for $7 \times 10^7$ iterations. For this case, after statistical processing over the results produced by the set of 1200 patterns, analytical results are presented in Figs. 3(b) and 3(c). In Fig. 3(b) we see the path loss values

![Figure 3](image-url)
yielded by the MLP-NN, versus the expected values in accordance with the Ray Tracing model. The respective histogram of the difference \( D \) is presented in Fig. 3(c). The mean value of this statistical distribution is 2.46 dB and the estimated mean error 2.6\%.

The respective results received when the NN was tested via the Test\_non−unif set, are presented also in Fig. 3(a). It is shown that the mean value of the difference \( D \) remains larger than 8 dB for every iteration value, so the NN fails to closely approximate the expected path loss values. It is also observed that the above divergence is large even for small numbers of iterations or for large ones. This is due to the fact that few iterations are not enough for the learning of the NN and a large number of them make the NN over-adapted. This over-adaptation is enforced also by the large amount of information about the uniform environment given to the NN. This concept explains also the fact that either for moderate number of iterations(Fig. 3(a)) the divergence is large. The NN memorizes the training examples and can not generalize the non-uniform situation.

In order to avoid this over-adaptation a smaller training subset (Train 2) was created. The NN was trained by the new set and initially was tested with the Test\_nonunif using various epoch sizes and number of iterations. In each case the results were statistically processed and are presented in Fig. 4. It is shown that the best results have mean value of the difference \( D \) equal to 4.89 dB and are obtained with epoch size 32 and \( 10^5 \) iterations. For lower iteration values the NN seems to have not been trained sufficiently and for more than \( 10^5 \) iterations it is rather over-adapted. The latter concept is verified by the results of Fig. 4(b) where it is confirmed that the best result for the convergence between the expected and the received path loss value is about 4.9 dB for epoch size 32 and \( 10^5 \) iterations. For this case statistical processing over the results of the 580 patterns of the Test\_nonunif set, was made and they are depicted in Fig. 5. In Fig. 5(a) we see the path loss values yielded by the MLP-NN, versus the expected values in accordance with the Ray Tracing model. The respective histogram of the difference \( D \) is presented in Fig. 5(b). The mean value of this statistical distribution is 4.89 dB and the estimated mean error is 5.3\%.

![Figure 4](image_url)

Figure 4: Results received by the NN when trained via the Train 2 set. (a) the mean value of difference \( D \) versus the number of epochs (b) results as a function of the number of iterations, for epoch size equal to 32.

![Figure 5](image_url)

Figure 5: Results received by the NN when trained via the Train 2 set. (a) results for \( 10^5 \) iterations with epoch size equal to 32 (b) statistical distribution of the difference \( D \), mean value 4.89 dB, mean error 5.3\%. 
4. CONCLUSION

An alternative NN based procedure for the prediction of the path loss in urban environment is proposed. The basic idea is to yield results via the NN, giving to it detailed information about the profile of the built-up environment. This information is obtained, using a virtual grid covering the area under investigation and creating by this an approximate scheme of the terrain of the area. The MLP architecture is proposed for the procedure. In the present work the NN was trained using theoretically calculated data for uniform built-up surroundings and using the Ray Tracing model. The methodology is general and can be used for any type of environment employing training data which come from measurements or from theoretical calculations by other predicting models. However, we believe that when training with the Ray-Tracing method we inherently insert to the procedure a certain physical basis which make the NN more flexible to adapt to arbitrary environments. The results show that a large number of training patterns, epochs of small size and a large number of iterations are necessary to ensure the accurate prediction for uniform environments. This accuracy is approximately equal to $\pm 2.5\, \text{dB}$. For the prediction of the path loss in non-uniform built-up areas, small training sets, moderate size of epoch and moderate number of iterations are indicated. In this case the accuracy is about $4.9\, \text{dB}$. A better approximation would be obtained if the NN is trained using data calculated for non-uniform built-up areas and this would be the issue of a future investigation.

REFERENCES


