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Mobile radio propagation path loss prediction using Artificial Neural Networks with optimal input information for urban environments

Sotirios P. Sotiroudis, Katherine Siakavara *

Radiocommunications Lab, Department of Physics, School of Sciencies, University of Thessaloniki, Thessaloniki 54124, Greece

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ABSTRACT

The propagation of radio waves in a built-up area is of great importance for the design of a mobile communication network and the Path Loss (PL) of the transmitted power is one of the characteristic parameters of the space channels. Traditional methods applied for the estimation of the PL are theoretical and empirical models proposed and well known in the literature. The Artificial Neural Network (ANN) methodology has been introduced as an alternative method for the PL prediction and has been proved effective in finding, via a stochastic evolutionary procedure, the influence of the configuration of the built up urban environment to the signal attenuation during its propagation through it. In most of the ANNs applied for this purpose general parameters, as the mean values of geometrical characteristics of roads and built blocks are used. In this paper the research has focused on the synthesis of ANNs which could obtain PL prediction of sufficient accuracy, using small amount but of proper kind input data. Analytical results are presented, which compared with respective ones received via theoretical methods, prove that the proposed ANNs technique with the optimal input information, is effective in estimating the power PL of the transmitted signals.

1. Introduction

The prediction of radiowave propagation in a wireless communication environment, as in every type of radio access technology, is crucial for the planning of a mobile network being the physical layer of its operation. It is also a difficult task for several physical mechanisms, as the reflection, the diffraction and generally the scattering of the waves as well as the multipath phenomenon contribute to the transmission of the signal power. Taking into account the continuous movement of the users, the profile of the radio channel changes in real time and the parameters of the propagation process become random variables. The quantities, the values of which, have to be predicted are (a) the reduction of the mean power level of the signal versus the distance from the transmitter (Trx), termed as the 'large scale' attenuation and known as Path Loss (PL) prediction and (b) the usual rapid variation of the signal power inside a small area around any point of the path, known as 'small scale' variation. What makes, the a priori estimation of both type transmission characteristics, be complicated, is that the propagation occurs in random manmade environment. So, the synthesis of a global model suitable for every built-up area profile, is very difficult. For all that, several PL prediction models have been proposed in the literature. These models, used extensively in communication network planning and signal interference studies, can broadly be classified [1–9] as (a) empirical and (b) deterministic. The models of the former class are easier to implement and require less computational effort but are less sensitive to the environment's physical and geometrical configuration. Those of the latter category have a certain physical basis and are more accurate but at the cost of more computation effort and the necessity of more detailed information about the coverage area. All the aforementioned methods, being flexible and reliable tools for the PL estimation, can effectively replace the realization of measurements, an also efficient process, which, however requires the installation of a complete system of suitable equipment.

The work at hand proposes Artificial Neural Network (ANN) models for the PL prediction in urban environments. The ANN technique has been introduced in several articles of the literature, for the solution of this problem [10–19]. The majority of these works use, as input to the ANNs, information which concern general parameters of the manmade terrain as, the mean road width, the mean height and length of built blocks, the percentage coverage of the built area, etc. These formulations lead to easy to handle simple ANNs, because small amount and easy to be gathered input information is required. However this kind of data give to the ANNs, substantially very little information for the relief of the

* Corresponding author. Tel.: +30 2310998055.
E-mail addresses: ssoti@physics.auth.gr (S.P. Sotiroudis), skv@auth.gr (K. Siakavara).

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environment and lead inevitably to results of decreased accuracy for points at which the built-up characteristics diverge significantly from their mean values over the entire area. On the other hand there have been proposed ANN techniques of large ANNs [16], which use detailed information for the environment thus obtaining accurate prediction but at the cost of the requirement of a large amount of information data to be selected for the area under consideration. The present work focuses on finding the appropriate kind and amount of input information in a way that, on the one hand this information to include details for the terrain of the environment and on the other hand the amount of data given to the ANNs, namely the number of its input nodes, to be small. The research was made at 900 MHz and the pre-condition in finding these optimal input data, was the ensuring, as far as possible, of the accuracy of the prediction

2. The ANN architecture and training

The idea to employ ANN algorithms for the solution of a problem is based on the general ability of these stochastic and evolutionary procedures, to find out the relationship among the physical parameters of the problem and the results coming from it, even if the physical procedure which relates them is complicated. So, in the case of PL estimation, a properly designed ANN, trained with information data for the build-up area of the communication network, would be capable of finding the relation among these data and the resulting PL. Not any mathematical formulae for the calculation of the PL is necessary, as the ANNs can inherently find out the impact of various mechanisms of the propagation procedure on the signals' PL. It is well known that the propagation of radio waves in built-up areas is strongly influenced by the nature of the environment. In particular, the size and the density of the buildings are parameters crucial for the power attenuation of the signal as well as for the signal multipath phenomenon and also urban areas are dominated by tall building blocks with high density and non uniform distribution. As a consequence the more accurately the 'image' of the manmade terrain of the communication network coverage area is presented to the input of the ANN, the most accurate the PL prediction is expected to be. For this purpose and taking into account that empirical models use general and not site-specific parameters of the manmade terrain, in the work at hand, the site-specific RT technique was selected for the gathering of the input training data of the synthesized ANNs.

All the synthesized ANN models are built via the Multiple Layer Perception (MLP) architecture, as shown in Fig. 1.

The number of input layer nodes depends on the kind of information shown to the ANN. The selection of the number of the hidden layers and of their nodes, was crucial because accurate prediction was required and simultaneously the ANN had to converge, being not saturated and/or overtrained. During the investigation it was found that all these requirements were matched via one hidden layer with only $K=10$ nodes. The output is a single node layer which carries out the predicted PL value.

For the training of the ANNS, a collection of N_{tr} input–output data vectors, of equal in number training locations, was used. The calculation of the output data was made via the Ray Tracing (RT) method which, as explained previously, would potentially increase the prediction ability of the ANN. For the test of the ANNs sets of N_{test} input–output patterns, were created. The results yielded, during the test phase, show the level of the ANNs' efficiency. Thus the well trained ANNs are ready to accept, at their input, the terrain information of a random area of interest as well as the coordinates of the point at which the estimation of the path loss is required, and to exhibit at their output the respective path loss value.

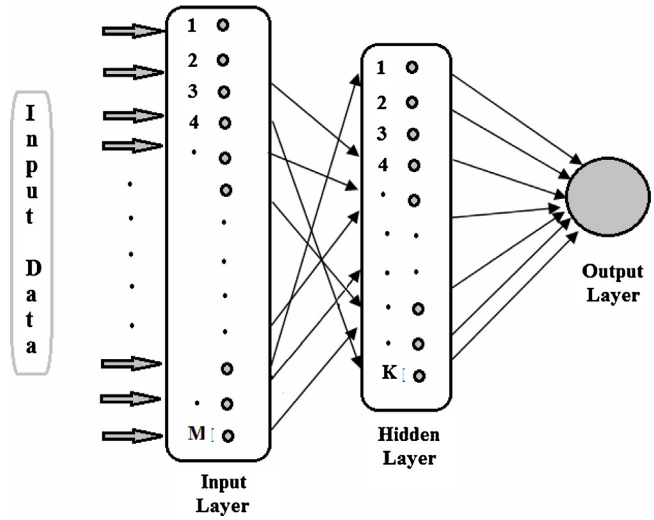

Fig. 1. The general architecture of the synthesized ANNs.

The ANN's output is described by Eq. (1)

$$y_o(p) = F^{ho}\sum_{j=1}^{K} w_j^{ho}\left(F^{ih}\sum_{n=1}^{M} w_n^{ih}x_n^p\right) \tag{1}$$

where $\{w^{ih}\}$ and $\{w^{ho}\}$ are the synaptic weight vectors from the input to hidden and from hidden to output layer, respectively, $\{x^p\} \rightarrow \{x_1^p, x_2^p, \ldots\ldots, x_M^p, x_o^p\}$ is the p^{th}, $p = 1, 2, \ldots\ldots, N_{tr}$, training pattern of the training population, x_m^p is the corresponding mth parameter which describes one of the used characteristics of the environment and x_o^p is the PL for the corresponding training location. Functions F^{ho}, F^{ih} are the respective activation functions from the hidden to output and from the input to hidden layer. As F^{ho} the linear function 'purelin' and as F^{ih} the function 'tansig' were used, both in accordance to software MATLAB2010b. For the synaptic weights' adaptation, during the training phase, the negative gradient of the error function rule was applied. The criterion for the estimation of the ANN's convergence was the value of the mean square error (MSE) function as defined in Eq. (2)

$$\text{MSE} = \frac{1}{N_{tr}}\sum_{p=1}^{N_{tr}}[d(p) - y_o(p)]^2 \tag{2}$$

where $d(p)$ is the PL value which corresponds to the pth input pattern as predicted by the RT method and $y_o(p)$ is the output of the ANN, when the pth input pattern is presented to its input.

The minimization of the MSE value appoints the termination of the learning process and the ANN is ready to undergo test for its prediction accuracy. The ANN test phase was proceeded via sets of N_{test} vectors of input–output information data, not have been shown to the ANN during the training, and gathered via RT method from various icons of built areas of coverage. The statistical indices, over the test results, were the mean absolute error (MAE), the root mean square error (RMSE) and the mean absolute percentage error defined by Eqs. (3)–(5).

$$\text{MAE} = \frac{1}{N_{\text{test}}}\sum_{p=1}^{N_{\text{test}}}\left|d(p) - y_o(p)\right| \tag{3}$$

$$\text{RMSE} = \sqrt{\frac{1}{N_{\text{test}}}\sum_{p=1}^{N_{\text{test}}}[d(p) - y_o(p)]^2} \tag{4}$$