Neural Network-Based Path Loss Model for Cellular Mobile Networks at 800 to 1800 MHz Bands

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Abstract

Nowadays, the need for more mobility and to be able to share or exchange information at any time, using mobile devices (cell phones, laptops) encouraged the researchers To continue developing mobile phone networks. But the problems in the communication system made that really hard, the most serious problem is the loss of information in the links between the transmitter and the receiver. Many models have been made to predict coverage using so-called propagation models. But the models characterizing the losses are semi-empirical models incapable of giving satisfying results in all cases. The purpose of this paper is to propose an applicable model to predict the path loss in mobile networks based on artificial intelligence techniques. Our experiments showed an encouraging prediction results in rural and suburban environments.

Keywords Mobile Networks, Predictive Models, Artificial Neural Networks.

1. Introduction

Propagation models are used when designing a radio interface to optimize performance and also when deploying systems in the field to determine radio coverage. The models will be implemented in engineering tools to predict different quantities useful for the deployment of radio telecommunications systems as well as for the study of radio coverage (choice of sites, allocation of frequencies, definition of powers) and the definition of interference. The outdoor models are very dependent on geographic databases comprising elements relating to topography and types of land use. This is because the way in which ultra high frequency (UHF) radio waves will propagate in a given space is intimately linked to the obstacles (buildings, tree trunks, mountain sides, etc.) encountered along the propagation channel. Therefore, the modeling of geographic objects is essential in any UHF wave propagation model [1]. But in the indoor propagation models the data bases of the propagation environment have to be very determined. Signals may propagate through a window across the street. They may or may not propagate through the corner inside a building and other architectural standards. So it is really hard to make an accurate model.

Propagation models are used when designing a radio interface to optimize performance and also when deploying systems in the field to determine radio coverage. The models will be implemented in engineering tools to predict different quantities useful for the deployment of radio telecommunications systems as well as for the study of radio coverage (choice of sites, allocation of frequencies, definition of powers) and the definition of interference. The models are very dependent on geographic databases comprising elements relating to topography and types of land use. This is because the way in which UHF radio waves will propagate in a given space is intimately linked to the obstacles (buildings, tree trunks, mountain sides, etc.) encountered along the propagation channel. Therefore, the modeling of geographic objects is essential in any UHF wave propagation model [2].

The rest of this paper is organized as follows. In Section two some propagation models that are frequently used in path loss prediction are presented. Related works are summarized in Section three. In section four, the neural network architectures such as MLP and the adopted neural network architecture are showed with details of database processing. We present our loss prediction results based on network training in Section six. Section seven is the conclusion.

2. Classification of Propagations Models

In the field of mobile radio communications, there are two basic approaches to predicting the behavior of a transmission channel. The first approach is to model the channel statistically. The second method consists in using a direct analytical resolution of the propagation equations or in simulating the signal paths in the propagation medium.

The type of model chosen will depend on the level of estimation desired: rough or precise estimation. In addition, available field data plays an important role. After the prediction estimate, field measurements must be performed in order to validate the model. This step usually requires readjustment of the parameters.

The two main types of models resulting from these approaches are theoretical models, based on theoretical models, and empirical models. Semi-empirical models using the previous approaches are also defined. They take into account the theoretical propagation equations and are parameterized using the results of real measurements.

Deterministic models give much more precise results but require a significant amount of information about the area where they will be applied. In addition, they require a long computation time. They are generally reserved for particular places where other models cannot be used. They are based on geometric optics calculations (reflection, diffraction, etc.). This method is called the ray method.

A number of path loss propagation models have been developed in the past and are being published to predict coverage [3]. These models cannot be considered generalized because the environment developed is different from the one in which they were applied. This means that the physical structure, topology and weather conditions in the deployment area vary. The attenuation due to the environment can be distinguished by a pattern of loss of the terrain path. The average path loss for an arbitrary transmitter/receiver separation is given as a function of distance by [3]:

$$\mathrm{L_p(dB)} = \mathrm{L_p(d_0)} + 10\mathrm{nLog_{10}}(\frac{\mathrm{d_i}}{\mathrm{d_0}}) \quad (1)$$

- n: path loss exponent
- d_i: measured distance
- d_0: reference distance
- $L_p(d_0)$: path loss at reference distance

In general, whether empirical or semi-empirical, are useful for giving orders of magnitude but their lack of precision often makes them unsuitable for the implementation of satisfactory engineering. Moreover, the establishment of such models is done from a grid of parameters, it will be difficult to extend it to a new range of use, since we do not have the reference of the laws of electromagnetism to assess the change this can make on precision results. In addition, the comparison of the results provided by these models with reality made it possible to conclude that this category of models, although it undergoes a calibration and refinement operation, has precision defects, especially in places with a high density of buildings.

3. Related Works

3.1. New empirical path loss model for wireless sensor networks in mango Greenhouses (NEPL):

This experiment has done in mango greenhouse in the north of Malaysia to create a new model for wireless sensor networks (WSNS). It based on the empirical models (COST35,ITUR) to create the new model with considering the factors that effected at signal propagation like diffraction ,reflection, and scattering, without forgetting the factor of distance between the transmitter and the receiver and the factor of foliage [5].

3.2. Semi Deterministic Hybrid model for Path Loss prediction improvement (SDH)

This experience to create hybrid model for path loss prediction from merged the models (empirical model (cost hata231), semi empirical (Walfish_Ikegami)) with statistical processing of the empirical measurement in GSM mobile network with 900 MHZ as a frequency in city of southern India[6].

3.3. LTE Maritime Coverage Solution and Ocean Propagation Loss Model

The experiment has done in the East Sea of South Korean using two base-station sites, one can provide a service coverage of 0~100 km with the antenna height of 350 meter above the sea level and the other can provide a service coverage of 80~180 km with the antenna height of 1,585 meter and a pair of antennas of 6 dBi gain were set up on top position of a ship, and connected to an LTE maritime router. From the obtaining results the feasibility of an LTE maritime system has approved with coverage ranging up to 180 km with multi-cell configuration. Three propagation models have tested with the obtained data. Free space path loss (FSPL) model defines how much strength of the radio signal is lost during propagation from transmitter to receiver in free space environment used the frequencies and the distances as a parameters. Long Range Ocean Radio Propagation model it use the distance, antenna heights and frequency as a parameters. Finally Three-Slope Propagation Model for Ocean Environment (proposed model) after Implementing the results they realized that the curves of propagation loss can be modeled as a three-slope characteristic. After the comparison between the three models the proposed model is well matched for base-station transmit antenna height higher than 300 meter. can be useful and effective in cell design for ocean coverage, considering the fact that LTE maritime systems require long ocean coverage and the transmit antenna height of 350 meter can achieve the propagation loss of 160 dB at 100 km, which is the maximum coverage typical LTE can have [7].

3.4. Stanford University Interim (SUI) Model

IEEE 802.16 Broadband Wireless Access working group proposed the standards for the frequency band below 11 GHz containing the channel model developed by Stanford University, namely the SUI models [8][9]. This prediction model comes from the extension of Hata model with frequency larger than 1900 MHz. The correction parameters are allowed to extend this 29 model up to 3.5 GHz band. In the USA, this model is defined for the Multipoint Microwave Distribution System (MMDS) for the frequency band from 2.5 GHz to 2.7 GHz [8].

3.5. Comparison

Next table summarizes the characteristics of the previous models:

Table 1 Comparison between models

Models	Type	Frequency band	H eight of base station antenna	Height of mobile station antenna	Distance	The propagation type
Okumara-hata [1]	Empirical	150MHZ-1.5GHZ	30m-200m	1m-10m	1km-20km	• Urban • Suburban • Rural
Egli [2]	Empirical	90-1000MHz	30m-200m	1m-10m	1km-20km	• Urban • Rural
COST 231-Hata [13]	Empirical	1800MHz	38m	1.5m	50m-1km	• Urban • Suburban
Walfisch-Ikegami [4]	Semi Empirical	800-2000 MHZ	4m-50m	1m-3m	20m-5km	• Urban
ECC-3 [14]	Empirical	150MHZ-3.5GHZ	30m-200m	1m-10m	1km-20km	• Urban • Suburban
SUI [8].	Semi Empirical	2.5-2.7 GHZ	10m-80m	2m-10m	0.1km-8km	• Urban • Suburban • Rural
NEP [5].	Empirical	2.45GHZ	5m	0.5-3.5m	50 m as a length, 10 m as a width, and 5 m as a height	• Indoor model
SDH [6].	Semi Empirical	800-200MHZ	10 m	1.5m	3km	• Urban

4. ARTIFICIAL NEURAL NETWORKS

From the hypothesis that intelligent behavior emerges from the structure and behavior of the basic elements of the brain that artificial neural networks have developed. The interest of neurons lies in the properties that result from their associations in networks. A network of artificial neurons, is a set of formal neurons (of simple computing units, of processor nodes) associated in layers (or subgroups) and operating in parallel [10].

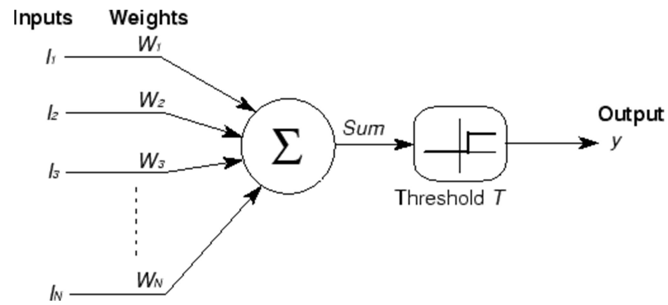

Fig. 1 Mcculloch's formal neuron model.

4.1. MLP network

A back-propagation network is a multi-layered MLP network consisting of at least one input layer, one hidden layer and one output layer (Fig. 2). Each layer contains one or more neurons that depends on the number of data that we want to teach the network, and number of output we want. There is no precise method for determining the number of layers and neurons, it depends on the complicity of the problem to be solved [10].

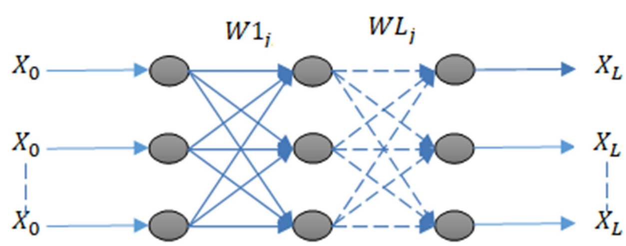

Fig. 2 Architecture of an MLP network

4.2. OUR ARCHITECTURE

Our goal is the design of an MLP type neural model for which planning and densification of a GSM network can be done.

The main step is the collection of an experimental database that contains the following parameters: Base Station Height (Hb), Mobile Antenna Height (Hm), Frequency, Distance and the loss recorded at each measurement point.

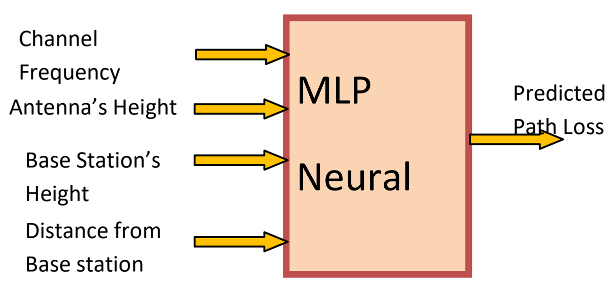

Fig. 3 Our neural network architecture

4.3. Formatting the database

Databases must pass through a preprocessing phase in order to be adapted to neural inputs and to make neural network training more efficient [11]. A common pretreatment is to eliminate artificial discontinuities in the input function space and to bring the problem entries back to an appropriate set of information [12]. Then an appropriate standardization must be made, taking into account the range of values accepted by the network.

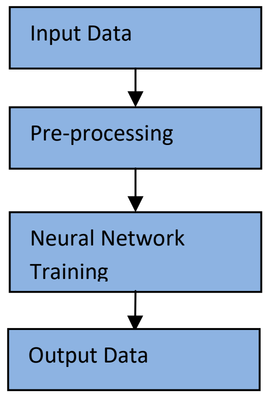

Fig. 4 Preprocessing phase of the database

4.4. Architecture optimization

After learning, it is necessary to test the neural network on a different database that has been used for learning. This test is to assess the performance of the network with nearly unseen data. If the performance is not satisfactory, the architecture of the network will change to enhance it. We choose an initial architecture to be used in learning and testing. If the performance is achieved, then the settings are saved, otherwise we change the architecture and we start over.

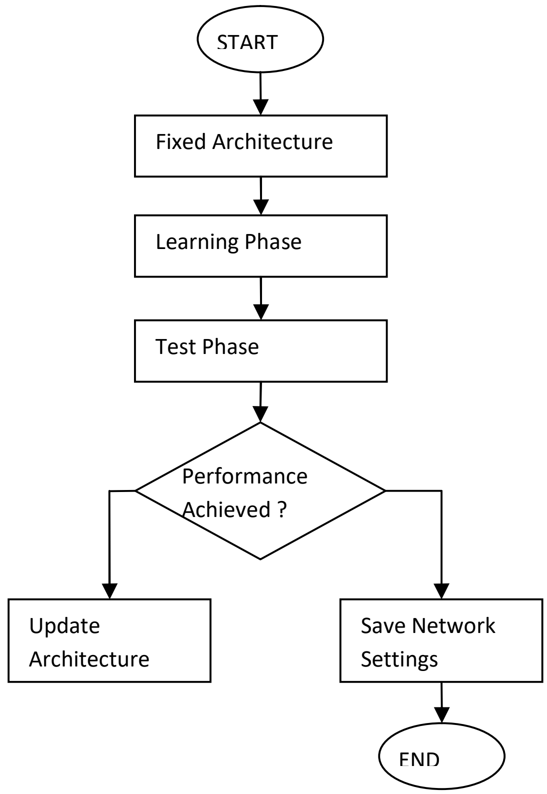

Fig. 5 Optimization of the neural network architecture

5. RESULTS AND INTERPRETATIONS

5.1. Architecture Optimization (Suburban Environment)

In order to validate the predictive property of the optimized network structure, the test and training sets were compared to the response of the neural model. Figures 6 and 7, show that in both cases, a very good agreement between the experimental results and the expected results (ANS) was obtained. Therefore, the optimized structure can be used to predict other combinations of the input variables.

In the following, we will interpret the performance of the optimized MLP network by comparing our results with the actual measurements.

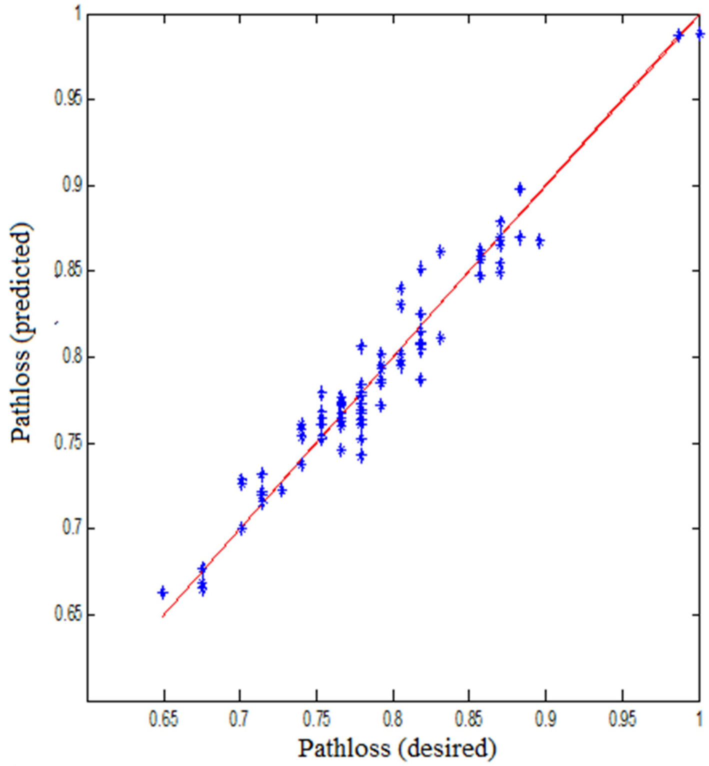

Fig. 6 Validation of our neural model for the learning set (Suburban Environment)

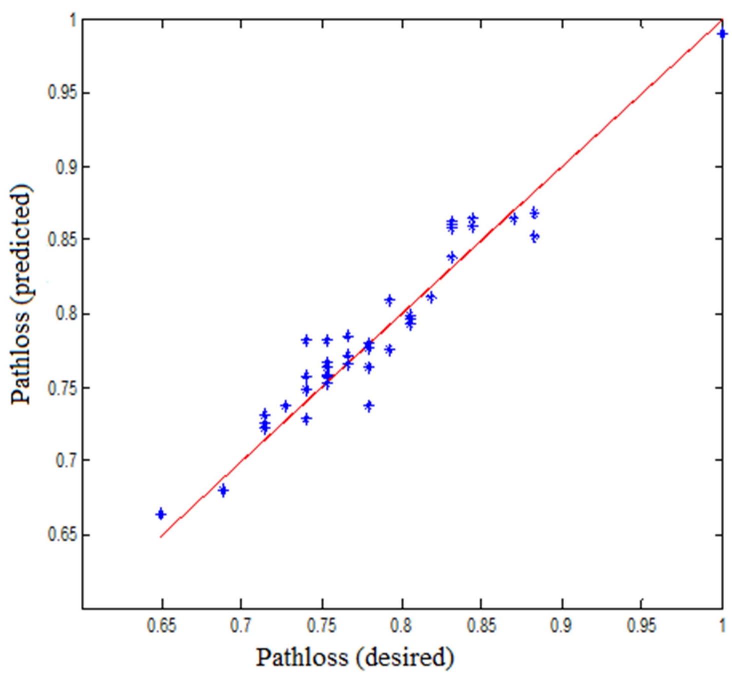

Fig. 7 Validation of our neural model for the test set (Suburban Environment)

Figure 8 shows a comparison between results predicted by the neuronal model (RNA) for different distances d(m) and with those measured in the case of a suburban environment.

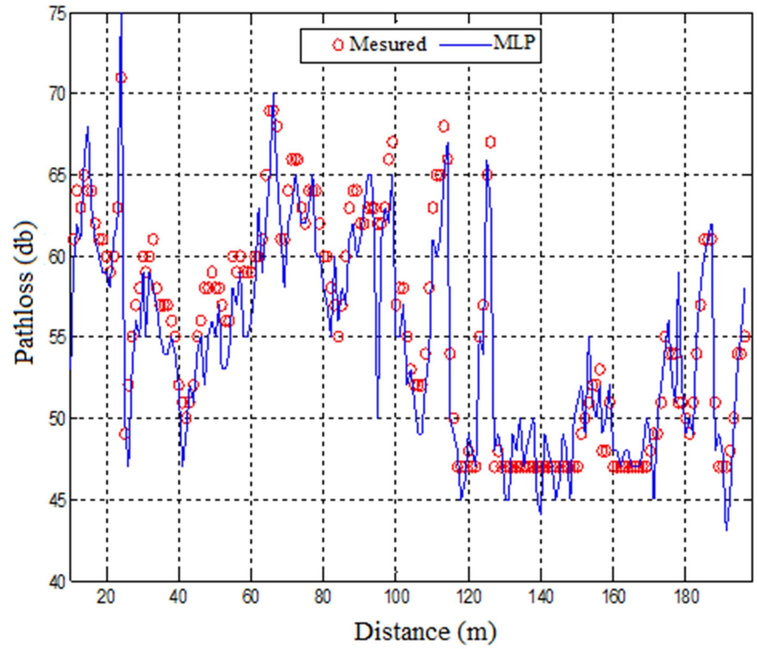

Fig. 8 Comparison of measured results and MLP (Suburban Environment)

As shown in Figure 8, a total harmony can be observed for the entire simulation range. This last observation shows the applicability of artificial neural networks to the study of losses in the GSM network.

5.2. FINAL MODEL (SUBURBAN ENVIRONMENT)

After having modeled the MLP network and made the necessary optimizations, we were able to choose the best structure which is shown in Table 2.

Table 2 MLP training parameters (suburban environment)

Architecture	Feed - Forward MLP				
Hidden layer	2				
Learning algorithm	Back propagation of errors				
Number of neurons	Input layer	4			
	1st hidden layer	15			
	2nd hidden layer	10			
	Output layer	1			
Transfer function	Input layer	Log-sigmoid			
	1st hidden layer	Log-sigmoid			
	2nd hidden layer	Log-sigmoid			
	Output layer	Linear			
Definition of inputs		fr (MHz)	Hb (m)	Hs (m)	D (km)
	Max	1800	35	2	2.3
	Min	957.4	18	1	0.01
Threshold	$< 4 \times 10^{-4}$				
Database	Learning	88			
	Test	64			
	Validation	44			

5.3. Optimization of architecture (Rural environment)

The correlation between the two outputs (desired and those obtained by the network) use for the test set and the learning set. The latter will be highlighted from figures 9 and 10 clearly represent that the two results (outputs) are almost identical for the test set and for the set of learning.

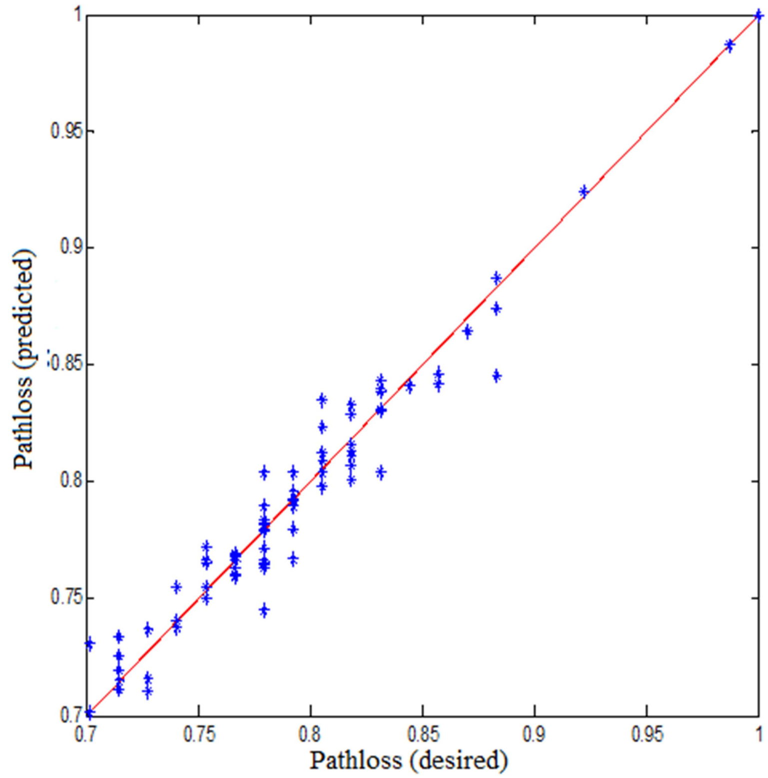

Fig. 9 Validation of our neural model for the learning set (Rural environment)

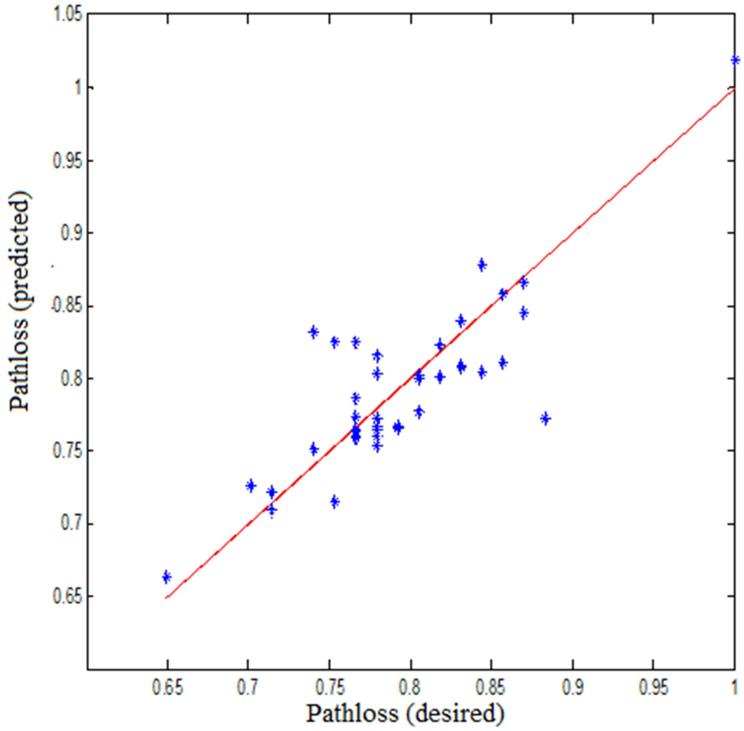

Fig. 10 Validation of our neural model for the test set(Rural environment).

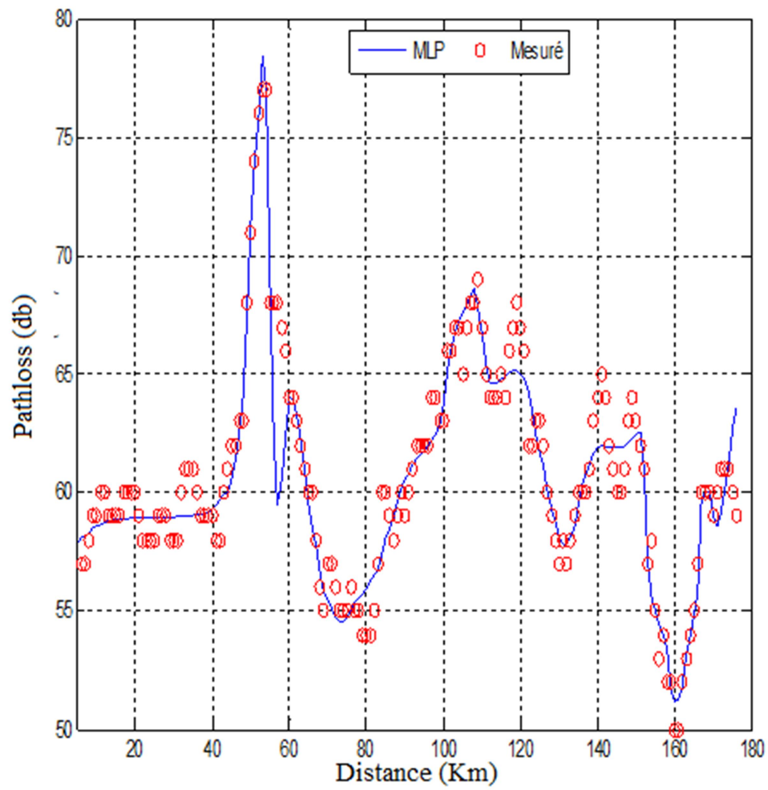

Fig. 11 Comparison of measured results and MLP (Rural Environment)

Figure 11 presents the comparison between the results predicted by the neuronal model (RNA) for different distances d(m) with those measured in the case of a rural environment. It shows an agreement between them that can be observed for the entire simulation range.

5.4. Final model (Rural environment)

After having modeled the MLP network and made the necessary optimizations, we were able to choose the best structure which is shown in Table.2.

Subsequently we will compare the results found by this model with other empirical models.

Table 3 MLP training parameters (rural environment)

Architecture	Feed - Forward MLP				
Hidden layer	2				
Learning algorithm	Back propagation of errors				
Number of neurons	Input layer		4		
	1st hidden layer		15		
	2nd hidden layer		10		
	Output layer		1		
Transfer function	Input layer		Log-sigmoid		
	1st hidden layer		Log-sigmoid		
	2nd hidden layer		Log-sigmoid		
	Output layer		linear		
Definition of inputs		fr (mhz)	Hb (m)	Hs (m)	D (km)
	Max	1800	21	2	2.3
	Min	957.4	20	1	0.01
Threshold	$< 4 \times 10^{-4}$				
Database	Learning		84		
	Test		61		
	Validation		41		

5.5. Comparison of results obtained by our model and two empirical models:

We will present the results obtained for 2 different suburban and rural environments, two different Hb, the results obtained by the empirical model cost-231hata and the empirical model Okumura without forgetting the type of environment will be compared with those obtained by the MLP .the results are shown in figures 12 and 13 for Hb = 35m, Hb = 18m respectively.

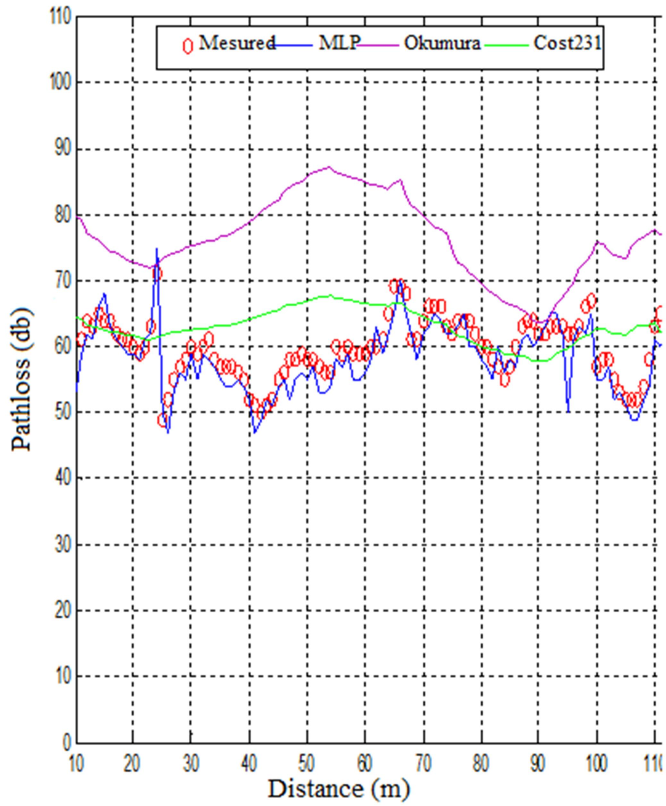

Fig. 12 Evolution of pathloss as a function of distance for: Hb = 35m.

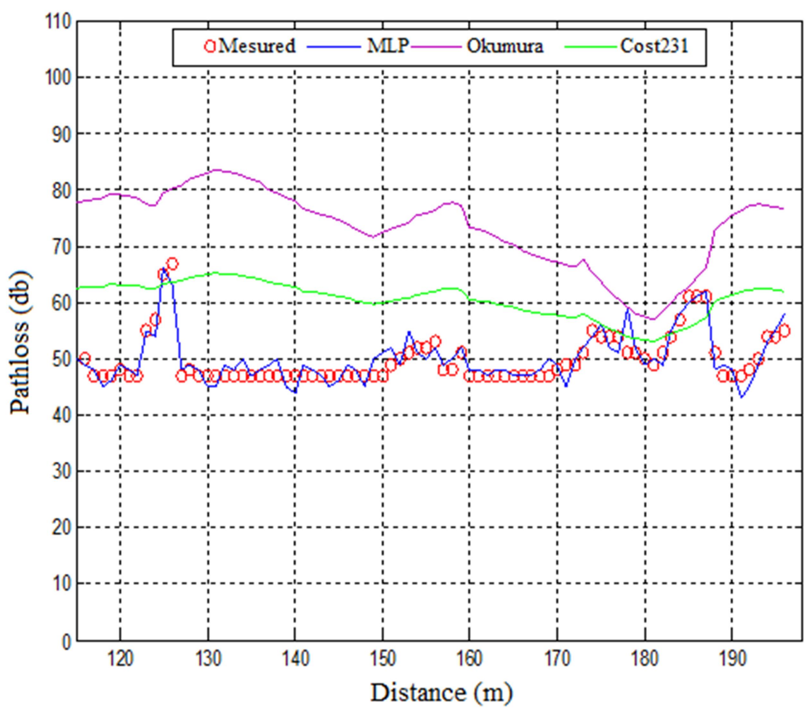

Fig. 13 Evolution of Pathloss as a function of distance for: Hb = 18m

The results shown in figures 14 and 15 for hb = 21m, hb = 20m respectively.

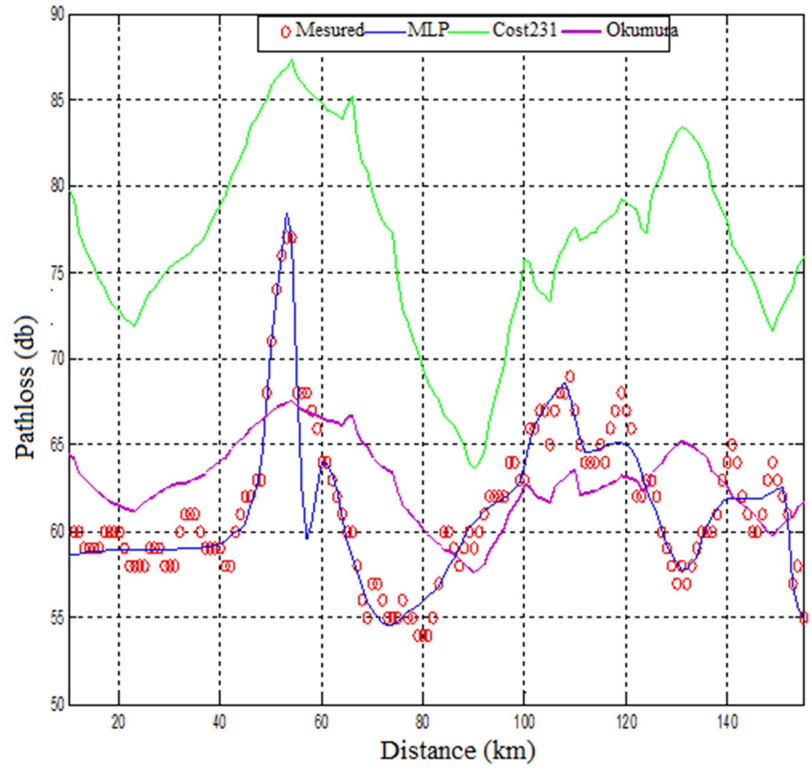

Fig. 14 Evolution of Pathloss as a function of distance for: Hb = 21m.

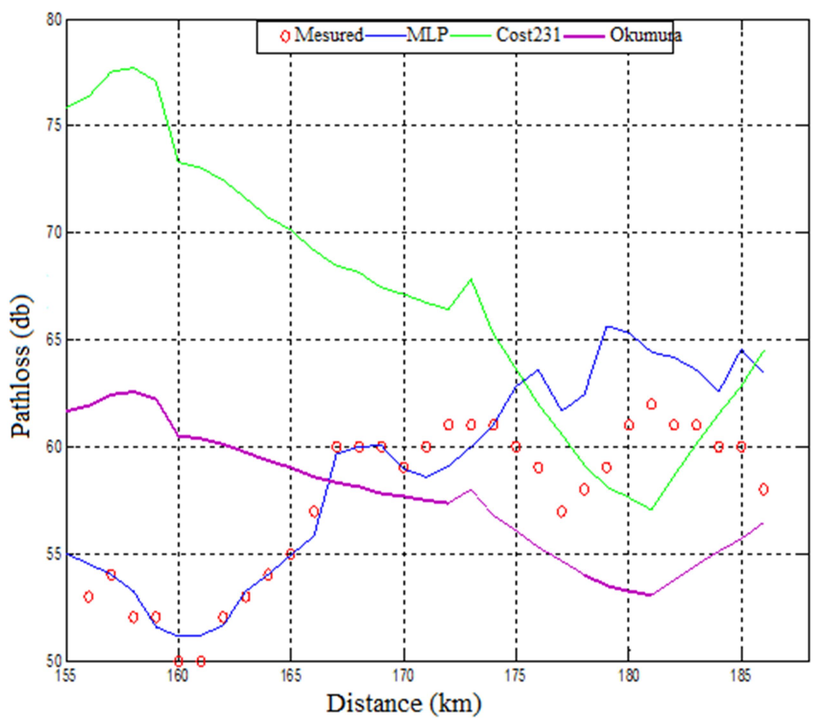

Fig. 15 Evolution of Pathloss as a function of distance for: Hb = 20m.

From Figures 12 and 13 the results clearly show that the measured path loss is less than that predicted by a difference varying from 4 to 20 dB. However, there are several reasons that can cause these significant differences. First of all, in Japan, there are few domains nearly satisfying the conditions of open space; and where appropriate, they are narrow. Due to this reason Okumura chose the value of urban (suburban) area as the standard for the open area. In addition, the geographic location of Japan is different from that of Algeria due to geographic differences. Figures 14 and 15 show that for a rural setting, the Okumura model has a better estimate of the loss than the COST231 model.

6. CONCLUSION

In this paper, we are interested in deterministic, empirical and semi-empirical propagation prediction models. We have shown that these propagation models are only mathematical formulas obtained from statistics on a very large number of measurements. These models allow rapid calculations and do not take into account the topology of the terrain such as flat or harsh terrain. The lack of precision of these models directs us to another solution: the use of artificial intelligent networks. We aimed to predict the loss of the GSM network signal path. There are many methods of prediction based on deterministic processes thanks to the availability of improved data values, but the Okumura-Hata model is the most commonly used. However, prediction models differ in their applicability to different environmental and field conditions. Therefore, further improvement of the propagation models in the open area has been suggested. This improvement was achieved by using artificial neural networks between measured and predicted loss values to provide sufficient MSE for prediction. The use of neural networks in the modeling process enables our model to obtain the accuracy and speed of the calculation. Furthermore, if multiple datasets is used for training, the neural model gives more robust results, better prediction results could be achieved.

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