A Wireless Propagation Channel Model with Meteorological Quantities Using Neural Networks

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Abstract— **Deterministic channel modeling approaches are slow to run, require a detailed description of the environment (which is sometimes expensive or even impossible to obtain) and may be difficult to implement. A new approach for the modeling of wireless propagation in LOS environment is presented. We treat the meteorological conditions by weather variations through using neural networks. The aim of the paper is to propose a neural model for understanding the relation between the path loss, the propagation delay and the atmosphere parameters such as humidity, pressure, temperature. It is clarified the propagation factors affecting the wireless channel in the frequency range 300 MHz to 100 GHz. We use grey box approach based on fundamental principles of radio wave propagation physics and measurement data. To verify the accuracy of the model, evaluation and validation of the model are performed by simulating the channel using different sets of actual data from different situations. It is shown that this model can handle unusual atmosphere conditions and the model can be applied to better calculate the delay propagation.**

Keywords—**Propagation modeling, atmospheric effects, neural networks**

1. Introduction

The effect of the earth's atmosphere on radio propagation may soon find invaluable use in tracking weather systems and looking for signs of global change.

Wireless propagation over weather variations is of great importance to design of fixed and mobile radio systems, especially in positioning systems. To enhance deployment, optimization and maintenance of wireless systems, channel models have been developed to analyze propagation and transmit/receive effects in a channel [5]. An overview of spatial channel models is presented in [6]. The behaviour of propagating electromagnetic waves through LOS and NLOS environments has been studied in the last decades. However, all this studies do not include propagation on a free space environment with respect to meteorological conditions. The aim of the present paper is to propose a neural model for understanding the relation between the path loss, the propagation delay and the atmosphere parameters such as humidity, pressure and temperature.

In recent years, artificial intelligence has been incorporated in communication systems and modeling of nonlinear systems such as memory less channels [2], [4] and satellite communication channels [2], [3]. We use artificial neural network (ANN) as function approximators in a structure that guarantees that the overall model is expressed in discrete-time so it is compatible with standard formulations. While our ANNs are described with sets of parameters (biases and weights), they inherit all the flexibility of multilayer networks, such as the ability to approximate all memoryless nonlinearities of practical interest [1].

2. Channel modeling

Signal propagation models are used to predict the mean signal strength for an arbitrary distance between transmitter and receiver (T-R Separation). The propagation model which is studied in our work is to estimate the coverage of area of transmitter over long distances or long time intervals (large scale propagation).

There are several factors affecting electromagnetic propagation; they can be generally classified into three attributes-reflection, diffraction and scattering. Furthermore the channel has a behaviour that is subject to changes because of external effects variations (e.g., temperature, humidity and pressure of the environment). For the purposes of this paper, we discuss only the meteorological effects on a free space environment with direct propagation (a single line of sight path). In this situation many characteristics of the propagation are important for wireless communication, but for our work, the nine most studied are the transmitted and received average power in space over each sampling time, the time delay spread-the spread in transient time from the transmitter to receiver, the carrier frequency of the signal, the altitude of transmitter, the distance between transmitter and receiver, the temperature, pressure and water vapour partial pressure of air. Though, some our results can be extended to the quantities which are related to these quantities. In order to gauge whether a propagation model is sufficiently accurate, we take as a target that the error statistics- the difference between the mean power predicted by the model and the actual power should have a mean less than 3 dB and a standard deviation less than 6 dB.

In the previous work modeling wireless propagation, according to this formula,

$$P_r = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2 L} \tag{1}$$

Where P_t is the transmitted power, P_r is the received power, G_t is the transmitter antenna gain, G_r is the receiver antenna gain, d is the T-R separation, L is the system loss factor not related to propagation ($L \geq 1$), and λ is the wavelength in meters.

The average received power is a function of distance between transmitter and receiver. In this case, the main assumption is that the path of propagated wave is a straight line. However the real world, a transmitter on the far side of a planet would send a radio wave through the planet's atmosphere that would bend around the planet and travel on to the surface, where a receiver picked up the signal references. The bending and slowing are caused by the refractivity of the atmosphere. This, in turn, affects the path and speed of a radio wave. So, instead of following a straight line, a radio signal will twist and bend continuously as it traverses a path into and out of the earth's atmosphere. One of the limiting error source induced by these path changes is separated into dry and wet-path delays. Another approach in looking at the earth's atmosphere might be to use refractivity itself, without separating out temperature and moisture. Therefore to illustrate the variation of the average received signal strength, it is required to obtain the relation between the received average power and atmosphere quantities. There is not any implicit relation to represent it, so we resort to an empirical approach using the measured experimental data by the proposed model in this work (Section 4.1).

3. Meteorological Viewpoint

Wireless transmission mainly includes the following propagation impairments: effects related to the troposphere (or weather) and the effects due to the environment in the vicinity of receiver. The former includes run attenuation, gaseous absorption, clouds and fog attenuation and depolarization attenuation. The later basically consists of shadowing/blockage and multipath fading effects [7]. Furthermore the channel is influenced by atmospheric quantities such as temperature and pressure itself, without separating out the first two effects. Our work deals with the last effects. The propagation of waves inside the troposphere is essentially a function of the value of refractive index and its gradient. Therefore the main quantity is influenced by atmospheric conditions is the refractivity. We can present this influence by the following formula:

$$N = 77.6\frac{P}{T} + 3.73\times 10^5 \frac{e}{T^2} \qquad (2)$$

Where T is the absolute temperature in K, P is the atmospheric pressure in hPa (or in mb), and e is the water vapour partial pressure in hPa which is connected to humidity and to saturation vapour pressure of air.

The refractive modulus, N, provides a practical value of the refractive index n (ITU-R 1996):

$$N = (n-1)10^6$$

Since the decrease of the atmospheric pressure follows an exponential law, the decay law of the refractive index is also exponential [9]. This led to the introduction of a reference atmosphere for refraction, defined by the following equation (ITU 2000):

$$N(h) = N_{\circ}\exp\left(-\frac{h}{h_{\circ}}\right) \qquad (3)$$

Where $N_{\circ}$ is the average value of refractivity extrapolated to the level of the sea (315 N-units), h is the height above the sea level and $h_{\circ}$ is the reference height ($h_{\circ} = 7.35$ km in general).

4. Soft Measurement Model using Neural Networks

4.1. Model Structure

The soft measurement model has 10 input and 2 output variables. The time interval of the inputs and outputs are one minute (this value is selected based on the time constant of the weather quantities). Fig. 1 shows the main structure of the identification model based on MLP.

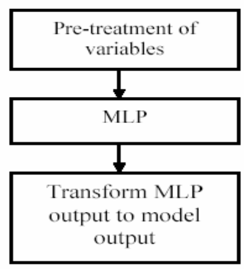

Fig. 1 The structure of model

The pre-treatment of the variables includes filtering and normalizing of the variables that are online measurement value of the channel, is required. Because, the online data include much noise, is usually very harmful for the stability of the model. Especially for a model based on artificial neural network, a small change of input can result large output change. In output model, the pre-treatment allows applying the average value over a short time interval of the signal strength to the network. Also a data analysis associated with a numerical filtering is then performed in order to eliminate the fast variations due to Rayleigh fading from the slow medium-scale and large-scale variations which can be modeled. Since the model inputs are, temperature, pressure and the water vapour partial pressure of air which do not change very fast, an FIR (Finite Impulse Response) filter is designed to treat the input data, and the length of filter's window is one minute.

The last unit of the model transforms the output of MLP, which is a normalized value ranging from 0 to 1, to a simulation value. Also there is a filter used to enhance the stability of the model output.

4.2. Neural Network Structure

The multilayer perceptron network considered here has the following structure. The input layer has 7 neurons for 7 input variables, including the temperature (T), pressure

(P), and the water vapour partial pressure of air (e), the distance between transmitter and receiver (d), the carrier frequency of the signal (f_c), the altitude of transmitter (h), and the transmitted average power (p_t). There are four neurons in the hidden layer and two neurons in the output layer for output variables which are the received average power (p_r) and the spread in transient time from the transmitter to receiver (Δt) (Fig. 2).

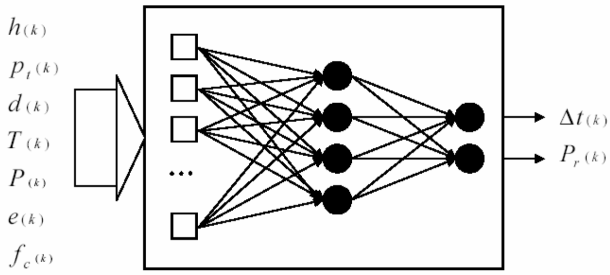

Fig. 2 The structure of MLP

4.3. Training Algorithm

Backpropagation trough time [8] is used to train the network of this model. The performance index of the algorithm is,

$$J = \sum_{k=0}^{\infty} \left\| e(k) \right\|^2 \qquad (4)$$

Where $e(k)$ is the error between model output and training goal. Then the chain rule of each error's gradient can be expressed as Eq. (5),

$$\frac{\partial J}{\partial w_{ij}^l} = \sum \frac{\partial J}{\partial y_j^{l+1}(k)} \bullet \frac{\partial y_j^{l+1}(k)}{\partial w_{ij}^l} \qquad (5)$$

Where

w_{ij}^l : The weight of the neuron i in the l^{th} layer to the neuron j in the $(l+1)^{th}$ layer

y_i^l : The output of the neuron i in the l^{th} layer and for the layers between $1 \le l \le L-1$

$$\frac{\partial y_{jm}^{l+1}(k)}{\partial x_j^l(k)} = \begin{cases} w(t-k), & 0 \le t-k \le T_l \\ 0, & Others \end{cases} \qquad (6)$$

From Eqs. (4)-(6), Eqs.(7) and (8) can be obtained as the weight modification algorithm used to train the network.

$$w_{ij}^l(k+1) = w_{ij}^l(k) - \eta \delta_j^{l+1}(k) x_i^l(k) \qquad (7)$$

$$\delta_j^l(k) = \begin{cases} -2e(k) f[y_j^l(k)], & l = L \\ f[y_j^l(k)] \sum_{m=1}^{N_{l+1}} \Delta_m^{l+1}(k) w_{jm}^l, & 1 \le l \le L-1 \end{cases} \qquad (8)$$

Where

$\Delta_m^l(k) = [\delta_m^l(k) \;\; \delta_m^l(k+1) \; \ldots \; \delta_m^l(k+T_{l-1})]$

η : The coefficient used to adjust the step of algorithm, usually $0 < \eta < 1$ here, $\eta = 0.7$

x_i^l : The input of the neuron i in the l^{th} layer

$f()$: The Sigmoid function used in the neuron

5. Results

During the simulation, the input data to the network is averaged measured data over 1 minute. Since these soft measured data are collected over wide range of carrier frequency and altitudes, it is estimated the effects of each input variation on each output in different situations. Figures 3 and 4 show the comparison of the responses observed of the mathematical point view, the responses generated from the trained neural network model and the experimental data. They show that in contrast with theoretical aspect, the neural model represents the propagation channel very well, not only in low altitudes but also in high altitudes. With comparing simulation results of the spread in transient time from the transmitter to receiver, it can be estimated the time delay error of propagation. This comparison shows that this delay is appeared more striking through altitudes of 100 to 5000 meters. To demonstrate the weather influences on wireless propagation in term of frequency, we considered different bands of frequency ranges from UHF to EHF, the simulation results are shown in Fig. 5. This figure shows that the whether conditions effects, are more striking in frequencies over 20 GHz, than lower frequencies.

6. Conclusion

This paper has introduced three aspect of modeling of wireless channels. Firstly a method of data feeding to neural network for system identification has proposed, which involves simultaneously data with extremely high and extremely low frequencies. This method was based on averaged data and pre-filtering. This has helped to demonstrate the general applicability of identification using neural techniques. Secondly, survey of meteorological quantities effects on wireless propagation channel with respect to frequency has presented. Thirdly, the system delay has considered as a variable for training the neural network. This led to propose a new method to estimate time delay error for positioning systems. The model structure included pre-treatment of the input variable, a MLP network identifier and a transformer

MLP outputs to model output. To illustrate the efficiency of the model, the approach was compared with theoretical data and experimental data.

In future work we will examine the effects of each model inputs on each model outputs. We will also explore the model's sensitivity to various factors such as noise, number of neurons and the activation function used. These studies will be supplemented by the qualitive and quantitive comparisons and validated by computer simulation.

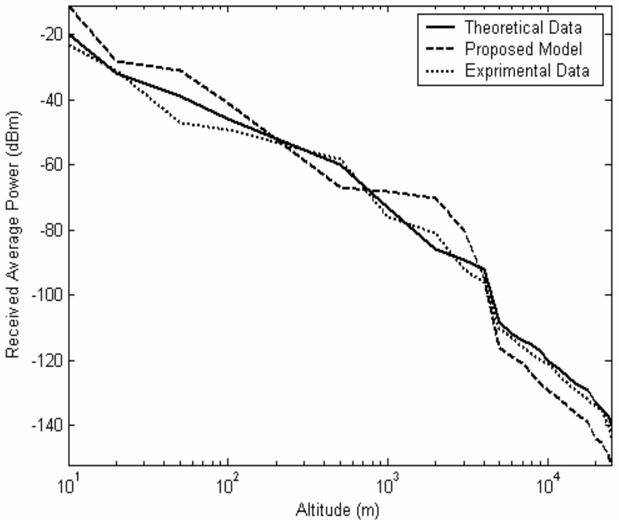

Fig. 3. Variation of the received average power with altitude of the theoretical, Proposed Model and experimental results.

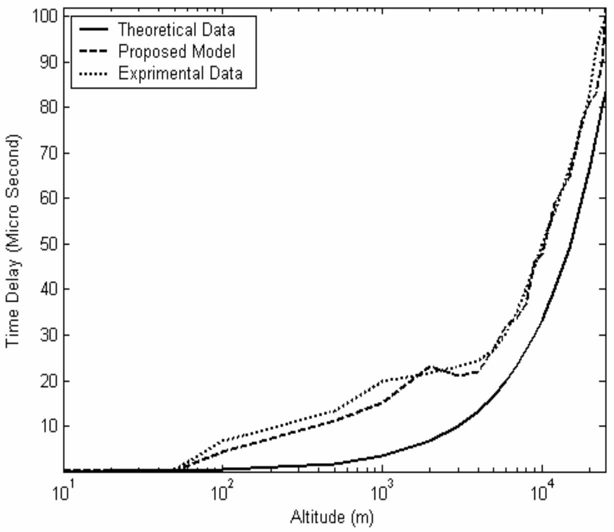

Fig. 4. Variation of the time delay with altitude of the theoretical, Proposed Model and experimental results.

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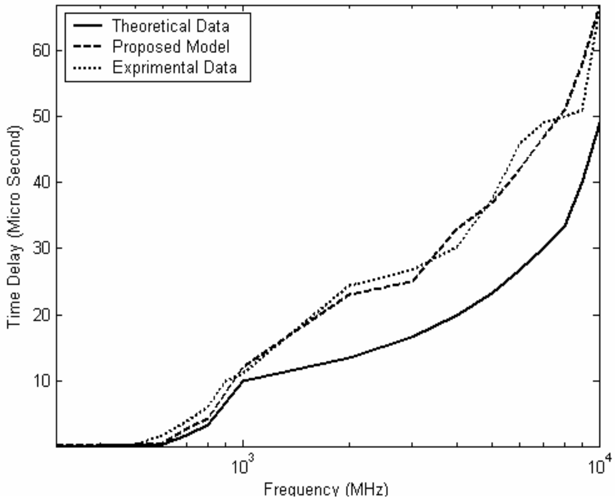

Fig. 5. Variation of the time delay with frequency of the theoretical, Proposed Model and experimental results.

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