Comparative Study on a 60 GHz Path Loss Channel Modeling in a Mine Environment Using Neural Networks

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***Abstract*- A precise and accurate channel model is essential in conceiving and designing wireless telecommunication systems. However, modeling the channel in a confined and harsh environment such as an underground mine is more complicated and challenging. In this paper, we present an experimental study on modeling a 60 GHz path loss fading based on experimental measurements made in an underground former gold mine. To address the accuracy of artificial neural networks (ANN) in modeling problems, an approach based on two well-known ANN, Multilayer Perceptron (MLP) and Radial Basis Function (RBF) is considered, and a comparison between them in modeling the path loss attenuation is evaluated.**

Keywords—Artificial neural networks, Channel modeling, Mine environment, Radio propagation, 60 GHz channel.

I. INTRODUCTION

The mine environment is a complex electromagnetic environment. To improve the production through automation, to reduce the maintenance costs and to allow the transfer of voice, data and video, in any remote location of the mine, wireless technology is required in the mining industry [1]. In fact, 60 GHz wireless communication systems are promising wireless gigabit transmission supports for short-range multimedia communications and presents an attractive solution to enhance wireless technology in mine environment.

In 2001, the FCC allocated 7 GHz in the 54-66 GHz in the unlicensed use. This 60 GHz frequency band presents a great importance, since it allocates a considerable amount of spectral band (5-7 GHz) for short range communication systems. Moreover, it provides a high available bandwidth, high capacity, a frequency reuse, and supports very high data rate applications [2].

However, a transmitted signal propagating through a wireless channel arrives at the receiver via many different paths (multipath propagation). Moreover, in a harsh environment such as mine environment and due to the different compositions and characteristics of floor, walls and ceiling, the signal propagation undergoes many physical phenomena such as reflection, refraction, diffraction and scattering. Thus, to obtain high quality information transmission, knowledge of the channel is required. This objective can be achieved by studying the channel modeling. Nevertheless modeling the channel, with high accuracy, in this environment is a difficult issue to be accomplished.

When channel simulators are implemented, the performance of different transmission technologies and signal processing can be studied without the need to perform field trials or tests for every scenario [2].

Moreover, modeling a channel in a mine environment allows developing a reliable channel emulator which can be used to overcome going underground to test filters, equalizers or to develop transceivers or amplifiers.

In general, approaches used to achieve channel modeling can be deterministic or stochastic approaches. Deterministic models can be: a) closed form approach that allows theoretical and analytical analysis, but it is too complicated (even impossible) to represent accurately the environment, b) empirical approach, a very accurate approach that extracts channel parameters, but very complex due to the large amount of measurements needed, c) Ray tracing approach which is highly environment-specific but the most complex and computationally expensive approach. On the other hand, the stochastic approaches are less complex, and provide accurate channel information. They can be divided into geometry-based and correlation-based, and their effectiveness is related to the implementation complexity and accuracy [2].

In this paper a non-traditional approach in modeling the path loss attenuation as a function of distance and frequency is presented. It is based on artificial neural networks (ANN). Also, it shows a comparative experimental study between two types of ANNs, and reveals the efficiency of this approach in underground channel modeling.

The remainder of this paper is organized as follows. In section II the 60 GHz channel modeling in a mine environment is presented. Section III describes the ANNs used. Simulations and results are given in section IV, and section V concludes this work.

II. 60 GHZ CHANNEL MODELING IN A MINE ENVIRONMENT

In wireless communication, the propagation characteristics have an impact on systems designs. However, most cellular radio systems operate in areas where there is no direct line of

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sight path between the transmitter and the receiver. Hence, multipath fading is caused, and the strength of the waves decreases as the distance between the transmitter and the receiver increases [3]. Thus, in order to avoid losing or noising information, a realistic channel model is required. In literature, many models are proposed as well as their enhancements, such as Okumura model, Cost-231 Hata Model, Lee model, Manhattan Model, and many more.

A generic 60 GHz channel model that takes clustering into account is proposed by Spencer et al. [4]. This cluster model is based on the extension of the Saleh–Valenzuela (SV) model to the angular domain.

IEEE 802.15.3c and IEEE 802.11ad are two industry standard channel models used for the evaluation of 60 GHz communications system. The IEEE 802.15.3c channel models are derived based on wideband measurement results conducted in office, residential, library and desktop environments. In the IEEE 802.11ad channel model, two types of models have been developed under the 11ad Task Group (TGad) framework [2]. The first one uses ray tracing to derive statistical models and the second one relies on channel measurement to derive a statistical channel model [2].

To limit the scope of this work, we focus our research on path loss (PL) defined as the ratio of the received signal power to the transmit signal power, describing thereby the attenuation of the mean power as a function of the travelled distance. The PL metric is very essential for link budget analysis and network planning to ensure that the deployment meet the target coverage [2].

Several measurement campaigns to characterize the channel of an underground mine were conducted at the "Télébec Underground Communications Research Laboratory" (LRTCS) located in Val-d'Or, Québec, Canada [5]. Results obtained in [6] are used for our study. Measurement campaigns are performed in a mine gallery at level 40 m depth in line of sight condition (LOS) in mine CANMET (Canadian Centre for Minerals and Energy Technology), a former gold mine used to train miners or perform different types of experiment.

This gallery is approximately 3.8 meters width and 3.9 meters high, with irregularities in walls and a dry floor. A vector network analyzer (VNA-Agilent E8363B) is used to measure the complex frequency response of the channel. It is capable of measuring frequencies from 10 Mhz to 40 GHz; hence, the system used converts the signal to get the 60 GHz frequency band [6].A local oscillator frequency(LO=14.25 GHz) is multiplied by four, and is then mixed with the intermediate frequency (IF=3GHz). Hence, a 60 GHz signal is obtained at the output of the mixer. A 60 GHz filter and a 60 GHz power amplifier are placed between the mixer and a directional transmitter antenna which transmits frequencies between 59 and 61 GHz. The output port of the VNA is connected to the IF mixer input of 60 GHz upconverter. At the reception, the received signal passes through a 60 GHz low noise amplifier and is then mixed with the 54 GHz signal (LO*4) to obtain an output from 5 GHz to 7 GHz. Finally, the signal is filtered and connected to the input port of VNA [6].

The measurements were made between 1 m and 6 m with an interval of 1 m. The VNA is set to sweep 6401 discrete frequencies ranging between 5 and 7 GHz, corresponding to frequency ranging from 59 to 61 GHz, with a resolution frequency of 0.97 Mhz. The scattering parameters S_{21} are obtained by the VNA; they are complex values proportional to the frequency response of the transmission channel. At each position the channel transfer function is measured 15 times in order to reduce the effects of the random noise.

The channel is assumed to be stationary, since neither movement nor person was present in the mine gallery.

III. Neural Networks

Over the last thirty years, the field of artificial neural networks (ANN) has become an important research theme, as they have been developed as generalizations of mathematical models of human cognition or neural biology. ANNs are used for statistical analysis, data modeling, and problems of classification, approximation, prediction, and optimization.

Simple process elements, neurons, are interconnected to form network, and offer an alternative to conventional computing approaches. These elements (nodes) are organized in layers. The strength of the connection between nodes is defined by its weight.

An ANN is a massively parallel-distributed processor made up of simple processing units. It is concerned with transformations than algorithms and procedures. It stores experiential knowledge and makes it available for use [7].

Many types of ANN were used in channel modeling and in signal estimation in multipath mobile communications [8].

Using a learning process (also called training), neural networks can achieve complicated input-output mappings, without explicit programming or prior knowledge, and can extract relationships (both linear and nonlinear) between data sets. This is achieved by modifying the synaptic weights of the network to attain a desired design objective [7].

The most popular neural networks used in supervised learning are Multilayer Perceptron (MLP) and Radial Basis Function (RBF) networks. They are presented in sub-sections below.

A. Multilayer Perceptron

The Multilayer Perceptron Network is a feed-forward neural network with one input, one output, and one or more hidden layers (cf. fig.1). The error back propagation (EBP) algorithm is the learning algorithm the most used in this type of ANN; it is composed of three stages: the feed-forward of the input training pattern, the back-propagation of the associated error, and the adjustment of the weights [7].

To perform the training process, each output unit compares its computed activation with its target to determine the associated error, and then the weights are adjusted to minimize the resulting error. Activation functions used should be continuous, differentiable and monotonically non-decreasing. They can be linear (or ramp), threshold, or sigmoid functions.

The number of hidden layers as well as the number of nodes forming each layer depends on the complexity of the modeling problem.

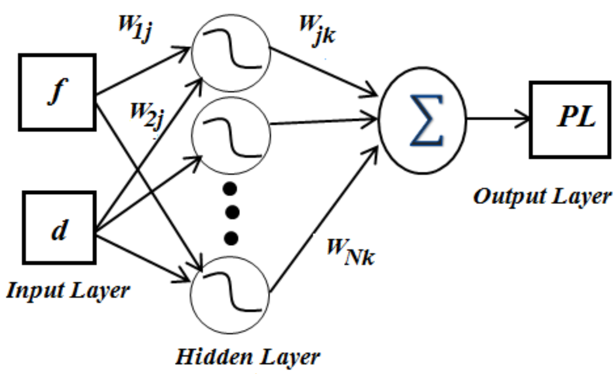

Fig.1 MLP neural network architecture

The modification of synaptic weights w_{ij} between two neurons i and j at iteration n is done according to the delta rule (Eq.1)

$$w_{ij}(n) = -\eta \frac{\partial e(n)}{\partial w_{ij}(n)}. \tag{1}$$

With $e(n)$ being the error between desired and calculated outputs (by neural network), and η being the learning parameter.

B. Radial basis function

On the other hand, a RBF neural network is composed of only three layers: input layer, a linear output layer and one nonlinear hidden layer (cf. fig.2). The nonlinear activation function used can be Gaussian, Multiquadric, Inverse Multiquadric or Cauchy function.

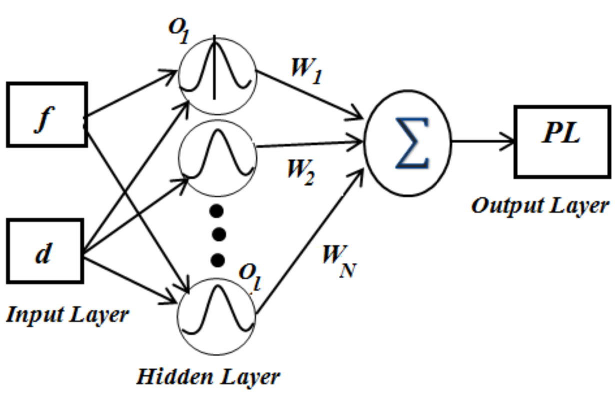

Fig.2 RBF neural network architecture

In this work we choose the Gaussian function as an activation one in the hidden layer.

Unlike nodes' connections in the MLP, the connections between the input and the hidden layers are not weighted in a RBF network. Hence, the inputs are transmitted to the hidden layer unchanged. Using the non-linear activation function the output of the hidden neuron is presented by (Eq.2)

$$y_l = e^{-\|x-o_l\|^2 / 2\sigma_l^2}. \tag{2}$$

Where x is the input data, o_l is the center of the l^{th} Gaussian function (l^{th} neuron of the hidden layer),σ_m is the width of the Gaussian, and y_l is the output of the l^{th} Gaussian. Then, neurons of the output layer implement a weighted sum of hidden nodes outputs.

C. Models descriptions

In this study we use two models (RBF and MLP); both consist of three layers. The inputs at the first layers are the frequency f varying from 59 to 61 GHz and the distance d varying from 1 to 6 m. The output at both networks is the path loss PL. Measurements done in [6] are used to model only the path loss obtained from S_{21} parameters. An average value for the 15 values for each frequency at each distance (1 to 6 m)is computed.

Hence, for each distance we have 6400 data points. A portion of this data served as a training set for the ANN and another portion, not presented to the ANN during the training, served as a testing set.

In order to build the relationship (Mapping) between the inputs-targets pairs, a training process should be established. This latter consists in adjusting the weights during the process of learning to reach the minimal tolerated error (by comparing the output of the ANN with the desired target). Secondly to verify the performance and the efficiency of the ANN in estimating correctly the desired output for a given data entry, a testing phase takes place. Neural networks behave differently, producing therefore different results.

IV. Simulations and Results

In this section, we will present results obtained from using ANN in modeling the path loss at 60 GHz in a mine environment as well as a comparison between the two types of networks.

A small portion of measurements has been used in the training process. Only 5% of the data present the learning samples (1600 of 32000 points). The tool used to fulfill this work is the Matlab Neural Network Toolbox.

In the MLP model the hyperbolic tangent sigmoid (Tansig) function is used as an activation function in hidden nodes, whereas, the output layer has linear function (Purline). As we mentioned above, the frequency and the distance are the inputs of the network, and the path loss is the output. The learning parameters are selected as follow: the number of epochs used for training is 500 and the training parameter goal is 10^{-4}.

As for the RBF model, the inputs and the output are the same as the MLP network, and a single hidden layer with a Gaussian activation function is used. The input samples were scaled, and the learning parameters are selected as follow: the spread of the Gaussian is 0.01, and the training parameter goal is same as in MLP.

Figure 3 and Figure 4 present respectively the estimated path loss using MLP ANN and RBF ANN on a test set (0.1 % of data).

The blue dotted curves present the real measured data in the mine environment, while the red curves present the path loss estimated at the output of the ANNs.

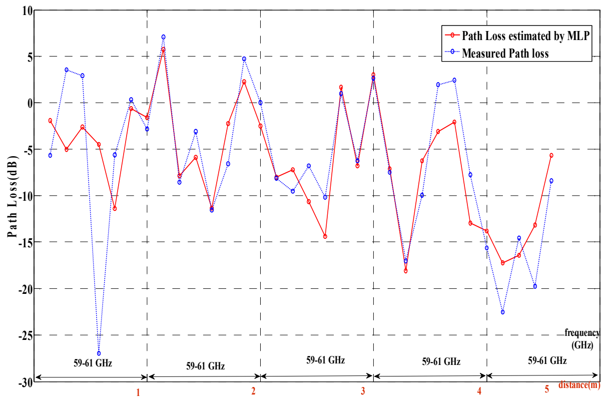

Fig.3 Estimated path loss by MLP ANN using 0.1% of data

The results obtained by the MLP show a good performance of this type to predict and model the channel in a mine environment at 60 GHz, with a mean square error (MSE) equal to 0.115, calculated over 0.1% of the data set.

Also, the results obtained in fig.4 show the efficiency of the RBF ANN in modeling the channel in an underground mine, as we can see the two curves are almost superposed in some parts ; besides, the value of MSE equals 0.3 shows the accuracy of this type.

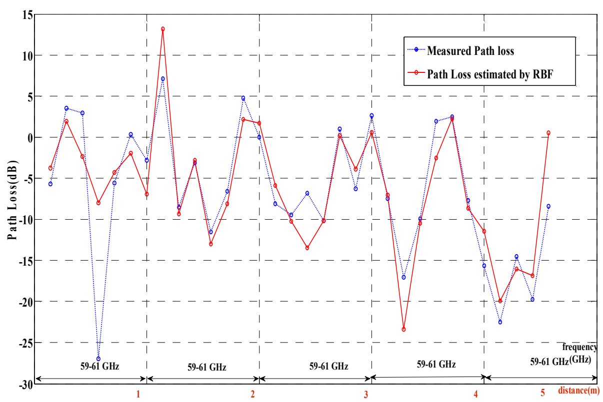

Fig.4 Estimated path loss by RBF ANN using 0.1% of data

Results obtained show the ability and efficiency of ANNs in predicting the path loss in a mine environment with high accuracy. Although the MLP presents less error, we can conclude that both types have the same potential in predicting the path loss in the mine environment. However, this study should be completed to evaluate the capacity in estimating the phase, as well as different propagation conditions and different galleries in this mine.

On the other hand, the RBF type requires a large number of hidden neurons unlike the MLP ANN; since it necessitates that there will be as many RBF centers as there are distinct data points in the input space [9]. Therefore, the computation complexity will increase by increasing the number of hidden neurons, and the training process in this type requires more time than that required in the case of MLP. Nevertheless, since the training process is an offline procedure, we can neglect the time factor.

Moreover, using this approach, based on neural networks, the path loss can be estimated for any frequency and distance desired owing to their capability of modeling the path loss as a function of the distance and the frequency.

V. Conclusion

The aim of this paper was to present a different approach than traditional ones in modeling a 60 GHz channel in a mine environment, based on neural networks. The effectiveness of this method is arguably promising as shown by obtained results. A comparison between two types of ANN is presented, to help to choose the appropriate type to model the channel in a mine environment. Further work can be done such as estimating the phase of the scattering S_{21} parameter given by the vector network analyzer, modeling in different mine galleries using 60 GHz technology, as well as in different propagation conditions (LOS and NLOS).

Besides, the ANN can be implemented in a hardware circuit in order to emulate the 60 GHz channel in a mine environment, and reflects the channel behavior as a function of frequency and distance.

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