Neural networks model of an UWB channel path loss in a mine environment

M. Kalakh, N. Kandil, *Member, IEEE*, and N. Hakem, *Member, IEEE*

Abstract— **this paper aims to present an UWB propagation channel modeling with neural networks in a mine environment, focusing on the change in the path loss attenuation as a function of distance and frequency.**

A trained neural network can be used for high-level design, providing fast and accurate answers to the task it has learned. Neural networks are effective alternatives methods to conventional methods such as statistical and stochastic modeling methods, which could be computationally expensive, or to analytical methods which could be difficult to obtain for new environments, or to empirical modeling solutions which range and accuracy may be limited.

***Index Terms*—ultra-wide-band (UWB); neural networks (NN); modeling an UWB channel; underground mine environment; multi-layer perceptron (MLP).**

I. INTRODUCTION

Prediction of the propagation channel model in a Mine Environment with an ultra-Wideband technology is known to be a difficult problem, due to diffractions, reflections and scatterings of radio signal.

Ultra-wideband technology offers many advantages, mainly, the high-speed data transmissions, the short duration pulse, and the low power communication compared to wideband wireless systems. A modern exploitation of mineral resources, particularly in an underground mine, requires remote control and high speed audio/video data transmission be available. To achieve these objectives, the characterizations of the UWB channel are conducted in a typical underground environment [11].

Numerous wideband propagation measurements in an underground mine were taken by researchers of the Underground Communications Research Laboratory (LRCS) as a part of a collaborative research effort, in CANMET, (Canadian Center for Minerals and Energy Technology), experimental mine in Val d'Or, Canada.

We apply a neural network learning algorithm to predict the received power of a radio signal as a function of distance *d* and frequency *f* based on UWB measurements in a mine.

A neural network (NN) is a natural choice for modeling linear and nonlinear dynamic systems, since it can approximate any continuous function arbitrarily well [5].

Many works on neural networks have been published in the literature. NN have, hence, been used for modeling communication system [6] like satellite channels [7] or localization in mines [2]. Also they have been used for modeling UWB channels [4]. But there are no publications for the modeling of an UWB channel in a mine environment using neural networks.

Consequently, it is important to present a work which studies the propagation channel measurements in an underground environment applying neural networks, since it presents a new application in such environment.

The remainder of this paper is arranged as follows: in section II we present the UWB channel modeling. In section III we present a description of the underground mine environment and measurements done in this environment. The neural network learning algorithm is discussed in section IV. In Section V we show results. The last section is devoted to the conclusion and to the discussion of future work.

II. UWB CHANNEL MODELING

The ultimate performance limits of any communication system are determined by the channel it operates in. For an UWB system, this is the UWB propagation channel, which differs from conventional (narrowband) propagation in many aspects. The performance of a system thus can only be evaluated when realistic channel models are available. For any channel model, we must make a trade-off between the prediction reliability with computation expense, as with the measurement resolution. In our case, we are limited to signal envelope measurements.

The simplest UWB channel model is the stochastic delay line model given by:

$$h(t,\tau)=\sum_{l=1}^{L} a_l(t)\delta(t-\tau_l(t)) \qquad (1)$$

$h(t,\tau)$ is the channel impulse response at time t, δ is the Dirac function, L is the number of multipath components, a_l and τ_l are the fading amplitude and the time of arrival of the *l* path [11].

III. MINE ENVIRONEMENT

The measurements are performed in various galleries in an old gold mine at a level of 70 meters underground. The environment consists mainly of very rough walls and non flat floor containing puddles. The size of the corridors of the mine varies between 2.5 m and 3 m wide and about 3 m high. Measurements were taken in both line of sight (LOS) and non line of sight (NLOS) scenarios. Fig 1 shows the photograph of the underground tunnel.

978-1-4673-0990-5/12/$31.00 ©2012 IEEE

The CANMET gallery at 40 m depth, in which the previous wideband measurements were performed, was quite different than the one at 70 m depth, as it was characterized by a width and height of both approximately 5 m [8].

Fig.1 Photograph of the underground gallery.

The UWB measurements were performed in frequency domain using the frequency channel sounding technique based on the module of the S21 scattering parameter obtained by a vector network analyzer.

In fact, the system measurement setup consists of E8363B network analyzer (PNA) and two different kinds of antennas, with directional and unidirectional radiation patterns, respectively. There are no amplifiers used during the measurements because the distance between the transmitter and the receiver was just 10 meters. The transmitting port of the PNA swept 16001 discrete frequencies ranging from 3 GHz to 10 GHz uniformly distributed over the bandwidth, and the receiving port measured the magnitude and the phase of each frequency component.(In our work we were limited to the magnitude)[12].

IV. Neural Networks

A. Model description

Neural networks (NN) are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. You can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Typically, neural networks are adjusted, or trained, so that a particular input leads to a specific target output. The next figure illustrates such situation. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically, many such input/target pairs are needed to train a network. NN have been trained to perform complex functions in various fields, including pattern recognition, identification, classification, speech, vision, and control systems. NN can also be trained to solve problems that are difficult for conventional computers or human beings [10].

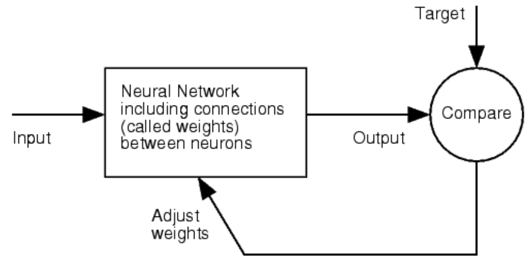

Fig. 2 Operation of the neural network

Neural networks can learn from the given cases and summarize the internal principles of data even without knowing the potential data principles ahead. And it can adapt its own behavior to the new environment.

There is no good way to determine the number of hidden layers of neural network and the number of hidden nodes in each layer currently. In order to overcome the problem, we determine the hidden layers and nodes in each hidden layer by training the system. Through the operation of neural network, we select a neural network model with smaller average error [9].

The most important work in building a NN power forecasting model is the selection of input variables. There is no general rule that can be followed in this process. It depends on engineering judgment and experience and is carried out almost entirely by trial and error [3].

Our network is multi-layer perceptron (MLP) type feed forward architecture .It is based on a supervised training using the method of back propagation. We use hyperbolic tangent sigmoid function (Tansig) in the hidden layers and linear function (Purline) in the output layer.

At the beginning we started with a perceptron of three layers, two hidden layers and one output layer, we varied the number of neurons per layer to improve performance and that by using several ways; one of them is by reducing the number of layers in the network since an architecture with multiple hidden layers will increase the precision of estimates. However, the number of connections will be higher and the learning curve will be slower. One problem we encountered is showing the realism of our model and identifying its inputs because in the case of UWB, the received power varies with frequency and distance and in our study we set to work a very large number of measures which must be arranged to be used by the network. We went through several experiments and models to identify realistic entries. Then we tried learning with a single hidden layer (figure 3) with different number of neurons. We found that with a number of neurons equal to eighty the mean square error (MSE) obtained is the lowest.

In this system, we use a neural network model that consists of an input layer which contains two inputs, frequency f and distance d, a single hidden layer of 80 neurons and an output which is the path loss attenuation (L) in the output layer. The changing of the learning rate used in the phase of training is related to the number of training data (input data).

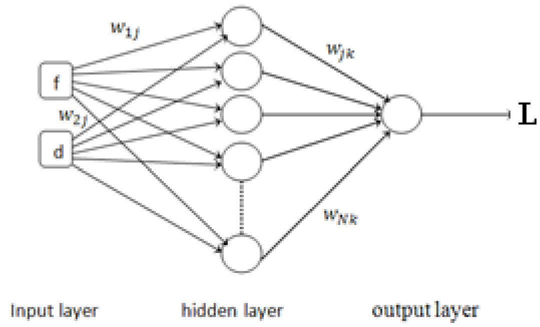

Fig.3. NN with two input nodes, 80 hidden nodes, and one output node, the two input nodes correspond to frequency and distance, The Output node corresponds to the Power. W presents weights.

B. Operating Model

When training, we present the neural network a set of similar data. We train the model by performing a sufficient number of experiments to verify the validity of results and the model. During the prediction phase, we test the model by estimating its accuracy to predict correctly the values of the received power. If the accuracy is acceptable then we can use the model, else we have to repeat the cycle of the model construction. Finally for a new environment, presenting other data without knowing a priori the relation linking the inputs to the outputs, this model can be used

V. RESULTS

A. UWB channel modeling in a mine at 70m depth

The objective of this part is to find the most accurate NN parameters and evaluate mismatching between measurements and NN model.

1) Training the network with 50% of measures and testing with 50% of measures:

In this step we use the half of measures to train the network and half to test. We obtain the results shown in Fig.4 with MSE equal to 1.0359 dB. This error can be considered a very low error.

As it shown, the blue curve shows path loss attenuation measured in terms of distance and frequency, such that for each distance the frequency varies from 3 to 10 GHz with a step of 0.875MHz where the red curve sowing NN model path loss is fully under blue one which shows a perfect fitting. Fig.5 shows a zoom in of red circle on Fig.4 and red curve path loss. Therefore, we conclude that our model is able to correctly predict path loss as a function of frequency and distance.

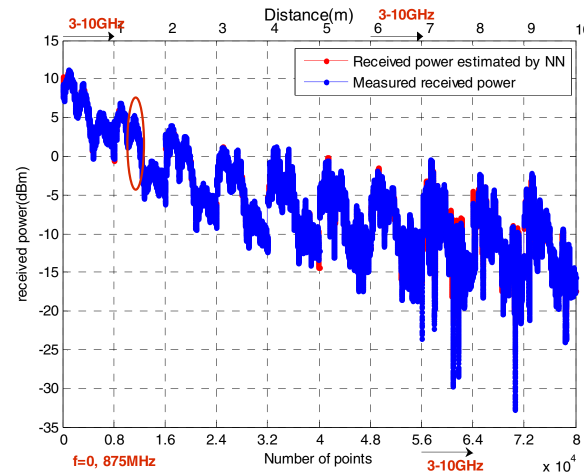

Fig.4: Path loss as a function of distance and frequency with 50% measurement for training process

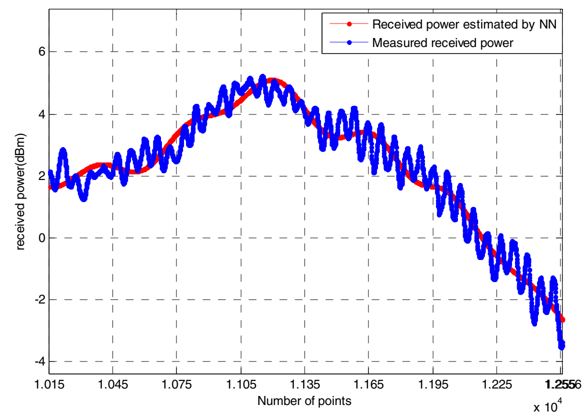

Fig.5: Zooming of red circle in Fig.4

2) Training the network with 10% of measures and testing with 50% of measures:

In this part we reduce the number of training process input to 10% of measures, then as it shown in the fig.6, we get a result of 1.0445dB MSE error, which is as small as previous result with 50% training process.

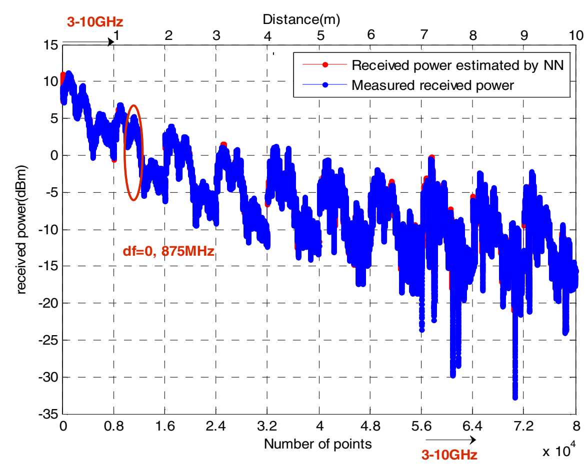

Fig. 6 Path loss as a function of distance and frequency with 10% measurement for training process

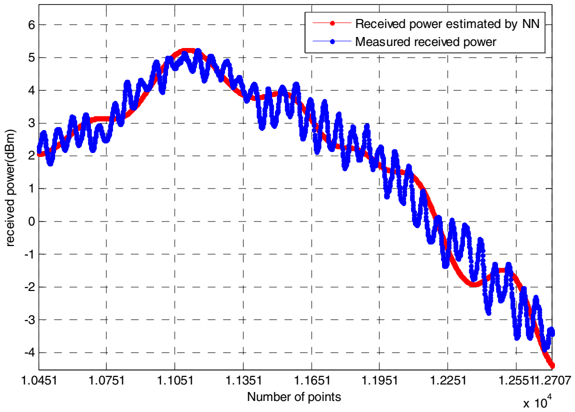

Fig.7: Zooming of red circle in fig.6

Although we reduced the measurements used for training process in our model, this latter is able to accurately estimate the change in power as a function of frequency and distance.

3) Training the network with 1% of measures and testing with 50% of measures:

In the same way to previous subsection, the measurements used in training process are reduced to 1% and results are plotted in Fig.8 and Fig.9. The obtained MSE error is slightly small than 4 dB.

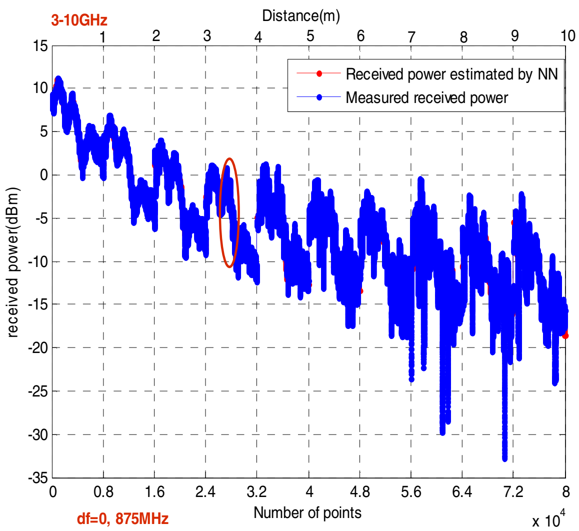

Fig.8: Path loss as a function of distance and frequency with 1% measurement for training process

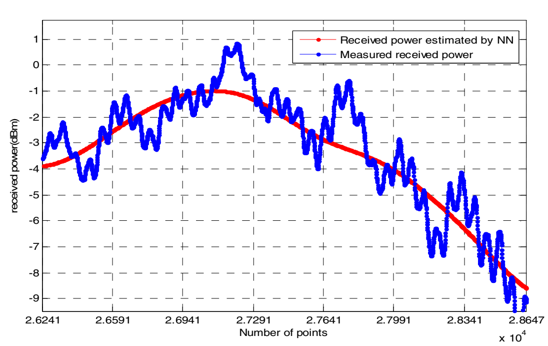

Fig.9: Zooming of red circle in Fig.8

Although the training process uses only 1% of the measurements, the accuracy of NN path loss model is reduced but, it remains very moderate and the model predict correctly path loss as a function of frequency and distance.

4) Training the network with 10% of measures and testing with 1% of measures:

In opposite way, we increase the number of measurements in training process and reduce them in testing one.

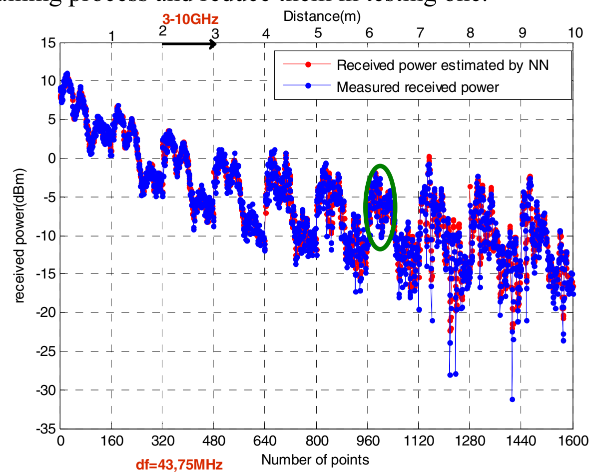

Fig.10: Path loss as a function of distance and frequency with 10% measurement for training process and 1% for testing process

Fig.10. and the corresponding zoom in Fig.11 show path loss attenuations as function of the frequency and distance with a 1.12 dB MSE fitting error. We can note that the results are clearer because the measurements used for testing process are lower compared to the previous subsections.

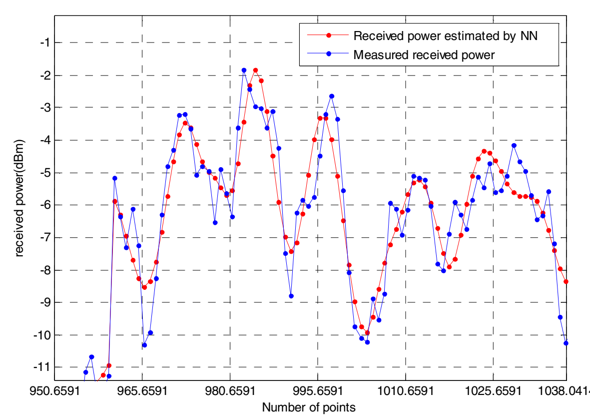

Fig.11: Zooming of green circle in Fig.10

B. Evaluation of NN model in other mine gallery

After showing the performance of our neural network in modeling path loss attenuation in a mine tunnel at 70m depth, we evaluate fitting of our model with experimental measurement coming from another tunnel located at 40 m of depth in the same mine environment.

The fitting results are plotted in the Fig.12. The MSE error is 6.7561dB, this latter has increased but even so, we can see in the Fig.13 that the model is still able to correctly predict the evolution of the path loss attenuations as function of frequency and distance. Therefore, use of one tunnel measurement to predict the path loss behavior of another tunnel in the same mine is viable with a less accuracy, about 6 dB in our scenario.

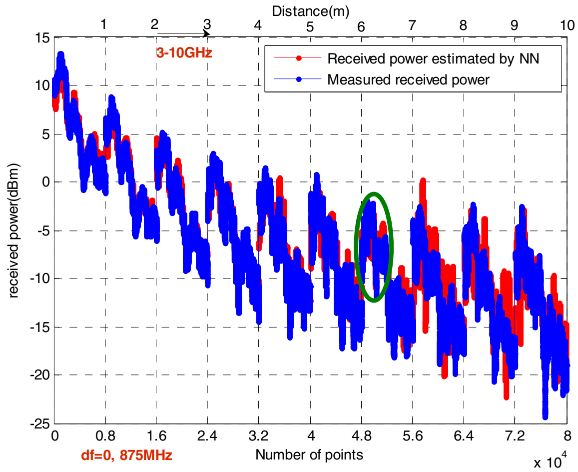

Fig.12: Path loss as a function of distance and frequency with measurement coming from tunnel 40m depth

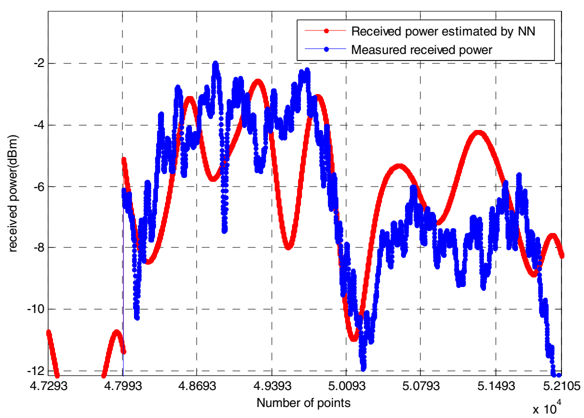

Fig.13: Zoom of green circle in fig.12

VI. CONCLUSION

The neural networks allow the modeling of complex problems in various fields. Unlike statistical models, the NN can discover the form of the function linking the input variables to output variables to support the update of the values of its weights to learn. During our work we are interested precisely by the variation in path loss attenuation of UWB signal in underground harsh mine environment as a function of distance and frequency. However, the frequency varies between 3GHz and 10 GHz, and the distance varies from 1 to 10 meters. We build a NN model using multilayer perceptron based on the method of backpropagation for learning network. Indeed, the most important phase in building a neural model is to determine the inputs and outputs of the network. Then, by comparing the results obtained by the neural model and the experimental measured values, we note that our model is able to correctly predict the variation of path loss attenuation in an UWB channel in a mine environment for two different galleries and give an acceptable accuracy with very few experimental measurements. Therefore, we show in this work that neural network is a feasible solution for the channel modeling in a mine considered as harsh environment. Finally our work can be considered as the beginning of other work that can be run in this area, for example we can work on other parameters of the UWB channel, and we can also choose other types of neural networks for modeling.

REFERENCES

[1] L.Qiu, D.Jiang, and L.Hanlen, "Neural Network Prediction of Radio Propagation," Proceedings 6th Australian Communications Theory Workshop, 2-4 February 2005, Brisbane, pp. 272-277. ISBN 0-7803-9007-5, 2005.

[2] Anthony Taok, Nahi Kandil, Sofiène Affes, "Neural Networks for Fingerprinting-Based Indoor Localization Using Ultra-Wideband," JCM 4(4): 267-275, 2009.

[3] N. Kandil, V.K. Sood, and M. Saad, "Use of ANNs for Short-Term Load Forecasting," the Canadian Conference on Electrical and Computer Engineering, CCECE'99, Edmonton, Alberta, Canada, Mai 1999.

[4] M. Isaksson, D. Wisell, and D. Rönnow, "Wideband dynamic modeling of power amplifiers using radial-basis function neural networks," IEEE Trans. Microwave Theory Tech., vol. 53, pp.3422-3428, 2005.

[5] M. Ibnkahla, "Neural Network Modeling and Identification of Nonlinear Channels with Memory: Algorithms, Applications asn Analytic Models,"IEEE Trans, On Signal processing, vol 46, no. 5, pp.1208-1220, 1998.

[6] S. Haykin, Neural Networks, 2nd ed. Upper Saddle River, NJ: Prentice-Hall, 1999.

[7] M. Ibnkahla, "Applications of neural networks to digital communications—A survey," J. Signal Process., vol. 80, pp. 1185–1215, 2000.

[8] M. Boutin, A. Benzakour, Charles L. Despins, and S. Affes, "Radio Wave Characterization and Modeling in Underground Mine Tunnels,"IEEE transaction on antennas and propagation, Vol.56,No. 2, February 2008.

[9] T. Guo, Gui-Yang Li, "NEURAL DATA MINING FOR CREDIT CARD FRAUD DETECTION," Machine Learning and Cybernetics, 2008 International Conference on, pp. 3630 - 3634, 2008.

[10] Howard Demuth, and Mark Beale, Neural networks Toolbox for use wiht MATLAB, 2004.

[11] A. Chehri, P. Fortier, P. -M Tardif "Frequency Domain Analysis of UWB Channel Propagation in Underground Mines," IEEE VTC'06-fall, September 25-28, 2006, Montreal, Canada.

[12] B. Nkakanou, N. Hakem, G. Y. Delisle, "Experimental Evaluation of the Ultra-Wideband Propagation Channel in an Underground Mine, " Antennas and Propagation Society International Symposium (APS/URSI), Jul 2011, pp. 2781-2784, 2011.