Efficient Neural Model for Estimation of the Microwave Antenna Noise Temperature

Ivan Milovanovic[1], Zoran Stankovic[2], Marija Agatonovic[2] and Marija Milijic[2]

Abstract – **This paper presents efficient neural model for estimation of the microwave antenna noise temperature which can accelerate the prediction procedure of the external noise level at the receiving point of a wireless communication systems. Were taken into account only the effects of natural noise sources, which are surrounded by the antenna system and considerably more stable than artificial. The case of microwave wireless transmission, where dominated influence of noise generated by emissions of gases from the atmosphere (primarily oxygen and water vapour), is considered. Accordingly, we developed a neural network model for antenna noise temperature prediction of the RF receiver based on Multilayer Perceptron (MLP) network. The architecture of this model, the results of its training and testing and simulation results are presented in this paper in the appropriate sections.**

Keywords – **Neural network, Antenna Noise, Brightness temperature.**

I. Introduction

The outburst of wireless systems presents a growing number of technical challenges for performance demand, necessary to support vast number of wireless applications. The wireless system design goal is to achieve the largest possible coverage area in which the received power is sufficiently strong compared to background noise. Consequently, one of fundamental parameters in wireless communication is signal-to-noise power ratio that indicates the reliability of the link between the transmitter and receiver. Therefore, it certainly helps to have a reliable tool to estimate noise power during the process of wireless systems designing.

Now, the most frequently used recommendation is ITU-R P.372-10 for estimation of extern noise of RF transmitters [1]. Recommendation ITU-R P.372 provides data on radio noise external to the radio receiving system which derives from the following causes: radiation from lightning discharges (atmospheric noise due to lightning); aggregated unintended radiation from electrical machinery, electrical and electronic equipments, power transmission lines, or from internal combustion engine ignition (man-made noise); emissions from atmospheric gases and hydrometeors; the ground or other obstructions within the antenna beam; radiation from celestial radio sources. Many noise dependences [1,2] are represented by formula whose parameters should be determined from a lot of complex figures. Classical use of Recommendation ITU-R P.372 requires figures visual reading with applying challenging interpolation methods resulting in time-consuming, forceful process with non-satisfactory accuracy.

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The application of Artificial Neural Network (ANN) is proven as a good tool for overcoming all of the specified problems. ANN is very sophisticated modeling techniques capable of modeling extremely complex functions. Indeed, anywhere that there are problems of prediction, classification or control, neural networks can be introduced. ANN has the capability of a functional dependence's modeling exclusively on the basis of input data [3-6]. Neural network architecture which is consisted of connected small processing units (neurons). In this way, neural network can be used for modeling high-distributed and high-parallel problems [3-6]. The second is neural network ability to learn function dependence on the basis of solved examples rather then to learn to execute some well known function dependence. After successful learning process of neural network, it can be used not only for known examples but also for unknown examples (generalization).

Neural network has been applied for estimation level of RF receiver external noise taking only frequency as a factor, not taking into account the parameters that describe the antenna environment [5]. In this paper, neural model for prediction of the microwave antenna noise temperature is developed resulting in more effective estimation of receiver external noise dependence on water vapor concentration in atmosphere, frequency and antenna elevation in microwave range. This model is established by further developing of the model that is presented in the reference [7]. Model in reference [7] in calculation of brightness temperature takes only frequency and antenna elevation.

II. Specification of Noise Intensity of Wireless Communication System

The noise factor, f, for a receiving system is composed of a number of noise sources at the receiving terminal of the system [1,2]. Both internal and external noise must be considered. For receivers of the wireless communication system, the system noise factor is given by [1]:

$$f = f_a + (f_c - 1) + l_c(f_t - 1) + l_c l_t (f_r - 1) \tag{1}$$

where l_c is antenna circuit loss, l_t is transmission line loss and f_r is noise factor of ideal antenna and f_t is the noise factor associated with the transmission line losses. f_a is the external noise factor defined as:

$$f_a = \frac{p_n}{k t_0 b}, \qquad F_a = 10 \log f_a \tag{2}$$

where p_n is available noise power from an equivalent lossless antenna, k is Boltzmann's constant = 1.38×10^{-23} J/K, t_0 is reference temperature taken as 290 K and b[Hz] is noise power bandwidth of the receiving system [1,2].

External noise factor can be presented using effective temperature of antenna noise t_a:

$$f_a = \frac{t_a}{t_0}, \qquad t_a = \frac{P_a}{kB} \tag{3}$$

where P_a is external noise power collected by antenna.

The available noise power is obtained by summing the contributions of each individual noise sources. To be able to perform the calculation it is necessary to introduce a parametar that determines the noise radiation sources. The parameter used in that sense commonly is brightness [8,9]. Taking into account the Planck law of black body radiation in the radio frequency spectrum and using the Raleigh-Johnson approximation, the brightness in the direction θ, φ from which noise of frequency f comes can be expressed as:

$$S(f,\theta,\varphi) = \frac{2kt_b(\theta,\varphi)}{\lambda^2} \tag{4}$$

where $t_b(\theta,\varphi)$ brightness temperature in the observed direction θ, φ, which originates from noise sources. Accordingly, effective temperature of brightness t_b from the body radiating noise is defined using power of noise radiation P_b [2,8]:

$$t_b = \frac{P_b}{kB} \tag{5}$$

Integrating noise power at all spatial angles and taking into account the characteristics of antenna $F(\theta,\varphi)$antenna noise temperature can be expressed in a way [6,8]

$$t_a = \frac{\int_0^{2\pi}\int_0^{\pi} F(\theta,\varphi)\, t_b(\theta,\varphi) \sin\theta \, d\theta \, d\varphi}{\int_0^{2\pi}\int_0^{\pi} F(\theta,\varphi) \sin\theta \, d\theta \, d\varphi} \tag{6}$$

Natural source noise can be atmospheric noise, cosmic noise, noise from Earth and noise from different cosmic objects. Cosmic noise decreases approximately with the square of the frequency so that the above 1 GHz is very small and can be ignored by receiver operating in the microwave range. Noise from Earth, that correlates average noise temperature of 254 K, is important only for satellite antenna with the main radiation bean directed to Earth. There are number noises from many cosmic objects, but the only significant is the noise from the Sun. The Sun noise significantly affects on antenna noise only when large direction antenna with main radiation beam directed to the Sun. Atmospheric noise can derive from two sources. In The first is electrostatic discharge in atmosphere that overcomes for frequency range bellow 50 MHz. The last is emission in atmosphere due to water vapor and oxygen that is dominant in high frequency range. Figure 1. shows temperature of atmosphere brightness versus antenna elevation and frequency when average concentrate of tropopause water vapor is 10 g/m^3. [2]. Considering only atmospheric influence and if space angle of antenna effective radiation Ω_a, is less then space angle of noise source radiation Ω_b, temperature of antenna noise can be equalized with temperature of noise source brightness

$$t_a \approx t_b \quad , \quad \Omega_a < \Omega_b \tag{7}$$

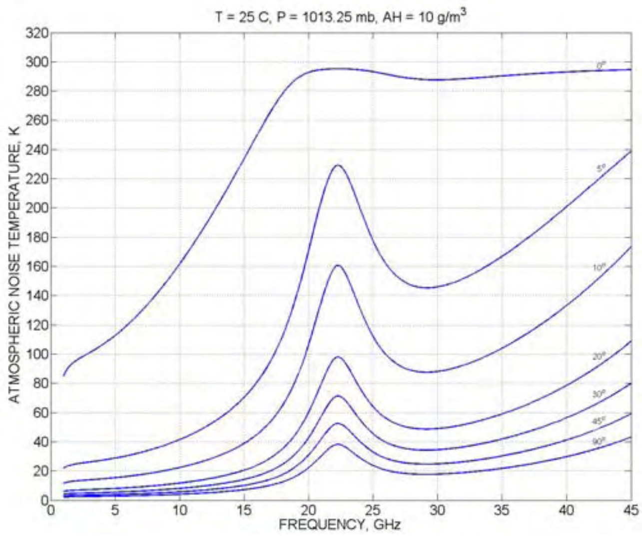

Figure 1. Temperature of atmosphere brightness versus antenna elevation and frequency when average concentrate of tropopause water vapor is 10 g/m^3 for calm and good in standard atmosphere weather

III. Neural Model of Microwave Antenna Noise Temperature

The model of noise temperature of receiver antenna in wireless communication system in microwave range considers only influences by atmosphere as dominant noise source while other noise sources are taken as inappreciable. For large space angle of antenna radiation, antenna noise temperature is approximately equal as temperature of antenna brightness from atmosphere that radiates noise. Also, it considers calm and good weather with constant atmospheric pressure 1013.25 mb and atmospheric temperature T=25° C. For given conditions, brightness temperature depends on water vapor concentration a_h, antenna elevation angle θ and frequency f. The problem should be modeled as the function

$$t_b = g(a_h, \theta, f) \tag{8}$$

The neural model given as function $\mathbf{y}=y(\mathbf{x},\mathbf{w})$, where y is neural network function and $\mathbf{w}$ is a connection weight matrice among neurons [3,4], has input vector $\mathbf{x}=[a_h, \theta, f]^T$ and output vector $\mathbf{y}=[t_b]$. The modeling brightness is done by using Multilayer Perceptron Network (MLP) with appropriate MLP neural model defined as:

$$t_b = y([a_h,\theta,f]^T, \mathbf{w}) = f_{MLP}(a_h,\theta,f,W) \tag{9}$$

where f_{MLP} is transfer function of MLP network used for realization neural model. If weight matrice $\mathbf{w}$ is presented as matrix structure, it can cause difficulties in implementation neural network and in its training algorithm. For this reason, neural network weight matrice **w** is replaced by set of neural network weights whose elements are weight matrices and vector of biases of neural network layers. During process of training, values of weights W change to adjust function f_{MLP} to model function.

The figure 2. presents the architecture of MLP neural model of antenna brightness temperature versus atmosphere in microwave range while the atmosphere conditions are constant. The vector of l-th hidden layer outputs can be presented using vector $\mathbf{y}_l$ with dimension $N_l \times 1$ where N_l is number of neurons in l-th layer. i-th elements of vector $\mathbf{y}_l[i]$ is output of i-th neurons from s-th neural layer (s=l+1 considering input layer also) $v_i^{(s)}=v_i^{(l+1)}$, viz $\mathbf{y}_l = [v_1^{(l+1)}, v_2^{(l+1)}, \ldots, v_{N_l}^{(l+1)}]^{\mathrm{T}}$. Further

$$\mathbf{y}_l = F(\mathbf{w}_l \mathbf{y}_{l-1} + \mathbf{b}_l) \qquad (10)$$

where $\mathbf{y}_{l-1}$ is a $N_{l-1} \times 1$ vector of (l-1)-th hidden layer outputs, $\mathbf{w}_l$ is a $N_l \times N_{l-1}$ connection weight matrix among (l-1)-th and l-th hidden layer neurons, and $\mathbf{b}_l$ is a vector containing biases of l-th hidden layer neurons. In the above notation $\mathbf{y}_0$ represents outputs of the buffered input layer $\mathbf{y}_0 = \mathbf{x}$. The element $\mathbf{w}_l[i,j]$ from weight matrix $\mathbf{w}_l$ represents connection weight between i-th neuron of (l-1) hidden layer and j-th neuron of l hidden layer, viz between i-th neuron network layer s=l and j-th neuron in network layer s=l+1, while $b_i^{(l)}$=$\mathbf{b}[i]$ is bias value of i-th neuron in hidden layer l. F, the transfer function of hidden layer neurons, is hyperbolic tangent sigmoid

$$F(u) = \frac{e^u - e^{-u}}{e^u + e^{-u}} \qquad (11)$$

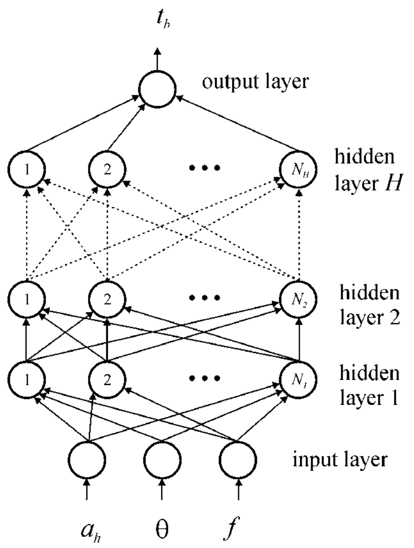

Figure 2. The architecture of MLP neural model of antenna brightness temperature t_b versus water vapor concentration a_h, antenna elevation angle θ and frequency f

All neurons from the last hidden layer H are connected with the neuron of the output layer. Since the transfer function of output layer is linear, the output of the network is:

$$t_b = \mathbf{w}_o \mathbf{y}_H \qquad (12)$$

where $\mathbf{w}_o$ is a $1 \times N_H$ connection weight matrix among the H-th hidden layer neurons and output layer neurons (Figure 3). Thus, set of network weights is presented as

$$W = \{\mathbf{w}_1, \ldots, \mathbf{w}_H, \mathbf{w}_o, \mathbf{b}_1, \ldots, \mathbf{b}_H\} \qquad (13)$$

The notation of MLP models MLPH-N_1-…-N_i-…-N_H where H represents hidden layers number and N_i is the numbers of neurons of i-th hidden layer.

IV. Modelling Results

MatLab 7.0 software development environment is used for realization and training MLP model. The training of neural model is done using 1110 samples that are visual read from the graphics in [2] (One graphic for water vapor concentration a_h = 10 g/m^3 is shown in Figure 1.). The samples are read in frequency range 2 GHz ≤ f ≤ 45 GHz for antenna elevation θ = 0°, 5°, 10°, 20°, 45° and 90°, and for water vapor concentration a_h, = 0, 3, 7.5, 13 and 17 g/m^3. Levenberg-Marquartd method is used for training neural model with accuracy 10^{-5}. To achieve the best trained MLP model, many different MLPH-N_1-…-N_i-…-N_H models are trained where H = 2 and 4 ≤ N_i ≤ 30.

Table I. The testing results for eight MLP models

MLP model	WCE [%]	ACE [%]	r^{PPM}
MLP2-9-8	5.51	1.05	0.9986
MLP2-9-5	6.80	1.04	0.9984
MLP2-10-9	6.85	1.06	0.9984
MLP2-8-8	7.05	1.01	0.9984
MLP2-10-4	7.15	1.11	0.9984
MLP2-10-9	7.21	1.05	0.9983
MLP2-9-9	7.46	1.06	0.9981
MLP2-9-5	5.93	1.20	0.9980

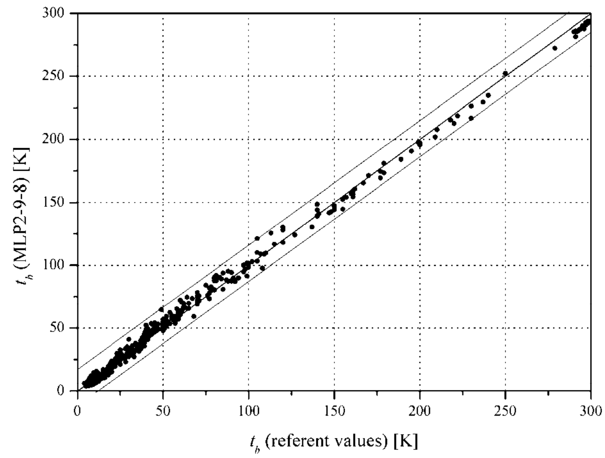

Figure 3. Scattering diagram for MLP2-9-8 model

The test of every trained MLP model is done with the set of 444 samples that are read in frequency 2 GHz ≤ f ≤ 45 GHz for antenna elevation θ = 30° and for water vapor concentration a_h, = 0, 3, 7.5, 13, and 17 g/m^3, as well as for antenna elevation θ = 0°, 5°, 10°, 20°, 30°, 45° and 90°, and for water vapor concentration a_h = 10 g/m^3. These test samples have not been used in training. The basic criterion for selection the best MLP network is the maximum value of Pearson Product-Moment correlation coefficient r^{PPM}. [2-5]. Test results of successfully trained MLP networks are presented in the Tables I together with the average test error (*ATE*) and the worst case error (*WCE*).

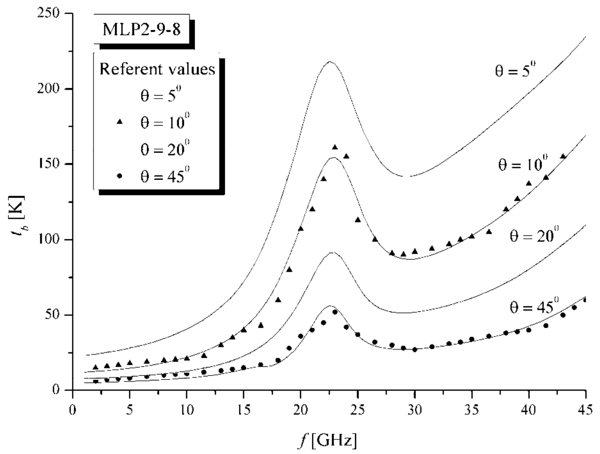

Figure 4. Antenna brightness temperature caused by atmospheric noise versus frequency obtainet by using MLP2-9-8 model for water vapor concentration a_h, = 10 g/m^3 and antenna elevation θ = 5°, 10°, 20° and 45° and comparison these values with referent values read from the graphics in [2]

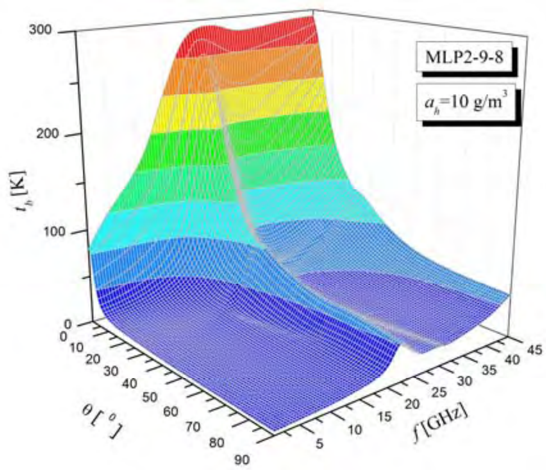

Figure 5. 3D presentation of antenna brightness temperature caused by atmosphere that radiates noise versus antenna elevation and frequency for water vapor concentration a_h, = 10 g/m^3 (results were obtained by using MLP2-9-8 model)

The model MLP2-9-8 is chosen as representative model of antenna brightness temperature caused by atmospheric noise. Figure 3. shows the scattering diagram that this model gives in testing process. It can be seen very satisfying agreement between neural model output and samples that are visual read from the graphics in Figure 1.

The model MLP2-9-8 is used for simulation of antenna brightness temperature caused by atmosphere that radiates noise versus antenna elevation and frequency. Figure 4. show simulation results for antenna elevation θ = 5°, 10°, 20° and 45° and comparison these values with referent values read from the graphics [1,2]. It can be seen very satisfying agreement between these results and referent values proving the choice of this model. Figure 5. presents 3D dependence of antenna brightness temperature versus atmosphere that radiates noise versus antenna elevation and frequency using 8099 points per surface. This dependence is got for less then 3 seconds using Pentium IV 1.4 GHz and 2GB RAM proving great simulation speed of chosen neural model.

V. CONCLUSION

During the process of designing the modern wireless communication systems, procedures for estimation of external noise have a very important role due to external noise can significantly influences to services quality of wireless systems. Classic way of visual reading from different printed graphics can be time consuming and with great error possibility because of visual reading and applying interpolation formulas. The good alternative can be neural networks models of complex graphs from various recommendations for antenna noise calculation. Neural model can avoid errors due to manual graphs reading enabling faster calculation of the level of external noise of receiver.

Neural model also enables the automation of the process of predicting noise power of receiver making one suitable method for the efficient analysis of the entire coverage area of wireless communication system transmitters in a big number of points that is of vital importance for the design and analysis of all components of modern wireless communication systems.

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