Modeling a Planar Circular Loop Antenna using Artificial Neural Networks

Ksenija Pešić[1], Zoran Stanković[2] and Nebojša Dončov[3]

Abstract - **In this paper we present a neural model for planar circular loop antenna based on multilayer perceptron (MLP) network. This model is realized by means of two coupled MLP networks which separately provide the resonant frequency and the minimum value of S_{11} parameter for specified antenna dimensions. The model is trained within the certain range of input parameters (radius of the antenna and the ratio of the radius and the width of loop antenna) that allows for design of planar circular loop antennas operating in the frequency band (500 - 2800) MHz.**

Keywords - **Circular Loop Antenna, Neural model, Neural network**

I. Introduction

Thanks to the development of microwave technology and the introduction of new technologies for conducting electromagnetic (EM) waves based on the use of printed planar structures, realized in microstrip and other similar techniques, printed antennas are being developed [1]. Simplicity production, small dimensions and weight, adaptability to the housings in which they are installed, low price, the ability to work in multiple frequency bands and large mechanical reliability are the features of printed antennas that justify their exceptional popularity and use [1,2]. All these advantages compensate for the disadvantages of printed antennas, such as low bandwidth and low gain, which are a consequence of the manufacturing technology.

Analytical techniques that solve the problems of propagation of EM waves, based on appropriate solutions of Maxwell's equations, are usually applicable for design of antennas with simple configuration. Since in general all antennas, including printed antennas, in real application can be very complex, the use of a numerical model of Maxwell's equations is the only alternative to analytical solutions. There is a large number of numerical techniques able to provide an efficient solution of EM problems, such as the finite element method (FEM) [3], the method of moments (MoM) [3,4], the split-step parabolic equation (SSPE) [4] method, the finite difference time-domain (FDTD) method [3,4] and the transmission line matrix (TLM) method [3,5]. However, these techniques are numerically demanding and careful programming is required in order to reduce time and memory consumption. During antenna design, it is usually necessary to consider a large number of geometrical parameters combinations in order to find a configuration that provides its optimal working performances in a frequency range of interest. Therefore, a process of designing antenna by using any of available numerical techniques can be even more time and memory demanding. Alternative to classical EM simulators may be a use of antenna models based on Artificial Neural Network (ANN) [6,7]. The process of developing a neural model can be also difficult and time consuming as for classical EM models, however when a neural model is successfully developed its speed exceeds the speeds of classical EM models [7-10]. Antenna modeling by using ANN has recently attracted more attention because of the convenience they offer [8-12]. The ANN approach proved to be good in [13,14] when it comes to modeling the resonant frequency and minimum values of S_{11} parameter of planar bowtie dipole and microwave slot antennas considered in [13] and [14], respectively.

In contrast to [13,14] where a model based on one multilayer perceptron (MLP) neural network with two outputs was used, in this paper we propose a neural model that consists of two MLP networks with one output. Each MLP network separately provides one antenna output parameter for input parameters of antenna. In this way, a dependence of each output parameter on input parameters is modeled independently allowing for better accuracy of neural model. The proposed model accuracy and efficiency is illustrated here on the example of design of planar circular loop antenna. Model is able to provide the resonant frequency and the minimum value of S_{11} parameter for specified circular loop antenna dimensions (radius of the antenna R and the ratio of the radius and the width of loop antenna k). Such designed antenna due to its radiation characteristics and the fact that it is soft, portable and very grateful for the extension of the frequency range because it can retain the low value of S_{11} parameter is a good candidate to be used in real-time locating system (RTLS). Nowadays, there is an increasing use of RTLS system that can accurately locate, track and manage assets, inventory or people and help companies make decisions based on the collected location data [15].

II. EM Model of the Planar Circular Loop Antenna

Fig. 1 shows the architecture of a planar circular loop antenna used for both the EM model and the neural model. The basic geometrical parameters are: $R -$ radius of the antenna and $d -$ the width of the loop antenna. Loop antennas are usually classified into two categories, electrically small (circumference is usually less than about one-tenth of a wavelength) and electrically large (circumference is about a free-space wavelength).

The input impedance of a small circular loop antenna made of a thin wire of radius a can be determined by an approximate formula [1]:

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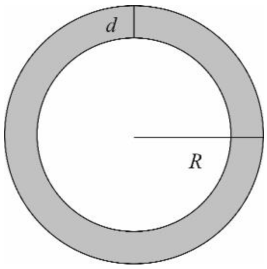

Fig. 1. Architecture of a planar circular loop antenna

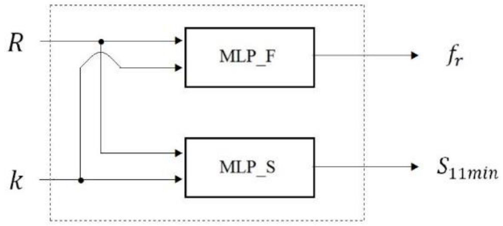

Fig. 2. The neural model of the planar circular loop antenna

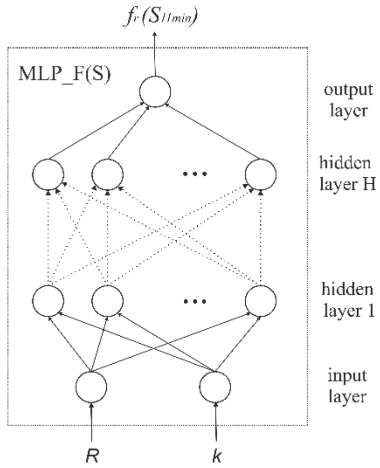

Fig. 3. Architecture of MLP_F(S) neural network

$$Z_{in} = \left(\frac{7.86 \cdot Rf}{10^8}\right)^4 + j \cdot 2\pi f \mu R \left(\ln\left(\frac{8R}{a}\right) - 1.75\right) \quad (1)$$

where f and μ represent the frequency of the signal and the magnetic permeability of the medium, respectively. When a circular loop antenna is made in a planar shape, its cross section should also be taken into account, so analyzes of frequency characteristics of antenna is much more complex and it cannot be performed with a direct usage Eq. (1). This equation will not give accurate results and instead EM simulator has to be used. Using the functions of the Toolbox Antenna in the MATLAB software environment [16], an EM model can be created in order to analyze the characteristics of this antenna. Antenna Toolbox uses the method of moments (MoM) to compute antenna properties such as input impedance, surface properties such as current and charge distribution, and field properties such as the near-field and far-field radiation pattern [16,17]. The basic function in Antenna Toolbox for creation of the circular antenna object is *loopCircular(Name,Value)*. This function creates a one wavelength circular loop antenna, with additional properties specified by one, or more name-value pair arguments [16]. Due to the small size of the antenna, the ratio of radius to width was used, and not the width of the antenna itself. This ratio is defined as $k = R / d$, where R is the radius of the loop and d is the width of the antenna. Accordingly, in the EM model, the variable parameters are the radius of the antenna and the previously defined ratio k. On the created loop antenna object we can use standard functions for network configuration in MoM method, antenna structure presentation, radiation pattern presentation, estimation of radiation in the plane of azimuth and elevation (*show*, *pattern*, *patternAzimuth*, *patternElevation*, *sparameters*) [16,17].

III. Neural Model of the Planar Circular Loop Antenna

The neural model of the planar circular loop antenna consists of two multilayer perceptron networks (MLP_F and MLP_S) and its architecture is shown in Fig.2. The main purpose of the model is to perform the mapping from a space of physical parameters of the antenna (radius of the antenna R and the ratio of the radius and the width of loop antenna k) to a space of antenna operating characteristics consisting of resonant frequency f_r

$$[f_r] = f_{MLP\_F}(R,k) \quad (2)$$

and minimum value of S_{11} parameter (value of S_{11} parameters at antenna resonant frequency - S_{11min})

$$[S_{11min}] = f_{MLP\_S}(R,k) \quad (3)$$

at the given feed line impedance (z_f =const). Neural networks MLP_S and MLP_F have the same architecture which is represented in Fig. 3.

In matrix representation, the neural model will have the vector of input variables $\mathbf{x} = [R \quad k]^T$. The vector of output variable in the MLP_F network will be $\mathbf{y} = [f_r]$, while in the MLP_S network the vector of the output variable is $\mathbf{y} = [S_{11min}]$. MLP neural network for both cases can be described by $\mathbf{y} = y(\mathbf{x}, W, B)$, where y is a network processing function, W is a set of connection weighting matrices $\mathbf{w}_i$, $W = \{\mathbf{w}_1, \mathbf{w}_2, \ldots \mathbf{w}_{H+1}\}$ and B is a set of bias vectors $\mathbf{b}_i$, $B = \{\mathbf{b}_1, \mathbf{b}_2, \ldots \mathbf{b}_{H+1}\}$ (H is the total number of hidden layers of the MLP network). Accordingly, part of the neural model for the MLP_F and MLP_S networks can be described as:

$$[f_r] = y([R \;\; k]^T, W, B) \quad (4)$$

$$[S_{11min}] = y([R \;\; k]^T, W, B) \quad (5)$$

respectively. Output of MLP l-th hidden layer, $\mathbf{y}_l$, is represented by the following function:

$$\mathbf{y}_l = F(\mathbf{w}_l\mathbf{y}_{l-1} + \mathbf{b}_l) \quad l = 1,2,\dots H \tag{6}$$

where $\mathbf{y}_{l-1}$ vector represents the output of (l-1)-th hidden layer, the output of the input layer is a vector $\mathbf{y}_0 = \mathbf{x}$, $\mathbf{w}_l$ is a connection weight matrix among (l-1)-th and l-th hidden layer neurons and $\mathbf{b}_l$ is the vector containing biases of l-th hidden layer neurons. Hyperbolic tangent sigmoid transfer function:

$$F(u) = \frac{e^u - e^{-u}}{e^u + e^{-u}} \tag{7}$$

is used as an activation function of neurons in hidden layers. Activation function of neuron in the output layer is linear so that the output of MLP network is:

$$\mathbf{y} = \mathbf{w}_{H+1}\mathbf{y}_H + \mathbf{b}_{H+1} \tag{8}$$

where $\mathbf{w}_{H+1}$ is the connection weighing matrix between neurons of H-th hidden layer and neurons of output layer and $\mathbf{b}_{H+1}$ is the vector containing biases of output layer.

The notation for such defined MLP neural model, that will be used further in the paper, is MLPH-N_1-…-N_i-…-N_H. N_i represents the number of neurons in the i-th hidden layer. Each network was trained three times with new initial connection weights and thresholds, whose values are random numbers in the interval [-1 1], in order to obtain the best trained model. For example, the notation MLP2-22-15 is used for the MLP model whose neural network has a total of 4 layers (input, output and two hidden layers), this model has 22 neurons in the first and 15 neurons in the second hidden layer.

Neural model was implemented in the MATLAB software environment [16]. For MPL training and testing we generated training and test sample sets by using the EM model of the circular loop antenna described in section II. This data sets have the following format $\{(\mathbf{x}^t, \mathbf{y}^t)\}$, or format $\{([R^t\ k^t], [f_r^t\ S_{11min}^t])\}$ where $\mathbf{x}^t$ is the vector of input combinations of the variables R^t and k^t, while $\mathbf{y}^t$ is vector that contains desired outputs of the neural network f_r^t and S_{11min}^t for given input. The notation t in the superscript means that the samples are belonging to training and testing set. The range of input parameters for which the network is trained is $R\ [m] \in [0.020 - 0.100]$ and $k \in [10 - 100]$. This range of input parameters provides achieving resonant frequency for which holds $f_r^t = [500 - 2800]\ [MHz]$, that means that the output band of the model belongs to UHF band as defined according International Telecommunication Union (ITU).

By using the EM model of the planar circular loop antenna and uniform distribution of samples, the following sets for training and testing were generated:

$$\left\{([R^t\ k^t]^T, [f_r^t,\ S_{11\min}^t]) \mid R^t \in [0.02 : d_1 : 0.100], k^t \in [10 : d_2 : 100]\right\} \tag{9}$$

where parameters d_1 and d_2 represent steps and their values d_1 = 0.005 m and d_2 = 2 were used to generate the training set, the values d_1 = 0.007 m and d_2 = 3 were used for the test set. As a result, the training and test sets with 782 and 372 samples, respectively, were obtained. Levenberg-Marquardt training method [7] was used during the model training. Since there are two MLP networks (MLP_F and MLP_S), the appropriate columns from the test and training files are used for each of the networks. In order to obtain the best possible model, the training of a number of MLP neural networks with two hidden layers and different number of neurons in them, was performed. In this process, training and test sets were preprocessed by normalizing the inputs and targets so that they were in the interval [-1,1]. During the training, the target value of the mean square error of the model outputs on the training set was 10^{-4}. During the testing of both networks, three test metrics were observed: values of the worst case error (WCE), values of average test error (ATE) and correlation coefficient [7] for both network outputs, $r^{PPM}(f_r)$ and $r^{PPM}(S_{11\min})$. The goal was to find a neural network with good generalization properties. The testing results for the six MLP_F neural networks with the best test statistics are shown in Table I.

TABLE I
TESTING RESULTS FOR SIX MLP_F NETWORKS WITH THE BEST TEST STATISTICS

MLP_F	WCE[%]	ATE[%]	$r^{PPM}(f_r)$
MLP2-20-15	0.4702	0.1043	0.99999003
MLP2-12-8	0.5881	0.1399	0.99998983
MLP2-17-9	1.1560	0.1775	0.99998961
MLP2-9-6	0.7387	0.1962	0.99998829
MLP2-9-5	0.6632	0.1334	0.99998768
MLP2-10-8	1.1873	0.2896	0.99998756

For the MLP_F part of the neural model, the neural network MLP2-20-15 was chosen, which has the highest value of the correlation coefficient and the lowest value of the worst case error (WCE). The scattering diagram of the MLP2-20-15 neural network on the test set for the output f_r is shown in Fig. 4. The output of the neural model f_r has a very little scatter in relation to the reference values.

The testing results for the six MLP_S neural networks with the best test statistics are shown in Table II.

TABLE II
TESTING RESULTS FOR SIX MLP_S NETWORKS WITH THE BEST TEST STATISTICS

MLP_S	WCE[%]	ATE[%]	$r^{PPM}(S_{11\min})$
MLP2-5-5	26.6089	2.8374	0.9759
MLP2-6-6	28.1494	2.8188	0.9754
MLP2-9-6	25.4494	2.8850	0.9734
MLP2-8-8	26.3811	2.9488	0.9731
MLP2-10-10	24.0547	2.9181	0.9730
MLP2-10-4	30.1837	2.8648	0.9715

For the MLP_S part of the neural model, the neural network MLP2-5-5 was chosen, which has the highest value of the correlation coefficient. The scattering diagram of the MLP2-5-5 neural network on the test set for the output S_{11min} is shown in Fig. 5.

In Fig.5 it can be seen that for $S_{11min} \geq$ -20 dB the scattering for this output of the model is small to moderate. For $S_{11min} <$ -20 dB the scattering is more pronounced which is expected due to the presence of sharp deep peak change in S_{11} values around the resonant frequency.

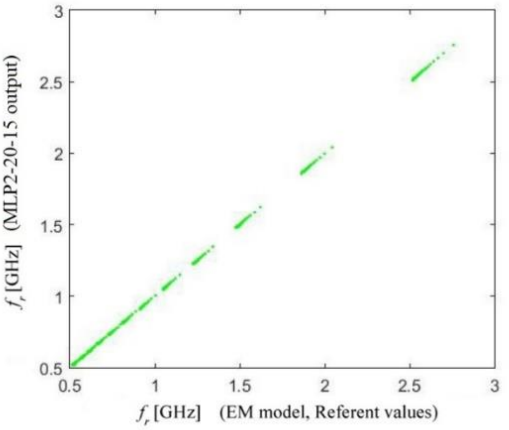

Fig. 4. Scattering diagram of MLP2-20-15 neural model on the test set for f_r output

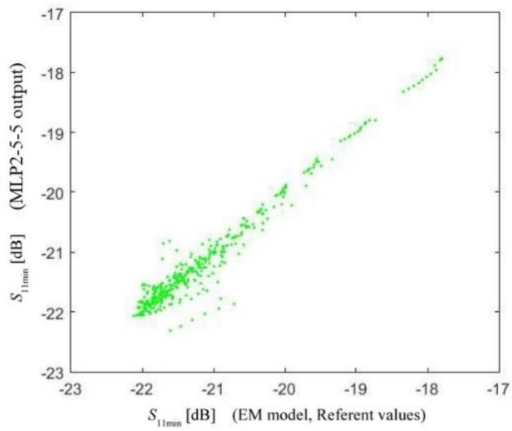

Fig. 5. Scattering diagrams of MLP2-5-5 neural model on the test set for S_{11min} output

However, in that case antenna is already well matched so the reduced model accuracy will not significantly limit its use for an analysis of antenna frequency characteristics such as determining the boundaries and bandwidth of antenna operating frequency range.

Time required to the proposed neural model to simulate 372 points of the test set was 0.04 seconds, while for the same number of points the EM model performed the simulation in 3.23 seconds. Both simulations were performed on a platform whose processor is Intel Core i7 and RAM 12 GB.

IV. Conclusion

Using neural models of planar circular loop antenna, results can be obtained faster and in a simpler way by avoiding complex calculations of Maxwell's equations that take a very long time. The proposed neural model has shown satisfactory accuracy which is very close to the accuracy of EM simulator. Further development will be focused on the optimization of this model, in order to provide the possibility of quickly finding the input parameters for the desired output quantities.

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References

[1] Balanis, C. A., *Antenna Theory: Analysis and Design*, Wiley, New York, 2005.
[2] R. Waterhouse, *Printed Antennas for Wireless Communications*, John Wiley & Sons, Ltd, 2007.
[3] Matthew N. O. Sadiku, *Numerical techniques in electromagnetics*, 2nd edition, CRC Press LLC, 2001.
[4] Levent Sevgi, *Electromagnetic Modeling and Simulation*, First Edition. The Institute of Electrical and Electronics Engineers, Inc. Published by John Wiley & Sons, Inc., 2014
[5] J. Joković, T. Dimitrijević, N. Dončov, "Efficient Modeling of a Circular Patch-Ring Antenna Using the Cylindrical TLM Approach", *IEEE Antennas and Wireless Propagation Letters*, Vol. 16, No. 4, pp. 2070-2073, 2017.
[6] S. Haykin, *Neural Networks*, New York, IEEE, 1994.
[7] Q. J. Zhang, K. C. Gupta, *Neural networks for RF and microwave design*, Boston, MA: Artech House, 2000.
[8] M. Milijić, Z. Stanković and B. Milovanović, "Efficient model of slotted patch antenna based on neural networks,"*2009 9th International Conference on Telecommunication in Modern Satellite, Cable, and Broadcasting Services*, Nis, 2009, pp. 384-387.
[9] M. Pandit, T. Bose, "Application of Neural Network Model for designing Circular Monopole Antenna", *International Symposium on Devices MEMS, Intelligent Systems & Communication (ISDMISC) - Proceedings published by International Journal of Computer Applications (IJCA)*, April 2011, Gangtok, Sikkim, India, pp. 18 -21.
[10] M. Chetioui, A. Boudkhil, N. Benabdallah and N. Benahmed, "Design and optimization of SIW patch antenna for Ku band applications using ANN algorithms,"*2018 4th International Conference on Optimization and Applications (ICOA)*, Mohammedia, 2018, pp. 1-4. DOI: 10.1109/ICOA.2018.8370530.
[11] U. Ozkayaa, L. Seyfia, "Dimension Optimization of Microstrip Patch Antenna in X/Ku Band via Artificial Neural Network", *Procedia - Social and Behavioral Sciences* 195 (2015), pp. 2520 – 2526.
[12] R. Ghayoula, A. Gharsallah, N. Fadlallah and M. Rammal, "Artificial Neural Networks ANN Approach for the Synthesis of Patch Antennas,"*2007 IEEE Radar Conference*, Boston, MA, 2007, pp. 285-290. DOI: 10.1109/RADAR.2007.374229
[13] M. Sarevska, Z. Stankovic, N. Doncov, I. Milovanovic and B. Milovanovic, "Design of well-matched UHF Planar Bowtie Dipole Antenna using Neural Model," 2019 14th International Conference on Advanced Technologies, Systems and Services in Telecommunications (TELSIKS), Nis, Serbia, 2019, pp. 331-334, doi: 10.1109/TELSIKS46999.2019.9002319.
[14] Z. Stankovic, N. Doncov, B.Stosic, M. Sarevska and I. Milovanovic, "Design of well-matched Microwave Slot Antenna on a Flat Metal Grounded Plate using Neural Model", 2020 Information, Communication and Energy Systems and Technologies (ICEST)
[15] https://www.atlasrfidstore.com/what-is-rtls-an-introduction-to-real-time-location-systems/
[16] https://www.mathworks.com
[17] http://ece.wpi.edu/mom/