Efficient Neural Models for Electromagnetic Field Characterisation – Application in RF Communications

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Abstract – **New approaches of modelling in RF Communications using neural networks are presented in this paper. New neural models are exposed in way that integrate current empirical or semi-empirical knowledge from the problem domain, which highly increases the efficiency of modelling. The capabilities of presented neural models are demonstrated through results of modeling in the area of RF communications and mobile communications, which have been realised in the Laboratory for Microwave Technique and Satellite Communications at the Faculty of Electronic Engineering in Niš.**

Keywords – **RF Communications, neural networks, modelling, neural model.**

I. Introduction

Today the expansion of RF Communications, utilization of more complex RF equipment and systems, and setting up more and more severe requests concerning performance and quality of their services certainly leads in appearing of a faster, more reliable and accurate tools for designing adequate reliable models. Methods for designing that are based on detailed physical-electromagnetic models are complex and very requesting concerning hardware platform and necessary computation time. Simpler models, whether they are empirical, semi-empirical or statistical, usually have limitations, like achieved accuracy. The reason for that is the approximation used as a tool for simplification.

As a good alternative to go beyond these problems can be RF modelling based on artificial neural networks (ANNs) [1]. Encouraging results that have been achieved in this area showed that neural models can be much faster than EM models and also more accurate than different empirical and approximate models. There are two main characteristics of ANN. The first is that it represents highly parallel distributed architecture which is built from highly connected small processing units – neurons. This enables the modelling of a highly dimensional and highly nonlinear problems using fast data transfer from input to output of the neural model. The second characteristic is that ANNs are not programmed to execute functional dependences designated in advance. These functional dependences are learned on the basis of group of solved examples.

When the learning process of ANN is finished, it gives good results not just for solved examples that have been presented to it during the process of learning, but also it is used for predicting solutions and examples that have not been presented during the training process. This is called a generalization characteristic.

This enables modelling of problems for which the EM nature is not known enough.

Great amount of encouraging results have been already achieved in the area of applying neural networks in the EM waves' propagation modelling and designation of service areas of broadcasting and mobile communication systems [2-8]. In the past few years neural networks are applied in the modelling of a passive [9-12] and active [13-16] RF/microwave components, as well as RF microwave circuit's modelling [17,18]. Certain success is achieved in the area of applying neural networks in antenna modelling [7,19,20] and in radar techniques concerning problem of detection and tracking of radar targets [21]. Results that are derived by scientists from Laboratory for Microwave Technique and Satellite Television at the Faculty of Electronic Engineering in the area of Broadcasting and mobile communications will be presented in this paper.

II. Main concept of neural networks and types of neural models

Owing to the capability of a functional dependence's modelling exclusively on the basis of input data, Multilayer Perceptron Network (MLP) is a type of neural network that can be successfully applied in the modelling of a large number of RF communication problems.

If we want to obtain MLP model with satisfactory accuracy we should provide large number of samples for training process. This may lead to large problems in using MLP neural models. The first one is that obtaining such a large number of samples can be difficult because usually they can be generated by time-consuming numerical methods or obtained by complex measurements. The second is that training of MLP neural network with such large number of samples can have implementation limitations, and can take long time without knowing the final results.

If there is a certain knowledge about the problem that is modelled, it can be build in neural model with aim to significantly decrease the number of training samples and also to provide a more efficient modelling process. This knowledge is presented by known empirical or semi-empirical functions that represent connections between input and output parameters. Those functions don't have to describe the influence of all input parameters and to cover whole range of input values. They have importance to help neural network to model all desirable functional dependences, even when there are limited and small number of training samples. Model that

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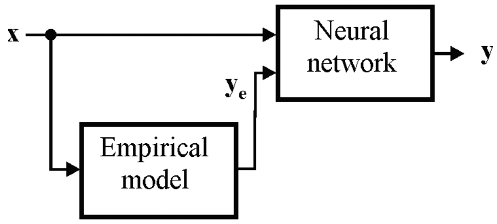

Fig. 1. Hybrid empirical-neural model based on input knowledge

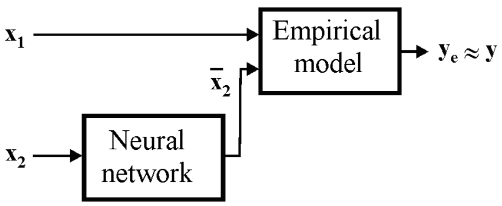

Fig. 2. Hibrid empirical-neural model based on mapping the input values

uses this knowledge can much faster and reliable solve the problem that is modelled.

We can apply two different approaches in realization of such model. The first one is using hybrid empirical-neural model (HEN). Basic idea in using HEN model is that with appropriate connection with neural model, empirical model can enlarge generalization and extrapolation capabilities of the neural network. Presenting additional information about functional dependences of problem does this.

Depending on which way empirical and neural model are connected in neural model we can differentiate two types of models that we used: HEN model based on input knowledge and HEN model based on mapping the input range.

HEN model which is based on input knowledge [18] (Fig. 1) is realized by taking the output from the empirical model as an additional input in neural network that models the problem. It can be presented as:

$$\mathbf{y} = \mathbf{y}(\mathbf{x},\mathbf{w},\mathbf{b},\mathbf{y_e}(\mathbf{x})) \tag{1}$$

Additional input in neural network is called the input of knowledge because empirical model use it to present empirical pre-knowledge about the problem that is modelled.

HEN model which is devised on mapping the input values (Fig.2) consists of neural network that have to map values of one part of input parameters $\mathbf{x_2}$ into new values $\bar{\mathbf{x}}_2$ that will enable the output of empirical model to be approximately equal to desired ones. This HEN model can be functionally described as:

$$\mathbf{y} \approx \mathbf{y_e} = \mathbf{y_e}(\mathbf{x_1}, \bar{\mathbf{x}}_2(\mathbf{w}, \mathbf{b}, \mathbf{x_2})) \tag{2}$$

III. Application of Neural Networks in Broadcasting

The development of models for electromagnetic field level prediction, which properly describe realistic propagation conditions, is very important for designing of modern broadcasting systems. Large number of global and local parameters such as relief, object along propagation path, climate zone, refraction coefficient in atmosphere, multipath propagation etc., have great influence on electromagnetic wave propagation. Existing statistical or deterministic models mostly take partially in consideration those influences. Among current statistical models for electromagnetic field level predicting in broadcasting, the most often applicable method is proposed by ITU-R, proposal 370-7[2,3]. This method is based on visual reading of electromagnetic field level directly from the curve, which gives dependence of field strength level from distance and effective height of antenna. This read values has to be then corrected in accordance with values read from the curve which gives correction according to undulation of terrain, and values read from the curve which gives correction according to clearance angle of terrain. The main disadvantage of this method is that visual reading is time-consuming and inaccurate. It can be eliminated by automatisation by neural models developed in [2-4].

Empirical or semi-empirical propagation models for urban area, which are mostly used today, are based on too rough approximations without including in an appropriate manner the properties of the environment through which the signal is propagating. Frequently used COST 231 Walfisch-Ikegami model assumes that all streets in propagation area are parallel with the same width; all buildings are of the same height and equally spaced. In paper [5], the architecture of HEN model that maps the input values is presented. It takes into consideration parameters that characterize specificity of the propagation area through which the signal propagates. Urban environment is divided into areas in which a particular type of objects is dominating (low buildings-houses, high buildings, green areas), characteristic parameters for every type of area are defined, and then every type is modelled by specific HEN model. In [5] is developed approximate model, which is based on measurements obtained in Niš (80-120 measurements for specific area) and which is used as empirical model in HEN model. According to this model the path loss of propagation area is:

$$A = \sqrt{\rho_k}\,\Delta r\,\overline{X} + 5n\log\Delta r \tag{3}$$

where A is the path loss value along the section with the length Δr from the beginning of the area with the mean building density ρ_k,, average partial loss of single building $\overline{X}$ and exponential loss index n. Parameters $\overline{X}$ and n can be obtained according to measured values. The approximate model presumes that the signal loss induced by a single building is the same along the whole section in the propagation area. However, during the propagation, electromagnetic wave encounters objects with different

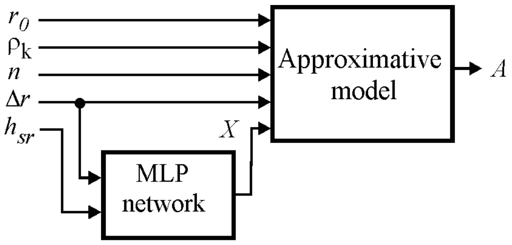

Fig. 3. Hybrid empirical neural model of propagation area

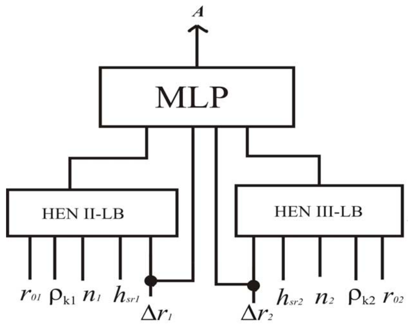

Fig. 4. Two HEN models integrated in complex HEN model

TABLE 1
PARAMETERS OF LOW AND HIGH BUILDINGS AREA

Oblast	Low buildings				High buildings			
	L-I	L-II	L-III	L-IV	H-I	H-II	H-III	H-IV
ρ_k [10^{-3} m^{-2}]	1.88	2.12	2.66	3.23	0.32	0.38	0.58	0.73
h_{sr} [m]	13	7	10	9	24	22	30	20
d [m]	420	280	420	420	250	200	250	160
r_0 [m]	2350	2312	2664	2236	1224	1792	1064	3056

geometries and compositions, so the average partial loss of a single building $\overline{X}$ changes with the distance Δr.

Neural network in HEN model (Fig. 5) is used to correct this weakness of approximate model by modelling the partial loss of a single building, which changes according to function:

$$X = f(\overline{X}, \Delta r) \tag{4}$$

New value of partial loss X which is brought to approximative model can correct its accuratness by providing more accurate value for propagation loss.

Parameters of urban propagation area of Niš with low and high buildings, that HEN models are developed for, are showed on Table 1. Comparison of results obtained from approximative and HEN model with measured values for one area with low buildings (L-II) is presented on figure 5. Results obtained in area where measurements for checking accurateness and not realization are applied (L-III) are showed on figure 6. Good results in this area show that HEN model can be applied for electromagnetic field level predicting in the area where no measurements are taken out which can be the main advantage of this model. Propagation loss on path which

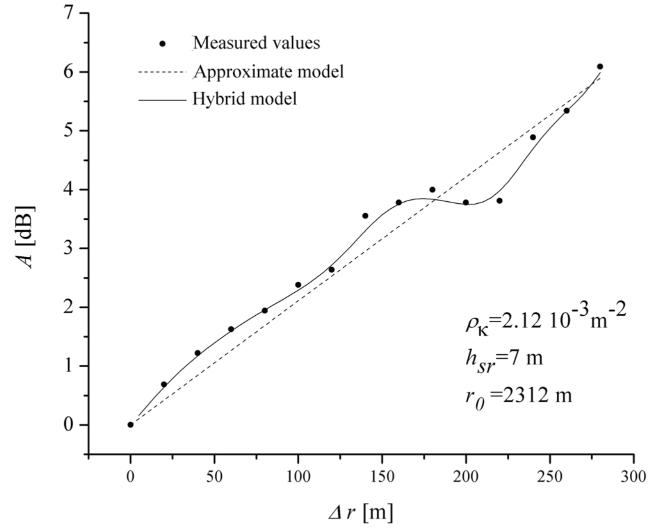

Fig. 5. Comparison of results obtained by approximative and HEN model with measured values for L-II area

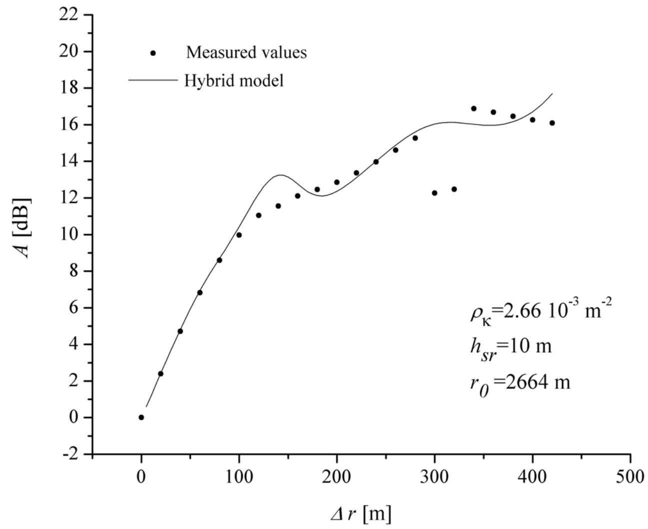

Fig. 6. Comparison of results obtained by HEN model with measured values for area L-III

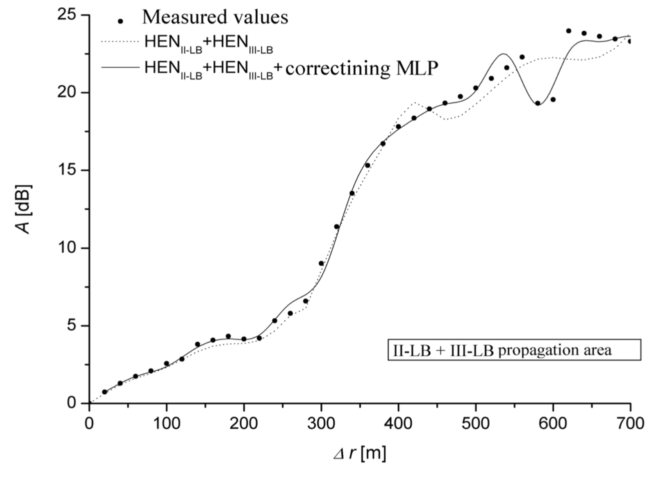

Fig. 7. Propagation loss of area that passes through propagation areas II-LB i III-LB obtained by HEN models and complex HEN model

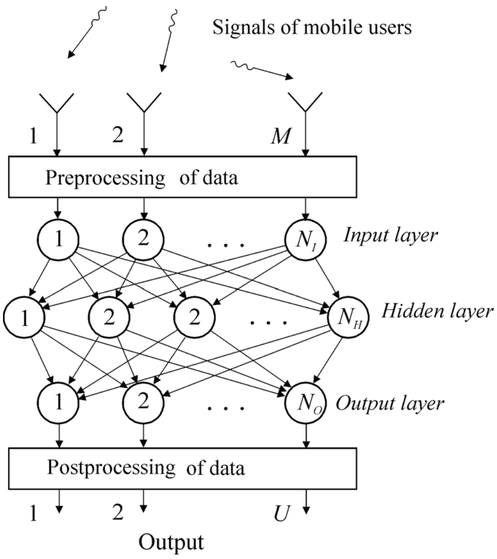

Fig. 8. RBF neural network for DOA estimation

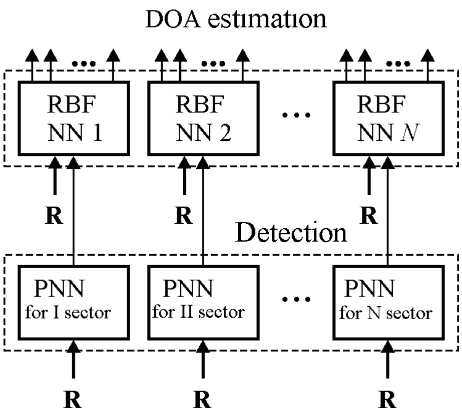

Fig. 9. HNM for detection and DOA estimation of EM waves

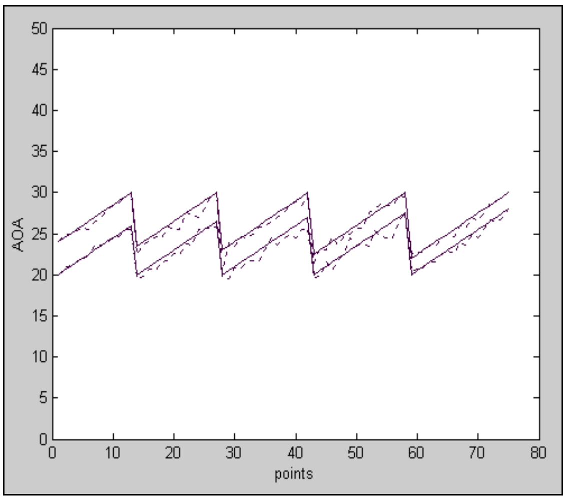

Fig. 10. Results of simulation by HN model for two users at distance 4°, 3.5°, 3°, 2.5°, and 2°

passes through two or more area of different type can be obtained by addition propagation losses of each area. Better results (Fig. 7.) are obtained when each HEN model is linked with correctioning MLP network (Fig. 4) for whole propagation area. Obtained model is called complex HEN model.

IV. APPLICATION OF NEURAL NETWORKS IN MOBILE COMMUNICATIONS

Enlarging covering area, number of subscribers and the quality of subscriber services is not possible without effective interference problem solving. One way to solve this problem is to apply the DOA (*Direction Of Arrival*) estimation algorithm in order to determine the direction of electromagnetic radiation. DOA estimation algorithm in first step is used for determination of the locations of mobile subscribers between which interference arises, and then in second step, using adaptive antenna array the radiation is routed to desired subscribers. The most often used algorithm for DOA estimation is MUSIC algorithm (*Multiple Signal Classification*). It is hard to be implemented in real time because of its time consuming computation. The good alternative for DOA estimation can be neural networks. The optimal solution for this problem is RBF (*Radial Basis Function*) neural network since it possesses the universal and also the best approximation property of neural networks. The conventional back-propagation neural networks are hard to be trained for this problem or easily can trap in a local minima while training. Architecture of RBF neural network for DOA estimation of U mobile subscribers in the radiation area of M-element linear antenna array is showed at figure 8 [6,7]. It models the mapping $F:C^M \to R^U$ of output values of antenna array $\{\mathbf{x}(t)=[x_1(t),...,x_M(t)]\}$ to values in DOA space $\{\boldsymbol{\theta}=[\theta_1,...,\theta_U]\}$, where C is the set of complex values, R is the set of real values, $x_i(t)$ is signal at the output of the i-th array element, and θ_m is the angle of arrival of the m-th subscriber. Signal $x_i(t)$ is determined as:

$$x_i(t) = \sum_{m=1}^{U} s_m(t) \cdot e^{-j(i-1)\cdot(\omega_0 d/c)\cdot \sin(\theta_m)} + n_i(t) \qquad (5)$$

where $s_m(t)$ is the signal of m-th subsriber, $n_i(t)$ is noise at i-th antenna element, and d is the mutual distance between elements of the antenna array. The output of antenna array $\mathbf{x}(t)$ is changable in time so during the preprocessing of data, spatial correlation matrix $R=E\{\mathbf{x}(t)\mathbf{x}^H(t)\}$is formatted and brought at the input of the network [6,7]. In order to decrease the number of training samples instead one RBF neural network, a hierarchical neural model (HN) [6] is used where the space of mobile subscribers is divided in sectors which are modelled by corresponding RBF neural network. The DOA problem is solved in to phases: signal detection and DOA estimation. Since the signal detection is a vector clasification problem, a good alternative is to use PNN (*Probabilistic* NN) in signal detection stage instead of RBF neural network[7]. Figure 9 is presenting HN model which in first level detects any possible active subscriber in i-th sector by PNN, and then in second level the DOA estimation is performed by RBF network of i-th sector which is activated by the output of the PNN network. In Figure 10 the results of simulation by HN model are presented (dashed line) with referent values (prompt line) for two mobile subscribers which changes their mutual distance from 4° to 2° (with step 0.5°) for linear antenna array with M=10 elements, mutual element distance of one half wavelengths, and SNR= 10 dB. It is obvious that the neural network antenna system successfully tracks both users.

V. CONCLUSION

New approaches of modelling in RF communications based on neural networks application can go beyond different kind of limitations in application of existing electromagnetic and empirical models. For that purpose neural models have ability to use existing empirical or half analytical knowledge from the problem domain, which can make neural modelling very efficient. Results that are presented in this paper support this fact.

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