ARTIFICIAL NEURAL NETWORKS IN MACROCELL FIELD STRENGTH PREDICTION

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ABSTRACT

This paper deals with the utilization of the radial-basis artificial neural networks for field strength prediction in macrocells. Model, which is currently in progress, is intended for irregular terrain and for the GSM frequency band. The article describes a structure of artificial neural networks, irregular terrain field strength prediction methods and a uniting those principles in the model.

1 INTRODUCTION

Present progress of mobile radio communications networks, like GSM system, requires systems for simulation of radiowave propagation. Modelling and simulations of radio wave propagation carry a lot of advantages. Making the design of radio-network faster is the great positive of this modelling. It can bring the saving money beside the saving time.

The main problem with the statistical (empirical) models is usually the accuracy, while the site-specific (deterministic approach) models lack computational efficiency. The use of artificial neural networks (ANNs) has shown very good performance in solving problems with signal strength prediction, because of their ability to process noised data from measurement [5] and good computational efficiency with satisfying accuracy [4].

2 OVERVIEW OF ARTIFICAL NEURAL NETWORKS

Artificial neural networks are the man made systems, which has similar structure like the human brain and which also work similar [1].

Artificial neural networks consist of a large number of neurones, which are divided in layers. Neurones are relatively simple function blocks. Their role is to form output signal from signals on their inputs. A basic neural model (see on fig. 1) can be characterized by the functional descriptions of the connection network and the network activation. Each neural cell (processing unit) has an input activation values $x_{i,j}$. Those values are propagated through a network of unidirectional connections to other cells in the network. The connection networks are mathematically represented by a basis function $u(w,x)$, where w stands for the weight matrix, and x for the input vector.

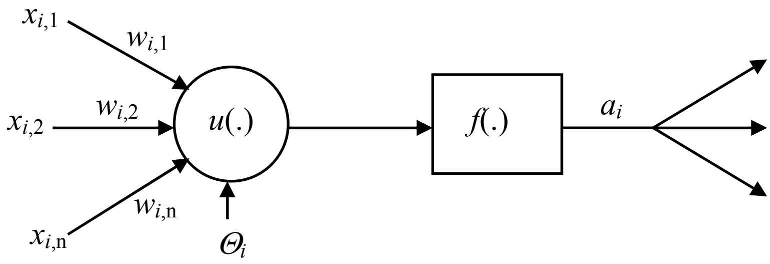

Fig. 1: *Basic neuron structure.*

The basis function has two common forms:

1. Linear-Basis function (LBF) is a hyperplane-type function. This is a first-order basis function. The net value is a linear combination of the inputs,

$$u_i(w,x) = \sum_{j=1}^{n} w_{ij} x_j \tag{1}$$

2. Radial-basis function (RBF) is a hypersphere-type function. This involves a second-order (nonlinear) basis function. The net value represents the distance to a reference pattern,

$$u_i(w,x) = \sqrt{\sum_{j=1}^{n} \left(x_j - w_{ij}\right)^2} \tag{2}$$

The net value as expressed by the basis function, (1, 2), will be transformed by an activation function of the neuron. For example, the most common activation functions are step, ramp, sigmoid (uni or bipolar), gaussian and linear function.

Neural network training process sets optimal values of synaptic weights. This process is time-consuming and needs set of correct data, often from the measurement.

3 METHODS OF IRREGULAR TERAIN SIGNAL PROPAGATION MODELLING

Effects of scattering and diffraction are important to include in a real terrain conditions. This become necessary when line-of-sight does not exist. There are several methods which are suitable to model signal propagation in irregular terrain. These empirical terrain-dependent factors are usually used:

- The effective height of antenna [2], [3]
- The terrain clearance angle CLA [2], [3], [4]
- Portion through the terrain (ppt) [4]
- Rolling factor Δh [2], [4]
- Land use factor [4]

See on fig. 2 for explanation of those factors. A distance from the antenna (for CLA factor) varies from 1 to 10 km in dependency on considered area [2], [4].

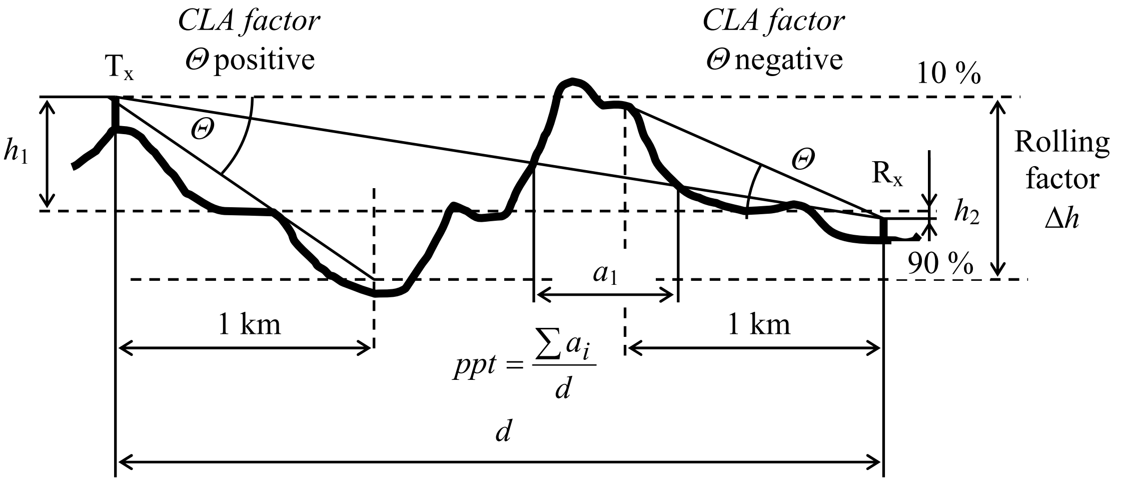

Fig. 2: *Factors for in regular terrain signal propagation modelling.*

4 MODEL DEVELOPMENT

Model is designed for the Digital map of terrain application. This map contains altitudes of the terrain. Altitudes are written for the points of 100 x 100 m net. This map does not contain any other data like land use. So, only dimensional oriented factors can be used. This fact allows utilization only in the areas with similar or uniform land use.

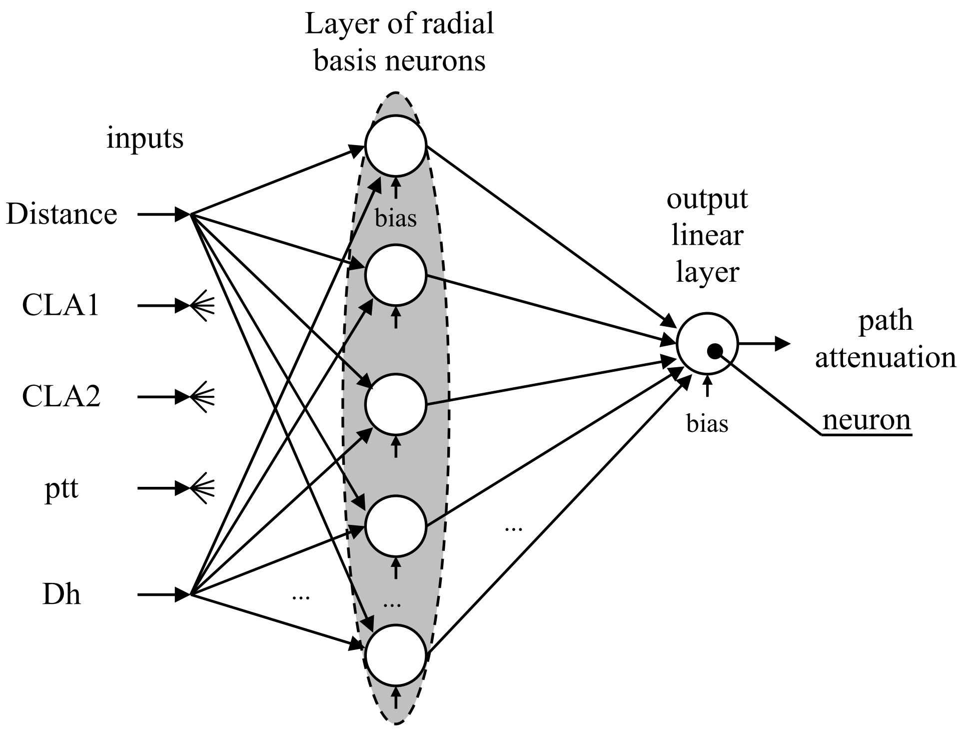

Fig. 3: *ANN for field strength prediction.*

The model has the radial basis ANN form with 5 inputs and one output (see on fig. 3). One of the inputs is the direct distance d from the transmitter to the receiver. Second group of inputs (four inputs) is based on the terrain profile analysis. These inputs are: ppt - portion through the terrain; modified CLA factors for both transmitter and receiver sites [4]; and Dh - rolling factor. All inputs are normalized (to range from 0 to 150) because of permanent saturation prevent [4]. Normalization also improves learning process control. The output of this model is only one. This is a power path lost. It should be noted that the proposed architecture of the ANN model fully supports the reciprocity principle.

To overcome problems with slow convergence and unpredictable solutions during learning, radial-basis function (RBF) neural network is used [5], [6].

It is necessary to have a training data from field strength measurement for completing the model. Model performance is tested with synthesised data, because measured data is not available jet. Some irregular terrain profiles are made (see on fig. 4). These profiles are analysed and results applicable as correct input-output data are obtained. Gaussian noise added to this correct data represents random measurement error (see on fig. 5). Ability of radial-basis ANN to overcome random data errors in training data is so tested.

5 RESULTS

Features of created radial-basis ANN that has only 75 neurones in RB layer were verified. Ability to overcome random data errors in training data was confirmed (see on fig. 5). Model was able to make true trends advantageous and to reduce errors at the same time. This feature depends on the number of neurones and on the spread of radial-basis function. Number of training data is obviously the most significant.

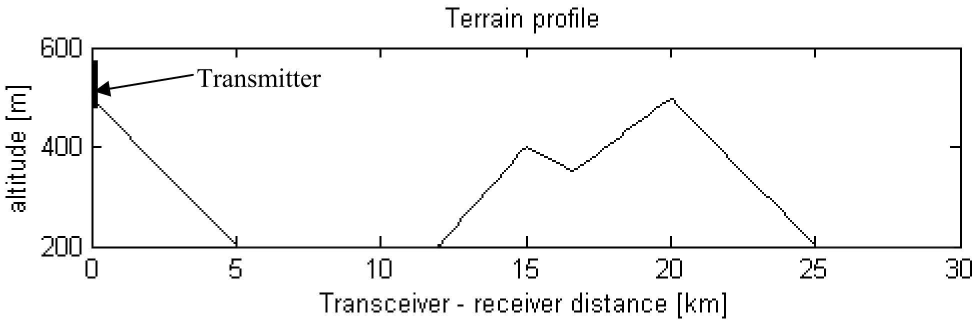

Fig. 4: *Terrain profile no. 1 used in simulation.*

6 CONCLUSION

Designed ANN based model is not finished in this time. With respect to existing utilization of those principles, it is possible to expect good results of this model [4], [6]. Excluded land use factor is probably the main disadvantage of this model. Thus the model should be used for homogenous environment. It is possible to think about including groundcover like forests lakes and urban area to the model by scanning of a map.

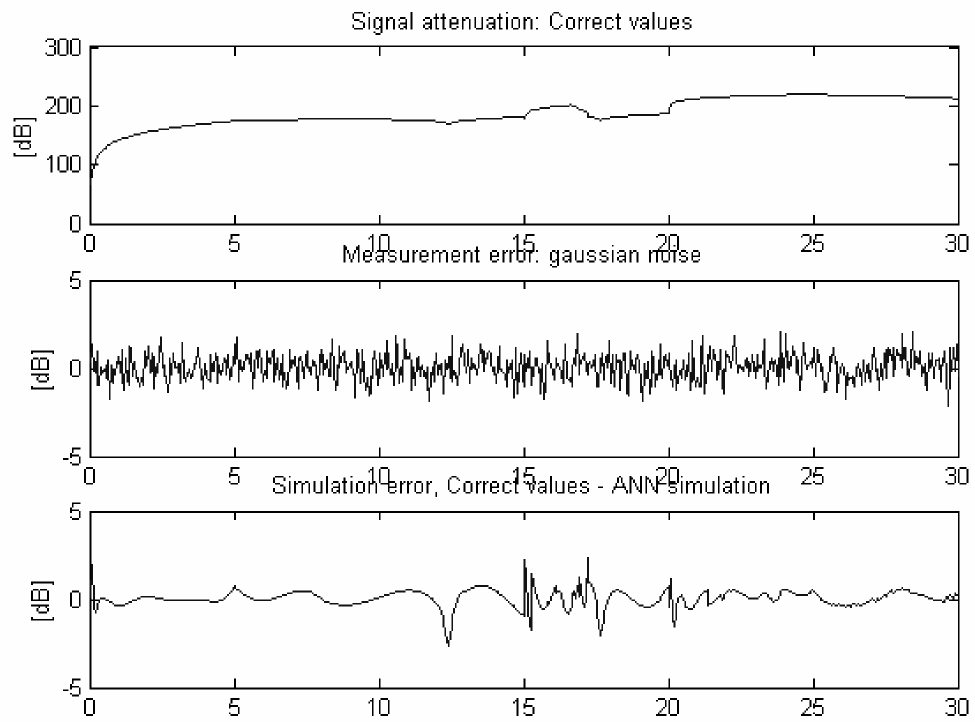

Fig. 5: *ANN model simulation results.*

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