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Feedforward neural network and adaptive network-based fuzzy inference system in study of power lines

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ABSTRACT

Over the past several decades, concerns have been raised over the possibility that the exposure to extremely low frequency electromagnetic fields from power lines may have harmful effects on human and living organisms. This paper presents novel approach based on the use of both feedforward neural network (FNN) and adaptive network-based fuzzy inference system (ANFIS) to estimate electric and magnetic fields around an overhead power transmission lines. An FNN and ANFIS used to simulate this problem were trained using the results derived from the previous research. It is shown that proposed approach ensures satisfactory accuracy and can be a very efficient tool and useful alternative for such investigations.

1. Introduction

According to the contemporary epidemiological researches, there are some indications that extremely low frequency electromagnetic fields harm human health which has been proved through numerous scientific studies published in recent years (Draper, Vincent, Kroll, & Swanson, 2005; Li et al., 2007). Several credible reports which serve as summaries of these studies have been published (Cotton, Ramsing, & Cai, 1994; WHO/IARC, 2002). Related to that, general public concern about possible detrimental health effects of this kind of fields near power lines has raised. In recent years many states have taken regulatory actions to limit the intensity of electric and magnetic fields on the edge of the transmission line right-of-way (ROW). Today, most countries use the ICNIRP (1998) guidelines and Council Recommendation (1999) as the scientific basis for their recommended levels of exposure. Belgium, Italy, Estonia and Switzerland have implemented stricter legislation making reference to the precautionary principle. As in Serbia there are no such guidelines and recommendations, an extreme attention should be paid to investigation of the electromagnetic fields surrounding power lines as well as of definition of ROW corridor.

Related to this, there is a necessity for calculation of electromagnetic (EM) field in the surround of an electric power transmission lines, and a number of methods are suggested (Abdel-Salam, Abdallah, El-Mohandes, & El-Kishky, 1999; Hameyer, Mertens, & Belmans, 1995). Radulović (2000) supposed an analytical approach for solving the problem of the current conductor above semi-conducting half-space. It is based on some transformations, which substitute Somerfeld's integral, the solution obtained by the integral transformation method, with Henkel's function and their asymptotic expansion. Henkel's functions represent linear solution combinations of the Bessel's functions of the first and of the second kind (Abramowitz & Stegun, 1972). Numerical procedure for calculation of electromagnetic field of the current conductor above semi-conducting half-space, using Charge Simulation Method, is proposed by Radulović (2000) and Veličković and Radulović (2002). Charge Simulation Method is based on the theorem of equivalence of different electromagnetic systems (Malik, 1989; Salon & Chari, 1999; Singer, Steinbigler, & Weiss, 1974). The considered model of the current conductor above semi-conducting half-space has been applied to real, significant high voltage transmission line problems (estimation of intensity of electric and magnetic fields around an overhead 400 kV and 750 kV power transmission lines), by Radulović (2000).

Artificial intelligence techniques, such as artificial neural networks and fuzzy logic, have been recognized as a powerful tool which is tolerant of imprecision and uncertainty, and can facilitate the effective development of models by combining information from different sources. These techniques have been used in a wide variety of applications in engineering, science, business, medicine, psychology, and other fields.

One of successful fuzzy and neural network applications is to model complex nonlinear systems. Hornik (1991) showed that multilayer feedforward networks with as few as a single hidden layer and arbitrary bounded and smooth activation functions are universal approximators. Kosko (1994) proved that a fuzzy system can uniformly approximate any real continuous function on a

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closed and bounded domain to any degree of accuracy. ANFIS is also universal approximator.

Artificial intelligence techniques have been successfully applied to a number of power systems problems during recent years (Warwick, Aggarwal, & Ekwue, 1997). Fuzzy logic is used for magnetic field estimations at transformer substations (Kosalay, 2008). Damouis, Satsios, Labridis, and Dokopoulos (2001, 2002) used Takagi–Sugeno fuzzy system to determine the magnetic field induced by a faulted transmission line on a buried pipeline. The genetic algorithm has been developed for the adjustment of the fuzzy parameters. Artificial neural networks are addressed in order to give accurate solutions to high voltage transmission line problems by Ekonomou, Kontargyri, Kourtesi, Maris, and Stathopulos (2007).

This paper presents a novel approach based on the use of FNN and ANFIS to estimate electric and magnetic fields around an overhead power transmission lines. The backpropagation is the most popular algorithm to train FNN (Rumelhart, Hinton, & Williams, 1986). Jang (1993) presented architecture and learning procedure of the fuzzy interference system implemented in the framework of adaptive networks.

The paper is organized as follows. In Section 2, the basic structure of the FNN and ANFIS is presented. The results of the simulation are shown in Section 3. Two FNN and two ANFIS are trained. Finally, in Section 4 concluding remarks are presented.

2. Feedforward neural network (FNN) and adaptive neuro-fuzzy inference system (ANFIS)

In this work two layer neural network and ANFIS are used to estimate electric and magnetic fields around an overhead power transmission lines.

2.1. Feedforward neural network (FNN)

The two-layer neural network with m inputs and one output is shown in Fig. 1. It is composed of an input buffer, a nonlinear hidden layer, and a linear output layer. For adapting parameters is used the backpropagation algorithm. The backpropagation is the most popular algorithm to train FNN (Rumelhart et al., 1986).

The inputs $x = (x_1, x_2, \ldots, x_m)$ are multiplied by weights $\omega_{ij}^{(1)}$ and summed at each hidden node. Then the summed signal at a node activates a nonlinear function (sigmoid function). Thus, the output y at a linear output node can be calculated from its inputs as follows:

$$t = \sum_{i=1}^{n_H} \omega_{i1}^{(2)} \frac{1}{1 + e^{-\left(\sum_{j=1}^{m} x_j \omega_{ij}^{(1)} + b_i^{(1)}\right)}} + b_1^{(2)} \tag{1}$$

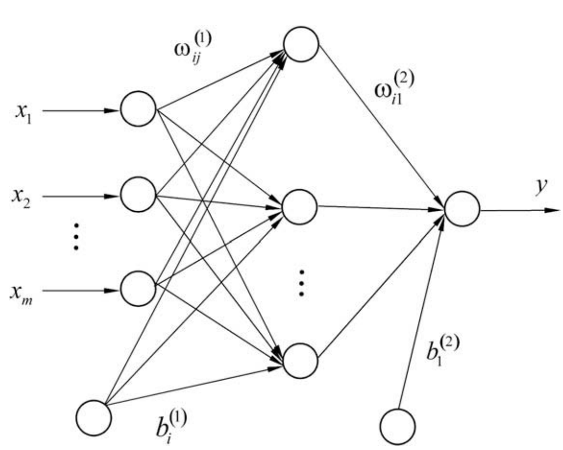

Fig. 1. Feedforward neural network with one hidden layer.

where m is the number of inputs, n_H is the number of hidden neurons, x_j is the jth element of input, $\omega_{ij}^{(1)}$ is the first layer weight between the ith hidden neuron and jth input, $\omega_{i1}^{(2)}$ is the second layer weight between the ith hidden neuron and output neuron, $b_i^{(1)}$ is a biased weight for the ith hidden neuron and $b_1^{(2)}$ is a biased weight for the output neuron.

The FNN and ANFIS are trained off-line using the training set $\boldsymbol{P} = \{\boldsymbol{p}_1, \boldsymbol{p}_2, \ldots, \boldsymbol{p}_r\}$. Each element of the set, $\boldsymbol{p}_k = (\boldsymbol{x}_k, t_{zk})$ is defined by the input vector $\boldsymbol{x}_k = (x_{1k}, x_{2k}, \ldots, x_{mk})$ and the desired response t_{zk}.

The weight updating law minimizes the function:

$$\varepsilon = \frac{1}{2}(t - t_z)^2 \tag{2}$$

The backpropagation update rule for the weights with a momentum term is:

$$\Delta\omega(t) = -\eta \frac{\partial \varepsilon}{\partial \omega} + \alpha \Delta\omega(t-1) \tag{3}$$

where η is the update rate and α is the momentum coefficient. Specifically,

$$\frac{\partial \varepsilon}{\partial \omega_{ij}^{(1)}} = (t - t_z)\omega_{i1}^{(2)} x_j \frac{e^{-\left(\sum_{j=1}^{m} x_j \omega_{ij}^{(1)} + b_i^{(1)}\right)}}{\left[1 + e^{-\left(\sum_{j=1}^{m} x_j \omega_{ij}^{(1)} + b_i^{(1)}\right)}\right]^2} \tag{4}$$

$$\frac{\partial \varepsilon}{\partial b_i^{(1)}} = (t - t_z)\omega_{i1}^{(2)} \frac{e^{-\left(\sum_{j=1}^{m} x_j \omega_{ij}^{(1)} + b_i^{(1)}\right)}}{\left[1 + e^{-\left(\sum_{j=1}^{m} x_j \omega_{ij}^{(1)} + b_i^{(1)}\right)}\right]^2} \tag{5}$$

$$\frac{\partial \varepsilon}{\partial \omega_{i1}^{(2)}} = (t - t_z) \frac{1}{1 + e^{-\left(\sum_{j=1}^{m} x_j \omega_{ij}^{(1)} + b_i^{(1)}\right)}} \tag{6}$$

$$\frac{\partial \varepsilon}{\partial b_1^{(2)}} = t - t_z \tag{7}$$

2.2. Adaptive neuro-fuzzy inference system (ANFIS)

The ANFIS architecture (Jang, 1993) (type-3 ANFIS) is shown in Fig. 2.

Suppose that Takagi–Sugeno fuzzy system has m inputs $(x_1, x_2, \ldots, x_m)$ and one output t. Linguistic labels x_i are $A_{1i}, A_{2i}, \ldots, A_{ni}$. The rule base contains $p = n^m$ if-then rules:

$$\begin{aligned}
R_1: &\ \text{if } x_1 \text{ is } A_{11} \text{ and } x_2 \text{ is } A_{12} \ldots \text{ and } x_m \text{ is } A_{1m} \text{ then} \\
&\ f_1 = p_{11}x_1 + p_{12}x_2 + \cdots + p_{1m}x_m + c_1 \\
R_2: &\ \text{ako } x_1 \text{ is } A_{11} \text{ and } x_2 \text{ is } A_{12} \ldots \text{ and } x_m \text{ is } A_{2m} \text{ then} \\
&\ f_2 = p_{21}x_1 + p_{22}x_2 + \cdots + p_{2m}x_m + c_2 \\
\ldots & \\
R_k: &\ \text{ako } x_1 \text{ is } A_{21} \text{ and } x_2 \text{ is } A_{22} \ldots \text{ and } x_m \text{ is } A_{2m} \text{ then} \\
&\ f_k = p_{k1}x_1 + p_{k2}x_2 + \cdots + p_{km}x_m + c_k \\
\ldots & \\
R_p: &\ \text{ako } x_1 \text{ is } A_{n1} \text{ and } x_2 \text{ is } A_{n2} \ldots \text{ and } x_m \text{ is } A_{nm} \text{ then} \\
&\ f_p = p_{p1}x_1 + p_{p2}x_2 + \cdots + p_{pm}x_m + c_p
\end{aligned}$$

The number of linguistic rules is $p = n^m$.

Layer 1. The outputs of layer are fuzzy membership grade of inputs $\mu_{A_{ij}}(x_j)$. If the bell shaped membership function is taken $\mu_{A_{ij}}(x_j)$ is given by:

$$\mu_{A_{ij}}(x_j) = \frac{1}{1 + \left[\left(\frac{x_j - a_{ij}}{c_{ij}}\right)^2\right]^{b_{ij}}}, \quad i = 1, n,\ j = 1, m \tag{8}$$