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AN ANFIS BASED APPROACH TO APPROXIMATION OF ELECTROMAGNETIC FIELD AROUND OVERHEAD POWER TRANSMISSION LINES

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Abstract. *This paper presents a novel approach based on the use of adaptive network-based fuzzy inference systems (ANFIS) to estimate electric and magnetic fields around an overhead power transmission line. There are many numerical methods for electric and magnetic field estimation in the surroundings of power transmission line, but it usually takes substantial execution time, especially when the high accuracy of obtained solutions is required. An ANFIS used for simulation of this problem was trained using the results derived from the previous research performed by the authors of this paper. It is proved that proposed approach ensure satisfactory accuracy and time efficiency, and can be a very useful alternative for such investigations.*

Key words: *electromagnetic fields, power line, ANFIS*

1. INTRODUCTION

Very often, especially in practice, there is a necessity for calculation of electromagnetic (EM) field in the surroundings of a power conductor [1,2], which represents thin, current conductor, located in the air, above the semi-conducting earth. An analytical approach for solving the problem of the current conductor above semi-conducting half-space is supposed in [3,4]. 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 [5]. New numerical procedure for calculation of electromagnetic field of the current conductor above semi-conducting half-space, using Charge Simulation Method, is proposed in [4, 6]. Electromagnetic field of the power line conductors under semi-conducting earth is calculated in [7].

Fuzzy logic systems are successfully applied for the electromagnetic field problem. In [8,9] Takagi-Sugeno fuzzy system is used to determine the magnetic field induced by a

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faulted transmission line on a buried pipeline. The genetic algorithm has been developed for the adjustment of the fuzzy parameters.

Artificial neural networks also are used for estimating electromagnetic field, [10,11].

This paper presents a novel approach based on the use of adaptive network-based fuzzy inference systems (ANFIS) to estimate electric and magnetic fields around an overhead power transmission line.

ANFIS has been successfully applied to a number of engineering problems during recent years. In [12] is presented architecture and learning procedure of this fuzzy interference system implemented in the framework of adaptive networks. One of ANFIS applications is modeling complex nonlinear functions by a set of fuzzy rules. Neural network and fuzzy logic system are universal approximators.

In the second section of the paper the basic structure of the ANFIS is presented. The results of the simulation are shown in the third section. Two ANFIS are trained using hybrid learning algorithm. The output of the first ANFIS is intensity of electric field E_e, while the output of the second neural network is intensity of magnetic field H_e. Results obtained in [4,7] are used for training of ANFIS. The fourth section contains the concluding remarks.

2. Adaptive Neuro-Fuzzy Inference System (ANFIS)

In this work ANFIS is used for estimating electric and magnetic fields around an overhead power transmission line.

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

R_1 : if x_1 is A_{11} and x_2 is A_{12} ... and x_m is A_{1m} then

$$f_1 = p_{11}x_1 + p_{12}x_2 + ... + p_{1m}x_m + c_1$$

R_2 : if x_1 is A_{11} and x_2 is A_{12} ... and x_m is A_{2m} then

$$f_2 = p_{21}x_1 + p_{22}x_2 + ... + p_{2m}x_m + c_2$$

...

R_k : if x_1 is A_{21} and x_2 is A_{22} ... and x_m is A_{2m} then

$$f_k = p_{k1}x_1 + p_{k2}x_2 + ... + p_{km}x_m + c_k$$

...

R_p : if x_1 is A_{n1} and x_2 is A_{n2} ...and x_m is A_{nm} then

$$f_p = p_{p1}x_1 + p_{p2}x_2 + ... + p_{pm}x_m + c_p$$

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

The equivalent ANFIS architecture [12] (type-3 ANFIS) is shown in Fig. 1.

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:

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

where: a_{ij}, b_{ij}, c_{ij} are the parameters of the membership function or premise parameters.

The Gaussian membership function is given by:

$$\mu_{A_{ij}}(x_j) = e^{\left(-\frac{(c_{ij} - x_j)^2}{2\sigma_{ij}^2}\right)}, \; i = 1, n, \;\; j = 1, m \tag{2}$$

where: a_{ij}, σ_{ij} are the centre and width of the fuzzy set A_{ij}

Layer 2

Every node in this layer is a fixed node. The output of nodes can be presented as:

$$u_1 = \mu_{A_{11}}(x_1) * \mu_{A_{12}}(x_2) ... * \mu_{A_{1m}}(x_m)$$

$$u_2 = \mu_{A_{11}}(x_1) * \mu_{A_{12}}(x_2) ... * \mu_{A_{2m}}(x_m)$$

$$...$$

$$u_k = \mu_{A_{21}}(x_1) * \mu_{A_{22}}(x_2) ... * \mu_{A_{2m}}(x_m)$$

$$...$$

$$u_p = \mu_{A_{n1}}(x_1) * \mu_{A_{n2}}(x_2) ... * \mu_{A_{nm}}(x_m)$$

* denotes *T*-norm. Nodes is marked by a circle and labeled $\prod$.

Layer 3

The output of each fixed node labele with N can be presented as:

$$\overline{u}_i = \frac{u_i}{\sum_{i=1}^{p} u_i} \tag{3}$$

Layer 4

Every node in this layer is a square. The outputs of this layer are given by:

$$\overline{u}_i f_i = \overline{u}_i \left(\sum_{j=1}^{m} p_{ij} x_j + c_i\right) \tag{4}$$

Layer 5

Finally, the output of the ANFIS can be presented as:

$$t = \sum_{i=1}^{p} \bar{u}_i f_i = \frac{1}{\sum_{i=1}^{p} u_i} \sum_{i=1}^{p} u_i \left(\sum_{j=1}^{m} p_{ij} x_j + c_i\right) \tag{5}$$

In [12] the hybrid learning algorithm is used for updating the parameters. For adapting premise parameters a_{ij}, b_{ij}, c_{ij} gradient descent method is used. The least squares method is used for updating the consequent parameters.

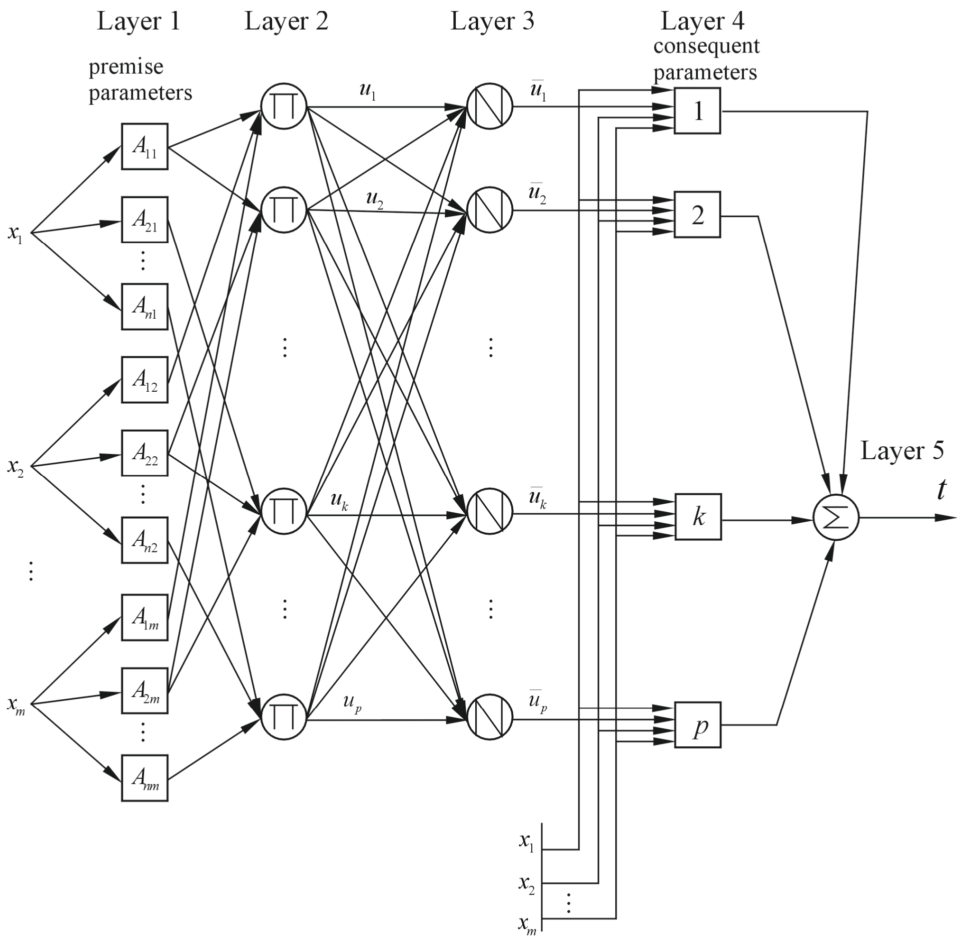

Fig. 1 *m*-input ANFIS with *p* rules

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

3. Simulation Results

ANFIS has been used to determine the electromagnetic field in transmission line system shown in Fig. 2. The values of voltage and currents flowing through the conductor are: $U_f = 400\ \text{kV}/\sqrt{3}$, $I_l = 50\text{A}$, $s = 2\pi/3$, radius of conductor is $a_n = 15\text{mm}$ and coordinate of protective ropes are: $x_7 = 26$ m, $y_7 = -7$ m, $x_8 = 26$ m, $y_8 = 7$ m.

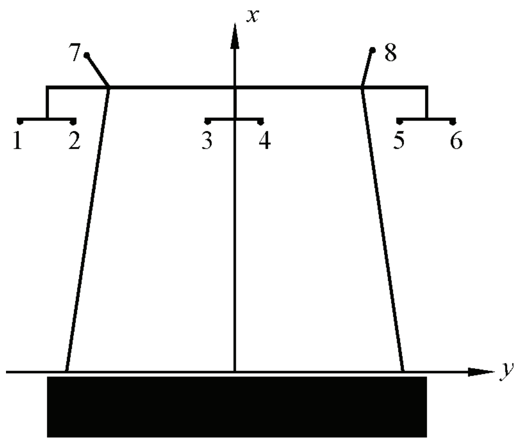

Fig. 2 Cross-section of the 400 kV power transmission line

The coordinate of the power line is shown in Table 1 .

Table 1 Coordinate of the power transmission line

	phase *I*		phase *II*		phase *III*	
n	1	2	3	4	5	6
x_n (m)	21.5	21.5	21.5	21.5	21.5	21.5
y_n (m)	-11.2	-10.8	-0.2	-0.2	10.8	11.2

The inputs of ANFIS are the coordinates ($x_1 = x$, $x_2 = y$) from the space. In this paper two input variables are chosen. It is possible to add more variables, such as, for example, earth resistivity, the position of the phase conductors, etc. We restricted the number of the input variables because we wanted to show, in a simple way, the effectiveness of the proposed approaches. Each of the two ANFIS has one output variable, E_e and H_e. ANFIS is trained using a hybrid learning algorithm [12]. The training data set is shown in Table 2.

Table 2 Training data set

y \ x	E_e 0	E_e 2	E_e 5	H_e 0	H_e 2	H_e 5
0	0.648	0.761	1.352	0.983	1.1	1.339
2	0.718	0.873	1.38	0.988	1.111	1.354
5	1.014	1.099	1.507	1.004	1.127	1.362
7	1.211	1.296	1.648	1	1.129	1.339
10	1.521	1.592	1.873	0.984	1.111	1.311
13	1.714	1.782	2.035	0.936	1.039	1.232
16	1.803	1.873	2.042	0.893	0.995	1.146
18	1.81	1.866	1.993	0.854	0.946	1.089
20	1.753	1.796	1.894	0.825	0.896	1.029
23	1.606	1.606	1.662	0.771	0.841	0.932
25	1.472	1.472	1.532	0.743	0.796	0.875
28	1.289	1.289	1.331	0.693	0.729	0.789
31	1.119	1.119	1.133	0.636	0.664	0.725
34	0.951	0.951	0.951	0.593	0.611	0.664
37	0.824	0.824	0.824	0.539	0.568	0.611
41	0.683	0.683	0.683	0.493	0.511	0.55
44	0.585	0.585	0.585	0.461	0.471	0.511
47	0.51	0.51	0.51	0.425	0.457	0.479
50	0.431	0.431	0.431	0.4	0.421	0.442

In Fig. 3 is shown membership functions of input variables, x and y, after parameter adjustment using hybrid optimization procedure during ANFIS training process. Gaussian function was used as a membership function in the ANFIS model.

The rule base of the ANFIS for E_e:

If x is small and y is small then $f_1 = 0.1051x + 0.1378y + 0.7088$

If x is small and y is big then $f_2 = -0.1564x + 0.04459y - 2.144$

If x is big and y is small then $f_3 = 0.2743x + 0.1074y + 0.06638$

If x is big and y is big then $f_4 = -0.3609x + 0.04062y - 0.09911$

The rule base of the ANFIS for H_e:

If x is small and y is small then $f_1 = 0.191x + 0.004974y + 1.089$

If x is small and y is big then $f_2 = 0.02403x - 0.0009426y + 0.4061$

If x is big and y is small then $f_3 = 0.2574x + 0.002872\,y + 0.135$

If x is big and y is big then $f_4 = 0.0242x + 0.004821y + 0.03016$

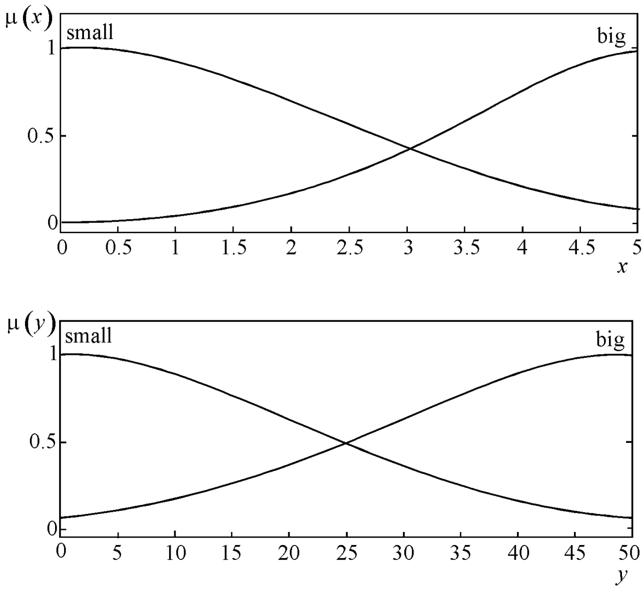

Fig. 3 Membership function of E_e after learning

Fig. 4 illustrates the memberships functions of input variables, *x* and *y* after training.

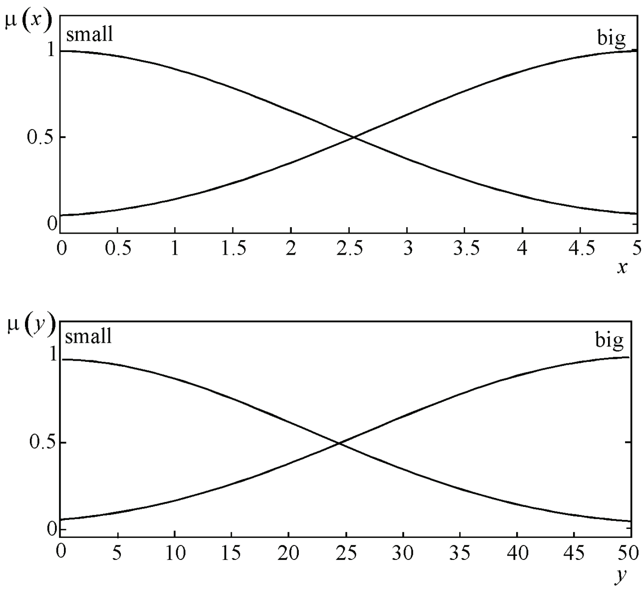

Fig. 4 Membership function of H_e after learning

Table 3 summarizes test results where E_e and H_e calculations by the ANFIS ($E_{e(ANFIS)}$, $H_{e(ANFIS)}$) and the method proposes in [4,7] have been compared.

The absolute errors have been computed as:

$$e_E = \left| \frac{E_e - E_{e(ANFIS)}}{E_e} 100 \right| \text{ and } e_H = \left| \frac{H_e - H_{e(ANFIS)}}{H_e} 100 \right|$$

Table 3 Intensity of electric and magnetic field for several new configuration cases of the examined electromagnetic field problem, obtained by the method proposes in [4,7] the ANFIS

x	y	E_e	H_e	$E_{e(ANFIS)}$	e_E (%)	$H_{e(ANFIS)}$)	e_H (%)
0.5	10.5	1.5428	1.0165	1.5548	0.7778	1.0151	0.1377
1.55	18.65	1.8015	0.9354	1.7839	0.9770	0.95	1.5608
2	5.07	1.1623	1.1267	1.2042	3.6049	1.1118	1.3224
3.025	22.05	1.6955	0.8499	1.7182	1.3388	0.8526	0.3177
3.55	15.86	1.9578	1.0014	1.9437	0.7202	0.9949	0.6491
4.065	32.65	1.0751	0.6389	1.0962	1.9626	0.6291	1.5339
4.87	29.5	1.2347	0.7598	1.2513	1.3445	0.7517	1.0661
5	48.07	0.4467	0.4671	0.4284	4.0967	0.4748	1.6485

Distribution of the electric and magnetic fields obtained by the ANFIS is shown in Fig. 5 and Fig. 6

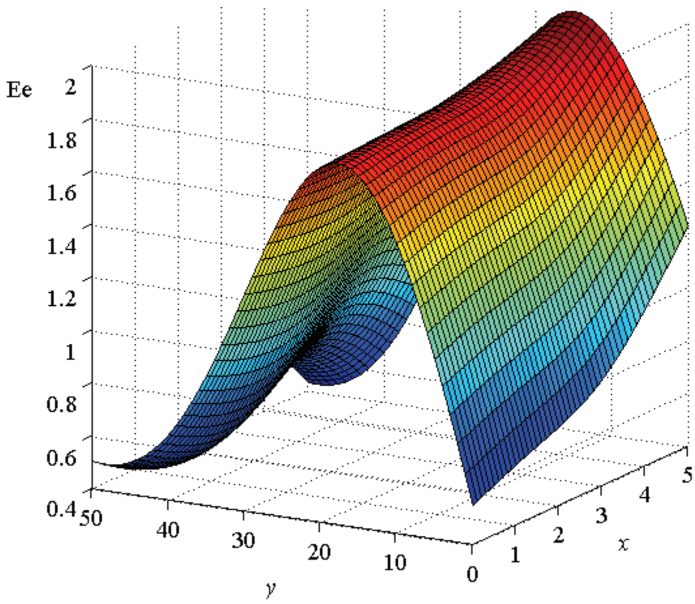

Fig. 5 Distribution of the electric field

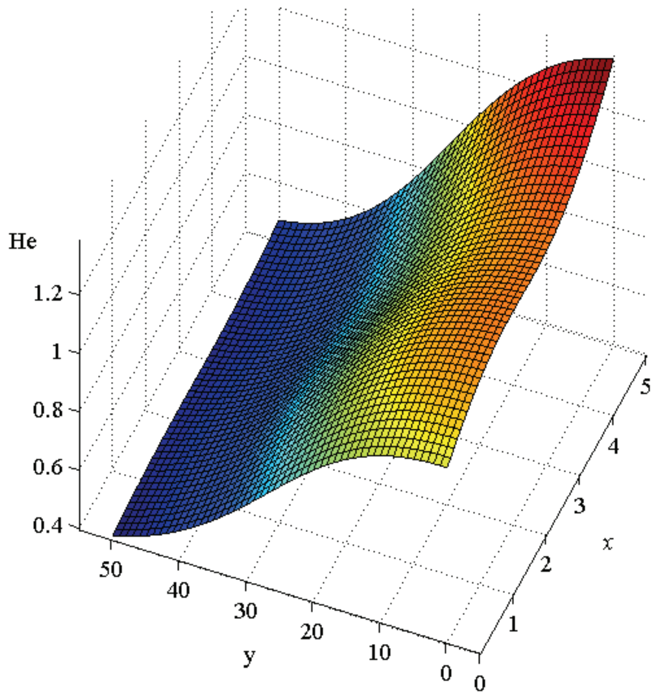

Fig. 6 Distribution of the magnetic field

4. Conclusions

In this paper, ANFIS is addressed in order to estimate the electric and magnetic field around an overhead power transmission line. Results of the simulations presented in this paper show that the application of the ANFIS to electromagnetic field approximation gives satisfactory results. ANFIS test are in a very good agreement with the results obtained in [4,7]. Maximal absolute error is less then 5%.

Each of the two ANFIS used here contains a total of 20 fitting parameters, of which 8 are the premise parameters and 12 are the consequent parameters. The optimal values of the premise parameters and consequent parameters are obtained by the hybrid learning algorithm.

Electromagnetic fields which originate from power transmission lines may be implicated in a number of adverse health effects. It is very important to know the intensity of the components of these electromagnetic fields. The method suggested, in this paper, gives the results of a satisfying convergence and accuracy obtained by short execution time.

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APROKSIMACIJA ELEKTROMAGNETNOG POLJA U OKOLINI DALEKOVODA POMOĆU ADAPTIVNOG NEURO-FAZI SISTEMA

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Ovaj rad predstavlja novi pristup baziran na korišćenju ANFIS-a za estimaciju električnog i magnetnog polja u okolini dalekovoda. Postoje brojne numeričke metode za estimaciju električnog i magnetnog polja u okolini dalekovoda ali obično je znatno vreme izračunavanja, posebno kada se zahteva velika tačnost. ANFIS koji je korišćen za simulaciju ovog problema je obučen korišćenjem rezultata dobijenih u prethodnim istraživanjima autora ovog rada. Pokazano je da predloženi metod obezbeđuje zadovoljavajuću tačnost i vreme izvršenja i da može biti vrlo koristan alternativni metod za rešavanje razmatranog problema.

Ključne reči: *Elektromagnetno polje, dalekovod, ANFIS*