Proceedings of the 2nd World Congress on Electrical Engineering and Computer Systems and Science (EECSS'16)
Budapest, Hungary – August 16 – 17, 2016
Paper No. EEE 142
DOI: 10.11159/eee16.142

Prediction of the Electric Field Emissions around the High-voltage Power Lines using Neural Network Algorithms

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Abstract - *In this study, Artificial Neural Network (ANN) Algorithms are used to estimate the electric field around the power transmission lines as an alternative approach. Firstly, electric field levels around the high voltage power transmission lines are measured, and then analytically calculated. Moreover, the field levels around these power lines have been predicted by using multilayer perceptron artificial neural network, radial basis function, and generalized regression neural network models. Electric field levels occurrence around the power transmission lines have been predicted with ANN models with high accuracy.*

Keywords**:** Electric Field Exposure, Power Transmission Lines, Charge Simulation Method, MLPNN, RBFNN, GRNN

1. Introduction

Growing interest in epidemiological studies aims at establishing possible links between an exposure of residential or occupational to power frequency fields and the onset of a number of diseases, including cancer and leukemia have been witnessed in the last few years [1-3]. Past epidemiologic studies have been criticized for some methodological shortcomings, especially regarding the way such exposure were evaluated [4-6].

Table 1: ICNIRP Exposure Limits for Electrical Workers (at 50 Hz) [7].

	General Public	Occupational
Electrical Field Strength (E)	5 kV/m	10 kV/m
Magnetic Flux Density (B)	200 µT	1000 µT

In the studies of the high voltage power line, researchers have focused more on the magnetic field exposure in the literature. However, outdoor exposure of the electric fields around the power transmission lines can have harmful effects on human health and should be taken into account for the human health. In particular, the electric field exposure for workers of power lines and public living in the vicinity of power lines is critical. Furthermore, these electric field intensity values will generate an important database for studies of the human health researchers.

This study will shed light on the comparison of traditional methods with the method of artificial neural networks to be able to estimate the electric fields on the power lines. For this goal, electric field variations around the typical power lines used in Turkey are investigated. A number of analytic and numerical methods for calculation of electric field around the electric power transmission and distribution lines are implemented. Artificial neural networks have been widely used in recent years at various research applications such as predictions, pattern recognitions, classifications, medical applications, automatic control and signal processing. Many interesting applications have been presented in power systems, such as load forecasting, fault classifications and locations in transmission lines, voltage stability analysis and power systems economics. The Multi-Layer Perceptron (MLP) which is trained by the back propagation algorithm is the most popular artificial neural networks in engineering problems.

2. Electric Field Calculation and Measurement

In this study, Charge Simulation Method (CSM) was implemented to obtain the electric fields around the high voltage transmission lines [8]. Residential electric fields radiated from typical high voltage power lines settled in Turkey were measured by using CA42 LF field meter, the Chauvin Arnoux. Electric field measurements were taken at 1m height from the ground level and physical characteristic of the 154 kV power lines is denoted in Fig. 1.

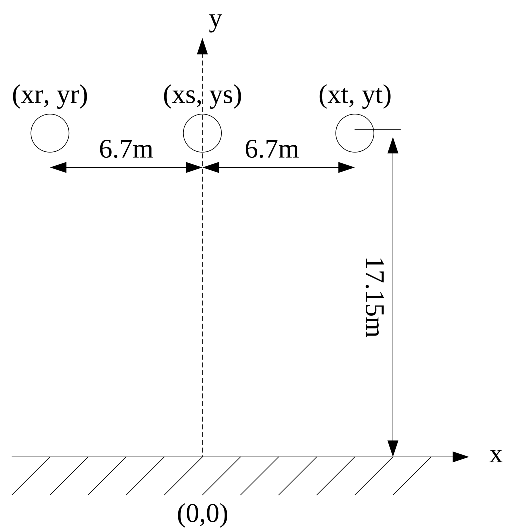

Fig. 1: Cross-section of 154 kV energy power transmission lines.

3. Artificial Neural Network Algorithms

The electric fields are determined by the prediction methods and measurements. For the long term prediction of this field, load characteristics of the lines are considered for a year period. In the literature, there are limited number of studies implemented with the electric fields for exposure analysis using Multilayer artificial neural network algorithms. These studies present an alternative approaches. Generally, researchers focused on the magnetic field exposure, but electric and magnetic field components can be induced to the human body with together. Electric field variations around the lines are determined by using Charge Simulation Method (CSM). A computer program is developed to simulate electric field variation around the power transmission lines.

MLPNN is used as one of the most common Neural Network Algorithms. MLPNN may include two or more layers. Input layer has neurons which are equal to the number of selected specific features and output layer determines the desired output classes which decide the number of the neurons in the output layer. The hidden layers which are between input and output layers may be used for optimizing of MLPNN especially for nonlinear systems. It is typical using just one hidden layer with a try and-error based number of neurons. The most common method to find the optimal number of neurons and hidden layers is by try-and-error method [9]. The RBFNN is an alternative method of MLPNN and requires less computation time than the MLPNN as a network training. RBFNN is comprised of one input layer, one kernel (hidden), and one output layer. The input variables are assigned to the nodes within the input layer and connected to the hidden layer without weights. The transfer functions in the hidden nodes are RBF that means symmetrical function centered upon a given mean value in a space. The parameters are optimized during the network training in RBFNN. When the training vectors are measured up to presumed level, linear combinations of RBFs can be found at the training vectors. The method of fitting RBF's to data is closely related to the distance weighted regression, for function approximation. There is also another important Neural Network Algorithm which is the GRNN algorithm. It comprises of four layers; input layer, pattern layer, summation layer and output layer [10].

4. Results & Discussion

In this study, three ANN method results are compared for calculating the electric field. These methods are Multilayer Perceptron Neural Networks (MLPNN), Radial Basis Function (RBF) and Generalized Radial Basis Neural Networks

(GRNN). The MLPNN trained by the back propagation algorithm is the most popular method in engineering problems [9, 11]. The training dataset is shown in Table 2.

Table 2: Training Dataset.

X(m)	**Y(m)**									
	0,2		**0,5**		**1**		**1,5**		**2**	
	Ecal	Emeas.	Ecal	Emeas.	Ecal	Emeas.	Ecal	Emeas.	Ecal	Emeas.
0	1,124	1,164	1,16	1,18	1,224	1,26	1,294	1,3	1,369	1,4
3	1,101	1,13	1,136	1,1	1,198	1,22	1,265	1,255	1,338	1,37
6	1,036	1,1	1,068	1,032	1,123	1,16	1,183	1,14	1,248	1,3
9	0,9396	0,95	0,9659	0,93	1,012	0,98	1,062	1,1	1,115	1,119
12	0,8261	0,798	0,8466	0,81	0,8826	0,905	0,9206	0,928	0,961	0,98
15	0,7106	0,735	0,7259	0,75	0,7524	0,742	0,7801	0,81	0,8092	0,842
18	0,6037	0,59	0,6148	0,59	0,6337	0,64	0,6533	0,67	0,6736	0,68
21	0,5106	0,53	0,5185	0,535	0,5318	0,521	0,5455	0,531	0,5595	0,56
24	0,4323	0,42	0,4379	0,45	0,4473	0,448	0,4569	0,44	0,4666	0,464
27	0,3675	0,358	0,3716	0,35	0,3783	0,365	0,3851	0,4	0,3919	0,4
30	0,3145	0,32	0,3174	0,3	0,3223	0,31	0,3272	0,332	0,332	0,321
33	0,271	0,28	0,2731	0,26	0,2767	0,276	0,2803	0,283	0,2838	0,29
36	0,2352	0,228	0,2368	0,24	0,2395	0,235	0,2421	0,246	0,2447	0,254
39	0,2056	0,199	0,2068	0,21	0,2088	0,21	0,2108	0,21	0,2128	0,22
42	0,1809	0,182	0,1819	0,187	0,1834	0,177	0,185	0,18	0,1865	0,19
45	0,1602	0,163	0,161	0,155	0,1622	0,165	0,1634	0,17	0,1646	0,162
48	0,1428	0,139	0,1434	0,139	0,1443	0,141	0,1453	0,14	0,1462	0,15
51	0,1279	0,124	0,1284	0,131	0,1292	0,13	0,1299	0,126	0,1307	0,132
54	0,1152	0,111	0,1156	0,112	0,112	0,117	0,1168	0,12	0,1174	0,115

In order to obtain the Neural Network performance, following steps have been implemented:

1. The normalization of input and output dataset are implemented with the maximum-minimum mapping in the range of -1 and 1. Input values are horizontal and vertical distance values. The output values are inserted as the measured electric field values. The ANN structure has two input and one output values.
2. The database is divided randomly into 60 % train, 15 % validation and 25 % test data.
3. The target values are determined according to the maximum minimum mapping.
4. The MLPNN structure comprises of an input layer including two neurons and three hidden layers. While, first and third layer have two neurons, the second layer has three neurons which have tangent sigmoid transfer function. The output layer has single neuron which has linear transfer function.
5. The structure is determined experimentally and this structure achieves the highest score.
6. The structure is trained using Levenberg-Marquardt algorithm that determines the optimum trainng results between other back propagation training algorithms used as an experimental comparison.
7. Test accuracy of training & testing simulations is determined according to Mean Squared Error (MSE) scores.
8. The success of this method is compared with the other methods with regard to mse scores.

In the RBF analysis, database is selected as 75% for training and 25% for test. It has an input layer with two neurons, one hidden layer including radial basis functions and one output layer having one neuron. Input data is directly connected to the hidden layer without having weighted in contrast to the MLPNN model [12-13]. The sensitivity of the hidden layer is adjusted by the selection of the spread factor, where a smaller spread factor states more precision. The spread factor is chosen as 0.6 by trial and error method. In the GRNN analysis, database is selected as 75% for train and 25% for test similarly with the RBF structure. It has an input layer with two neurons, one pattern layer including radial basis functions, a summation layer and one output layer having a single neuron. Spread factor which is the only adjustable parameter in GRNN structure is selected as 0.5 experimentally. The spread parameter is the distance of an input vector from the weight vector of a neuron.

Table 3: Mean Squared Error values for proposed methods.

Method	MSE (Mean Square Error)
MLPNN	2.2164E-04
RBF	0.0068
GRNN	5.5240E-04

The relative error is calculated mathematically,

$$e_{MLPNN} = \left| \frac{E_{meas} - E_{cal(MLPNN)}}{E_{meas}} \right| \times 100 \tag{1}$$

where, E_{meas} is measurement value of the electric field, $E_{cal(MLPNN)}$ is the value of MLPNN output.

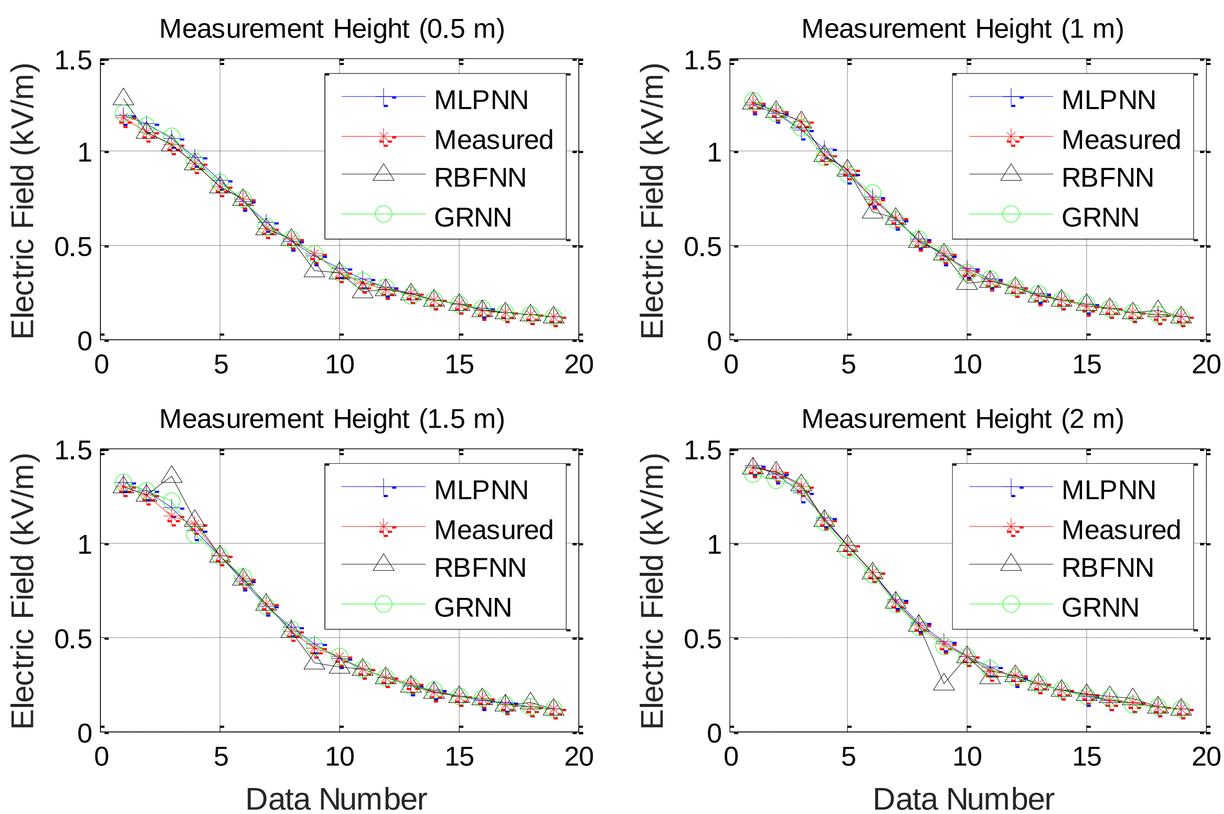

Fig. 2: Predicted Electric Field Intensity Values at Different Heights Obtained with 3 different artificial neural network algorithms (MLPNN, RBFNN & GRNN Methods) and Measured Values.

Table 4: Electric field values obtained at different coordinates by implementing theoretical calculation, MLPNN, RBF, GRNN methods, and measurements. Relative errors are figured out with respect to the measurement results.

Hor. Dist. (m)	**Ver. Dist. (m)**	**Electric Field Meas. (V/m)**	**Electric Field Theo. (V/m)**	**MLPNN Calc. (V/m)**	**RBF Calc. (V/m)**	**GRNN Calc. (V/m)**	e_{theo} (%)	e_{MLPNN} (%)	e_{RBF} (%)	e_{GRNN} (%)	e_{theo}-e_{MLPNN} (%)
24	0.2	0.420	0.4323	0.4339	0.2825	0.4480	2.93	3.32	32.73	6.67	0.38
30	0.2	0.320	0.3145	0.3163	0.2289	0.3111	1.72	1.17	28.47	2.77	0.56
42	0.2	0.182	0.1809	0.1805	0.1940	0.1869	0.60	0.84	6.58	2.70	0.23
51	0.2	0.124	0.1279	0.1285	0.1450	0.1310	3.15	3.63	16.95	5.65	0.47
0	0.5	1.180	1.16	1.1914	1.2836	1.2064	1.69	0.97	8.78	2.24	2.71
24	0.5	0.450	0.4379	0.4383	0.3588	0.4480	2.69	2.61	20.27	0.44	0.09
30	0.5	0.300	0.3174	0.3184	0.2511	0.3124	5.80	6.14	16.29	4.15	0.32
48	0.5	0.139	0.1434	0.1428	0.1384	0.1398	3.17	2.77	0.40	0.57	0.39
15	1	0.742	0.7524	0.7561	0.6749	0.7770	1.40	1.90	9.05	4.71	0.49
27	1	0.365	0.3783	0.3783	0.2993	0.3561	3.64	3.64	17.99	2.43	0.00
42	1	0.177	0.1834	0.1827	0.1811	0.1835	3.62	3.24	2.30	3.67	0.37
51	1	0.130	0.1292	0.1296	0.1517	0.1311	0.62	0.32	16.67	0.85	0.30
6	1.5	1.140	1.183	1.1812	1.3493	1.2173	3.77	3.62	18.36	6.78	0.15
9	1.5	1.100	1.062	1.0621	1.1121	1.0417	3.45	3.45	1.10	5.30	0.01
24	1.5	0.440	0.4569	0.4588	0.3588	0.4480	3.84	4.28	18.46	1.82	0.42
27	1.5	0.400	0.3851	0.3863	0.3391	0.3939	3.73	3.43	15.23	1.54	0.31
36	1.5	0.246	0.2421	0.2432	0.2385	0.2441	1.59	1.16	3.05	0.77	0.43
51	1.5	0.126	0.1299	0.1305	0.1522	0.1319	3.10	3.58	20.76	4.67	0.47
54	1.5	0.120	0.1168	0.1189	0.1126	0.1157	2.67	0.91	6.16	3.56	1.81
24	2	0.464	0.4666	0.4741	0.2485	0.4480	0.56	2.17	46.45	3.45	1.60
30	2	0.321	0.332	0.3358	0.2783	0.3296	3.43	4.61	13.29	2.67	1.14
42	2	0.190	0.1865	0.1871	0.1949	0.1800	1.84	1.53	2.59	5.25	0.32
45	2	0.162	0.1646	0.1647	0.1876	0.1694	1.60	1.68	15.81	4.56	0.07
48	2	0.150	0.1462	0.1465	0.1734	0.1401	2.53	2.36	15.59	6.59	0.18

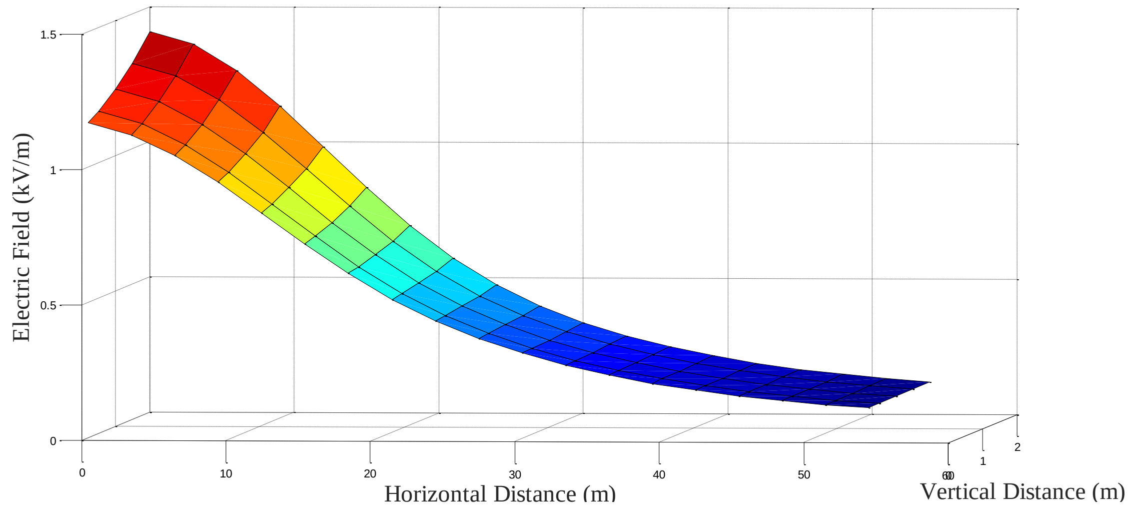

Fig. 3: Electric Field Intensity values with respect to different coordinates. Results are obtained by MLPNN algorithms for different heights.

According to the mean square error analysis, and relative errors with respect to the measured values, the best results are acquired by the MLPNN Algorithm. Numerical results are shown in Table 3 & Table 4. In Fig. 2., electric field intensity values at different heights are denoted. These results are obtained using 3 different neural network algorithm methods. To make a comparison and evaluating the accuracy precision, measured values are also denoted in these graphs. While other two methods allow to alter just one parameter, MLPNN method allows to change more parameters which are neuron numbers, layer numbers, activation function types etc.. Therefore, the most accurate result is obtained by the MLPNN algorithm.

Fig. 2. depicts the accuracy of the neural network algorithms, particularly the MLPNN algorithm. Electric Field Intensity values are shown with respect to horizontal and vertical locations (see Fig. 3). MLPNN results are depicted in Fig. 3. As it can be seen from the Fig. 3., results are obtained very precisely by using the MLPNN algorithm. Measured, theoretical and predicted neural network algorithm results are obtained in consistency. This shows the success of the neural network algorithms. Finally, results show that the most successful neural network algorithm for predicting the electric field intensity around the power transmission lines is the MLPNN method.

6. Conclusions

In this study, three ANN methods are compared for the determination of Electric field intensity. The MLPNN method has the best accuracy results relatively. The mean square error (mse) of MLPNN algorithm is obtained as 2.2164×10^{-4}. On the other hand, RBFNN algorithm has 0.0068 mse and GRNN has 5.5240×10^{-4} mse. Furthermore, maximal absolute errors of neural network methods are 6.17 % for MLPNN, 46.45% for RBFNN and 6.78% for GRNN algorithms with respect to the measurement database. As a result, the RBFNN is not sufficiently good for the determination of the electric field intensity. As it is seen from the numerical analysis, MLPNN algorithm is the best method for calculation of the electric field intensity. The prediction of the electric field intensity can be implemented with very low error by the Neural Network Algorithms, especially MLPNN method by defining the line voltage level and the physical properties of the line.

Results of the study indicate that Neural Network Algorithms particularly MLPNN can be used as a complementary tool with the conventional methods for the prediction of electric field intensity around the power transmission lines for the study of bio-electromagnetic, occupational health and safety, and electromagnetic risk analysis. To keep the general public and occupational exposure under control, electromagnetic analysis of power transmission lines should be implemented daily at the existing and recent power line project designs.

Acknowledgments

The research is supported by the Research Project Department of Akdeniz University, Antalya, Turkey.

References

[1] G. Draper, et al., “Childhood cancer in relation to distance from high voltage power lines in England and Wales: a case–control study,” *British Medical Journal*, vol. 330, pp. 1290, 2005.

[2] J. G. Gurney, et al., “Childhood cancer occurrence in relation to power line configurations: a study of potential selection bias in case–control studies,” *Epidemiology*, vol. 6, pp. 31–35, 1995.

[3] S. Ozen, “Low-frequency transient electric and magnetic fields coupling to child body,” *Radiat Prot Dosim*, vol. 128, no. 1, pp. 62–67, 2008.

[4] A. Albohm, et al., “Review of the epidemiologic literature on EMF and health, Environmental Health Perspectives,” vol. 109, pp. S6, 2001.

[5] J. Michaelis, J. H. Olsen, T. Tynes, and P. K. Verkasalo, “A pooled analysis of magnetic fields and childhood leukemia,” *British Journal of Cancer*, vol. 83, no. 5, pp. 692–698, 2000.

[6] N. Il, S. Ozen, M. Cakir, and H. F. Carlak, “Shielding and Mitigations of the Magnetic Fields Generated by the Underground Power Cables,” in *PIERS Proceedings*, pp. 1436-1439, 2015.

[7] ICNIRP - International Commission on Non-Ionizing Radiation Protection, “Exposure to static and low frequency electromagnetic fields, biological effects and health consequences (0-100 kHz),” J. H. Bernhardt, et al., eds. Oberschleissheim, International Commission on Non-ionizing Radiation Protection, 2003 (ICNIRP 13/2003).

[8] S. Ozen, E. G Ogel, and S. Helhel, “Residential Area Medium Voltage Power Lines; Public Health, and Electric and Magnetic Field Levels,” *Gazi University Journal of Science*, vol. 26, no. 4, pp. 573-578, 2013.

[9] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, “Learning representations by back propagating errors,” *Nature*, vol. 323, pp. 533–6, 1986.

[10] D. Specht, “A general regression neural network,” *Neural Networks, IEEE Transactions*, vol. 2, no. 6, pp. 568-576, 1991.

[11] L. V. Fausett, *Fundamentals of Neural Networks Architectures, Algorithms, and Applications*. Prentice-Hall, 1994.

[12] C. Bishop, “Improving the generalization properties of radial basis function neural networks. Neural Computation,” 3:579AS-588, 1991.

[13] S. Bilgin, O. H. Çolak, O. Polat, and E. Koklukaya, “Determination of Sympathovagal Balance in Ventricular Tachyarrhythmia Patients with Implanted Cardioverter Defibrillators Using Wavelet Transform and MLPNN,” *Digital Signal Processing*, vol. 19, no. 2, pp. 330-339, 2009.