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ARTIFICIAL NEURAL NETWORK APPROACH TO ELECTRIC FIELD APPROXIMATION AROUND OVERHEAD POWER TRANSMISSION LINES

Anant Oonsivilai, Rattarong Boonwutiwiwat, Thanatchai Kulworawanichpong, Padej Pao-La-Or
Power and Energy Research Unit, School of Electrical Engineering
Institute of Engineering, Suranaree University of Technology
Nakhon Ratchasima 30000, Thailand
anant@sut.ac.th;
rattarong@hotmail.com;
thanatchai@gmail.com;
padej@sut.ac.th

ABSTRACT
This paper presents the use of artificial neural networks (ANN) to estimate electric fields around an overhead power transmission line. Although, there exist many efficient numerical methods, e.g. finite difference method (FDM), finite element method (FEM), boundary element method (BEM), etc, to estimate electric field distribution caused by live conductors, it typically consumes substantial execution time when high accuracy of obtained solutions is required or especially when time-varying field is involved. Therefore, to estimate the electric field strength using ANN employing feedforword network with backpropagation learning can be an alternative. To evaluate its use, overhead 22-kV single-phase power line of 100 m^2 test area and 230-kV three-phase power lines of 400 m^2 test area were simulated. The results obtained from the ANN are compared with those obtained by the analytical method, the FDM and the FEM.

KEY WORDS
electric field strength, finite difference method (FDM), finite element method (FEM), artificial neural network **(ANN)**, boundary conditions, estimation

1. Introduction

The computation of electric fields is complex and difficult to find an exact solution [1]. Several numerical techniques have been increasingly employed to solve such problems since availability of high performance computers. Among these, finite difference method (FDM), finite element method (FEM) and boundary element method (BEM) are very popular [2]. Although they are simple and useful to estimate electromagnetic fields, it typically consumes substantial execution time when high accuracy of obtained solutions is required or especially when time-varying field is involved. Utilizing some efficient intelligent methods such as artificial neural networks (ANN) is able to estimate an electric field via an appropriate neural model. This technique is very useful when some environmental factors (e.g. temperature, moisture, etc) are taken into account [3]. The neural model is very flexible. When its weighting parameters are successfully trained corresponding to appropriate input variables, electric field estimation of any input values can be made rapidly.

The prediction of electric field intensity is very important in many aspects nowadays. Due to difficulty and time consuming of electric field measurement, numerical calculation can be applied to evaluate electric field distribution. In addition, since serious effects on health risk caused by electric field strength have been reported [4], recommendation and guidelines of electric-field-related tasks such as an overhead power transmission line are released to prevent a careless activity that might be performed close to the restricted area around the live conductor.

In this paper, exploitation of neural modeling to estimate electric field strength at any point around an overhead transmission line is demonstrated. The popular feedforward network with backpropagation learning is used. First of all, Section 2 presents an analytical solution of electric fields around an overhead power line system of single-phase and 3-phase conductors. Also, brief explanation of FDM and FEM to estimate electric field solutions is included. The neural model of electric field estimation is described in Section 3. Section 4 and 5 show numerical results and conclusions respectively.

2. Electric Field Calculation of a Single - conductor System

Fig. 1 shows a single conductor system in 2D. Points 1 and 1' in the figure represent the live conductor with potential V_1 and its image potential, respectively.

To compute the electric field strength at a point P(x,y) can be performed in many different ways. Some require tedious and substantial mathematical expression. Whereas some employ a simple formula, but obtained solutions are less accuracy.

In this paper, an analytical solution derived from Maxwell' equations, the FDM and the FEM are summarized.

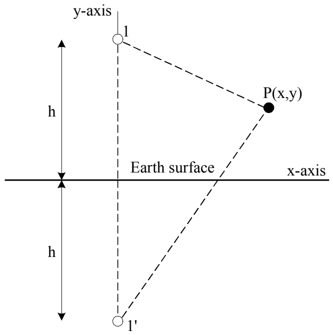

Fig. 1. A single conductor system

2.1 Analytical method

From Maxwell's equations electric field strength at a specified point P(x,y) can be expressed [5] as follows

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$$E(x,y)=\frac{2hV_1}{\ln\left(\frac{2h}{r}\right)\sqrt{x^4+y^4+h^4+2h^2x^2+2x^2y^2-2h^2y^2}} \quad (1)$$

Where r is a conductor radius

h is a distance between the conductor and the earth surface underneath

V_1 is a conductor potential

Beside the analytical approach, numerical solutions can be alternatively obtained by using the FDM and the FEM.

2.2 Finite Difference and Finite Element Methods

Solutions of partial differential equations such as Laplace or Poison equations can be obtained numerically by using the FDM and the FEM. These two methods divide a domain into many small discrete elements to formulate a set of algebraic difference equations characterizing electric flux of the domain. With given boundary conditions on the solution region, an approximate solution is simply obtained by solving such algebraic equations. In 2D problems, rectangular grid and linear triangular elements as shown in Fig. 2 are the most commonly used domain discretization [6] for the FDM and the FEM respectively.

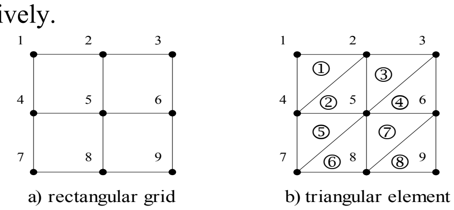


Fig. 2. Domain discretization of the FDM and FEM

After all node equations or all element equations are successfully derived, they must be assembled altogether to represent the unified characteristic of the entire domain. The entire system is expressed in matrix form as [C][V] = [F], where [C] is a coefficient matrix, [V] is a vector of unknowns and [F] is a vector of external forces. Its solutions can be obtained with many efficient techniques of handling a set of linear equations, e.g. Gaussian elimination, matrix factorization, conjugate gradient method, etc.

Although the FDM is straightforward and simple, it is not widely used when a non-uniform domain shape and heterogeneous conditions are involved. The FEM is more acceptable to deal with nonlinear problems. However it can be computationally expensive for large problems. Furthermore, to include effects of conductor size, unstructured and non-uniform grid must be used inevitably. Hence, the overall execution time is very expensive.

3. Electric Field Model using Artificial Neural Networks

The ANN is well-known and widely used in several research areas [7]. The ANN typically consists of a set of processing elements called neurons that interact by sending signals to one another along weighted connections. The connection weights, which can be determined adaptively, specify the precise knowledge representation. Usually it is not possible to specify the connection weights beforehand, because knowledge is distributed over the network. Therefore, a learning procedure is necessary in which the strengths of the connections are modified to achieve the desired form of activation function.

In electromagnetic problems, a small number of publications have been found. The implementation of ANN model for electric field problems requires electric field database of a 2D field domain. This paper focuses on the estimation of the electric field strength. Hence a single output structure of the ANN is presented as shown in Fig. 3.

All weighting parameters are obtained by backpropagation training in order to minimize mean square error or so-called loss function. Fig. 4 shows training structure of a simple feedforward network. The training problem can then be formulated as the following optimization problem.

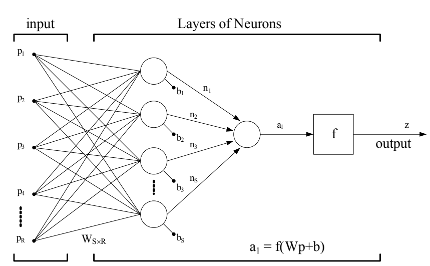


Fig. 3. Simple structure of a feedforward neural network

$$\underset{w\in\Re^{S\times R}}{\text{minimize}} \quad MSE=\frac{1}{2}\sum_{i=1}^{M}\left(z_{d,i}-z_i\right)^2=\frac{1}{2}\sum_{i=1}^{M}\left(z_{d,i}-f\left(Wp+b\right)\right)^2 \quad (2)$$

Some efficient classical optimization techniques such as steepest descent methods, Newton and quasi-Newton methods, etc, are applied to find a set of optimal weighting parameters [8].

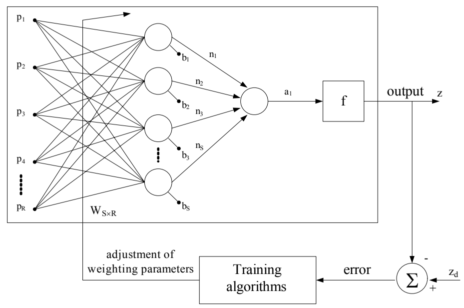


Fig. 4. Training structure of a simple feedforward network

In this paper, when a solution region is defined, electric field strength depends on a position of measured points, boundary conditions, conductor radius, environmental conditions, etc. All physical factors can be taken into account as many as possible, as shown in Fig. 5.

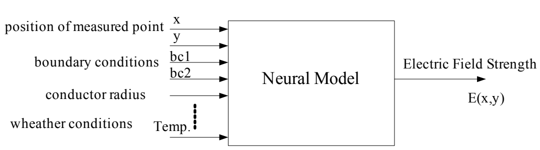


Fig. 5. Relation among physical factors via neural model

4. Numerical Results

100 m^2 area near an overhead power transmission line as shown in Fig. 6 is situated as the test system. The voltage distribution standard level of Thailand (22 kV, 50 Hz) is applied as the surface conductor potential. For benchmarking, calculation lines of 2-m, 4-m, 6-m above the earth surface and the earth surface level are defined.

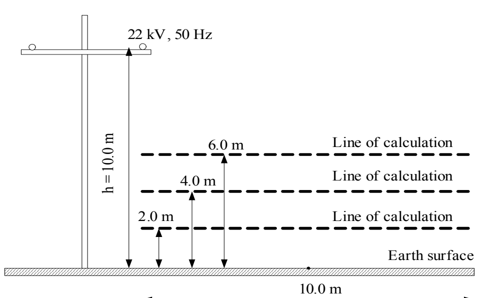
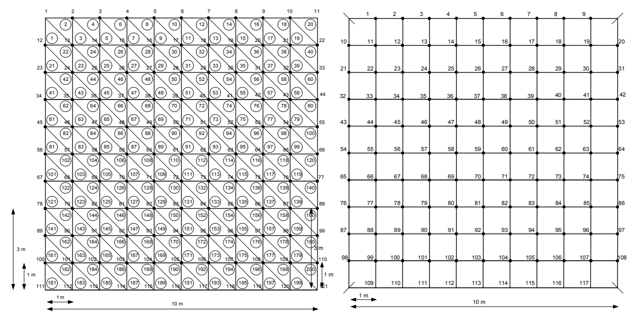


Fig. 6. Test domain of an overhead power transmission line

For comparison, the solution domain for the FDM and the FEM can be discretized as shown in Fig. 7.

The neural model used in this paper consists of two layers with 500 nodes and 1 node respectively. The transfer function of the first layer is the log sigmoid transfer function, while the linear transfer function is applied to the second layer. The training process corresponds to electric field strength as a function of Cartesian coordinates (x,y), conductor radius and boundary conditions. The training of the neural network is carried out through 108 training points, 36 training for each radius (35 70 and 150 mm^2 AAC: All Aluminium Conductor) as shown in Fig. 8.



a) FDM domain b) FEM domain

Fig. 7. Solution domain of the FDM and the FEM

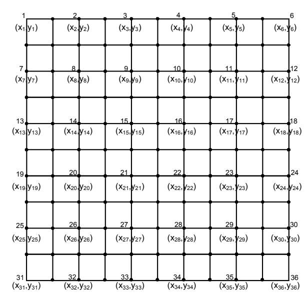


Fig. 8. 36 training points for a fixed radius of the neural network model

After the training, electric field strength at test positions along the calculation lines can be achieved and graphically presented in Figs 9,10 and 11.

As a result, the neural network model gives good performances for the electric field strength estimation. With the training algorithm, this model can account effects of some key environmental factors such as conductor size, temperature, moisture and humidity, dirt or fog condition, etc. This leads the neural network approach to overcome other efficient numerical methods like the FDM and the FEM in this aspect.

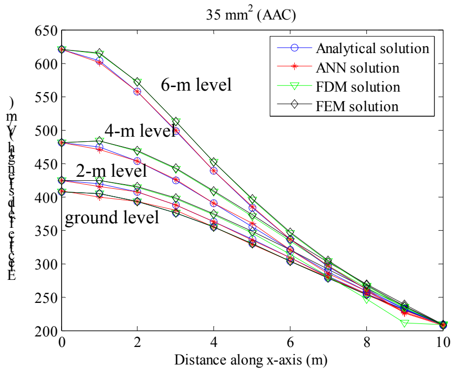


Fig. 9. Electric field strength caused by 35 mm^2 ACC conductor size

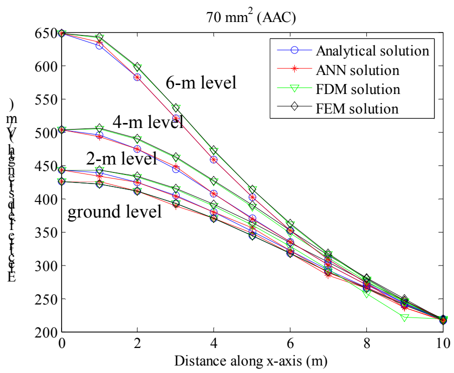


Fig. 10. Electric field strength caused by 70 mm^2 ACC conductor size

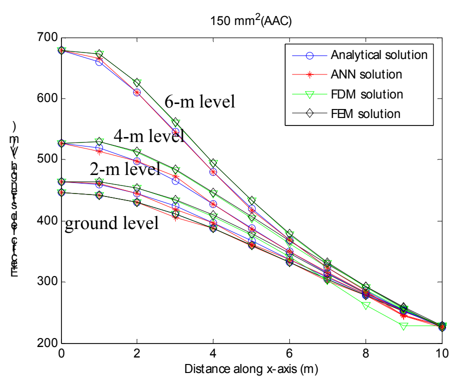


Fig. 11. Electric field strength caused by 150 mm^2 ACC conductor size

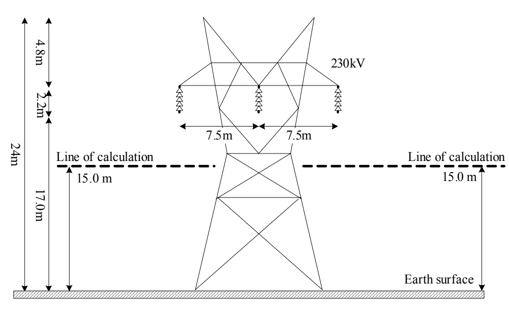


Fig. 13. Test domain of an overhead power transmission line

The second test is a 400 m^2 cross-area around an overhead power transmission line as shown in Fig. 13. The voltage distribution standard level of Thailand (230 kV, 50 Hz) is assumed as the surface conductor potential. For benchmarking, calculation lines of 15-m above the earth surface and the earth surface level are defined.

In the same manner, the electric field distribution of this test can be characterized by the FEM, FDM and ANN. They can be depicted as shown in Fig. 14. Also, comparative results among them are illustrated graphically in Fig. 15.

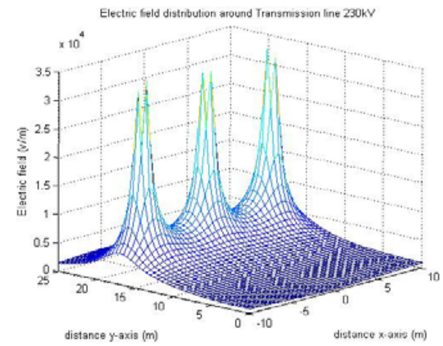


Fig. 14. Electric fields around the 3-phase power line

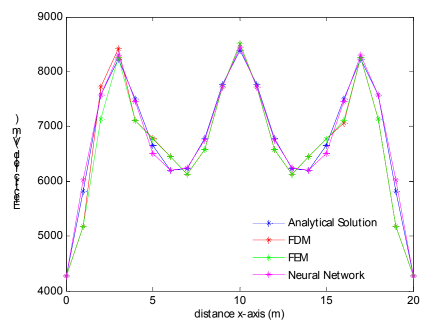


Fig. 15. Electric fields around the power line at y-axis = 15m

From the calculation, the level from 15-m above the ground to the conductor is critical due to the excessive electric field strength (greater than the maximum allowance of 5 kV/m that human body can stand) according to the international radiation protection association (IRPA) [9].

5. Conclusion

Estimation of electric field strength can be performed by using the neural network model. In this paper, overhead 22-kV and 230-kV power transmission lines are used for test as solution domains. The first test, the 22-kV system, consists of 121 nodes. The training of neural network is based on training data, which correspond to the electric field strength at given points. This system is simple and the analytical solution is available for comparison. With 108 training data, optimal weighting parameters are obtained by minimizing the mean square error. The test of the network is challenged with 36 test points along four calculation lines above the earth surface. The second test, the 230-kV power transmission line, consists of 441 nodes. The training of neural network is based on training data, which correspond to the electric field strength at given points. With 200 training data, optimal weighting parameters are obtained by minimizing the mean square error. The test of the network is challenged with 121 test points along four calculation lines above the earth surface. The numerical results present good agreement with that obtained by the analytical method, while the FDM and the FEM do not**.** It is very important to be in evidence that the neural model gives good results in electric field estimation. This might imply that the neural network approach can be further used to predict electric field distribution around an overhead power transmission line under an unexpected weather condition, e.g. rainy, foggy, dirty, or other extreme conditions.

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