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PREDICTING MAGNETIC FIELD IN PROXIMITY OF POWER TRANSMISSION LINES USING ARTIFICIAL NEURAL NETWORKS

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Abstract

The work investigate the predictability of using flexible artificial neural networks for calculation the magnetic field in proximity of 5th ring road power transmission lines at state of Kuwait. This paper brings together important and vital concepts, calculations, test results, and case study. Artificial neural network has been employed, in order to predict the magnetic fields established by currents in normal and faulted transmission lines. Reductions in computation time and memory requirements have been achieved in this approach. The absolute mean value error percentage for estimating magnetic field was calculated to be 2.53% and 2.48% for the x-component and y-component, respectively. Three-phase magnetic field calculation has been shown to be readily presented. The evaluation of the magnetic field in a wide range of configurations arising in practice can be done. Example of existing power transmission line shows practical applications.

Key Words
Artificial neural networks; magnetic field; memory; power transmission lines; reduction; simulation.

1. Introduction

In recent years magnetic radiation has been implicated as a contributory factor in a variety of adverse health effects. Some studies highlighted the added risk of miscarriage, childhood leukaemia, brain cancer and a greater incidence of suicide as some of the health risks associated with exposure to electric and magnetic fields from power lines [1-4].

Magnetic fields from power lines are an issue of public concern in scientific studies. Electrical environmental effects of power transmission lines have confirmed the need for evaluating the magnetic field in proximity to power lines. Solving magnetic field in proximity of power transmission lines is still being actively researched. In this regard, an artificial neural networks (ANNs) procedure has been proposed to analyze the magnetic field in proximity of power transmission line. The primary objective is to create rigorous methodology and software capable of solving magnetic field in 3-phase systems. Using the analytical solution to provide the result of magnetic field near overhead power transmission line is considered a valid technique. However, this solution is usually limited to classical and simple shapes.
Large and sophisticated problem domain size (large systems that comprise long-distance power transmission lines) needs alternative technique to handle the huge number of calculation points at the problem domain size. For this case, the flexible Artificial Neural Networks method makes it possible to compute the magnetic field distribution with acceptable accuracy. The key innovation in this paper is using the ANN technique in combined with the analytical solution for describing a methodology useful for computing complex-magnetic fields.

2. Artificial Neural Networks Brief

ANNs consist of highly interconnected simple processing elements called nodes (or neurons). One of most used schemes for a node is shown in figure 1. The node y output is given by:

$$y = f\left[\left(\sum_i w_i \cdot x_i\right) - b\right] \tag{2.1}$$

where x_i is the node input supplied by weight link w_i, b is the characteristic node offset (bias), and f is the transfer function. In general, for the applications that require an ANN with continuous outputs, the transfer function is a sigmoid function:

$$f(a) = \frac{2}{1+\exp(-a)} - 1 \tag{2.2}$$

The range of the sigmoid function in (2.2) is (-1, 1). There are applications that utilize sigmoid function ranging from 0 to 1, i.e., $f(a) = 1/[1 + \exp(-a)]$. An ANN, therefore, is composed of a set of these nodes interconnected and organized in layers. The most popular ANN structure is the feed-forward multi-layer perceptron (MLP) [5], [6].

Figure 2 shows an example of a three-layer perceptron network. Each layer has a specified number of nodes; the interconnections are only between nodes of adjacent layers, and each node belonging to a layer is connected to all nodes of adjacent layers. The ANN is capable of learning by example, i.e., the network is forced to furnish the desired outputs on the basis of the inputs supplied to it. This is carried out through learning algorithms that suitably modify the interconnection weights and biases. Once learning is complete, the neural network is capable of providing not only the desired outputs for the known inputs, but also outputs (in relation to the learning that it has undergone) corresponding to any inputs. A learning algorithm is a recursive process that adapts the connecting weights among the nodes and biases to minimize the square errors between the network outputs and the desired outputs for training. One of the most used learning algorithms is the back-propagation, which can be applied to feed-forward MLP (see [5], [6] for more details on the back-propagation algorithm).

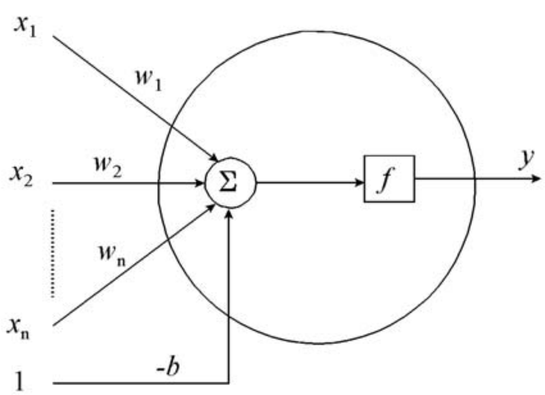


Figure 1: Schematic diagram of a node (processing element).

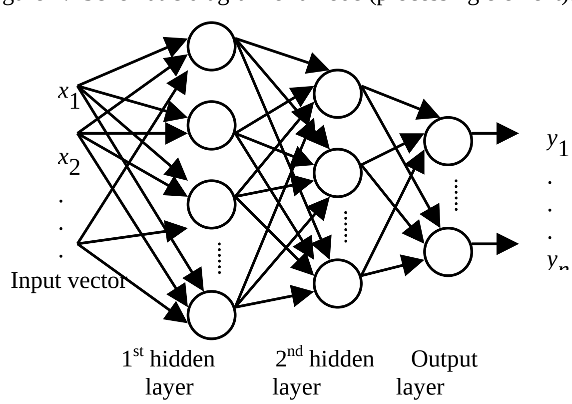


Figure 2: Three-layer, feed-forward perceptron network

3. Fifth Ring Road Power Transmission Line

The purpose of this paper, is designing a fast and compact procedure to compute the magnetic field with wide applicability. Using the ANNs technique is very powerful, and it is easily extended to multidimensional and space-time situations.

Fifth ring road power transmission line in state of Kuwait has been selected as a physical example for studying purposes. The model developed in the project gives high flexibility in evaluating the magnetic field in a wide range of configurations arising in practice. Figure 3 shows 5th ring rood terminal double circuit suspension assembly quad conductor. Figure 4 shows over head transmission line at 300 kV quad conductors. The study will investigate and quantify the existing geometry. It is important to notice how the tower is located relative to the Y-axis for late graphical interpretation.

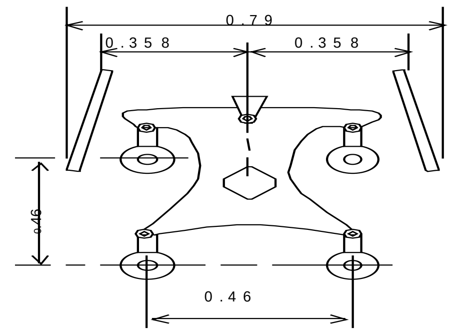


Figure 3: Fifth ring rood terminal 300 kV double circuit suspension assembly quad conductors (meters).

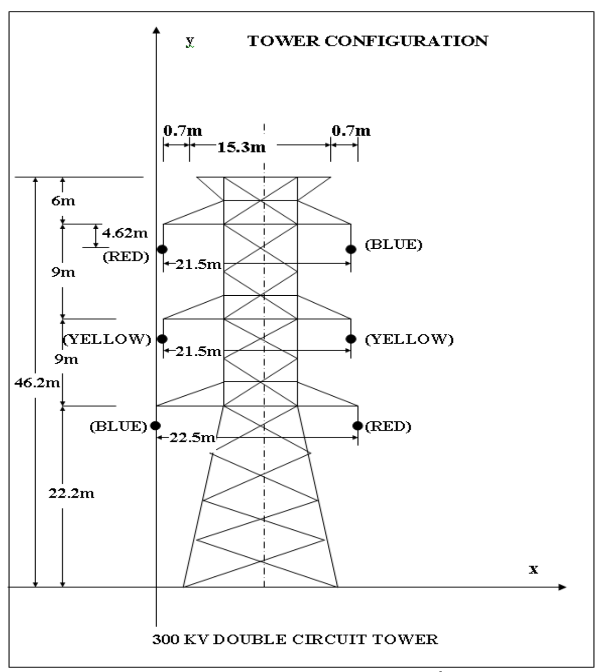


Figure 4: Tower configuration for 5th ring road.

4. Carson's Assumptions

A system of conductors parallel to the earth plane is considered. In this case, the field problem is reduced to one with two dimensions only. On the basis of Parallel-conductor system, the classical formulations by Carson and Pollaczek [7] that considered wave propagation along the axis parallel to the conductor system solved the Maxwell's equations to give a set of expressions for self and mutual impedances.

The region around a power transmission line is reduced to two dimensions, those perpendicular to the line as shown in Figure 5. The region is subdivided into two areas with a common boundary on which *H* (magnetic field) is continuous, but not essentially differentiable in space across the ground surface (see [8]).

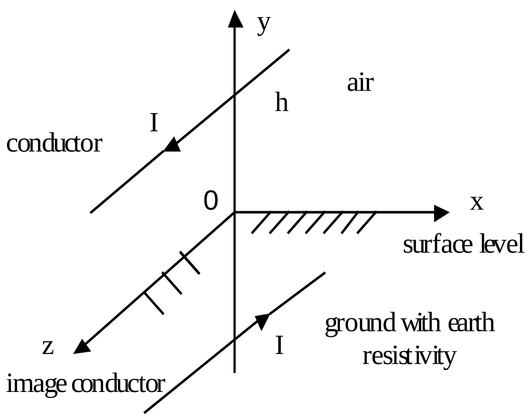


Figure 5: Co-ordinate system in Carson's formulation

5. Strategic Calculation Points of Magnetic Field Components *Hx* and *Hy*

In an early paper [8], the authors presented a formulation starting from Maxwell's equation describing electromagnetic fields established by the voltages and currents in the conductor systems of the power lines, and approximate boundary conditions. In this paper, a system of conductors parallel to the earth plane is considered.

However, the extension to a 3-dimensional case will be conceptually straightforward. The main contribution of the magnetic field will be created by the conductor/s. Expressions for the fields due to the conductor are given by:

$$H_{xc}(x,y) = \frac{(h-y)I}{2\pi(x^2+(h-y)^2)} \qquad (5.1)$$

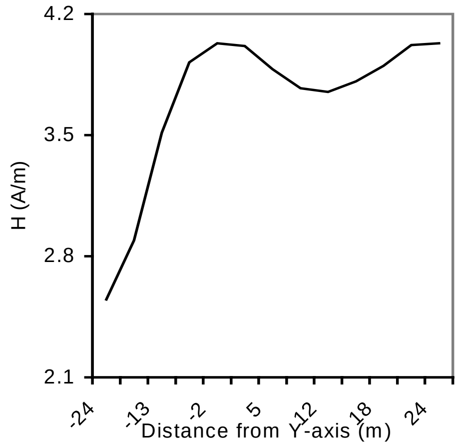
$$H_{yc}(x,y) = \frac{xI}{2\pi(x^2+(h-y)^2)} \qquad (5.2)$$

Where *I* is the conductor current and *h* is the conductor height above ground. The magnetic field of selected points at the problem domain size has been calculated using the equations (5.1) and (5.2). These calculation points are the parameters of the neural input, where the artificial neural network used for predicting the rest of calculation points, at the same problem domain size.

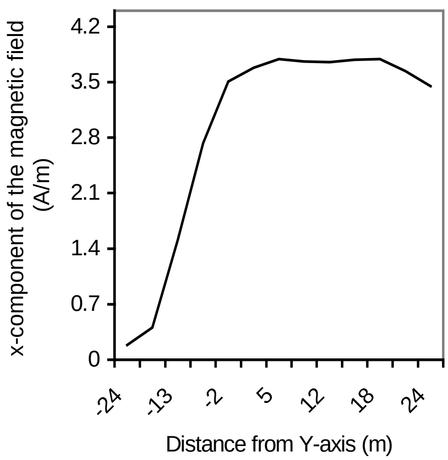
6. ANNs Computation and Simulation Results

A dedicated computer program has been developed, powerful enough to analyze magnetic field and yet easy to use by engineers with limited expertise on the subject. The flexibility of the program will permit expansion into a wide practical application for electric power transmission line industries. Results are compared very closely with analytical solutions to the set of Maxwell's equations expressed in the form of infinite integrals [8-9]. The typical parameters used in the test are: frequency 50 Hz, earth resistivity 200 ohm-m, and current 250 Amp. Figure 6 shows the magnetic field results on surface level. The simulation nature of this work has been chosen to present an opportunity for an in depth look at the physical aspects of the magnetic fields set up by overhead transmission lines.

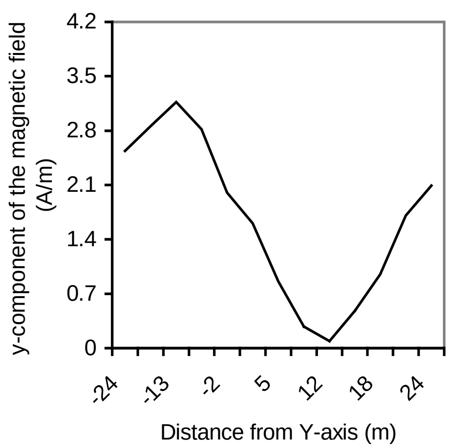
After examining several ANN structures, one type of ANN was found to be well suited to the study. Multi-layer feed-forward back-propagation (MLF-BP) is used for the magnetic field estimation problem. MLF-BP is one of the most widely used neural network paradigms, which has been applied successfully in application studies, e.g, [10]. MLF-BP can be applied to any problem that requires pattern mapping. Given an input pattern, the network produces an associated output pattern. Its' learning and update procedure is intuitively appealing because it is based on a relatively simple concept. The network is supplied with both a set of patterns to be learned and the desired system response for each pattern.



(a) Total magnetic field on surface level.



(b) X-component of the magnetic field on surface level.



(c)Y-component of the magnetic field on surface level.

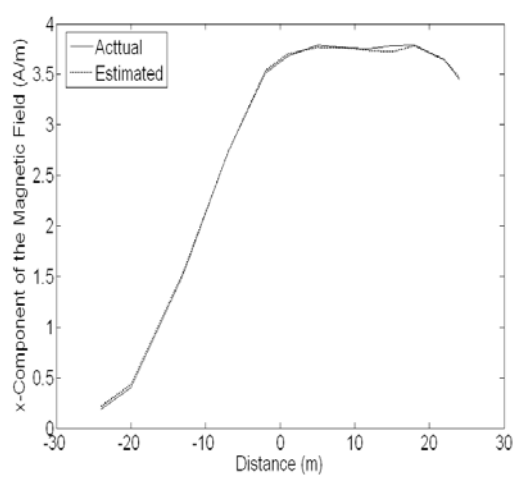
Figure 6: Total magnetic field, x-component and y-component of the magnetic field respectively, in 5th ring road transmission line.

If the network gives the wrong answer, then the weights are corrected so that the error is reduced. As a result, future responses of the network are more likely to be correct. It has been shown [6], [11] that all continuous functions could be approximated with a three-layer (i.e., two hidden layers and an output layer) network of sigmoidal or hyperbolic tangent nodes.

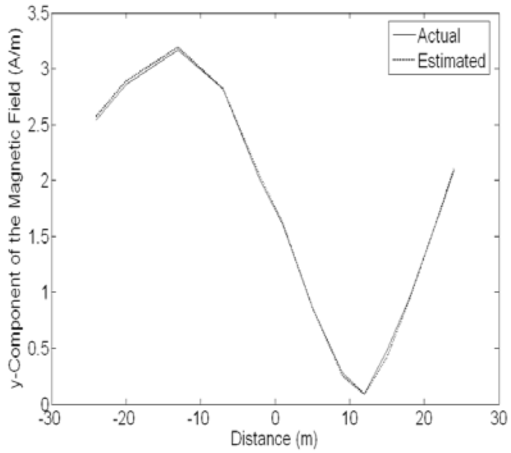
The number of nodes for the output layer depends on the specific application. In our case, since the magnetic field is estimated, the output layer will consist of one node. However, there is no clear rule on choosing the number of nodes for the hidden layers. The choice of the number of nodes is based, for the moment, on the type of the available input data and ANN accuracy in preliminary tests. In fact, optimizing this choice is currently a significant topic in studies of artificial intelligence researchers (e.g., [6]).

Several ANNs of various node numbers were tested and analyzed. It is found that MLF-BP network with 5-3-1 neurons in the first-hidden layer, second-hidden layer and output layer, respectively, is suited for the estimation problem.

Eighty percent (80%) of the data were used for training the MLF-BP network, and the remaining 20% were used for testing the network performance. Figure 7 shows a comparison between the actual analytical solution and the estimated magnetic filed magnitude (x- and y-components). The percentage absolute value error is calculated to be 2.53% and 2.48% for the x-component and y-component magnetic field, respectively.



(a)



(b)

Figure 7: Magnetic field according to distance from over-head power transmission line: (a) actual analytical solution and estimated x-component magnetic field, (b) actual analytical solution and estimated y-component magnetic field.

7. Conclusions

The level of success achieved by artificial neural network is highly acceptable. The study revealed that the artificial neural network is a powerful tool for computer solutions of many kinds of power system simulation. This scheme introduces good benefits in avoiding the most time-consuming procedure inherent in conventional integral techniques. Moreover, this technique uses computer resources efficiently within the constraint of control on error. Furthermore, this technique is efficient to handle large problem domain size, where reduction in memory requirements has been achieved.

The maximum complex magnetic field would be present under maximum current condition, at locations directly under the line, near mid-span, and with the conductors at minimum clearance. Excellent agreement has been achieved between the ANN and analytical results.

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