Estimation of Magnetic Field Strength near Substation Using Artificial Neural Network

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***Abstract*—In this paper, an efficient neural network based estimation technique has been studied to estimate the magnetic field strength near any power substation, and to assess the possible exposure to electromagnetic radiation received by the residents living near that substation. The measurement and the estimation were carried out in close proximity to different high powered equipment at four different substations near Brunei Darussalam. Initially, the measurement was performed using the TM-191 gaussmeter for all four 66/11kV substations. In the measurement process the highest magnetic field of 12.5mG was recorded near the lightning arrestor at Telisai substation and the lowest value of 0.1mG was recorded at Lamunin substation for the same equipment. Later on, the magnetic field strengths were estimated using single-layer and two-layer feed-forward artificial neural networks (ANN). The highest value of coefficient of determination was found to be 98% using single-layer ANN estimation while the coefficient of determination was found to be around 99% by using two-layer ANN estimation. These coefficients of determination values indicate that the artificial neural network can predict the magnetic field strength with high accuracy.**

***Index Terms*—substation, magnetic field, coefficient of determination, single-layer and two-layer ANN**

I. INTRODUCTION

Any electric power generation and transmission entity creates an electromagnetic field (EMF) that generates electromagnetic radiation (EMR). An electrical substation, which deals with high electrical power generation, transmission and distribution schemes, is a huge source of EMR. Therefore, there is a great deal of public interest and concern regarding potential health hazards due to EMR from power lines and substations (e.g., see [1]-[4]). The electromagnetic field focuses primarily on exposure to magnetic fields and that entails the requirement of the magnetic field-strength measurement around any electrical substation. Different research investigations have been carried out so far, either to evaluate the EMF effect or to minimize it on the living entities, especially, on human beings and animals. R. J. Caola *et al.* [1] have recorded the magnitude of the EMF adjacent to the New Freedom-Deans 500kV transmission line in New Jersey. In this case, two of the homes were close to the transmission line and the other was far away from it. R. Tukimin *et al.* [2] have studied the effect of extremely low frequency electromagnetic fields, generated by the overhead transmission power lines, on the residents located at Kelang Valley. The authors in [3] have calculated and measured the EMF in the vicinity of 400kV and 220kV transmission lines in Sarajevo. Kenji Tanaka *et al.* [4] have gathered various calculative results of power frequency on electric and magnetic fields, which were generated by power facilities, such as transmission lines, substations for comparison with an international cooperative research. C. Garrido *et al.* [5] have measured the magnetic field created by electrical appliances and high voltage lines and analysed the degree of compliance with European regulation. The simulation of the magnetic field generated by electrical lines through a simple model accurately predicted the measured values. In this case, a Fast Fourier Transform (FFT) analysis of the magnetic field waveform was performed to study the frequency and amplitude of the possible induced currents. A. H. Hamza *et al.* [6] have presented a thorough investigation on the evaluation of the internally induced electric fields and induced current densities that were induced inside the human body due to the exposure to the external magnetic fields produced by a conventional 220/66kV power substation. It has been demonstrated that the exposure to power frequency of the magnetic fields including those resulting from electrical power substations was playing a vital role in the human biological study.

N. A. Rahman *et al.* [7] have presented a study which was carried out on the Extra High Voltage (EHV) transmission lines specifically on the quadruple circuits of 132kV and double circuits of 500kV tower designs in Malaysia. M. A. Salam *et al.* [8] have established a direct relationship among the electric field, magnetic field and soil resistivity near quadruple transmission lines in Malaysia. The authors in [9] carried out experimental investigations to measure EMF near 500kV transmission lines. The electric and magnetic field have been measured inside and around power facilities in Colombia, Cuba, Indonesia, Thailand and USA [10].

An electromagnetic field strength measurement system at a power frequency has been developed, which included wireless transmission, and tests have been carried out to confirm its anti-interference feature. Tests have been

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carried out at a 750kV transformer substation [11]. Measurements of power frequency fields have been carried out inside and outside of the building which is 30ft away from the high voltage transmission lines [12]. The electromagnetic pollution existing in the high voltage equipment has been analyzed and measured [13]. A Babouri *et al.* [14] have simulated electric and magnetic field from 0m to 20m near high voltage transmission lines using the software *COMSOL*. The simulation and experimental measurement of electric and magnetic field have been carried out near 20-400kV transmission lines [15].

In this paper, the magnetic field strength has been measured near different high power equipment at four different 66/11kV substations in Brunei Darussalam, and an ANN estimation technique has also been used to estimate the magnetic field strength. There are many residential areas near the transmission lines and substation in Brunei Darussalam. Therefore, it is very important to know the level of EMR in those residential areas to assess the possible exposure to EMR received by the residents.

II. Mgnetic Field Measurement

The measurement of magnetic field strength has been carried out in the vicinity of different high voltage equipment at the Manggis (Muara), Salambigar (Muara), Telisai (Tutong), Lamunin (Tutong) 66/11kV substations using the TM-191 gaussmeter shown in Fig. 1. In this practical measurement, lightning arrestor, disconnector switch, bus selector and voltage and current transformers are considered as high voltage equipment, which are shown in Fig. 2. The magnetic field measurement is carried out at a distance of 3 meter away from each of these pieces of equipment. Considering the 3 meter location as the reference distance (zero distance), this measurement has been performed in steps from this reference point up to a distance of 20 feet. In order to estimate magnetic field strengths a feed-forward artificial neural network (ANN) has been used by considering two different approaches: Single-Layer single input/output approach and Two-layer approach.

Figure 1. TM-191 gauss meter

(a) Lightning arrestor

(b) Disconnector switch

(c) Bus selector arrestor

(d) Voltage and current transformer

Figure 2. High voltage equipment

III. Single-Layer Single Input/Output ANN

In the first approach, a feed-forward back-propagation ANN has been used to estimate the magnetic field strength based on single input parameter i.e. distance from the source. For each source at different locations, a neural network was trained and tested. The feed-forward back-propagation ANN is a supervised learning method based on the generalization of least mean square error (LMS) algorithm. In this case, the cost function is determined by computing the mean square difference between target and actual outputs which is then minimized by using the gradient descent method [16]. In this estimation process, the input parameter (distance) was first normalized using z-normalization technique. There were different numbers of cases considered for each of the substations with one input parameter and one output parameter. Based on these cases, the neural network was designed by using one input neuron and one output neuron as shown in Fig. 3. The number of optimum hidden layers and hidden layer neurons were determined based on trying different combinations, and finally one hidden layer with 15 neurons was chosen based on the minimum value of the cost function.

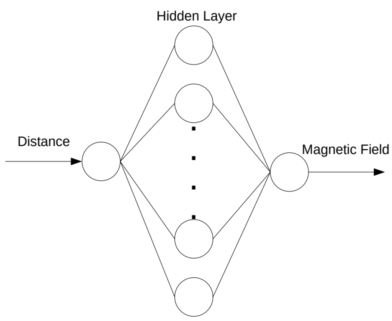

Figure 3. ANN model to estimate magnetic field.

The *TanSig* and *LogSig* activation functions were used in hidden and output layers respectively and the output of each layer has been calculated using (1) and (2) given below.

$$Output_{hidden} = TanSig\left(\sum_{i=1}^{P}\left(input_{h,i} \times w_{h,i} + b_h\right)\right) \quad (1)$$

where:

$Output_{hidden}$ is the output of the current hidden layer unit h,

P is either the number of units in the previous hidden layer or number of network inputs,

$Input_{h,i}$ is an input to unit h from either the previous hidden layer unit i or network input i,

$w_{h,i}$ is the weight modifying the connection from either unit i to unit h or from input i to unit h,

b_h is the bias for unit h.

Similarly, the output of the output layer can be calculated as:

$$Output_{out} = LogSig\left(\sum_{i=1}^{P}\left(input_{h,i} \times w_{h,i} + b_h\right)\right) \qquad (2)$$

where:

$Output_{out}$ is the output of the current output layer unit h,

P is the number of units in the previous hidden layer,

$input_{h,i}$ is an input to unit h from the previous hidden layer unit i,

$w_{h,i}$ is the weight modifying the connection from unit i to unit h,

b_h is the bias for unit h.

The *TanSig* and *LogSig* activation functions are defined as follows:

$$TanSig(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \qquad (3)$$

$$LogSig(x) = \frac{1}{1+e^{-x}} \qquad (4)$$

The weights for the connections were initially assigned randomly and the learning rate (η) was set to 0.1. The testing and validation steps of the trained proposed approach have been carried out by using Leave-One-Out Cross Validation (LOOCV) method [17]. In LOOCV method, one observation from the sample is used as validation data and rest of the observations are used for training the network. This process is repeated for all of the observations of the given data set. In this study, the network for each source at each substation was trained on $N-1$ samples from the dataset and one sample was left as the validation sample, where N was the total number of samples at each substation for each source. This process was repeated N times and the coefficients of determinations (R^2) for each substation were computed for the lightning arrestor, disconnector switch, bus selector and voltage and current transformers as shown in Table I to Table IV, respectively, in which, the coefficient of determination provides the estimation accuracy of the measured data. The graphical representation of the test results for current transformer (CT) and voltage transformer (VT) sources at different stations are shown in Fig. 4 to Fig. 7. In these figures, the x-axis (case number) represents the number of instances and/or records used for training and testing the ANN while the y-axis represents the normalized distance, which has been normalized over the maximum distance value for each case. Similar results were found for lightning arrestor. In case of disconnector switch and bus selector equipment, the estimated results were less accurate as compared to other two pieces of high voltage equipment. In the Salambigar substation, near the disconnector and the bus selector switches, the coefficient of determination is little bit lower than other high voltage equipment. This may be due to the particular time of the day when the equipment was not operated with its full capacity while the measurement was taken.

TABLE I. ESTIMATION ACCURACY OF LIGHTNING ARRESTOR

Substation	Coefficient of determination (R^2) %
Manggis	98.31198
Salambigar	98.88151
Telisai	98.14306
Lamunin	97.86697

TABLE II. ESTIMATION ACCURACY OF DISCONNECTOR SWITCH

Substation	Coefficient of determination (R^2) %
Manggis	87.96637
Salambigar	70.90391
Telisai	93.32277
Lamunin	98.15445

TABLE III. ESTIMATION ACCURACY OF BUS SELECTOR

Substation	Coefficient of determination (R^2) %
Manggis	90.53163
Salambigar	85.73928
Telisai	89.31915
Lamunin	96.51823

TABLE IV. ESTIMATION ACCURACY OF CURRENT AND VOLTAGE TRANSFORMERS

Substation	Coefficient of determination (R^2) %
Manggis	97.43372
Salambigar	98.51424
Telisai	97.52532
Lamunin	97.98059

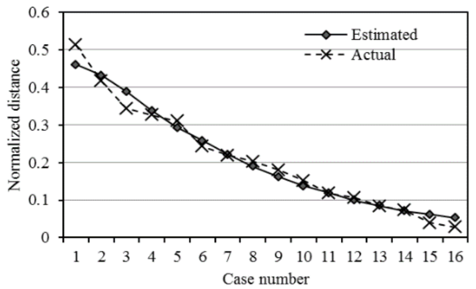

Figure 4. Test results for CT and VT at Mannggis substation.

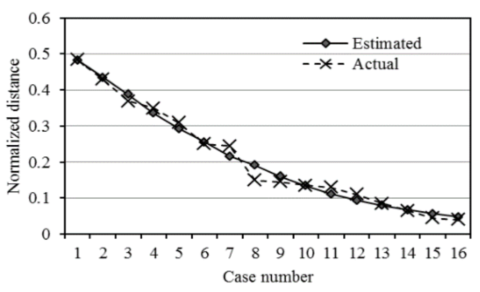

Figure 5. Test results for CT and VT at Salambigar substation.

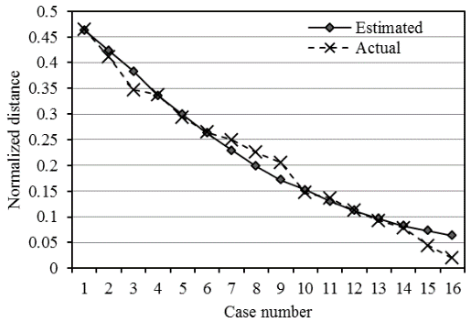

Figure 6. Test results for CT and VT at Telisai substation.

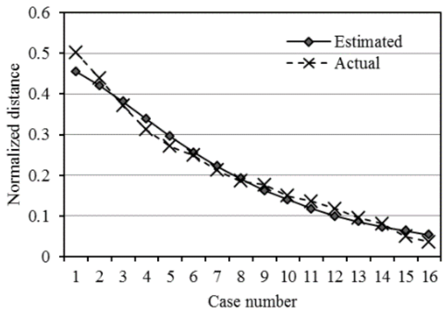

Figure 7. Test results for CT and VT at Lamunin substation.

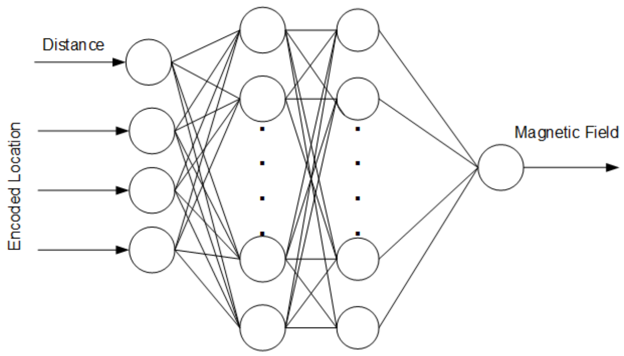

Figure 8. Two-Layer feed-forward ANN.

IV. Two-Layer Feed-Forward ANN

In the second approach, the estimation of measurement of magnetic field strength was performed based on different locations and at varying distances from different high voltage equipment such as voltage and current transformers, bus selector, disconnector switch etc. by using a two-layer feed-forward ANN as shown in Fig. 8. The neural network can map the numerical inputs (distance values) to the numerical targets (magnetic field values). In order to perform this mapping, the Neural Network Fitting Tool (NNFT) from MATLAB was used. By using the *NNFT*, input data from different locations were selected, the network was created and trained, and the performance evaluation was carried out based on mean square error and regression analysis. A two-layer feed-forward network was created with sigmoid hidden neurons and linear output neurons (NEWFIT), and the network was trained with Levenberg-Marquardt backpropagation algorithm (TRAINLM) [18], [19]. The Levenberg-Marquardt algorithm is an iterative technique to find the minimum value of a function of the form of sum of squares and it can be written as:

$$S(\beta) = \sum_{i=1}^{m} (y_i - f(x_i, \beta))^2 \tag{5}$$

where:

x_i is the input parameters (distance and locations),

y_i is the output parameter (magnetic field),

m is the total number of data points,

β is the parameter of the model curve $f(x, \beta)$.

The raw input data consisted of distance from the source and the locations were transformed using normalization (z-score) and encoding (categorical to binary) mechanisms respectively. In order to train and test the neural network model, the data was distributed into three groups: training (70% of the total data), validation (15% of the total data) and testing (15% of the total data). The network was then trained based on the training data, and the network generalization was measured by using validation data during training mode. The training sequence was stopped when an increase in the mean square error of the validation samples was observed. Once the network was trained, the test data were used to provide an independent measurement of the network performance. To evaluate the estimation accuracy for different devices, the regression coefficient for each device has been derived and recorded in Table V.

TABLE V. Estimation Accuracy for Different Devices for All Combined Locations

Devices	Regression coefficient %
Lightning arrestor	99.819
Disconnector switch	99.416
Bus selector	99.278
Current and voltage transformer	99.716

As shown in Table V, the regression coefficient values for the ANN estimation of the magnetic field strength has been found to be more than 0.99 for different high voltage equipment when all locations were combined to test the network. This indicates that the magnetic field strength could be obtained with a 99% confidence. The training, validation and testing regression plots for two-layer ANN are shown in Fig. 9 to Fig. 12 for the four selected equipment. In these figures, the x-axis (target) represents the actual/desired output of the system while the y-axis (Output) shows the computed/predicted output of the system. In case of lightning arrestor and current and voltage transformers, the regression coefficients for test phase were found to be more than 0.99 accurate which indicated a very high confidence for the determination of magnetic field strength. By observing the overall results, it can be concluded that the ANN approach estimates the magnetic field of the lightning arrestor, and voltage and current transformers better than the bus selector and disconnector switches.

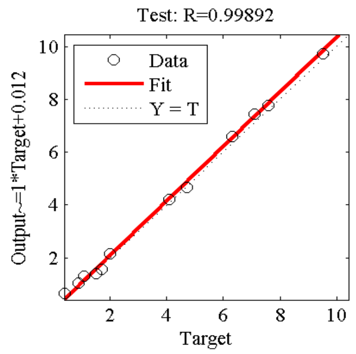

Figure 9. Test results for lightning arrestor.

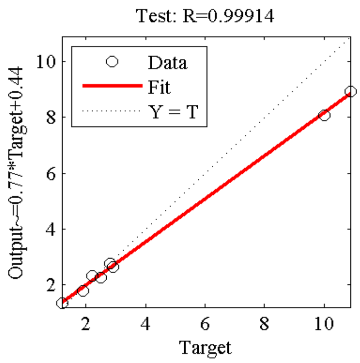

Figure 10. Test results for disconnector.

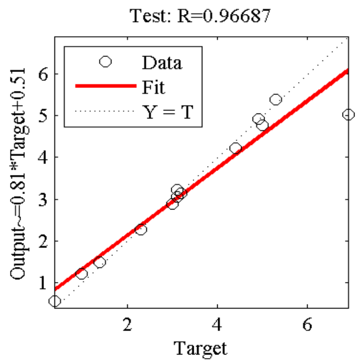

Figure 11. Test results for bus selector.

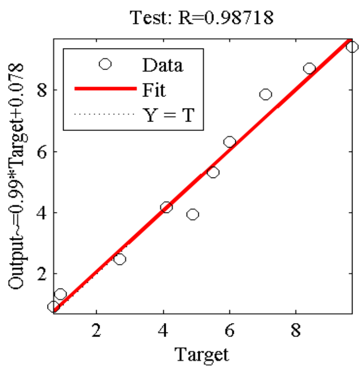

Figure 12. Test results for current and voltage transformer.

V. Conclusion

An experimental measurement of magnetic field has been carried out near high voltage equipment of different substations. Based on the experimental measurement, a single-layer and a two-layer ANN models have been developed to estimate the magnetic field near different high voltage equipment. The regression coefficient of the magnetic field has been found to be 0.99 using ANN estimation when all locations were combined for testing the network. The regression coefficients for testing phase of lightning arrestor, and current and voltage transformers have been found to be more than 0.99. High coefficients of determination indicated that the ANN estimation technique could determine the magnetic field strength with high confidence. Highest and lowest magnetic field strengths were found near lightning arrestor at Telisai and Lamunin substations, respectively.

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