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AN ARTIFICIAL NEURAL NETWORK FOR ESTIMATING THE GROUND RESISTANCE

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Abstract - The objective of this paper is the development of an artificial neural network model based on resistivity measurements and weather conditions for the prediction of the ground resistance. On that purpose extensive experiments were carried out and the resistivity of the soil was measured. Then, an artificial neural network has been applied on the experimental data for the estimation of the ground resistance. The correlation being achieved between the measured and the estimated values of the ground resistance is more than satisfactory.

1 - INTRODUCTION

The purpose of any grounding system is to provide a path of low resistance to faults and lightning currents and to assure the protection of any person in the vicinity of the grounded facilities [1]. The value of the ground resistance greatly depends on the grounding system and the properties of the soil, where the system is embedded. The earth resistivity, in turn, varies with temperature, moisture, salt content and compactness of the soil [2], [3], [4], [5], [6]. Since these parameters vary during the year, the grounding system cannot be characterized by a single value of resistance. So far several approaches, which are based on empirical and approximating equations, have been developed for the estimation of the ground resistance. The approach proposed in this paper, takes advantage of the capability of the artificial neural networks (ANNs) to recognize relationships among quantities, that otherwise would be difficult to be modeled. So far, ANNs have been successfully used by Salam et al. [7] for modeling and predicting the relationship between the length of the buried electrode and the grounding resistance. Amaral et al. [8] have implemented an ANN approach in order to map the relationship among the soil resistivity, grounding resistance, frequency, and current peak. In this paper an ANN has been trained and validated by using experimental data of ground resistivity and rainfall in order to predict the ground resistance.

2 – BASIC CONSIDERATION

2.1 – SOIL RESISTIVITY MEASUREMENTS

Many techniques have been developed for the measurement of soil resistivity. The most important of them are: a) the Wenner method, b) the Schlumberger method, c) the dipole method and d) the alternate configuration method. The Four-Point (Wenner) method [2] is the most accurate for the determination of the average soil resistivity.

The measurements of the soil resistivity [3] were conducted in the area of Athens from October up to July, whereas the meteorological data were provided by the National Meteorological Authority of Hellas. In Fig. 1 the rainfall data are presented.

The measurements of soil resistivity were conducted according to the Wenner method by using the NORMA 1805 GB 2D/E ground tester.

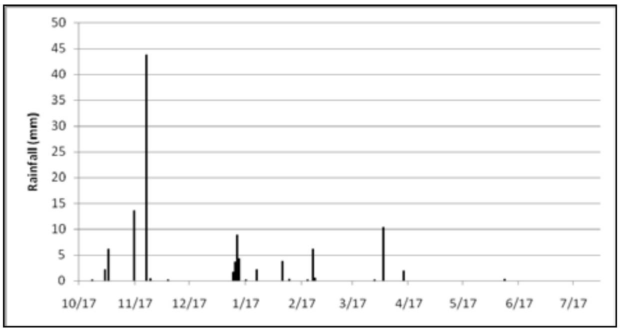

Figure 1- Rainfall (mm)

As shown in Fig. 2 four electrodes 45cm in length are driven in line, in a depth *b* at equal distances *α* from each other. A test current (*I*) is injected at the two terminal electrodes and the potential (*V*) between the two middle electrodes is measured. The ratio *V/I* gives the apparent resistance *R* (in Ohms). The apparent soil resistivity *ρ* is given by the following formula [2]:

$$\rho = \frac{4\cdot\pi\cdot a\cdot R}{1+ \dfrac{2\cdot a}{\sqrt{a^2+4\cdot b^2}} - \dfrac{a}{\sqrt{a^2+b^2}}} \quad (1)$$

If $a >> b$ the apparent resistivity is calculated by:

$$\rho = 2\cdot\pi\cdot R\cdot a \quad (2)$$

Measurements have been carried out on a 40m line at spacings between the electrodes of 1, 2, 3, 4, 5, 6, 8, and 10m [3].

The ground resistance is measured according to the fall of potential method and the 62% rule [2]. The distance between the current electrode and the electrode being tested (1.5m long) is 40m, while the potential electrode is placed 24m away from the electrode under test (Fig. 3).

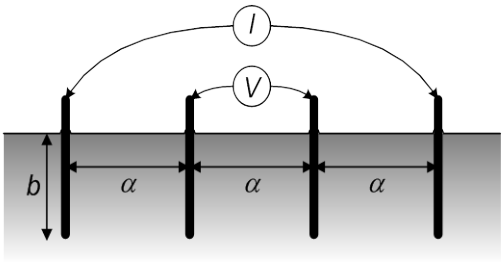

Figure 2 - Wenner method for measurement of apparent resistivity.

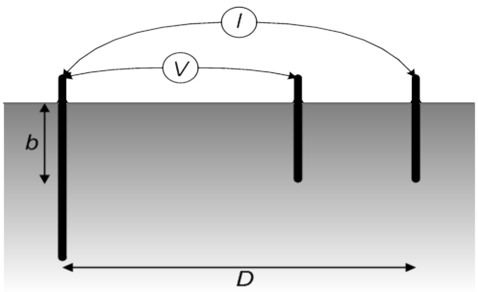

Figure 3 – The fall of potential method for measurement of ground resistance

The measurements were repeated in scheduled time intervals in order to evaluate the effect of weather conditions.

In Figs. 4 - 5 the seasonal variation of the resistivity for different distances between the four electrodes and the ground resistance are presented.

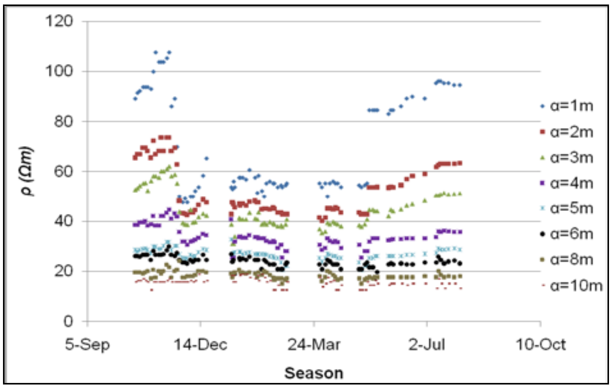

Figure 4 - Seasonal variation of the soil resistivity for different distances between electrodes.

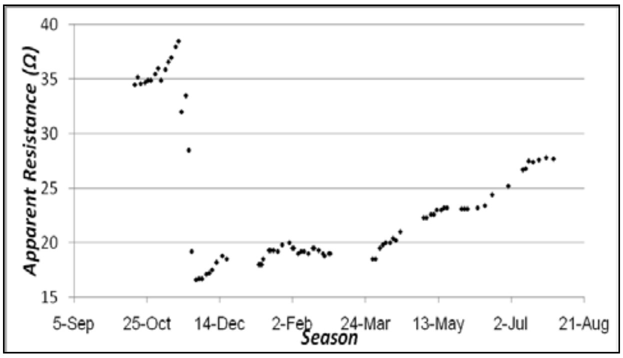

Figure 5 - Seasonal variation of the ground resistance.

2.2 – ARTIFICIAL NEURAL NETWORK APPROACH

ANNs are a useful tool in recognizing and modeling linear and nonlinear relationships among quantities. A typical ANN comprises three layers: the input, the hidden and the output layer. The number of nodes of the input layer and the number of neurons at the output layer are equal to the number of input and output variables respectively. Each ANN can be comprised by more than one hidden layers. According to Kolmogorov's theorem [9], if the number of the neurons of the hidden layer is properly chosen, an ANN with a single hidden layer can solve the problem.

For the optimization process the input and the output data are randomly divided into three sets:

- The training set, which is used until the network has learned the relationship between the inputs and the outputs.

- The evaluation set, which is used for the selection of the ANN parameters (number of the neurons in the hidden layer, the forms and the parameters of the activation functions). The parameters are selected so that the maximum correlation index (R^2) between the actual and the estimated values for the evaluation set is achieved. It is noted that:

$$R^2 = r_{y-\hat{y}}^2 = \frac{\left(\sum_{i=1}^{n}\left(\left(y_i - \bar{y}_{real}\right)\cdot\left(\hat{y}_i - \bar{y}_{est}\right)\right)\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}_{real}\right)^2 \cdot \sum_{i=1}^{n}\left(\hat{y}_i - \bar{y}_{est}\right)^2} \qquad (3)$$

  where y_i is the experimental value of the ground resistance, $\bar{y}_{real}$ the mean experimental value of the respective data set (training, evaluation or test), $\hat{y}_i$ the estimated value, $\bar{y}_{est}$ the mean estimated value of the data set, *n* the population of the respective data set.

- The test set which provides an independent test of the network generalization ability to data that the network has never seen.

The weights of the ANN are adjusted according to the scaled conjugate gradient algorithm [10] until one of the stopping criteria, is fulfilled. The stopping criteria comprise the weight stabilization criterion, the error function minimization and the maximum number of epochs criterion [11].

3 – DEVELOPMENTS

In this paper the ANN approach described above, has been applied for the estimation of the ground resistance. The training and the evaluation set are formed by 65 vectors (different from the test set), whereas the test set is comprised by 16 vectors.The basic steps of the methodology are presented in the flow chart of Figure 6.

The input variables consist of data regarding soil resistivity measurements (in Ωm) for different electrode distances, and rainfall (in mm); whereas the output variable is the ground resistance (in Ω).

Data are examined for normality, in order to modify or delete values that are obviously wrong (noise suppression). Moreover, the input and output data have different ranges, thus, the feeding of the original data to the ANN leads to a convergence problem. In order to avoid saturation problems, the input and the output values are normalized according to the following expression:

$$\hat{x} = a + \frac{b-a}{x_{max} - x_{min}}\left(x - x_{min}\right) \qquad (4)$$

where $\hat{x}$ is the normalized value for variable x, x_{min} and x_{max} are the lower and the upper values of variable x, a and b are the respective values of the normalized variable.

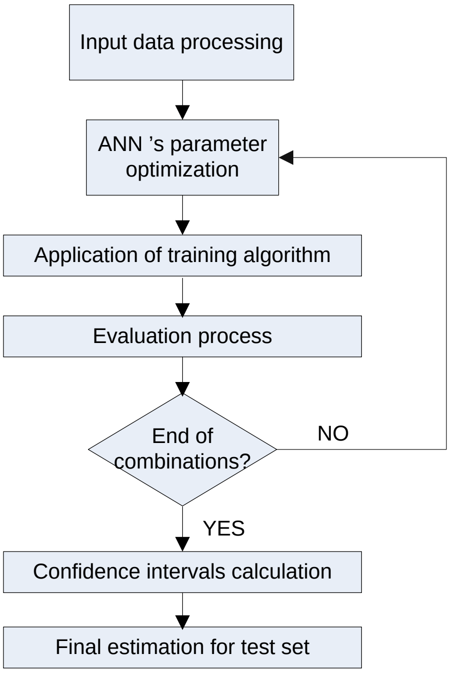

Figure 6 – Flowchart of the ANN methodology for the estimation of the ground resistance.

Due to the non linearity of the problem, the hyperbolic tangent given by (5)

$$\phi(x) = \tanh(a \cdot x + b) \qquad (5)$$

is used as an activation function for the hidden and the output layer.

The parameters of the network (number of neurons *N*, parameters (*a*, *b*) of the activation function, maximum number of epochs, and parameters of the scaled conjugate gradient algorithm (σ and λ_0)) are optimized through a set of trials.

Firstly, the optimal number of neurons is determined by giving fixed values to the rest of the parameters and by varying the number of neurons from 2 to 25 with step 1. The optimal value for *N* is selected as the one with the smallest G_{av} for the evaluation set. G_{av} is given by (6)

$$G_{av} = \frac{1}{N}\sum_{n=1}^{N} G(n) \qquad (6)$$

where $G(n) = \frac{1}{2}\sum_{j \in C} e_j^2(n)$ is the sum of the square errors for all output neurons for the n-th pattern and *N* is the total number of patterns.

As it can be seen from Fig. 7 the minimum G_{av} is achieved when *N=11.*

Since the hyperbolic tangent is used as an activation function for both layers (hidden layer and output layer), the parameters *a* and *b* of (5) need to be specified. The values intervals for these parameters are *a*=0*,* 0.025, 0.05…,1.5 and *b*=0, 0.1, ., 1. It is deducted that the minimum G_{av} of the validation set is achieved for a_1=0.875, a_2=0.2, $b_1=b_2=0$.

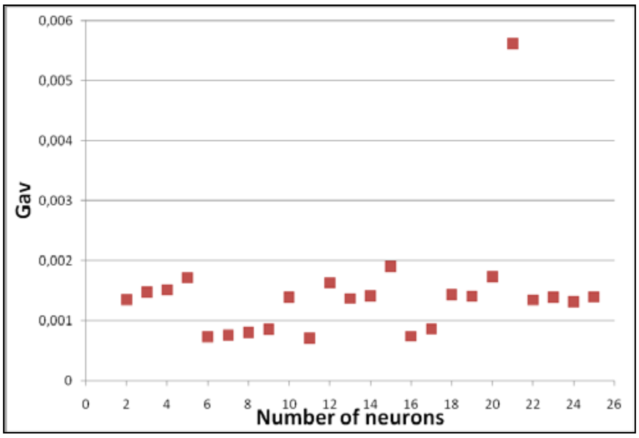

Figure 7 – G_{av} for the evaluation test along with the number of neurons.

Moreover the parameters σ and λ of the scaled conjugate gradient algorithm are determined. Different values are tested ($\sigma=10^{-5}$, 10^{-4}, 10^{-3}, $\lambda=10^{-6}$, 10^{-7}, 10^{-8}). It is concluded that minimum G_{av} is achieved when $\sigma=10^{-4}$ and $\lambda=10^{-6}$.

The combination of parameters which achieves the minimum error in the prediction of the evaluation set is used for the estimation of the ground resistance. In Table 1 the values of the parameters provided by the optimization process are tabulated.

Number of neurons (*N*)	11
Activation function for the hidden layer	$\phi(x) = \tanh(0.875 \cdot x)$
Activation function for the output layer	$\phi(x) = \tanh(0.2 \cdot x)$
σ	10^{-4}
λ	10^{-6}

Table 1 - Parameters of the ANN

Following, the confidence intervals for the evaluation and the test set are calculated using the re-sampling method for a specific tail probability *p*. These intervals are extended in order to describe the values of the test set estimating the respective confidence interval with probability (1-2*p*).

4 - RESULTS

The performance of the ANN for the optimum combination of parameters is presented in Table 2 where the measured and the estimated by the ANN values of the ground resistance of the test set are tabulated. In Fig. 8 the measured and the estimated values of the ground resistance for all sets are presented along with their confidence interval with 5% probability. The mean absolute percentage error (MAPE) given by (7):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_t - E_t}{A_t}\right| \qquad (7)$$

where A_t is the actual value and E_t is the estimated value of the test set is 5.68%.

The correlation R^2 between the actual and the estimated values for the evaluation set is 0.9897, whereas the correlation for the test set is 0.9567 (Fig. 9), respectively. This fact depicts the success of the method in estimating the ground resistance.

	Ground resistance values (Ω)				
	ANN estimation	Measured		ANN estimation	Measured
1	35.2	34.7	9	19.294	19.3
2	35.1	34.9	10	15.894	19.5
3	37.4	36.0	11	19.104	19.2
4	37.4	37.0	12	21.031	19.3
5	29.9	28.5	13	18.458	18.5
6	15.0	16.6	14	22.391	18.5
7	18.5	17.5	15	23.041	23.1
8	16.6	18.0	16	22.822	24.4

Table 2 – Measured ground resistance values against ANN's estimations.

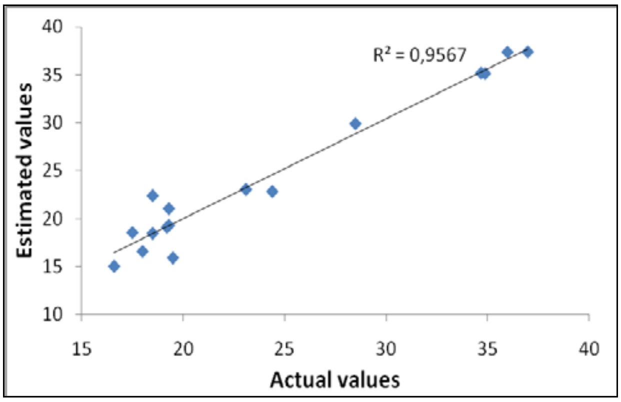

Figure 9 – Correlation berween actual and estimated values of the ground resistance for the test set.

5 – CONCLUSIONS

By applying a neural network on experimental data of grounding resistivity and rainfall, the ground resistance is evaluated. The achieved correlation between actual and estimated values of the test set 0.9567 is more than satisfactory proving that the application of the proposed ANN methodology is a useful tool for estimating the performance of the ground resistance during the year. Moreover, it is possible to achieve higher correlation by increasing the number of input variables (parameters such as the soil composition, temperature etc. can be used on that purpose).

6 –ACKNOWLEDGMENT

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