Artificial Neural Network Approach on the Seasonal Variation of Soil Resistance

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***Abstract*— Objective of this paper is the development of a methodological approach for estimating the ground resistance by using artificial intelligence techniques (specifically, Artificial Neural Network). The value of the ground resistance greatly depends on the grounding system and the properties of the soil, where the system is embedded. Given that the value of soil resistivity fluctuates during the year, the ground resistance does not have one single value. The approach proposed in this paper, takes advantage of the capability of artificial neural networks (ANNs) to recognize linear and non-linear relationships between various parameters. By taking into account measurements of resistivity and rainfall data accrued for previous days, the ground resistance is estimated. On that purpose ANNs have been trained and validated by using experimental data in order to examine their ability to predict the ground resistance. The results prove the effectiveness of the proposed methodology.**

I. Introduction

Purpose of any grounding system is to ensure safe and proper operation of any electric installation and to avoid exposure of any individual in the vicinity of the grounding system to dangerous step and touch voltages. In order to meet these goals, the grounding system's resistance should be maintained as low as possible.

The ground resistance (R_g) is defined by the size of the grounding system and soil resistivity (ρ), within which the grounding system is embedded. The value of soil resistivity varies significantly with location, depending on the nature of the soil, the amount of salts dissolved in it, the moisture content, the temperature and the compactness of the soil. Additionally, soil resistivity of the upper soil layer is subjected to seasonal variation due to ice or drought [1], [2]. Since these parameters vary throughout the year, the grounding system cannot be characterized by a single value of ground resistance [3], [4], [5], [6]. Therefore, these values should be subjected to monitoring on a yearly basis, a time-consuming and cost-demanding task.

At this point an approach based on Artificial Neural Networks (ANN) can be useful, since ANNs can model relationships between quantities without requirement of knowledge of the exact formula among them.

Aim of this paper is the study, analysis and modeling of changes in ground resistance of grounding systems over time, using artificial neural network techniques. The results are based on extended experimental measurements of existing grounding system arrangements, throughout the year.

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] successfully attempted to map the relationship among the soil resistivity, grounding resistance, frequency, and current peak. This paper is complementary to the research presented in [9], [10] in an attempt to delve into the problem and its parameters by using different training algorithms and by using an extended set of input data.

The rest of the paper is organized as follows: Paragraph II refers to the experimental procedure of the measurements (ρ, R_g, rainfall). In section III the ANN training algorithms are presented and the training procedure is described. The obtained results are presented in section IV along with the conclusions.

II. Soil Resistivity And Ground Resistance Measurements

The variation of depth method, the two-point method and the four-point method are the methods for measuring the soil resistivity. Among them the four-point method (Wenner) is the most accurate in practice. However, within the scope of our experiment the Wenner method [2] has been implemented for the determination of the average soil resistivity.

The measurements of the soil resistivity were conducted in the area of Athens from October up to July [5], whereas the meteorological data were provided by the National Meteorological Authority of Hellas.

In Fig. 1 the rainfall data are presented.

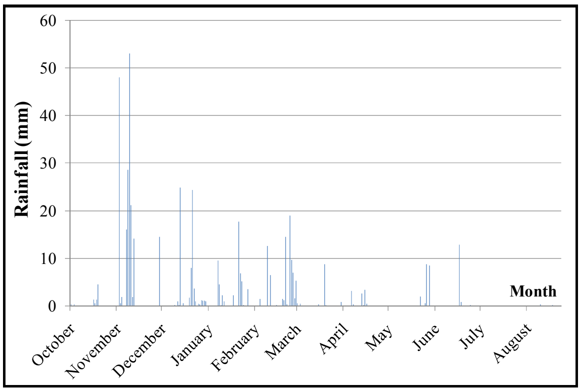

Fig. 1 Rainfall (mm)

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]:

$$\rho = \frac{4 \cdot \pi \cdot a \cdot R}{1 + 2 \cdot a \Big/ \sqrt{a^2 + 4 \cdot b^2} - a \Big/ \sqrt{a^2 + b^2}} \tag{1}$$

Measurements have been carried out on a 40m line at spacings between the electrodes of 1 and 2m [5].

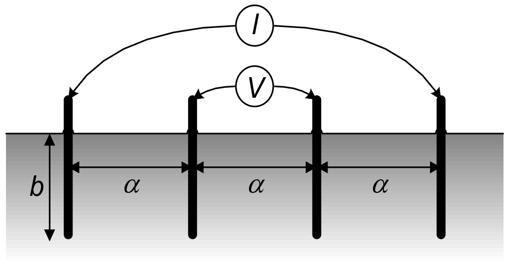

Fig. 2 Wenner method for measurement of apparent resistivity.

The ground resistance was 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).

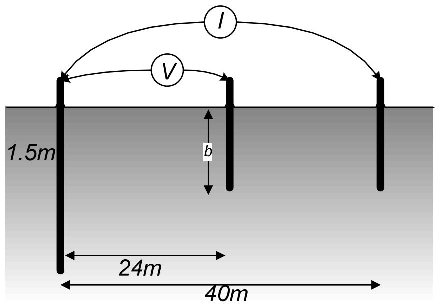

Fig. 3 The fall of potential method for measurement of ground resistance

The measurements were repeated in scheduled time intervals.

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

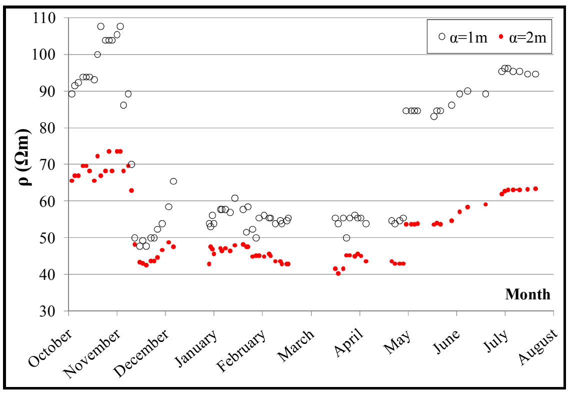

Fig. 4 Seasonal variation of the soil resistivity for distance between the electrodes 1m and 2m.

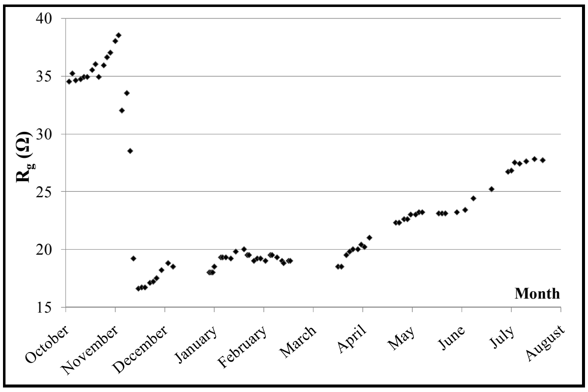

Fig. 5 Seasonal variation of the ground resistance.

III. Artificial Neural Network Methodology for the Estimation of Ground Resistance

ANNs constitute a useful tool in the field of establishing relationships between quantities, that otherwise would have been difficult to model. A typical ANN is composed by three layers, the input, the hidden and the output layer. In Fig. 6 a schematic diagram of the ANN structure of our problem is presented. The input layer (input vector ($I_1 \ldots I_5$)) comprises the soil resistivity measurements (in Ωm) for electrode distances at 1m and 2m, the average rainfall during previous week, the rainfall during the day on which the ground resistance is estimated (in mm) and the average resistance during previous week (in Ω). The output layer (output variable) of the ANN is the ground resistance (in Ω).

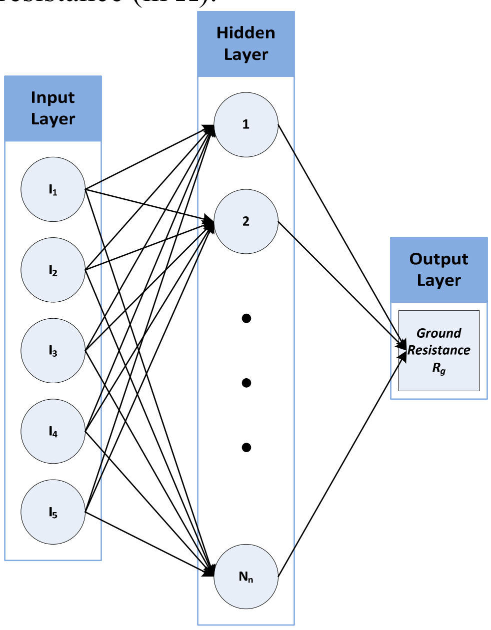

Fig. 6 ANN structure.

The ground resistance of the rod is estimated by applying the methodology presented in Fig. 6.

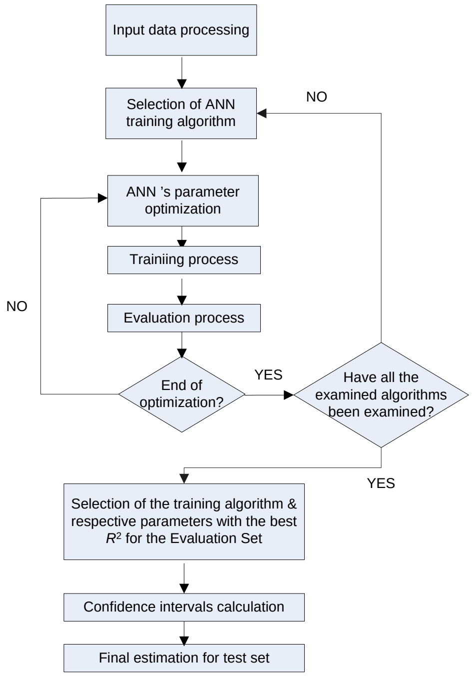

Fig. 7 Flowchart of the ANN methodology for the estimation of the ground resistance [11].

Before proceeding to the training of the ANN the input data are normalized in order to achieve convergence and avoid saturation problems of the algorithm according to the expression:

$$\hat{x} = a + \frac{b-a}{x_{\max} - x_{\min}}\left(x - x_{\min}\right) \qquad (1)$$

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.

Following the experimental data are divided into three sets:

- The training set (53 cases), which is used for training until the network has learned the relationship between the input(s) and the output.
- The evaluation set (14 cases), which is used for the selection of the ANN parameters (number of the neurons in the hidden layer, the type and the parameters of the activation functions, learning rate, momentum term). 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.

- The test set (10 cases) which verifies the generalization ability of the ANN by using an independent data set.

The ANN is trained by applying the back propagation algorithm and its variations, which are presented in Table I. During the execution of the training algorithm the free parameters (weights) of the network are adjusted in order for the average error function between the estimated and the actual value to be minimized. The average error function for all N patterns is given by (3):

$$G_{av} = \frac{1}{2N}\sum_{n=1}^{N}\sum_{j\in C}(d_j(n) - y_j(n))^2 \tag{3}$$

where C is the set of neurons, $d_j(n)$ the desirable output and $y_j(n)$ the actual output of the j-neuron.

TABLE I
TRAINING ALGORITHMS

	Training algorithm
1	Stochastic training with learning rate and momentum term
2	Stochastic training with use of adaptive rules for learning rate and momentum term
3	Stochastic training with constant learning rate

The weights are adjusted by random presentation of every input vector (stochastic mode) according to the following criteria:
1) the stabilization of the weights (4),
2) the minimization of the error function (5) and
3) the maximum number of epochs criterion (6),
which are respectively described by the following expressions:

$$\left|w_{kv}^{(l)}(ep) - w_{kv}^{(l)}(ep-1)\right| < \text{limit}_1, \forall k, v, l \tag{4}$$

$$\left|RMSE(ep)\text{ - }RMSE(ep\text{ -}1)\right| < \text{limit}_2 \tag{5}$$

$$ep \geq \max\_\,epochs \tag{6}$$

where $w_{kv}^{(l)}$ is the weight between l- layer's k-neuron and (l-1)- layer's v- neuron, $RMSE = \sqrt{\frac{1}{m_2 \cdot q_{out}}\sum_{m=1}^{m_2}\sum_{k=1}^{q_{out}} e_k^2(m)}$ is the root mean square error of the evaluation set with m_2 members and q_{out} neurons of the output layer (in this case q_{out} =1), $\max\_\,epochs$ is the maximum number of the epochs.

Two variations have been applied for each training algorithm. In the first one (a) all the above criteria are applied, whereas in the second variation (b) only the first and the third criterion are applied.

The parameters of each ANN algorithm are optimized according to the procedure described in [9] - [11]. These parameters are: the number of neurons of the hidden layer, the formula and parameters of the activation function of the hidden and output layer, and various other parameters depending on the training algorithm.

After optimizing the parameters of every training algorithm, the one, which presents the highest correlation index (R^2) between the experimental and the estimated values of ground resistance for the evaluation set, is selected. It is noted that:

$$R^2 = r_{y-\hat{y}}^2 = \frac{\left(\sum_{i=1}^{n}\left((y_i - \bar{y}_{real})\cdot(\hat{y}_i - \bar{y}_{est})\right)\right)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_{real})^2 \cdot \sum_{i=1}^{n}(\hat{y}_i - \bar{y}_{est})^2} \tag{7}$$

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

In Table II the optimized parameters (number of neurons (N_n), learning rate (a_0), constant term of learning rate (T_a), momentum term (η_0), constant term of momentum (T_η), activation functions for the hidden (f_1) and the output layer (f_2)) of each variation are presented. For all the variations of the training algorithm, the maximum number of epochs is selected to be equal to 7000.

In Table III the average error (G_{av}) and the correlation (R^2) between the estimated and the measured values of ground resistance are tabulated for the training, evaluation and test set.

TABLE II
PARAMETERS OF THE TRAINING ALGORITHMS

Training Algorithm	N_n	a_0	T_a	h_0	T_h	**Activation Functions**
1a	2	0.9	1400	0.7	1000	$f_1(x)= 1/(1+e^{-1.9x})$ $f_2(x)=0.3x$
1b	18	0.5	1500	0.9	1600	$f_1(x)=\tanh(1.9x)$ $f_2(x)=1/(1+e^{-0.4x})$
2a	23	0.4	1300	0.7	1500	$f_1(x)=\tanh(1.2x)$ $f_2(x)=\tanh(0.3x)$
2b	10	0.5	1500	0.5	1400	$f_1(x)=\tanh(1.4x)$ $f_2(x)=0.2x$
3a	7	-	-	1.3	-	$f_1(x)=\tanh(1.3x)$ $f_2(x)= \tanh(0.2x)$
3b	9	-	-	0.8	-	$f_1(x)=\tanh(1.4x)$ $f_2(x)=1/(1+e^{-0.4x})$

TABLE III
AVERAGE ERROR AND CORRELATION BETWEEN THE ESTIMATED AND MEASURED VALUES OF RESISTANCE

Training Algorithm	$Gav{\times}10^{-3}$			R^2		
	training set	evaluation set	test set	training set	evaluation set	test set
1a	0,5487	0,5289	0,3619	0,9909	0,9920	0,9953
1b	0,2621	0,3128	0,3595	0,9954	0,9953	0,9961
2a	0,1711	0,1925	0,3377	0,9971	0,9969	0,9953
2b	0,1685	0,2379	0,3642	0,9977	0,9971	0,9955
3a	0,1923	0,1932	0,3583	0,9969	0,9969	0,9949
3b	0,1462	0,2075	0,3362	0,9975	0,9968	0,9957

The performance of the ANN for the optimum combination of parameters for each training algorithm is presented in Table IV where the experimental values of the ground resistance and those estimated by the ANN for the test set are tabulated. In the same table the mean absolute percentage error (MAPE) given by (8) is recorded.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \qquad (8)$$

where y_i is the actual value and $\hat{y}_i$ is the estimated value of the ground resistance.

The low values of MAPE for each training algorithm depict the success of the method in estimating the ground resistance.

TABLE IV
REAL AND ESTIMATED VALUES OF GROUND RESISTANCE OF THE TEST SET PER ALGORITHM

	Ground resistance values (Ω)						
	Training Algorithm						Measured
	1a	1b	2a	2b	3a	3b	
1	35.1	35.3	34.9	34.8	34.9	34.9	34.9
2	38.4	38.5	38.3	38.5	38.3	38.7	38.0
3	18.9	18.9	18.8	18.9	18.7	18.7	19.3
4	18.8	19.1	19.1	19.4	19.0	19.2	19.5
5	20.0	19.9	19.6	19.7	19.6	19.5	20.0
6	27.8	28.0	27.9	27.9	27.8	27.8	27.8
7	17.1	17.4	17.0	16.7	17.2	16.9	16.7
8	18.7	18.5	18.1	18.3	18.0	18.2	18.2
9	19.7	19.8	19.9	20.1	19.9	19.9	19.5
10	20.0	19.9	20.0	20.2	20.0	19.9	18.8
MAPE%	1.98	2.10	1.86	1.71	2.10	1.81	

From Table III it can be easily observed that the training algorithm which provides the highest correlation between the estimated and the measured data for the evaluation set is the stochastic training algorithm with use of adaptive rules for learning rate and momentum term with two termination criteria (2b).

In Figs. 8 and 9 the measured and the estimated values of the ground resistance for the best training algorithm for the evaluation and the test set along with the confidence intervals with 5% probability are presented.

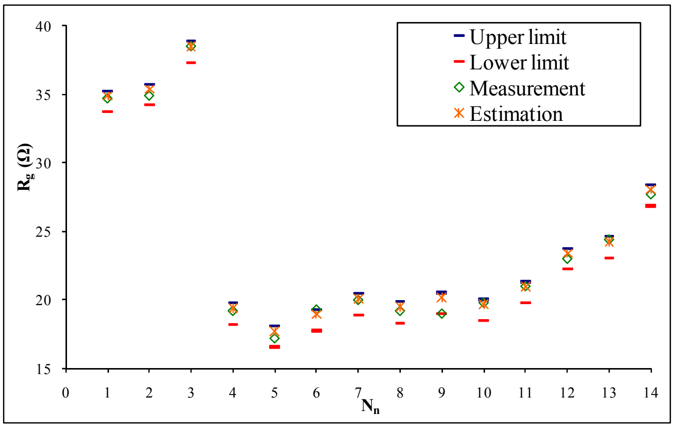

Fig. 8 Actual and estimated values of the ground resistance for the evaluation set for stochastic training algorithm with use of adaptive rules for learning rate and momentum term (algorithm 2b).

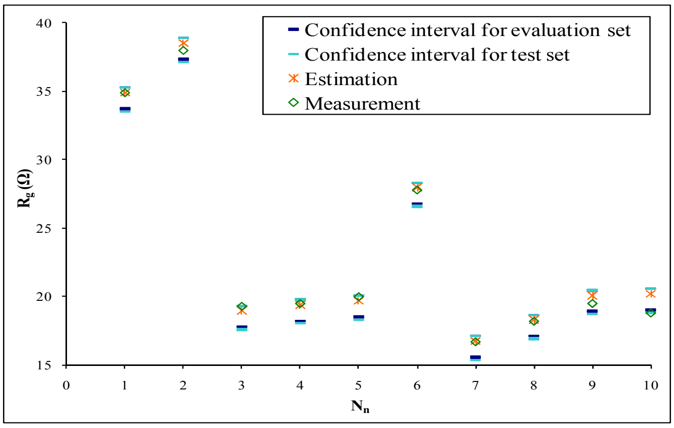

Fig. 9 Actual and estimated values of the ground resistance for the test set for stochastic training algorithm with use of adaptive rules for learning rate and momentum term (algorithm 2b).

IV. CONCLUSIONS

ANNs have been trained and validated for estimating the ground resistance of a grounding rod given soil resistivity and rainfall data from previous week measurements. The back propagation algorithm with stochastic presentation of the training vectors has been used and the estimated values of the ground resistance are found to be in good agreement with the experimental data. Among the training algorithms, the one with use of adaptive rules for learning rate and momentum term with use of two stopping criteria provides the highest regression index of the evaluation set. The effectiveness of the ANN in predicting the ground resistance is verified by the fact that the regression index of the test set is respectively high.

Furthermore, the absence of limitations regarding number of the input and the output variables of the ANN makes possible the incorporation of experimental data for longer time periods, new parameters such as soil temperature, water content, type and size of the grounding system. However, one should always keep in mind that ANNs have the ability to learn the relationship between inputs and output according to the patterns that have been presented and have been used for the training. Therefore, in case data for a different type of grounding system is used as test set it is expected that ANN will not be effective and retraining of the ANN is required. Besides, the sensitivity of the ANN on different training scenarios can be verified by taking into consideration that in [10] the same experimental data have been used however different training and test sets have been formed. In [10] the best training algorithm was stochastic training with learning rate and momentum term with two stopping criteria. The regression being achieved was 99.78% for the evaluation set and 97.46% for the test set.

Consequently, it is recommended that whenever the grounding system's characteristics change the ANN should be retrained in order to achieve the best performance. However, in case the behaviour of a similar grounding system should be examined a previously trained ANN could be used and is expected to produce satisfactory results.

As a conclusion it can be stated that the work presented in this paper could be used as a guideline for further research on the applicability and the development of artificial intelligence techniques for grounding systems. In future work new scenarios for different grounding systems can be examined while the sensitivity of the ANN to variations of the training and test sets should be investigated.

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