

# Artificial Neural Network Methodology for the Estimation of Ground Resistance

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*Abstract:* - Aim of this paper is the estimation of the variation of ground resistance throughout the year by using Artificial Neural Networks. Based on measurements of soil resistivity, temperature, and rainfall during a period of time, various algorithms for training Artificial Neural Networks have been tested regarding their ability to predict the ground resistance. In order for the parameters of each training algorithm to be selected; an optimization procedure has been followed. The effectiveness of the Artificial Neural Network is proved through the high correlation index between the estimated and the measured values of the ground resistance.

*Key-Words:* - Soil resistivity measurements, ground resistance, Artificial Neural Network (ANN), back propagation algorithm.

## 1 Introduction

The role of the grounding system for a power installation is undoubtedly very important, as it provides a low resistance path to fault current, protects personnel against electric shocks due to dangerous step and touch voltages and reduces the damages to electric and electronic equipment. The contribution of soil resistivity in the value of ground resistance ( $R_g$ ) is great. Soil resistivity ( $\rho$ ) depends on many factors, such as moisture, temperature, salt content, type of the soil etc. [1], [2] and varies significantly throughout the year, reaching maximum values during summer months [3]. The purpose of this study is to predict the behaviour of the ground resistance of a single rod during a period of time by using Artificial Neural Networks (ANNs) that have been trained with experimental data of soil resistivity and weather conditions. On that purpose a methodology for the optimization of the parameters of different training algorithms and the selection of the optimum algorithm has been implemented. So far the methodology has been successfully applied in [4]-[6]. Moreover, ANNs have been used by Salam et al. [7] and Amaral et al. [8] for modeling the ground resistance behavior

## 2 Artificial Neural Network Methodology

ANNs are programmed computational models that aim to replicate the function of the human brain. They have gained wide acceptance due to their features that include: solving complex problems, identifying non-linear relationships among data that are known to be difficult to model using classical methods, ability to generalize and learn (produce adequate responses to unknown situations), and capability of greater fault tolerance.

### 2.1 Type of ANN

There are many kinds of ANN structures with different characteristics and implementations. In this study a Multilayer Perceptron (MLP) has been used. A typical MLP consists of three layers: the input, the hidden and the output layer. The number of neurons of the input and output layer are equal to the size of the input and output data vector respectively, while the number of neurons of the hidden layer (or layers) has to be determined. According to Kolmogorov's theorem if the number of neurons of the hidden layer is properly selected, then a single hidden layer is enough [9].

## 2.2 Normalization

Prior to conducting the training operation, the input and output values are normalized, in order to avoid saturation problems, caused when non-linear activation functions are used. The normalized value  $\hat{x}$  (for the variable  $x$ ) is given by (1):

$$\hat{x} = \alpha + \frac{b - \alpha}{x_{\max} - x_{\min}}(x - x_{\min}) \quad (1)$$

where  $x_{\min}$  and  $x_{\max}$  are the minimum and the maximum values of variable  $x$ ,  $a$  and  $b$  are the respective values of the normalized variable [5], [6].

## 2.3 Data set

The experimental data set (which comprises 81 vectors of input-output data) is divided randomly into three sets:

- The training set (50 cases) is used until the network has learned the relationship between the inputs and the outputs.
- The evaluation set (17 cases) is used for the selection of the ANN parameters.
- The test set (14 cases) provides an independent test of the network generalization ability to data that have never been presented to the network before.

## 2.4 ANN training algorithms

The ANN is trained with the use of Back Propagation Algorithm and its variations. Table 1 shows the algorithms that have been used [6]. The purpose of the training process is to minimize the average error function between the estimated and the actual value, by adjusting the free parameters (weights) of the network. The adjustment of the weights is performed using two different methods with regard to the timing: in the stochastic mode (algorithms 1-3) each input vector is randomly presented, in the batch mode (algorithms 4-11) the adjustment of the weights is performed after the serial presentation of all the input vectors has been completed. The average error function for all  $N$  patterns is given by (2):

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

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

## 2.5 Stopping Criteria

The weights of the ANN are adjusted until one of the stopping criteria is fulfilled. The three stopping criteria are: the weights' stabilization criterion, the error function's minimization criterion and the maximum number of epochs' criterion [6]. It should

be mentioned that two cases have been examined for each algorithm regarding the convergence. In case (a) all three criteria were used, while in case (b) only the first and the third.

Table 1 ANN's training algorithms

1	Stochastic training with learning rate and momentum term (decreasing exponential functions)
2	Stochastic training, use of adaptive rules for the learning rate and the momentum term
3	Stochastic training, constant learning rate
4	Batch mode, constant learning rate
5	Batch mode with learning rate and momentum term (decreasing exponential functions)
6	Batch mode, use of adaptive rules for the learning rate and the momentum term
7	Batch mode, conjugate gradient algorithm with Fletcher-Reeves equation
8	Batch mode, conjugate gradient algorithm with Fletcher-Reeves equation and Powell-Beale restart
9	Batch mode, conjugate gradient algorithm with Polak-Ribiere equation
10	Batch mode, conjugate gradient algorithm with Polak-Ribiere equation and Powell-Beale restart

## 3 Soil Resistivity Measurements

In order to train the ANN, the soil resistivity and ground resistance of a rod have been measured for a period of 10 months [3].

The measurements of soil resistivity were conducted according to the Wenner method. As shown in Fig.1 four electrodes 50cm in length are driven in line, in a depth of 45cm ( $b$ ) at equal distances  $\alpha$  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  $\Omega$ .

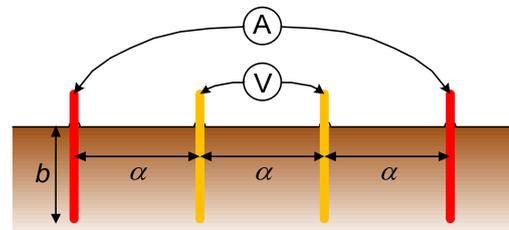


Fig.1 Wenner method

The apparent soil resistivity  $\rho$  in  $\Omega m$  is given by the following formula [1]:

$$\rho = \frac{4\pi\alpha R}{1 + \frac{2\alpha}{\sqrt{\alpha^2 + 4b^2}} - \frac{\alpha}{\sqrt{\alpha^2 + b^2}}} \quad (3)$$

If  $a \gg b$  the apparent resistivity is calculated by:

$$\rho = 2\pi\alpha R \quad (4)$$

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

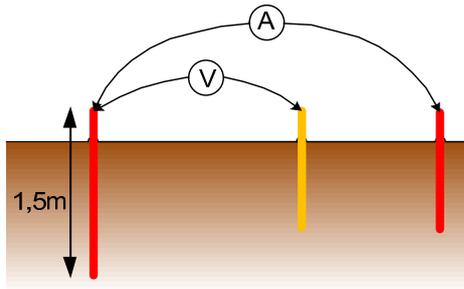


Fig.2 Fall of potential method

The ground resistance  $R_g$  is measured according to the fall of potential method and the 62% rule [1]. 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.2).

In Figs. 3-4 the seasonal variation of the resistivity for different distances between the four electrodes and the ground resistance, respectively, are presented. In order to evaluate the effect of weather conditions the measurements were repeated in scheduled time intervals. In Figs. 5-6 the respective weather conditions are given. The National Meteorological Authority of Hellas provided the meteorological data (average day rainfall and temperature).

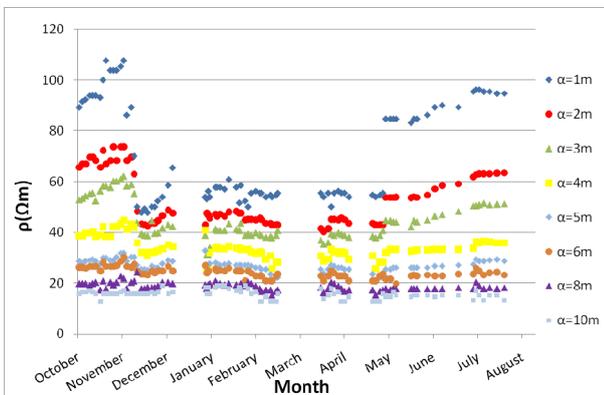


Fig.3 Seasonal variation of soil resistivity for different distances between the electrodes

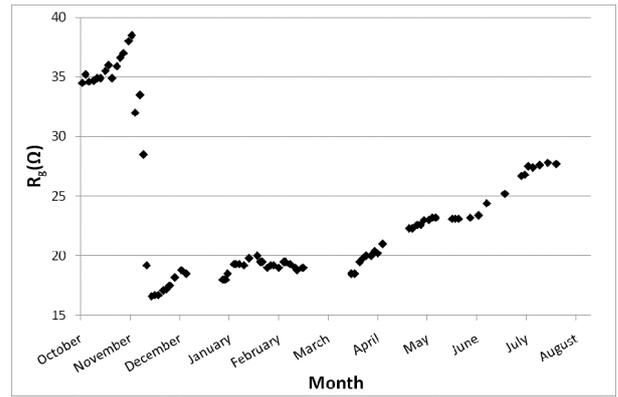


Fig.4 Seasonal variation of ground resistance

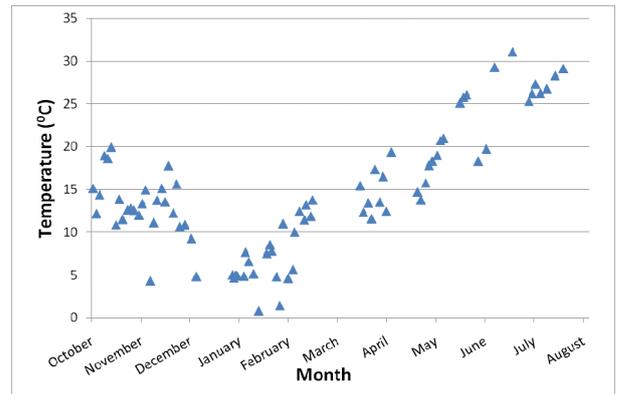


Fig.5 Average day temperature

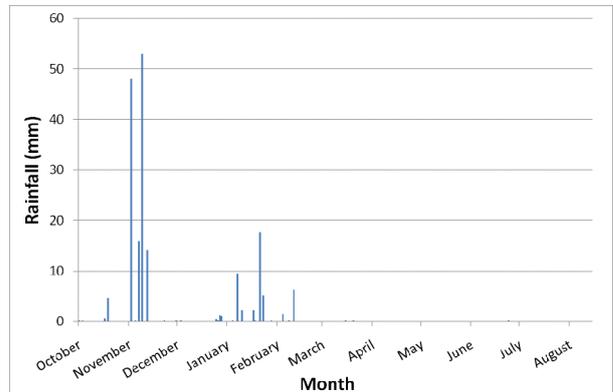


Fig.6 Average day rainfall

## 4 Application of the Artificial Neural Network Methodology

### 4.1 Input-Output Data

The input vector consists of 12 variables: 8 measurements of soil resistivity for various spacings between the electrodes, the average day temperature and the average day rainfall of the same and the previous day from the measurement. The output variable is the ground resistance.

### 4.2 Optimization process

The parameters of each algorithm are determined through an optimization process (set of trials). The parameters that have to be determined are: the

number of neurons of the hidden layer, the form and parameters of the activation function of the hidden and output layer, and various other parameters depending on the training algorithm. The methodology, which is developed, is described analytically for the case of 5b algorithm which was proven to have given the best results for this application (highest correlation between estimated and experimental values for the test set).

1. Firstly, the optimal number of neurons  $N_n$  is determined. All the other parameters of the network are given fixed values while the number of neurons varies. The maximum number of epochs is set to 7000. The optimal  $N_n$  is selected as the one with the smallest average error function ( $G_{av}$ ) for the evaluation set. In the case of 5b algorithm, the variation of  $G_{av}$  for all sets with variation of neurons from 2 to 50 is seen in Fig.7. It is chosen  $N_n=49$ , which minimizes the average error of the evaluation set.

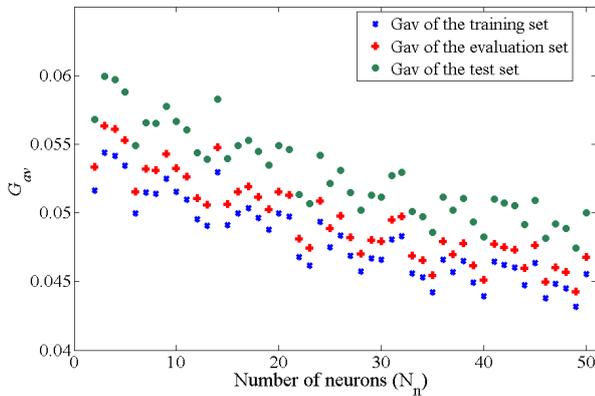


Fig.7  $G_{av}$  for all sets while varying the number of neurons

2. While the number of neurons is held constant (as it was determined in the first step), the parameters of the algorithm [6] are varied in a proper interval. The other ANN's parameters (maximum number of epochs, type and parameters of activation functions) are still given fixed values. With the criterion of minimum  $G_{av}$  for the evaluation set the proper values are selected.

In the case of 5b algorithm, the time parameter  $T_a$  and the initial value of the momentum term  $\alpha_0$ , were varied as seen in Figure 8a. It is chosen  $T_a=3000$ ,  $\alpha_0=0.9$ . Figure 8b shows the variation of  $G_{av}$  for the evaluation set with variation of the time parameter  $T_n$  and the initial value of the learning rate  $\eta_0$ . It is selected  $T_n=4500$  and  $\eta_0=4$ .

3. The next step is the determination of the type of the activation functions. In this study three activation functions can be used:

Logistic:  $f(x)=1/(1+e^{-ax})$  (5)

Hyperbolic tangent:  $f(x)=\tanh(ax+b)$  (6)

Linear:  $f(x)=ax+b$  (7)

By making every possible combination for the activation functions of the hidden and the output layer and by changing the values of the parameters a and b, the most suitable functions for each method are selected. In 5b case it is selected:  $f_1(x)=\tanh(1.4x)$  for the hidden and  $f_2(x)=1/(1+e^{-0.7x})$  for the output layer. The  $G_{av}$  for this combination with variation of parameter  $a$  is given in Fig.9.

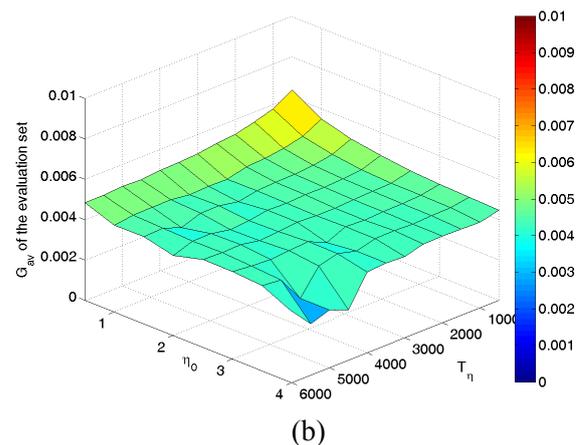
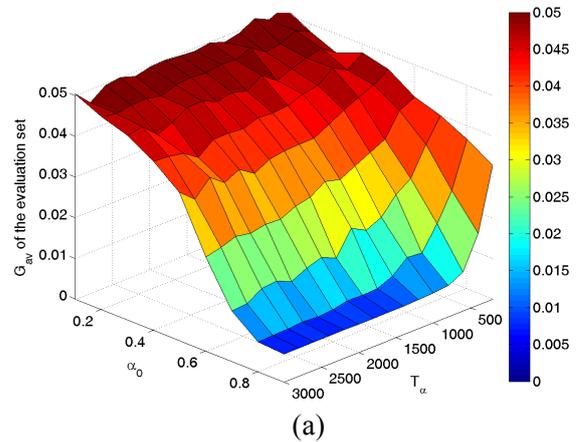


Fig.8  $G_{av}$  of the evaluation set with variation of the parameters of (a) momentum term (b) training term

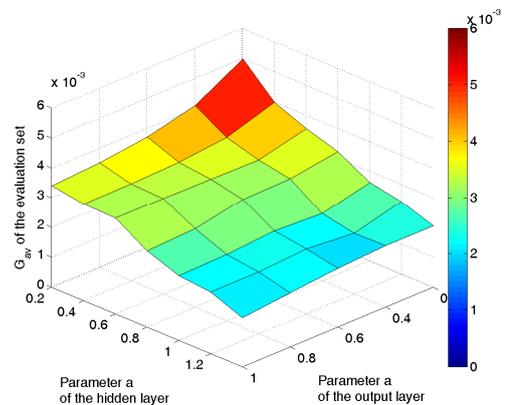


Fig.9  $G_{av}$  of the evaluation set when hyperbolic tangent activation function for the hidden layer and logistic for the output layer is used

4. When the optimization process for all training algorithms is completed, the proper training

algorithm is selected, as the one that gives the maximum correlation index ( $R^2$ ) between the actual and the estimated values of the evaluation set. The correlation index is given by the following formula:

$$R^2 = r_{y-\hat{y}}^2 = \frac{\left( \sum_{i=1}^n ((y_i - \bar{y}_{real}) \cdot (\hat{y}_i - \bar{y}_{est})) \right)^2}{\sum_{i=1}^n (y_i - \bar{y}_{real})^2 \cdot \sum_{i=1}^n (\hat{y}_i - \bar{y}_{est})^2} \quad (8)$$

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 respective data set.

### 3.8 Results

Table 2 shows the results for all training algorithms. It is observed that when using the criterion of

maximum correlation index for the test set, the algorithm 1b -Stochastic training with learning rate and momentum term and 2 stopping criteria- gave the best results among the stochastic training methods. The  $R^2$  achieved is 0.997821. Among all training methods, 6a algorithm- Batch mode with use of adaptive rules for the learning rate and momentum term and 3 stopping criteria- gave the maximum correlation index, 0.984362, between actual and estimated values (Fig. 10). In Table 3 the experimental and the estimated values of ground resistance as derived by the application of training algorithm 1b for the test set are presented.

Fig.11 depicts the success of 1b algorithm in estimating the ground resistance. In the same graph the confidence intervals of the evaluation and test set with 5% probability in each tail are shown. For the calculation of confidence intervals the re-sampling method has been used.

Table 2 Results of the ANN algorithms

Algorithm	$N_n$	Algorithm parameters	Activation functions	$R^2$ of the evaluation set	$R^2$ of the test set
1a	24	$\alpha_0=0.9, T_a=3000, \eta_0=0.9, T_\eta=2200$	$f_1(x)=\tanh(1.9x), f_2(x)=1/(1+e^{-0.25x})$	0.996224	0.987479
1b	24	$\alpha_0=0.9, T_a=3000, \eta_0=0.9, T_\eta=2600$	$f_1(x)=\tanh(1.95x), f_2(x)=1/(1+e^{-0.475x})$	0.997821	0.974564
2a	2	$\alpha_0=0.9, T_a=2600, \eta_0=0.6, T_\eta=2200$	$f_1(x)=\tanh(1.35x), f_2(x)=1/(1+e^{-0.4x})$	0.985354	0.985175
2b	3	$\alpha_0=0.9, T_a=1600, \eta_0=0.9, T_\eta=1600$	$f_1(x)=1/(1+e^{-2x}), f_2(x)=1/(1+e^{-0.05x})$	0.988076	0.970205
3a	22	$\eta_0=0.5$	$f_1(x)=\tanh(1.9x), f_2(x)=1/(1+e^{-0.2x})$	0.979209	0.982914
3b	4	$\eta_0=3.65$	$f_1(x)=\tanh(0.9x), f_2(x)=1/(1+e^{-0.1x})$	0.99104	0.988155
4a	2	$\eta_0=3.9$	$f_1(x)=\tanh(3.5x), f_2(x)=1/(1+e^{-0.25x})$	0.976697	0.983866
4b	2	$\eta_0=3.9$	$f_1(x)=\tanh(3.5x), f_2(x)=1/(1+e^{-0.25x})$	0.976697	0.983866
5a	23	$\alpha_0=0.95, T_a=4000, \eta_0=4, T_\eta=5600$	$f_1(x)=\tanh(x), f_2(x)=1/(1+e^{-0.8x})$	0.969811	0.988255
5b	49	$\alpha_0=0.9, T_a=3000, \eta_0=4, T_\eta=4500$	$f_1(x)=\tanh(1.4x), f_2(x)=1/(1+e^{-0.7x})$	0.96804	0.989945
6a	2	$\alpha_0=0.9, T_a=5500, \eta_0=5, T_\eta=2000$	$f_1(x)=1/(1+e^{-5x}), f_2(x)=1/(1+e^{-0.95x})$	0.984362	0.984262
6b	2	$\alpha_0=0.9, T_a=5500, \eta_0=5, T_\eta=2000$	$f_1(x)=1/(1+e^{-4.95x}), f_2(x)=1/(1+e^{-x})$	0.982636	0.985433
7a	2	$s=0.2, T_{bv}=20, T_{trix}=50, e_{trix}=10^6$	$f_1(x)=\tanh(0.9x), f_2(x)=0.35x$	0.975551	0.983509
7b	2	$s=0.2, T_{bv}=20, T_{trix}=50, e_{trix}=10^{-6}$	$f_1(x)=1/(1+e^{-1.9x}), f_2(x)=1/(1+e^{-0.4x})$	0.979862	0.983866
8a	6	$s=0.2, T_{bv}=20, T_{trix}=50, e_{trix}=10^{-6}$ $\lim_{orthogonality}=0.1$	$f_1(x)=\tanh(1.8x), f_2(x)=0.5x$	0.981427	0.979565
8b	6	$s=0.2, T_{bv}=20, T_{trix}=50, e_{trix}=10^{-6}$ $\lim_{orthogonality}=0.5$	$f_1(x)=\tanh(1.15x), f_2(x)=1/(1+e^{-0.5x})$	0.967882	0.988632
9a	7	$s=0.2, T_{bv}=20, T_{trix}=50, e_{trix}=10^{-6}$	$f_1(x)=\tanh(1.15x), f_2(x)=1/(1+e^{-0.5x})$	0.967233	0.984342
9b	7	$s=0.2, T_{bv}=20, T_{trix}=50, e_{trix}=10^{-5}$	$f_1(x)=\tanh(1.2x), f_2(x)=1/(1+e^{-0.55x})$	0.967902	0.982775
10a	6	$s=0.2, T_{bv}=20, T_{trix}=50, e_{trix}=10^{-5}$ $\lim_{orthogonality}=0.1$	$f_1(x)=\tanh(1.15x), f_2(x)=0.55x$	0.977824	0.977903
10b	5	$s=0.2, T_{bv}=40, T_{trix}=50, e_{trix}=10^{-6}$ $\lim_{orthogonality}=0.9$	$f_1(x)=\tanh(x), f_2(x)=1/(1+e^{-0.6x})$	0.975018	0.989508

Table 3 Measured ground resistance values against ANN's estimations by training algorithm 1b

Ground resistance values ( $\Omega$ )					
	Estimated	Measured		Estimated	Measured
1	34.9	34.6	8	19.4	19.0
2	35.4	35.5	9	19.7	18.5
3	36.0	37.0	10	17.6	20.2
4	31.0	28.5	11	23.3	23.2
5	17.1	17.2	12	22.6	23.2
6	18.0	18.0	13	24.6	24.4
7	19.3	19.2	14	27.4	27.6

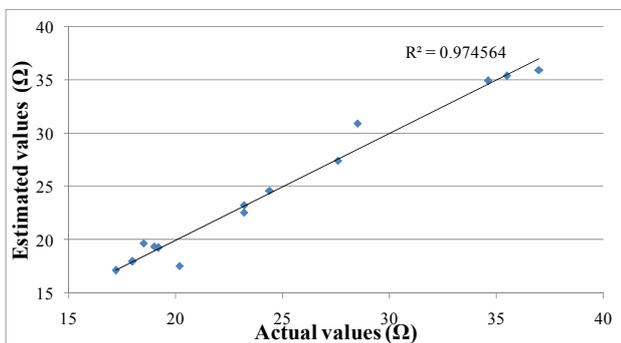


Fig.10 Correlation between estimated and actual values of the ground resistance for the test set (1b algorithm)

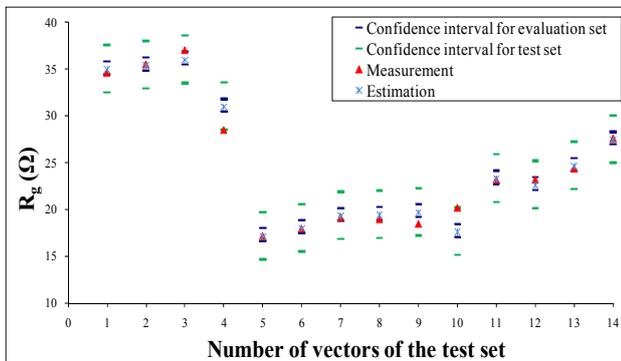


Fig.11 Actual, estimated values and confidence intervals of the evaluation and test set (algorithm 1b)

## 4 Conclusion

Several ANN models are developed and trained with 10 different methods, in order to predict the variation of ground resistance during the year. The data that were used for the training include not only measurements of soil resistivity and ground resistance, but also weather conditions. An optimization methodology, which is described in detail, is applied for every ANN. The results predicted by the proposed ANNs were more than satisfactory in all cases. In the best case the correlation between the actual and the predicted

values of the test set reached 99.7821%. The model is effective in predicting the ground resistance. The methodology is flexible and adjustable, therefore more parameters, if provided, can be used, for example soil humidity, soil composition, data for different ground systems, size of grounding system etc.

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