Estimation of Ground Enhancing Compound Performance Using Artificial Neural Network

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***Abstract*-Grounding system constitutes an essential part of the protection system of electrical installations and power systems against lightning and fault currents. Therefore, it is of paramount importance that engineers ensure as low values for grounding resistance as possible, during the designing phase as well as the lifecycle of the grounding system. A widely used technique of reducing the grounding resistance value, in case of high soil resistivity values, or lack of adequate space for the installation of grounding systems, is the use of ground enhancing compounds. This paper presents a methodology, for the evaluation of grounding resistance, under various meteorological conditions, of grounding systems embedded in natural soil as well as in ground enhancing compounds, using Artificial Neural Network (ANN). The ANN training is based on field measurements that have been performed in Greece during the last year. As a matter of fact, this is a first step to develop a new method for estimating variations of grounding resistance value.**

I. Introduction

Grounding plays an important role in transmission and distribution network for the safety operation of any electrical installation. A grounding system in order to be effective, its grounding resistance must be maintained in low levels during the whole year [1-2]. However, most of the cases of electrical installations are characterized by some specific technical difficulties, such as the lack of space for the installation of the grounding systems, the huge cost which often maybe prohibitive for the construction and the soil type where the system is about to be installed, because it plays a major role in determining the grounding resistance value. The soil type has to be taken severely into consideration in designing a grounding system due to, either its possible high soil resistivity, or its particularly corrosive environment. Furthermore, the varying weather conditions around grounding system area, in combination with the soil texture, compose a complex factor which crucially effects on the grounding resistance during the year.

A widely used technique of reducing the grounding resistance value, in case of high soil resistivity values, or lack of adequate space for the installation of grounding systems, is the use of ground enhancing compounds. The usage of ground enhancing compounds is strongly recommended especially in rocky soil, which is a usual attribute on many sites in Greece, due to the large number of rocky mountains. These materials are laid inside the trench, where the grounding electrode is installed and mixed with the natural soil. In this way, the soil resistivity around the electrode decreases, which results in a corresponding decrease of the grounding resistance value.

In bibliography, there is no reference recorded about studies on predicting the behavior of grounding systems, which are combined with ground enhancing compounds and moreover, based on field measurements performed in the past few years. This, may happen due to the fact that weather conditions vary constantly, so their effect on grounding resistance value is too difficult to be quantified. Therefore, Artificial Neural Networks (ANN) can confront with this challenge, because of their capability of recognizing the relations between quantities that are extremely difficult to be modeled.

Researchers, as Salam et al. [3] and L. Ekonomou [4], have successfully used ANNs to correlate electrode length with grounding resistance value. Amaral et al. [5] used an ANN in order to correlate soil resistivity, injection current frequency and peak current with grounding resistance value. Gouda et al. [6] developed an ANN for grounding system designing, consisted of vertical rods, while studies have been carried out aiming to investigate the seasonal variation of soil resistivity through an ANN approach [7].

II. Experimental Procedure

A. Installation and Experimental Array

In this work, five ground enhancing compounds were evaluated in field conditions. Five main grounding rods, *St/e-Cu* type A, dimensioned 17x1500mm, with a minimum copper thickness 254μm, have been driven, each one of them in different ground enhancing compounds. Apart from the five main rods, another one has been driven directly to natural soil as a reference electrode (see [8] for the installation details). The electrodes were tagged as follows: G_1: natural soil, G_2: conductive concrete, G_3: bentonite, G_4: chemical compound A, G_5: chemical compound B and G_6: chemical compound C

Additionally, seventeen auxiliary electrodes, of the same type with the main one, but 0.5m length, were installed permanently at different spots, for the soil resistivity and grounding resistance measurements (see [8] for details).

The measurements performed at the experimental field, in daily basis for one year, are [8]: i) Soil resistivity, ii) Grounding resistance of grounding rods and iii) Rainfall height.

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The experimental results for the variations of the soil resistivity and the grounding resistance of the enhancing compounds are presented in Figs. 1 and 2.

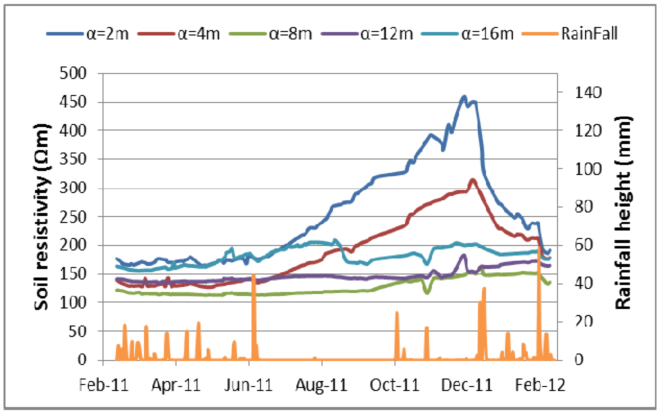

Figure 1. Soil resistivity versus time and rainfall height.

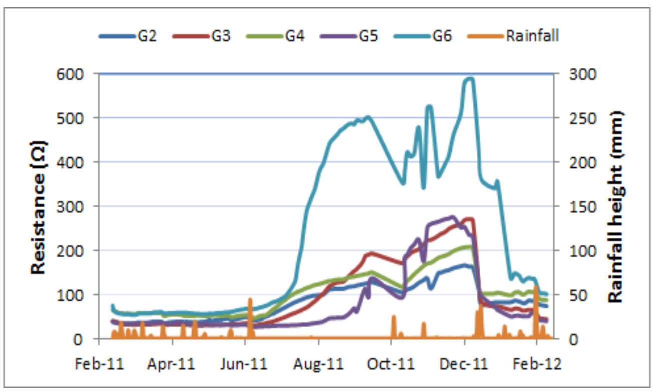

Figure 2. Grounding resistance of ground enhancement compounds versus time and rainfall height .

B. *Artificial Neural Network Methodology for the Estimation of Grounding Resistance*

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 nonlinear 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. In this study a Multilayer Perceptron (MLP) has been used.

A typical ANN is composed of three layers, the input, the hidden and the output layer. The input layer comprises the soil resistivity measurements (in Ωm) for electrode distances at 2m, 4m, 8m, 12m and 16m during previous week, average soil resistivity for electrode distances at 2m and 4m during previous month, the average rainfall height during previous week, the average rainfall height during previous month, and the rainfall height during the day on which the grounding resistance is estimated (in mm). The output variables (output layer) of the ANN are the grounding resistance of each grounding system (in Ω).

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.

The grounding resistance of the rod is estimated by applying the methodology presented in Fig. 3.Prior to conducting the training operation, the input and output values are normalized, in order to avoid saturation problems, caused when nonlinear activation functions are used. The normalized value $\hat{x}$ (for the variable x) is given by (1):

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

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 set (which comprises 126 vectors of input-output data) is divided randomly into three sets:

- The training set (102 cases) is used until the network has learned the relationship between the inputs and the outputs.
- The evaluation set (26 cases) 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 test set (24 cases) verifies the generalization ability of the ANN by using an independent data set.

The ANN is trained with the use of Stochastic training with learning rate and momentum term (decreasing exponential functions). 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 as follows: each input vector is randomly presented; the adjustment of the weights is performed after the random presentation of all the input vectors has been completed 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 (2):

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

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

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, which are respectively described by the following expressions:

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

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

$$ep \geq \max\_epochs \quad (6)$$

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.

The parameters are selected so that the minimum G_{av} for the evaluation set is achieved.

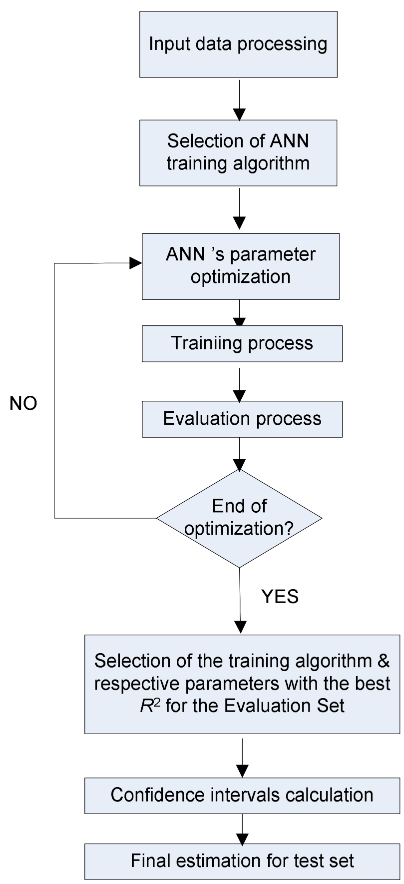

Figure 3. Flowchart of the ANN methodology for the estimation of the grounding resistance.

III. Application of ANN

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 Fig. 4 the G_{av} of the evaluation sets with variation of neurons from 2 to 25 is presented. The number of neurons is chosen to be N_n=21.

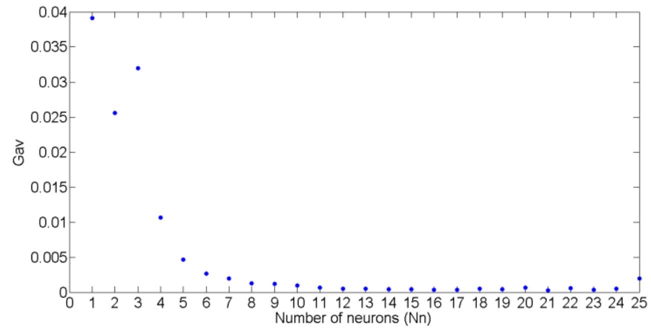

Figure 4. Gav for the evaluation set for varying number of neurons.

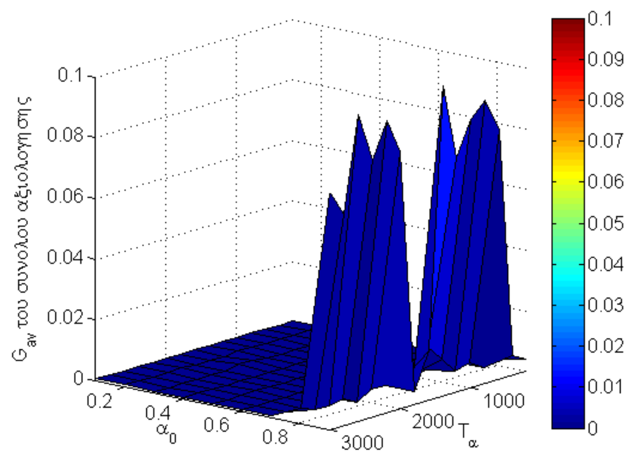

Figure 5. Gav of the evaluation set with variation of the parameters of momentum term.

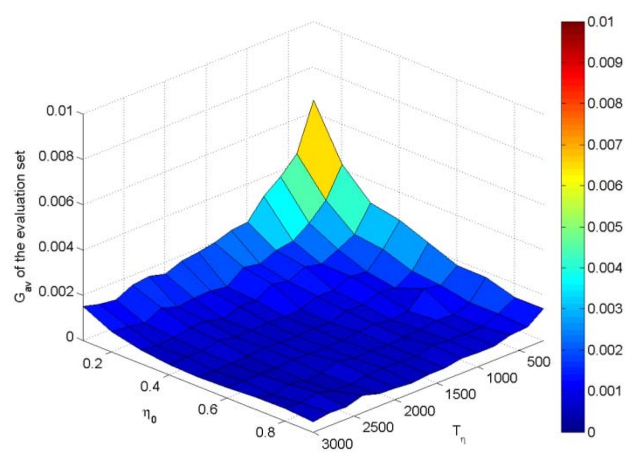

Figure 6. Gav of the evaluation set with variation of the parameters of training term.

Afterwards, the number of neurons is held constant (equal to 21), the parameters of the algorithm are varied in a proper interval. The time parameter T_α and the initial value of the momentum term α_0, were varied as seen in Fig. 5. It is chosen T_α=1500, α_0=0.4. Figure 6 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 η_0. It is selected T_n=2400 and η_0=0.8. Then the type of the activation functions is determined. The following activation functions have been examined:

Logistic: $f(x) = 1/(1 + e^{-ax})$ (7)
Hyperbolic tangent: $f(x) = tanh(ax + b)$ (8)
Linear: $f(x) = ax + b$ (9)

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 our case it is selected: $f_1(x) = tanh(2x)$ for the hidden and $f_2(x) = 1/(1+e^{-0.5x})$ for the output layer. The G_{av} for this combination with variation of parameter a is given in Fig. 7.

In Table I the experimental and the estimated values of the grounding resistance, as derived by the application of the training algorithm for the test set, are presented. In the same table also presented the regression estimated by (7):

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

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

TABLE I
MEASURED GROUNDING RESISTANCE VALUES AGAINST ANN'S ESTIMATIONS

	Ground Resistance values (Ohm)											
	G_1		G_2		G_3		G_4		G_5		G_6	
	actual	estimated	actual	estimated	actual	estimated	actual	estimated	actual	estimated	actual	estimated
1	141.9	143.7	38.2	37.7	32.6	31.9	57.9	57.6	35.2	36.2	58.3	55.8
2	109.6	118.9	34	37.1	32	30.7	51.2	55.2	33.2	32.4	57.3	56.9
3	134.1	127.8	38.7	39.3	32.4	32.2	53.6	53.7	33.8	34.5	58.6	57.6
4	112.3	108.7	37.5	36.9	29.7	29.5	51	51.8	30.1	31.3	55	56.3
5	115.4	115.0	40.6	38.7	30	30.6	51.9	52.0	31.1	31.5	56.3	58.5
6	122.3	115.2	42	41.6	30.8	31.7	52.3	51.4	31.4	30.4	58.4	62.1
7	101.6	147.6	41.3	44.0	32	33.5	48.8	54.1	29.7	32.8	60.6	64.1
8	115.3	119.6	45.6	46.7	33	33.5	52.1	53.2	30.7	30.9	64.9	63.8
9	106	109.1	45.1	46.8	32.6	33.6	52.2	52.6	27.1	27.4	71.6	71.4
10	119.8	123.0	56	58.1	38.8	40.2	66.2	67.2	28.8	29.0	82.2	81.4
11	138.6	133.6	70.5	69.4	48.8	47.0	87.3	86.5	29.4	29.8	95.2	94.2
12	183.7	184.8	89.8	89.2	66.6	68.1	111	112.5	31.7	31.4	233	223.2
13	247.4	235.7	98.3	99.3	92.3	89.1	123.2	121.6	36.2	33.3	372.4	371.2
14	326.8	327.7	112.2	112.7	121.3	124.6	131.3	133.3	46.2	47.5	449.4	450.0
15	238	236.9	107.3	107.5	180.8	174.3	123.6	125.3	183.5	170.0	377	406.7
16	428	413.8	149.3	145.2	237.2	232.9	185.1	178.8	267	267.5	375	365.1
17	143	132.7	77.1	74.3	46.8	46.9	90	87.8	42.5	43.8	105	110.7
18	180.5	174.1	80.6	83.4	63.2	63.2	99.5	102.9	50.5	51.5	130	132.8
19	174	265.4	77.3	94.0	84	135.0	102.6	123.1	98	90.4	363	292.3
20	477	485.4	164.2	165.6	260	268.9	205	209.2	252	258.5	511	571.2
22	222	314.5	110	113.8	128	219.7	120	162.5	125	268.0	430	503.4
22	384	385.9	123.4	124.7	173.7	178.1	144.8	145.4	101	90.7	493	499.1
23	212	234.3	104.3	106.0	171	167.1	116.9	121.4	93	154.8	354	410.6
24	137	129.8	36.1	36.2	31.9	30.7	57.5	57.0	34.8	34.8	57.1	54.9
R^2	0.932		0.990		0.924		0.958		0.851		0.979	

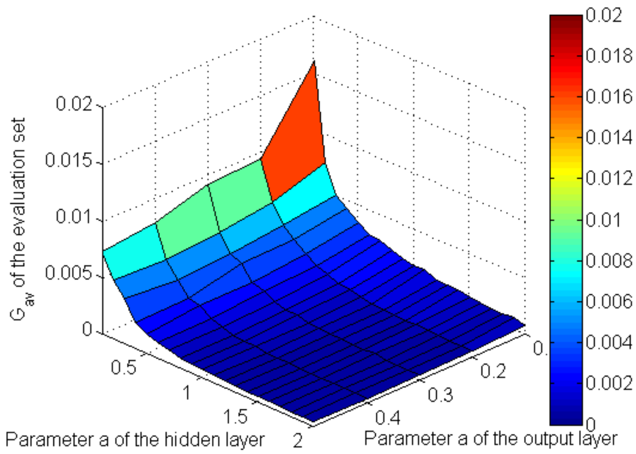

Figure 7. Gav of the evaluation set when hyperbolic tangent activation function for the hidden layer and logistic for the output layer is used.

IV. Discussion - Conclusions

An ANN based on back propagation algorithm with stochastic training method with learning rate and momentum term was trained in order to predict the variation of grounding resistance of different grounding systems during the year. The data that were used for the training include measurements of soil resistivity at different depths and rainfall height data for previous time periods (previous week and previous month). An optimization methodology, which is described in detail, is applied for the optimization of the parameters of the ANN. The outputs of the ANN were the values of the grounding resistance for electrodes buried in ground enhancing compounds and in natural soil. The results predicted by the proposed ANNs were more than satisfactory in all cases. The highest regression between experimental and estimated grounding resistance values has been achieved for G_2 grounding system. Whereas the correlation between estimated and measured values of the grounding resistance of G_5 reached 0.851. If all the grounding system data are considered, the overall regression is 0.962. Moreover, this deviation in regression factors among the grounding systems can be attributed to the fact that the optimization procedure is based on minimizing the overall G_{av} and not maximizing the regression index of each output.

In general, it can be stated that the model is effective in predicting the grounding resistance. The methodology is flexible and adjustable. More parameters, if provided, can be added, for example soil temperature, soil type, size of grounding system as well as the number of outputs can be adjusted according to the need.

However, one should keep in mind that the ANNs have the ability to learn the relationship between inputs and output according to the patterns that have been used for the training. Therefore, in case of using data for a different grounding system type as a test set, it is expected that ANN will not be effective and retraining of the ANN is required.

References

[1] ANSI/IEEE Std 80-2000, "IEEE Guide for safety in AC substation grounding", 2000.

[2] ANSI/IEEE Std 81-1983, "IEEE guide for measuring earth resistivity, ground impedance, and earth surface potentials of a ground system", 11 March 1983.

[3] M. A. Salam, S. M. Al-Alawi and A. A. Maquashi, "An artificial neural networks approach to model and predict the relationship between the grounding resistance and the length of the buried electrode in soil", *Journal of Electrostatics*,vol. 64, 2006, pp. 338-342.

[4] L. Ekonomou, "High voltage transmission lines studies with the use of artificial intelligence", *Electric Power Systems Research*, 79, 2009, pp. 1655-1660.

[5] F. C. L. Amaral, A. N. de Souza and M. G. Zago, "A novel approach to model grounding systems considering the influence of high frequencies", *Proceedings of the 5th Latin-American Congress: on Electricity Generation and Transmission* (*CLAGTEE 2003)*, Sao Pedro, Brasil, November 16-20, 2003.

[6] O. E. Gouda, M. G. Amer and M. T. El Saied, "Optimum design of grounding systems in uniform and non-uniform soils using ANN", *International Journal of Soft Computing*, vol. 1, no. 3, 2006, pp. 175-180.

[7] F. E. Asimakopoulou, G. J. Tsekouras, I. F. Gonos and I. A. Stathopulos, "Artificial neural network approach on the seasonal variation of soil resistance", *Proceedings of the 7th Asia-Pacific International Conference on Lighnting* (*APL 2011*), Chengdu, China, pp. 794-799, November 1-4, 2011.

[8] V. P. Androvitsaneas, I. F. Gonos and I. A. Stathopulos, "Performance of ground enhancing compounds during the year", *31st International Conference on Lightning Protection-ICLP*, Vienna, Austria, September 2nd–7th, 2012, in press.