Electromagnetic field identification using artificial neural networks

T.I. MARIS[1] L. EKONOMOU[2] G.P. FOTIS[3] A. NAKULAS[4] E. ZOULIAS[3]

[1]Technological Educational Institute of Chalkida, 334 40 Psachna Evias
[2]Hellenic Public Power Corporation S.A., 22 Chalcocondyli Str., 104 32 Athens
[3]National Technical University of Athens, 9 Iroon Politechniou Str., 157 80 Athens
[4]National & Kapodistrian University of Athens, 11 Asklipiu Str., 153 54 Athens
GREECE

Abstract: This work presents a novel method based on artificial neural networks (ANNs) for the prediction of the transient electromagnetic field radiating by generators of electrostatic discharges constructed according to an IEC standard. Actual input and output data collected from measurements carried out in the High Voltage Laboratory of the National Technical University of Athens are used in the training, validation and testing process. The proposed ANN method which can easy and accurate assesses the electromagnetic field produced by electrostatic discharges by simply measuring the discharge current can be used by laboratories facing either a lack of suitable ESD test equipment or want to compare the results to their own measurements.

Key-Words: Electrostatic Discharge (ESD), Equipment Under Test (EUT), Electric Field, Magnetic Field, Artificial Neural Networks, Pellegrini Target, International Standard IEC 61000-4-2, ESD generators.

1. Introduction

Electrostatic Discharge (ESD) is a common and destructive phenomenon. Robustness of the electric and electronic equipment towards ESD is tested according to the IEC 61000-4-2 Standard [1]. The standard describes the test procedure of electric and electronic equipment under electrostatic discharges and defines the waveform of the discharge current that the ESD generators must produce.

This paper presents measurements of the electric field using H and E-field probes, with the aim of contributing the upcoming version of the standard [1]. Many researchers have been involved in the study of the transient electromagnetic field radiating by electrostatic discharges [2-6]. It was observed that there is a strong probability that the Equipment Under Test (EUT) will pass a test, when conducting measurements using a certain Electrostatic Discharge (ESD) generator and fail when using another, both cases referring to the same charging voltage and to the same discharge current. This rises from the fact that each ESD generator produces a different electromagnetic field, causing the induced voltage to differ. This work aims to study the produced electric field, when the Pellegrini target is mounted on an insulating material instead of a metal plate as the standard defines, because this way there is a closer approach to the real ESD event.

In this paper artificial neural networks (ANNs) are addressed in order to assess the electric and the magnetic field radiating by electrostatic discharges. ANNs have seen increased usage in recent years in various fields such as finance [7], medicine [8], industry [9] and engineering [10, 11], due to their computational speed, their ability to handle complex non-linear functions and their robustness and great efficiency, even in cases where full information for the studied problems is absent.

Actual electromagnetic field measurements, radiated by electrostatic discharges carried out in the High Voltage Laboratory of the National Technical University of Athens are used in order to train, validate and test the proposed ANN model. The proposed ANN model can be used by laboratories facing either a lack of suitable ESD test equipment or want to compare the produced results to their own measurements. Having in mind that in the forthcoming revision of the IEC 61000-4-2 [1], measurements of the radiating electromagnetic field during the verification of ESD generators will be almost certainly included, the authors strongly believe that the proposed ANN method will be broadly useful, since the electromagnetic field produced by electrostatic discharges, can be easily and accurately assessed by simply measuring the discharge current.

2. Experimental setup

Fig. 1 shows the experimental set-up for the measurement of the magnetic and electric field respectively. The current and the magnetic field (H-field) or the electric field strength (E-field) for various charging voltage levels were measured simultaneously, by the 4-channel Tektronix oscilloscope model TDS 7254B, whose bandwidth ranged from dc to 2.5GHz. The electrostatic discharges were contact discharges and they were conducted using two Schaffner's ESD generators. The experiment was conducted only for contact discharges, because air discharges are difficult to be reproduced.

The ESD generators used were the NSG-433 and the NSG-438. The discharge electrode in both generators had the same length and it was equal to 5 cm. In order for the measurement set-up to be unaffected by surrounding systems, the experiment was conducted in an anechoic chamber. The generator's capacitance was charged at ±2 kV and ±4 kV the discharge electrode of the ESD generator used for the contact discharge measurements had a sharp point. The temperature and relative humidity were 23 ± 1 ^{o}C and 40 ± 4 %, respectively. For the current measurement a resistive load was used, as the IEC defines. This resistive load (Pellegrini target MD 101) was designed to measure discharge currents by ESD events on the target area and its bandwidth ranged from dc to above 1 GHz. The Pellegrini target was mounted on an insulating material made of plastic. This material was placed on a wooden surface, as it can be seen in Fig. 1. The pulses that the ESD generators produce are reproducible, as it was found by the palm graphs of the ESD current for many electrostatic discharges for the same charging voltage and for both the ESD generators [12].

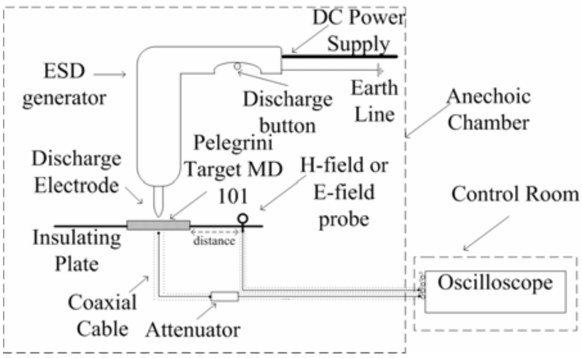

Fig. 1: Experimental set-up for the measurement of the electric or magnetic field.

The probes that were used for the experiment were the loop probe of 3 cm in diameter and the sphere probe of 3.6 cm in diameter of the HZ-11 set of Rohde & Schwarz, for the measurement of the magnetic and electric field respectively. The probes were placed at various distances and in two perpendicular directions (X and Y axis) at the horizontal plane from the discharge point, as it can be seen in Fig. 2. At each point (Fig. 2) six measurements were conducted measuring each time the discharge current and the electric or magnetic field. This was done in order to calculate the average and the standard deviation of the electric field at each point.

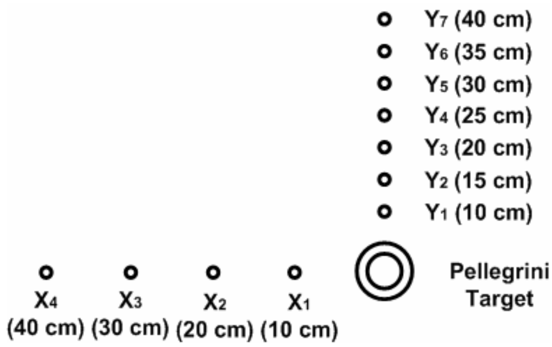

Fig. 2: The measurement points in the two perpendicular directions on the HCP (Horizontal Coupling Plane) where the field probes were placed.

3. Experimental results

Fig. 3(a) and Fig. 3(b) depict representative H-field waveforms in relation to the discharge current for the first 200 ns, respectively, when the H-field sensor are placed at a distance of 10 cm (Y1 point) from the discharge point for the two ESD generators. Fig. 4 and Fig. 5 depict the peak H-field and E-field, respectively, for charging voltage of ±2 kV for the NSG-433 and NSG-438 ESD generators. It is obvious that each generator produces different electromagnetic field.

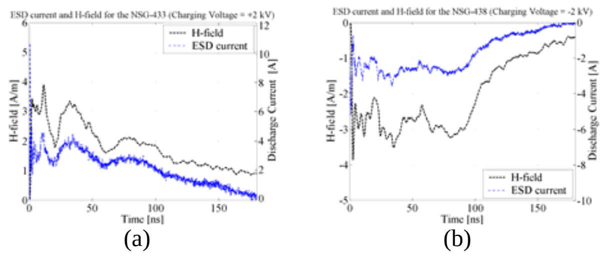

Figure 3: ESD current and H-field for the two ESD generators 10 cm from the discharge point.

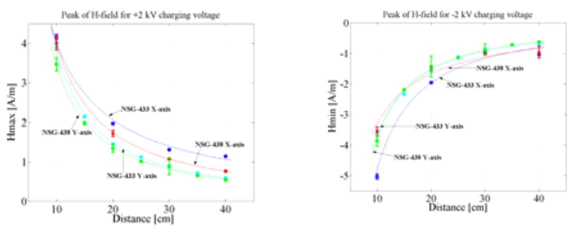

Figure 4: Peak of H-field for various distances in the two perpendicular directions from the discharge point, using the NSG-433 and NSG-438 ESD generators and for two different charging voltages

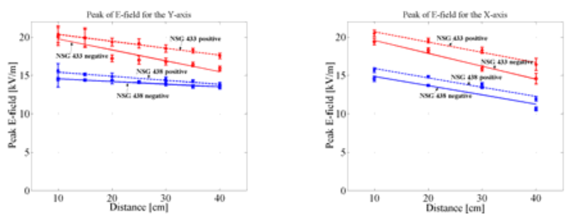

Figure 5: Peak of E-field for various distances from the discharge point at the X and Y-axis using the ESD generators NSG-433 and NSG-438.

4. Artificial neural networks

Artificial neural networks represent a parallel multilayer information processing structures. The characteristic feature of these networks are that they consider the accumulated knowledge acquired during training and respond to new events in the most appropriate manner, giving the experience gained during the training process. The model of an ANN is determined according to the network architecture, the transfer function and the learning rule. In this work a typical neural network model known as conventional multilayer perceptron model (MLP) has been used. The conventional MLP network consists of nonlinear differentiable transfer functions. The backpropagation learning rules are used to adjust the weights and biases so as to minimize the sum squared error of the network. This is achieved by continually changing the values of the network weights and biases in the direction of steepest descent with respect to error [13].

In order to train the network, a suitable number of representative examples of the relevant phenomenon must be selected so that the network can learn the fundamental characteristics of the problem. The backpropagation training may lead to a local rather than a global minimum. The local minimum that has been found may be satisfactory, but if it is not, a network with more layers and neurons may do a better job. However, the number of neurons or layers to add may not be obvious. Conventional MLP architecture is generally decided by trying varied combinations of number of hidden layers, number of nodes in a hidden layer etc. and selecting the architecture which has a better generalizing ability amongst the tried combinations [14].

Once the training process is completed and the weights and bias of each neuron in the neural network is set, the next step is to check the results of training by seeing how the network performs in situations encountered in training and in others not previously encountered.

5. Artificial neural networks implementation

The goal of this work is to develop an ANN model capable to assess with accuracy the electric and magnetic field radiating by ESD generators. Eight parameters that play important role in the assessment of the electric and magnetic field radiating by electrostatic discharges are considered as the inputs to the neural networks, while as outputs are considered the peak value of the electric and the peak value of the magnetic field. These data, presented in Table 1, constitute actual data recorded during measurements carried out in the High Voltage Laboratory of the National Technical University of Athens, using the method and the measurement system presented in section 2.

Table 1: ANN input and output data.

Input Variables	**Output Variables**
- ESD generator (*G*)	- peak value of electric field (E_{max})
- charging voltage (*U*)	- peak value of magnetic field (H_{max})
- rise time (t_r)	
- maximum discharge current (I_{max})	
- current at 30 ns (I_{30})	
- current at 60 ns (I_{60})	
- distance (*d*)	
- direction (*D*)	

Several hundreds of measurements have been performed using each one of the two ESD generators, i.e. the NSG-433 and the NSG-438 produced by Schaffner. In each one measurement the parameters which varied and could take different values were: a) the type of the ESD generator (NSG-433 or NSG-438), b) the generator's charging voltage (±2 kV, ±4 kV), c) the two perpendicular directions (direction X and direction Y) (Fig. 2), d) the distances from the discharge point on the metal plane (10 cm, 20 cm, 30 cm, 40 cm for direction X and 10 cm, 15 cm, 20 cm, 25 cm, 30 cm, 35 cm, 40 cm for direction Y) and e) the current waveform parameters (rise time, maximum discharge current, current at 30 ns and current at 60 ns). Thus, these several hundreds of measurements constitute combinations of all the above varying parameters.

In order to address the assessment of the electric and magnetic field radiating by electrostatic discharges a multi layer perceptron ANN was considered. As it is mentioned earlier each ANN model is determined according to its structure, the transfer function and the learning rule, which are used in an effort the network to learn the fundamental characteristics of the examined problem. The structure of the networks i.e. the number of hidden layers and the number of nodes in each hidden layer, is generally decided by trying varied combinations for selecting the structure with the best generalizing ability amongst the tried combinations, considering that one hidden layer is adequate to distinguish input data that are linearly separable, whereas extra layers can accomplish nonlinear separations [15]. This approach was followed, since the selection of an optimal number of hidden layers and nodes for a MLP network is still an open issue, although some papers have been published in these areas [16]. The designed and tested MLP ANN models were combinations of three learning algorithms (the Gradient Descent, the Quasi-Newton and the Levenberg-Marquardt), three transfer functions (the Hyperbolic Tangent Sigmoid, the Logarithmic Sigmoid and the Hard-Limit) and several different structures (1 to 3 hidden layers and 2 to 30 neurons in each hidden layer).

The proposed ANN models were trained using the MATLAB Neural Network Toolbox [17]. One thousand seven hundred and sixty values of each input and output data, were used to train and validate the artificial neural network. These data refer to measurements conducted with each one of the two ESD generators in every possible combination of generator's charging voltage, distance from the discharge point on the metal plane, perpendicular direction and current waveform parameter. In each training iteration (epoch), 20 % of random data (i.e. three hundred fifty two) were removed from the training set and a validation error was calculated for these data. The training processes were repeated until a root mean square error between the actual outputs (peak value of electric field and peak value of magnetic field) and the desired outputs reach the goal of 0.5 % or a maximum number of epochs (it was set to 10,000), is accomplished [18].

Finally, the estimated values of the electric and magnetic fields were checked with the values obtained from situations encountered in the training, i.e. the one thousand seven hundred and sixty values and others which have not been encountered.

Table 2: ANN architectures.

No.	Structure	Epochs	Learning Rule	Transfer Function
1	8/19/8/2	8348	Lev-Mrq	Log-Sig
2	8/13/11/2	9629	Grd-Desc	Log-Sig
3	8/22/24/2	10000	Lev-Mrq	Hyp-Tang
4	8/11/26/4/2	9711	Grd-Desc	Hyp-Tang
5	8/7/8/10/2	9509	Grd-Desc	Log-Sig
6	8/26/21/2	10000	Qua-New	Log-Sig
7	8/10/11/14/2	8612	Grd-Desc	Log-Sig
8	8/14/23/2	9890	Lev-Mrq	Hyp-Tang
9	8/9/8/5/2	9935	Qua-New	Hard-Lim
10	8/14/8/2	10000	Grd-Desc	Log-Sig
11	8/19/25/2	9881	Lev-Mrq	Hyp-Tang
12	8/8/8/15/2	10000	Lev-Mrq	Hard-Lim
13	8/10/13/2	8427	Grd-Desc	Log-Sig
14	8/29/23/2	10000	Qua-New	Log-Sig
15	8/12/9/20/2	10000	Grd-Desc	Hyp-Tang

After extensive simulations with all possible combinations and the construction of several models, it was found that the ANN model that has presented the best generalizing ability, had a compact structure, a fast training process and consumed lower memory than all the other tried combinations was consisted of 2 hidden layers with 19 and 8 neurons in each hidden layer and was using the Levenberg-Marquardt learning rule and the Logarithmic Sigmoid transfer function. The mean square error of the selected model was minimized to the final value of 0.005 within 8348 epochs. Table 2 presents the fifteen best ANN architectures which all fulfill almost equally the pre-mentioned criteria.

6. Results

The trained ANN for the estimation of the electric and magnetic field radiating by electrostatic discharges has been applied to twenty different case studies, which have not taken part in the training, validation and testing processes. The produced ANN results, which are presented in Table 3, have been compared to actual values of electric and magnetic field measured during experiments performed in the N.T.U.A.'s High Voltage Laboratory for exactly the same parameters (table 3).

Table 3: Measured electric and magnetic field versus ANN results.

No. of sets	E_{max} (kV/m)		H_{max} (A/m)	
	Measured	ANN	Measured	ANN
1	14.56	14.14	-1.04	-1.09
2	20.07	20.17	-3.57	-3.41
3	19.92	19.72	-2.34	-2.45
4	17.21	17.60	-1.59	-1.45
5	17.00	16.68	-1.10	-1.14
6	-28.71	-27.86	4.99	5.19
7	-27.34	-26.43	2.49	2.52
8	-27.01	-28.09	1.65	1.62
9	-25.11	-26.11	1.42	1.38
10	-32.80	-34.11	5.06	5.16
11	21.47	20.87	-4.22	-3.45
12	19.41	20.72	-2.52	-2.46
13	16.81	17.40	-1.69	-1.67
14	-27.32	-28.75	4.81	5.11
15	25.61	26.43	-2.36	-2.48
16	21.91	21.79	-1.61	-1.69
17	-28.43	-28.57	2.59	2.72
18	-27.70	-26.81	1.81	1.92
19	-26.93	-26.01	1.44	1.31
20	27.35	27.44	-4.65	-4.78

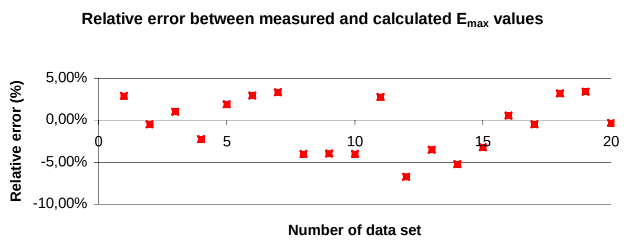

Fig. 6: Relative error between measured and calculated E_{max} values.

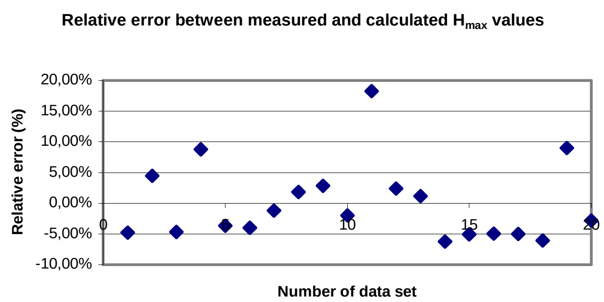

Fig. 6: Relative error between measured and calculated H_{max} values.

The results obtained using the developed ANN model are very close to the actual measured ones, something which clearly implies that the proposed ANN method is well working and has an acceptable accuracy. Figs 6 and 7 present the percentage error between actual measured and ANN's results.

7. Conclusions

In this paper an artificial neural network is addressed in order to estimate the electric and magnetic field radiating by electrostatic discharges. The results of the developed ANN model proved its accuracy, since they are very close to the actual measured ones, something which clearly implies that the proposed ANN method is well working. With the proposed ANN method, the produced electromagnetic field radiating by electrostatic discharges, can be calculated easily and accurately by measuring the discharge current. This will be extremely useful for the laboratories involved in the ESD tests since they will be able to conduct the verification of the ESD generators, after the revision of the current standard in which measurements of the electromagnetic field will be compulsory.

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