Estimation of the flashover voltage on insulators using Artificial Neural Networks

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Abstract: **-** This work attempts to elucidate the potentials of Artificial Neural Networks (ANNs) in high voltage applications and especially to estimate the flashover voltage on polluted insulators, using an ANN which is trained with the error backpropagation algorithm. For this purpose, an ANN was constructed in MATLAB and has been trained with several MATLAB training functions, while tests regarding the number of neurons, the number of epochs and the value of learning rate have taken place, in order to find which net architecture and which value of the other parameters give the best result. Some of the data had resulted from former experiments, while some other had resulted by applying a mathematical type based on a simplified model for the calculation of the flashover voltage.

Key-Words: - Insulators, flashover, critical voltage, pollution, artificial neural networks, error backpropagation

1 Introduction

The critical flashover voltage of a polluted insulator is a significant parameter for the condition of power systems. The reliability of a power system is dependent on environmental and weather conditions, which cause flashovers on polluted insulators, leading to system outages. Therefore several approaches have been developed for the estimation of the flashover voltage on polluted insulators.

The two types of insulator pollution are marine and industrial. The coexistence of both pollution (marine and/or industrial) and moisture (as dew, fog or drizzle rain) is an unfavorable condition for the operation of insulators. The presence of electrolytic particles and moisture can form a thin film with high conductivity on the insulating surface. This layer reduces the surface resistance, leading to the flow of a leakage current. The result of this current is the ohmic heating of the surface and the creation of dry bands. Once a dry band is formatted, partial discharges can take place within it and if the voltage and the leakage current reach certain values, there can start the flashover phenomenon [1].

There are several techniques used for smoothing this phenomenon and some of them include a periodical cleaning of the polluted insulators. However, if the washing and maintenance program is not reliably established, the cost increases dramatically. Therefore it is very important to know which are the parameters that affect the flashover phenomenon and for which values of these parameters the risk of a flashover is increased. The way each of these parameters contributes to the appearance of a flashover is usually not known; or perhaps, the complexity of the flashover phenomenon introduces an uncertainty. In this point, ANNs prove to be a very useful tool for the estimation of the flashover voltage of insulators. The ANNs have the ability to automatically “learn” approximate relations between inputs and outputs, without being affected by the complexity or the size of the problem.

In the field of high voltage insulators, ANNs can be used to estimate the pollution level [2, 3], to predict a flashover [4, 5], to analyse surface tracking on polluted insulators [6] and also to estimate the critical flashover voltage on a polluted insulator. This last case will be examined thoroughly later.

2 Experimental measurements and data collection

Data concerning cap and pin type insulators was used for the training and testing of the ANN. Specifically, the following geometric characteristics were used as input variables: the maximum diameter D_m (in cm) of the insulator, its height H (in cm), the creepage distance on it L (in cm), its form factor F and the layer conductivity σ_s (in μS), while the output variable was the critical flashover voltage U_c (in kV).

The experiments were carried out in an insulator test station, installed in the High Voltage Laboratory of Public Power Corporation's Testing, Research and Standards Center in Athens [7] and according to the IEC standard 507:1991 [8]. In this station tests have been performed on artificially polluted insulators, in order to determine the critical flashover voltage. The pollution was simulated according to the solid layer-cool fog method. Apart from this set of experimental measurements, other measurements were used too, from experiments performed by Zhicheng et al [9] and Sundararajan et al [10].

The mathematical model for the evaluation of the flashover process of a polluted insulator consists of a partial arc spanning over a dry zone and the resistance of the pollution layer in series, as shown in Figure 1, where V_{arc} is the arcing voltage, R_p the resistance of the pollution layer and U a stable voltage supply source.

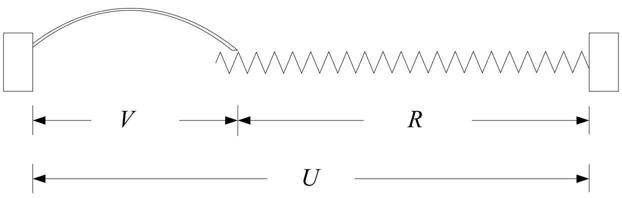

Fig. 1: Equivalent circuit for the evaluation of the flashover voltage.

The critical voltage U_c (in V), which is the applied voltage across the insulator when the partial arc is developed into a complete flashover, is given by the following formula [11]:

$$U_c = \frac{A}{n+1} \cdot \left(L + \pi \cdot n \cdot D_m \cdot F \cdot K \right) \cdot \left(\pi \cdot A \cdot D_m \cdot \sigma_s \right)^{-\left(\frac{n}{n+1}\right)} \quad (1)$$

where A and n are the arc constants. The calculation of the constants A and n is described thoroughly in [12] and their values are 124.8 and 0.409 correspondingly.

3 ANN algorithm

ANNs can model, with a great accuracy, a certain problem, utilizing the data from a learning set. This model can then be used to estimate the output variable for given values of the input variables. ANNs are trying to simulate the learning process, which is followed by the human brain, so they do not require certain mathematical functions, but examples in order to be trained.

An ANN consists of a number of single units, called neurons, bonded with weighted connections. In a successful learning process, the weights are gradually being modified in order to give an output close to the expected. An ANN can have three types of layers: the input layer, one or more hidden layers and the output layer. When creating an ANN one must first decide how many the neurons in each layer will be [13].

An ANN is usually trained with the error backpropagation algorithm, in which the occurring errors of the output layer return in the input layer to modify the weights. This procedure is repeated until the occurring errors reach accepted values.

In the present work an adaptive ANN has been designed in MATLAB and trained to estimate the critical flashover voltage, when the geometric characteristics of an insulator mentioned above are given. The total number of vectors, which include the input and output variables, was 118. The 80% of these 118 input-output patterns was decided to be used to train the network, while the rest 20% was used to test the function of the network. That means that the training set consisted of 94 vectors and the testing set consisted of 24 vectors. The initial set of 118 vectors was separated into two sets using a program in MATLAB. The separation was random, although the training set included the maximum and minimum values for each of the input variables.

The ANN was designed through an algorithm that used functions of MATLAB. The data used to train and test the network was set as matrices in different files, which were then called by the program. By changing some parameters in the code of this program, tests could be made with different training methods, in order to see which function gave the best results. The four training methods that were tested were: traingd, traingda, traingdx and trainlm and are all variations of the basic error backpropagation algorithm [14]. With traingd the network is trained according to the gradient descent backpropagation, with traingda the network is also trained according to the gradient descent backpropagation with adaptive learning rate. The function traingdx combines adaptive learning rate with momentum training. An adaptive learning rate is a learning rate that is adjusted according to an algorithm during training to minimize training time. Finally, trainlm uses the Levenberg-Marquardt

backpropagation [14].
For each one of those training methods a set of scenarios was taken, in which the parameter that was changing was the number of epochs. One epoch is the presentation of the set of training (input and target) vectors to the network and the calculation of new weights and biases. So, for each training method, there was a set of 10 scenarios, for a change at the number of epochs from 500 to 5000 with a step of 500. In each scenario there was an inner change of the number of neurons (from 2 to 25), in order to find the best architecture for the network, i.e. the number of neurons in the hidden layer that gives the minimum root mean squared error (*RMSE*) that is defined by the following type:

$$RMSE = \sqrt{\frac{1}{m_2}\sum_{i=1}^{m_2} e_k^2(i)} \qquad (2)$$

where m_2 is the number of the testing vectors and e_k the absolute difference between the real and the estimated flashover voltage for the testing set.

4 Results

For each training function, a 3D graph of the *RMSE* versus the number of neurons and the epochs has been made, in order to see which are the "areas" that minimize the error. Those 3D graphs are presented in Fig. 2 – Fig. 5.
As it is shown by the four figures below, the best results (minimum *RMSE*) are given by traingdx (gradient descent backpropagation with adaptive learning rate and momentum) for 6-12 neurons and approximately 1500 epochs. For over 13 neurons the network becomes unstable, giving very big errors. This was to be expected, as – according to an empiric rule – the number of neurons in the hidden layer should not be greater than the twofold of the input variables. The next step is to define for which value of the learning rate, this network gives minimum *RMSE*. To obtain this, the number of epochs was kept constant, the number of neurons changed from 6 to 12 (because the best results appeared in this area) and using as training method the traingdx, the learning rate altered from 0.1 to 0.9 with a step of 0.05. The minimum *RMSE* appeared for learning rate 0.3, 12 neurons and its value was 0.31. The momentum constant during the whole procedure had the default value 0.9, as defined by MATLAB.

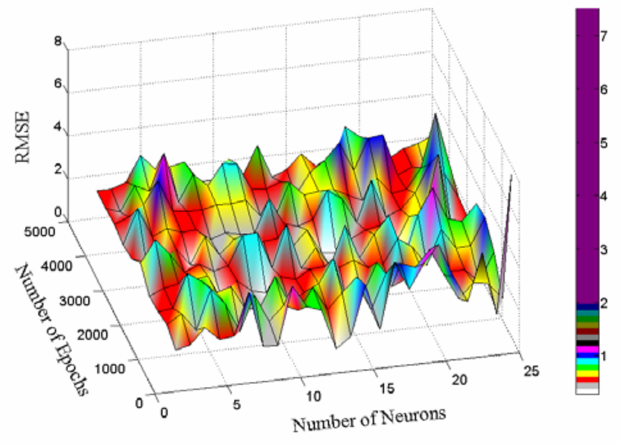

Fig. 2: *RMSE* versus number of neurons and number of epochs for traingd.

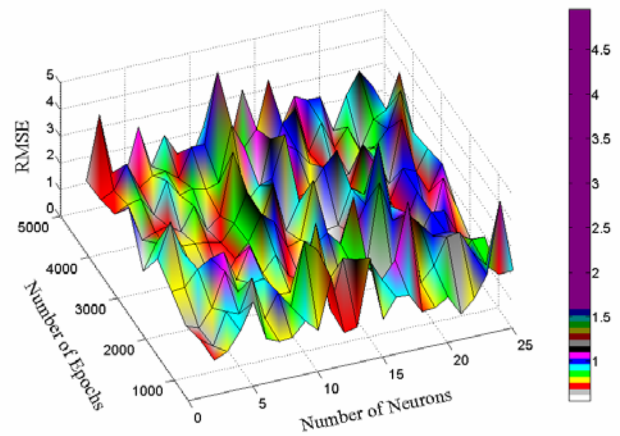

Fig. 3: *RMSE* versus number of neurons and number of epochs for traingda.

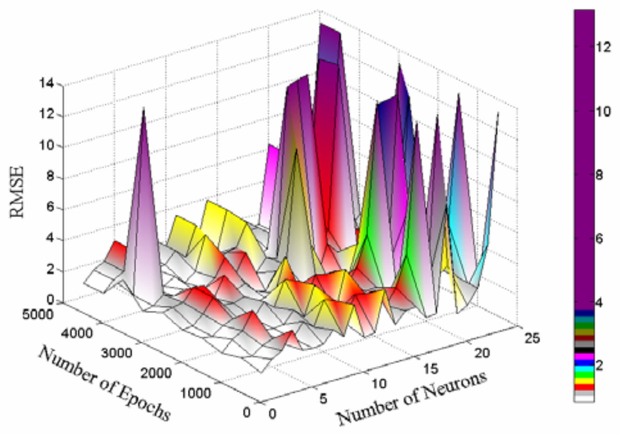

Fig. 4: *RMSE* versus number of neurons and number of epochs for traingdx.

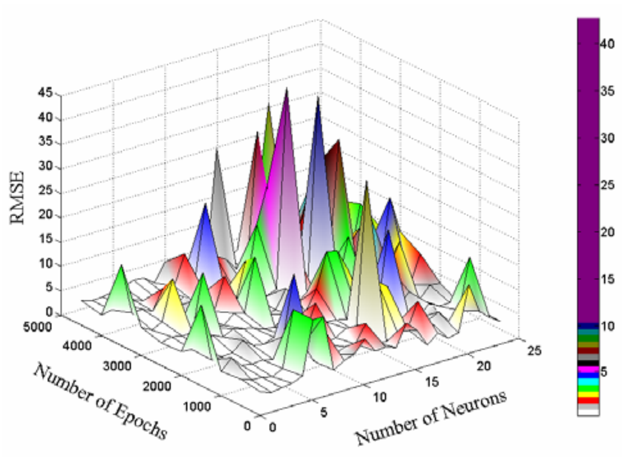

Fig. 5: *RMSE* versus number of neurons and number of epochs for trainlm.

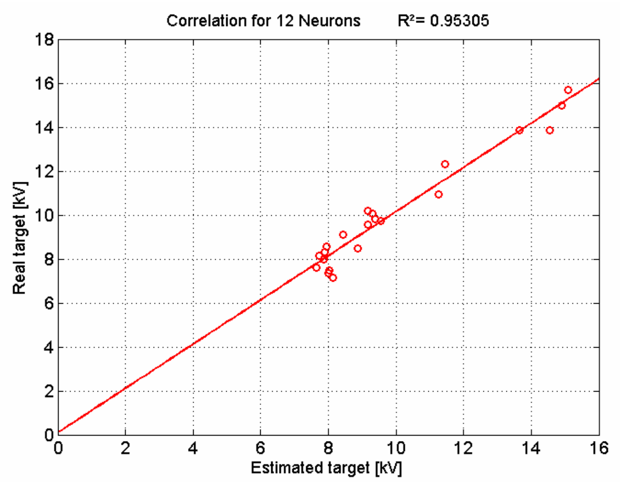

Fig. 6: Correlation between real and estimated values of U_c, for learning rate equal to 0.3.

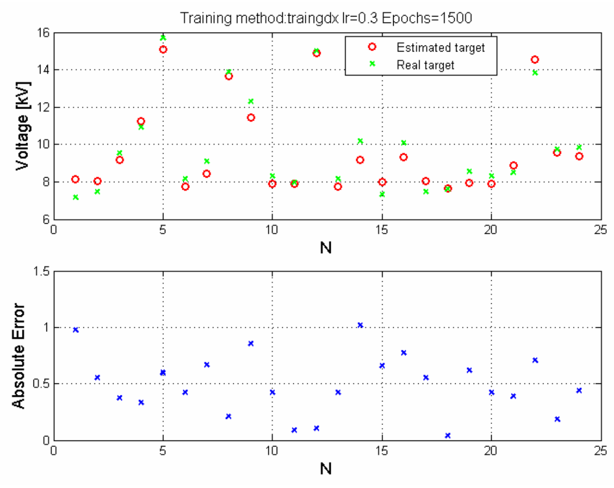

Fig. 7: Common graph for the 24 elements of the testing set and the 24 estimated values when the *RMSE* is minimum.

The correlation between real and estimated targets for this case is shown in Fig. 6, while Fig. 7 presents the 24 elements of the testing set (real values) and the corresponding 24 values given by the ANN (estimated values). As it is shown, the correlation is $R^2 = 0.95305$. It must be mentioned that the ideal value for the correlation is 1, so 0.95305 is not only an acceptable value, but also a very good one.

5 Conclusions

In this paper an ANN has been successfully applied for the estimation of the flashover voltage on polluted insulators. The network was trained to estimate the critical flashover voltage when some of the insulator's characteristics are given. This ANN was designed in MATLAB, using fixed functions for the construction of it, the initialization of the weights, the training procedure and the calculation of the errors. After performing several tests regarding the training method, the number of neurons in the hidden layer, the number of epochs and the value of the learning rate, it became clear that the combination which gave the best results were the following: the best training method appeared to be the gradient descent backpropagation with momentum and adaptive learning rate (traingdx) and the network showed a good convergence for about 12 neurons in its hidden layer, 1500 epochs and an initial value of 0.3 for the learning rate. The term "initial value" is used because the learning rate is adaptive; it means that it adapts during the learning proccess and according to the change of weights, so this initial value can change. However, a disadvantage is that no one can influence on the learning rate variation upon the time. Also, the momentum is kept constant during the learning process. If the ANN was designed in another programming language all these parameters could be adjusted to give the best results. Still, within the advantages of this network is the fact that programming in MATLAB is easier and more approachable to someone who is not accustomed to programming languages. A basic characteristic of MATLAB is that it makes possible the error handling (in that way, it is not possible for someone to make a logical error without noticing it), it is user friendly and the algorithm for the construction of the ANN is relatively small.
Something that could be examined in the future is the performance of some other tests with different populations, i.e. different training and testing sets. For example, instead of using the 80% of the total data as training set and the rest 20% as testing set,

the data of the training set could vary between 70% - 90%, respectively the data of the testing set could vary between 30% - 10% of the total data, in order to see the effect of that to the convergence of the network. To sum up, ANNs are a very useful tool with a big range of applications. One of these applications could be the estimation of the flashover voltage on insulators. Of course, as with every mathematical model, ANNs do not always give correct results (for example in cases of instability); however, there's, in any case, the possibility of improvement, since the first results are satisfactory.

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