Use Of Artificial Intelligence Techniques To Estimate The Flashover Voltage

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Abstract: *First this work present an optimization method based on genetic algorithms for the determination of the arc constants, using experimental results from artificially polluted insulators. The well known model of Obenhaus for pollution flashover is used. This model results in a system of equations which cannot be solved with conventional arithmetic methods. The application of genetic algorithms enables the definition of the arc constants, resulting also in the calculation of the critical conditions at the beginning of the pollution flashover mechanism. In this way a mathematical model is established, which simulates accurately the experimental results.*
Second this work attempts to apply an artificial neural network in order to estimate the critical flashover voltage on polluted insulators. The artificial neural network uses as input variables the following characteristics of the insulator: diameter, height, creepage distance, form factor and equivalent salt deposit density, and estimates the critical flashover voltage. The data used to train the network and test its performance is derived from experimental measurements and a mathematical model.

Keywords: *High voltage insulators; Polluted insulators; Critical flashover voltage; Genetics algorithms; Artificial neural network*

1. Introduction

The critical voltage flashover of a polluted insulator is a significant parameter of the reliability of a power system, where several approaches have been developed to estimate the flashover voltage.

The exposure of insulating material to different environmental conditions and pollution, in particular, is inevitable in all energy systems.

The experimental study of the critical voltage flashover takes a long time and encounters several obstacles, such as high cost and the need for special equipment, which are at the origin of the development of several approaches for estimating the flashover voltage of polluted insulators.

In insulators, artificial intelligence can be used to estimate the degree of pollution, prediction of the flashover, the analysis of tracks on the surfaces of polluted insulators and also the estimation of the flashover voltage an insulator polluted. This case will be carefully considered in this work.

This work tries to use the experimental values and the results of theoretical approaches to build and establish an ANN (neural network) which can estimate the value of the critical voltage flashover, and an AG (genetic algorithm) which determines the arc constants "*A*" and "*n*" of the mathematical model which gives the best results, using as data the characteristics of the insulator.

2. The Genetic Algorithms

The mathematical algorithm equivalent to the natural process of genetic biology used as an optimization technique is called genetic algorithm artificial.

Consider the problem of maximizing the function $f(x)$ where x ranges from "m" to "n". The function $f(x)$ is called the appropriate function (fitness). The initial population of chromosomes is randomly generated, ie the values of the variable "x" are randomly selected between "m" and "n". Suppose the values are $x_1, x_2, \ldots, x_L$ where "L" is the size of the population, they are called chromosomes in the biological context.

Genetic operators such as crossover and mutation are made for $2L$ chromosomes as described below:

Two chromosomes are randomly selected from the population, i.e. two numbers are selected.

The operation of crossing generates two other numbers y_1 and y_2 using the numbers selected.

Either the selected numbers are x_3 and x_9. y_1 is calculated as follows:

$$y_1 = r \cdot x_3 + (1-r) \cdot x_9 \quad (1)$$

And even y_2 is calculated:

$$y_2 = (1-r) \cdot x_3 + r \cdot x_9 \quad (2)$$

Where "r" is a random number generated from "0" and "1".

The same operation is repeated "L" times to obtain "$2L$" new chromosomes generated. The mutation operation is made for chromosomes obtained to move to $2L$ mutated chromosomes. i.e. the number generated y_1 is mutated to obtain z_1 which is calculated mathematically as:

$$z_1 = r_1 \cdot y_1 \quad (3)$$

Where "r_1" is a random number generated from "0" and "1".

So the new group of chromosomes obtained after crossover and mutation is [z_1, z_2, …., z_{2L}].

Among $2L$ values obtained after the genetic operations, "L" values will be selected by the law of wheel [1].

2-1. Mathematical model

The process of polluted insulators flashover has been carefully studied by several researchers. The simplest model of the pollution layer is the one developed by Obenhaus [2] which consists of an arc which shorts the dry zone in series with an equivalent resistance in the wetted area. Applying Ohm's law to the circuit of "Figure1":

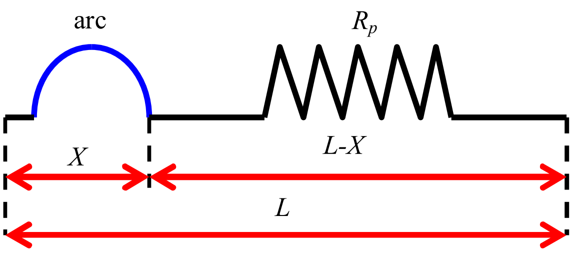

Figure 1
Equivalent circuit model of Obenaus

Thus the voltage across the insulator will:

$$U = x A I^{-n} + (L-x) R_p I \quad (4)$$

Where:

xAI^{n} : is the arc voltage. $(L-x)\ R_pI$: the voltage in the layer of pollution.

x : The length of the arc. L : The creepage distance of the insulator.

R_P : The resistance per unit length of the pollution layer.

I: Leakage current. A et n : are the constants of the arc.

Measure the resistance R_p of the wetland is very complicated. So it can be substituted for the conductivity σ_p of the layer of pollution [3] :

$$\sigma_p = (369.05 \cdot C + 0.42) \cdot 10^{-6} \quad (5)$$

C : is the equivalent salt density deposition (ESDD) in mg/cm^2

To validate the relation (4) at the critical moment of flashover. Wilkins has introduced a coefficient k to change the resistance RP of the layer of pollution considering the current concentration at the foot point of arc, the simplified formula for the calculation of k for cap and pin insulators is:

$$k = 1 + \frac{n+1}{2 \cdot \pi \cdot F_i \cdot n} \cdot Ln\left(\frac{L}{2 \cdot \pi \cdot F_i \cdot R}\right) \quad (6)$$

R: is the radius of the arc foot (in cm) and is given by [3]:

$$R = 0.469 \cdot (\pi \cdot A \cdot D \cdot \sigma_p)^{\frac{1}{2 \cdot (n+1)}} \quad \textbf{(7)}$$

And the critical voltage is calculated by:

$$U_c = \frac{A}{n+1} (L + \pi \cdot D \cdot F_i \cdot k \cdot n) \cdot (\pi \cdot D \cdot \sigma_p \cdot A)^{\frac{-n}{n+1}} \quad (8)$$

Where D is the diameter of the insulator.

2-2. Application to the estimation of flashover voltage

Most work on polluted insulators uses characteristic constants of the arc "A" and "n" for various atmospheres assuming that the discharge propagates through a humid atmosphere or in water vapor. Gonos and topalis [4] have proposed A = 124.8 and n = 0.409, these values can converge to good results for most problems. Farzaneh [5] recommend a combination A = 208.9 and n = 0.449 on a surface covered with ice Using a sample of ice triangular. Ghosh and Chatterjee [6] found that the values of "A" and "n" depends on chemical pollutants. Zegnini [7] showed using the equation of Ayrton, that the variation of the arc length has a significant effect on these constants. M El-A.Slama et al in their turn have shown that these characteristics are not static and have a relationship with the equivalent circuit parameters and thermal characteristics of the discharge.

Hence the difference in the values proposed for the constants "A" and "n" (table.1)[8].

Table 1.

The constants « A » and « n »

Autors	The constant « A »	The constant « n »
Alston et Zol	63	0,760
Wilkins	63	0,760
Rahal	220	0,310
Claverie	100	0,500
Hampton	530	0,240
Obenaus	100	0,700
Renyu	138	0,690
Farzaneh	208.9	0,449
Ghosh	360	0,590
Topalis	131.5	0,374

In this work we built a database from the results of the work of many researchers in this domain and we tried in first to propose values for "A" and "n" by solving the equation of Obenaus's model by a numerical method which is the genetic algorithm.

Consider the optimization problem to maximize the function :

$$F_g = 1 - \underbrace{\sum_{i=1}^{196} \left| U_{ci} - f_i(A, n) \right|}_{h} \qquad (9)$$

Of course the maximum value of Fg is the minimum value of "h" which leads to determine "A" and "n" which satisfy this condition.

In the literature it was found that "A" is between "0 and 500", and "n" between "0 and 1".

Numbers between "0 and 1" by a step of 0.001 for "n" and between "0 to 500" by a step of 0.01 for "A", are treated as chromosomes. That is to say, we used chromosomes floating, a population of size of 20 chromosomes is chosen at the beginning, an arithmetic crossover is used as a genetic operator, to obtain 40 chromosomes among which we must select others 20 chromosomes which is the size which must survive in each generation.

the selection by wheel consists in considering the obtained chromosomes after crossover, as sectors with each sector has an area proportional to $f(z_1)$, $f(z_2)$, ... until $f(z_{2L})$ (here $2L$= 40), where $f(x)$ is the appropriate function ($f_i(A, n)$), these areas will be arranged to form an appropriate vector [$f(z_1)$, $f(z_2)$, $f(z_3)$, ... $f(z_{2L})$].

This vector must be normalized to obtain [$f_n(z_1)$, $f_n(z_2)$, $f_n(z_3)$, ... $f_n(z_{2L})$], such that the sum of the normalized values of the vectors be equal to 1.

The normalization of the values of the appropriate vector is made as follows:

Take for example $f(z_1)$ the first value of the vector, its normalized value is:

$$f_n(z_1) = \frac{f(z_1)}{f(z_1) + f(z_2) + f(z_3) + \dots\dots\dots + f(z_{2L})} \qquad (10)$$

And similarly we normalize the other values. The cumulative distribution of the appropriate vector normalized:

[$f_n(z_1)$, $f_n(z_1)+f_n(z_2)$, $f_n(z_1)+f_n(z_2)+f_n(z_3)$, ………, 1]

The generation of random number r by the random function simulates the rotation of the wheel. We compare the generated number r with the elements of the vector of the cumulative distribution, if "$r < f_n(z_1)$ and $r > 0$" the chromosome z_1 is selected for the next generation in the same way if "$r < f_n(z_1) + f_n(z_2)$ and $r > f_n(z_1)$" the chromosome z_2 is selected for the next generation and so on.

The experimental values are given by the following table [3]:

Table 2.

The experimental values for different types of insulators

Type	L (cm)	D (cm)	F	C (mg/cm2)	U_c (KV)
Type 1	27.9	25.4	0.68	0.13	12
	27.9	25.4	0.68	0.16	11.1
	27.9	25.4	0.68	0.23	8.7
	27.9	25.4	0.68	0.28	9.1
	27.9	25.4	0.68	0.34	7.5
	27.9	25.4	0.68	0.37	7.8
	27.9	25.4	0.68	0.49	6.2
	27.9	25.4	0.68	0.52	6.8
Type 2	30.5	25.4	0.70	0.02	22
	30.5	25.4	0.70	0.05	16
	30.5	25.4	0.70	0.1	13
	30.5	25.4	0.70	0.16	11
	30.5	25.4	0.70	0.22	10
Type 3	43.2	25.4	0.92	0.05	19
	43.2	25.4	0.92	0.1	15
	43.2	25.4	0.92	0.16	13
	43.2	25.4	0.92	0.22	12
	43.2	25.4	0.92	0.3	10.5
Type 4	43.2	22.9	1.38	0.02	23.5
	43.2	22.9	1.38	0.03	20.9
	43.2	22.9	1.38	0.04	19.4
	43.2	22.9	1.38	0.05	18.3
	43.2	22.9	1.38	0.06	16.9
	43.2	22.9	1.38	0.1	15.8
	43.2	22.9	1.38	0.2	13.6

Where :L : Length of the creepage.

D : Average diameter of the insulator.

C :The ESDD (equivalent salt density deposition). F : Form Factor.

U_c : The critical flashover voltage.

2-3. Application and results

The training of genetic algorithm is made on the basis of data collected from publications on the domain of flashover of polluted insulators [1][9][10][11][12][13][14] (Table 3).

The application gives the results for "A" and "n" (Table 4):

Table 3.

Types of insulators

Type	*D* (cm)	*L* (cm)	*F*
1	26.8	33	0.79
2	26.8	40.6	0.86
3	25.4	43.2	0.9
4	25.4	31.8	0.72
5	29.2	47	0.92
6	27.9	36.8	0.76
7	32.1	54.6	0.96
8	28	37	0.8
9	25.4	30.5	0.74
10	20	40	1.29
11	25.4	27.9	0.68
12	25.4	30.5	0.70
13	25.4	43.2	0.92
14	22.9	0.92	1.38

Table 4.

Values of "A" and "n" after the application of genetic algorithms

Generation	The constant « *A* »	The constant « *n* »
1	134.8184	0.3238
2	137.9150	0.3101
3	127.5301	0.3959
4	130.8851	0.3470
5	126.0758	0.3955
6	130.1165	0.3418
7	131.2313	0.3472
8	133.1253	0.3395
9	131.5862	0.3455
10	131.0845	0.3540
14	133.1144	0.3382
17	131.9228	0.3479
20	131.9534	0.3474
23	131.9510	0.3475
26	131.9303	0.3474
29	131.9243	0.3475
33	131.9237	0.3474
35	131.9240	0.3474
39	131.9237	0.3474
40	131.9237	0.3474

From this table we see that the best solution is obtained at the 39th iteration, which corresponds to A =131.9237 and n= 0,3474.

To get an idea of the convergence of the genetic algorithm the table is shown as curves in "Figure 2".

2-4. Validation

The training of genetic algorithm is made using the values collected on insulators of table (3), which can be represented as curves, and of course if we apply the values of the constants of the arc "A" and "n" in the equation of the mathematical model we can also draw graphs from the data in this table.

We chose as example 4 types of insulators (1,5,7,11). The "Figure 3" shows that the curves and the empirical values estimated by the AG are almost identical. Hence the successful application of the GA.

Now we proceed to another verification, we will expose our proposed model with the experimental values in Table (2), these values were not used in training, and in addition we will make a comparison with the model of IF Gonos that is a reference in this domain "As shown in Figure 4".

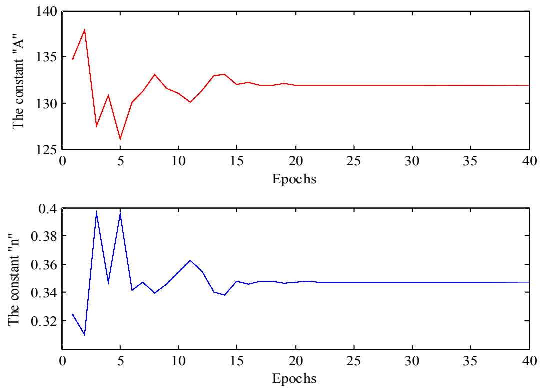

Figure 2

Convergence of arc constants

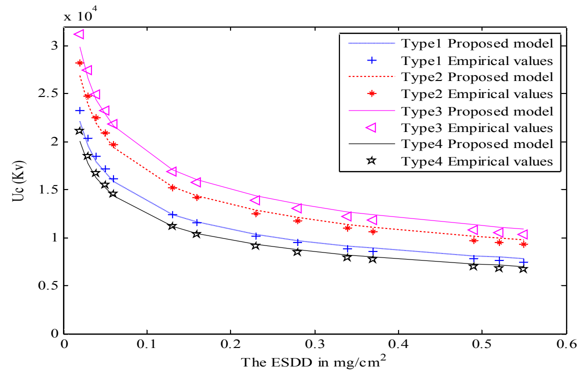

Figure 3

The critical voltage according to the ESDD

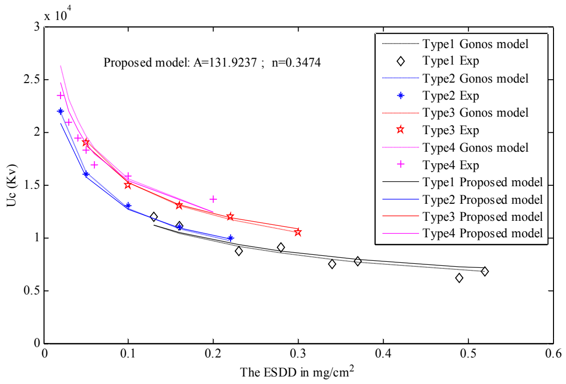

Figure 4
Comparison between the values given by the model proposed by IF Gonos and the values $n = 0.3474$; $A = 131.9237$

We note that the proposed model is in perfect agreement with that of Gonos in several points, it gives a less accurate estimation in other points, and the rest of the points it gives a better estimate.

3- Neural Networks

3-1. The ANN algorithm : (Neural Networks Algorithm)

The ANN can use data read to model some problems with high accuracy. This model can be used to estimate the output variables from the data input variables. It tries to simulate the reasoning process of human intelligence and therefore be used instead of mathematical functions.

The ANN may have three types of layers, the layer of inputs, one or more hidden layers and the layer of the outputs. To create the ANN, the first thing is to decide on the number of neurons in each layer. The artificial neural network is generally established with a backpropagation algorithm of the error, when the error happens at the output layer, it returns to the input layer to modify the weights. This procedure is repeated until reaching values of acceptable errors.

In the present work, an adapted ANN is built in Matlab and developed to estimate the flashover voltage of insulator according to these characteristics. The variable which is given as input is: C: ESDD in mg/cm2, while the output variable is the flashover voltage Uc (in kV).

The input-output data are normalized before the network training to ensure good convergence and an accuracy during the training process [15]. We tried nine different schemes to standardize training models input-output. The details of these schemes normalization are discussed [16]. These different schemes for the normalization using the minimum and maximum values of the data vector components of output and also the average value and standard variance (standard deviation) SD of input-output variables, are presented in the following table:

Table 5

Number of schems	input	output
1	Max	Max
2	Max	Max Min
3	Max	Mean & S.D
4	Max Min	Max
5	Max Min	Max Min
6	Max Min	Mean & S.D
7	Mean & S.D	Max
8	Mean & S.D	Max Min
9	Mean & S.D	Mean & S.D

3-2. Artificial neural networks

Once the connection weights are adjusted by backpropagation algorithm, the ANN can estimate the experiment flashover voltage . Three points should be noted:

- Stopping criteria:

The calculation is repeated by epoch (an epoch is the representation of group of experiences, inputs and targets, vectors of the network and the calculation of the new weights) until the weights have stabilized or error functions are minimized, or the maximum number of epochs is reached.

In our case the error function is the square root of the mean error of the evaluation group according to RMSE

$$RMSE = \sqrt{\frac{1}{m_2 q_{out}} \sum_{i=1}^{m_2} \sum_{k=1}^{q_{out}} e_k^2 (i)} \qquad (11)$$

Where q_{out} is the number of neuron in the output layer and $e_k(i)$ is the error of the k^{th} output neuron for the i^{th} sample of the evaluation group.

If one of the three criteria is true, the main core of the back propagation algorithm tends towards the end otherwise the number of epochs is increased by 1, the adaptation rules are applied and the calculation is repeated.

- Validation criteria:

For all evaluation, the root mean square error *RMSE*, the square of the mean absolute error *MAE*, and correlation can be calculated.

$$MAE\ (k) = 100\ \%. \frac{\sum_{i=1}^{m_2} \left| t_k(i) o_k - (i) / t_k(i) \right|}{m_2} \quad (12)$$

Where $t_k(i)$ and $o_k\ (i)$ are the real and estimated value of the k^{th} output neuron for the i^{th} sample of the evaluation assembly.
For the estimate of the final flashover voltage, the equations (11) and (12) can be applied.
- Activation functions:
A number of activation functions, called transfer function, can be applied. The "logsig" (sigmoid) function, the "tansig" (hyperbolic) function and the "purelin" (linear) function.

3-3. Application of the ANN to estimate the flashover voltage

Using 14 types of insulators as in genetic algorithm, we used the mathematical model proposed for inputting 167 values for the learning (training) and 29 values for the test.
167 values were used for training and 29 values for the test. And we chose in first the hyperbolic function as activation function, α = 0.3, η = 0.9, a single hidden layer, and 500 iterations. We varied the number of the schemes and the number of neurons, the *RMSE* has assumed values of the "Figure 5".

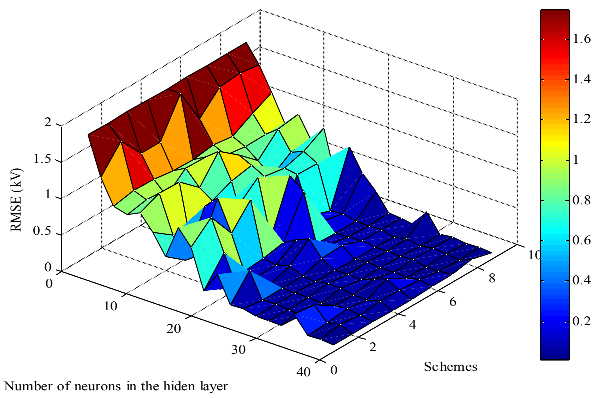

Figure 5
The RMSE for one hidden layer

"Figure 5" shows that the number of neurons and the number of the arrangement have a great influence on the *RMSE* and greater the variation of the error function of these two parameters is not linear, so we had to find the best combination that gives the smallest error. The best results are given for the scheme number 8 and the number of neurons is between 25 and 40 but we take the number 27 which corresponds to the best *MAE* "As shown in Figure 6".This figure also shows that the variation of the *MAE* in depending on number of neurons is not linear.

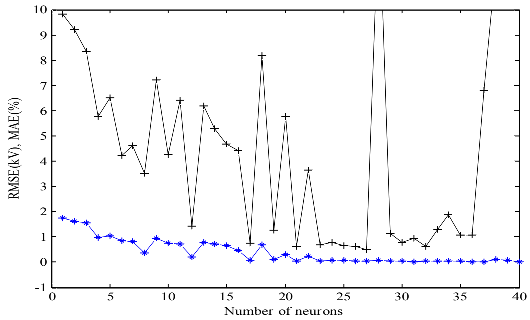

Figure 6
The RMSE and The MAE in depending on number of neurons

After we tried with two hidden layers while keeping α = 0.3, η = 0.9 and 500 iterations, but changing the activation function to the sigmoid function (logsig), fixing the number of schemes to 8 and varying the number of neurons in the first and the second hidden layer, the RMSE values are given in "Figure 7".

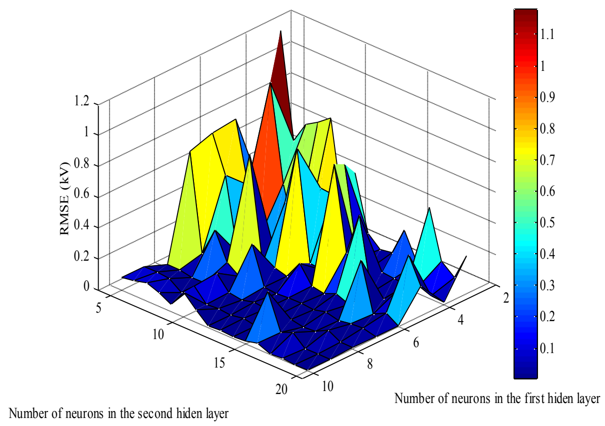

Figure 7
The RMSE for 2 hidden layers

Even notice the variation of the RMSE is not linear, so we must select the best combination carefully, because we can see that for a larger number of neurons we can find a smaller error, as there may be a greater error.
The best result was given for 8 neurons in the first hidden layer and 11 neurons in the second hidden layer where RMSE = 4.10-3 kV.

In the end we changed the activation function for the last case ie α = 0.3, η = 0.9, S = 8, 8 neurons in the first layer and 11 neurons in the second layer and 6000 iterations, we found the following table which gives the *RMSE* (kV) as a function of the various combinations of the activations functions.

Table 6

		La fonction d'activation pour les couches cachées		
		Logsig	Tansig	Purelin
La fonction d'activation pour la couche de sortie	Logsig	0.0083	0.04	0.002
	Tansig	0.003	0.192	0.0028
	Purelin	0.0003	0.012	0.0027

We note that the function logsig for the hidden layers and purelin (linear) for the output layer gives the best results.

After we did a little statistical analysis of the obtained results based on the confidence interval of 95% and the experimental values [3] of Table (2) we found the results in "Figure 8".

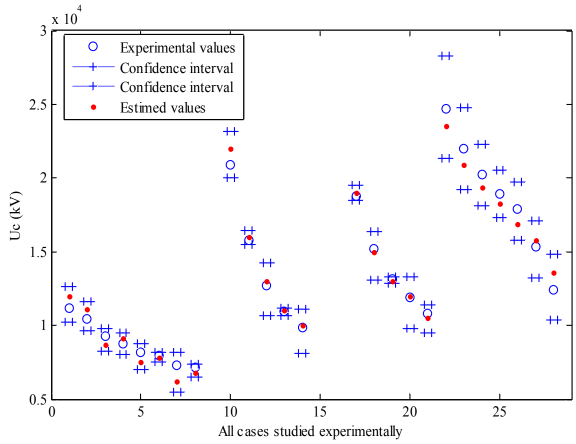

Figure 8
Situation of experimental values and these estimated by the ANN compared to the confidence interval

A confidence interval is a tool to express our degree of certainty about the parameters of a statistical model [9]. The estimation of the sample mean μ by confidence interval is commonly used in practice. It increases the level of information in relation to a point estimate. It provides an overview of possible values for μ. Confidence interval to 100 (1-α)% for μ is to find two terminals, top and bottom, which depend on the sample drawn. If one draws a large number of times a sample, and for each one we calculate a confidence interval , so in 100 (1-α)% of cases the parameter μ should be in the confidence interval.

In our case if we take α = 0.05 there will be a 95% chance that the estimated value of the measurements is within the interval.

"Figure 8" shows that all values estimated by the ANN are within the confidence intervals of measures. It was also noticed that the width of the intervals is not the same for all measurements, this is due to the values collected, if they are close the interval will be narrow if not it will be large.

At the end we did a little comparison with the mathematical model proposed in the first part of this work and the model of IF Gonos [4] by referring to experimental values "As shown in Figure 9, 10".

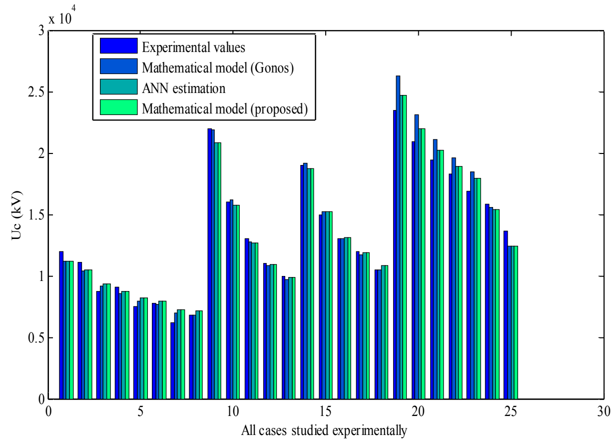

Figure 9
Comparison between the values of the mathematical models and those of ANN taking as a reference the experimental values

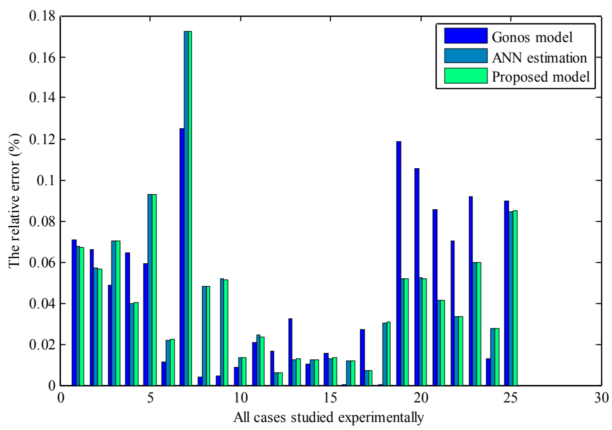

Figure 10
Comparison between the relative error of the mathematical models and the ANN compared to the experimental values

We note that the two methods used in this work (ANN and GA) give almost the same results, and comparing them to the model of IF Gonos which is a reference in this field we find that they are better in most cases (13 of 25) with respect to the experimental values.

Conclusions

Two artificial intelligence techniques were used in this work, which are genetic algorithms and neural networks to estimate the flashover voltage of polluted insulators.

The validity of results and statistical analysis performed at the end of the work show that these methods have been successfully applied and that their use in this field can effectively replace experimental works which are costly, takes time and requires special equipment. And therefore these techniques can provide a more in research to reduce the defect of flashover and improve the functioning of insulators.

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