Estimation of the Critical Flashover Voltage for Different Polluted Insulators by Particle Swarm Optimization

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Abstract: *This article presents an optimization method to determine the arc constants used in the mathematical model which concerns the critical flashover voltage of a polluted insulator. These constants must be standard for many insulators, hence the establishment of a model that very accurately simulates the experimental results.*

The optimization method based on Particle Swarm Optimization (PSO) that resolves a problem by iteratively trying to improve a candidate solution with regard to a given measure of validity.

It can be seen that the calculated results by application of PSO has allowed to define the constants of the arc where the establishment of a model that simulates the experimental and analytical results of other researchers.

Keywords: *High voltage insulators; Polluted insulators; Critical flashover voltage; Particle Swarm Optimization (PSO), equivalent salt density deposition ESDD.*

1. Introduction

Exposure of insulating material to different environmental conditions is inevitable in all energy systems. And based on it, the reliability of the power system mainly depends on this conditions, which cause in some cases the flashover on polluted insulators.This undesirable phenomenon leads to premature aging and depreciation of hardware, system failures, and influences power quality.

A major problem of insulation systems is the accumulation of airborne pollutants due to natural, industrial or even mixed pollution, during the dry weather period and their subsequent wetting, mainly by high humidity.[1-3]

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 critical values, there can start the flashover phenomenon [4]

There are several techniques used for the reduction of this phenomenon and some of these techniques include periodic cleaning of polluted insulators. However, if the cleaning and maintenance program is not well established it can be expensive.

In order to avoid this phenomenon, the study of critical flashover voltage of a polluted insulator is a very important parameter, and the determination of the latter allows to obtain an idea leads to avoid the electrical discharge undesirable.[2]

In other order, the experimental study of critical flashover voltage is time consuming and encounters several obstacles, such as very high cost and the need for special equipment, which have led to resorting to the development of several numeric approaches for voltage estimation flashover polluted insulator. Based on this reason, several approaches have been developed for the estimation of the flashover voltage of polluted insulators. Most are based on mathematical models and analytical relationships. In this case, the artificial intelligence technique can be used in problems requiring approximation functions, classifications and schematic knowledge, estimates and predictions, such as:

1- Schematic classifications and knowledge,

2- Estimates and predictions for estimating the degree of pollution,

3- The prediction of a bypass,

4- Analysis of tracks on the surfaces of polluted insulators

5- And also the estimate of the flashover voltage of a polluted insulator.

This work tries to use the experimental values and the results of the theoretical approaches to build a numerical model ensures the estimation of the flashover voltage of a polluted insulator, by the determination of the constants of the arc "A" and "n “ of the mathematical model that gives the best results, using the characteristics of the insulator as data.[2]

2. Mathematical model development

The process of flashover polluted insulators has been studied by several researchers. In this work, the simplest model is studied, which is developed by Obenaus [5], which consists of an arc which short-circuits the dry zone, placed in series with an equivalent resistance to the wet zone (Figure1). Applying Ohm's law to the circuit in Fig. 1 give:

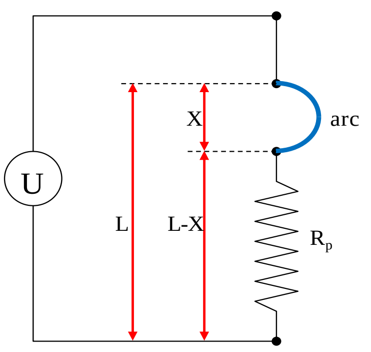


Fig.1 Equivalent circuit model of Obenaus

$$U = xA\,I^{-n} + (L - x)R_pI \tag{1}$$

Or :$xA\,I^{-n}$: is the arc voltage

$(L - x)R_pI$: is the voltage in the pollution layer.
x :The arc length
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 arc constants.

Resistance measuring (R_p) of the wetland is very complicated. So we can substitute it for the conductivity σ_p of the pollution layer.[6]

$$\sigma_p = \frac{1}{R_p}F_i \tag{2}$$

F_i : is the form factor of the insulator which is given by:

$$F_i = \int_0^L \frac{1}{\pi D(l)}\,dl \tag{3}$$

Where D(l) is the diameter of the insulator which varies according to the line of get-away [2,7]. The critical condition for the discharge to propagate along the surface of the insulator to cause flashover is:

$$\frac{dl}{dx} > 0 \tag{4}$$

And the voltage under this critical condition becomes:

$$U_c = x_cA\,I_c^{-n} + (L - x_c)k\,R_pI_c \tag{5}$$

The coefficient k is added to validate the relation (5) at the critical moment of the flashover. Wilkins introduced this coefficient to modify R_p the resistance of the pollution layer by considering the current concentration at the point of the arc pitch, a simplified formula for calculating k for cap-and-pin insulators**[**8,9**]**.

$$k = 1 + \frac{L}{2\pi F_i(L-x_c)}Ln\frac{L}{2\pi F_i\sqrt{\frac{I_c}{1{,}45\pi}}} \tag{6}$$

At the critical condition, the length of the arc takes the value:

$$x_c = \frac{1}{n+1}L \tag{7}$$

After an analysis of the system of equations at the time of flashover the critical current becomes **[**4,10**]**:

$$I_c = (\pi D_r \sigma_p A)^{\frac{1}{n+1}} \quad (8)$$

The critical voltage:

$$U_c = \frac{A}{n+1}(L + \pi D_r F_i kn)(\pi D_r \sigma_p A)^{\frac{-n}{n+1}} \quad (9)$$

When D_r is the diameter of the insulator.

Equation (9) provides the critical value of voltage at flashover as a function of insulator dimensions (D_r and L),

Arc constants A, n and pollution σ_p while F_i and k are also depending on the dimensions of the insulator.

The critical voltage can be calculated after determining the arc constants. These are the unknown parameters of the model. [3,7**]**

3. Particle swarm optimization algorithm

Particle swarm optimization (PSO) is a kind of artificial intelligence simulation method, which is proposed by Kennedy and Eberhard in 1995. It is a stochastic optimization algorithm based on swarm intelligence theory **[**11**]**.

Particle swarm optimization (PSO) achieves the evolution of individuals by moving to the optimal individual and the optimal position.[12]

The PSO starts with a swarm consisting of a number of particles, which are randomly generated in the search space of the objective function. Particles fly through the search space by the help of their velocities[13] .

Velocities that determine particles flying direction are obtained for each particle based on its previous best position and the characteristics of a particle with the best position in the whole swarm.

The best position of the swarm is the corresponding position of a particle that has the minimum (or maximum) objective function value among all particles in the swarm.

This strategy for calculating velocities increases the probability of migration of the particles to regions with the lower objective function. Particle positions are changed after each flight and the corresponding objective function value of the particles are evaluated for updated positions.

Schematic flight of a particle in the PSO is shown in Figure 2. [14]

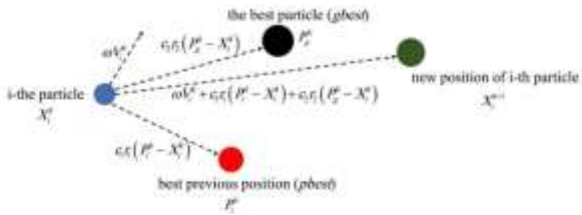


Fig. 2 The schematic illustration of a flight in the PSO

For particle i, in each iteration, the previous position of the particle is changed according to the following equations:

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 (P_i^k - X_i^k) + \ldots$$

$$\ldots + c_2 r_2 (P_g^k - X_i^k) \quad (10)$$

$$X_{i+1}^k = X_i^k + V_i^{k+1} \quad (11)$$

Where:

k : indicates a pseudo-time increment;
$V_i^k$and X_i^k: The current position and the velocity of the ith particle;
P_i^k: The best previous position of the ith particle at time k (called pbest);
P_g^k: The best global position of the swarm at time k (called gbest);
r_1,r_2: Two uniform random sequences generated uniformly between 0 and1;
c_1, c_2: Constants in PSO algorithm;
ω: The inertia weight used to discount previous velocity of the particle preserved.

3.1 Algorithm:

The basic PSO has the shortcoming of premature convergence, which is related to the quality of the initial population. Here, the idea of random direction was employed to produce high-quality initial population to ensure that the algorithm can find the optimal solution and avoid stagnating while the normal particles are in the search midway. [15]

The detailed Algorithm is given below:

Step 1: Determining the initial search space according to the problem to be solved.

Step 2: Generating initial swarm

PSO starts with an initial population called "swarm". Each swarm contains several particles. and selecting a random position x_j in the search space as base position, $x_i = [x_1, x_2, x_3 \ldots\ldots x_j]$ Where j is the dimension of the optimization problem.

Step 3: Initializing array $x(k)$ for storing population individuals and k is the total number of individuals in the population.

Step 4: Producing a random vector $\vec{v_j}$ in the given search space.

Step 5 : Evaluation of fitness function, when he is calculated and will be the initial particles of the swarm which are set as the initial Pbest values of the particles. The best value among all Pbest values is identified as gbest.

Step 6: Producing individual $x_{j+1} = x_j + \vec{v_j}$ in sequence.

Step 7: Comparing x_{j+1} with x_j to judge whether they are beyond the search space, if X_{j+1} is better than x_j, x_{j+1} is reserved, $j = j + 1$and return to Step 5.

Otherwise, return to Step 4 until the particle is generated which meets the terminate conditions.[15, 16]

3.2 Application to the estimation of flashover voltage

The PSO algorithm maintains a set of candidate solutions in the search space. The algorithm iteratively evaluates the adequacy of the solution by the optimized objective function.

Each particle in the swarm represents a candidate solution to the optimization problem. In the first step of the algorithm, it randomly selects candidate solutions from the search space, which is composed of all possible solutions. The PSO algorithm has no prior knowledge of the objective function, and so the search is to determine which solution is close to the local or global minimum. The PSO algorithm simply uses the objective function to evaluate its candidate solutions and operates on the resulting fitness values [17].

Various factors are known to influence the performance of the PSO, including the size of the swarm, the size of the neighborhood, the values of the acceleration coefficients, the velocity update method, and the swarm topology used.[18]

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. When the pollution flashover mechanism can be analyzed into for phases:

I- Accumulation of contaminants

II- Wetting of the surface

III- Formation of dry bands

IV- Arcing of dry bands which may lead to flashover

These phases are non-uniform in nature. It would be difficult to incorporate all of these complicated phases in the development of the model. Therefore, certain assumptions are made, such as that the insulator will have a uniform distribution of pollution and wetting on its surface, and a single arc will be dominant on the surface leading to flashover.

In generally, the previous researcher's experimental and numerical model results estimate the value of constants A and n between

(31-530) and (0.24-1.13) respectively, that leads to programming the numerical model under these values.[19]

Swarm size is set to 300, inertia weight is set to 1, and acceleration coefficients (c1, c2) are set both to 2.05.

All algorithms are run 20 runs 100 iterations each. These settings are suggested from initial examinations.

4. Validation

The results of the work of many researchers has given a large database which allows the use of artificial intelligence to develop a numerical method which is the PSO in order to propose values for "A" and "n" by solving the equation of the Obenaus model from 14 insulators with 14 value of ESDD for each.[2]

Where the optimization operation is the minimization of the function:

$$Fg = \sum_{i=1}^{196} |f_i(A,n)| \quad (12)$$

The proposed model results are compared with four available experimental results and also valued with analytical model results of insulators from ten types.

The experimental values are given by the following table (Table.1) [2,9]:

Table 1.
The experimental values for different types of insulators

Type	*L* (cm)	*D* (cm)	*F*	*C* (mg/cm^2)	*Uc* (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	0.34	7.5
	27.9	25.4	0.68	0.49	6.2
	27.9	25.4	0.68	0.55	6.1
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

L : *Length of the creepage*, D: *Average diameter of the insulator*, C:*The ESDD (equivalent salt density deposition)*, F: *Form Factor*, Uc: *The critical flashover voltage.*

The application of the PSO algorithm is done using the values collected on the insulators of table (2) at the level of the Obenaus formula which can be represented in the form of curves, and of course if we apply the values of the arc constants "A" and "n" in the equation of the mathematical model, we can also draw graphs from the data in this table [20-26] (Table 2).

Table 2.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

The application of PSO method gives the results for "A" and "n" (Table 3):

Table 3.Values of "A" and "n" after the application of PSO method

Iteration	The constant « A »	The constant « n »
1	145.0000	0.3500
2	140.3136	0.3235
3	134.3530	0.2993
4	133.9739	0.3040
5	137.4207	0.3219
10	136.9607	0.3096
15	136.6714	0.3058
20	136.7483	0.3100
25	136.4450	0.3114
30	136.5072	0.3111
35	136.4797	0.3109
40	136.4373	0.3111
45	136.5165	0.3110
50	**136.4992**	**0.3114**

From this table, we see that the best solution is obtained after the 10th iteration, which slowly approaches to A= 136.4992 and n = 0.33114 until the 50th iteration. To get an idea of the convergence of the PSO algorithm the table.3 is shown as curves in Figure 3 and Figure 4.

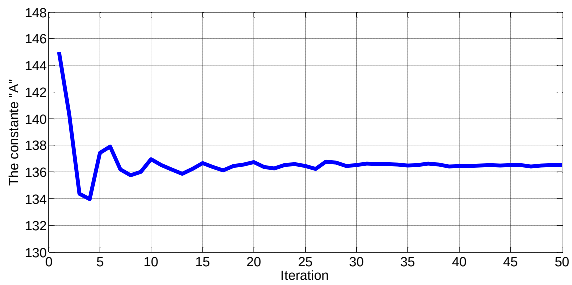


Fig. 3 Convergence of arc constants « A »

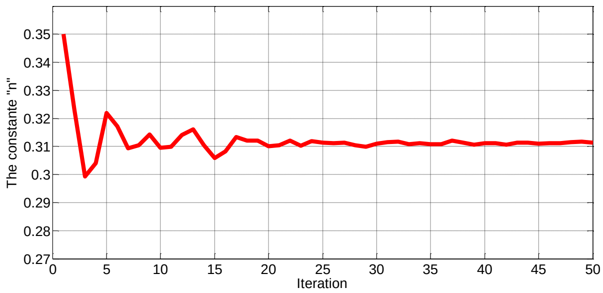
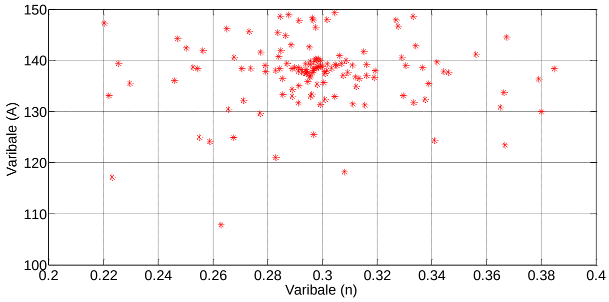
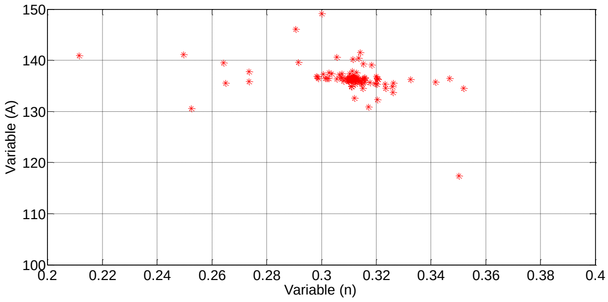


Fig. 4 Convergence of arc constants « n »

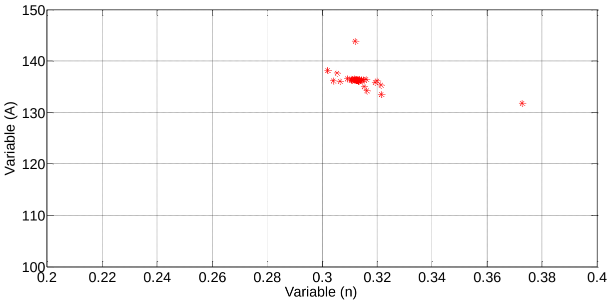
Figure 5 shows the distributions of swarms in some iterations of PSO method.



Iteration n°5



Iteration n°25



Iteration n°45

Figure 5: Distributions of swarms in some iteration.

Figure 6 shows that the curves and the empirical values estimated by this PSO method are almost identical for three types.

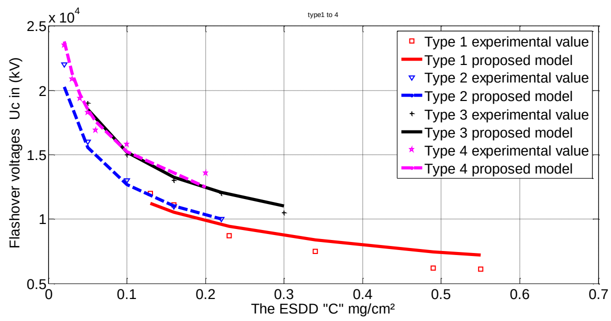


Fig. 6 The critical voltage according to the ESDD

5. Conclusion

According to the objective function, a guaranteed convergence can be obtained in all operating states, but not necessary to a global optimization, which can be useful for certain applications when one is looking for sub-optimal solutions.

The results and statistical analysis carried out at the end of the work showed that this method, although slow, has been successfully applied and that its use in this field can effectively replace experimental work, which is expensive, time-consuming and special equipment.

Estimation by numerical methods makes it possible to avoid undesirable phenomena with the predictive information of the flicker voltage, thereby improving the operation of the insulators.

The values obtained by the approved method gave numerical results in previously reached fields [19] and therefore they can be accepted in general. The work on developing research methods remains a guarantee to reach optimal values.

6. Perspective

From the perspective, the PSO approach accepts development in its performance, and this has been proven by many works, and it remains to direct efforts to change the work method in the practical steps of the theory that may give better results, which can be verified easily.

7. References

[1] Bessedik, S. A., & Hadi, H. (2013). Prediction of flashover voltage of insulators using least squares support vector machine with particle swarm optimisation. *Electric Power Systems Research*, *104*, 87-92.

[2] Kherfane, R. L., & Mimoun, Y. (2014). Use Of Artificial Intelligence Techniques To Estimate The Flashover Voltage. *Journal of Electrical Engineering*, *14*(1), 8-8.

[3]Badachi, C., & Dixit, P. (2016). Prediction of pollution flashover voltages of ceramic string insulators under uniform and non-uniform pollution conditions. *Journal of Electrical Systems and Information Technology*, *3*(2), 270-281.

[4] Kontargyri, V. T., Gialketsi, A. A., Tsekouras, G. J., Gonos, I. F., & Stathopulos, I. A. (2007). Design of an artificial neural network for the estimation of the flashover voltage on insulators. *Electric power systems research*, *77*(12), 1532-1540.

[5]F. Obenaus, *Fremdshichtuberschlag und Kriechweglang*, Deutch Elektrotechnick, Vol, *4*, pp. 135-136, (1958).

[6] Yang, H., Cao, W., Wen, R., Wang, Y., Shen, W., & Zhang, L. (2022). Study on surface conductivity distribution of pollution layer during the propagation of local arc on the wet polluted insulation surface. *AIP Advances*, *12*(1), 015311.

[7]Erenturk, K. (2009). Adaptive-network-based fuzzy inference system application to estimate the flashover voltage on insulator. *Instrumentation Science and Technology*, *37*(4), 446-461.

[8] Li, J., Zhou, J., Guan, Z., & Wang, L. (2021). Novel residual pollution layer model related to the arc propagation along the surface based on discretisation. *High Voltage*, *6*(1), 25-33.

[9]Wilkins, R., & Al-Baghdadi, A. A. J. (1971, December). Arc propagation along an electrolyte surface. In *Proceedings of the Institution of Electrical Engineers* (Vol. 118, No. 12, pp. 1886-1892). IET Digital Library.

[10]Asimakopoulou, G. E., Kontargyri, V. T., Tsekouras, G. J., Asimakopoulou, F. E., Gonos, I. F., & Stathopulos, I. A. (2009). Artificial neural network optimisation methodology for the estimation of the critical flashover voltage on insulators. *IET Science, Measurement & Technology*, *3*(1), 90-104.

[11] Kennedy, J., & Eberhart, R. (1995, November). Particle swarm optimization. In *Proceedings of ICNN'95-international conference on neural networks* (Vol. 4, pp. 1942-1948). IEEE.

[12] Ding, Z. (2017, May). Research of improved particle swarm optimization algorithm. In *AIP Conference Proceedings* (Vol. 1839, No. 1, p. 020148). AIP Publishing LLC.

[13] Mashayekhi, M., Harati, M., & Estekanchi, H. E. (2019). Development of an alternative PSO-based algorithm for simulation of endurance time excitation functions. *Engineering Reports*, *1*(3), e12048.

[14] Mashayekhi, M., Harati, M., & Estekanchi, H. E. (2019) On the optimal parameters of a PSO-based

algorithm for simulation of Endurance Time Excitation Functions.https://doi.org/10.1002/eng2.12048

[15] Li, Y., Peng, Y., & Zhou, S. (2013). Improved PSO algorithm for shape and sizing optimization of truss structure. *Journal of Civil Engineering and Management*, *19*(4), 542-549.

[16] Zakaria, Z. N., Azmi, A., Laili, M. S., Jamalil, S. A. S., & Sulaiman, M. H. (2013, December). An extension of particle swarm optimization (E-PSO) algorithm for solving economic dispatch problem. In *2013 1st International Conference on Artificial Intelligence, Modelling and Simulation* (pp. 157-161). IEEE.

[17] Koohi, I., & Groza, V. Z. (2014, May). Optimizing particle swarm optimization algorithm. In *2014 IEEE 27th Canadian conference on electrical and computer engineering (CCECE)* (pp. 1-5). IEEE.

[18] Khairy, M., Fayek, M. B., & Hemayed, E. E. (2011, June). PSO2: Particle swarm optimization with PSO-based local search. In *2011 IEEE Congress of Evolutionary Computation (CEC)* (pp. 1826-1832). IEEE.

[19] Badachi, C. A., & Dixit, P. (2015). Analytical model to predict pollution flashover voltages of porcealin disc insulators.Acta Electrotechnica et Informetica 15 (1), (pp. 42–49).

[20] Gopi, E. S. (2007). *Algorithm collections for digital signal processing applications using Matlab*. Springer Science & Business Media.

[21] Asimakopoulou, G. E., Kontargyri, V. T., Tsekouras, G. J., Elias, C. N., Asimakopoulou, F. E., & Stathopulos, I. A. (2011). A fuzzy logic optimization methodology for the estimation of the critical flashover voltage on insulators. *Electric power systems research*, *81*(2), 580-588.

[22] Gencoglu, M. T., & Cebeci, M. (2009). Computation of AC flashover voltage of polluted HV insulators using a dynamic arc model. *European Transactions on Electrical Power*, *19*(5), 689-701.

[23]Gençoğlu, M. T., & Cebeci, M. (2008). The pollution flashover on high voltage insulators. *Electric Power Systems Research*, *78*(11), 1914-1921.

[24]Gençoğlu, M. T., & Cebeci, M. (2009). Investigation of pollution flashover on high voltage insulators using artificial neural network. *Expert Systems with Applications*, *36*(4), 7338-7345.

[25]Kazemi, A., Hassanzadeh, M. T., & Gholami, A. (2008, December). Artificial neural network for insulator leakage currents prediction from environmental data. In *2008 IEEE 2nd International Power and Energy Conference* (pp. 13-17). IEEE.

[26] Kontargyri, V. T., Gialketsi, A. A., Tsekouras, G. J., Gonos, I. F., & Stathopulos, I. A. (2007). Design of an artificial neural network for the estimation of the flashover voltage on insulators. Electric power systems research, 77(12), 1532-1540.