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PARTICLE SWARM OPTIMIZATION OF A NEURAL NETWORK MODEL FOR PREDICTING THE FLASHOVER VOLTAGE ON POLLUTED CAP AND PIN INSULATOR

Amel BELKEBIR [1], Yacine BOUREK [1], Hani BENGUESMIA [2, 3, *]

[1] Department of Electrical Engineering, Faculty of Applied Sciences, University of Ouargla, Road Ghardaia, 30000 Ouargla, Algeria
[2] Laboratoire de Génie Electrique (LGE), Université de M'sila, M'sila, Algérie.
[3] Electrical Engineering Department, Faculty of Technology, University of M'sila, M'sila, Algeria
[*] Corresponding author, e-mail: hani.benguesmia@univ-msila.dz

Abstract

This paper proposes training an artificial neural network (ANN) by a particle swarm optimization (PSO) technique to predict the flashover voltage of outdoor insulators. The analysis follows a series of real-world tests on high-voltage insulators to form a database for implementing artificial intelligence concepts. These tests are performed in various degrees of artificial contamination (distilled brine). Each contamination level shows the amount of contamination in milliliters per area of the isolator. The acquisition database provides values of flashover voltage corresponding to their electrical conductivity in each isolation zone and different degrees of artificial contamination. The results show that ANN trained by PSO can not only provide better prediction results, but also reduce the amount of computation efforts. It is also a more powerful model because: it does not get stuck in a local optimum. In addition, it also has the advantages of simple logic, simple implementation, and underlying intelligence. Compared to the results obtained by practical tests, the results obtained present that the PSO-ANN technique is very effective to predict flashover of high-voltage polluted insulators.

Keywords: flashover voltage, particle swarm optimization, prediction, artificial pollution, neural network

1. INTRODUCTION

One of the most significant problems in power transmission is the pollution flashover, which occurs with insulators in high voltage transmission for many reasons, like the different densities of pollution in different regions, the inhomogeneous distribution of contamination on the insulation surface, and the unspecified influence of humidity on the pollution [1-3].

The cap and pin type performance is regarded as an essential factor in determining the reliability of the electrical system. The necessary items for the insulators not only resist the normal operating voltage, but also prevent flashovers from occurring. The reduced performance is mainly due to airborne dirt deposits which, with mist or moisture, can form a conductive or partially conductive surface layer and increase the risk of flashover [4].

Among neural networks, the most common and famous is the Multi-Layer Perceptron neural network applied using the normalized BP algorithm (back-propagation) or one of its derivatives, which is called BPNN. If the initial weight set is not chosen correctly, the BP algorithm using the steepest descent search technique is likely to get stuck in a local optimum. Sometimes, computations may even overflow or oscillate between optimal computations. The BPNN limitations motivated many researchers to look far off the existing models to find more powerful optimization techniques for improving methods to optimize solutions [5].

An important discovery of these powerful techniques is the application of evolutionary algorithms (EA) to optimize neural networks. Particle swarm optimization (PSO) is one of these evolutionary computing techniques, its study subject was suggested by Eberhart and Kennedy, and it was derived from simulating flocks of birds and fish behavior [6]. The native purpose was to graphically simulating flocks of birds' graceful but unpredictable dance. At some stage in the development of the algorithm, has been achieved that the conceptual model was actually improved, so many unoptimized parameters were removed, resulting in the basic PSO algorithm. Karpat and Ozel proposed optimization of multi-objective optimization using neural network modeling and flock intelligence for hard turning [7].

Zhang and Shao explain a new scalable algorithm to develop ANNs dependent on the particle swarm optimization technique wherein the ANN architecture and weights are adaptively adjusted based on the quality of the neural network to reach an optimal architecture or stopping criterion [8]. The fulfillment of the basic PSO algorithm and the constrained PSO algorithm are compared (with and without mutation) on some test operations of different dimensions by Stacey et al [9]. They found that, in some cases, the use of restricted mutant PSOs could be significantly improved.

To avoid premature convergence an upgraded PSO algorithm was suggested to train neural networks using a population diversity approach by Zhao et al [10].

Parameters of grinding process such as work piece speed, ring depth and feed rate are optimized using PSO technology by Asokan et al [11].

In this work, PSO trained an ANN is proposed for predicting the flashover voltage on polluted of a 175CTV type outdoor insulator, widely used by (SONELGAZ) the Algerian Electricity and Gas Company. This was not used only to measure the improved predictive power of this relatively new computer intelligence technique relative to existing traditional techniques, but also to focus on the intelligence behind group migration, which involves individual and social cooperation, a union that was thought to be swarm intelligence [5].We considered in our work other important parameters influencing the insulator flashover: the high applied voltage, electrical conductivity in each isolation zone and different degrees of artificial contamination unlike other authors who used only the leakage current as an essential parameter to study the insulator flashover phenomenon in their published works.

2. ALGORITHM PSO

Eberhart and Kennedy introduced and elaborated the PSO (a swarm algorithm) that is inspired by particle social animals' behaviour like fish or birds. It has been categorized as one of the metaheuristic techniques [12]. It has been viewed in the statistics community as an evolving computational technique with many benefits [13-16].

This optimization method is based on the collaboration of individuals with each other. It also has similarities with ant colony algorithms, which are also based on the concept of self-organization. This idea holds that a group of unintelligent individuals can possess a complex global organization.

Thus, thanks to very simple displacement rules, the particles can gradually converge towards a global minimum. However, this metaheuristic seems to work better for spaces in continuous variables [17].

PSO explores the search space through successive trials of boid positions, their movements being managed by simple equations. Thus, the location of each boid in the search space represents a potential solution to the optimization problem. And the "quality" associated with each of these solutions is quantified by the objective function, optimized little by little according to the positions, more or less optimal. Each particle is informed of the best point found in its neighborhood and tends to move towards that point [18].

There are three important parameters which have an essential role: position, speed and fitness. To solve an optimization problem using PSO, we follow:

a. Initialize a population of individuals (particles) with random velocities and positions in the problem domain.
b. Fitness calculation value for all particles
c. Particles investigating fitness.
d. Update of particle velocity and position using equations (1) and (2).

$$V_{ij}^{t} = x\left[wv_{ij}^{t-1} + c_1 r_1 (p_{ij}^{t-1} - x_{ij}^{t-1}) + c_2 r_2 (G_j^{t-1} - x_{ij}^{t-1}\right] \quad (1)$$

$$x_{ij}^{t} = x_{ij}^{t-1} + v_{ij}^{t} \quad (2)$$

With $c1$ and $c2$ are two positive constants called acceleration constants. r1 and r2 random numbers, w is an inertia weight, x the particle current position, p^t and G^t indicate the particle best position (p_best) and the swarm best position (g_best) , respectively[19].

The advantage of PSO is the simple coding and its low computational cost [20]. Since PSO algorithm performed accurately to solve global optimum, it was applied to train the MLP in the current study.

3. ARTIFICIAL NEURAL NETWORK

Like a powerful analysis method, ANNs behave similarly to human and animal system of biology [21-22]. They are important to find the inputs and outputs relationship in a noisy and complex data set. The multilayer perceptron (MLP) is one of its important types.

The experience determines mainly the structure of multi-layer predictive networks and it was found that there is no valid formula suitable for different situations according to previous studies. An MLP network is composed of one or more input layers, one or more of hidden layers and an output layer [23]. Recently, ANNs have been widely and successfully used [22-24].

We express the mathematical formulation of MLP as follows:

$$S_j = F\left(\sum_{j=1}^{n} w_{kj} E_j + B_j\right) \quad (3)$$

Where F indicate the activation function, n represent the number of nodes. w_{kj} and B_j indicate the connection of the weights and polarization, respectively. It can also be noted that E_j and S_k are the node value in the previous layer of j and the node value in the current layer of k, respectively [25].

Typical ANN model as shown in figure 1, training the network is the next task once the structure of the ANN is formed.

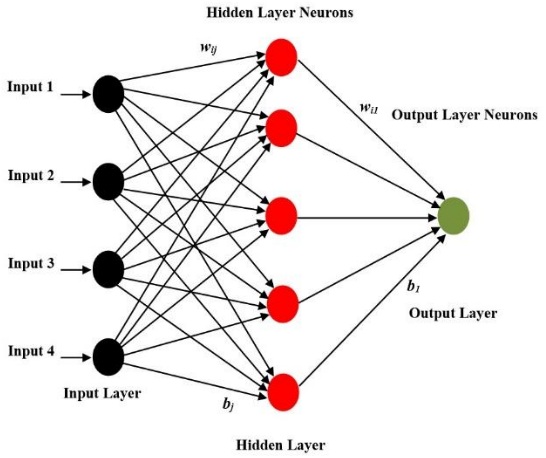

Fig. 1.A typical artificial neural network (ANN)

4. Test object

A 175CTV high-voltage glass insulator is used as the test object, as shown in figure2. The insulation is artificially soiled and tested in our laboratory, as shown in figure 3 [26-28].

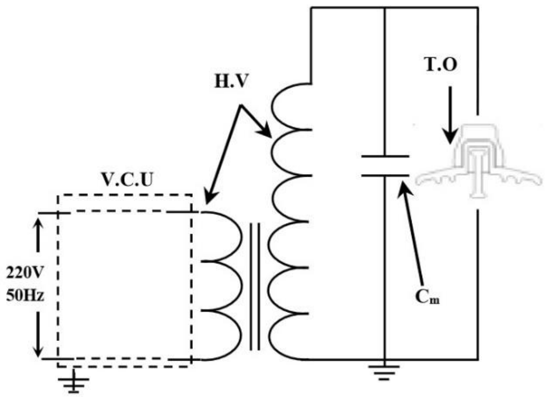

Fig. 2. Experimental setup at industrial frequency 50Hz

Where:

V.G.U: Voltage control unit, **T.O**: Test object (175 CTV insulator),

R.T: Regulating transformer, **H.V**: High voltage transformer,

C_m: A capacitive for measuring the applied voltage.

5. PREPARING THE INSULATOR

Artificial contamination consists of saline solution and distilled water. This artificial contamination is poured into each area of insulation. Figure 3 and table 1 show the quantity of each fixed saline solution for different insulator levels [26-28].

We repeat the test performance five times changing the values of conductivity of the brine poured in each zone. The average value of the five measured voltages is considered as the value of the flashover voltage. This is done with the cleaning of the insulator surface after each test to remove dirt or grease.

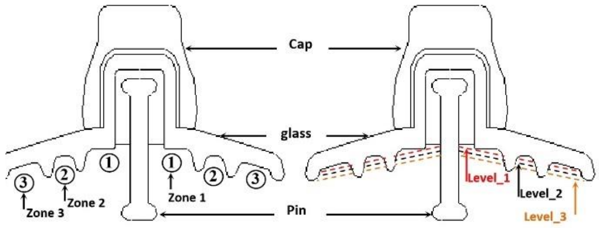

Fig. 3. The cap and pin insulator 175CTV real model, (insulator zones+levels)

Table 1. The artificial pollution levels and polluted zones

Zones	Pollution levels (ml)		
	Level_1 (L1)	Level_2 (L2)	Level_3 (L1)
Zone 1	11.60	23.30	34.90
Zone 2	13.30	26.60	39.90
Zone 3	23.30	46.60	69.90

6. PREDICTION OF INSULATOR FLASHOVER VOLTAGE BY PSO-ANN IN MATLAB

The following seven steps were used to train ANN with PSO:

Step 1. Data collecting.
Step 2. Network creating.
Step 3. Network configuration.
Step 4. Initializing the weights and biases.
Step 5. Training the network using PSO .
Step 6. Validating the network.
Step 7. The network use.

The optimal parameters for ANN-PSO were as follows:

(a) Ten (10): number of hidden neurons;
(b) Six thousands (6000): number of iterations;
(c) One hundred (100): number of particles;

(d) Acceleration constants c1=1 and c2 = 2.

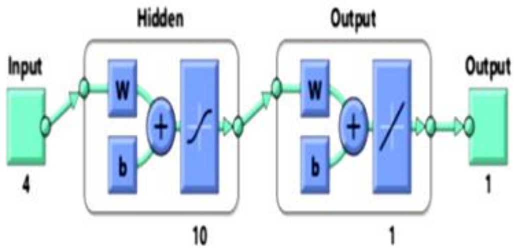

Fig. 4. The training network model in MATLAB

7. EVALUATION PERFORMANCE INDICES

The performance of particle swarm optimization for training artificial neural networks is expressed in terms of root mean square error (RMSE), can be computed by the following equation:

$$RMSE = \left\{\frac{\sum_{i=1}^{NU}(y_{tes,i} - y_{pre,i})}{NU}\right\}^{1/2} \quad (4)$$

NU stands for the number of instances, y_{prei} and $y_{tes,i}$ indicates the predicted and the testing value of one data point i, respectively [29].

To assess the quality of the PSO-ANN models, determination coefficient (R^2) and mean absolute percentage error (MAPE), were used as the indicators of the model's performances.

We express the mathematical formulation of R^2 and *MAPE* as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{NU}\left(y_{tes,i} - \overline{y_{pre,\iota}}\right)^2}{\sum_{i=1}^{NU}\left(y_{tes,i} - \overline{y_{tes,\iota}}\right)^2} \tag{5}$$

$$MAPE = 100\% \frac{\sum_{i=1}^{NU}\left[y_{tes,i} - y_{pre,i}\right]/y_{tes,i}}{NU} \tag{6}$$

8. RESULTS AND DISCUSSION

The insulation flashover voltage values are calculated by the proposed PSO-ANN concept knowing the conductivity of the artificial contamination and level of pollution in each insulator area.

8.1. The two algorithms parameter settings

The essential parameters used in the PSO technique are the number of generation periods, the acceleration constants values c1 and c2 (and therefore the value of the limiting factor k), group size (number of birds), and the inertial weight ω.

To predict insulator flashovers, we use a neural network of a three-layer as shown in figure 4: four input neurons(three levels and pollution conductivity), ten neurons in the hidden layer, and one output neuron.

Perform a series of test runs (with fixed values of parameters c1 and c2) to determine the best architecture by calculating the average error of the trained network (up to 6000 iterations).

8.2. Performance of the PSO -ANN

Table 2 shows the performance of the neural network trained by PSO. The table appears that an upgraded prediction results for the flashover voltage of outdoor insulators provided by the PSO- ANN.

The parameters in the table show the higher learning ability of the network resulting from the inherent robustness of the PSO algorithm in finding the optimal solution.

The parameter R shows the target output and the predicted output correlation by network and the ideal value of R equals one. Figure 6 shows estimated and actual values correlation of critical flashover voltage for the training set.

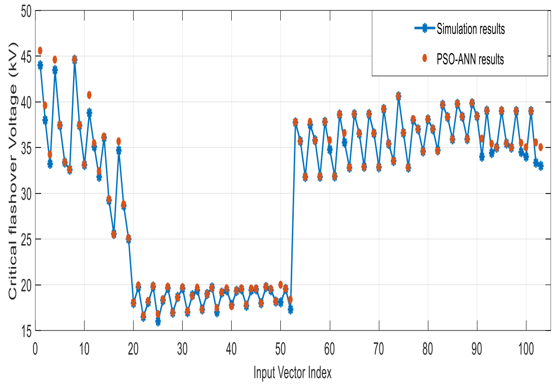

Fig. 5. The performance of PSO -ANN model for training

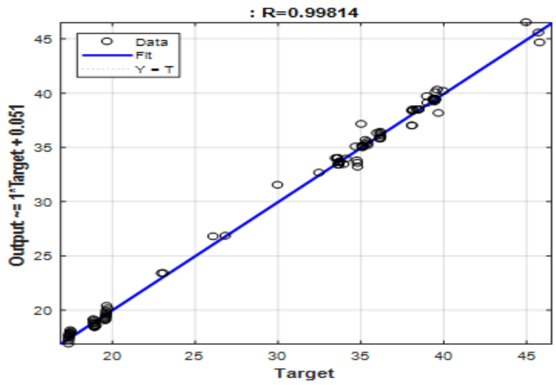

Fig. 6. Estimated and actual values of critical flashover voltage on the training dataset of the PSO –ANN model correlation

Estimated and actual values of critical flashover voltage for the testing set correlation was shown in figure 8. The points are clearly located almost on the line of bestbackdown, which means the network predict the duty ratio for testing data set very well.

Figure 8 shows the constract between the predicted data and the experimental data which isused to evaluatethe performance of the model prediction.We notice in this figure, there is an adequate agreement between the simulated and experimental values and an improved performance of the PSO-ANN model.

The obtained results showed thePSO-ANNmodel compatibility and efficiency to solve problems of environment.

Table 2. Statistical model validation parameters performance

Coff.of correlation R_train	Coff.of correlation R_test	Coff.of determination $(R\_train)^2$	Coff.Of determination $(R\_test)^2$	MAPE_test	RMS_test
0.99814	0.99821	0.99628	0.99642	1.1969	0.5406

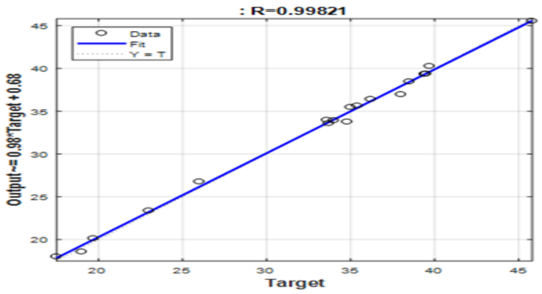

Fig. 7. Estimated and actual values of critical flashover voltage on the testing dataset of the PSO –ANN model correlation

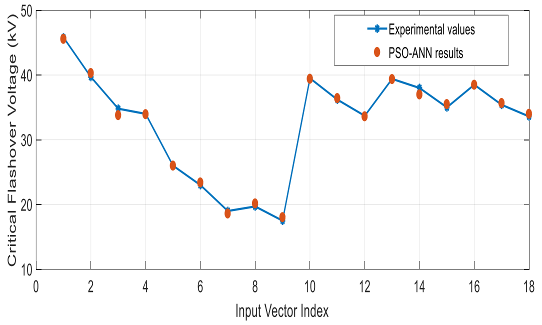

Fig. 8. The performance of PSO -ANN model for testing

9. CONCLUSION

This paper focuses on swarm intelligence importance, such as PSO, in predicting insulator flashovers. The proposed method is simulated with MATLAB. To do this, PSO used to train the performance of the neural network. The main step in this study is to gather the necessary databases. Accurate selection of the parameters of this technique will lead to better results. Insulator flashover based on many parameters; but we only considered the high applied voltage values, the amount of artificial contamination, and the artificial contamination conductivity in our work. The PSO-ANNperformance is demonstrated byroot mean square error (RMSE), determination coefficient (R^2) and mean absolute percentage error (MAPE). The risk of insulation flashover increases as contaminants build up on the insulating layer and the contaminants become more conductive. The respective results show that PSO for training ANNs models are acceptable.

Thus, the suggested method may be more practicle in estimating the critical flashover voltage of different polluted insulators. The results of upgraded prediction proove the validity of the particle swarm optimization in using individual and swarm intelligence to find the best solution.

APPENDIX

The experimental data are given in Table 3

Zones conductivity (g/ml)	Zone 1(ml)	Zone 2(ml)	Zone 3(ml)	Applied voltage (kV)	Practices tests
7.5	11.6	13.3	23.3	45.8	Flashover
	23.3	26.6	46.6	39.7	Flashover
	34.9	39.9	69.9	34.8	Flashover
20	34.9	39.9	69.9	23	Flashover
	23.3	26.6	46.6	26	Flashover
	11.6	13.3	23.3	34	Flashover
50	7.2	15	10	19	Flashover
	4.1	19.4	33.2	19.7	Flashover
	5.5	7.5	14	17.5	Flashover
80	8.2	38.8	38.8	39.4	Flashover
	14.4	30	20	38	Flashover
	10.1	15	28	35	Flashover
100	8.2	38.8	67.4	39.4	Flashover
	14.4	30	20	38	Flashover
	10.1	15	28	35	Flashover
120	11.6	13.3	23.3	38.5	Flashover
	23.3	26.6	46.6	35.4	Flashover
	34.9	39.9	69.9	33.6	Flashover

Author contributions: *research concept and design, B.A.; Collection and/or assembly of data, B.A.; Data analysis and interpretation, B.A., B.Y.; Writing the article, B.A.; Critical revision of the article, B.Y., B.H.; Final approval of the article, B.H.*

Declaration of competing interest: *The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.*

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Amel BELKEBIR was born in Ain-Azel, Setif, Algeria. She received Her DEUA diplomain 2000, her Engineering Diploma in 2003, her magister Degree in 2006,from Batna University, Algeria, Her main research interests include high voltage, flashover voltage of high voltage insulators, artificial intelligence application in HV insulation diagnosis, numerical modeling and simulation. She is currently a professor at OuarglaUniversity (Algeria).
E-mail address: belamel19@yahoo.com

Yacine BOUREK is Professor in the Department of Electrical Engineering, Ouargla University, He was born in Arris (Batna), Algeria in march 1977. He received the engineer degree in Electrical Engineering (2002), and Magister in Electrical Engineering Materials (2005) from the Electrical Engineering Institute of Batna University, his PhD in 2016 Algeria, and his HDR in 2020 in Electrical Engineering from Batna University, Algeria. His principal research interests include gases discharges and artificial intelligence applications.

Hani BENGUESMIA was born in Bousaada, M'sila, Algeria. He received his DEUA diploma in 2006, his Engineering Diploma in 2009, his magister Degree in 2012, his PhD in 2018 in Electrical Engineering from Mohamed Kheider University, Biskra, and his HDR in 2020 in Electrical Engineering from Mohamed Boudiaf University, M'sila, Algeria. He has been working for more than five years with the Department of Electrical Engineering, University of M'sila, as a Professor. His main research interests include high voltage, outdoor insulation, CFD simulation, numerical modeling and simulation. He is the author or co-author of several technical papers published in different journals and reviews.
E-mail address: hanibenguesmia16@gmail.com & hani.benguesmia@univ-msila.dz