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OPTIMIZING ARTIFICIAL NEURAL NETWORKS WITH PARTICLE SWARM OPTIMIZATION FOR ACCURATE PREDICTION OF INSULATOR FLASHOVER VOLTAGE UNDER DRY AND RAINY CONDITIONS

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ABSTRACT

Outdoor insulators are highly susceptible to environmental factors, such as moisture, rain, and contaminants, which significantly degrade their efficiency and durability. These factors contribute to surface flashovers, leading to insulation failures in outdoor power systems. This study presents a novel application of advanced machine learning techniques to predict the flashover performance of glass insulators under diverse environmental conditions, focusing on dry and rainy scenarios. The research emphasizes the critical role of raindrops in reducing flashover voltage. A hybrid model combining Artificial Neural Networks (ANN) with Particle Swarm Optimization (PSO) is developed to address these challenges. The PSO algorithm optimizes the ANN's hyperparameters, enabling the model to establish a nonlinear relationship between key insulator characteristics, including standard and anti-pollution profiles and their critical flashover voltage. Rigorous testing demonstrated exceptional accuracy, with a mean absolute percentage error (MAPE) of 0.2458 and a near-perfect coefficient of determination (R^2) of 0.999. These findings highlight the robustness and reliability of the proposed hybrid model in predicting flashover voltage under varying environmental conditions. This work provides a powerful tool for enhancing the design, maintenance, and operational reliability of outdoor insulators, particularly in regions prone to high levels of pollution and moisture, contributing significantly to the advancement of sustainable power transmission systems.

I. INTRODUCTION

insulators are critical components of power transmission and distribution systems, ensuring electrical insulation between conductors and grounded towers while supporting overhead lines. However, their performance is significantly affected by environmental conditions, material properties, and surface contamination [1].

Contaminants such as dust and industrial emissions significantly threaten outdoor insulators. They cause problems with performance and decrease the life of an insulator faster. This accumulation of arcing and corona discharges erodes the insulator surface finish, leaving flashover paths and accelerating the aging process. These pollutants lead to surface cracking and erosion, increasing the leakage current path over the insulator's surfaces and aggravating this fault by the conduction flow along its surface. Therefore, researchers must study the long-term behavior of insulators in outdoor environments [2],[3].

To cope with different environmental conditions, insulators are designed with varying profiles. Standard profile insulators are widely used in areas with low pollution, as they are more economical. In contrast, anti-pollution profile insulators are specifically designed for regions with moderate to high pollution levels, where they provide better performance under challenging conditions [4]. The behavior of these two insulator types differs significantly when exposed to pollutants, particularly under dry and wet conditions. The situation becomes even more complex when multiple insulators are connected in chains, which is common in modern high-voltage transmission systems [5].

Many studies have focused on assessing insulator performance under pollution stress, employing various physical and mathematical models [6]. Experimental research has developed much over the years, as evidenced by the early analyses of this topic [7],[8]. Better characterization of the physical environment through simulation tools, which represent the complexity of environmental conditions that insulators are subjected to, has dramatically helped to understand the mechanism of pollution-induced performance degradation. Such development helps in a better characterization of insulator behavior under a broad range of stresses, as well as for the development of improved predictive models, which aim to reduce the risk of flashover.

The literature includes several advanced predictive models, such as time-series simulations, regression techniques, and artificial intelligence methods like artificial neural networks (ANN) [9], adaptive neuro-fuzzy inference systems (ANFIS), [10] and least squares support vector machines (LS-SVM) [11]. These models have been applied extensively to forecast the behavior and performance of insulators in polluted environments.

Among neural network architectures, the Multi-Layer Perceptron (MLP) is one of the most widely recognized and applied models, typically utilizing the backpropagation (BP) algorithm or one of its derivatives, known as the Backpropagation Neural Network (BPNN). However, the BP algorithm's reliance on the steepest descent search technique makes it prone to convergence issues, such as getting stuck in local optima, or in some cases, even leading to computational overflow or oscillation. These limitations have driven researchers to explore more powerful optimization techniques to enhance the effectiveness of neural networks [9].

A breakthrough in this regard is the application of evolutionary algorithms (EA) to optimize neural networks. One of the most effective of these techniques is Particle Swarm Optimization (PSO), introduced by Eberhart and Kennedy, inspired by the social behavior of birds and fish flocks [12]. Initially developed to graphically simulate the graceful, yet unpredictable, movements of flocks, the PSO algorithm was later refined to improve its performance by removing unnecessary parameters, resulting in the basic PSO algorithm.

Recent research has focused on training Artificial Neural Networks (ANNs) using the Particle Swarm Optimization (PSO) technique to predict the flashover voltage of outdoor insulators. This approach leverages data from real-world experiments conducted on high-voltage insulators to build a comprehensive database for applying artificial intelligence methodologies. These experiments involve varying levels of artificial contamination using distilled brine, with each contamination level quantified by the amount of brine applied per unit area of the insulator [13]

In this study, we propose a PSO-trained ANN model to predict the flashover voltage of standard and anti-pollution profile glass insulators under dry and rainy conditions. These insulators, extensively deployed by SONELGAZ in Algeria, are critical for reliable power delivery in diverse environmental settings. By addressing key limitations of traditional methods, our approach aims to provide a robust predictive tool for optimizing insulator performance, with implications for power utilities globally.

II. PARTICLE SWARM OPTIMIZATION (PSO)

The PSO algorithm was first developed by Kennedy and Eberhart in 1995 [12], inspired by the collective behavior observed in animal groups, such as flocks of birds and schools of fish. A semi-evolutionary swarm intelligence algorithm is one way to describe this particular method.

The process is driven by randomly picking and testing solutions and then using the results to find, step by step, a better one [14]. Every solution scanned in this process is attached to a search strategy that works at the speed and with the memory of the best condition it was ever exposed to.

There are three critical elements that play a crucial role: position, velocity, and fitness. To address an optimization issue using PSO, the steps are as follows:

- Generate an initial population of particles with random positions and velocities within the problem space.
- Calculate the fitness value for each particle.
- Update the particle positions and velocities based on equations (1) and (2)[15].

The PSO method employs equation 1 to do the update on velocity.

$$v_{ij}(t+1) = wv_{ij}(t) + c_1r_1\big(pB_{ij}(t) - x_{ij}(t)\big) + c_2r_2\big(gB_{ij}(t)\, x_{ij}(t)\big) \quad (1)$$

Where pij(t) represents the best personal memory, gi (t) represents the best collective memory, W represents the factor of inertia weight of particle, c1, and c2 represent the coefficients of individual learning, and r1 and r2 rep3resent the coefficients of collaborative learning [13].

To determine the positions of any newly introduced particles, this method relies on Equation 2 [14].

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

III. NEURAL NETWORK MODEL

In principle, ANNs are similar to the biological systems that humans and other animals have, so they have become an excellent tool for analyzing complex data sets [9]. They excel at revealing less apparent relations between the inputs and the output, even if the data set is pretty noisy but complicated. The most widely used neural network architecture is the multilayer perceptron (MLP). However, prior research indicates that the brute force design of these networks is important, as only some formula works in every case [16].

In addition to its essential function, the ANN model created and trained in this paper predicts the flashover voltage of polluted glass insulators in extreme environments (both dry and rainy) and for different designs (standard and anti-pollution) as a function of time. The main objective of this study is to reach the topmost performance for the model by carefully refining the model architecture, determining the best fitting of activation functions thirdly, and tuning the training algorithms to gain exact prediction so that it can be highly reliable and robust for flashover voltage prediction in different surrounding such as high voltage power system dependability domain.

IV. ANN ARCHITECTURE AND OPTIMIZATION APPROACH

Our ANN model follows a multilayer perceptron (MLP) architecture known for its robustness in learning and predictive power. The MLP architecture consists of:

- **Input Layer**: Incorporates features related to the insulators, humidity, rainfall intensity, and insulator profile (standard vs. anti-pollution). These input variables provide the data needed for predicting flashover voltage across different scenarios.

• **Hidden Layers**: Hidden layers allow the ANN to process and interpret complex interactions between input variables. By applying nonlinear activation functions like the sigmoid or tangent-sigmoid (Logsig), the model is able to capture subtle relationships within the data.

• **Output Layer**: Provides the flashover voltage prediction based on the input variables and learned relationships. The output is a continuous value that represents the expected flashover voltage for each insulator configuration.

The mathematical formulation behind the MLP can be described as follows [9]:

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

Where:

• Sj is the neuron output in the current layer,
• F is the activation function,
• wkj and Bj are the weights and biases, respectively,
• Ej represents the node values from the preceding layer.

As depicted in figure 1, once the structure of the ANN is established, the subsequent step involves training the network.

IV.1 MODEL DEVELOPMENT

In this study, we employed a hybrid approach that combines Particle Swarm Optimization (PSO) and Artificial Neural Networks (ANN) to accurately forecast flashover voltage. The PSO algorithm optimizes the neural network's weights and biases, improving the model's performance in terms of both speed and accuracy.

Given its powerful capability for data-driven simulations and optimization, MATLAB was used to build the PSO-ANN model. The methodology started with collecting a data set that comprised numerous influencing factors as input variables such as insulator geometrical features (the spacing between the two consecutive insulator threads, S; in mm), diameter Dm (in mm), leakage length of one-piece and the number elements in the chain of insulator NE. The model's output is flashover voltage prediction (Vc, in kV) concerning two kinds of conditions: dry and rainy.

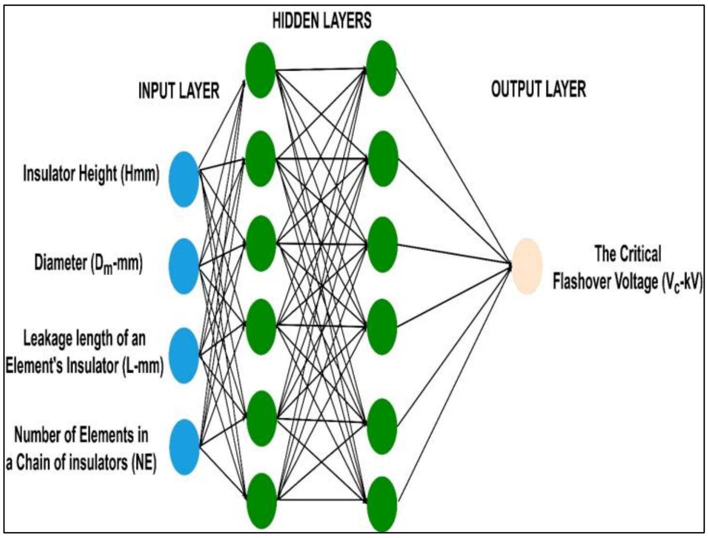

Figure 1: A standard representation of an artificial neural network (ANN).
Source: Authors, (2025).

The first step was to structure the dataset, ensuring that the input features (insulator spacing (S, in mm), diameter (Dm, in mm), leakage length of the insulator element (L, in mm), and the number of elements in the insulator chain (NE) were properly normalized. Then, the PSO algorithm was configured to optimize the initial weights and biases of the neural network.

After the ANN structure was defined consisting of input, hidden, and output layers the PSO algorithm iteratively adjusted the network's parameters, seeking the configuration that minimized the mean squared error (MSE) between predicted and actual flashover voltages. The optimization process continued until convergence, with the best particle's position representing the optimal set of network weights.

$$MSE = \left(\frac{1}{N}\right) \sum_i |t_i - o_i|^2 \quad (4)$$

Once training was complete, the model was validated using test data that were not part of the training process.

The process of training the ANN using PSO involved seven key steps:

1. Collecting the necessary data.
2. Creating the neural network.
3. Configuring the network.
4. Initializing the weights and biases of the network.
5. Training the neural network using the PSO algorithm.
6. Validating the network to assess its performance.
7. Applying the trained network for predictions.

The optimal configuration for the ANN-PSO model was established as follows: (a) The hidden layer comprised 10 neurons. (b) The training process was run for 6000 iterations. (c) The particle swarm consisted of 100 particles. (d) The acceleration constants were set at c1 = 1 and c2 = 2.

A three-layer neural network predicts insulator flashovers (Figure 2). The network architecture includes four six neurons, a hidden layer with 10 neurons, and a single output neuron. The parameters c1 and c2 are kept constant; for each config file, multiple test metrics are run to determine the better network configuration. We calculate the average deviation to find a network trained for up to 6000 iterations with minimal error. Iteratively undergoing this process ensures the model's capability to generalize in any situation and reduce predictive error.

IV.2 DATA SELECTION

In the testing process for insulators, including those featured in this study, a comprehensive evaluation of both electrical and mechanical parameters is conducted to ensure their performance and reliability under various operational conditions. A critical aspect of this evaluation is the flashover voltage test, which assesses the insulator's ability to withstand high voltages without experiencing flashover, a disruptive electrical discharge across its surface. The flashover voltage is measured under both dry and wet conditions, simulating real-world environmental factors such as rain or humidity that could impact the insulator's performance.

Each insulator model is subjected to stringent mechanical and electrical rating tests as per international standards, such as IEC 60305, ANSI, and BS [17]. These tests are essential for ensuring the insulator's capability to endure stresses encountered across different voltage ranges and environmental pollution levels. Additionally, insulators are categorized into various profiles standard and anti-pollution profile to optimize performance in specific environments, such as low-pollution areas or regions exposed to heavy pollution or desert conditions. This rigorous testing protocol ensures the reliability and operational safety of insulators used in high-voltage transmission systems worldwide.

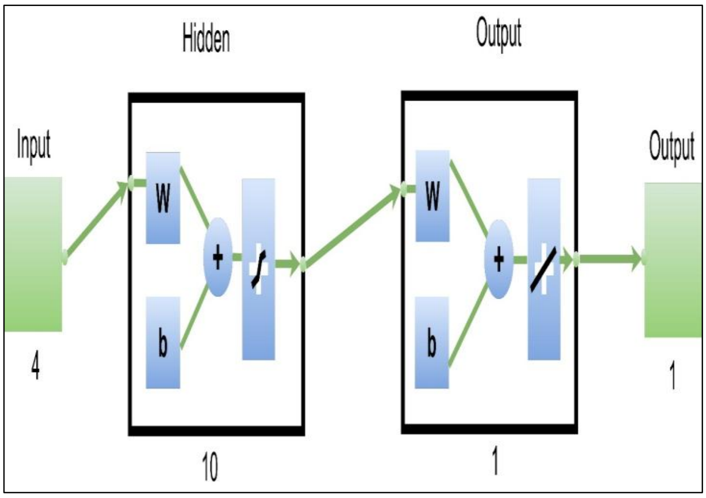

Figure 2: The network training model in MATLAB.
Source: Authors, (2025).

In this study, we focused on data derived from experimental results for the prediction of flashover voltage on two types of insulators: the standard profile insulator and the anti-pollution profile insulator, both tested under dry and rainy conditions. Our objective was to investigate the impact of rain on the flashover voltage. To achieve this, several key parameters were selected as input vectors for the predictive model, including insulator spacing (S, mm), diameter (Dm, mm), leakage length of the insulator element (L, mm), and the number of elements in a chain of insulators (NE). The predicted output is the flashover voltage (Vc, kV) under both dry and rainy conditions. In our investigations, the number of insulator elements in the chain varied, ranging from a minimum of two to a maximum of thirty, allowing us to comprehensively study the effects of different configurations and environmental conditions on the flashover voltage. This approach provides valuable insights into how rain affects the electrical performance of insulators, particularly in polluted and extreme environmental settings [17] .

Table 1 presents the characteristics and specifications of various types of insulators.

IV.3 CASE STUDIES

To effectively evaluate the predictive accuracy of the ANN -PSO model, it is necessary to use a dataset of diverse species in the testing phase that was not used in the training phase. This approach allows the creation of a representative and unbiased test set.

Splitting the data correctly can be particularly important when creating machine learning models, especially during training and testing. According to available research, 70-80 % of the data (for training) and 20-30% (for testing) can yield optimal performance. [18],[19]. For our model, 75 % of the data is reserved for training, and 25 % is reserved for testing, with the split being consistent on whether the data belongs to type 1 or type 2 insulators.

The test set data is then used to test the models' predictive accuracy. This allows the model to be trained on the given data with as slight bias and training error as possible but still retain the ability to be generalized to new data with as slight variance and test error as possible.

Table 2 presents various case studies, detailing the number of elements in the insulator chain for each type of insulator. Additionally, it includes the number of training data points and testing data points for each of the three types of insulators.

Table 1: Key features of the insulators examined in the study [17].

Insulator Type (Model)		S (mm)	D(mm)	L(mm)
Standard profile insulators	NB-70-146	146	255	320
	NB-100-146	146	255	320
	NJ-120-146	146	255	320
	NK-180-146	146	280	320
	NK-220-156	156	280	380
Anti-pollution profile insulators	NB-100PPZ-146	146	*280*	445
	NJ-120PPZ-146	146	280	445
	NJ-140PPZ-146	146	280	445
	NK-160PZ-171	171	330	545
	NK-222PZ-171	160	330	545

Source: Authors, (2025).

Table 2:The different cases studied.

	Standard profile insulators	Anti-pollution insulators
NE in train Case	22	22
NE in test case	7	7
Training data	110	110
Testing data	35	35

Source: Authors, (2025).

IV.4 PERFORMANCE EVALUATION METRICS

This study selected various performance metrics were selected to evaluate the proposed models and identify the most accurate one for predicting the Flashover output voltage. These metrics included the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute percentage error (MAPE). The following formulas were applied to compute these indices: [10]

$$R^2 = 1 - \frac{\sum_{k=1}^{n}\left(y_{tes,k} - y_{pre,k}\right)^2}{\sum_{k=1}^{n}\left(y_{tess,k} - \overline{y_{tes,k}}\right)^2} \quad (5)$$

$$RMSE = \left\{\frac{\sum_{k=1}^{n}\left(y_{tes,k} - y_{pre,k}\right)}{n}\right\}^{1/2} \quad (6)$$

$$MAPE = 100\%.\frac{\sum_{k=1}^{n}\left|y_{tes,k} - y_{pre,k}\right|/y_{tes,k}}{n} \quad (7)$$

V. RESULTS AND DISCUSSION

The assessment of insulator performance in different environmental conditions is crucial for comprehending the mechanisms underlying arc initiation and flashover incidents. This research focuses on examining insulator behavior in both dry and rainy settings, with a particular emphasis on how these conditions affect their electrical characteristics.

The findings shed light on the way environmental elements impact key parameters like flashover voltage, underscoring the necessity for customized predictive models tailored to diverse insulator types and weather circumstances.

The study was conducted in two distinct phases: the first phase focused on determining the critical flashover voltage under dry conditions, while the second phase examined the same under wet conditions, utilizing experimental test data from previous research [17].

The performance of the model developed using the ANN-PSO approach was thoroughly evaluated, yielding superior results compared to existing methodologies. These findings are presented in Figures 3 to 6. Figures 3 and 4 present the performance of the ANN-PSO model in predicting the flashover voltage using the testing dataset for the standard profile insulator under dry and rainy condition. The model demonstrates a remarkable ability to closely replicate the trend of the experimental data, indicating that it has been effectively trained to capture the complex, nonlinear relationships governing flashover voltage behavior. The significant overlap between the experimental results and the ANN-PSO predictions during the testing phase underscores the model's high degree of accuracy and its capability to generalize the intricate characteristics of flashover voltage for both insulator profiles.

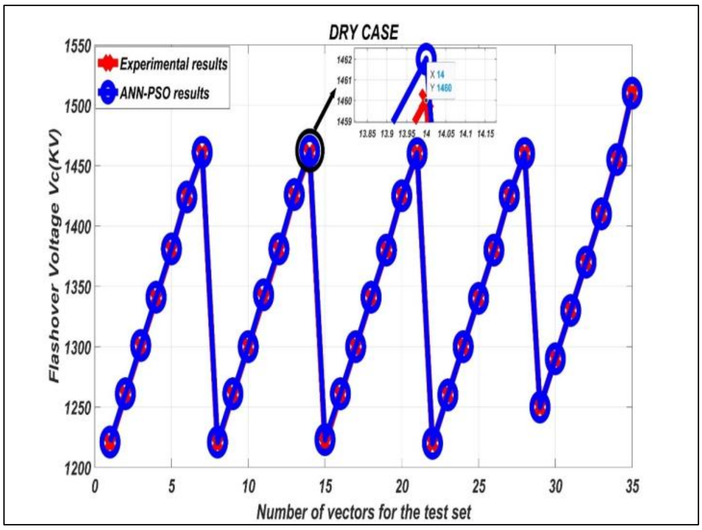

Figure 3: ANN-PSO model performance for testing (standard profile under dry conditions)
Source: Authors, (2025).

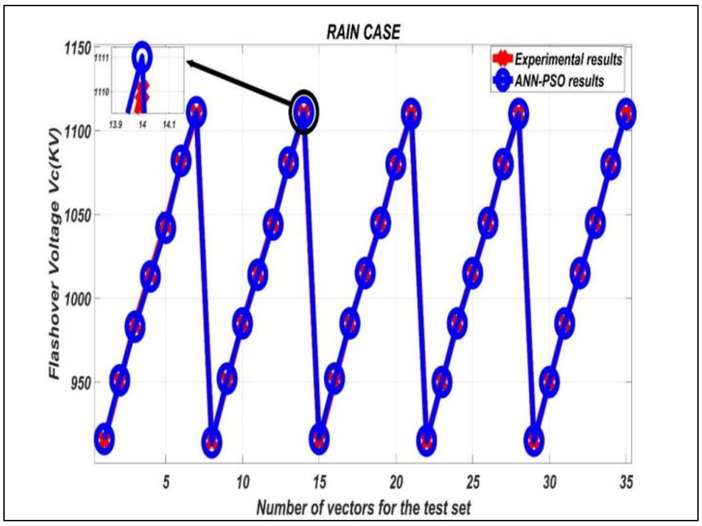

Figure 4: ANN-PSO model performance for testing (standard profile under Rain conditions)
Source: Authors, (2025).

Figures 5 and 6 evaluate the model’s performance using an independent testing dataset for the anti-pollution profile insulator, offering additional confirmation of its predictive accuracy.

Even when faced with data points not previously encountered during training, the ANN-PSO model consistently produces predictions that closely match the experimental results. This reliability under
unfamiliar conditions underscore the model’s robustness and its strong ability to generalize beyond the training dataset.

The results highlight the model's potential as an effective tool for predicting critical flashover voltage, with implications for optimizing insulator design and improving the reliability of high-voltage systems under diverse operating conditions.

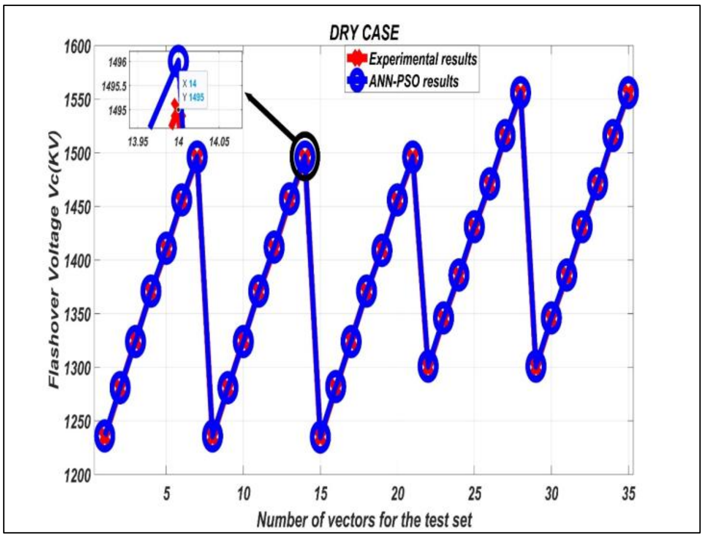

Figure 5: ANN-PSO model performance for testing (Anti-pollution profile under dry conditions)
Source: Authors, (2025).

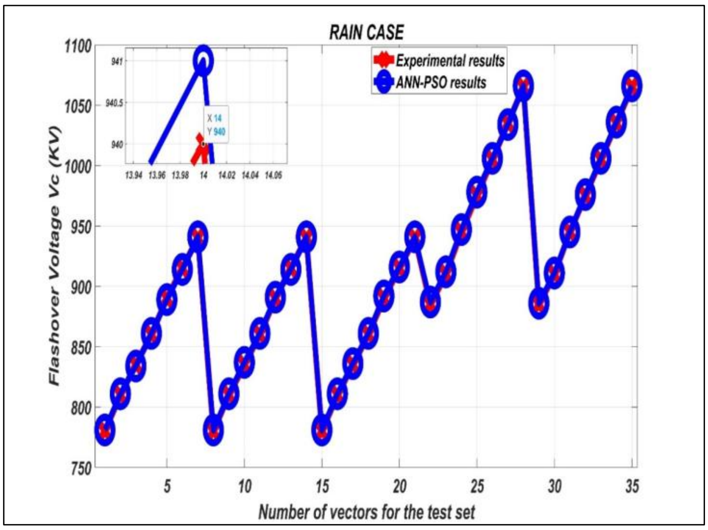

Figure 6: ANFIS-PSO model performance for testing (Anti-pollution profile under Rain conditions).
Source: Authors, (2025).

According to the results presented in Figures 3 through 6, the flashover voltage of insulators under rainy conditions is significantly lower compared to dry conditions. This explains how the deposition of water droplets on the surface of insulators alters the resistance Rp. Rain introduces water on the insulator's surface, which can significantly reduce the surface resistance, especially if the water contains dissolved salts or other contaminants.

The presence of water promotes the formation of a conductive path along the insulator's surface, leading to a substantial decrease in flashover voltage. This means that under wet conditions, the insulator is more prone to flashover at lower voltages compared to dry conditions. By comparing the values of flashover voltage in dry and rainy conditions, we can calculate the mean percentage as follows:

For standard profile : $\frac{V\,Dry}{V\,Rain}=1.3423$,

For anti-pollution profile: $\frac{V\,Dry}{V\,Rain}=1.4600$,

Anti-pollution profile insulators exhibit clear superiority over standard profile insulators due to their enhanced design features tailored for polluted and challenging environments. With increased leakage distances and optimized profiles, they effectively reduce surface electric field intensity and mitigate the risk of flashovers caused by contamination and moisture.

Unlike standard insulators, which are more susceptible to flashovers under polluted or wet conditions, anti-pollution insulators demonstrate higher flashover voltage and better performance, even in regions with heavy industrial emissions, salt deposits, or extreme weather. Their self-cleaning capability allows rain and wind to remove contaminants more efficiently, maintaining their insulating properties and reducing maintenance requirements.

Additionally, anti-pollution insulators are more resistant to surface erosion and material degradation, ensuring longer operational life and greater reliability in high-voltage applications. These attributes make them the preferred choice for ensuring the safety and efficiency of power transmission systems in harsh environmental conditions.

To evaluate the precision of the ANN-PSO model, one approach is to analyse the correlation between the actual critical flashover voltage (V_c) and the estimated values produced by the ANN-PSO. With the maximum possible correlation being one, a correlation value closer to 1 indicates a higher performance level of the model. Figures 7 and 8 display the correlation for the estimated versus actual values of V_c for the Anti-pollution profile insulator under both dry and rainy conditions, which were used to assess the model.

The data points almost perfectly align with the line of best fit, demonstrating the model's strong ability to accurately predict the duty ratio for the test dataset. Specifically, the correlation for the test set under dry conditions reached 0.99812, while under rainy conditions, it was 0.999, showcasing the model's high accuracy in both scenarios. Evaluating the ANN-PSO model's performance involves comparing it with other models, a key step in assessing its effectiveness.

To do this, validation indices such as RMSE, MAPE, and R^2 were measured against results previously reported in literature for two specific scenarios, as detailed in Table 3. From the comparison outlined in Table 3 with other intelligent methods, it is evident that the model we propose stands out by securing a higher coefficient of determination (R^2=0.999) and exhibiting a remarkably low root mean square error (RMSE=0.00288), clearly surpassing other modelling approaches in effectiveness.

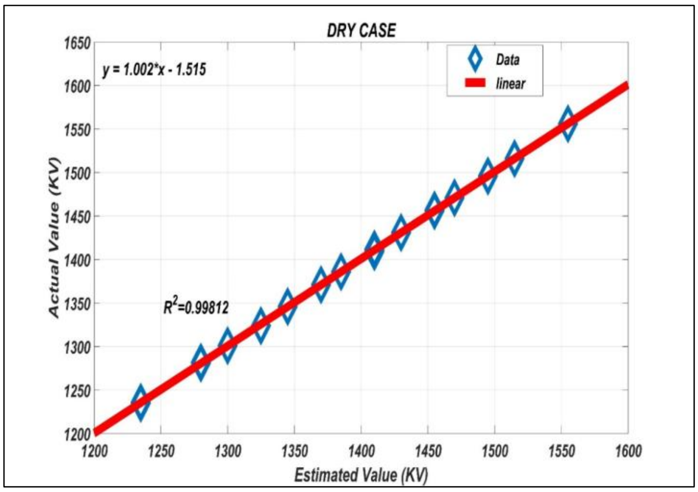

Figure 7: Correlation between predicted and actual Critical Flashover Voltage values for Anti-pollution profile insulators tested under dry conditions.
Source: Authors, (2025).

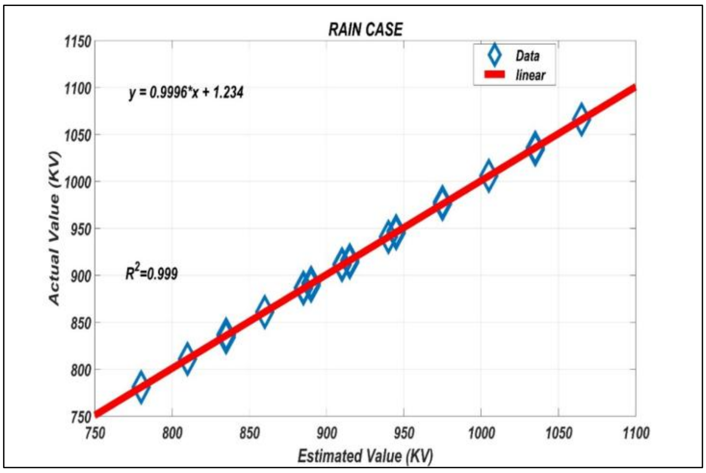

Figure 8: Correlation between predicted and actual Critical Flashover Voltage values for Anti-pollution profile insulators tested under Rainy conditions.
Source: Authors, (2025).

Table 3: Evaluating the suggested ANN-PSO models against other modelling approaches.

Methods	(RMSE)	(R^2)	(MAPE)
GMDL Dry [17]	-	0.9929	-
GMDL Rain [17]	-	0.998	-
LS-SVM Dry [17]	0.0389	0.997	-
LS-SVM Rain [17]	0.371	0.9983	-
ANN-PSO Dry	0.00288	0.999	0.2458
ANN -PSO Rain	0.00295	0.99812	0.3546

Source: Authors, (2025).

The findings indicate that an ANN trained with PSO not only offers more accurate predictions, but also requires fewer computational resources. This approach is particularly robust, as it avoids becoming trapped in local optima. Moreover, it benefits from straightforward logic, ease of implementation, and built-in intelligence. When compared to results from practical experiments, the PSO-ANN technique proves to be highly effective in forecasting flashover in high-voltage polluted insulators.

VI. CONCLUSIONS

This study introduces an advanced Artificial Neural Network (ANN) model optimized using the Particle Swarm Optimization (PSO) algorithm to predict the flashover voltage of glass insulators with standard and anti-pollution profiles under dry and rainy conditions. The research highlights the significant influence of raindrops on reducing flashover voltage, emphasizing the critical implications for the reliability of high-voltage insulation systems.

The ANN's parameters were meticulously fine-tuned by leveraging the PSO algorithm, enabling the model to effectively capture the complex interactions between insulator characteristics, environmental conditions, and flashover performance. The findings indicate that this model excels at forecasting flashover voltages for contaminated high-voltage insulators in various weather conditions.

To evaluate the effectiveness of the suggested model, several statistical measures were utilized, including the Root Mean Square Error (RMSE), the Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). The analyses and outcomes of this study, including comparisons with other methodologies such as GMDL, ANFIS, and LSSVM models, distinctly highlight the proficiency of the proposed ANN-PSO modelling approach. It effectively predicts the critical flashover voltage for various insulator types across different regions, by providing comprehensive data on the electrical transmission system.

To construct a more comprehensive and adaptive predictive framework, future research could enhance this study by integrating additional environmental and climatic variables, such as temperature, humidity, wind speed, and varying pollution levels. Incorporating real-time monitoring data from power systems would enhance the model's precision and applicability in dynamic operational settings. Moreover, exploring hybrid optimization techniques or ensemble learning approaches could augment the model's performance, improving its predictive accuracy and robustness under complex scenarios.

VII. AUTHOR'S CONTRIBUTION

Conceptualization: Lazreg Taibaoui, Abdelhalim Mahdjoubi and Boubakeur Zegnini.
Methodology: Lazreg Taibaoui, Boubakeur Zegnini and Abdelhalim Mahdjoubi.
Investigation: Lazreg Taibaoui and Abdelhalim Mahdjoubi.
Discussion of results: Lazreg Taibaoui, Abdelhalim Mahdjoubi and Boubakeur Zegnini.
Writing – Original Draft: Lazreg Taibaoui.
Writing – Review and Editing: Lazreg Taibaoui and Abdelhalim Mahdjoubi.
Resources: Lazreg Taibaoui.
Supervision: Abdelhalim Mahdjoubi and Boubakeur Zegnini.
Approval of the final text: Lazreg Taibaoui, Abdelhalim Mahdjoubi and Boubakeur Zegnini.

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