Volume 11. No 3, September 2024
e-ISSN: 2527-9572 / ISSN: 2354-8924

A Novel Model for Prediction of Flashover 150kV Polluted Insulator Based on Nonlinear Autoregressive External Input Neural Network

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***Abstract* – This study aims to use an artificial neural network to forecast the flashover voltage of a polluted high-voltage insulator. Practical tests were conducted on a high-voltage insulator to gather data for the neural network. These tests were carried out with varying levels of real contaminants from used insulators, with each level of contamination measured in milliliters. The collected data provides flashover voltage values corresponding to different pollution amounts and their conductivity in each insulator zone. The Nonlinear Autoregressive External Input Neural Network (NarxNet) is employed to predict the flashover voltage and assess the pollution state of the insulator. The results demonstrate that the NarxNet method achieves a 93.74% accuracy rate in predicting the flashover voltage of high-voltage insulators, compared to the results from practical tests.**

Keywords: Flashover, Prediction, Contamination, Insulator, Neural Network, ESDD, NSDD.

I. INTRODUCTION

For the future, urbanization and the exponential growth of industrialization will lead to a large increase in energy demand [1]. This demand requires reliable generation and distribution of electrical energy. Especially for ultra-high voltage transmission lines, the reliability of such transmission lines is determined by the performance of well-designed insulators. The insulator is an important component in the electrical energy distribution system. Failure or damage to insulators is the main cause of failure of electric power transmission systems. The reliability of insulators is largely responsible for the safety and reliability of uninterrupted operation of electrical systems. Insulators used in high voltage overhead transmission lines are always subject to contamination and can trigger flashover.

When insulators are used in coastal or mountainous areas, contaminated salt and dust particles in the air can accumulate on the surface of the insulator and form a thick layer of contaminants. This condition causes the dielectric strength of the insulator to decrease, which can cause flashover. To overcome this so that the performance of the insulator becomes better, it is very important to study and analyze the behavior of the insulator in naturally contaminated conditions.

Recent research has also focused on the impact of various types of insulator contaminants on flashover performance. Several previous studies have reported that flashover in insulators due to pollution is influenced by various factors such as temperature, humidity, location, design and insulator material [2]. Several studies [3]–[6] developed pollution models, both static and dynamic, for flashover voltage prediction in contaminated insulators . Experimental data collection is needed to identify factors influencing insulator performance and understand the causes of failure.

Additionally, artificial intelligence based optimization techniques have been studied extensively to predict flashover voltages in insulators [1], [7]–[14]. Many studies have confirmed that artificial intelligence techniques such as Support Vector Machine (SVM), Artificial Neural Network (ANN), fuzzy logic (FL), and Adaptive Fuzzy Inference System (ANFIS) can be used to predict flashover voltage. These techniques have shown significant results in predicting flashover stresses in contaminated insulators. Asimakopoulou, et al used a fuzzy logic model to predict critical voltages in contaminated insulators [13]. More techniques such as Particle Swarm Optimization (PSO) combined with LS-SVM are proposed to predict the flashover voltage of contaminated insulators, insulator dimensions, and contamination level used as input to the network. The research results show that the relative error is quite large, so the proposed approach is less accurate [14].

In addition, prediction of flashover in 150 kV insulators under contaminated conditions using neural networks has experienced significant progress in recent years. Current standards in this area involve the use of artificial intelligence (AI) to predict insulator flashover voltages under contaminated conditions.

Despite progress, there are still gaps in current research. For example, most existing models do not consider the impact of weather such as temperature and humidity on flashover performance. In addition, a more comprehensive model is needed that can accurately predict flashover pressure under various contamination conditions. The contribution to the proposed research is expected to address this gap. The aim of this research is to develop a better neural network model for flashover prediction by considering various external factors such as temperature and humidity. Contaminant levels are measured by equivalent salt deposit density (ESDD) and non-soluble deposit density (NSDD). It is hoped that this will provide more accurate and comprehensive input for predicting flashover voltages, thereby increasing the reliability and safety of the power system.

II. Method

The method used in this research is laboratory measurements which consist of measuring flashover and contamination levels in the insulator. The method to measurement the contaminant based on ESDD and NSDD are explained as follows:

A. *Metode Equivalent Salt Deposit Density (ESDD)*

This method is used to calculate the level of salt deposit density to determine the degree of salt deposit density [15]:

$$ESDD = \frac{Sa \times V}{A} \quad (1)$$

where

$$S_a = 5.7 \times (\sigma_{20})^{1.03}$$

$$\sigma_{20} = \sigma_0 \times \left[1 - (B \times (\theta - 20))\right]$$

$$A = \pi \times S \times (R + r)$$

$$S = \sqrt{(R-r)^2 + (h)^2}$$

The nomenclature in this equation can be explain as below:

ESDD = Equivalent Salt Deposit Density(mg/c)
Sa = Salinity (mg/cm^3)
V = Aquades Volume (cm^3)
A = Insulator Surface (cm^2)
σ_{20} = Conductivity at 20℃ (uS/cm)
σ_θ = Conductivity at θ℃ (uS/cm)
b = Correction Factor at θ℃
θ = Temperature Liquid (℃)
S = Length of Insulator Blanket (cm)
R = Outer Radius of Insulator (cm)
r = Inner Radius of Insulator (cm)
h = Thickness of Insulator (cm)

Correction factor b at 5℃ to 30℃ used in calculations based on IEC 507: 1991. Value of correction factor can be seen in Table 1 below.

Table 1. Correction Factor Value Based on IEC 507: 1991

θ (℃)	b
5	0.03156
10	0.02817
20	0.02277
30	0.01905

The determination of the pollution level of the ESDD method insulator based on the IEC 815 standard is shown in the following table.

Table 2. ESDD Pollution Levels Based on IEC 815: 1986

Contaminant Level	ESDD (mg/Cm^2)
Light	0.03-0.06
Medium	0.06-0.3
Heavy	0.3-0.6
Very Heavy	>0.6

B. *Metode Non Soluble Deposit Density (NSDD)*

This method is used to calculate the level of pollutants that do not contain salt and are difficult to dissolve in water. The equation used to determine the level of non-salt pollution is [16]:

$$NSDD = \frac{B_2 - B_1}{A} \quad (2)$$

where:

NSDD = Non Soluble Deposit Density (mg/cm^2)
B_1 = Initial mass of clean condition paper or before screening (mg)
B_2 = Final mass of paper pollutant condition or after screening (mg)
A = Insulator surface area (cm^2)

In this NSDD method, the pollution level of the insulator is classified into four parts as follows.

Table 3. NSDD Pollution Levels Based on IEC 815: 1986

Contaminant Level	ESDD (mg/cm^2)
Light	0.01-0.1
Medium	0.1-1
Heavy	1-4
Very Heavy	4-10

C. *Non-linear Auto Regressive External Input*

NARX (Nonlinear Autoregressive with External Input) is a type of network for predicting time series by considering past values, feedback, and external time series. It has a recurrent dynamic structure with the advantages of good learning, fast convergence, and better generalization compared to other neural networks [17].

The NARX model is characterized by the following equation:

$$y(t) = f\left[x(t-1), x(t-2), \dots, x(t-n_x), y(t-1), y(t-2), \dots, y(t-n_y)\right] \quad (3)$$

In this context, the equation states that y(t), the output signal of the NARX model, is determined by a nonlinear function f involving y(t) and x(t). Here, x(t) represents the input data of the NARX model, while nx and ny indicate the sum of the previous output and input terms, respectively.

In this study some parameters regarding to high voltage insulator such as humidity, temperature, ESDD and NSDD are used as an input to neural network prediction. Some hidden layers are employed to get minimum error. The flashover voltage is a target of prediction. An narx neural network architecture can be seen in Figure 1.

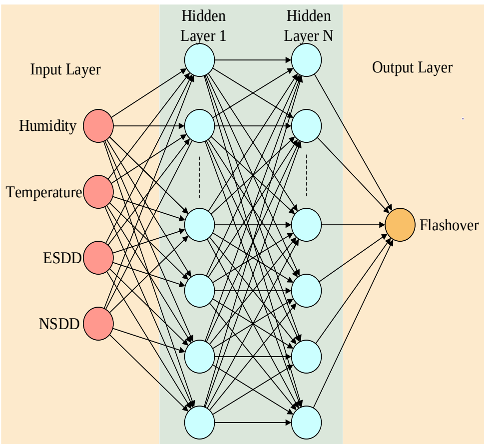

Figure 1. Narx Neural Network Architecture

Flashover measurements was conducted following the laboratory setup show in Figure 2, and the flowchart for predicting flashover using Narxnet is illustrated in Figure 3.

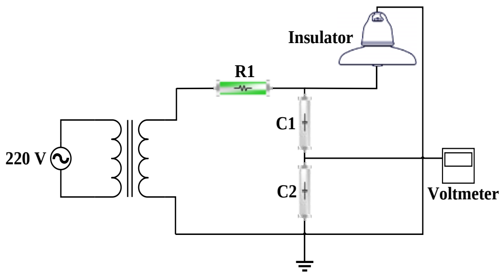

Figure 2. Laboratory Setup of Flashover Measurement

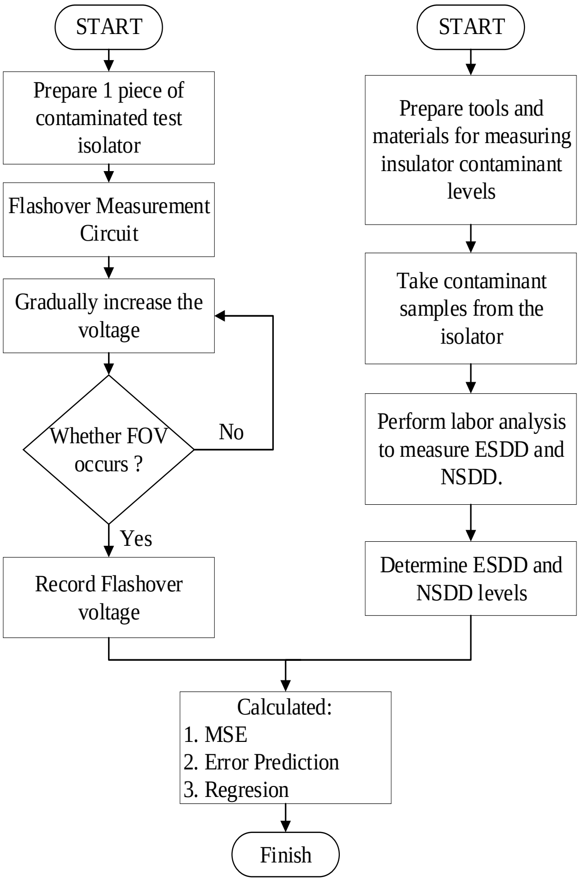

Figure 3. Flowchart of the prediction flashover using Narxnet

III. Results and Discussion

A. *Results*

The flashover testing process is carried out by applying voltage to an insulator sample contaminated with natural pollutants. The voltage is gradually increased until flashover occurs, which is when the voltage exceeds the insulation limit and an electric spark occurs across the insulator surface. The flashover voltage is then recorded as a test result as well as other parameters such as temperature and humidity at the time of the test. Figure 4 shown the insulator flashover testing.

Furthermore, measurement for contaminants is carried out in several steps: first, the contaminated insulator is washed thoroughly so that no contamination remains in the insulator where all contaminant dissolved in wash water. This wash water is collected in to container. The mass of contaminant is filtered using filter paper and measure using a digital microscale. The next process is poured the contents of container into another container. By placing the filter paper on top of second container so the water contain contaminant can be filtered by the paper. Next, the filter paper was dried, and the mass of the filter paper was measured. Tests were conducted as shown Figure 5.

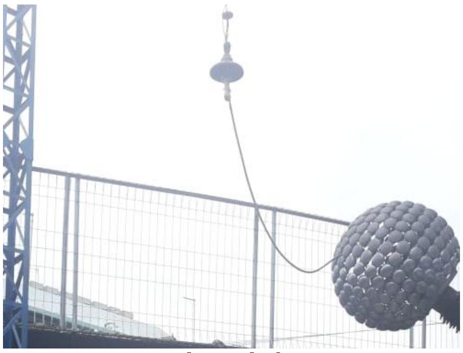

Figure 4. Insulator Flashover Testing

Figure 5. ESDD and NSDD Measurement

Table 5 shows the tabulation of part experimantal data that become a data input for narx neural network. All data are 120 data which consists of humidity, temperature, ESDD and NSDD. From this data, 80% for training data, 10% for validation data and the rest of 10% as testing data.

Table 5. Part of 120 Experimental Data

No.	Humid (Hg)	Temp (°C)	ESDD (mg/cm^2)	NSDD (mg/cm^2)	FOV (kV)
1	77.26	29.06	0.432	1.877	8.499
2	77.89	29.00	0.414	1.751	8.154
3	77.32	28.91	0.530	1.687	9.111
4	70.00	28.98	0.539	1.407	9.273
5	76.68	29.07	0.356	1.791	7.921
6	77.62	29.08	0.447	1.680	8.949
7	77.29	29.00	0.434	1.724	8.780
8	77.23	29.05	0.494	1.544	8.874
9	77.30	29.08	0.513	1.425	9.020
…	…	…	…	…	…
120	75.97	29.61	0.054	0.081	11.161

The narx neural network prediction results show in Figure 6, 7, 8 and 9 respectively. Figure 6 show the best validation performace of NarxNet result is 0.0379 at epoch 13.

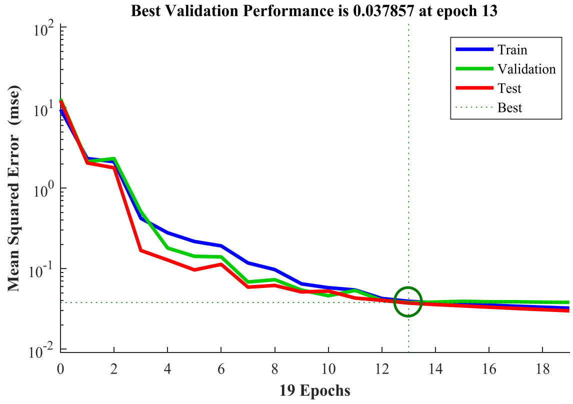

Figure 6. Best Validation Performance of NarxNet Result

Figure 7 show plot of training, validation and testing result of FOV prediction. From Figure 7 can be seen that 96 training data agree between target and prediction with small error. Also validation result shows significant number. Prediction still have some error its about 6.26% that can be seen in error prediction result at Figure 8 and in regression result at Figure 9.

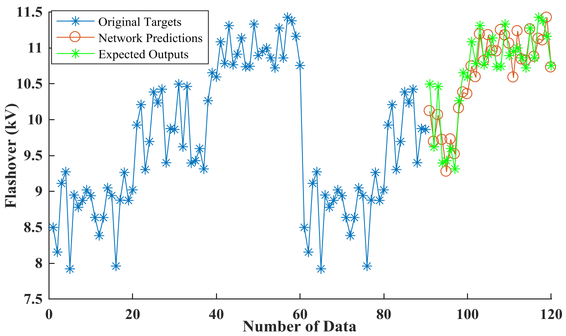

Figure 7. Plot of Training, Validation and Testing Result of FOV Prediction

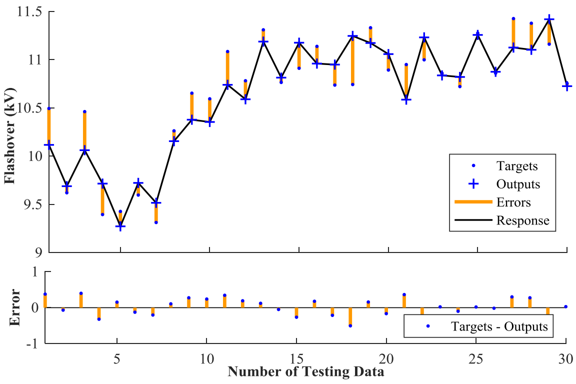

Figure 8. Plot of Error Prediction Result

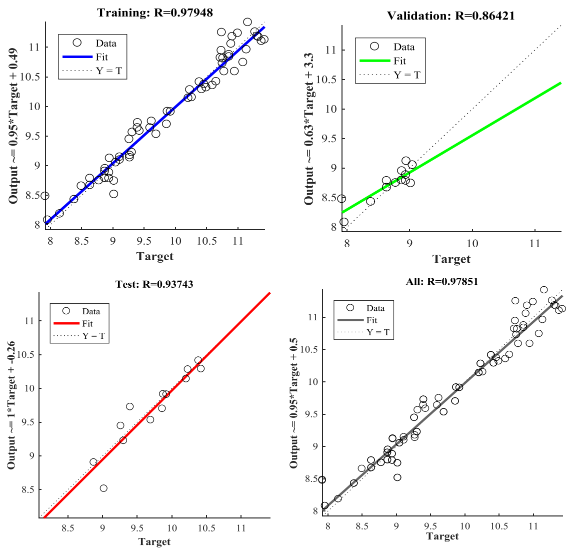

Figure 9. Regresion Results

B. Discussion

The data input to the neural network is the result of measurements in the laboratory in the form of humidity, temperature nsdd and esdd. The prediction neural network uses a Nonlinear Autoregressive External Neural Network (Narx) with 4 inputs and 1 output in the form of flashover predictions. There are 10 hidden layers with an input delay of 1: 2 and a feedback delay of 1: 2. The prediction results from the Narx neural network show the best validation performance at the 13th epoch with a low error rate. Although most of the training data matches the target, the validation set shows some error of around 6.23%. Nevertheless, the discussion focused on potential model optimization and future research directions to improve the accuracy and reliability of insulator flashover predictions

IV. Conclusion

This study successfully achieved its objective of predicting the flashover voltage of contaminated high-voltage insulators through the application of an artificial neural network, specifically the Nonlinear Autoregressive External Input Neural Network (NarxNet). The practical tests conducted on high-voltage insulators provided valuable data that served as the foundation for implementing the artificial neural network concept. By exploring different levels of real contaminants derived from used insulators. The insulator flashover depends on several parameters; in our work just considered the humidity, temperature, ESDD and NSDD. The flashover voltage values obtained from this database are associated with different levels of contamination. The results showed that the NarxNet method demonstrated a remarkable level of accuracy in predicting flashover voltage on high-voltage insulators. The accuracy achives about 93.74 % that means error prediction is 6.26%.

V. Acknowledgments

The author would like to express gratitude to Electrical Engineering Department, Engineering Faculty, Universitas Andalas and all those who have supported and assisted in this research.

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