Experimental Study of the Artificial Neural Network Solutions for Insulators Leakage Current Modeling in a Power Network

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***Abstract*—The leakage current which flows through insulators is dependent on many different environmental variables like temperature, humidity, wind and pollution. The leakage current rate varies during a daily period; so the leakage current curve versus time in a 24 hour period will be nonlinear. Implementing field experiments in a Research Site, the leakage current peak amounts were collected in different intervals and using two neural network methods of Feed Forward BP algorithm and Radial Based Function, the relation between leakage current and variation of effective parameters of leakage current was studied in this paper and the most effective algorithm revealed.**

***Index Terms*—ANN, environmental variables, insulator, leakage current**

I. Introduction

Electrical insulators are physically link conductors to energy transmission towers and distribution poles. Normally, a little amount of current passes along an insulator which is called: “leakage current” (LC). While the insulator is not contaminated, the capacitive partial is significant; but conduction increase on the insulation surface makes the current more resistive [1]. Outdoor insulators are exposed to different environmental conditions and natural and industrial contaminations; while the pollution is dry, it does not affect the insulator’s leakage current significantly but as it gets moist, the polluted layer acts as a current conductor. Due to this current, the layer heats up and the heat, causes the contamination layer to get drier. Usually these layers are closer to high voltage electrodes. These dry layers are not dependent on the insulator’s type [2]. Modeling of the passing current of the insulator is complicated, since different factors like insulator form, different pollution densities; wind velocity, temperature and humidity rate affect it [3].

Due to the nonlinear characteristic, several methods and algorithms have been used to describe the insulators leakage current behavior. Thanks to excellent performance of the artificial neural network (ANN) to approximate optimal nonlinear function, it has been used by researchers for this purpose [4]. Two of the ANN methods have been applied more: The first method is to estimate the flashover voltage through geometric characteristics of the insulator which has been mentioned in some papers. The neural network has been used as an estimating function to model flashover voltage, insulators diameter (D), Creepage length (L), barometric pressure and Equivalent Salt Deposit Density (ESDD). The second method is to estimate the equivalent ESDD conductivity rate according to environmental parameters. Based on this method, the pollution rate and washing intervals are determined. Normally ESDD estimation based methods are time and cost consuming, so they are modeled by ANN [5].

To sum up, although there have been many qualitative studies on applying Artificial Neural Networks for modeling the insulators leakage current, there are few studies on evaluating these methods in order to develop them and choose the most effective one. In this paper back propagation technique and radial based function method are assessed. To do this, an experimental study was accomplished in a research site in Hormozgan along the coastal area of Persian Gulf.

II. The Relation between Leakage Current and the Flashover Voltage

Generally, the electric flashover happens in some steps as follows [6]:

- Contaminated layers creation
- The Insulator and the contaminated layers interaction
- The surface wetting
- The electric field’s effect on the water droplets and their closeness
- Partial discharges between layers close to each other
- Flashovers resulted by positional arcs

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A technique for calculating the flashover voltage in an insulator is to choose a rectangular which its area is equivalent to the insulators outer and side areas. A simple form of a modeled insulator by a rectangular is shown in Fig. 1.

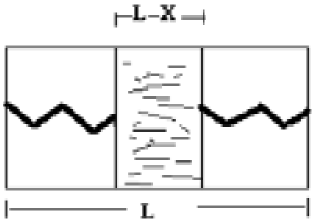

Figure 1. The rectangular equivalent to the insulators surface.

As it is seen, the equivalent area is composed of 3 parts of which two side parts relate to electrical arc and the middle part is related to conductors' surface.

The electrical arcs characteristics are defined as follows:

$$U_{dc} = 138XI^{-0/69} \quad (1)$$

$$U_{ac} = 140XI^{-0/67} \quad (2)$$

where:
Udc = dc flashover voltage
Uac = ac flashover voltage
I = arcs current
X = arcs length

Flashover voltage is proportional with the surface conductivity at the critical point ahead of the flashover start and the surface conductivity is determined by γ_c [7]. So the insulators resistance determination will be necessary. The insulators resistance based on the arc is:

$$R(X) = \frac{1}{\pi\gamma_c}.Ln\frac{L-X}{r0} \quad (3)$$

where:
γ_c = critical conductivity
L = creepage path length
X = arc length
r0 = arc root radius

Relation 3 is validated for suspension and integrated insulators.

III. Leakage Current Estimation Based on Environmental Parameters by Neural Network Algorithm

The main part of ANN implementation is to have or get input and output patterns. Having these patterns, the nonlinear function can be approximated and estimated using the inputs by neural network construction.

A. The Leakage Current

The leakage current is an index which determines the probability of flashover occurrence [8]. The Verma experimental relation defines the leakage current peak in a cycle before the flashover as follows:

$$I_{max} = \left(\frac{S_{CD}}{15.32}\right)^2 \quad (4)$$

in which:
SCD is the specific creepage distance which is defined as:

$$S_{CD} = \frac{L}{U_{max}} \quad (5)$$

where:
L = the creepage distance of the whole insulator by mm
Umax = the maximum phase to phase voltage on the insulator

B. Measurement and the Site Facilities

The leakage current measuring equipment is an instrument which locates in the insulators leakage current path and measures the leakage current amounts and the environmental parameters at the same time. So the input and output data are acquired within 24 hours.

In this study, the insulator samples were installed in Hormozgan research field. After exposing to the local environmental conditions for 12 months, the samples were used for leakage current tests. All the weather parameters in this period were recorded. At the end of the period, ESDD_NSDD method was used for performance assessment and operation results analysis. The samples used in this research were distribution level type insulators. Table I shows the insulator samples characteristics.

Fig. 2 shows the test site and pattern insulators. The insulators were mounted on an H Pole in 20 Kv distribution network.

TABLE I. Insulator Sample Characteristics

No.	Code	Ins. Type	Creepage distance(mm)	substance
1	In1	8 Shell Pin	825	Porcelain
2	In2	6 Shell Pin	696	Porcelain
3	In3	56-2 Pin	432	Porcelain
4	In4	Langrad	655	Porcelain
5	In5	Anti-frog Suspension	432	Porcelain
6	In6	56-3 Pin	686	Porcelain
7	In7	Polymeric 1	900	Silicon Rubber
8	In8	Polymeric 2	470	Silicon Rubber
9	In9	Std. Suspension	290	glass

The leakage current measuring system including 9 LC sensors can measure and analyze 9 insulators LC at the same time. Fig. 3 shows a typical connection pattern of the sensors to the sample insulator.

LC sensors are Hall Effect converters with high accuracy which act based on magnetic compensation. Also these instruments are equipped with environmental sensors like temperature, humidity, wind direction, velocity and UV radiation amount sensors.

Figure 2. Test site, the sample insulators and monitoring equipment.

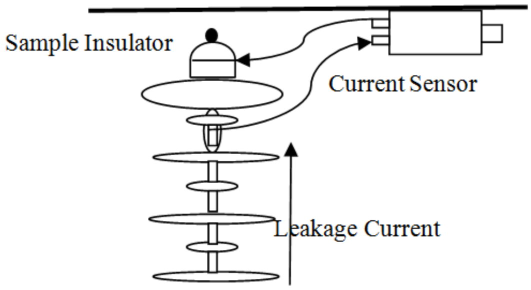

Figure 3. An LC sensor-insulator connection.

IV. Input and Output Data

The input and output data for simulation is as follows:

- Inputs: temperature, humidity, wind velocity, wind direction, UV radiation
- Output: Leakage Current

The data is collected from the pattern insulators and will be used for implementation. Fig. 4 shows a 24 hour curve of the Insulator No. 2. This curve is used as the optimal value in the neural network.

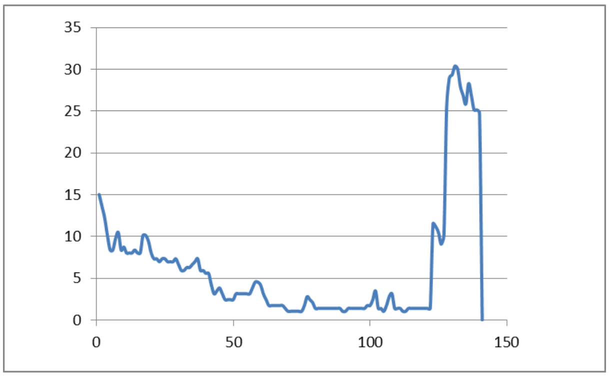

Figure 4. Leakage current in a 24 hour period.

Two ANN methods have been considered for insulators simulation; the back propagation technique (BP) ANN and the radial base function (RBF) ANN. In BP ANN, the input and hidden layers activating functions are tangent sigmoid type and linear activating function is used fort the last layer [9]. The input and output data should be scaled to get proportional with the ANN measures. In RBF ANN which is made of middle and output layers, the main layers activating function is a goussian radial type which varies between 0 and 1; so this neural network also needs input and output scaling.

There are various methods for input and output data scaling; some of them are as follows:

- Dividing the input and output data by the maximum input and output values respectively

$$n_{nar} = \frac{P_i}{\max(p)}$$

- Subtracting data from the minimum value and dividing its result by the minimum values from maximum values subtraction

$$n_{nor} = \frac{P_i - \min(p)}{\max(p) - \min(p)}$$

- Or using this relation:

$$n_{nor} = \frac{Pi - avg}{Variance}$$

There are 141 data for each input as well as output from which 100 data has been selected randomly for network test.

V. The Approperiate Neural Network Selection

Choosing a proper ANN and the number of layers and neurons is the challenge ahead of any research using this tool. Some patterns could be used as criteria:

If the input values or patterns have small variation and vary around a specific point, RBF is preferred; otherwise, BP method would be a better choice.

However, regarding the input and output values of each insulator, the proper ANN could be selected and regarding it, the learning algorithm can be implemented. In this study the 6-shell porcelain Insulator (Ins.2) will be simulated using RBF and BP Artificial neural networks (Fig. 5).

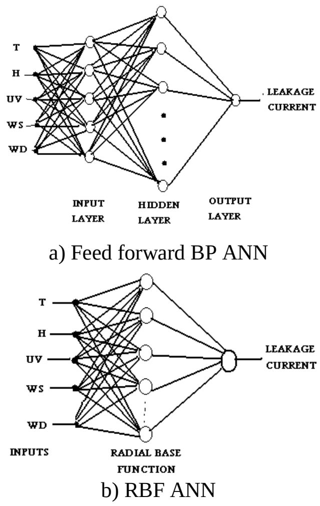

Figure 5. BP and RBF neural networks schematics.

VI. Simulation Using ANN

To analyze the simulation results various scenarios should be evaluated such as: the number of hidden layers, the number of neurons in each layer and the speed of convergence.

A. Feed Forward BP ANN for Ins.2

In this simulation method, varying layers and neurons of each layer, effects on fault rate and convergence speed will be studied. The number of hidden layers was set on 12, 20, 55, 70, 100 and simulation was carried out by Matlab. The network output according to desired value without scaling for hidden layer with 12, 20, 55, 70, 100 neurons is presented in Fig. 6.

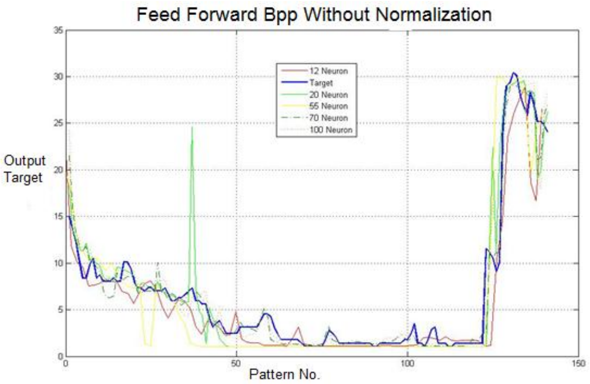

Figure 6. ANN output comparison by desired value in hidden layer with 12, 20, 55, 70, 100 neurons.

Performance, epoch, the patterns correlation and learning in neural networks with 12, 20, 55, 70, 100 neurons without scaling has been presented in Table II.

It is expected to get better results by normalizing input and output data; therefore in the second method, the data is normalized. The output and desired values are shown in Fig. 7. The relating table of performance for Feed Forward BP ANN is presented in Table III.

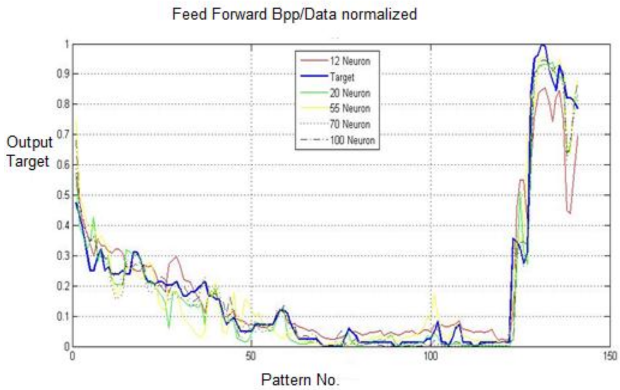

Figure 7. Five conditions outputs comparison with desired value for normalized data.

TABLE II. PERFORMANCE, EPOCH, CORRELATIONS AND ERROR VALUE FOR 12, 20, 55, 70, 100 NEURONS WITHOUT SCALING

No. of Neurons in hidden layer	Epoch	All Patterns Correlation (R)	Test Pattern Correlation (R)	Error
12	1301	0.9794	0.9607	0.8382
20	2000	0.9472	0.8776	3.861
55	1400	0.9236	0.8248	4.531
70	1870	0.9838	0.9803	3.526
100	1206	0.9810	0.9344	2.398

TABLE III. FEED FORWARD ANN PERFORMANCE WITH HIDDEN LAYERS OF 12, 20, 55, 70, 100 NEURONS

No. of Neurons in hidden layer	Epoch	All Patterns Correlation (R)	Test Pattern Correlation (R)	Error
12	2000	0.9608	0.8970	0.00043
	2000	0.9758	0.9589	0.00265
	1634	0.9771	0.9735	0.00574
20	1135	0.9790	0.9220	00.3860
	1265	0.9775	0.9631	0.00540
	1370	0.9823	0.9893	0.001193
55	753	0.9671	0.9325	0.00910
	644	0.9762	0.9371	0.00520
	833	0.9785	0.9573	0.00670
70	1832	0.9847	0.9185	0.00150
	910	0.9794	0.9742	0.00367
	1021	0.9812	0.9471	0.00090
100	1195	0.9777	0.9822	0.00797
	535	0.9722	0.9652	0.00810
	778	0.9657	0.8862	0.00203

B. RBF Neural Network for Ins.2

According to Fig. 3, Activating functions in RBF neural networks consist of a single core with Gossian activating function. Every neuron in RBF ANN has a radial symmetric response around its central vector.

In the usual learning method, randomly several input vectors to the network are set as the radial activating functions center so that the hidden layer gets regulated. The outer layer weights are regulated by decreasing the least square errors. It should be considered that the performance of the RBF ANN is dependent on the radial activating functions center selection and number of the neurons needed in this layer however it may lead to numeric calculation errors.

The number of the hidden layer is set equal to the input patterns; on the other hand, the radius(r) value in any function will be equal to one of the patterns in learning collection so that the radiuses will not be equal.

Here, among 141 collections of data, 100 input-output pattern data were used according to Table II, Table III and 41 collections of data were used for the network test. Output and the desired values for an accepted error of 0.01 are seen in Fig. 8.

Considering data normalization and approaching the desired value with network output, decreasing the acceptable error to 0.001, a more reasonable result will be achieved which can be seen in Fig. 9. Fig. 10 shows the error curve versus epoch number.

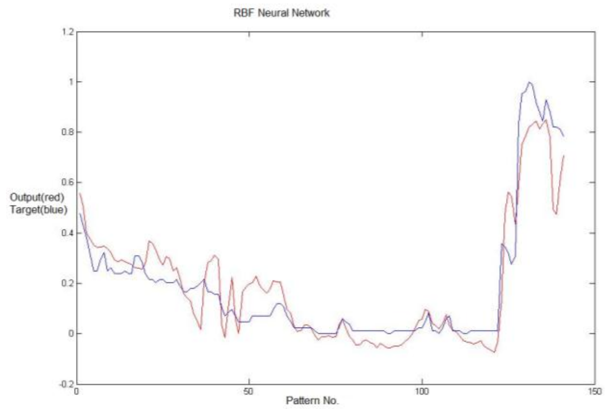

Figure 8. The network output and desired values.

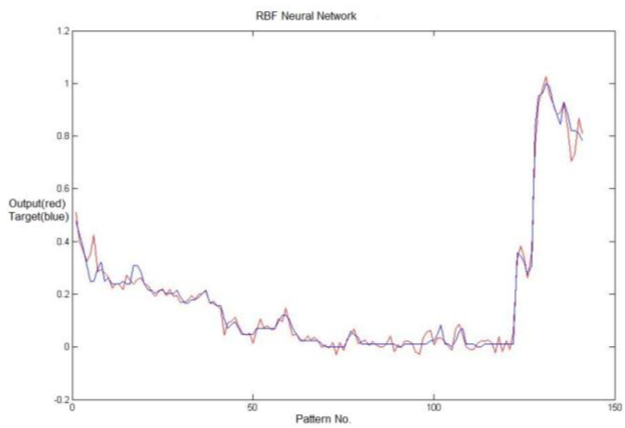

Figure 9. The network output and desired values for acceptable error of 0.001.

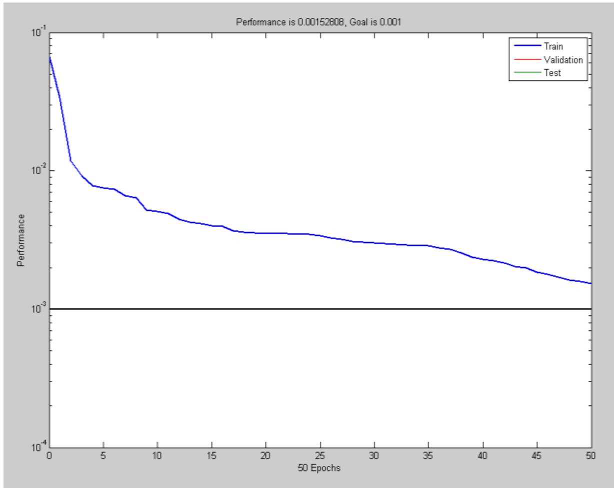

Figure 10. Error curve based on the number of epoch.

VII. Data Analysis

According to Fig. 6-Fig. 10, the following results can be addressed:

In Feed Forward Algorithm with back propagation technique, data normalization leads to results improvement which can be seen in Fig. 6 and Fig. 7. In unscaled neural network, the least error relates to the 12 neuron hidden layer construction; the epoch number is 1301 times and the correlation rate between input and output for all the patterns and the sample patterns, were 0.9794 and 0.9607 respectively. The correlation rate between input and output in 70 neuron construction was much better but with more epoch numbers.

In normalized neural network, the least error was 0.0043 with the hidden layer consisting of 12 neurons and the number of epoch was 2000 times; the input and output correlation rate for all learning and test samples, were 0.9608 and 0.8970, respectively. In 70 neurons construction, the Input to output correlation is 0.98126 and 0.9471, respectively which is a better result. The number of epoch is 1021 which is less than 12 neurons construction. Considering the output and desired values, the 70 neurons construction presents the best approximation.

It should be noted that increasing hidden layers during simulation, decreases simulation velocity and generates numerical errors. So the number of neurons in RBF Neural Network affects convergence velocity and systems response accuracy. This matches other researches results. On the other hand, according to Table III, Table IV and Fig. 6, Fig. 7, it can be noticed that in BP neural network, the number of layers in hidden layer, the number of neurons and data normalization greatly influences accuracy and velocity.

Considering Fig. 8 and Fig. 9, it can be seen that The RBF ANN with acceptable errors of 0.01 and 0.001, is a good estimator as the leakage current approaches the curve significantly. It can be seen in Fig. 9 that after 50 epochs, the error rate tends to the specified limit. So the RBF ANN shows better performance in comparison to the Feed Forward BP ANN.

VIII. COCLUSION

Power insulators flashover voltage and leakage current behavior were reviewed and modeled using mathematical relations. Due to nonlinear nature of the leakage current and its complicated dependence on geometrical characteristics and environmental conditions, the Artificial Neural Network Methods are used for estimation of the nonlinear functions. Using leakage current measuring instrument and environmental parameters, Input and output data was collected during 24 hour periods and normalized to be applied to the neural network.

After various tests, an important result was achieved: the type of input and output data and their distribution pattern is a key factor for a proper neural network selection. In this study both the BP ANN and RBF ANN models were considered and various simulation scenarios like the number of hidden layers, different number of neurons, convergence and errors were studied. This research indicated that the RBF ANN can be regarded as a good estimator for insulators leakage current behavior and a proper tool for design and utilization of insulators as essential elements in power delivery networks.

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