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Artificial Neural Networks Approach to the Modelling of AC Arcs Maintenance Conditions on Ice-covered Insulators

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Abstract: This study is about a kind of ANN for applications in multivariate nonlinear regression, in order to further knowledge and understanding of discharge on an iced insulator surface and the development into a flashover AC arcs. The propagation of local arcs is necessary for a flashover to occur on an ice-covered insulator. It was supposed that the local AC arc extended when it satisfied the arc re-ignition conditions. Therefore, the minimum applied voltage for maintaining an arc burning steadily across an air gap under various conditions is a major parameter and it is referred as arc maintenance. Although ANNs have usually achieved good performances in several domains, those performances and the ANN training process are directly influenced by an appropriate choice of the network architecture. In this study an attempt has been made to model $V_a = f(I, L, x)$ for estimating the arc re-ignition conditions as estimator function of leakage current, air gap length and insulator length using multi-layer feed-forward neural network with back propagation technique and the Radial Basis Function (RBF) neural network with Orthogonal Least-Squares (OLS) learning method. A number of test results taken from the CIGELE models were simulated and analyzed and a comparison between RBF network and BP network is presented. The RBF ANNs model was found to be reliable in predicting the arc maintenance voltage, under any given set of leakage current, insulator length and air gap length. A satisfactory agreement will be observed between the simulated and experimental results.

Key words: Arc maintenance voltage,, ANNs, ice-covered insulator, modelling, estimator function, critical voltage, CIGELE model

INTRODUCTION

In several cold regions ice and snow accumulation on power lines results not only in mechanical damage to towers and conductors, but also the iced-insulator flashover. This problem has motivated a number of studies in this field, particularly experimental investigations made it possible to further the knowledge of the different effects of ice and insulator parameters on critical flashover voltage on ice-covered insulators by the GIGELE researchers at the university of Quebec in Chicoutimi (UQAC), (Farzaneh and Drapeau, 1995). The flashover process on an artificially ice-covered insulator string includes different stages: first, several violet arcs appear across the air gaps, then of the AC arcs extended along the ice surface, forming a white arc and finally when the white arc reaches a critical length, flashover occurs suddenly (Fig. 1). It may be noted

that this situation less similar to dry bands in series with a wet pollution layer. There are some differences between AC arc propagation processes on ice and polluted surfaces. In case of pollution the arc extended on the wet polluted surface and its length changes according to applied voltage while in case of ice, the arc may propagate in two ways: ice surfaces and along the air gaps during its enlargement caused by ice melting and ice falling down (Farzaneh *et al.*, 1997; Farzaneh-Dehkordi *et al.*, 2004). In regard to the understanding discharge initiation local AC arcs formation and the mechanism of their development on ice surfaces, previous publications (Farzaneh and Zhang, 2000) were used regression methods to establish a mathematical relationship between re-ignition constant, leakage current I and the ice sample length L . It was found that arc maintenance condition can be expressed by the following Equation:

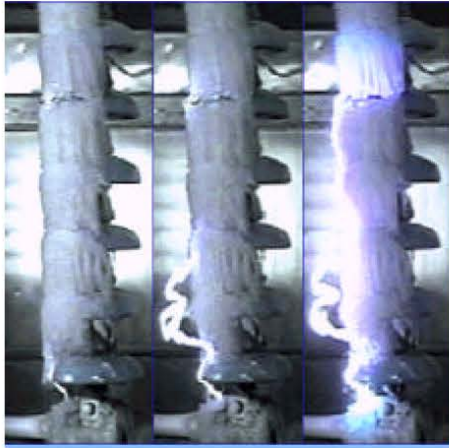


Fig. 1: Flashover on ice-covered insulator string

$$V_a = \frac{k'x}{I^b} \quad (1)$$

k' and b' re-ignition constant depend on ice sample length L .

This Eq. 1 allows to calculate the minimum applied voltage V_a to reach an arc length of x having a leakage current I . However this research on mathematically expressing the non linear relationship between the arc maintenance voltage and the air gap as well as the insulator length and diameter needed a perfect model which can predict this relationship for any given ice-covered insulators parameters. In this study, new approach using Artificial Neural Networks (ANNs) as function estimator have been developed and used to model accurately the critical condition of AC arc propagation on ice-covered insulators. Recently, Artificial Neural Network (ANNs) has gained a good success in many power applications (Coury and Jorge, 1998), (Aggarwal *et al.*, 1999). Among the various ANNs structures, the multi-layer feed forward network with back-propagation and radial basis function RBF neural network with OLS learning procedure are chosen for supervised learning. The process of sampling data for training and testing will be introduced. A number of test results taken from CIGELE laboratory are simulated and analyzed. It is found that the BP neural network is a non-linear regression technique which attempts to minimize the global error. Its training process includes the forward and backward propagation, with the desired output used to generate error values for back propagation to iteratively improve the output. The BP neural network can yield very compact distributed expressions of complex data sets. However BP is limited partly by the slow training

performance, so RBF neural network was developed instead. RBF networks may require more neurons than standard feed-forward BP networks, but often they can be designed in a fraction of the time it takes to train standard feed-forward networks (Chen *et al.*, 1991).

MATERIALS AND METHODS

Experimental set up and procedures: These experiments were carried out by the GIGELE researchers at University of Quebec in Chicoutimi (UQAC). In order to determine the arc maintenance conditions. Different types of industrial station post insulators were used. The ice was formed artificially in a climate room using insulator units, installed vertically (Fig. 2). According to required insulator length, an electrode was placed at the desired position. During the icing period, the temperature of the climate room was maintained at $-12 \pm 0.2^\circ\text{C}$.

A relatively uniform wind velocity of 3.3 m sec^{-1} was generated using a system of 12 fans placed behind a

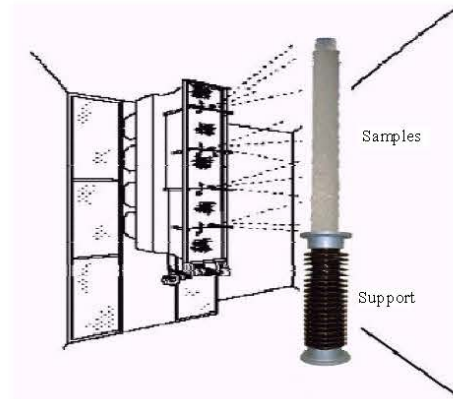


Fig. 2: CIGELE climate room and installed insulator

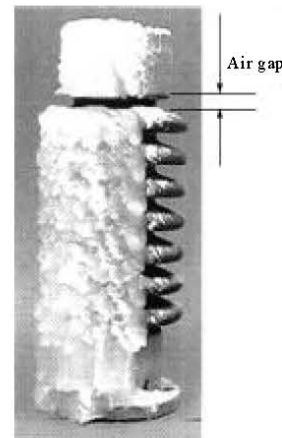


Fig. 3: The ice sample

Table 1: Tests CIGELE model

Test	Air gap length $\times$ (cm)	Insulator length L (cm)
A	26	259
B	36	259
C	46	259
D	36	309
E	36	206
F	16	161

honeycomb diffusing panel for transporting the water droplets to insulator surface. The ice was formed by spraying super cooled water droplets on insulator surface. This allowed the insulator to accumulated uniform ice thickness. This thickness was checked by measuring on a monitoring conductor 3.8 cm in diameter and rotating at 1 rpm. (Farzaneh, 1997) noted that the flashover voltage of ice-covered insulators decreases with the ice thickness and tends to saturation value at round 15 mm. Once the ice thickness on insulator reached this value, the icing process was stopped and, then, an artificial air gap with a given length was made near the high voltage electrode. The ice sample and the test circuit are shown in Fig. 3. The alternating high voltage was supplied by a 350 kV/700 kVA transformer and a 700 kVA regulator. The overall short-circuit of the high voltage system is about 20 A at the maximum operating voltage of 350 kV_{ms}. In order to perform the test, the voltage applied to the ice sample, during the melting period at 0°C, was raised at a constant rate of 3.9 kV/s until the breakdown of the air gap occurred and an arc was established across it. Then, the applied voltage was reduced until the arc extinguished. A Data Acquisition System (DAS) was used to record the applied voltage, the voltage on the measuring electrode and the leakage current.

Farzaneh and Zhang (2000b) were tested different types of industrial station post insulators in order to determine the arc maintenance conditions. Six tests were applied to investigate the effects of air gap length and insulator length on the arc maintenance voltage (Table 1).

Multi-layers Neural Networks Back-Propagation algorithm: Artificial Neural Network algorithm has been used successfully in many applications, including electrical power systems and high voltage engineering (Khaparade *et al.*, 1991; Ho, 1992; Foo and Ghosh, 2002; Zegnini *et al.*, 2004). It is useful because it acts as a model of real-world system or function. The model then stands for the system it represents, typically to predict or t control it. ANN can model a function even if the equation describing it is unknown the only prerequisite is representative sample of the function from the theoretical understanding. In this study, we have employed the multilayer feed forward neural network approach. The

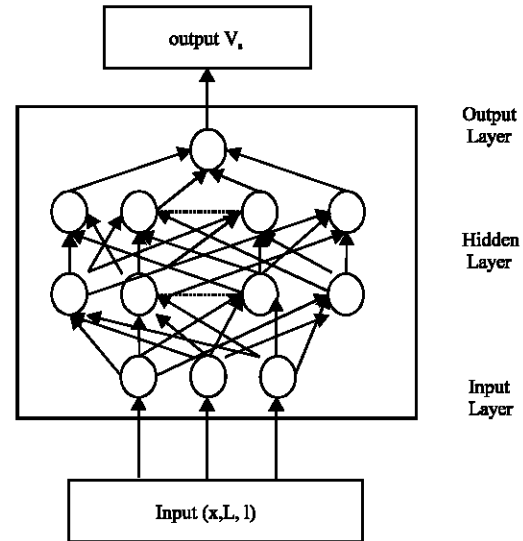


Fig. 4: Structure of multilayer feedforward ANN

neurons in the network can be divided into three distinct layers: input layer, output layer and hidden layers. The data for modelling $V_a = f(x, L, I)$ were obtained from laboratory experiments (tests CIGELE model) the input parameters are air gap length x , insulator length L and leakage current I and the output parameter is the arc maintenance voltage V_a (Fig. 4). Each neuron of the input layer receives a signal from all input neurons via hidden a long connections with modifiable weights. With the use of appropriate learning process, the connection weights are adjusted to enable the neural network to identify input pattern vectors.

The ANN used in this work employs the back propagation learning algorithm to facilitate the learning process (Rumelhart-Hinton *et al.*, 1986). The back propagation learning algorithm is a generalization of the Wodrow-Holf error correction rule (Wirdrow and Holf, 1986) is most popular method in training ANN. This learning algorithm is represented here brief. For each neuron in the input layer, the neuron outputs are given by:

$$O_i = \text{net}_i \quad (2)$$

Where net_i is the input of neuron i and O_i output of neuron i .

Again, for each neuron in the output layer, the neuron inputs are given by:

$$\text{net}_k = \sum_{j=1}^{N_j} w_{kj} O_j \quad k = 1, \dots, N_k \quad (3)$$

Where w_{kj} is the connection weight between neuron j and neuron k and N_j , N_k are the number of neurons in the hidden and outputs layers.

For each neuron in the output layer, the neuron outputs are given by:

$$O_k = \frac{1}{1 + \exp\left(\frac{-(\text{net}_k + \theta_k)}{\theta_0}\right)} = f_k(\text{net}_k, \theta_k, \theta_0) \quad (4)$$

Where θ_k is threshold of neuron k and the activation-function f_k a sigmoidal function.

For the neuron in the hidden layer, the input and the output are given by the relationships similar to those given in the Eq. 3-4, respectively. The connection weights of the feed forwards network are divided from the input-output patterns in the training set by the application of generalization delta rule. The algorithm is based a minimization of the error function of each pattern p , by the use of the steepest-descent method (Wirdrow and Holf, 1986). The sum of squared errors which is the error function of each pattern is given by:

$$E_p = \frac{1}{2} \sum_{k=1}^{N_k} (t_{pk} - O_{pk})^2 \quad (5)$$

Where t_{pk} and O_{pk} are target and calculated outputs for output neuron k , respectively.

The overall measure of the error for all the input-output patterns is given by:

$$E = \sum_{p=1}^{N_p} E_p \quad (6)$$

Where N_p is number of input-output patterns in the training set. When an input pattern p with the target output vector t_p is presented, the connection weights are updated by using the equations:

$$\Delta w_{kj}(p) = \eta \delta_{pk} O_{pj} + \alpha \Delta w_{kj}(p-1) \quad (7)$$

Where η is learning rate and α the momentum constant. Now, δ_{pk} is defined in two different ways.

For each neuron in the output layer:

$$\delta_{pk} = (t_{pk} - O_{pk}) \cdot O_{pk} (1 - O_{pk}) \quad (8)$$

And for each hidden layer neuron;

$$\delta_{pj} = O_{pj} (1 - O_{pj}) \cdot \sum_{k=1}^{N_k} \delta_{pk} \cdot w_{kj} \quad (9)$$

The training accuracy of ANN is measured with the help of Root Mean Square Error (RMSE). Once the network is trained it is tested using test data patterns and the efficacy is judged on the basis of %MAE (Mean Absolute Error). In this applied work on feed forward neural nets extensive studies have been carried out to choose the best combination parameters of conventional learning algorithm on the convergence rate of the learning process. Using the property of function approximation of neural networks, the arc maintenance conditions on ice-covered insulators can be expressed as a nonlinear function in terms of the three independent variables the leakage current, insulator length and along air gap. The network weights can be adjusted offline to get the network model by providing a set of training patterns then applying the well known algorithm, back-propagation, to adjust these weights so the output of the network a given input matches its corresponding target. We have written a script file using the powerful MATLAB 6.5 software (neural network toolbox) and the Levenberg-Marquardt algorithm for training which is a modified back-propagation algorithm with adaptive learning step and momentum which have a very significant effect on the convergence rate (Demuth and Beale, 1998).

The algorithm is summarized as follows:

Step A: Give the training set (input/target) pairs,

Step B: Pre-processing: Input/Output normalization.

Step C: Feed forward Neural network construction: Create a neural network structure (number of layers, number of neurons, activation function).

Step D: The training parameters (learning rate, momentum coefficients iterations)

Step E: Training.

Step F: Simulation of the network.

Step G: Then test the generalization of the net by supplying new data as input to the network then compare with the desired output.

RBF neural network model and learning procedure: Radial Basis Functions (RBF) are the simplest class of functions. Theoretically they can be used in different models (both linear and non-linear) and different networks (multilayered and single-layered). Traditionally the term

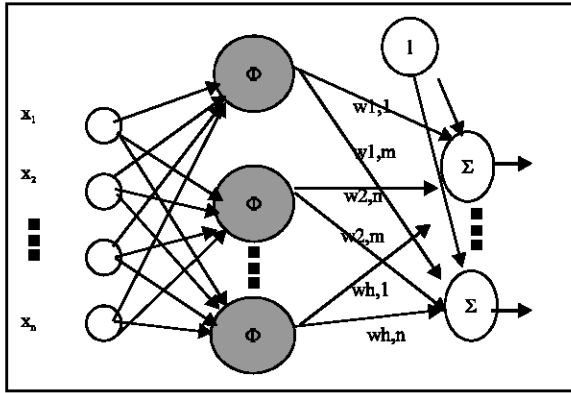


Fig. 5: RBF architectural Neural Network

‘RBF-networks’ is associated with radial basis functions in single-layered networks with the structure as shown in Fig. 5.

The RBF neural network is different from BP with sigmoidal activation functions utilizing basis functions in the hidden layer, which are locally responsive to input stimulus. These hidden nodes are usually implemented with a Gaussian kernel. Each hidden node in an RBF neural network has a radially symmetrical response around the center vector and the output layer is a set of linear combiner with weights. A common learning strategy is to randomly select some network input vectors as the RBF centers, effectively fixing the network hidden layer. The weights in the output layer can then be derived by using the least-squares (LS) method. However, performance of the RBF neural network critically depends upon the chosen centers, which may require an unnecessarily large RBF network to obtain a given level of accuracy and cause numerical ill-conditioning. The OLS learning procedure chooses appropriate RBF centers one-by-one from the training data until a satisfactory network is obtained, greatly reducing the network size (Freeman and Saad, 1996). The RBF network has a topology of one-hidden-layer. The input and output dimensions of the network are denoted by and respectively and is the number of hidden nodes. Each output node is a linear combiner defined by:

$$f_i(X) = \sum_{j=1}^{n_h} \Phi_j \|X - C_j\| \cdot \theta_{ji} \quad (10)$$

Where $X \in R^{n_l}$ is an input vector $C_j \in R^{n_l}$ are RBF centers, $\| \cdot \|$ denotes the Euclidean norm and θ_{ji} are weights the nonlinear $\Phi(\cdot)$ has a radially symmetric shape. Although there are a variety of choices, the Gaussian function was chosen in this study.

That is

$$\Phi(\gamma) \exp\left(-\frac{\gamma^2}{\sigma^2}\right) \quad (11)$$

Where σ is a real constant and $\Phi(\gamma) \rightarrow 0$ as $\gamma \rightarrow \infty$

The overall input-output mapping of the network is

$$F(X): R^{n_l} \rightarrow R^{n_o}$$

The method cannot guarantee adequate performance owing to the requirement that the centers should suitably sample the input domain. The OLS learning procedure Eq. 14 was proposed in this paper to select centers so that adequate and parsimonious RBF networks can be derived.

While Eq. 10 delineates the input-output relationship of the RBF network, the OLS procedure can be implemented by introducing an error term and Eq. 10 can be rewritten as:

$$d_i(X) = \sum_{j=1}^{n_h} \Phi_j \|X - C_j\| \cdot \theta_{ji} + e_i \quad 1 \leq i \leq n_o \quad (12)$$

Where d_i is the i th node value in the output layer.

The task of network learning is to choose appropriate centers C_j and determine the corresponding weights θ_{ji} based on a given set of training inputs and outputs. To avoid nonlinear learning, the RBF centers are to be selected from training data and it is a problem of subset model selection. The full model is defined by considering all of the training data $\{X(1), \dots, (N)\}$ as candidates for centers. Using matrix form, Eq. 11 can be expressed as

$$D = \Phi \cdot \Theta + E \quad (13)$$

The parameter matrix Θ can be solved by using the Least Squares (LS) principle. An orthogonal transformation can be performed by decomposing Φ

$$\Phi = W \cdot A \quad (14)$$

Where

$$W = \{w_1, \dots, w_N\} \quad (15)$$

With orthogonal columns that satisfy

$$w_i^T = w_j \quad i \neq j \quad (16)$$

Eq. 13 can be rewritten as

$$D = W.G+E \quad (17)$$

With orthogonal least squares (OLS) solution

$$G = \begin{pmatrix} g_{11} & \dots & \dots & g_{1n_0} \\ \dots & \ddots & \ddots & \ddots \\ \dots & \ddots & \ddots & \ddots \\ g_{N1} & \dots & \dots & g_{Nn_0} \end{pmatrix} \quad (18)$$

And the LS solution satisfies Θ the triangular system

$$A. \Theta = G \quad (19)$$

The standard Gram-Schmidt method may be used to derive A and G. Thus can be solved from Eq. 19.

Since the error matrix E is orthogonal to W, the error reduction ratio due to can be found by:

$$[err]_k = \left(\sum_{i=1}^{n_0} g_{ki}^2 \right) \cdot \frac{w_k^T \cdot w_k}{\text{trace}(D^T \cdot D)} \quad 1 \leq k \leq N \quad (20)$$

Based on this ratio, the significant regressors can be selected by OLS in a forward regression procedure. At the kth step, a candidate regressor is selected as the kth regressor of the subset network if it produces the largest value of $[err]_k$ from among the rest of the N-K+1 candidate. The selection is terminated when

$$1 - \sum_{k=1}^{n_{ko}} [err]_k \leq \rho \quad (21)$$

Where $0 < \rho < 1$ is a chosen tolerance.

In the context of a neural network, the OLS learning procedure chooses the radial basis function centers $C_1, C_2, \dots, C_{n_h}$ as a subset of training data vectors $X(1), X(2), \dots, X(N)$

Where $n_h < N$, which may greatly reduce the network size. The centers are determined one-by-one in a well-defined manner, following the Gram-Schmidt orthogonalization procedure until a network of adequate performance is constructed.

The process of sampling data for training and testing will be introduced. Basing on some set of experimental 'input-output' data, under complete uncertainty as to the form of possible functional dependence between input and output data an attempt is made to guess this dependence: nonparametric regression, function fitting, predictionetc, of $V_a = f(I, L, x)$. In neural networks it is called supervised or associative learning. It means that every sample of the training set contains independent

variables (inputs) and corresponding dependent variables (outputs). The goal of the learning is reduced to optimizing in accordance with some criterion the parameters of the system that does the required 'input-output' transformation. In our case we choose the integral square error criterion for the given training set can be used for this purpose. For this algorithm «OLS orthogonal Least Square», our choice therefore fell on the kernel Gaussian seen its characteristic asymptotiques. Radial basis functions can be related to kernel density functions used to estimate probability density functions which depends on parameters of this last one and the size of available samples. Our judgement is left at the time of the application of these estimators. Let's return to the RBF-network adjustment. If we presume that the parameters of function (bias c and radius r) are fixed, i.e., are already some how defined, then the problem of finding the weights and how to choose a number of neurons in the hidden layer in order to minimize the integral square error.

RESULTS AND DISCUSSION

Using the test method mentioned above, the arc maintenance condition is the minimum applied voltage for maintaining an arc burning steadily across the air gap can be determined by analyzing the waveforms recorded by the Data Acquisition System (DAS). Once the arc was established, V was reduced and when a certain value was reached, the arc extinguished and the leakage current tended to zero. The peak value of V in the last half cycle before arc extinction, at t_1 , is the arc maintenance voltage, V_a (Fig. 6).

In this investigation $V_a = f(x, L, I)$ modelling has been attempted based on ANN instead of any empirical approach. The proposed ANN modelling has been carried out using 84 input/output data sets collected from the simulated test CIGELE laboratory model. Out of 84 data

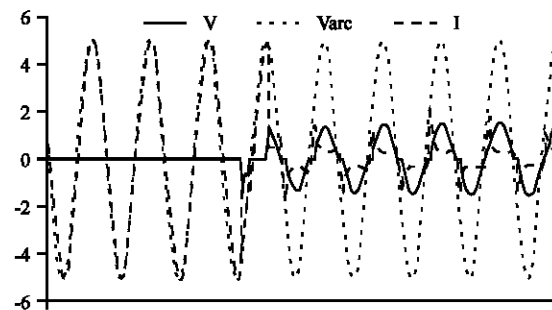


Fig. 6: Typical waveforms of voltages and leakage current versus Time

Table 2: Normalization schemes.

Scheme No.	Input	Output	MAE (%)
1	Max	Max	5.12
2	Max	Max min	4.97
3	Max	Mean and SD	3.66
4	Max min	Max	4.60
5	Max min	Max min	9.04
6	Max min	Mean and SD	5.66
7	Mean and SD	Max	6.85
8	Mean and SD	Max min	2.85
9	Mean and SD	Mean and SD	2.91

Table 3: The effect of different values of η and α on the convergence rate of the learning method

η	α	MAE (%)
0.2	0.7	6.75
0.2	0.8	4.30
0.2	0.9	5.40
0.25	0.7	2.95
0.25	0.8	3.34
0.25	0.9	2.85
0.3	0.7	6.38
0.3	0.8	6.33
0.3	0.9	4.41
0.35	0.7	5.21
0.35	0.8	4.18
0.35	0.9	4.47
0.4	0.7	5.09
0.4	0.8	3.34
0.4	0.9	4.77

Table 4: Calculated %MAE for different numbers of nodes in hidden layer

No. of nodes in hidden layer	MAE (%)
5	4.59
6	3.23
7	2.85
8	8.46
9	9.54

Table 5: The effect of numbers of hidden layers on the convergence rate of the training process.

No. of hidden layers	No. of nodes in hidden layers	RMSE	MAE (%)
1	7	0.0743	2.85
2	7, 7	0.0199	19.19
3	7, 7, 7	0.0197	26.06

Table 6: Optimized parameters for ANN

ANN parameters	Optimized parameters
Input-output patterns	3-1
Input Normalization	Mean, SD
Output normalization	Max, Min
Learning rate	0.25
Momentum constant	0.9
Hidden layer	1
Nodes in hidden layer	7

sets, 74 sets of input/output patterns are used as training data set in training process and 10 data sets were selected as test data patterns and not included in the training set. The ability and efficiency of ANN to model the arc maintenance voltage condition was gauged basing on the percentage of Mean Absolute Error (%MAE) between the test and predicted data. The scaling of the

input and output data has a significant effect on the convergence of the learning process. To avoid saturation of the sigmoidal activation function, the input and output parameters must be scaled and normalized to within 0 and 1. Nine normalization schemes were tested by (Ghosh *et al.*, 1995). For the conventional learning algorithm with the choice of recommended combination $\eta = 0.25$ and $\alpha = 0.9$ can yield good results for most problems (Rumelhart *et al.*, 1986) and seven hidden layers nodes, (Table 2). The number of iterations used in the training process is 1000. It was found that for input parameter normalized referenced to the mean value and standard deviation (Mean, SD) reading and the output parameter normalized according to Max, Min yielded the best % MAE at about 2.85%.

Most works on feed forwards neural nets use constant values of learning rate η and momentum constant α . But there is still no consensus as to what these values should be used in the learning process; rather, the optimal values of η and α may be problem dependent. In this research, 15 combinations of η and α were studied and the resultant % MAE for each combination was determined. It is evident from Table 3 that the best %MAE is obtained with for $\eta = 0.25$ and $\alpha = 0.9$.

The number of nodes in the hidden layer was also varied in this optimisation process. In this study different numbers of hidden layer nodes were studied and it was found that a net with 7 nodes in the hidden layer yield the best %MAE as indicated in Table 4.

Table 5 compares the effect of number of hidden layers on the convergence rate of the training process. It found that using one hidden layer has better effect on the convergence rate than when two and three hidden layer nodes.

The optimized parameters found for is the arc maintenance voltage conditions On Ice-covered Insulators given leakage current, air gap length and insulator length as input can be summarized as in Table 6.

Moreover, experimental and modeled data of the arc maintenance voltage conditions On Ice-covered Insulators V_a using the best combination of ANN parameters, are plotted against leakage current I for different air gap length x and insulator length L in Fig. 7.

The modeled output of the test data computed with the help of the best combination of modifiable parameters are tabulated in Table 7 against the target output, that is, the 3 selected test data. The mean absolute error %MAE of the model output is found to be 2.85%.

Several experimental procedures and methods, proposed various empirical mathematical models by applying regression analysis to the test results and there were some different conclusions suggested by different

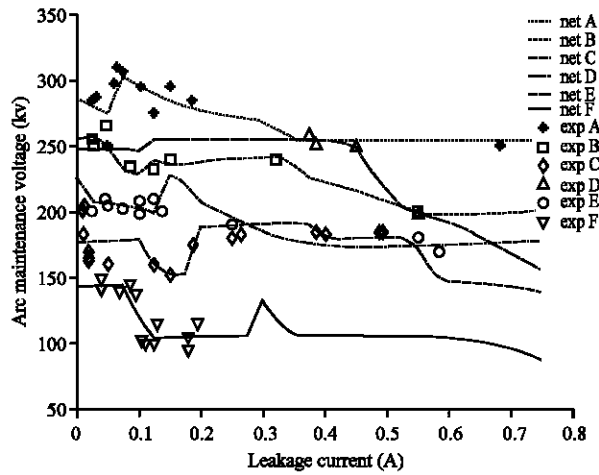


Fig. 7: Experimental and BP neural networks modeled data of the arc maintenance voltage conditions against leakage current for different CIGELE test

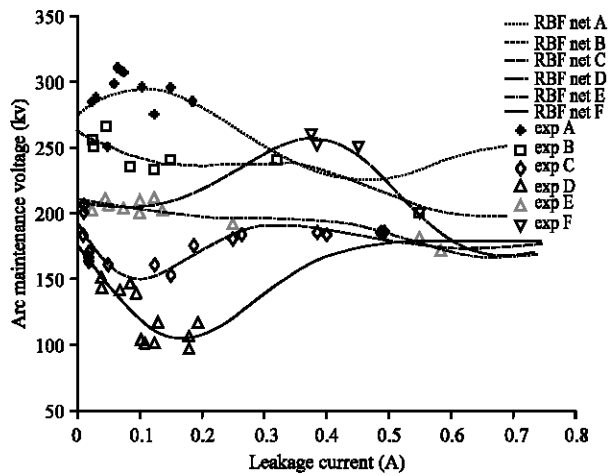


Fig. 8: Experimental and RBF neural networks modeled data of the arc maintenance voltage conditions against leakage current for different CIGELE test

Table 7: Comparison of Actual against Computed test data

Parameters	Actual	Computed
Air gap length $\times$ (cm)	36	36
	26	26
	16	16
Insulator length L (cm)	206	206
	259	259
	161	161
Leakage current I (A)	0.4	0.385
	0.45	0.435
	0.05	0.048
Arc maintenance voltage V_a (kV)	255	254.56
	180	177.13
	145	144.06
MAE (%)	2.85%	

researchers. The will need to established on a realistic approach to generate this problem by RBF neural network

measured with the adjustment of OLS parameters; based on minimization of the mean absolute error.

The ability and efficiency of ANN to model the arc maintenance voltage condition was gauged basing on the percentage of Mean Absolute Error (%MAE) between the test and predicted data.

For the adjustment of Parameters OLS, we took the following parameters:

A base of 84 data tests, with maximum number of neurons is 18 and the number of neurons to add between displays is 24.

Step (a) kernel Gaussian

Step (b) Given them are standardized on [0, 1] and center-reduced by the average and the standard deviation of the base of training.

Step (c) It receiving field is taken equalizes to 0.98.

Step (d) It criterion of stop of Akaike with seuil 0.01.

A number of test results we are simulated and analyzed. This algorithm is employed in the training process; it is found that the ANN modeling is very effective and accurate.

The training accuracy of ANN is measured with the help of Root Mean Square Error (RMSE). Once the network is trained it is tested using test data patterns and the efficacy is judged on the basis of %MAE (Mean Absolute Error). In this applied work on feed forward neural nets extensive studies have been carried out to choose the best combination parameters of conventional learning algorithm on the convergence rate of the learning process.

Simulation results of the trained RBF networks for modeling AC arc maintenance on iced-covered insulators are presented in Figure 8. It was found that the RBF neural networks model can be trained using a random set of data collected from CIGELE tests using training procedures with OLS algorithm are fast and the accuracy of the trained models with a %MAE of 1.90% was achieved.

CONCLUSIONS

This study presents the use of radial basis function networks for AC arcs maintenance modelling to predict the flashover on iced-covered insulators. It has shown that an RBF neural networks model can be trained faster than a multilayer feed forward BP. It has also been shown that the proposed RBF neural networks with OLS algorithm have satisfactory level of accuracy to recognize the arc maintenance voltage conditions on ice-covered insulators basing on insulator parameters, air gap length x , insulator length L and leakage current I have been

established. Modeling of the complex non-linear function $V_a = f(x, L, I)$, the equation which is unknown, has been successfully accomplished. Furthermore the effectiveness of RBF modeling a system from any unknown relationship is measured with the adjustment of OLS parameters; based on minimization of the mean absolute error %MAE. The model simulates the experimental results quite accurately and allows reliable applications to optimize the AC arc maintenance voltage conditions on ice-covered insulators.

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