MODELING AC ARC RE-IGNITION CONDITIONS ON ICE -COVERED INSULATORS USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

The propagation of local arcs are 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. In this paper an attempt has been made to model $V_a = f(I, L, x)$ for estimating the arc re-ignition conditions as function of leakage current and insulator length using multi-layer feed-forward neural network with back propagation technique. Once trained with experimental results taken from the CIGELE model , the proposed ANN model is then capable of predicting arc maintenance voltage , under any given set of leakage current and insulator length. With the use of the optimized ANN parameters , a prediction accuracy with a %MAE of 2.85% was achieved.

I. INTRODUCTION

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. 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. In regard to the understanding discharge initiation local AC arcs formation and the mechanism of their development on ice surfaces , previous publications [1-3] 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 :

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

k' and b' re-ignition constant depend on ice sample length L. This Equation. 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 paper, new approach using artificial neural networks (ANN) as function estimator have been developed and used to model accurately the critical condition of AC arc propagation on ice-covered insulators. Among the various ANN structures , the multi-layer feed forward network with back-propagation is chosen for supervised learning. It is found that the ANN modeling is very effective and accurate.

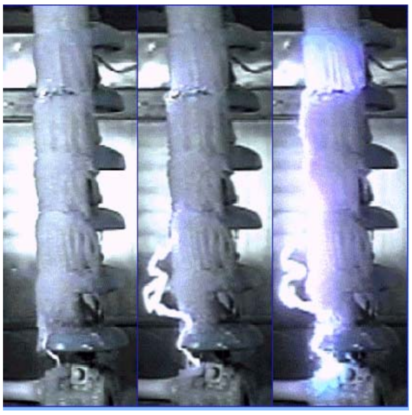

Figure 1. Arc extended on ice-covered insulators.

II. CIGELE TEST 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. The ice was formed by spraying supercooled water droplets on insulator surface. This allowed the insulator to accumulated uniform ice thickness. 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 Figure. 2.

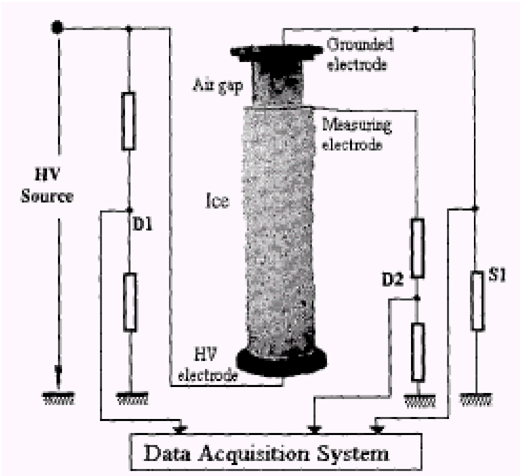

Figure 2. CIGELE model and test circuit.

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_{rms},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 (D.A.S) was used to record the applied voltage , the voltage on the measuring electrode and the leakage current.

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 (D.A.S). Once the arc was established, V_1 was reduced , and when a certain value was reached , the arc extinguished and the leakage current tended to 0 (Figure. 3). The peak value of V_1 in the last half cycle before arc extinction , at t_1, is the arc maintenance voltage , V_a .

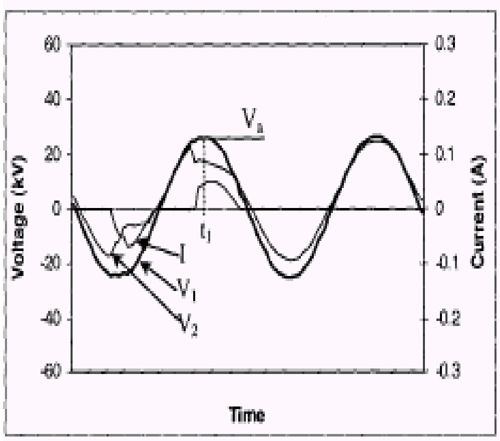

Figure 3. Typical waveforms of voltage and leakage current

Farzaneh and Zhang [4] 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. Test CIGELE model

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

From the results obtained on tests. They were found as the air gap length increases , the arc maintenance voltage increases as well. This means that is ,a higher applied voltage is needed for maintaining a longer arc burning. However as the leakage current increases the arc maintenance voltage decreases slightly and from the results obtained for a constant air gap length of . From these results they were observed that as the insulator length increases , the arc maintenance voltage also increases.

The arc maintenance voltage is not linear with leakage current , it depends on air gap length and the insulator length.

III. ANN ALGORITHM

Artificial Neural Network algorithm has been used successfully in many applications, including electrical power systems and high voltage engineering. 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 paper ,we have employed the multilayer feedforward neural network approach . The neurons in the network can be divided into three distinct layers: input layer, output layer and hidden layers.

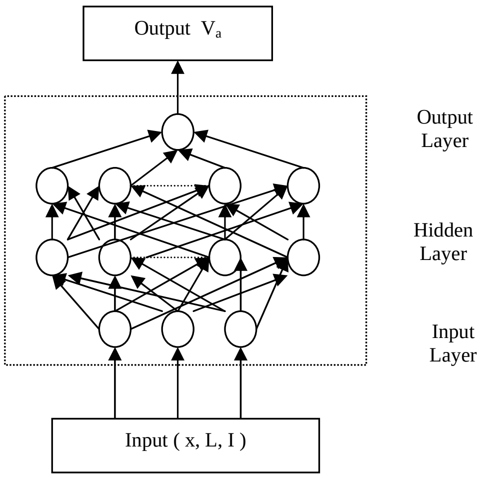

Figure 4. Structure of Multilayer Feedforward ANN.

The data for modelling V_a = f(x ,L ,I) were obtained from laboratory experiments (test 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 . Each neuron of the input layer receives a signal from all input neurons via hidden layer neurons along 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 [5]. The back propagation learning algorithm is a generalization of the Wodrow-Holf error correction [6] is most popular method in training ANN.

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[7].

The algorithm is summarized as follows:

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

Step B: Preprocessing : 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.

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

IV. ANN ANALYSIS RESULTS

In this study 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 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 [8]. For the conventional learning algorithm with the choice of recommended combination η = 0.25 and α = 0.9 can yield good results for most problems [5] 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 the standard deviation (Mean , S.D) reading and the output parameter normalized according to Max , Min yielded the best % MAE at about 2.85%.

Table 2. Normalization schemes.

Scheme Number	Input	output	% MAE
1	MAX	MAX	5.12
2	MAX	MAX MIN	4.97
3	MAX	MEAN & S.D	3.66
4	MAX MIN	MAX	4.60
5	MAX MIN	MAX MIN	9.04
6	MAX MIN	MEAN & S.D	5.66
7	MEAN & S.D	MAX	6.85
8	MEAN & S.D	MAX MIN	2.85
9	MEAN & S.D	MEAN & S.D	2.91

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 3 .

Table 3. Calculated %MAE for different numbers of nodes in hidden layer.

Number of nodes in hidden layer	%MAE
5	4.59
6	3.23
7	2.85
8	8.46
9	9.54

Table 4. The effect of numbers of hidden layers on the convergence rate of the training process

Number of hidden layers	Number 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 4 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. 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 Figure 5.

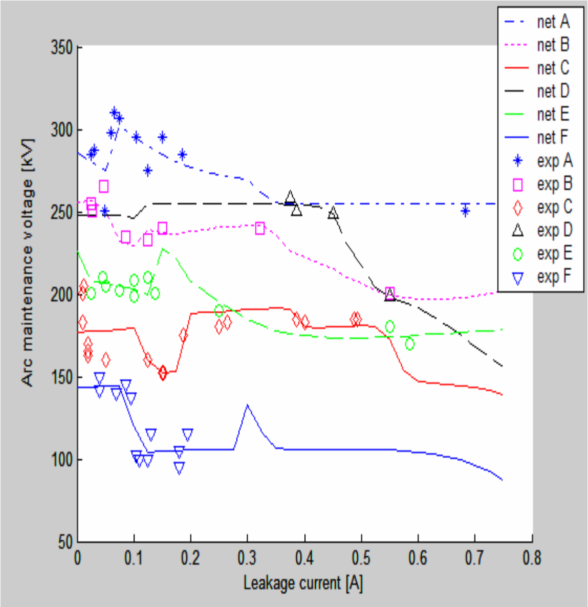

Figure 5. Experimental and modeled data of the arc maintenance voltage conditions against leakage current for different CIGELE test.

CONCLUSION

In this study , the ability of the ANN 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. With the use of the optimized ANN parameters , a prediction accuracy with a %MAE of 2.85% was achieved. The ANN model trained through this work allows for the possibility of the utilization of air gap length , insulator length and leakage current , to predict the arc maintenance voltage on ice-covered insulators.

ACKNOWLEDGEMENT

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