FLASHOVER VOLTAGE ESTIMATION BY ARTIFICIAL NEURAL NETWORK OF POLLUTED POST INSULATORS TRANSMISSION LINES AT HIGH ALTITUDE AREA

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Key words: post insulator, pollution flashover voltage, modelling, high altitude, ANN

ABSTRACT

In this work an attempt has been made to estimate the pollution flashover voltage under various meteorological factors using radial basis function (RBF) neural networks. Orthogonal least squares (OLS) learning method is used in order to improve the lines performance against the pollution flashover of the post insulators. The technique of RBF neural network is employed to model the relationship between pollution flashover voltage *and the line parameters*: diameter of shed, distance of leakage, pressure at different altitudes and salt deposit densities ESDD. The results show that a well trained RBF neural network achieved a better modelling accuracy and performance.

I. INTRODUCTION

The post insulators alternating voltage of transmission lines for a high altitude area reliability depends mainly on the environmental and weather conditions. In a transmission line which has a big diameter and shed shape, the pollution can be rapidly built on the surface of the insulators and form a conducting layer which leads to the flashover. Power outages caused by insulator combined with contamination at low atmospheric pressure have been reported from several regions. This has motivated researchers to investigate the involved phenomena and to do a considerable effort to look for concrete solutions in order to determine the effects of atmospheric icing, pollution and low pressure on the electrical performance. While some attempts have been made [1], [2], [3] to better understand flashover on a post insulator, which is a complex phenomenon that is influenced by a large number of parameters, such as insulator profile, testing methods, atmospheric pressure, rate of pollution, and ice type and thickness. The problem becomes technically more serious at higher levels of transmission voltage where the higher insulation level is not practical. Based on experimental data taken from different types of typical high intensity, big diameter post insulators, the artificial contamination tests are carried out in different pressure cases corresponding to high altitudes and in typical kinds of equivalent salt deposit density (ESDD). The present work led to the elaboration of a new approach using ANN as function estimator to model accurately the relationship between the critical flashover voltage, diameter of shed D, distance of leakage L, pressure P at different altitudes from 0 to 3000m and salt deposit density ESDD to predict the flashover voltage of ice-covered insulators at high altitudes. Among the various ANN structures the radial basis function (RBF) neural network with orthogonal least squares (OLS) learning method is chosen as a supervised learning method to train the network for the modelling task. The paper presents the structure of the model, the training procedures and simulation results.

II. EXPERIMENTAL

In order to clarify some of the above questions and to acquire a better idea of the effects of the mentioned factors on the critical flashover voltage of polluted insulators, we used the experimental results obtained from a joined investigation between the University of Quebec in Chicoutimi, Canada and Chongqing University in China [4].As the laboratory experiments on long insulators under ice and low atmospheric pressure conditions, the investigation is done using only a short porcelain post type insulator and a short string of three porcelain insulator units (Table I).

Table I. Insulators parameters

Insulator type	Diameter (mm)	Length (mm)
3 **XP-70**	255	295
3 **XWP-70**	255	400
FXBW-25/100	145/115	1200

These experiments were carried out in the artificial climate chamber which has a length of 4-meter and a diameter of 2-meter. The temperature of the chamber can be adjusted as low as -36 °C with a refrigerant system and the atmospheric pressure 34.7 kPa with the freezing water fog spraying, it can imitate natural icing and snowing conditions. Alternating voltage was supplied by the test transformer with a maximum output voltage of 150kV/ 900kVA. Because the contamination level in the high altitudes districts is light, the equivalent salt deposit density (SDD) of 0.01, 0.03, and 0.05 mg/cm^2 were picked up in the test. The contamination of the icing insulator was achieved by changing the conductivity of the spraying water or the freezing water. The effect of altitude on the ice insulator AC voltage is simulated by changing the pressure of the climate chamber with a vacuum pump (figure.1)

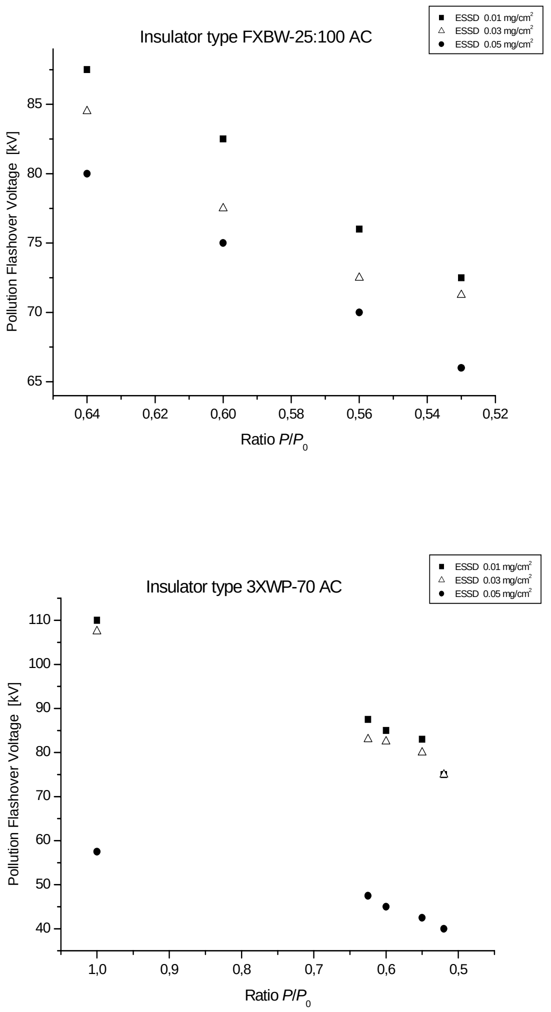

Figure 1. The effect of altitude on the polluted flashover AC voltage for FX BW-25:100 AC and 3XWP-70 AC type of insulators.

III. THE STRUCTURE OF ANN MODEL

In this paper, the effect of the altitude, the icing, the level of the contamination, the dimension and the shed profile of the post insulator parameters on AC flashover performances were investigated with Artificial Neural Networks so as to give suggestions to the external insulation design of the power transmission lines, because it is difficult to carry out these experiments at real and natural icing and snowing conditions in high altitudes. According to test results, it indicates that the flashover voltage of tested insulators present non linear function $V_f = f(D, L, P, ESDD)$. 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 ‘RBF-networks’ is associated with radial basis functions in single-layered networks with the structure as shown in figure.2.

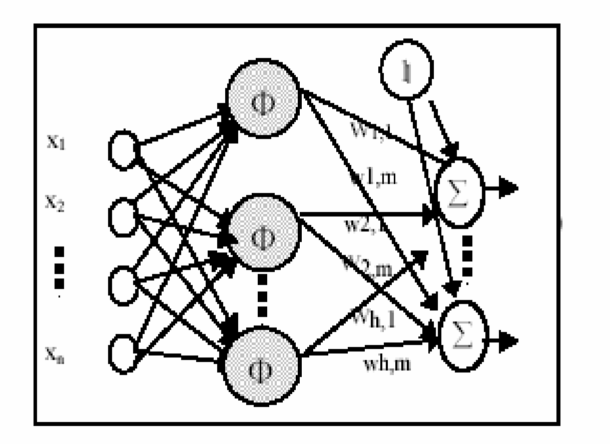

Figure 2. RBF architectural Neural Network

The RBF neural network is different from back propagation BP neural network with sigmoid 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 radial symmetrical response around the centre 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 centres, 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 centres, which may require an unnecessarily large RBF network to obtain a given level of accuracy and cause numerical ill-conditioning. Summarized RBF algorithm with OLS learning procedure was presented in our previous work [5].The objective 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. It is very important to known if the narrow kernel, density estimated becomes stops and marked by pick the estimated density the kernel is wide, the estimation becomes with a big tolerance and does not show enough details in density:

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. Therefore this algorithm allows doing an apprenticeship incrementally [6]:

- First it does the linear separation between the entry layer and the layer hidden, it creates the hidden neurones automatically while applying the gram-schmidt orthogonalization, which allows eliminating the redundancies of information, of other methods consist in to use genetic algorithms to minimize the number of neurones hide with a good generalization [7].

-Secondly to do apprenticeship between the layer hidden and the exit layer, while calculating the weight synaptiques all while basing itself on the method of the least squares.

IV. RESULTS AND DISCUSSION

The OLS learning procedure chooses appropriate RBF centres one-by-one from the training data until a satisfactory net- work is obtained, greatly reducing the network size. The process of sampling data for training and testing will be introduced. Generally methods based on empirical hypotheses to get relations where the source of information is only experimental input / output data are tedious and valid for a domain. However neural networks serve to solve this type of analytical problems without the need of any model of the investigated object at all. In this work RBF networks are used for this task for their property to approximate any unknown function.

The adjustment of neural network parameters is called supervised or associative learning. It means that every sample of the training set contains independent variables (inputs) and its corresponding dependent variables (outputs).

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 defined in a given manner, then the problem is how to choose the number of neurons in the hidden layer and how to adjust the weights in order to minimize the integral square error.

Generally speaking, the problem could be solved quite simply: by setting the number of neurons in the hidden layer the same as that of the input patterns in the training set, superposing the centre of every activation function with one of the patterns from the training set and setting their radius so that they do not overlap. And there is no training as such, one only has to calculate the output layer weights. Out of 84 data sets, 76 sets of input/output patterns are used as training data set in training process, and 8 data sets were selected as test data patterns and not included in the training set (Table II).

Table. II Parameters of Test Data Patterns.

Insulator type	Data Patterns	Ratio P/P_0	ESSD (mg/cm^2)	Pollution flashover voltage (kV)
3 **XP-70**	1	1	0.03	82.5
	2	0.625	0.01	85.5
	3	0.60	0.05	45
	4	0.52	0.03	57
3 **XWP-70**	5	0.64	0.03	84.5
	6	0.6	0.05	75
FXBW-25/100	7	0.625	0.05	47.5
	8	0.55	0.01	83

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. It was found that for input parameter normalized referenced to the mean value and standard deviation (Mean, S.D) reading and the output parameter normalized according to Max, Min yielded the best combination [8],[9].

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

A base of 84 data tests, with maximum number of neurons is 22 and the number of neurons to add between displays is 24.

- Kernel Gaussian

-Given them are standardized on [0, 1] and centre-reduced by the average and the standard deviation of the base of training.

- It receiving field is taken equalizes to 0.99.
- It criterion of stop of Akaike 0.01.

In this investigation 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 modelling the pollution flashover voltage under various meteorological factors are presented in table III, and comparisons between test data patterns which are not included in the training set and those optimized by RBF neural network was presented in figure 3.

Table. III Normalisation parameters of RBF Neural Network.

Adjustment parameters	Max number of neurons	Number of neurons to add between displays	RMSE	% MAE
	4	6	10.76	18.96
Kernel Gaussian	6	10	7.71	13.91
	8	10	5.95	11.73
	12	18	1.82	5.52
Normalisation	11	08	2.35	5.82
	15	12	1.68	5.88
Input(Mean, S.D)/ Output (Max, Min)	18	24	1.35	5.94
	19	18	1.08	4.25
	20	22	1.05	4.41
	22*	**24***	**0.79***	**4.91***
	23	24	0.65	5.77
	24	22	0.42	6.87

This mixed algorithm for training the RBF-network with Orthogonal Least Square algorithm much faster than the bank-propagation algorithm for training multilayered perceptrons as mentioned above. But an RBF-network is frequently required to contain too large number of hidden elements. This causes the RBF-network to function slower than the multiplayer perceptron.

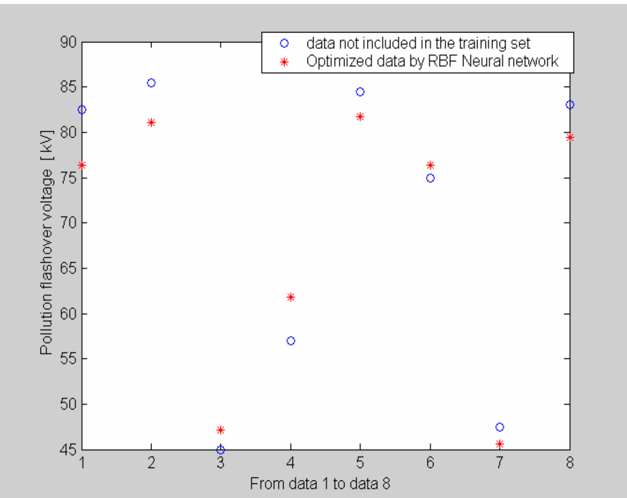

Figure3. Comparison between non selected data in training set and optimized data by RBF Neural Network.

V. CONCLUSION

RBF neural network model based on an improved version of Orthogonal Least Square algorithm is intended to optimize pollution flashover voltage of post insulator transmission lines in high altitude areas. This prediction approach has been used to determine the effects of low air pressure on the flashover performance of a polluted insulator which is a complex phenomenon, using the experimental data taken from test results. To generate this problem by RBF neural network measured with the adjustment of OLS parameters; based on minimization of the mean absolute error. Therefore instead to have a better accuracy and performance of polluted insulators in high altitudes.

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