MODELING PARAMETERS OPTIMIZATIONS OF 750kV INSULATORS FLASHOVER VOLTAGE UNDER POLLUTION CONDITIONS IN HIGH ALTITUDE AREAS USING RBF ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

In this paper an attempt has been made to estimate the pollution flashover voltage under various meteorological factors using the radial basis function (RBF) neural network with orthogonal least squares(OLS) learning method in order to test the lines design ability against the pollution flashover of the high voltage post insulators. 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 results show that RBF neural networks trained by the least orthogonal square have a better accuracy and performance to optimize flashover voltage of post insulator in high altitude areas.

Keywords: *flashover voltage, pollution, low pressure, post insulator, modeling, ANN, RBF, reliability.*

1. INTRODUCTION

Environmental conditions on the electrical performance of outdoor insulators, in addition to low air pressure, sometimes atmospheric icing combined with pollution may also affect the performance of insulator. Power outages caused by insulator this mixture contamination at low atmospheric pressure have been reported from several regions has motivated researchers to look for concrete solutions in order to determine the effects of atmospheric icing , pollution and low pressure on the electrical performance. It has never been reported for the research about the contamination flashover for the post insulator with high intensity and big diameter at high altitudes. But the problem of the external insulation of the 750 kV transformer equipments is more severe than that of the transmission lines. In order to supply the insulating dimension and the shed profile of the post insulator for the 750kV lines, it is necessary to carry out the artificial test for the post insulator high altitudes. Flashover on a post insulator, however, 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 While some attempts have been made [1-6] to better understand this phenomenon , very few studies have been carried out on the modeling of flashover arc on polluted iced surfaces at low air pressure, a number of questions regarding these phenomena still remain unanswered. The problem becomes more serious at higher levels of transmission voltage where the higher insulation level is not practical, technically. However, in spite of these efforts, due to the complexity of the flashover phenomena related to low air pressure, accumulation of pollutants and especially ice, various authors disagree over certain points and some questions are still unanswered. Also, very few studies have been reported on the flashover performance of insulators under the simultaneous presence of pollution, atmospheric ice and low pressure. Recently, artificial neural network (ANN) has gained a good success in many power applications [7-9]. Many advantages are inherent in ANNs, including the excellent noise immunity and robustness, making their use less susceptible to operating conditions than conventional approaches.

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 for predicting 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 for supervised learning. The paper presents the structure of the model, the training procedures and simulations results.

2. THE EFFECTS OF LOW AIR PRESSURE ON THE FLASHOVER PERFORMANCE OF POLLUTED INSULATORS

In 1889, Paschen's experimental results lead to the conclusion that the breakdown voltage V is solely the function of the product $P.d$:

$$V = f(P.d) \tag{1}$$

This is called Paschen's law, where V is the breakdown voltage, P is the gas pressure and d *is* the electrode separation. The general shape of the Paschen curve can be explained from the ionization theory of gases. Within a fixed-space gap at very low pressures, the collision frequency is low such that sufficient ionization is maintained only by increasing the probability of ionization at each collision. Consequently, the electron velocity, and thus the electric field must be high. Hence *V* must increase as *P* diminishes. At higher pressures, the collision frequency is high, which results in a high rate of energy loss. Therefore, the energy gained per free path is low unless the field is high. Correspondingly, *V* must increase when *P* increases. Therefore, the curve must show a minimum *V*. The actual discharge in air is under a relatively high *Pd* product. As mentioned above, the breakdown or flashover of external insulation depends upon the atmospheric conditions. At high altitude, the breakdown or flashover voltage decreases usually with the decrease of either air density or humidity. For the case of flashover on ice-covered insulators, the humidity normally reaches saturation around the arcs, and hence only air density is important.

According to IEC international standard, the standard reference atmospheric condition is:

- Pressure: *Po* =101.3 kPa (760 mmHg);
- Temperature: *To* = 20 °C;
- Absolute humidity: h_0 = 11 g/m^3.

Without correcting for air humidity, the flashover voltage in a given test condition, *V,* can be corrected to the corresponding value under standard reference atmosphere condition by using the following:

$$V_0=k_1V \tag{2}$$

where k_1 is the air density correction factor.

Both the pressure and temperature will influence air density. The air density correction factor depends on the relative air density δ and can be generally expressed as:

$$k_1=\delta^{m} \tag{3}$$

$$\delta=\frac{P}{P_0}.\frac{273+T_0}{273+T}$$

where *Po* and *P* are the standard atmospheric pressure (101.3 kPa) and the test ambient pressure respectively. *To* and *T* are the standard reference temperature of 20 °C and the test ambient temperature respectively. The value of exponent *m* is still under consideration.

The flashover performance of polluted insulators is influenced by a number of parameters, mainly air pressure, ice severity, and pollution level. Atmospheric pressure is one of the parameters that have considerable influence on the flashover performance of insulators.

The relationship between the critical flashover voltage of polluted or iced insulators and the air pressure is normally expressed as [10]:

$$\frac{V}{V_0}=\left(\frac{P}{P_0}\right)^m \tag{4}$$

where *V* and V_0 are respectively the critical flashover voltages of insulators at air pressure *P* high altitude and pressure at sea level P_0= 101.3 kPa; the exponent *m* is a constant whose value characterizes the influence of air pressure on the critical flashover voltage of insulators, and depends on several factors and parameters including insulator profile, the applied voltage, and rate of pollution [2], [4]. In order to determine the effects of low air pressure on the flashover performance of a polluted insulator, a large number of studies were conducted by many researchers. However, duo to the different experimental procedures and methods, by applying regression analysis to the test results, the values of exponent *m* were determined at different ice severities, SDD levels, and freezing water conductivities, for different insulators, there were some different conclusions. The different values for m suggested by different researchers are listed in Table 1.

Table 1 Value of exponent m

Countries	AC voltage	Notes	Reference
Sweden	$0.29_{(1)}$	(1) IEEE insulator	[11]
Japan	$0.5_{(1)}, 0.55_{(2)}$	(2) Anti-fog insulator	[12]
USA	$0.5_{(1)}, 0.55_{(3)}$		[13]
China	$0.42\text{-}0.81_{(2)}$	(3) Complex form insulator	[14]
	$0.4_{(4)}, 0.31_{(5)}$	(4) Cylindrical sample	[15]
Mexico	$0.5_{(1)}, 0.8_{(3)}$	(5) Triangle plate sample	[16]
Canada	$0.5_{(1)}$		[17]

At present, these is a lot of investigations on the AC flashover performances of the polluted insulators in high altitude, but there has been a very little investigations on the flashover performance of insulators in coexisting conditions of the high altitude of 4000 m and above, there are different opinions about the effects of the atmospheric pressure with the icing and contamination on the flashover voltage of the insulators , but the existing standardised pollution test methods are not very representative for real pollution conditions, which lead for improved environmental-related methods.

3. EXPERIMENTAL SYSTEM AND TEST PROCEDURE

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 [18].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. 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.

Three insulators with different parameters and shapes were tested at various contamination level in the high altitudes using the U-type flashover test method [19-21] to take minimum AC voltage of the tested icing insulators by the changing of the conductivity of the spraying water of the freezing (Table 2).

Table 2 Tested insulators parameters

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

When tested insulator were ready in the climate room the refrigeration was started at the ambient temperature of -12° C, then the tested insulator was iced with the freezing water at predetermined conductivity and ice amount .

The effect of altitude on the ice insulator AC voltage is simulated by changing the pressure of the climate chamber with a vacuum pump (Fig. 1), that is, when the ice-state of the tested composite insulator approaches a predetermined one, pumping out the air of the chamber with vacuum so as to depress the atmospheric pressure to predetermined value, then carrying out the flashover tests with even-rising voltage method. The results of this tests shown that , the relation between the average AC ice flashover voltage of the tested insulators during freezing condition and the pressure ratio (*P/Po)* under various icing-states at -15°'C, where the *P* is the actual pressure of the climate chamber in which the iced composite is tested, and P_0 the pressure at the referring standard atmospheric conditions, equals 101.3 kPa. It can be seen that the lower the pressure ratio, the lower the ice flashover voltage of the composite insulator. The average ice flashover voltage of the tested insulators decreases with decrease of (*P/Po*) by nonlinear function.

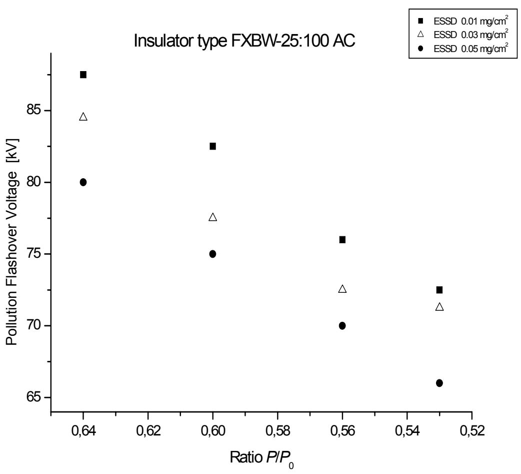

Fig. 1 The effect of altitude on the polluted flashover AC voltage for FXBW- 25:100 AC type insulators.

4. THE STRUCTURE OF RADIAL BASIS FUNCTION NEURAL NETWORK MODEL

In this work, 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:

$$V_f = f(D, L, P, ESDD) \tag{5}$$

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 Fig. 2.

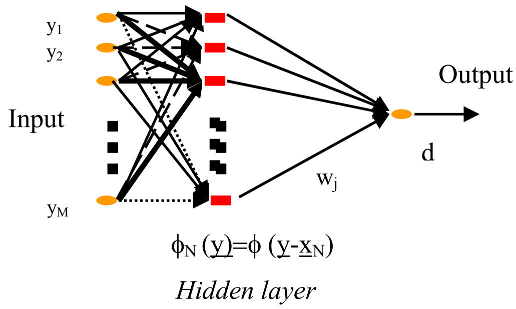

Fig. 2 Three-layer networks

So RBFs are functions taking the form:

$$\phi(\| \underline{x} - \underline{x}_i \|) \tag{6}$$

where f is a nonlinear activation function, $\underline{x}$ is the input and $\underline{xi}$ is the *i'th* position, prototype, *basis* or *centre* vector.

The idea is that points near the centers will have similar outputs (if $\underline{x} \sim \underline{x}_i$ then $f(\underline{x}) \sim f(\underline{xi})$) since they should have similar properties.

For example, the simplest form of *f* is the identity function f $(\underline{x}) = \underline{x}$ but this has some undesirable properties e.g. $f(\underline{xi}) = 0$. (*f is* still a non-linear function as it is only piecewise linear in $\underline{x}$).

Other types of RBFs include:

(a) Multiquadrics

(b) Inverse multiquadrics

(c) Gaussian

Inverse multiquadircs and Gaussian RBFs are both examples of 'localized' functions in which as distance from the centre increase the output of the RBF decreases, but multiquadrics RBFs are 'non localized' functions means as distance from the centre increases the output of the RBF increases.

$$\text{Output} = \sum w_i f_i(\underline{y}) \quad (7)$$

Adjustable parameters are weights wj
Number of hidden units = number of data points.

Idea is to use a weighted sum of the outputs from the basis functions which for e.g. classification, density estimation ... Theory can be motivated by many things (regularization, Bayesian classification, kernel density estimation, noisy interpolation etc), but all suggest that basis functions are set so as to represent the data. Thus centers can be thought of as prototypes of input data.

That is, given a set of N vectors $\underline{x}_i$ and a corresponding set of N real numbers, d_i (the targets), find a function F that satisfies the interpolation condition:

$$F(\underline{x}_i) = di \quad \text{for } i = 1,...,N \quad (8)$$

or more exactly find:

$$F(\underline{x}) = \sum_{j=1}^{N} w_j \phi(\| \underline{x} - \underline{x}_j \|) \quad (9)$$

Satisfying:

$$F(\underline{x}_i) = \sum_{j=1}^{N} w_j \phi(\| \underline{x}_i - \underline{x}_j \|) = d_i \quad (10)$$

$$\underbrace{\begin{pmatrix} \phi(\underline{x}_1 - \underline{x}_1) & -- & \phi(\underline{x}_1 - \underline{x}_N) \\ & \ddots & \\ \phi(\underline{x}_N - \underline{x}_1) & -- & \phi(\underline{x}_N - \underline{x}_N) \end{pmatrix}}_{\text{Interpolation Matrix}} \underbrace{\begin{pmatrix} w_1 \\ | \\ w_N \end{pmatrix}}_{\text{weight}} = \begin{pmatrix} d_1 \\ | \\ d_N \end{pmatrix}$$

$\phi(\underline{x}_i - \underline{x}_j)$: scalar function of distance between vector $\underline{x}_i$ and $\underline{x}_j$.

Equivalently:

$$\Phi . \underline{W} = \underline{D} \quad (11)$$

If Φ is inversable we have a unique solution of the above equation

$$\underline{W} = \Phi^{-1} \underline{D} \quad (12)$$

So provided Φ is non-singular then interpolation matrix will have an inverse and weights to achieve exact interpolation.

For instance, if we take $f(\underline{x}-\underline{y}) = 1$ if $\underline{x} = \underline{y}$, and 0 otherwise (e.g. a Gaussian with very small s), setting $w_i = d_i$ solves the interpolation problem. However, this is a bit trivial as the only general conclusion about the input space is that the training data points are different.

To summarized:

- For a given data set containing N points $(\underline{x}_i, d_i)$, $i=1,...,N$
- Choose a RBF function f
- Calculate $\phi(\underline{x}j - \underline{x}i)$
- Obtain the matrix Φ
- Solve the linear equation $\Phi \underline{W} = \underline{D}$
- Get the unique solution
- Done

5. THE TRAINING PROCEDURES

The RBF neural network is different from BP with sigmoidal activation functions utilizing basis functions in the hidden layers. 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 centres, 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 centres one-by-one from the training data until a satisfactory net- work is obtained, greatly reducing the network size [22],[23],. 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, prediction …, of $V_f = f(D, L, P, ESDD)$.

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 asymptotic. 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.

6. SIMULATIONS RESULTS

Out of 84 data sets, 75 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 (Table3). 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.

Table 3 Parameters of Test Data Patterns

Insulator type	Insulator geometry	Data Patt	Ratio P/P_0	ESSD mg/cm^2	Pollution flashover voltage (kV)	Optimize Pollution flashover voltage (kV) By RBF ANNs
3 **XP-70**	D=255mm	1	1	0.03	82.5	**79.78**
	L= 295mm	2	0.625	0.01	85.5	**81.98**
		3	0.60	0.05	45	**46.09**
		4	0.52	0.03	57	**59.67**
3 **XWP-70**	L= 255mm	5	0.64	0.03	84.5	**83.22**
	D=400mm	6	0.6	0.05	75	**76.03**
FXBW-25/100	L=145/115 mm D=1200 mm	7	0.625	0.05	47.5	**46.89**
		8	0.55	0.01	83	**80.93**

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 [7].

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
(a) Cores Gaussian
(b)Given them are standardized on [0, 1] and center-reduced by the average and the standard deviation of the base of training.
(c) It receiving field is taken equalizes to 0.99.
(d) It criterion of stop of Akaike.
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 [24].

Table 4 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	8	10	5.95	11.73
	12	18	1.82	5.52
	11	08	2.35	5.82
	15	12	1.68	5.88
Normalisation	18	24	1.35	5.94
	20	22	1.05	4.41
Input(Mean, S.D)/ Output (Max, Min)	**22***	**24***	**0.79***	**4.91***
	24	22	0.42	6.87

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). Simulation results of the trained RBF networks for modeling the pollution flashover voltage under various meteorological factors are presented in Table 4.

7. CONCLUSION

Using the experimental data taken from the artificial test for the post insulator high altitudes, a new approach prediction of the effects of low air pressure on the flashover performance of a polluted insulator based on improved RBF Artificial Neural Networks model with the adjustment of OLS training algorithm was proposed is this paper. A number of test results are simulated and analyzed. With this approach RBF networks model has been developed. Prediction performance of the various architectures is tested according to an evaluation uniform commonly accepted criterion in the literature. The model simulates the experimental results quite accurately and allows reliable applications to optimize the pollution flashover voltage under various meteorological factors.

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BIOGRAPHIES

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