Modeling of Various Meteorological Effects on Contamination Level for Suspension Type of High Voltage Insulators Using ANN

Ahmad S. Ahmad, P. S. Ghosh, Syed Abdul Kader Aljunid, Hussein Ahmad*

College of Engineering
Universiti Tenaga Nasional
Selangor - Malaysia
E-mail: ahmads@ieee.org

*Faculty of Electrical Engineering
Universiti Teknologi Malaysia
81310 Skudai
Johor - Malaysia

Abstract—**The performance of polluted insulators is very much dependent on the degree of contamination. For the high voltage insulators to be installed in areas especially near the coast, determination of the contamination level becomes the major task to design the insulators appropriately. The aim of this paper is to obtain accurate information about the degree of contamination which the high voltage insulators are exposed to when they are installed in coastal areas. Regression technique has been used successfully in estimating the level of contamination on high voltage insulators surfaces in terms of Equivalent Salt Deposit Density (ESDD). This paper has also used artificial neural network algorithm to model ESDD as a function of various meteorological parameters. A comparative analysis has also been carried out between the two methods in this work.**

Keywords--ESDD, Insulators, contamination, high voltage, ANN, regression analysis.

I. INTRODUCTION

Optimum design of transmission line insulators results in reduction of probability of failures. Contaminated atmosphere (salts, chemicals, etc.) is one of the main factors included in evaluating the insulation strength of an insulator string. The contamination composition in most cases is 70-75% NaCl and 25-30% $CaSO_4$ and Tonoko. Hygroscopic salts are most dangerous among the soluble components of pollution and such components are, among others: $CaCl_2$, $MgCl_2$, and K_2CO_3. They can cause a dangerous pollution level especially in presence of high humidity.

Contaminated atmosphere and the maximum fault voltage on unfaulted phases may be considered when examining the insulation strength for power frequency overvoltages. In areas where it is considered possible that the level of contamination may someday exceed than certain amount of ESDD, longer creepage length of the insulators will be required. It is necessary to choose an insulator type with high performance in order to avoid excessive string length especially for EHV line design.

Considerable number of insulation failures was found at the coastal areas contrary to the prevailing believe that these areas provide an ideal environment for power transmission line insulators because of the heavy rain factor [1]. Near the coastal areas, outdoor insulators are contaminated with salt deposit, which affects the performance of the insulators. Salts particles carried by the wind coming from the sea to the land accumulate on the surface of insulators and hence reduce the breakdown insulation level of the affected insulators especially when the salt layer is wet by absorbing water from the mist or fog. The conductive layer created by this way is very dangerous and may lead to flashover. To define insulation level of power lines in pollution mainly depends on many factors such as operating experience, the kinds of pollutant substance, pollution severity and weather conditions.

Works in [2-12] found considerable relationships between (ESDD) and flashover with respect to the meteorological parameters. But at the most the researchers studied the effect of one or more of these parameters on ESDD or on flashover. The site measurement of the pollution severity in terms of ESDD has been carried out with typical suspension type Cap-and-Pin glass insulators during dry season under five varying meteorological factors such as temperature, humidity, air pressure, rainfall and wind velocity.

Most of the plants and factories located near the sea suffer from the rapid build up of salt contamination. Paka Thermal Power Station in Peninsular Malaysia is located 500 meters from the coast of South China Sea in Terengganu State, and has been chosen for this study. Typical cap-and-pin glass insulators that are commonly installed on electrical power transmission lines are used in the experimentation. These samples were installed about 50 meters from the seacoast. Three types of insulator topology are employed, single units, suspension-type and tension-type. The contamination collection process was carried out daily for a period of four months and weather conditions are recorded twice daily during the dry and rainy seasons. Two months data from the rainy season and for suspension type of insulators are analysed to achieve the aim of the paper.

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II. MODELING OF ESDD USING REGRESSION TECHNIQUE

A. *Analysis of Residuals and Mathematical Model Development*

The severity of contamination is measured in terms of (ESDD) under five varying meteorological factors e.g. temperature (T), humidity (H), pressure (P), rainfall (R) and wind velocity (WV). Analysis of residuals in regression model is necessary to determine the adequacy of the least squares fit. It is helpful to examine a normal probability plots, plot of residuals versus fitted values and plot of residuals versus each regression variable. In general, when the model is correct, the standardized residuals tend to fall between +2 and -2 and are randomly distributed about zero. Data has been collected during the rainy season consisting of 50 days of experiments in a period of two months. Six data have been found with high residual value and it is larger than ∓ 2. They are considered as outliers and eliminated from this modeling. The process repeated again to improve the model. The outlier is a peculiarity and indicates a data point, which is not at all typical of the rest of the data. It is possible that some error has been made through the data recording. After removing the six data, it can be concluded that the model specification is satisfactory. The rest of data after that has been also used in ANN modeling.

The ESDD in this case can be pinpointed at the intersection of five scores: temperature, humidity, pressure, rainfall and wind speed. Accordingly, it has been decided to develop and test the relationship investigation on the basis of random samples of 44 data in which 34 have been used to develop the model and the rest 10 to test the model. The variables in this investigation, with their units of measurements are:

Temperature, independent variable (X_1) in $^{\circ}C$
Humidity, independent variable (X_2) in *%*
Pressure, independent variable (X_3) in *mbar*
Rainfall, independent variable (X_4) in *mm*
Wind speed, independent variable (X_5) in *m/s*
ESDD, dependent variable (y) in mg/cm^2

Multiple linear regression analysis has been used to study the influence of the five weather parameters on ESDD so, the predictor model form should be written as follows considering that all the parameters have positive sign:

$$y = B_o + B_1 X_1 + B_2 X_2 + \ldots\ldots + B_j X_j \qquad (1)$$

The value of B_o represents the predicted value of y when $X_1, X_2, \ldots X_j$ remain constant. Similarly, the value of B_2 gives us the predicted rate of response in y to the change in X_2 if $X_1, X_3, \ldots X_j$ remain constant, etc.. If the means and standard deviations of the predictors and criterion variables are significantly different which may cause the partial regression coefficient to be erroneous, the determination using a standardized model is used and it is more comprehensive and covers more area of estimation. This is as follows:

$$Z_Y = \beta_1 Z_1 + \beta_2 Z_2 + \ldots\ldots\ldots \beta_5 Z_5 \qquad (2)$$

in which β_j *(j=1, 2, ...5)* are called standardized partial regression coefficients, and Z_Y and Z_j *(j=1, 2.....5)* are the criterion variable and the predictor variables respectively expressed in standardized form as follow:

$$Z_y = \frac{y_i - \bar{y}}{S_y} \qquad (3)$$

and

$$Z_j = \frac{X_{ij} - \bar{X}_j}{S_j} \qquad (4)$$

in which $i = 1, 2, \ldots n$ is the number of observations, S_y is the standard deviation of the criterion variable and S_j *(j=1, 2....5)* are the standard deviations of the predictors variables. For the case studied the standardized regression was obtained as:

$$ZESDD = -0.5Z_1 \ -0.5Z_2 \ +0.65Z_3 \ -0.16Z_4 + 0.41Z_5 \qquad (5)$$

It should be noted that the standardized partial regression coefficient *(β's)* and the partial regression coefficient *(B's)* are related by:

$$B_j = \frac{\beta_j S_y}{S_j} \qquad (6)$$

Various criteria to judge the model have also been used and are stated below. The model has been tested using 10 data set and the result is plotted in Fig. 2.

B. *Coefficient of Determination (R^2)*

This value used as a summary measure to judge the fit of the linearity for the model. For this model, $R^2 = 0.72$, that is, 72% of the variability in the data is accounted for the model. The statistic R^2 should be used with caution since it is always possible to make R^2 unity by simply adding enough terms to the model. Also, R^2 will increase if any other variable is added to the model.

C. *Multiple Correlation Coefficient (R)*

In this model Multiple correlation coefficient *(R)= 0.854*. From this result, we can conclude that although the five variables tend to increase and decrease together, the positive correlation between the *X's* and ESDD (y) was especially strong and significant, and we can conclude that the sample of observations was drawn from a population in which a positive correlation existed.

III. ESDD MODELING USING ANN

A lot of works have been carried out on the application of ANN in many fields recently. It has been used successfully in capacitor control, a uniform and complex electric stress distribution along the insulator surface, alarm processing, in pattern recognition of partial discharges and pollution discharge modeling [13-18]. In this paper a new approach using ANN as function estimator has been developed and used to model the relationship between ESDD (the dependent factor) and the meteorological parameters (the independent factors) such as temperature, humidity, pressure, rainfall and wind speed. Among the various artificial neural network presented so far, the multilayer feed forward neural network is employed in this study. It is found that the ANN modeling is very effective and accurate. Among the various artificial neural network presented so far, the multi-layer feed-forward network with back propagation technique is employed in the present study to model $ESDD = f(T, H, R, P, WV)$. The neural network is trained with the help of data obtained from site measurement and the training accuracy has been assessed by root mean square error (RMSE).

A. *Details of ANN Algorithm*

ANN algorithm has been used successfully in many applications. 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 to control it. ANN can model a function even if the equation describing it is unknown-the only prerequisite is representative sample of the function behavior and that is from the experimental data and not from a theoretical understanding. Fig. 1 shows the schematic diagram of a multi-layer feed forward network used in this paper. The neurons in the network can be divided into three layers: input layer, output layer and hidden layers.

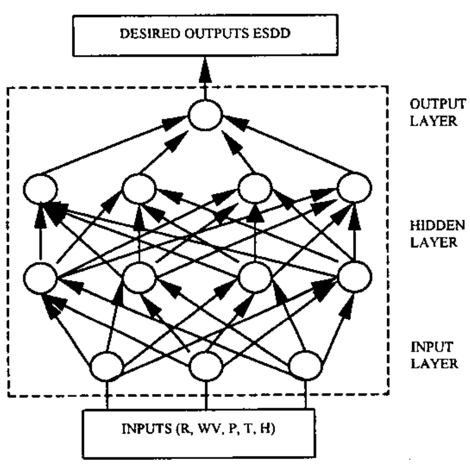

Fig. 1: The structure of a multi-layer neural network

It is important to note that the feed forward network signals can only propagate from the input layer to the output layer through the hidden layers. Each neuron of the output layer receives a signal from all input via hidden layer neurons along connections with modifiable weights. The neural network can identify input pattern vectors, once the connection weights are adjusted by means of the learning process. The back-propagation learning algorithm [19] which is a generalization of Widrow-Hoff error correction rule [20] is the most popular method in training the ANN and is employed in this work. This learning algorithm is presented here in brief. For each neuron in the input layer, the neuron outputs are given by

$$O_i = net_i \tag{7}$$

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;

$$net_k = \sum_{j=1}^{Nj} w_{kj} O_j, k = 1, \ldots.., N_k \tag{8}$$

wher w_{kj} is connection weight between neuron j and neuron k; and N_j, N_k are number of neurons in the hidden and output layers respectively; and the neuron outputs are given by

$$O_k = \frac{1}{1 + \exp(-(net_k + \theta_\kappa)/\theta_o)} = f_\kappa(net_k, \theta_\kappa, \theta_o) \tag{9}$$

where θ_k is threshold of neuron k; and the activation–functions f_k a sigmoidal function. For the neurons in the hidden layer, the input and the outputs are given by the relationships similar to those given in the equation (2) and (3) respectively. The connection weights of the feed forward network are derived from the input–output patterns in the training set by the application of generalization delta rule [19]. The algorithm is based on minimization of the error function of each pattern p by the use of the steepest descent method [19]. The sum of squared errors which is the error function of each pattern is given by

$$E_p = \frac{1}{2} \sum_{\kappa=1}^{N_\kappa} (t_{pk} - O_{pk})^2 \tag{10}$$

Where t_{pk} and O_{pk} are target and calculated outputs for output neuron k respectively. The overall measure of he error for all the input-output patterns is given by

$$E = \sum_{p=1}^{N_p} E_p \tag{11}$$

Where N_p is the 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

$$\Delta w_{kj}(p)=\eta\delta_{pk}O_{pj}+\alpha\Delta w_{kj}(p-1) \quad (12)$$

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:

$$\delta_{pk}=(t_{pk}-O_{pk})O_{pk}(1-O_{pk}) \quad (13)$$

and for each neuron in the hidden layer

$$\delta_{pj}=O_{pj}(1-O_{pj})\sum_{k=1}^{N_K}\delta_{pk}w_{kj} \quad (14)$$

It is important to know that the threshold of each neuron is learned in the way same as that for the other weights. The threshold of a neuron is regarded as a modifiable connection weight between that neuron and a fictitious neuron in the previous layer, which always has an output value of unity.

B. Problem Description

In this paper, *ESDD = f (T, H, P, R, WV)* modeling has been attempted based on artificial neural network instead of any empirical approach. Out of 44 data sets collected from site measurement, 34 sets of input/output patterns are used as Training Data Set in the training process. Each training presentation contains five input nodes characterizing meteorological parameters (T, H, P, R, WV) and one output node which provides corresponding values of ESDD. Once the neural network is trained by using 34 training sets, it is tested using 10 Test Data Set selected randomly from the remaining 44 data set. All inputs and outputs in the training patterns are normalized within the respective ranges as per different normalizing schemes before they are used for neural network training and testing. Finally, with the help of input pattern vectors of 10 test data set, estimated values of ESDD are computed using the trained ANN model i.e. *ESDD= f (T, H, R, P, WV)* and are plotted against the measured ESDD values as shown in Fig. 2.

C. Details of Work Done

In applying the learning rule described, there are several issues which should be addressed. The optimization process has been carried out based on %MAE and less oscillation in the error of convergence. From the results in Tables 1-5, the observations that can be made are:

a- in this study, it has observed that the number of input-output patterns presented in each iteration has a significant effect on the training and test data accuracies.
NS = NPR x NTSP
Where,
NS = total number of input-output patterns
NPR = number of presentations
NTSP = number of input-output patterns per presentation
The result of Table 1 indicates that for a combination of NPR = 17 and NTSP = 2 the %MAE is minimum. Thus it is understood that for the present study, this presentation is considered to be most effective.

TABLE 1
INPUT = MEAN & SD, OUTPUT = MAX, NIT = 1000, η= 0.2, α= 0.8, NO. OF HIDDEN LAYER NODES = 11

NPR	NTSP	RMSE	%MAE
34	1	0.1701	10.19
17	2	0.1683	8.41
2	17	0.1933	17.71
1	34	0.2088	19.00

b- For the convention learning algorithm with the choice of η =0.2, α =0.8 and eleven hidden layers nodes, the best normalization scheme is being optimized in Table 2. The number of iterations used in the training process is 1000. The results of Table 2 indicate that the scheme 7 of normalization is the best choice for the present work on the basis of minimum %MAE with no oscillation.

TABLE 2
NO. OF ITERATIONS =1000, NO. OF HIDDEN LAYER NODES=11, η =0.2, α =0.8

Scheme No.	Input	Output	RMSE	%MAE
1	Max	Max	0.2214	16.47
2	Max	Maximin	0.2430	16.30
3	Max	Mean & SD	0.2430	16.30
4	Maximin	Max	0.2210	18.29
5	Maximin	Maximin	0.2433	18.07
6	Maximin	Mean & SD	0.2433	18.07
7	Mean & SD	Max	0.1683	8.41
8	Mean & SD	Maximin	0.1849	9.88
9	Mean & SD	Mean & SD	0.1849	9.88

c- in the present work, extensive studies have been carried out on the effect of different values of η and α on the convergence rate of the learning method and are given in Table 3. It is evident from Table 3 that the best %MAE is obtained with no oscillation for η= 0.25, α= 0.95. Although minimum %MAE is obtained for η= 0.2 and α= 0.9, but there is oscillation in the error of convergence.

TABLE 3
NO. OF ITERATIONS=1000, NO. OF HIDDEN LAYER NODES=11,INPUT=MEAN & SD AND OUTPUT= MAX

η	α	RMSE	%MAE	Notes
0.1	0.8	0.1698	12.27	No oscillation
0.2	0.7	0.1693	11.03	Less oscillation
0.2	0.95	0.1669	11.25	Less oscillation
0.25	0.95	0.1671	8.55	No oscillation
0.3	0.6	0.1697	11.47	No oscillation
0.3	0.8	0.1681	8.24	High oscillation
0.4	0.7	0.1687	8.86	No oscillation

Whereas for η =0.25 and α =0.95 the MAE is slightly higher i.e. 8.55 but with no oscillation in the error of convergence. So the combination of η =0.25 and α =0.95 is the best choice with eleven nodes in the hidden layer. The number of iterations used in the training process is 1000.

d- from Table 4, the best %MAE is obtained with 9 hidden layer nodes i.e. 6.99%. Thus for the present work, on the basis of minimum %MAE, the number of nodes in the hidden layer is optimized at nine with the choice of η= 0.25, α= 0.95.

TABLE 4
NO. OF ITERATIONS 1000, η =0.25, α =0.95, INPUT=MEAN & SD, OUTPUT=MAX

No. of Nodes in Hidden layers	RMSE	Notes
6	0.1672	7.12
7	0.1673	11.16
8	0.1685	7.62
9	0.1675	6.99
10	0.1675	10.81
11	0.1671	8.55

e- Table 5 compares the effect of number of hidden layers on the convergence rate of the training process. It is found that, using one hidden layer has a better effect on the convergence rate than when two hidden layers are used. When two hidden layers are used, the RMS error and %MAE are increased. Thus, in the present work, the test outputs are calculated using one hidden layer with nine nodes.

TABLE 5
N0. OF HIDDEN LAYER NODES =9, η =0.25, α = 0.95,INPUT= MEAN & SD, OUTPUT= MAX

No. of layers	No. of Nodes in Hidden layers	RMSE	%MAE
1	9	0.1675	6.99
2	9, 99	0.1685	17.01

The discussion reveals that the excellent convergence characteristic for the present work is obtained using one hidden layer containing nine nodes with η= 0.25 and α= 0.95. The modeled output of the test data computed with the help of the best combination of the modifiable parameters are tabulated against the target output, that is data obtained from the site measurements in Table 6. The RMSE obtained in the training process for 1050 iterations is 0.1673 and the %MAE is found to be 3.897. Moreover, measured and estimated data of ESDD have been plotted for ten tests data chosen randomly from the data collected at the site as shown in Fig. 2. The figure below shows the comparison between the two methods employed to model ESDD = *f (T, H, R, P, WV)*.

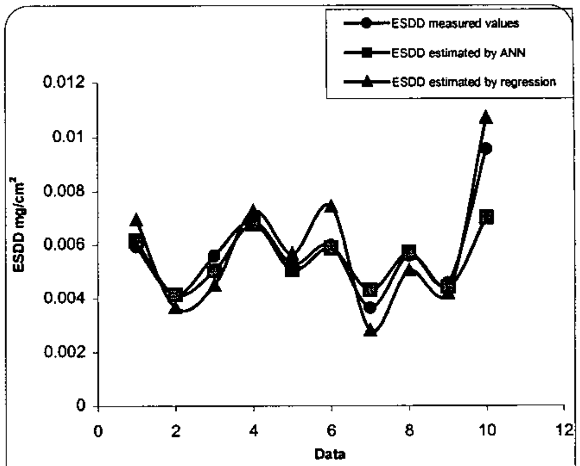

Fig. 2: Comparison between ANN and regression methods

IV. CONCLUSIONS

In this paper, regression technique and ANN have been applied successfully in pollution severity measurement studies. The two models showed the relationship between ESDD and five meteorological parameters viz. temperature, humidity, air pressure, rainfall, wind speed and wind direction during rainy season for suspension type of insulators, *ESDD= f (T, H, R, P, WV)*. Further comparative analysis of the estimated results with the measured data collected from the site measurement amply demonstrate the effectiveness of the use of ANN in modeling a system from the results of the site measurement only, where the real-world system has an unknown nonlinear relationship. This paper showed also the effectiveness of ANN in estimating ESDD compare to the regression technique method. The two models can be applied for finding ESDD of the insulators located at any site having meteorological characteristics similar to Paka Power Station site. The estimation of critical contamination level in terms of ESDD will help in the establishment of maintenance policies and for addressing an effective solution against pollution flashover of high voltage insulators.

TABLE 6: No. of Hidden layer = 1, No. of Hidden layer nodes = 9
NIT = 1050, Input = Mean & SD, Output = Max, η= 0.25, α= 0.95, RMSE = 0.1673

Rain (R) mm² Range (0-53.5)	Wind velocity (WV) m/s Range (1-5.5)	Pressure (P) mbar Range (1022-1028)	Humidity (H) % Range (77.5-92.5)	Temperature (T) °C Range (24.5-28.75)	ESDD measured values mg/cm²	ESDD estimated values mg/cm²	%MAE
0	4	1025	82	28.5	0.00595	0.00615	3.897
0	2	1023	84	26.5	0.00414	0.00414	
0.5	2	1022	77.5	28.75	0.00560	0.00505	
35	5	1027	83.5	27	0.00689	0.00676	

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