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A Neuro-Fuzzy Approach for Estimation of Time-to-Flashover Characteristic of Polluted Insulators

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***Abstract*— Function estimation is one of the major fields of fuzzy logic applications. Because of the useful properties of fuzzy systems such as adaptivity and nonlinearity, they are well suited to function estimation tasks where the equation describing the function is unknown as the only prerequisite is a representative sample of the function behavior. In this paper, a neuro-fuzzy approach for estimation of time-to-flashover of a polluted insulator under power frequency voltage is discussed. The prerequisite training data are available from experimental studies performed on models of polluted insulators. The results show the effectiveness of the proposed approach.**

***Keywords*—Neuro-Fuzzy; ANFIS; Polluted Insulator; Time-to-Flashover**

I. INTRODUCTION

The flashover of polluted transmission line and substation insulators is one of the major problems facing power engineers throughout the world especially in severe weather conditions areas, where pollution layers are progressively deposited on the insulating units. When moisture is added by dew deposition, fog or rain, an electrolyte wet conducting film is formed and a leakage current begins to flow [1]. Severe surface pollution and non-uniform voltage distribution along the insulator surface can cause scintillations in the form of glow discharges or quasi-stable arcs to take place [2]. For an arc or glow discharge to bridge completely the whole length of insulator (L), the applied voltage must be above the critical flashover voltage (V_C) [2]. For an applied voltage larger than or equal to the critical flashover voltage, glow discharges or the quasi-stable arcs elongate through successive root formation over the polluted insulator surface [3], which continues until the quasi-stable arcs reach a critical distance (X_C). From this critical distance, the flashover takes its final leap to accomplish bridging. Lengthening of the quasi-stable arcs during the elongation phase depends upon the velocity of the arc propagation, which is not a constant parameter but it depends on several factors such as: the resistance per unit length (R_P), the whole length of the insulator (L), and the applied a.c. voltage (V) [4].

On the other hand, neural network and fuzzy logic algorithms have been successful on very wide range of applications including speech processing, radar analysis, load forecasting, security evaluation, capacitor control, alarm processing, torsional oscillations analysis, pattern recognition of partial discharge, etc [5].

Another major branch of these algorithms application lies in function estimation. In function estimation, a model of a real-world system or function is developed. This model then stands for the system it represents, typically to predict or to control it [5]. In previous works [4-6], neural network has been used for obtaining insulator flashover characteristics. In this paper, a new approach using a neuro-fuzzy model is applied as a function estimator to derive the relationship between flashover time (t) and V, R and L.

II. NEURO-FUZZY MODEL THEORY

Suppose you want to apply fuzzy inference to a system for which you already have a collection of input/output data that you would like to use for modeling, model-following, or some similar scenario. You don't necessarily have a predetermined model structure based on characteristics of variables in your system.

There will be some modeling situations in which you can't just look at the data and discern what the membership functions should look like. Rather than choosing the parameters associated with a given membership function arbitrarily, these parameters could be chosen so as to tailor the membership functions to the input/output data in order to account for these types of variations in the data values. This is where the so-called neuro-adaptive learning techniques can help to obtain a neuro-fuzzy model of the system [7].

The basic idea behind these neuro-adaptive learning techniques is very simple. These techniques provide a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the fuzzy membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. This learning method works similarly to that of neural networks [8].

In this paper, Fuzzy Logic Toolbox of MATLAB7 is used to construct the neuro-fuzzy model of a polluted insulator. The Fuzzy Logic Toolbox function that accomplishes the fuzzy membership function parameter adjustment is called adaptive neuro-fuzzy inference system (ANFIS). The fuzzy inference method that is used in ANFIS is Takagi-Sugeno-Kang (TSK). TSK fuzzy model is identified in two steps [8]:

- A fuzzy clustering technique is applied to input-output space data, with a number of clusters equal to N_r.
- Assuming the cluster centers to be furnished by the previous step, the number of fuzzy rules equal to N_r and the spreads of the memberships functions equal to r, the model's parameters are identified by a recursive least-squares procedure.

A. FCM Clustering

Using the FCM method, data samples are organized in clusters, each of which is associated with a center. In this manner, the TSK model is based on a set of fuzzy IF–THEN rules, extracted by using the FCM clustering technique [8].

Supposing unlabelled patterns (input vectors), $X=(x_1,x_2,...,x_N)$, $x_i \in \Re^p$, where $\Re$ is the set of real numbers, and p is the dimension of pattern vectors. Clustering procedure is performed to minimize the following objective function [11]:

$$F_m(U,W)=\sum_{j=1}^{N_r}\sum_{i=1}^{N}(\mu_{ij})^M d_{ij}^2 \quad (1)$$

FCM, A two-step iterative process, works as follows:

- Given the membership values $\mu_{ij}^{(t)}$, the cluster center matrix W is calculated by:

$$w_j^{(t)}=\frac{\sum_{i=1}^{N}\left(\mu_{ij}^{(t-1)}\right)^M x_i}{\sum_{i=1}^{N}\left(\mu_{ij}^{(t-1)}\right)^M} \qquad j=1,...,N_r \quad (2)$$

- Given the new cluster centers $W(t)$, the membership values $\mu_{ij}^{(t)}$ are updated by:

$$\mu_{ij}=\frac{1}{\sum_{l=1}^{N_r}\left(\frac{d_{ij}}{d_{il}}\right)^{\left(\frac{2}{m-1}\right)}} \qquad i=1,...N \quad j=1,...,N_r \quad (3)$$

where, if $d_{ij}=0$ then $\mu_{ij}=1$ and $\mu_{ij}=0$ for $l \neq j$. The process stops when $\left\|U^{(t)}-U^{(t-1)}\right\| \leq \varepsilon$, or a predefined number of iterations is reached.

B. TSK model structure and parameters

For multi-input single-output systems, the typical TSK model consists of a set of IF–THEN rules having the following form [4,8]:

R_h: IF $\dot{x}_1$ is A_h^1 and … and $\dot{x}_p$ is A_h^q THEN y is f_h(x) (h=1,…,n)

where:

$$f_h(x)=a_{0h}+a_{1h}\dot{x}_1+a_{2h}\dot{x}_2+...+a_{ph}\dot{x}_p \quad (4)$$

in which $\dot{x}_{1,...,p}$ form the input vector (pattern) $x_i=\left[\dot{x}_1,...,\dot{x}_p\right]^T$, y is the output variable, $A_h^{1,...,q}$ are the fuzzy sets, and f_h(x) is a linear function which its parameters are calculated by the least-squares procedure.

For any input, x_i, the inferred value of the TSK model, is calculated as:

$$y=\frac{\sum_{h=1}^{n}A_h(x_i)*f_h(x_i)}{\sum_{h=1}^{n}A_h(x_i)}=\frac{\sum_{h=1}^{n}\tau_h*f_h(x_i)}{\sum_{h=1}^{n}\tau_h} \quad (5)$$

where the weight of each rule τ_h, for the current input x_i is determined by the Gaussian law, which ensures the greatest possible generalization:

$$\tau_h=\exp(-\alpha\left\|x-x_h^*\right\|^2) \qquad h=1,...,n \quad (6)$$

III. Time-to-Flashover Characterisitc of the Polluted Insulator

In this section, time-to-flashover characteristic of a polluted insulator is obtained based on neuro-fuzzy modeling approach. In order to train the model, experimental data of [5] is used. Training data and the simplified representation of the experimental set up are shown in Table I and Fig. 1, respectively. It is worthy to be noted that the tests are performed on a two-dimensional flat plate model of a practical insulator. Also, Electrolytes simulating artificial pollution of required R_P, which fill the groove of the flat plate model, are prepared with distilled water as solvent and NaCl as solute. The considered values of R_P are 1000, 1500, 2160 and 2500 kΩ/m. Fig. 2 shows the time-to-flashover characteristic of the polluted insulator obtained using neuro-fuzzy model for different values of R_P while L =0.12m. As seen, the model accuracy increases with R_P increase. It is because of more training (V,t) pairs being available at higher R_P values. Also, the characteristic for different values of L while R_P =2500(kΩ/m) is shown in Fig. 3. Again, the role of number of training pairs is significant.

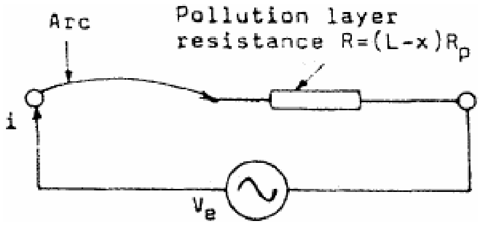

Figure 1. Simplified electrical equivalent circuit of the experimental set-up

TABLE I.
EXPERIMENTAL RESULTS USED IN THE TRAINING PROCESS

Rp (kΩ/m)	L=0.05 (m)		L=0.08 (m)		L=0.05 (m)		L=0.1 (m)	
	V kV	t ms	V kV	t ms	V kV	t ms	V kV	t ms
1000	7.0	11.3	11.0	36.2	13.0	79.8	16.0	87.2
	8.0	5.6	12.0	16.4	14.0	39.5	17.0	48.9
	9.0	2.7	13.0	5.5	15.0	20.4	18.0	27.9
	10.0	1.0	14.0	3.3	16.0	11.6	19.0	16.8
	-	-	15.0	1.0	17.0	6.5	20.0	11.1
	-	-	16.0	-	18.0	4.2	21.0	6.7
	-	-	-	-	19.0	1.0	22.0	3.3
	-	-	-	-	-	-	23.0	1.0
1500	8.0	13.3	12.0	35.7	15.0	78.6	18.0	124.0
	9.0	7.8	13.0	16.2	16.0	36.4	19.0	64.7
	10.0	2.7	14.0	8.8	17.0	14.6	20.0	29.6
	11.0	1.6	15.0	5.1	18.0	9.4	21.0	15.1
	-	-	16.0	2.9	19.0	5.5	22.0	8.5
	-	-	17.0	1.8	20.0	3.1	23.0	4.9
	-	-	-	-	21.0	1.6	24.0	2.9
	-	-	-	-	-	-	25.0	1.6
2160	9.0	21.1	14.0	81.7	17.0	119.1	20.0	153.6
	10.0	11.3	15.0	35.0	18.0	64.1	21.0	95.2
	11.0	4.5	16.0	12.1	19.0	30.3	22.0	49.3
	12.0	1.1	17.0	5.9	20.0	14.8	23.0	22.5
	-	-	18.0	2.5	21.0	8.1	24.0	13.5
	-	-	19.0	1.4	22.0	5.8	25.0	8.9
	-	-	-	-	23.0	4.0	26.0	6.2
	-	-	-	-	24.0	1.0	27.0	5.1
	-	-	-	-	-	-	28.0	4.0
	-	-	-	-	-	-	29.0	1.0
2500	10.0	36.8	15.0	94.1	18.0	134.5	21.0	154.2
	11.0	16.5	16.0	33.9	19.0	74.9	22.0	100.7
	12.0	13.3	17.0	12.1	20.0	35.1	23.0	53.0
	13.0	1.3	18.0	3.5	21.0	16.1	24.0	28.0
	-	-	19.0	1.7	22.0	9.6	25.0	18.2
	-	-	20.0	1.5	23.0	5.5	26.0	13.3
	-	-	-	-	24.0	3.5	27.0	11.1
	-	-	-	-	25.0	1.8	28.0	9.5
	-	-	-	-	-	-	29.0	7.0
	-	-	-	-	-	-	30.0	4.7
	-	-	-	-	-	-	31.0	1.8

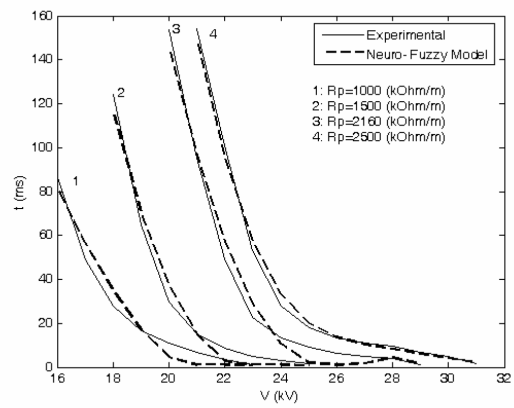

Figure 2. Time-to-flashover characteristic of the polluted insulator (L=0.12m)

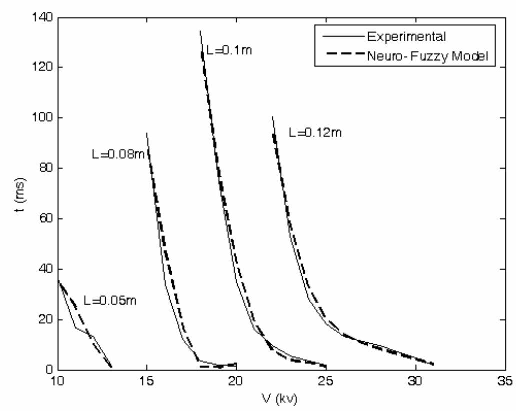

Figure 3. Time-to-flashover characteristic of the polluted insulator (R_P=2500 kΩ/m)

TABLE II.
NEURO-FUZZY AND NEURAL NETWORK MODELS ERROR

	Neuro-Fuzzy		Neural Network	
MAE(%)	L=0.05m	35.1	L=0.05m	46.6
	L=0.08m	10.3	L=0.08m	14.6
	L=0.1m	9.1	L=0.1m	10.6
	L=0.12m	4.5	L=0.12m	5.8

Mean absolute error (MAE) of the neuro-fuzzy model and the neural network model presented by Ghosh [5] are compared in Table II. MAE is calculated as follows:

$$MAE\,(\%) = \frac{\sum \left(|e_k - f_k| / e_k \right)}{n} \times 100 \qquad (7)$$

where e_k , f_k and n are measured value, estimated value and the number of available training (V, t) pairs, respectively.

As seen, the neuro-fuzzy model has a higher accuracy. Also, run times of the neuro-fuzzy and neural network models using a 2.4GHz PC are 90s and 130s (for 5000 iterations), respectively. So, the neuro-fuzzy modeling approach is better in terms of accuracy and run time.

IV. CONCLUSION

A neuro-fuzzy approach for obtaining time-to-flashover characteristic of a polluted insulator has been discussed. Comparison of the results of the nero-fuzzy and neural network modeling approaches shows the higher accuracy of the proposed model. Also, this model is better in terms of convergence time.

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