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Determination of dielectric properties of insulator materials by means of ANFIS: A comparative study

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ABSTRACT

In this study, dielectric properties of polyesters which have abundant use in communication cables and power systems are aimed to be determined by means of adaptive neuro-fuzzy inference system (ANFIS). Measuring the dielectric properties of insulators under various fields of application and operating conditions requires advanced equipments and takes a long time. After measuring in a wide range and different conditions, determining the other required dielectric properties by means of ANFIS will supplement time and cost. To this end, ANFIS models are trained which are built for every measurement value of dielectric permittivity (ε_r) and loss factor ($\tan\delta$) with respect to heat-frequency values of polyesters used as insulators. Then, used data in ANFIS and unused data are tested separately. In the models built for determining dielectric permittivity and loss factor, absolute mean percent error-cumulative absolute percent error are found to be 0.0030–0.1092% and 0.0021–0.0766%, respectively. The results of ANFIS are compared with a previous study of multilayer perceptron (MLP) artificial neural networks (ANN) in which the same data sets are used. ANFIS models exhibit good learning precision and generalization according to mean absolute errors (MAEs). Hence, it becomes easy to determine the dielectric permittivity and loss factor without measuring the given temperature–frequency values by ANFIS. The percent effects of dielectric permittivity and loss factor that are determined by ANFIS on total dielectric loss are discussed based on representative analyses.

1. Introduction

Nowadays, usage of electrical insulators is increasing along with technological improvements. They are principally used as main insulators in the application of high-voltage power system elements and high-frequency low-voltage systems. It is highly important to determine the change of electrical properties of these insulators in different conditions and wide tolerances for safe operation. To this end, measurement of dielectric properties such as dielectric permittivity and loss factor in different operational conditions and areas of insulators are to be determined. But measurements require high cost technology and take vast amount of time. Once a measurement is carried out for an insulator in different conditions and wide tolerances, determining the dielectric properties of the same material in any operational condition avoids cost and labour with the help of adaptive neuro-fuzzy inference system (ANFIS) models.

Suppose a system for which the input/output data have already been collected is modeled by the fuzzy inference system (FIS). It may not necessarily have a predetermined model structure based on characteristics of variables in the system. There would be some modeling situations in which someone cannot just look at the data and discern what the membership

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functions should look like. Rather than choosing the parameters associated with a given membership function arbitrarily, these parameters could be chosen so as to adjust the membership functions to the input/output data in order to account for these types of variations in the data values. This situation can be achieved by ANFIS with neuro-adaptive learning techniques. Using a given input/output data set, ANFIS constructs an FIS whose membership function parameters are adjusted using a backpropagation algorithm either alone or in combination with a least-squares type of method. This allows the fuzzy systems to learn from the data they are modeling. ANFIS, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters of outputs, can be used to interpret the input/output map. The parameters associated with the membership functions will change through the learning process. The adjustment of these parameters is facilitated by a gradient vector, which provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. Once the gradient vector is obtained, any of the several optimization routines could be applied in order to adjust the parameters so as to reduce some error measures which are usually defined by the mean squared difference between actual and desired outputs.

In this study, dielectric permittivity (ε_r) and loss factor ($\tan\delta$) values are trained by separate ANFIS models according to certain temperature and frequency values for polyesters used as insulator. Then, the trained ANFIS models are tested by data which are not used in the training procedure. Results are compared with a prior study that was carried out by multilayer perceptron (MLP) artificial neural networks (ANN) model (İnal and Aras, 2005) for same data set.

The dielectric permittivity of an insulator is proportional to both frequency (F) and temperature (T) (Solymar and Walsh, 1999):

$$\varepsilon_r = f(F, T) \tag{1}$$

Dielectric permittivity is one of the major factors affecting the capacitance of an insulator. On the other hand, changes in dielectric permittivity are affected by the aging of insulator. Loss factor is another significant parameter of the insulator. Theoretically insulators do not have any losses. In practice, leakage current (I_r) is observed in insulators which is defined as dielectric loss. These losses act as a thermal source under high-voltage or frequency conditions. Under these circumstances, the insulators undergo more thermal stress and are affected by the changes in their properties during operation. For this reason, it is more important to know the changes in loss factor during operation than selection of insulator with a small loss factor as soon as possible. $\tan\delta$ is defined as the ratio of I_r to the capacitive current (I_c) as follows:

$$\tan\delta = \frac{I_r}{I_c} \tag{2}$$

I_c changes depending on the frequency. Dielectric loss can be defined as follows:

$$W_d = 2\pi F C U^2 \tan\delta (w/m) \tag{3}$$

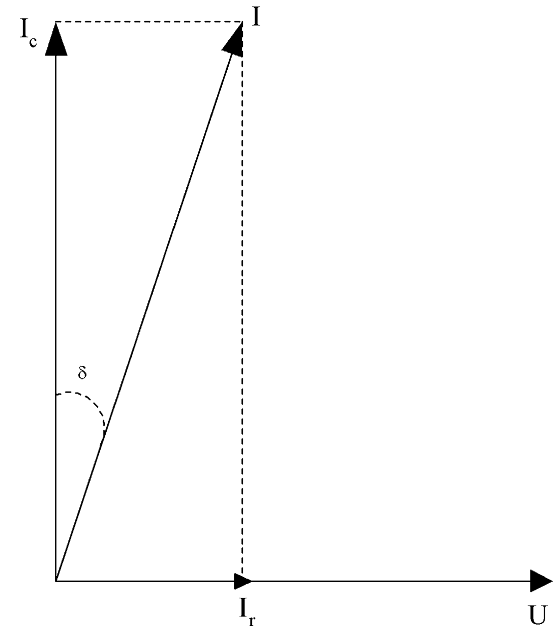

Fig. 1 – Vector diagram for parallel circuit model of dielectric losses.

where F represents frequency (Hz), C capacity (F) and U voltage (V).

The relation between C and ε_r is given in following equation:

$$C = \frac{\varepsilon_0 \varepsilon_r A}{d} \tag{4}$$

where A is the area of electrode, d diameter of the insulator (m), and $\varepsilon_0 = 8.854 \times 10^{-12}$ F/M.

Since Eqs. (2)–(4) are standard in dielectrics (ASTM D 150-95), their vector diagram and equivalent circuit can be properly represented as shown in Figs. 1 and 2, respectively. According to the Eq. (4), capacity is proportional to $\varepsilon_{r.}$ Calculating the effect of dielectric permittivity and loss factor to the total dielectric loss provides a relation. If ε_r is used instead of C and U^2 is assumed to be constant, the effects of ε_r and $\tan\delta$ to the

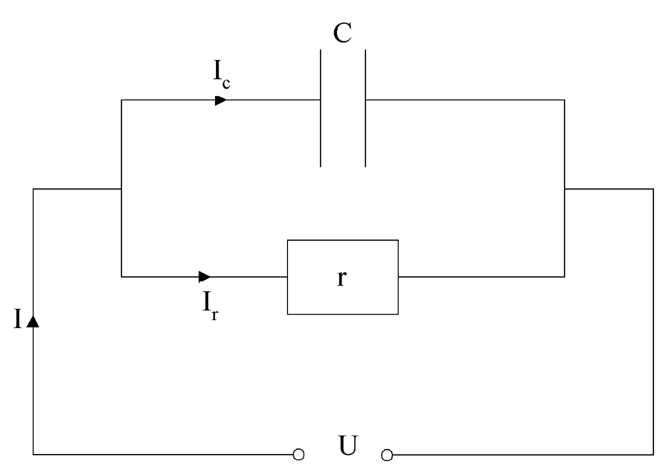

Fig. 2 – Parallel circuit model of dielectric losses.

total loss can be determined for variable frequency as follows:

$$T_{\text{loss}} = \varepsilon_r F \tan \delta \quad (5)$$

Since frequency plays an important role in dielectric loss, the total loss is calculated for communication cables. So, if the temperature is constant for communication cable then frequency affects the total loss. In this study according Eq. (5), the total dielectric loss is calculated for various frequencies such as [50 Hz–10 kHz] at 20, 50 and 80 °C temperatures.

There are several studies on dielectric properties of insulators in literature (Tuncer and Gubanski, 2001; Nguyen et al., 2004; Yılmaz and Kalanderli, 1997; Morgan, 1998; Liming Zong et al., 2004; Pfeiffer, 2001; Kühn and Kliem, 2004; Serdyuk et al., 2004). The dielectric data obtained from a silicone polymer based composite material were analyzed using Monte Carlo method by repeated fitting procedure with randomly selected relaxation times (Tuncer and Gubanski, 2001). Nguyen et al. (Nguyen et al., 2004) characterized frequency dependence of the dielectric properties of silicone rubber under various temperatures by using the Havriliak-Negami model. The properties of dielectric are still the subject of investigation under various operation conditions (Yılmaz and Kalanderli, 1997; Morgan, 1998; Liming Zong et al., 2004; Pfeiffer, 2001; Kühn and Kliem, 2004; Serdyuk et al., 2004). As the studies were carried out in different operational conditions and for the different materials, it is hard to make a comparative assessment. For the acceptance of these measurements, some standards are developed (ASTM D 150-95). The proper measurements for standards require high technology equipments and take longer time. In this study, regardless of developing a mathematical model due to physical measurement, an alternative approach is presented to describe the dielectric properties of insulators by means of ANFIS. Any required value is obtained more easily and economically in different operational conditions. The details of the applications which use Sugeno type FIS and ANFIS models with hybrid learning rules and the obtained results are given in this study.

2. Experiments data

The data used in this study are obtained using a thin film polyester material with a thickness of 0.036 mm produced by Hoechst AG. The main reason for the selection of polyesters is related to their wide area of use and good dielectric properties. HP 4192 A impedance analyzer is used in measurements according to the ASTM D 150_D1531 standard. First, polyester film specimens are cleaned and made in contact with silver coating. This is a costly stage and requires making flat surfaces. So, thin layer silver electrodes are produced by spraying and drying method. The dielectric permittivity and loss factor are measured in four different frequencies (50, 1000, 10,000, 100,000 Hz) using an impedance analyzer with frequency range of 5 Hz to 13 MHz in 18 different temperature values in a cabinet with tolerance of −40 to 350 ± 2% °C. Some of the obtained values shown in Table 1 are used in training of ANFIS models and the rest is used in testing the same models which are given in Table 2.

3. ANFIS

ANFIS is a neuro-fuzzy system developed by Roger Jang (Jang, 1992, 1993, 1997, 2007). It has a feed-forward neural network structure where each layer is a neuro-fuzzy system component. Fig. 3 illustrates ANFIS architecture for Sugeno type fuzzy inference system, where nodes of the same layer have similar functions. Assume that the fuzzy inference system under consideration has two inputs x and y and one output f, for example. For the first-order Sugeno fuzzy model a common rule set with two fuzzy IF-THEN rules is the following:

Rules 1 and 2, Eq. (6):

$$\begin{aligned}&\text{Rule 1 : IF } x \text{ is A1 AND } y \text{ is B1; THEN } f1 = p1x + q1y + r1;\\ &\text{Rule 2 : IF } x \text{ is A2 AND } y \text{ is B2; THEN } f2 = p2x + q2y + r2\end{aligned} \quad (6)$$

ANFIS structure contains five layers excluding input layer.

- Layer 0 is the input layer. It has n nodes where n is the number of inputs to the system.
- Layer 1 is the fuzzification layer in which each node represents a generalized bell curve membership function value of a linguistic term as follows:

  $$\mu A_i(x) = \frac{1}{1 + \left|(x - c_i)/a_i\right|^{2 \times b_i}} \quad (7)$$

  where a_i, b_i, c_i are parameters of the function. These are adaptive parameters. Their values are adapted by means of the backpropagation algorithm during the learning stage. As the values of the parameters change, the membership function of the linguistic term A_i changes. These parameters are called premise parameters. In that layer, there exist $n \times p$ nodes where n is the number of input variables and p is the number of membership functions. For example, if size is an input variable and there exists two linguistic values for size, which are SMALL and LARGE, then two nodes are kept in the first layer and they denote the membership values of input variable size to the linguistic values SMALL and LARGE.
- Each node in Layer 2 provides the strength of the rule by means of multiplication operator. It performs AND operation as follows:

  $$w_i = \mu A_i(x) \mu B_i(y) \quad (8)$$

  Every node in this layer computes the multiplication of the input values and gives the product as the output as in the above equation. The membership values represented by $\mu A_i(x)$ and $\mu B_i(y)$ are multiplied in order to find the firing strength of a rule where the variable x has linguistic value A_i and y has linguistic value B_i in the antecedent part of Rule i.

  There are p^n nodes denoting the number of rules in Layer 2. Each node represents the antecedent part of the rule.
  If there are two variables in the system namely x and y that can take two fuzzy linguistic values SMALL and LARGE, there exist four rules in the system whose antecedent parts are as follows:

Table 1 – Training data of ANFIS models

Temperature (°C)	Frequency (Hz)	Dielectric permittivity (eps – ε_r)	Loss factor (tnd – tan δ) $\times 10^{-4}$
−40	50	3.23	90
−40	1000	3.18	140
−40	10000	3.14	142
−40	100000	3.05	130
−20	50	3.29	68
−20	1000	3.25	120
−20	10000	3.21	155
−20	100000	3.13	150
0	50	3.35	42
0	1000	3.31	81
0	10000	3.29	145
0	100000	3.22	168
20	50	3.32	20
20	1000	3.30	50
20	10000	3.27	105
20	100000	3.22	171
40	50	3.28	10
40	1000	3.26	28
40	10000	3.25	80
40	100000	3.21	154
60	50	3.26	8
60	1000	3.24	20
60	10000	3.24	50
60	100000	3.21	110
80	50	3.26	12
80	1000	3.25	19
80	10000	3.24	36
80	100000	3.22	75
100	50	3.28	38
100	1000	3.28	30
100	10000	3.27	42
100	100000	3.25	62
120	50	3.38	155
120	1000	3.33	110
120	10000	3.32	92
120	100000	3.31	80
140	50	3.55	70
140	1000	3.46	105
140	10000	3.44	134
140	100000	3.46	147
150	50	3.62	50
150	1000	3.55	55
150	10000	3.55	110
150	100000	3.53	152

- IF x is SMALL AND y is SMALL
- IF x is SMALL AND y is LARGE
- IF x is LARGE AND y is SMALL
- IF x is LARGE AND y is LARGE

• Layer 3 is the normalization layer which normalizes the strength of all rules according to the following equation:

$$\bar{w}_i = \frac{w_i}{\sum_{j=1}^{R} w_j} \tag{9}$$

where w_i is the firing strength of the i_{th} rule which is computed in Layer 2. Node i computes the ratio of the i_{th} rule's firing strength to the sum of all rules' firing strengths. There are p^n nodes in this layer.

• Layer 4 is a layer of adaptive nodes. Every node in this layer computes a linear function where the function coefficients are adapted by using the error function of the multilayer feed-forward neural network.

$$\bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i) \tag{10}$$

p_i, q_i and r_i are the parameters where $i = n$ and n is the number of inputs to the system (i.e. number of nodes in Layer 0). In this example, since there exists two variables (x and y), there are six parameters (p_1, p_2, q_1, q_2, r_1 and r_2) in Layer 4.

$\bar{w}_i$ is the output of Layer 3. ANFIS uses a hybrid learning algorithm to identify these parameters of Sugeno type fuzzy inference systems. It applies a combination of the least-squares method and the backpropagation gradient descent method for training FIS membership function parameters to emulate a given training data set. ANFIS can also be invoked by testing data set for model validation.

Table 2 – Testing data of ANFIS models

Temperature (°C)	Frequency (Hz)	Dielectric permittivity (eps – ε_r)	Loss factor (tnd – tan δ) $\times 10^{-4}$
−30	50	3.25	80
−30	1000	3.21	132
−30	10000	3.16	150
−30	100000	3.09	140
−10	50	3.33	55
−10	1000	3.29	102
−10	10000	3.25	152
−10	100000	3.16	161
10	50	3.34	30
10	1000	3.32	63
10	10000	3.29	130
10	100000	3.23	171
30	50	3.29	16
30	1000	3.28	37
30	10000	3.26	97
30	100000	3.21	167
50	50	3.27	9
50	1000	3.25	22
50	10000	3.24	63
50	100000	3.21	132
70	50	3.25	9
70	1000	3.24	19
70	10000	3.24	40
70	100000	3.21	90
90	50	3.26	22
90	1000	3.26	21
90	10000	3.26	36
90	100000	3.23	65
110	50	3.32	70
110	1000	3.30	55
110	10000	3.28	60
110	100000	3.27	66
130	50	3.46	140
130	1000	3.40	130
130	10000	3.38	132
130	100000	3.40	110

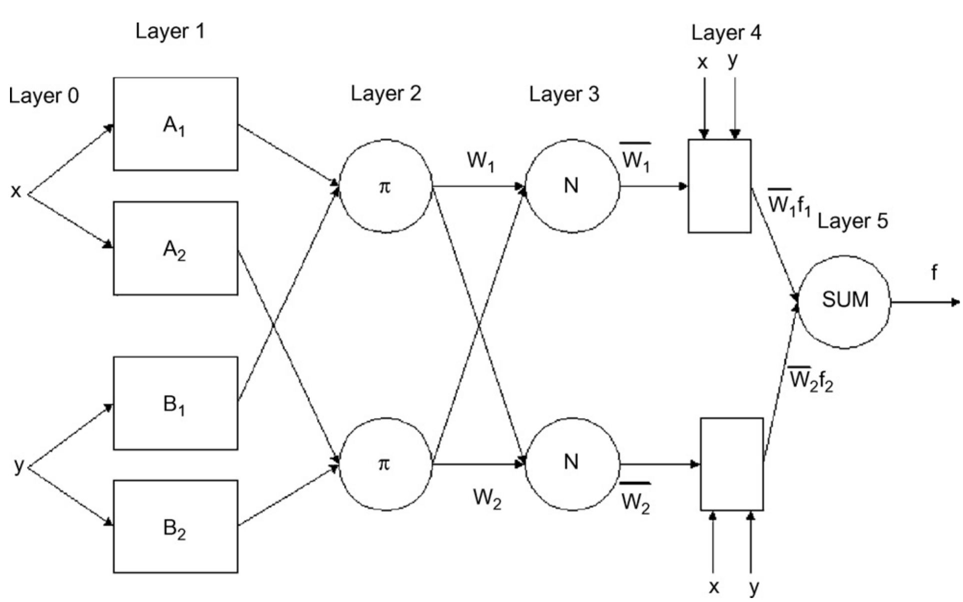

Fig. 3 – Basic ANFIS structure.

The learning algorithms are composed of two phases:
- In the forward pass of the hybrid learning algorithm, node output values go forward until Layer 4 and the consequent parameters are identified by the least-squares method.
- In the backward pass, the output errors are propagated backward and the premise parameters are updated by gradient descent method.

• Layer 5 is the output layer whose function is the summation of the net outputs of the nodes in Layer 4. The output f is computed as follows:

$$f = \sum_{i=1}^{n} \bar{w}_i f_i = \frac{\sum_{i=1}^{n} f_i}{\sum_{i=1}^{n} w_i} \tag{11}$$

where $\bar{w}_i f_i$ is the output of node i in Layer 4. It denotes the consequent part of rule i. The overall output of the neuro-fuzzy system is the summation of the rule consequents.

In this way adaptive networks that are functionally equivalent to a first-order Sugeno fuzzy model are constructed. From the ANFIS architecture shown in Fig. 3, it can be seen that when the values of the premise parameters (Layer 1) are fixed, the overall output can be expressed as a linear combination of the consequent parameters (Layer 4).

ANFIS uses a hybrid learning algorithm in order to train the network. For the parameters in Layer 1, backpropagation algorithm is used. For training the parameters in the Layer 4, a variation of least-squares approximation is used. The following example describes the processing of ANFIS over a data set.

Example: Dielectric permittivity data are processed by ANFIS.

ANFIS accepts the input data in the (temperature; frequency) format.

(1) An input data pair is given to the network.
(2) The network performs the forward pass, i.e. the output of the function which is dielectric permittivity is computed.
(3) Another input data pair is presented to the network and the above computation continues until the network is trained with data which are shown in Table 1.
(4) Error is computed for this epoch by using an error measure to compare the expected output to the output of the system.
(5) Training is performed by updating the parameters in Layer 1 (a_i, b_i and c_i) and in Layer 4 (p_i, q_i and r_i). This is offline learning, because all data sets are presented to the network at once and the parameters are updated.
(6) After a predetermined number of training epochs is reached, the training process terminates.

The fuzzy rules produced for dielectric permittivity (eps) in terms of parameters are as follows:

(1) IF (Temp is SMALL_1) AND (Freq is SMALL_1) THEN (eps = p_1*Temp + q_1*Freq + r_1)
(2) IF (Temp is SMALL_1) AND (Freq is SMALL_2) THEN (eps = p_2*Temp + q_2*Freq + r_2)
(3) IF (Temp is SMALL_1) AND (Freq is MEDIUM) THEN (eps = p_3*Temp + q_3*Freq + r_3)
(4) IF (Temp is SMALL_1) AND (Freq is LARGE_1) THEN (eps = p_4*Temp + q_4*Freq + r_4)
(5) IF (Temp is SMALL_1) AND (Freq is LARGE_2) THEN (eps = p_5*Temp + q_5*Freq + r_5)...
(21) IF (Temp is LARGE_2) AND (Freq is SMALL_1) THEN (eps = p_{21}*Temp + q_{21}*Freq + r_{21})
(22) IF (Temp is LARGE_2) AND (Freq is SMALL_2) THEN (eps = p_{22}*Temp + q_{22}*Freq + r_{22})
(23) IF (Temp is LARGE_2) AND (Freq is MEDIUM) THEN (eps = p_{23}*Temp + q_{23}*Freq + r_{23})
(24) IF (Temp is LARGE_2) AND (Freq is LARGE_1) THEN (eps = p_{24}*Temp + q_{24}*Freq + r_{24})
(25) IF (Temp is LARGE_2) AND (Freq is LARGE_2) THEN (eps = p_{25}* Temp + q_{25}* Freq + r_{25})

Dielectric loss factor data are processed by ANFIS as the same fashion employed above. In these examples, there are five fuzzy values SMALL_i, MEDIUM and LARGE_i for both temperature and frequency variables, where i denotes the index of the variable. Each fuzzy value such as SMALL_i is denoted by the parameters in the first layer (a_i; b_i and c_i). p_i, q_i and r_i are the parameters in the fourth layer where i denotes the rule. These are used in computing the output of the systems separately, that is the dielectric permittivity (eps – ε_r) and loss factor (tnd – tan δ). Both eps and tnd surfaces, which

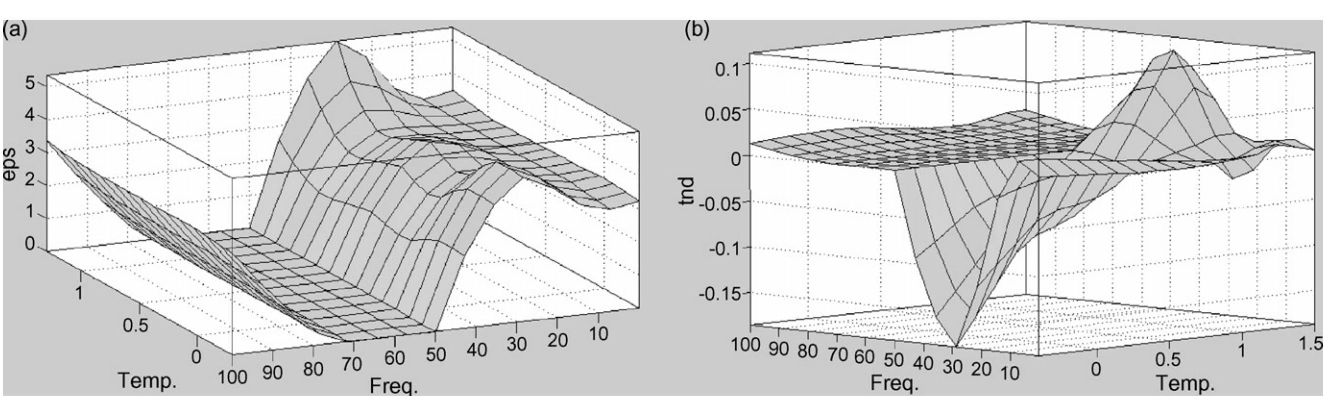

Fig. 4 – Surfaces of dielectric permittivity-eps (a) and loss factor-tnd (b).

Table 3 – MSEs and percent MSEs of training and testing data of ANFIS models

ANFIS models	MSE of training data	MSE of testing data	Percent MSE of training data	Percent MSE of testing data
Models eps	6.1664×10^{-9}	2.4361×10^{-6}	1.4014×10^{-8}	6.7669×10^{-6}
Models tnd	5.7635×10^{-8}	2.9440×10^{-6}	1.3099×10^{-7}	8.1777×10^{-6}

are shown in Fig. 4, indicate that the solutions obtained from ANFIS are continuous for all over the experiment data, and the functions of eps and of tnd are nonlinear and complicated.

The standard ANFIS structures were used to obtain ε_r and $\tan\delta$ values separately. The ANFIS structures contain twenty five rules, two inputs with five membership functions each generalized bell shaped with three nonlinear parameters (a_i, b_i and c_i). All the models have one output that is a linear function of the consequent parameters. The ANFIS models are trained and tested with the data which are shown in Tables 1 and 2, respectively. The modeling procedures were performed using Matlab® Fuzzy Logic Toolbox tools for ANFIS models. Training was performed off-line for both solutions. To normalize the training and testing data of temperature, frequency and dielectric permittivity are divided by 100, 1000 and 10 in the ANFIS models, respectively.

4. Experimental and evaluations

Mean squared errors (MSEs) and percent MSEs of training and testing results of ANFIS eps and ANFIS tnd models which are trained for 5000 and for 500 epochs, respectively are tabulated in Table 3. Iteration numbers versus training MSEs graphs of the Model eps and Model tnd are shown in Fig. 5(a) and in Fig. 5(b), respectively. The test data for dielectric permittivity and loss factor, which are shown in Table 2, are used for testing ANFIS eps and ANFIS tnd models. The testing results of the ANFIS Model eps and the ANFIS Model tnd which are held on measured real test data are shown in Fig. 6(a) and in Fig. 6(b), respectively.

Minimum–maximum absolute error pair of both Model eps and Model tnd is calculated as 0.000032–0.005567 and 0.000011–0.008028, respectively. MAEs of dielectric permittivity and loss factor are found as 0.0011 and 7.663454×10^{-4}. Also cumulative absolute errors (CAEs) of dielectric permittivity and loss factor are calculated as 0.0393 and 0.0276, respectively. Since dielectric properties have 36 test vectors, percent MAEs-percent CAEs of dielectric permittivity and loss factor are determined as 0.0030–0.1092% and 0.0021–0.0766%. With all data according to Tables 1 and 2, temperature versus dielectric permittivity and loss factor graphs for different frequencies are plotted as subplots shown in Figs. 7 and 8. As seen in Figs. 7 and 8, developed ANFIS models can be followed by

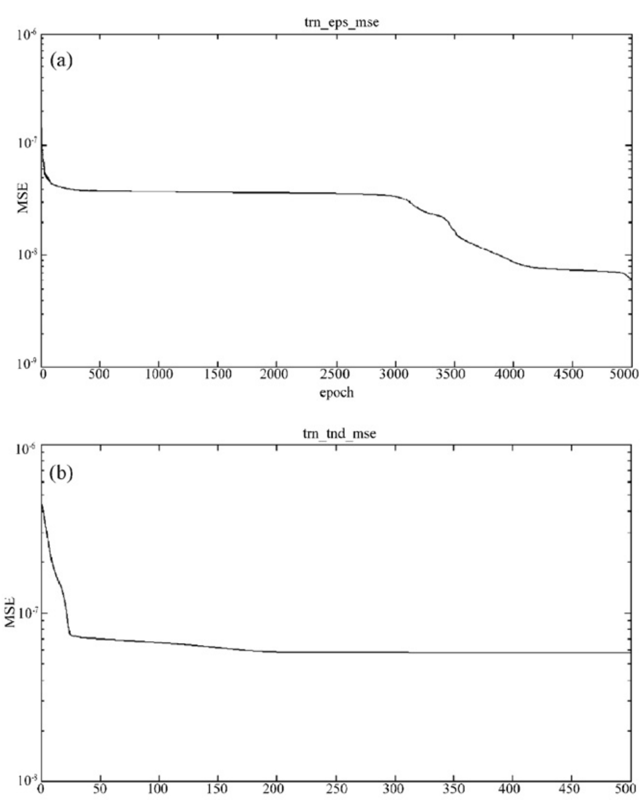

Fig. 5 – MSEs of training stage of the ANFIS models: (a) Model eps (b) Model tnd.

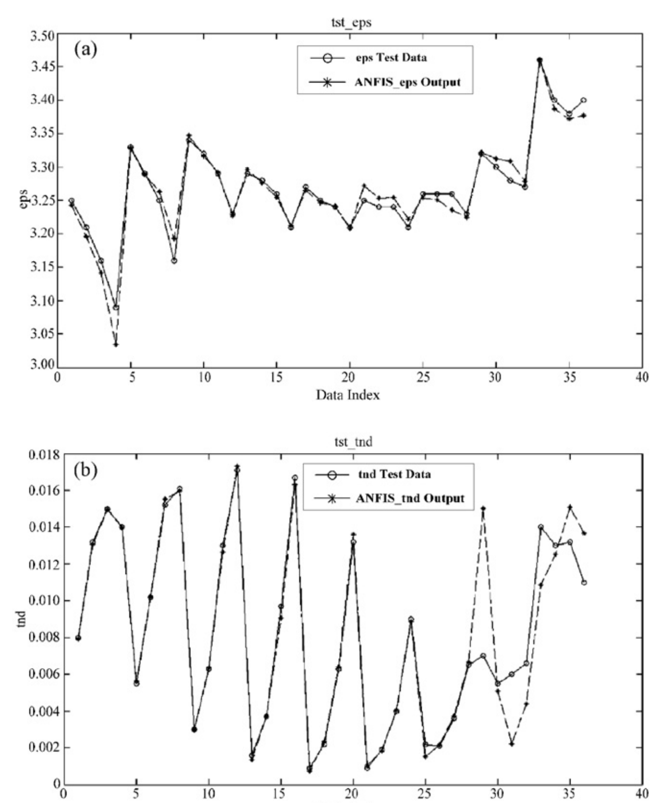

Fig. 6 – MSEs of testing stage of the ANFIS models: (a) Model eps (b) Model tnd.

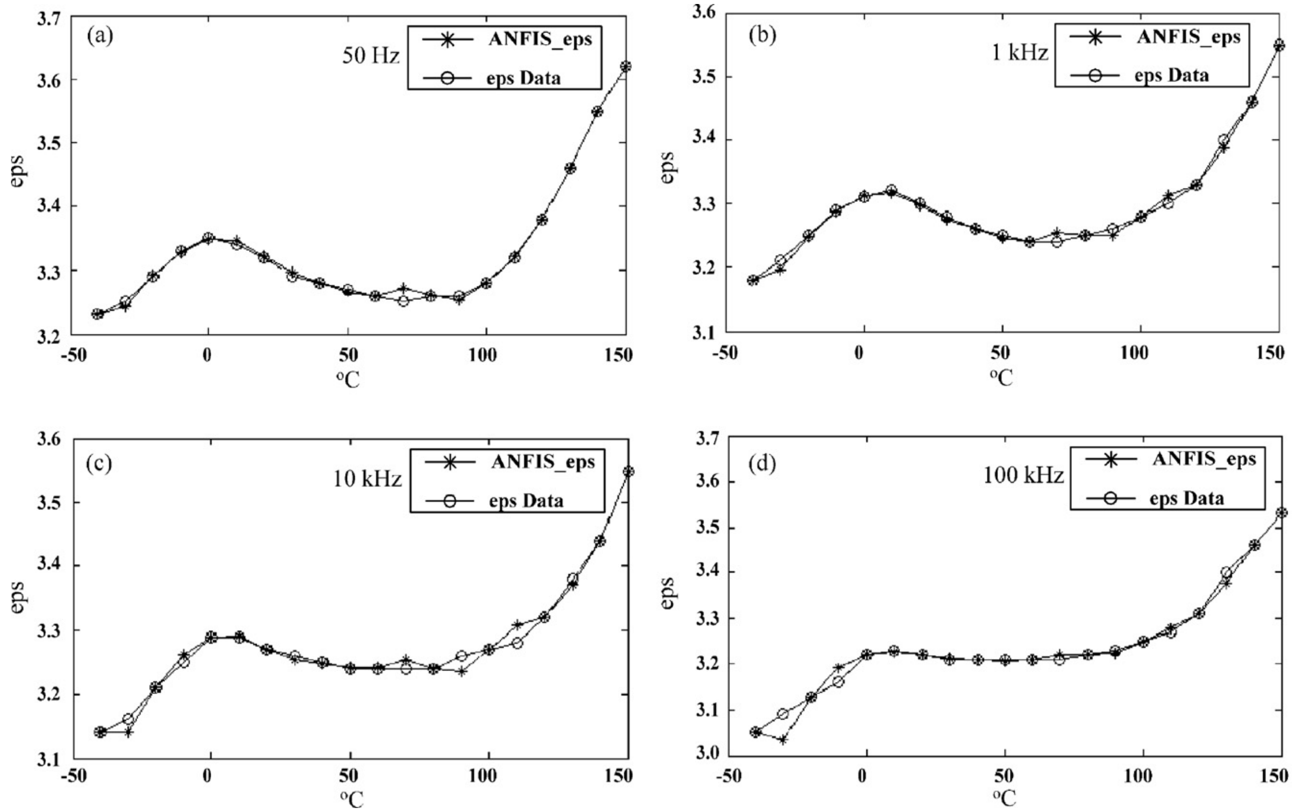

Fig. 7 – Temperature vs. dielectric permittivity graphs for different frequencies.

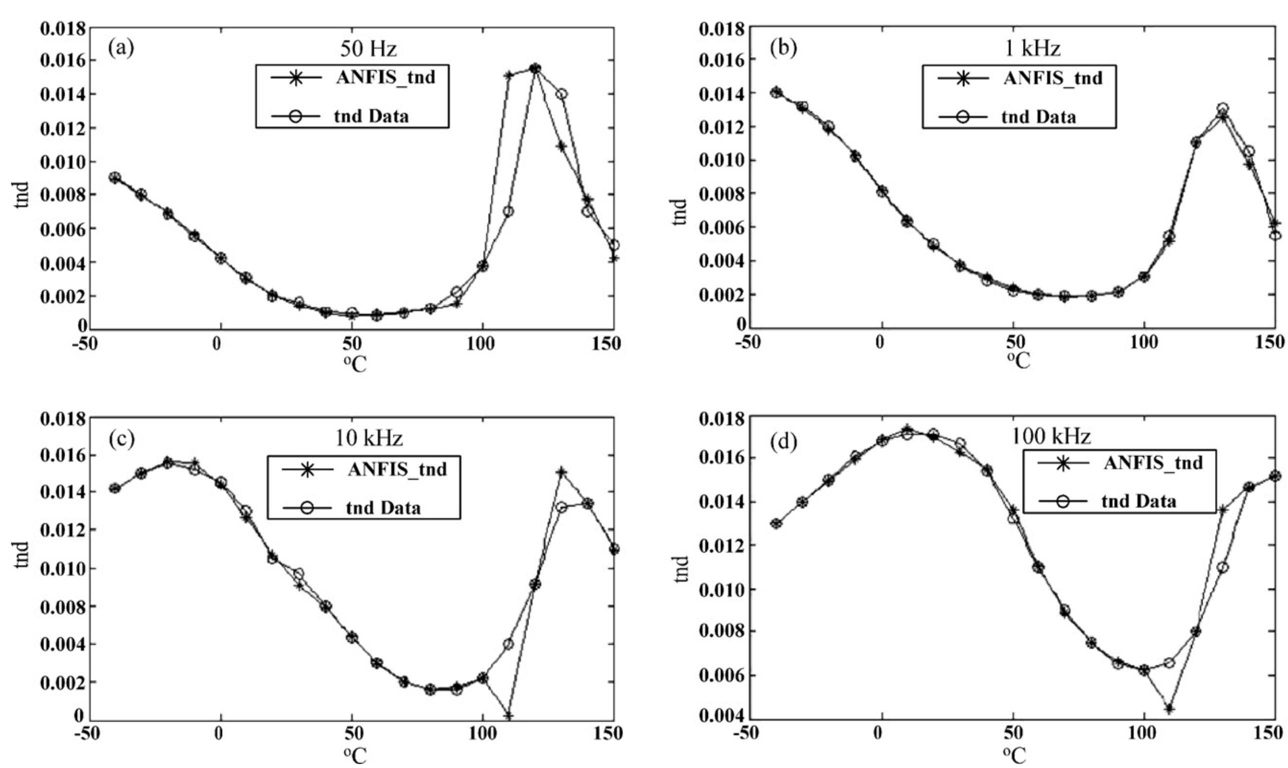

Fig. 8 – Temperature vs. loss factor graphs for different frequencies.

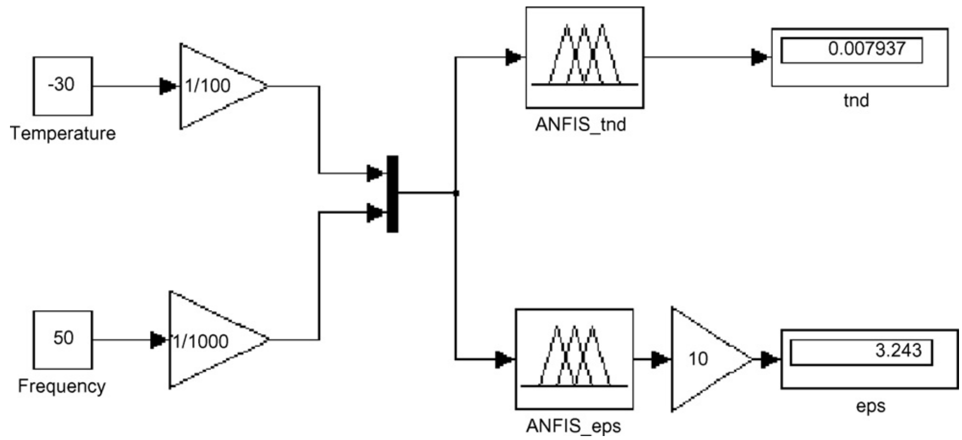

Fig. 9 – A simulation user interface with ANFIS models.

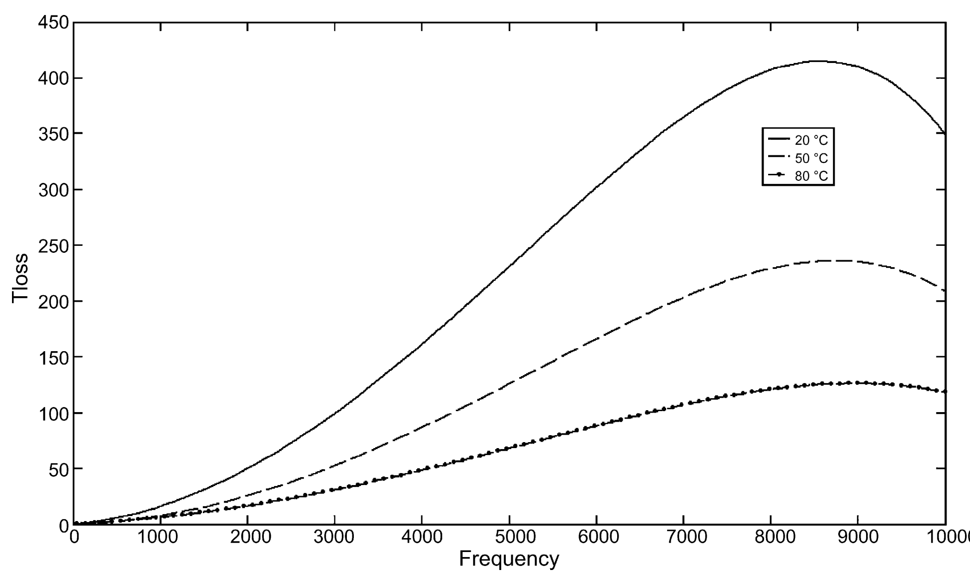

Fig. 10 – Frequency vs. T_{loss} graph for each temperature value.

the path of the measured data of both dielectric permittivity and loss factor properly even in high-frequencies. A simulation user interface as shown in Fig. 9 is designed with ANFIS models in Matlab® Simulink for determining dielectric permittivity and loss factor for any given temperature and frequency values.

Total dielectric loss due to frequencies in communication cables is calculated according to Eq. (5), taking especially the operational conditions into consideration in 20, 50 and 80 °C temperatures for 50 Hz–10 kHz range of frequencies. Frequency versus T_{loss} graph for each temperature value is drawn in Fig. 10 with respect to the calculation result. For 100 kHz frequency value is omitted for clearance of the figure. As it is seen in Fig. 10, when the frequency increases, total loss increases in spite of some decrease in high-frequencies. In fact total loss is somehow smaller in high temperatures. Actually, this condition is irrelevant of power cables. Because, total loss of power cables is proportional to the temperature.

In previous study, determination of dielectric properties of polyester films using MLP ANN is realized with the same measured data sets which are used in this study (İnal and Aras, 2005). The measured data of dielectric permittivity (ε_r) and loss factor (tan δ) of polyester insulating material under various frequencies and temperatures was used for training the MLP ANN. Then, the MLP ANN was tested using data which were not utilized in the training set. Various MLP architectures are evaluated for determining the optimum hidden layer(s) and number of neurons in each layer. The optimum architecture is determined by 2 hidden layers in order of 16 neurons in the first hidden layer and of 8 neurons in the second hidden layer. The activation functions of neurons in the hidden layers were chosen hyperbolic tangent sigmoids. The realized MLP ANN model predicted dielectric permittivity and loss factor within percent MAEs of 0.0355% and 0.0009%, respectively. The percent CAEs are also calculated as 1.2778% and 0.0334% for dielectric permittivity and loss factor, respectively (İnal and Aras, 2005). While MLP ANN uses Levenberg-Marquardt backpropagation algorithm, ANFIS models use combination of the least-squares method and the backpropagation gradient descent method for training FIS membership function parameters.

5. Conclusion

As a result, measurement of dielectric properties of insulation materials especially under low and high temperature conditions such as −40 °C and 150 °C requires intensive labor and is a costly procedure. This is because of the requirement of silver coating for many specimens and measurements. It is highly important to know the change in dielectric properties in different conditions so that the insulator acts as a thermal source in high-frequencies. These results are only obtained experimentally. Application of the ANFIS model overcomes all these handicaps as an alternative approach studied in this paper. In addition to this, it is easy to find any mid value in various operational conditions. In the evaluation of the results and used models in this study, the obtained percent MAEs performs better results for 0.0030% Model eps and 0.0021% Model tnd in general. When percent MAEs is compared with the same values of previous study in which MLP ANN model was used, 3.25% better result is obtained for dielectric permittivity (eps) with ANFIS eps model but also 0.12% better result is obtained for loss factor (tnd) with the MLP ANN model. Since the difference of MAE between ANFIS and MLP ANN models for loss factor is too small, both ANFIS and ANN models can be acceptable for modeling of loss factor data.

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