Electric Power Systems Research 149 (2017) 125–136

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

# Analysis of artificial intelligence expert systems for power transformer condition monitoring and diagnostics

Mileta Žarković*, Zlatan Stojković

School of Electrical Engineering, University of Belgrade, Bulevar Kralja Aleksandra 73, Belgrade 11020, Serbia

ARTICLE INFO

*Article history:*
Received 18 October 2016
Received in revised form 9 March 2017
Accepted 22 April 2017

*Keywords:*
Fault detection
Monitoring
Power transformer
Artificial intelligence
Fuzzy logic
Fault classification

ABSTRACT

A large amount of data is generated through monitoring, maintenance, repair and diagnostics of power transformer. However, all these data cannot preindicate the exact type and probability of failure. To overcome the problem this paper presents artificial intelligence based methodology for power transformers fault detection and classification. The possibility of presented monitoring methodology is to assist the operator's engineers in decision making about urgency of intervention and type of maintenance of power transformer. The article analyzes the application of Mamdani-model and Sugeno-model in fuzzy expert system for fault diagnosis based on the current state of the power transformer. Paper presents two case studies with one unique and five separate controllers. In the first case inputs of controller are results of on-line and off-line transformer tests: age, the overheating temperature of the hot spot, frequency response analysis, temperature of insulation, dissolved gas-in-oil analysis, tgδ and polarization index. Second case study in addition to the existing inputs includes previous measurements. A fuzzy controller (FC) is designed to characterize the operating condition and to determine the urgency of intervention with possibility to indicate probability of specific type of failure. Cumulative probability of occurrence of the faults is also observed in second case study. FCs are tested based on real measurements from Serbian transmission system. The results show acceptable effectiveness in detecting different faults and might serve as a good orientation in the power transformer condition monitoring.

© 2017 Elsevier B.V. All rights reserved.

## 1. Introduction

Power transformer is expensive and an important element in the transmission power system. The condition and proper operation of the transformer directly affect on the transmission power system reliability. The characteristics of the power transformer, which depend on the thermal and mechanical stress, irreversibly change during exploitation as a result of aging. Based on the results of regular tests and on line measurements it is difficult to predict fault and to establish the time frame for the repair, urgency of intervention. Sometimes it is difficult to make decisions about priorities which transformer is necessary to overhaul first. The results of bad decisions are the high cost of repairs and unacceptably long period of unavailability of the transformer. For this it is necessary to make the right decisions about condition based maintenance.

Advanced measurement techniques provide an increasing number of data which need to be processed and used in a smart way. Based on the analysis of these data, many papers [1–7] explain how to monitor the state of power transformer and made overhaul plan. In Ref. [4] are formulated the model for calculation of expected failure repair cost and the model for calculation of load curtailment cost. Paper [5] explains method for determining optimal power transformers exploitation strategy but shows that it is necessary to apply a multitude of different methods and advance techniques. Artificial neural networks (ANN) are used for conditions diagnostic of power transformer in papers [3,6]. Paper [7] uses ANN for transformer fault diagnosis using dissolved gas-in-oil analysis (DGA) and papers [8,9] described approaches for fault classification based on protection signals. Each paper that develops ANN need data base with clearly known outputs and papers [10,11] use EMTP for creation of that database. Cortez in paper [12] present an intelligent system based on cognitive systems for fault prognosis in power transformers. Support vector machine (SVM) is used in papers [13,14] for same purpose.

Fuzzy logic (FL) as part of the artificial intelligence is rarely used in the works, and offers the possibility of applying expert knowledge about the diagnosis of failure. FL is suitable for making a decision about maintenance of power transformer. There are not papers which detect fault of power transformer on the basis of several measured parameters, and FL allows us exactly that.

* Corresponding author. Fax: +381 113248681.
*E-mail addresses:* mileta@etf.rs (M. Žarković), zstojkovic@etf.rs (Z. Stojković).

http://dx.doi.org/10.1016/j.epsr.2017.04.025
0378-7796/© 2017 Elsevier B.V. All rights reserved.

@maghalecomputer

کانال مهندسی کامپیوتر

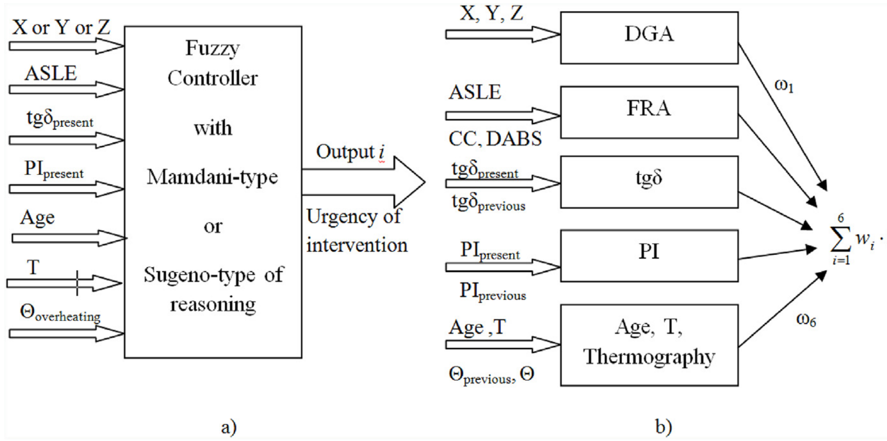


**Fig. 1.** Artificial intelligence controllers for power transformer fault detection (a) first case study with one controller (b) second case study with five controllers.

Also FL is not used for fault classification yet. Measuring methods whose results are used as controller inputs are thermography, dissolved gas analysis, frequency response analysis. Also controller takes into account age of the element, temperature of insulation, tgδ and polarization index. None of these input parameters for itself cannot clearly indicate malfunction and the urgency of intervention. Because of that this paper shows how to form multiparametric expert systems, FC. There is not a paper that compares other parameters and takes into account the life span of transformer. Limit parameter values from standard do not take into account lifetime of transformer. For this reason FL is used in order to overview the objective and realistic state of power transformers. Sensitivity analysis for creation of FC is presented. For each input and output is selected shape of membership functions (MF) in accordance with values from standards. The rule base has been designed from databases which are formed by large number of measurements from Serbian transmission system. Mamdani-type and Sugeno-type of FL are formed and tested in order to get the best possible solution of problem. One part of presented methodology takes into account previous measured values of parameters. On that way methodology like this is considered a power transformer past. The output information is the urgency of intervention which is actually the probability of failure. Output is connected and indicates the class of power transformer faults. This process is time consuming and requires a good experience about the system behavior, since careful adjusting steps must be effectuated to avoid bad decision and damages of power transformer. Each FC is applied on examples from Serbian transmission system. Results are compared and validated.

## 2. Multiparametric methodology for power transformer fault detection and classification

Monitoring systems for power transformer detect changes in insulation system in the form of an early warning system, due to thermal/dielectric/chemical or mechanical impact. Monitoring follow measured parameters required for proper operation of power transformer, and diagnostics compare values of these parameters with reference values. Based on this comparison and the values of the parameters in the past it is possible to detect fault or determined progression of pre-existing defect of power transformer. Based on this principle in this paper a FL is used to create fuzzy expert systems. On this way it can be detected: hotspots, degradation of the insulation, localized moisture in insulation and partial discharges and chemical or thermal aging [5]. None of these defects can be detected by a single diagnostic procedure and it is necessary to apply a multitude of different methods in order to enable a trend analysis and condition assessment. Because of that artificial intelligence is used to create multiparametric FCs for condition monitoring and diagnostics of power transformer. FL is good to be applied for managing and implementing human heuristic knowledge about how to make proper decisions when situation is complicated and measuring methods give different, not clearly results. One of the most important qualities of FL is its ability to express the degree of uncertainty in a person's thinking and his subjectivity. MATLAB® technical computing software has been used to design the two FCs with different type of reasoning and conclusion. The layouts of the performed controllers are displayed in Fig. 1. The first case study includes the most important indicator of testing measurements. Fig. 1a presents controller which can be with Mamdani-type and Sugeno-type of reasoning. The second case study presented a combination of multiple controllers that conclude separate results that create one final output Fig. 1b. In second case all indicator of methods are included and on that way fuzziness is increased. Second case study take into account previous measured values of parameters. On that way methodology like this considered power transformer past. Each output $i$ ("intervention") can get the weight factor $\omega_i$ and thus favoring one of the measuring methods.

Output of both case studies is number from interval 0 to 1. That number presents the probability of failure which indicate on urgency of intervention. Results of both case studies should be compared and analyzed. Results are similar and based on them proposed methodology could classify fault type. The proposed methodology algorithm is shown on Fig. 2. For different manufacturers some parameters and characteristics of transformer may slightly deviate from the usual values. In that case it is need to make changes in the formation of FCs. Because of that, detail explanation of FC formation is represented in next section. Fig. 2 also explains process of FL applying.

## 3. Implementation of fuzzy logic

The first step in applying FL is fuzzification which simply modifies the input signals, so that they can be properly interpreted and compared with the rules in the rule base. The inputs signals are converted into appropriate fuzzy shape by the MFs. MFs map the degree of the truth claims and classified inputs variables as the linguistic value. Measurements of testing methods are related to the standard condition tests through MFs and entered in the FCs.

@maghalecomputer
کانال مهندسی کامپیوتر

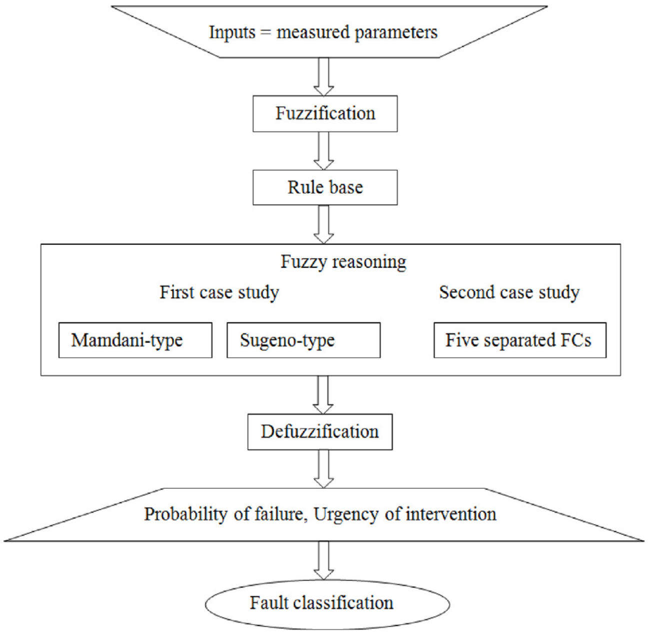


**Fig. 2.** The methodology algorithm.

### 3.1. Dissolved gas analysis – DGA

Dissolved gas-in-oil analysis (DGA) is a very sensitive and reliable technique applied to diagnose technical condition and the stress level of power transformers. Different developed DGA methods are: Key Gas, Rogers Ratio, Doernenburg, Logarithmic Nomograph and Duval Triangle. Each method analyzes different combination of gases and interpreting their significance. There are papers [15,16] that investigate the accuracy and consistency of these methods in interpreting the transformer condition. All diagnoses exist in internationally acknowledged IEC and IEEE standards [17–19]. In this paper we tried to include all diagnoses into FC (Fig. 3a). Based on all relevant diagnosis methods, controllers inputs are three most important gas rates (in ppm units – parts per one million):

$$x = \frac{CH_4}{H_2}; y = \frac{C_2H_2}{C_2H_4}; z = \frac{C_2H_4}{C_2H_6} \quad (1)$$

These parameters, rates, take values from four characteristic range: [0: 0,1), [0,1:1), [1:3) and [3:). These ranges are obtained by human experts who usually make the diagnosis by inspection of a power transformer. Inputs $x$, $y$, $z$ are represented with four MFs ($\mu_1$, $\mu_0$, $\mu_2$ and $\mu_2$) which take values from interval [0:5] (Fig. 3b). Triangular and trapezoidal MFs are used to create ranges of inputs $x$, $y$, $z$. All three indicators are not always available, precise and relevant. So in the first case study is allowed the freedom to choose which ratio of gases, $x$ or $y$ or $z$ will be the input of the FC. In second case all three indicators are inputs in first FC that is assigned to DGA (Fig. 3a). In forming MFs we made their mutual overlap that takes into account the measurement uncertainty of data. Specified ranges of rates, MFs, are in connection with standards classes, diagnosis: no fault, partial discharge of low energy, partial discharge of high

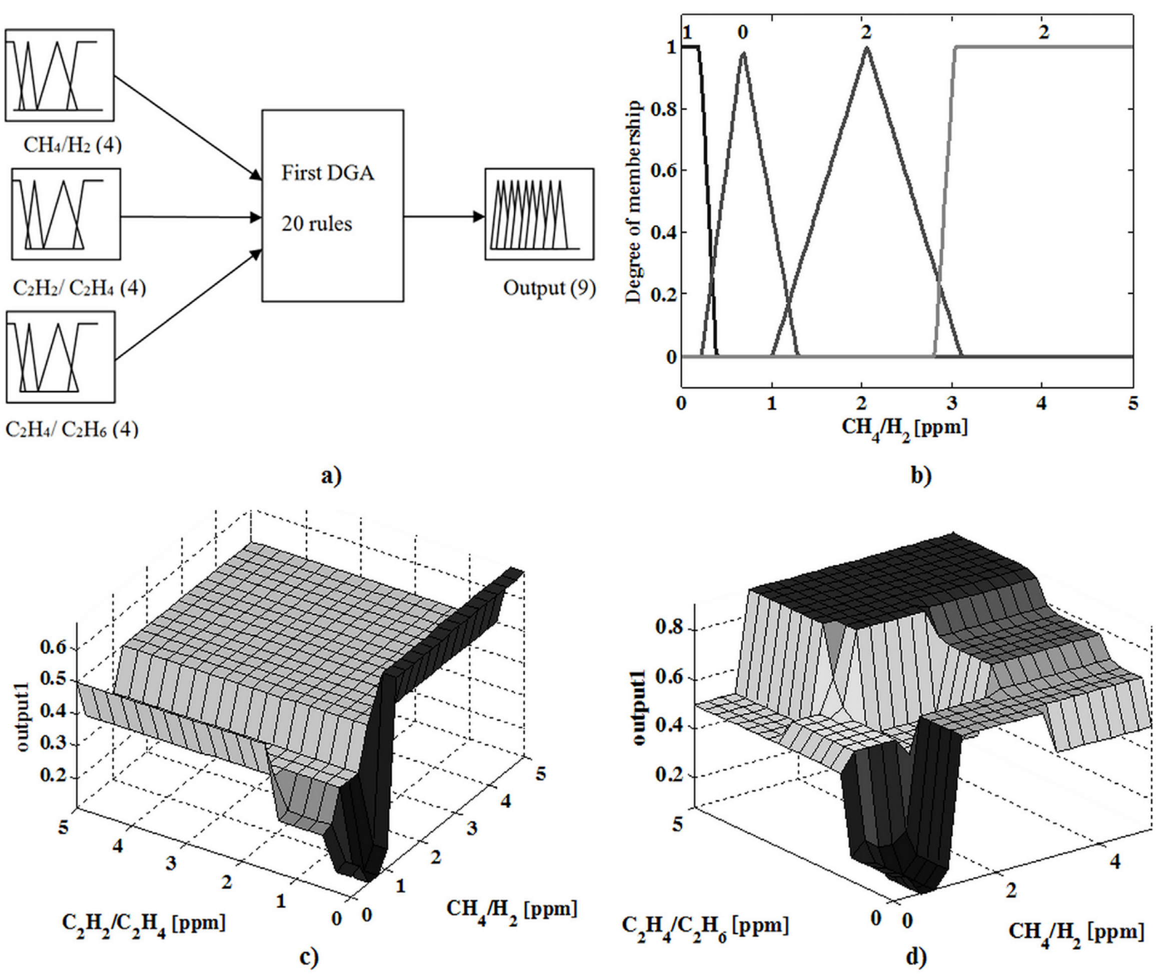


**Fig. 3.** Description of the first FC (a) DGA first controller (b) MF for $CH_4/H_2$ input (c) and (d) urgency of intervention in the function of the combinations of input gas rates.

@maghalecomputer
کانال مهندسی کامپیوتر

energy, disruptive discharge of low energy, disruptive discharge of high energy, overheating below 150 °C, overheating between 150 °C and 300 °C, overheating between 300 °C and 700 °C and overheating over 700 °C [15–19]. Output of DGA controller ($i_1$) is represented with nine triangular MFs which correspond to mention diagnosis (Fig. 3a). The connections between inputs and diagnosis are defined and implemented through a rule base. These rules are in accordance with the standards [17–19]. Fig. 3c and d represent results of controller and represent the behavior of output, depending on the combinations of input gas rates.

These diagnoses does not include all situations and conditions of transformer and because of that we have introduced new entries to controller.

### 3.2. Frequency response analysis – FRA

Frequency response analysis (FRA) technique uses frequency responses of the transformer winding to study the various defects and mechanical failures without opening the unit. FRA interpretation is based on experience and interpreting FRA results is not easy. FRA measurements include Sweep Frequency (SFRA) and low voltage impulse which is used in order to get transfer function as the ratio of input and output of transformer. Deformations and type of defects can be determined by comparing the transfer functions of new and exploited transformers [20–25]. Also progress of defects can be monitored through several successive time-spaced FRA tests. To establish the differences between transfer functions

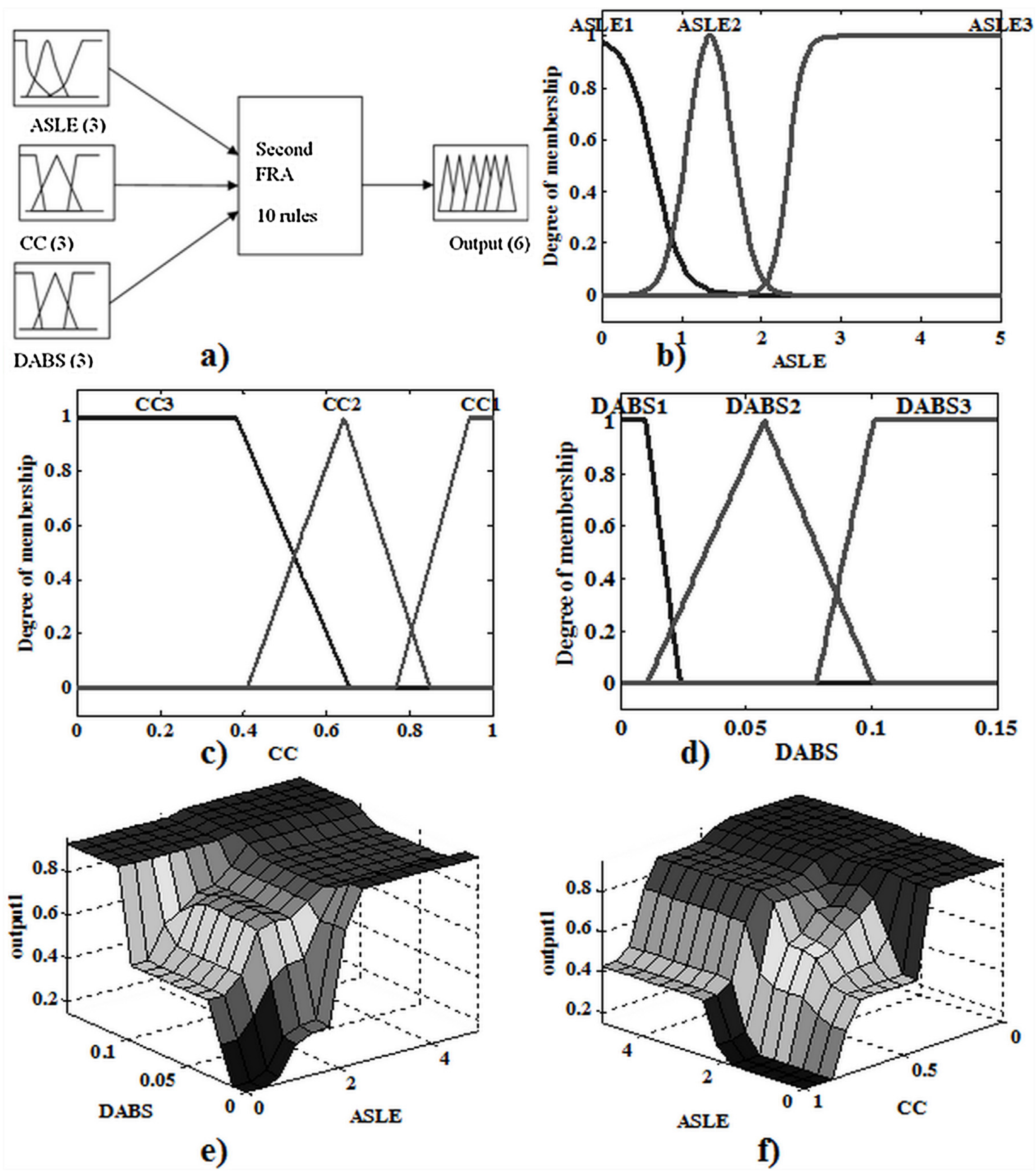


**Fig. 4.** FRA second controller, MFs for inputs (b) ASLE, (c) CC, (d) DABS, (e) and (f) urgency of intervention in the function of the combinations of FRA inputs.

@maghalecomputer
کانال مهندسی کامپیوتر

well known indicators have been considered: correlation coefficient, standard deviation, maximum absolute difference, sum of squares error, sum squared ratio error, sum square max–min error and absolute sum of logarithmic error (*ASLE*). The main characteristics of the FRA measured are twofold: frequency range and number of frequencies, which have been not clearly defined [24]. Also, in practice there are several sources of uncertainty and inaccuracies that can influence the measurement results. Because of that fuzzy expert system is ideal for diagnostics based on FRA. However, *ASLE* was presented as the most reliable parameter which was designed to make the fully log-scaled comparison in the magnitude frequency response [24]:

$$ASLE(x,y) = \frac{\sum_{i=1}^{N} |20\log_{10} y_i - 20\log_{10} x_i|}{N} \tag{2}$$

where $x_i$ and $y_i$ are the $i^{\text{th}}$ elements of the frequency responses to be compared and $N$ is the number of samples of transfer functions. As this *ASLE* is unique FRA input in first case study. As important indicator too correlation coefficient (*CC*) and maximum absolute difference (*DABS*) are defined and use in the second case study:

$$CC(x,y) = \frac{\sum_{i=1}^{N} y_i x_i}{\sqrt{\sum_{i=1}^{N} x_i^2 \sum_{i=1}^{N} y_i^2}} \tag{3}$$

$$DABS(x,y) = \frac{\sum_{i=1}^{N} |y_i - x_i|}{N} \tag{4}$$

The range for these indicators is varying and has not been set yet. The general rule in determining fault does not exist, but if deviation of transmission functions is larger than deformation and fault is more danger for transformer [26]. At begin of exploitation *ASLE* is usually zero, *CC* is 1 and *DABS* take values close to zero. Aging of transformer leads to increase of *ASLE* and *DABS* and decreasing of *CC*. It is assumed that if *ASLE* is greater than 2, i.e. *DABS* is greater than 0.1 or *CC* is less than 0.65, than the probability of fault is $i_2 = 1$. Output like this means that is necessary urgent intervention. In accordance with that FRA inputs of controller (Fig. 4a) are formed with three Gaussian MFs ($\mu_{ASLE1}$, $\mu_{ASLE2}$ and $\mu_{ASLE3}$) (Fig. 4b). MFs for *CC* and *DABS* are represented as one triangular and two trapezoidal functions (Fig. 4c and d). Each of these three functions includes characteristic range of values which are connected to small, medium and large deviation for two compared transfer functions. In the second case study all three indicators are inputs and output ($i_2$) is divided with six triangular MFs. In first case study only *ASLE* as best indicator is FRA input. Three-dimensional surfaces of the transfer which includes combination of *ASLE*, *CC* and *DABS* inputs are presented on Fig. 4e and f. Graphs logically show that the urgency of intervention increases with increasing *ASLE*, *DABS* and decreasing of *CC*.

### 3.3. Power losses and insulation resistance

Determination of the dielectric loss tangent winding power transformers is a preventive check and way to monitoring the progress during winding level. By measuring the dielectric loss factor is determined qualitatively humidity and/or the aging of insulation between the windings and the winding insulation to the earthed parts of the transformer.

Dielectrics insulation that have relatively low value losses of the tangent of the angle $\delta$ ($tg(\delta)$) are characterized by relatively low power losses and relatively large value losses of the angle $\delta$ are characterized by relatively high power losses at power transformer. The maximum values for the power losses depends on the frequency of oscillation achieved by dielectric particles which depends on temperature. So values of $tg(\delta)$ have to be corrected:

$$\tan\ \delta_{20} = \tan\ \delta_{\vartheta} \bullet e^{-0.0202\cdot(\vartheta-20)} \tag{5}$$

where $\tan\delta_{20}$ is recalculated dielectric loss factor of winding insulation and $\tan\delta_{\vartheta}$ is dielectric loss factor measured at a temperature $\vartheta$. Fig. 5a presents third controller which contain previous and present measurement of $tg(\delta)$ as inputs. MFs for $tg(\delta)$ are separate in three ranges which corresponds to big, medium and low values. Fuzzification of input $tg(\delta)$ include two trapezoidal and one triangular MFs. According to standard [27,28] maximal acceptable value of $tg(\delta)$ is 1.5%. Fig. 5b presents urgency of intervention in the function of the last two measurements of $tg(\delta)$.

Testing the insulation resistance is also important and it is depending on the temperature by formula:

$$R_{i20} = R_{i\vartheta} \bullet e^{0.6244\cdot(\vartheta-20)} \tag{6}$$

where $R_{i20}$ is recalculated insulation resistance and $R_{i\vartheta}$ is insulation resistance measured at a temperature $\vartheta$. Insulation resistance values depend on the voltage level of the transformer and because of that it is convenient to make decision based on polarization index. Measuring the polarization index is an extension of the insulation resistance measurement: measure the insulation resistance of $R_1$ after one minute and after 10 min $R_{10}$:

$$PI = \frac{R_{10}}{R_1} \tag{7}$$

For good insulation the *PI* has to be greater than 1 and high polarization index of an insulator implies healthiness of insulator. If *PI* is

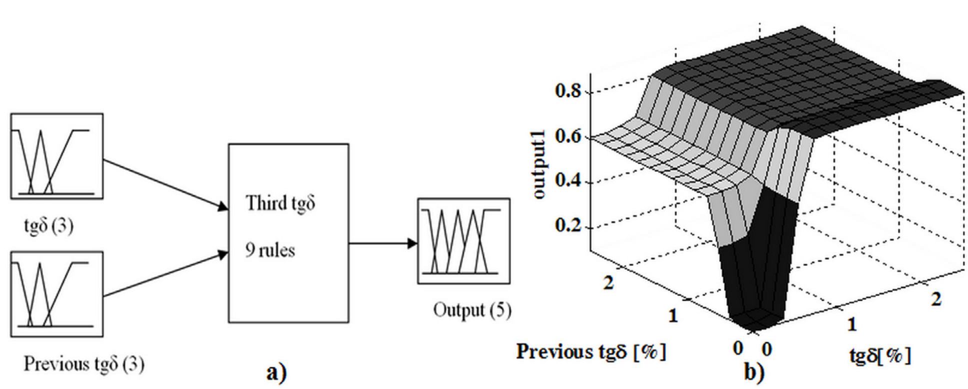


**Fig. 5.** (a) Third controller for $tg(\delta)$ and (b) urgency of intervention in the function of the combinations of present and previous measurement of $tg(\delta)$.

@maghalecomputer
کانال مهندسی کامپیوتر

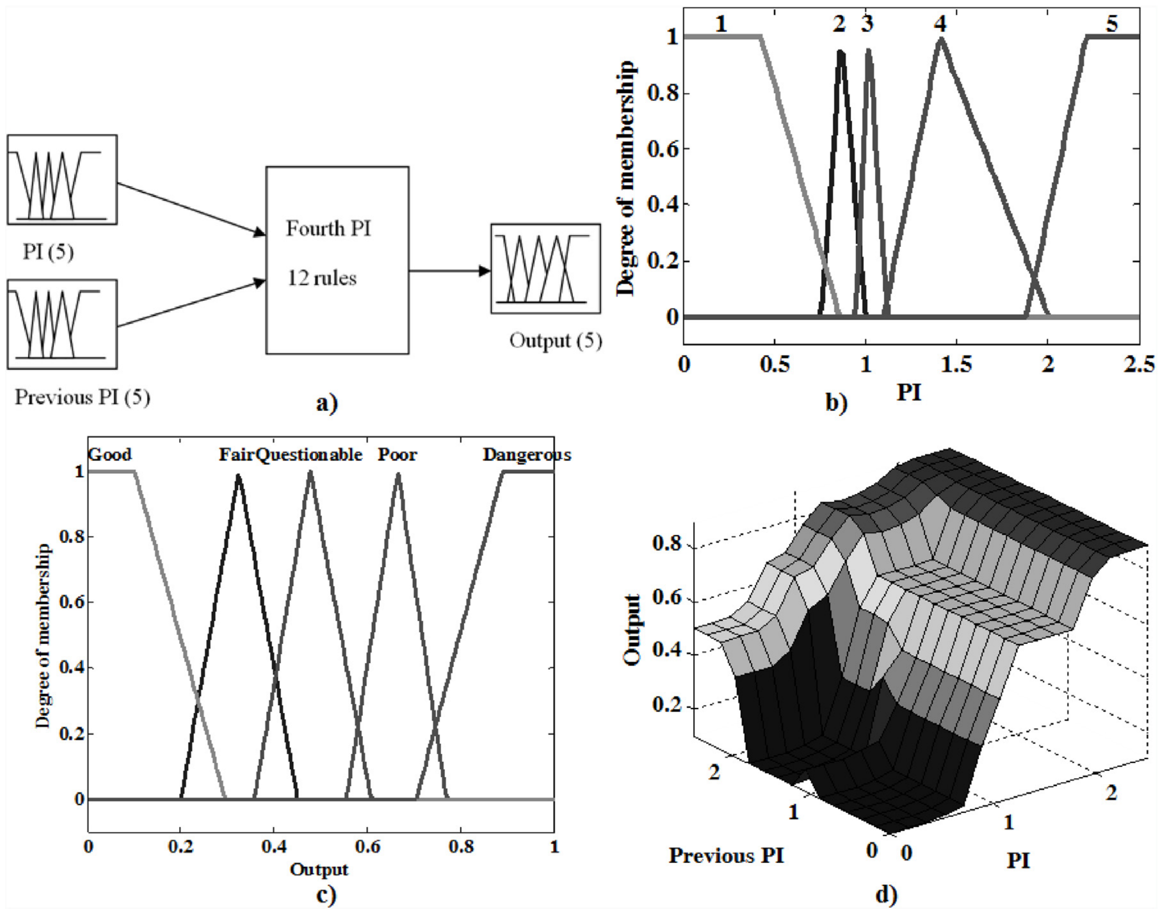


**Fig. 6.** (a) Fourth controller for *PI* (b) MFs for input *PI* (c) MFs for output ($i_4$) of fourth controller (d) urgency of intervention in the function of the combinations of present and previous measurement of *PI*.

greater then state of isolation is better and based on those MFs for *PI* and rule base in fourth controller (Fig. 6a) are created. Fuzzification of *PI* includes two trapezoidal and three triangular MFs (Fig. 6b). Those MFs correspond to ranges: [0:1], (1:1.1], (1.1:1.25], (1.25:2] and (2:). Characteristic ranges for output ($i_4$) are connected to: dangerous, poor, questionable, fair and good transformer insulation (Fig. 6c) [29]. In first case study is taken in account just one current measured value, and in second case study is considered value from the previous testing. Taking into account previous measured values we can follow the evolution of failure and the consequences of not reacting to the previous measurement. As a result of fourth controller is presented in Fig. 6d. Both indicators are depending on temperature of transformer so our next input is temperature.

### 3.4. Temperature and aging

The temperature of insulation is the main effect transformer aging. With temperature and time, the cellulose and oil insulation degrades and becomes increasingly worse. Load capability is commonly limited by the hottest section of the winding and insulation. The temperature of the transformer is directly related to load and life time of transformer. In paper [30] is presented age dependent maintenance strategies and the influence of temperature and lifetime on reliability model of transformer. Insulation lifetime $L$ can be modeled by the Arrhenius chemical equation:

$$L = A \cdot e^{\frac{a}{bT}} \tag{8}$$

where $L$ is life time, $A$, $a$, $b$ is characteristic constants and $T$ is temperature of insulation. Montsinger's rule [31] taken from transformer oil and solid insulation materials shows that the lifetime L decreases by 50% with increase of temperature $T$ by 10 K:

$$L(T + 10K) = 0.5 \cdot L(T) \tag{9}$$

Based on this rule MF for temperature ($\mu_T$) is modeled as an exponential to a maximum allowed temperature values. Based on standards [32–34] normal temperature of oil insulation is in interval of −20 °C to 105 °C, and that values are used for $\mu_T$ (Fig. 7d). It is understood that if the temperature of insulation is greater than value of urgency of intervention ($i$) and probability of failure is bigger. One more input is life time, i.e. the age of power transformer. Life time is introduced with two continuous MFs ($\mu_{EARLY}(x)$, $\mu_{OLD}(x)$,) which determines the degree of lifetime of power transformer. Input created like this (Fig. 7b) should be like the bathtub curve for failure rate. The probability of failure is initially high, but decreases during the period of early failure occurrence. After a long period of consistent low failure rates, the failure rate again raises near the end of the power transformer life due to aging. It is assumed that early working period is 5 years, and period of failures start from 20th years.

### 3.5. Thermography

One of the most commonly used on-line methods for the assessment of the high voltage equipment condition is a thermography [35–38]. But the problem that occurs after the thermography is to establish the time frame for the repair and urgency for intervention for the analyzed equipment. Because of that in papers [28,40] are discussed ways to use other available measurement data in order

@maghalecomputer
کانال مهندسی کامپیوتر

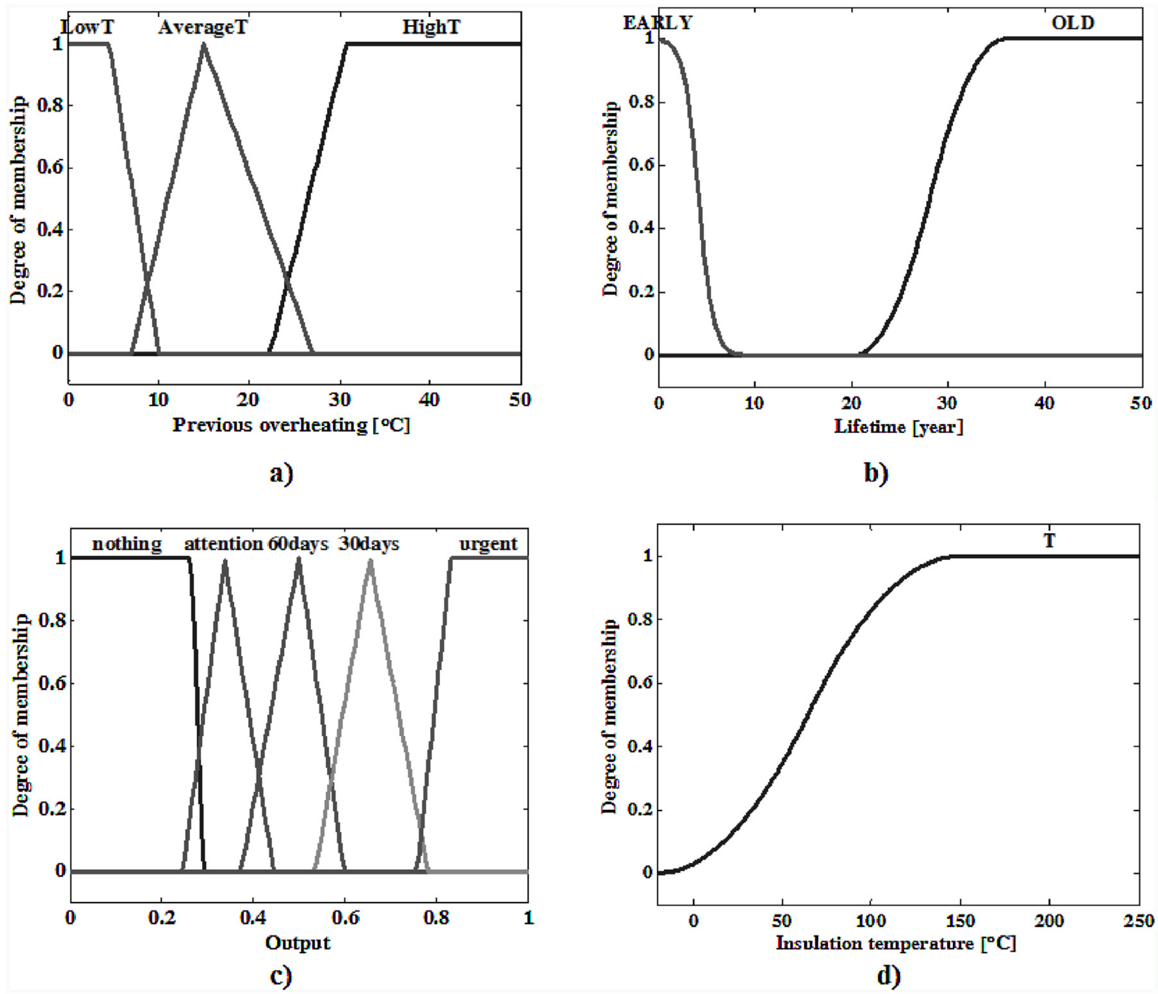


**Fig. 7.** Membership functions (MFs) (a) MFs for overheating, (b) MFs for lifetime, (c) MFs of output and (d) MF of insulation temperature.

to bring a better conclusion about the maintenance of the equipment. Controllers thermography input is overheating temperature which is difference between measured temperature of the hot spot and ambient temperature. According to Ref. [39], overheating is divided into three groups, used to assess defective equipment: up to 10 °C, between 10 °C and 30 °C and greater than 30 °C. Based on that fuzzification is obtained with two trapezoidal and one triangular MFs with some overlap (Fig. 7a). The first case study uses only present measured overheating temperature. The second case study uses previous measured values, similar to the other methods. MFs for the previous overheating temperature are the same as for present.

## 4. Fuzzy reasoning and rule base

General rules and experience of engineers from the standards related to testing methods are included in the rule bases of FCs. The best way to manage the FCs is described through sentences in a certain language. Rule base contains knowledge how to make proper decision, in the form of a set of logical (if – then) rules. The rules refer to the “linguistic” variables, their properties and knowledge. With aim to express the result produced by the current values of input variables, a set of rules has to be formed. These rules have the multiple parallel form of rules that are connected by the connectors “and” “or” and “not”. An example of the simplest rule in first controller (Fig. 8a):

“If the element is “OLD” and if the overheating temperature is “HighT”, between 20 and 30 °C, and gas rate $CH_4/H_2$ is “2”, and deviation at FRA input is “ASLE3”, and insulation temperature “T” is 120 °C, and PI is “5”, greater than 2, and tgδ take values bigger than 15% than it is clear that the urgent intervention is needed.” This is just one of several rules that need to be defined for functional fuzzy system. Aggregation in FL present combination of these rules in order to achieve a compact mathematical representation of the whole knowledge. Rules can be added, combined, modified to strive toward the desired output, but we will never be 100% sure of the end result of controller. Rule base of first case study is presented in Table 1 and contain 27 rules. Five lists, bases, of rules for second case study also exist.

The most common types of fuzzy reasoning that have been introduced in the literature and applied to different applications are Mamdani and Sugeno type models. In the first case study two FCs with Mamdani-type and Sugeno-type of reasoning are generated. In second case study every five controllers are with Mamdani-type of reasoning. The most fundamental difference between Mamdani-type and Sugeno-type of reasoning is the way the crisp output ($i$) is generated from the inputs.

Mamdani-type of reasoning has output MFs and uses the technique of defuzzification of a fuzzy output. The output signal for FC with Mamdani-type reasoning is a number from the interval [0,1] which refers to the condition of the element and the urgency of the intervention on it. If the output number is higher, closer to 1, the intervention is more urgent and the tested element is potentially

@maghalecomputer
کانال مهندسی کامپیوتر

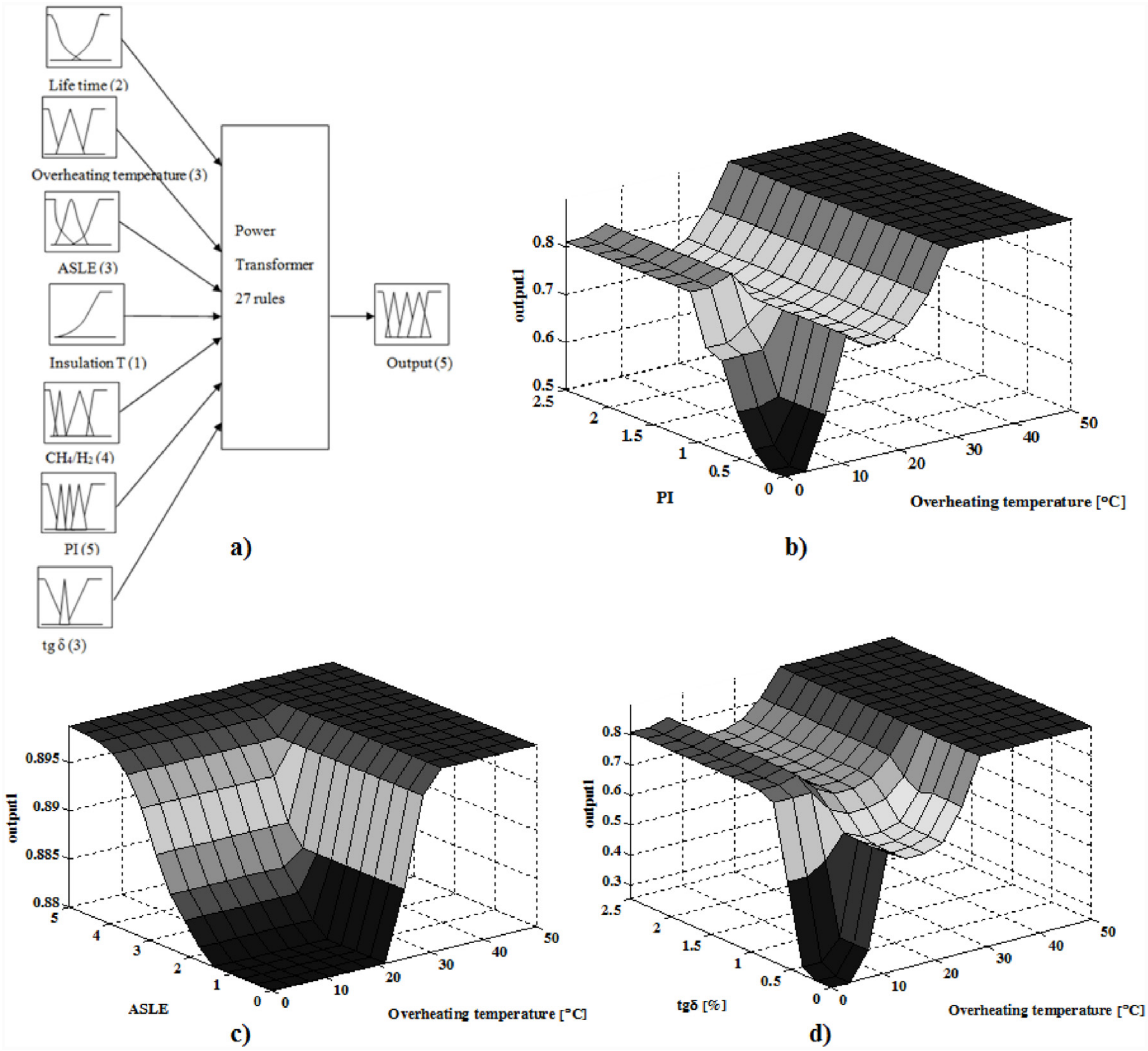


**Fig. 8.** (a) FC with Mamdani-type of reasoning in the first case study, urgency of intervention in the function of (b) the overheating temperature and the *PI*, (b) the overheating temperature and the *ASLE* and (d) the overheating temperature and the *tgδ*.

more defective. The output signal for fifth controller is shown in Fig. 7c has five MFs ($\mu_{OUTPUT}(i)$) that overlap and are related to: do nothing (element is correct), pay attention (element is uncertain), required intervention within 60 days, required intervention within 30 days and urgent (intervention is needed as soon as possible). Output like this is used in the first case and in the second case when measuring methods are separate in their own FCs (Fig. 1). Output in Mamdani-type of reasoning has to be defuzzificated and presented as real number. Defuzzification, transforms the interface conclusion and the most commonly used methods is the center of the gravity. This method is implemented in MATLAB® technical computing software by following expression:

$$OUTPUT = defuzzy(\mu_{OUTPUT}(i)) = \frac{\int \mu_{OUTPUT}(i) i di}{\int \mu_{OUTPUT}(i) di} \tag{10}$$

The results of rule base of first controller with Mamdani-type of reasoning are presented on Fig. 8b–d. Result is three dimensional transfer functions between combination if inputs and output *i*.

Sugeno-type of reasoning is similar to the Mamdani method and includes exactly the same fuzzification of the inputs and applying the fuzzy operators. Sugeno method has no output MFs and uses weighted average to compute the crisp output. Output MFs are either linear or constant. A simple rule in Sugeno fuzzy model has the form:

"If *Lifetime* = *x* and $CH_4/H_2 = y$, then Output is $i = ax + by + c$".

For a zero-order Sugeno model, the output level *i* is a constant ($a = b = 0$). Both output MFs are considered and results are given in section four of this paper. The output level $i_i$ of each rule is weighted by the firing strength $w_i$ of the rule. The final output of the system is the weighted average of all rule outputs:

$$i = \frac{\sum_{i=1}^{N} w_i \cdot i_i}{\sum_{i=1}^{N} w_i} \tag{11}$$

where *N* is the number of rules. In zero-order Sugeno model output is defined similar in range 0–1 where output constants mean:

- 0.05 is no mechanical and thermal fault and normal state of insulation,
- 0.15 is partial discharge of low energy, discharging the gas-filled cavities due to incomplete impregnation or overfitting or cavitations and high humidity,

@maghalecomputer
کانال مهندسی کامپیوتر

**Table 1**
Rule base of FC in the first case study.

| Rule No. | Rule |
|---|---|
| 1 | (overheating-temperature is HighT) & ($CH_4/H_2$ is 2) & (ASLE is ASLE3) & (Insulation-temperature is T) & (PI is 5) & (Tgδ is High) then (output = urgent) |
| 2 | (overheating-temperature is AverageT) & ($CH_4/H_2$ is 0) & (ASLE is ASLE2) & (Insulation-temperature is T) & (PI is 4) & (Tgδ is Medium) then (output = 30 days) |
| 3 | (overheating-temperature is AverageT) & ($CH_4/H_2$ is 1) & (ASLE is ASLE1) & (Insulation-temperature is T) & (PI is 3) & (Tgδ is Medium) then (output = 60 days) |
| 4 | (overheating-temperature is AverageT) & ($CH_4/H_2$ is 0) & (ASLE is ASLE1) & (Insulation-temperature is T) & (PI is 2) & (Tgδ is Low) then (output = attention) |
| 5 | (overheating-temperature is LowT) & ($CH_4/H_2$ is 0) & (ASLE is ASLE1) & (Insulation-temperature ~= T) & (PI is 1) & (Tgδ is Low) then (output = nothing) |
| 6 | (lifetime is OLD) & (overheating-temperature is AverageT) & ($CH_4/H_2$ is 2) & (ASLE is ASLE2) & (Insulation-temperature is T) & (PI is 4) & (Tgδ is Medium) then (output = 30 days) |
| 7 | (lifetime is OLD) & (overheating-temperature is AverageT) & ($CH_4/H_2$ is 2) & (ASLE is ASLE2) & (Insulation-temperature is T) & (PI is 5) & (Tgδ is High) then (output = urgent) |
| 8 | (lifetime is OLD) & (overheating-temperature is HighT) & ($CH_4/H_2$ is 0) & (ASLE is ASLE2) & (Insulation-temperature is T) & (PI is 3) & (Tgδ is Medium) then (output = urgent) |
| 9 | (overheating-temperature is HighT) then (output = urgent) |
| 10 | (ASLE is ASLE3) then (output = urgent) |
| 11 | (ASLE is ASLE3) & (PI is 5) then (output = urgent) |
| 12 | (CH4/H2 is 2) & (ASLE is ASLE3) & (Tgδ is High) then (output = urgent) |
| 13 | (overheating-temperature is LowT) & (Tgδ is Low) then (output = nothing) |
| 14 | (overheating-temperature is LowT) & (Tgδ is Medium) then (output = attention) |
| 15 | (overheating-temperature is AverageT) & (Tgδ is Medium) then (output = 60 days) |
| 16 | (overheating-temperature is AverageT) & (Tgδ is High) then (output = 30 days) |
| 17 | (overheating-temperature is LowT) & (Tgδ is High) then (output = 30 days) |
| 18 | (Tgδ is High) then (output = urgent) |
| 19 | (overheating-temperature is AverageT) then (output = 60 days) |
| 20 | (overheating-temperature is LowT) & (PI is 1) then (output = nothing) |
| 21 | (overheating-temperature is LowT) & (PI is 2) then (output = attention) |
| 22 | (overheating-temperature is AverageT) & (PI is 3) then (output = 60 days) |
| 23 | (overheating-temperature is HighT) & (PI is 5) then (output = urgent) |
| 24 | (overheating-temperature is AverageT) & (PI is 5) then (output = urgent) |
| 25 | (PI is 5) then (output = urgent) |
| 26 | (overheating-temperature is AverageT) & (PI is 5) then (output = urgent) |
| 27 | (overheating-temperature is AverageT) & (PI is 4) & (Tgδ is Low) then (output = urgent) |

- 0.25 is partial discharge of high energy, leads to the formation of conductive paths or holes in the solid insulation,
- 0.35 is disruptive discharge of low energy, continuous arcing in oil or breakthrough in oil from solids,
- 0.45 is disruptive discharge of high energy, breakthrough fields between fans and windings or between the windings and earth, problems with regulation switch,
- 0.55 is overheating below 150 °C, overheating of the insulated conductors and the start of mechanical problems,
- 0.65 is mechanical problems, mechanical defects of windings and core,
- 0.75 is overheating between 150 °C and 300 °C, local overheating of the core because of flux concentration,
- 0.85 is overheating between 300 °C and 700 °C, the appearance of small hot spots in the core, and
- 0.95 is overheating over 700 °C, copper overheating due to bad contacts or possible short circuit.

Constants are chosen to make the division of failures in ten groups, from the lightest to hardest failures. The interpretation of these constants can be that the first group has a 5% and last group has 95% probability of dysfunction of the transformer. Meaning of chosen constants, based on the rules, is in order to point out the problems that result from input parameters.

In order to take into account the history of test transformers each method is divided in one of the five controllers (Fig. 1b). In this second case study each output $i_{1\text{–}5}$ can get the weight factor $\omega_i$ and thus favoring one of the measuring methods. On this way we independently favor a particular method and therefore the rules within their controllers. The measuring methods are divided also because some of them point to the mechanical, thermal defects and other on problems with cooling and insulation. In this way, the decision-maker eases make classification of the failure. Results of second study are compared in section four of this paper.

## 5. Results

The FL controllers are developed and created using MATLAB® technical computing software [40]. FCs are tested and compared based on real measurements and data base from Serbian transmission system. Four results are obtained, three in first case study and one in second case study. In first case study FC with Mamdani and Sugeno-type (with linear and constant output) of reasoning characterize the operating condition of power transformer. Mamdani-type of reasoning determines as result the urgency of intervention. Sugeno-type of reasoning indicates probability of specific type of failure. In the second case study more data is used and each of five controllers gives probability of failure with possibility to observe which measuring method is more critical.

The study focused on four power transformers of different voltage levels. Field thermographic images are provided in Fig. 9 and their data in Table 2. Fig. 9a and b show thermal images of overheating the terminal bushing of power transformer 110/35 kV/kV and 220/110 kV/kV with temperature of overheating 19 and 29 °C, retrospectively. Fig. 9c shows problems inside the main tank, because temperature at the middle of transformer (400/220 kV/kV) tank is hotter than the top (18.6 °C). Abnormal state on transformer radiator show that temperature in second radiator fin is cooler (21.1 °C) than other radiator fins (Fig. 9d).

Result of this abnormal state is poor distribution of oil flow in power transformer (400/110 kV/kV). All results are presented in Table 3. It can be seen that results are similar, but some results are on side of safety. Each controller has its self advantages. Madmani-type controller is intuitive, has widespread acceptance and it is well suited to human input. Also it brings great crispy and fuzziness for inputs and outputs through their MFs.

The zero-order Sugeno-type controller is good way to classified failure, because each constant shows different class of faults. The linear Sugeno-type controller is computationally efficient and guaranteed continuity of the output surface. This type of controller is very similar to the second case study because each input can be intensified through the coefficients of the linear dependence. In the second case study all five controllers get more input data and take into account history of tested power transformer. In this case all parameters $w_{1\text{–}5}$ take value 1, so all five outputs are equal and final output is average value. In the first case study absence of parameters can be solved by the missing input take the worst possible value. In this way the controller works on the side of safety. If some

@maghalecomputer

کانال مهندسی کامپیوتر

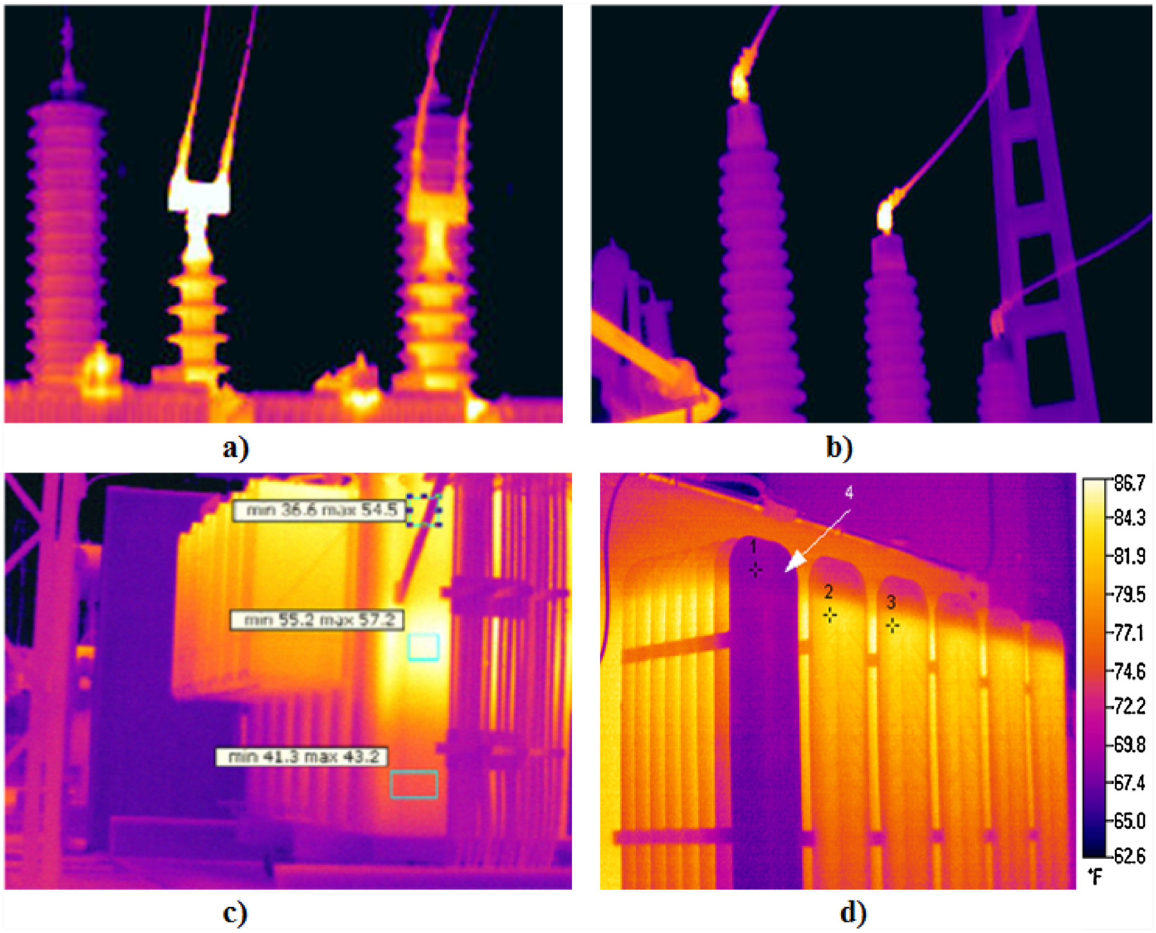


**Fig. 9.** Thermal image of terminal bushing of power transformer (a) 110/35 kV/kV and (b) 220/110 kV/kV, (c) abnormal on main tank on power transformer 400/220 kV/kV and (d) abnormal on radiator on power transformer 400/110 kV/kV.

measuring methods are missing, second case study can throw out that parameter or again missing parameter take its worst value in the final sum.

### 5.1. Methodology comparison and validation

In order to prove results of presented FCs the comparison and validation of the methodology with others techniques is done. The methodology that consider collected date of the various testing methods of power transformers are presented in papers [41–43]. Methodology with health index (*HI*) is presented in Refs. [41,42] and methodology with transformer status indicator (*TSI*) is presented in Ref. [43]. Both methodology contain an extensive experience and knowledge from conferences CIGRE and CIRED. Smaller values of both indicators (*TSI* and *HI*) point to worse condition of transformer, which means that these values are the opposite of the values of FC. In Table 4 it can be seen that the results of FC are approximately identical: *i* is 1-*TSI* and *i* is 1-*HI*/100%. It can be seen that all the coefficients indicate the same order of priority of the four transformers maintaining. Presented methodology with FL is better because it directly loading values of test measurements, while methods [41–43] ranked that input measurements with numbers 0, 1, 2, 3 or 4. Also methodology with FL classified faults based

**Table 2**
Data for power transformers.

| Condition data/Power transformer | 110/35 kV/kV | 220/110 kV/kV | 400/220 kV/kV | 400/110 kV/kV |
|---|---|---|---|---|
| $CH_4/H_2$ [ppm] | 0.3 | 0.7 | 3.8 | 0.08 |
| $C_2H_2/C_2H_4$ [ppm] | 0.02 | 0.03 | 0.05 | 0.06 |
| $C_2H_4/C_2H_6$ [ppm] | 1.9 | 2.6 | 2.8 | 0.7 |
| *ASLE* | 1.8 | 3.1 | 1.2 | 0.6 |
| *DABS* | 0.45 | 0.8 | 0.025 | 0.01 |
| *CC* | 0.97 | 0.87 | 0.98 | 0.99 |
| $Tg\delta$ [%] | 1.6 | 2.0 | 1.5 | 1.8 |
| Previous $tg\delta$ [%] | 12 | 13 | 1.3 | 1.5 |
| *PI* | 1.7 | 2.5 | 1.3 | 0.3 |
| Previous *PI* | 1.1 | 1.8 | 1.1 | 0.28 |
| Insulation temperature [°C] | 70 | 87 | 126 | 107 |
| Lifetime [years] | 10 | 25 | 16 | 4 |
| Previous temperature of overheating [°C] | 11 | 18 | 10 | 13 |
| Temperature of overheating [°C] | 19 | 29 | 18.6 | 21.1 |

@maghalecomputer
کانال مهندسی کامپیوتر

**Table 3**
Results of FCs.

| Fuzzy controller/Power transformer | 110/35 kV/kV | 220/110 kV/kV | 400/220 kV/kV | 400/110 kV/kV |
|---|---|---|---|---|
| First DGA | 0.575 | 0.625 | 0.863 | 0.175 |
| Second FRA | 0.152 | 0.464 | 0.151 | 0.133 |
| Third tgδ | 0.824 | 0.824 | 0.824 | 0.824 |
| Fourth PI | 0.663 | 0.894 | 0.663 | 0.104 |
| Fifth-thermogrphy | 0.585 | 0.898 | 0.647 | 0.624 |
| Second case study | 0.585 | 0.824 | 0.663 | 0.175 |
| Mamdani-type of reasoning | 0.744 | 0.899 | 0.738 | 0.289 |
| Sugeno linear-type of reasoning | 0.5 | 0.797 | 0.766 | 0.218 |
| Sugeno constant-type of reasoning (zero-order) | 0.55 | 0.65 | 0.85 | 0.15 |
| The urgency of intervention | 30 days | Urgent | 30 days | Nothing |
| Failure classification | Overheating of the insulated conductors | Overheating of the conductors and mechanical defect | The appearance of small hot spots in the core | Partial discharge of low energy |

**Table 4**
Results of comparison and validation.

| Methodology/Voltage level of transformer [kV/kV] | 110/35 | 220/110 | 400/220 | 400/110 |
|---|---|---|---|---|
| Second case study [0–1] | 0.585 | 0.824 | 0.663 | 0.175 |
| Mamdani-type of reasoning [0–1] | 0.744 | 0.899 | 0.738 | 0.289 |
| Sugeno linear-type of reasoning [0–1] | 0.5 | 0.797 | 0.766 | 0.218 |
| Sugeno constant-type of reasoning (zero-order) [0–1] | 0.55 | 0.65 | 0.85 | 0.15 |
| HI [%] | 53.572 | 23.095 | 32.612 | 63.624 |
| TSI [0–1] | 0.578 | 0.201 | 0.267 | 0.735 |

**Table 5**
Validation of first DGA FC.

| Gas concentration [ppm] | | | | | First DGA FC | DGA [46] | |
|---|---|---|---|---|---|---|---|
| $H_2$ | $CH_4$ | $C_2H_6$ | $C_2H_4$ | $C_2H_6$ | i | Fault type | |
| 117 | 17 | 1 | 3 | 1 | 0.173 | PD | PD |
| 32,930 | 2397 | 157 | 0.001 | 0.001 | 0.274 | PD | PD |
| 78 | 20 | 11 | 13 | 28 | 0.375 | D1 | D1 |
| 1230 | 163 | 27 | 233 | 692 | 0.5 | D2 | D1 |
| 8200 | 3790 | 250 | 4620 | 277 | 0.5 | D2 | D2 |
| 13 | 3 | 1 | 3 | 6 | 0.475 | D2 | D2 |
| 130 | 140 | 2 | 120 | 0.001 | 0.575 | T1 | T1 |
| 78 | 66 | 283 | 2.6 | 0.001 | 0.625 | T1 | T1 |
| 30.4 | 117 | 44.2 | 138 | 0.1 | 0.757 | T2 | T2 |
| 27 | 90 | 42 | 63 | 0.2 | 0.7750 | T2 | T2 |
| 1100 | 1600 | 221 | 2010 | 26 | 0.907 | T3 | T3 |
| 290 | 966 | 299 | 1810 | 57 | 0.937 | T3 | T3 |

*PD–partial discharge, D1–low discharge energy, D2–high discharge energy, T1–low thermal, T2–medium and T3–high thermal fault.

on output results, while methods [43–45] just indicate health of transformers.

A new DGA approach from paper [44] is used to demonstrate work of first DGA FC. Input parameters are gas concentration presented in Table 5. New DGA approach uses these inputs to calculate Total Combustion Gases (*TCG*) and Gas Concentration Percentage (*GCP*). Based on that approach detect different fault types: partial discharge (PD), low discharge energy (D1), high discharge energy (D2), low thermal (T1), medium (T2) and high thermal fault (T3). Table 5 presents input data from Ref. [44] and results. Based on these results it can be seen that first DGA FC made mistake just in one case. The advantage of first DGA FC is that offers the possibility of changing the rules based on subjective engineering experience.

## 6. Conclusions

This paper described the methodology how to use FL to evaluate the probability of failure and detect specific defect of power transformer. Methodology uses multiple parameters of different tests than the existing methods. Also, a method uses the past parameter values, which takes into account the history of test transformer. Analysis of fuzzy reasoning concluded that Mamdani-type and Sugeno-type perform quite similar results, but Sugeno-type brings more control to user and runs faster with better performance. Some controllers as a result provide the class of failure, others provide the fault probability and urgency of intervention, it may be concluded that all are helpful. In some situations it is good to have results of different controllers because they give probability of specific fault of power transformer. All formed controllers can be used, especially when different engineers and experts opinions in making decisions about the maintenance of power transformers exists. Also in the described mode controllers can be modified if there are other measurement data. Methodology validation is performed, and its advantages are clearly stated. The urgency of intervention can alert engineering about need maintenance and give him a time limit. The failure classification indicates the most probable defect and help engineers to reduce the time needed to find and fix the fault. Results of methodology are useful to operator to make proper

@maghalecomputer
کانال مهندسی کامپیوتر

and timely decision about power transformer maintenance. Output of methodology should be used for condition based management (CBM) or like input of risk maps. This paper provides good proposals for making the diagnostics interpretation more objective, on way to integrate human expertise along with the different kind of parameters obtained from the evaluation of the records in a monitoring of power transformer.

## Acknowledgments

The authors would like to thank the Ministry of Science and Technological Development of the Republic of Serbia which, within the framework of Project III 45003 “Optoelectronic nanodimensional systems – road towards applications”, Subproject: “Nanostructural optoelectronic sensing systems” and Project III 42009 “Smartgrid”, made this work possible.

The second author would like to thank the Alexander von Humboldt Foundation, Bonn, FR Germany, for its support for his scientific research work.

## References

[1] P.S. Szczepaniak, M. Kłosiński, DGA-based diagnosis of power transformers—IEC standard versus k-nearest neighbours, in: IEEE SIBIRCON-2010, Irkutsk Listvyanka Russia, 2010, pp. 740–743.
[2] M.N. Pradeep, B. Gunasekaran, A.D. Rajkumar, B.P. Singh, Frequency response analysis approach for condition monitoring of transformer, IEEE Annual Report Conference on Electrical Insulation and Dielectric Phenomena (2004) 186–189.
[3] Z. Moravej, D.N. Vishwakarma, S.P. Singh, Protection and conditions monitoring of power transformer using ANN, Electr. Power Compon. Syst. (2002) 217–231.
[4] V. Mijailovic, Method for effects evaluation of some forms of power transformers preventive maintenance, Electr. Power Syst. Res. 78 (2008) 765–776.
[5] O. Ristic, V. Mijailovic, Method for determining optimal power transformers exploitation strategy, Electr. Power Syst. Res. 83 (2012) 255–261.
[6] A. Ngaopitakkul, A. Kunakorn, Internal fault classification in transformer windings using combination of discrete wavelet transforms and back-propagation neural networks, Int. J. Control Autom. Syst. 4 (3) (2006) 365–371.
[7] C.A.R. Garcez, V. Miranda, An interpretation of neural networks as inference engines with application to transformer failure diagnosis, Electr. Power Energy Syst. 27 (2005) 620–626.
[8] T. Babanik, F. Gubina, Two approaches to power transformer fault classification based on protection signals, Electr. Power Energy Syst. 24 (2002) 459–468.
[9] S. Yan-jing, Z. Shen, M. Chang-xin, L. Jing-meng, Improved BP neural network for transformer fault diagnosis, J. China Univ. Min. Technol. 17 (1) (2007) 138–142.
[10] E.A. Mohamed, A.Y. Abdelaziz, A.S. Mostafa, A neural network-based scheme for fault diagnosis of power transformers, Electr. Power Syst. Res. 75 (2005) 25–39.
[11] Z. Moravej, Evolving neural nets for protection and condition monitoring of power transformer, Electr. Power Compon. Syst. 33 (2005) 1229–1236.
[12] S.F. Cortez, F.G. Guimarães, R.D. Duarte, A.J.R. Reis, A cognitive system for fault prognosis in power transformers, Electr. Power Syst. Res. 1027 (2015) 109–117.
[13] L.V. Ganyun, C. Haozhong, Z. Haibao, D. Lixin, Fault diagnosis of power transformer based on multi-layer SVM classifier, Electr. Power Syst. Res. 74 (2005) 1–7.
[14] K. Bacha, C. Souahlia, M. Gossa, Power transformer fault diagnosis based on dissolved gas analysis by support vector machine, Electr. Power Syst. Res. 83 (2012) 73–79.
[15] N.A. Muhamad, B.T. Phung, T.R. Blackburn, K.X. Lai, Comparative study and analysis of DGA methods for transformer mineral oil, IEEE Lausanne Power Tech 2007 (2007) 45–50.
[16] C. Perrier, M. Marugan, A. Beroual, DGA comparison between ester and mineral oils, IEEE Trans. Dielectr. Electr. Insul. 19 (5) (2012) 1609–1614.
[17] IEC Standard 60599, Mineral Oil-filled Electrical Equipment in Service—Guidance on the Interpretation of Dissolved and Free Gases analysis, IEC, 2015.
[18] M. Duval, Dissolved Gas Analysis and the Duval Triangle, TechCon Asia Pacific, Sydney Australia, 2006.
[19] IEEE Standard C57.104-2008, IEEE Guide for the Interpretation of Gases Generated in Oil-Immersed Transformers, IEEE, 2008.
[20] IEEE C57.149-2012, Guide for the Application and Interpretation of Frequency Response Analysis for Oil-Immersed Transformers, IEEE, 2012.
[21] M.N. Pradeep, B. Gunasekaran, A.D. Rajkumar, B.P. Singh, Frequency response analysis approach for condition monitoring of transformer, IEEE Annual Report Conference on Electrical Insulation and Dielectric Phenomena (2004) 186–189.
[22] A.P. Akshay, B.R. Parekh, Interpretation of Sweep Frequency Response Analysis (SFRA) traces for the open circuit and short circuit winding fault damages of the power transformer, Electr. Power Energy Syst. 62 (2014) 890–896.
[23] S.A. Ghania, Y.H.M. Thayoobb, Y.Z.Y. Ghazali, M.S.A. Khiar, I.S. Chairul, Condition monitoring of distribution transformer's mechanical parts using Sweep Frequency Response Analysis (SFRA), Procedia Eng. 68 (2013) 469–476.
[24] J.R. Secue, E. Mombello, Sweep Frequency Response Analysis (SFRA) for the assessment of winding displacements and deformation in power transformers, Electr. Power Syst. Res. 78 (2008) 1119–1128.
[25] L. Xiaochen, J. Shengchang, W. Wei, The application of FRA-SCR in the diagnosis of transformer coil deformation, in: IEEE International Conference on Condition Monitoring and Diagnosis, Bali Indonesia, 2012, pp. 450–453.
[26] M. Žarković, Z. Stojković, Artificial intelligence based thermographic approach for high voltage substations risk assessment, IET Gener. Transm. Distrib. 9 (14) (2015) 1935–1945.
[27] IEC Standard 60422-2013, Mineral Insulating Oils in Electrical Equipment—Supervision and Maintenance Guidance, IEC, 2013.
[28] IEEE Standard C57.12.90-1999, IEEE Standard Test Code for Liquid-Immersed Distribution, Power, and Regulating Transformers, IEEE, 1999.
[29] IEEE Standard C57.152-2013, Guide for Diagnostic Field Testing of Fluid-Filled Power Transformers, Regulators, and Reactors, IEEE, 2013.
[30] X. Zhang, E. Gockenbach, Age-dependent maintenance strategies of medium-voltage circuit-breakers and transformers, Electr. Power Syst. Res. 81 (2011) 1709–1714.
[31] V.M. Montsinger, Loading transformers by temperature, AIEE Trans. 67 (1948) 113–122.
[32] IEEE Standard C57.12.10-2010, IEEE Standard Requirements for Liquid-Immersed Power Transformers, IEEE, 2010.
[33] IEEE Standard C57.91-2011, IEEE Guide for Loading Mineral-Oil-Immersed Transformers and Step-Voltage Regulators, IEEE, 2011.
[34] IEC Standard 60076-7:2005, Power Transformer—Part 7. Loading Guide for Oil-Immersed Power Transformers, IEC, 2005.
[35] W.L. Chen, A.T.P. So, L.L. Loi, Three-dimensional thermal imaging for power equipment monitoring, IEEE Proc. Gener. Transm. Distrib. 147 (2000) 355–360.
[36] Carlos A.L. Almeida, A.P. Braga, S. Nascimento, V. Paiva, H.J.A. Martins, R. Torres, W.M. Caminhas, Intelligent thermographic diagnostic applied to surge arresters: a new approach, IEEE Trans. Power Deliv. 24 (2009) 751–757.
[37] A.G.G. Ramirez, L.A.M. Hernandez, R.A.O. Rios, J.P.B. Rangel, A.G. Perez, R.J.R. Troncoso, W.M. Caminhas, Fault detection in induction motors and the impact on the kinematic chain through thermographic analysis, Electr. Power Syst. Res. 114 (2014) 1–9.
[38] M. Žarković, Z. Stojković, Fuzzy logic and artificial neural network based thermography approach for monitoring of high voltage equipment, Int. J. Electr. Eng. Educ. 52 (1) (2015) 81–96.
[39] R. Billinton, G. Singh, Application of adverse and extreme adverse weather: modelling in transmission and distribution system reliability evaluation, IEEE Proc. Gener. Transm. Distrib. 153 (1) (2006) 115–120.
[40] Z. Stojković, Computer-Aided Design in Power Engineering—Application of Software Tools, Springer, Berlin Heidelberg, 2012, pp. 436.
[41] J. Naderian, R. Piercy, S. Cress, J. Service, F. Wang, An approach to power transformer asset management using health index, IEEE Electr. Insul. Mag. 25 (2) (2009) 20–34.
[42] M. Augusta Martins, Condition and risk assessment of power transformers: a general approach to calculate a health index, Ciênc. Tecnol. Mater. 26 (2014) 9–16.
[43] C.S. Vörös, G. Csépes, Health index as one of the best practice for condition assessment of transformers and substation equipments—Hungarian experience, in: A2-103 CIGRE 2014, Paris, 2014.
[44] S.S.M. Ghoneim, B.M.I. Taha, A new approach of DGA interpretation technique for transformer fault diagnosis, Electr. Power Energy Syst. 81 (2016) 265–274.

@maghalecomputer

کانال مهندسی کامپیوتر