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Research Article

Integrated Transformer Health Estimation Methodology Based on Markov Chains and Evidential Reasoning

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Due to the large number of power transformers (ETs) in the distribution system, there is a need for a relatively simple representation of the status of each unit in order to more easily determine where and how to allocate the budget for preventive and corrective maintenance. In recent years, the concept of the transformer health index (HI) as an integral part of resource management was adopted for the condition assessment and ranking of ETs. HI algorithms take different forms and can be determined based on a large number of specific parameters. However, the main problem in HI methodology or any modern diagnostic technique is the existence of regular measurements and inspections and accurate test results. The paper proposes a solution in the form of the upgraded HI and the novel methodology for ET ranking including the value of available information to describe ET current state. The confidence to the measurement results is calculated using evidential reasoning (ER) algorithm based on Dempster–Shafer theory. The contribution to the ER methodology is the calculation of the initial degrees of belief using Markov chains. The aging process of an ET and transition probabilities from state to state are modelled using the statistical data for the population of 300 ETs and 20 years monitoring data. The proposed methodology is tested on the real data for 110/35 kV transformer, and in the second case, compared to the sample of 30 110/x kV transformers with traditional HI calculation.

1. Introduction

Determining the health index (HI) of a transformer is a suitable tool that should provide in a reproducible and consistent way information about its condition, the operational correctness, and availability. Transformer indexing by operating condition, with additional risk analysis, enables a better understanding of the availability and reliability of large transformer populations [1]. HI is a tool that combines the results of in-service electrical testing, laboratory (chemical) testing of transformer oil, maintenance data, and work history data to manage basic resources and build priorities when designing maintenance plans using a numerical grade of transformer status. The choice of methodology depends on the technical capabilities of a particular ET in terms of the number and types of diagnostic tests used to evaluate the condition of transformer elements, as well as on the business and organizational arrangements for storing and updating data and expert teams involved in testing and diagnostics of transformer conditions.

Certain measurement methods are performed on a regular basis, such as oil diagnostics, insulation resistance tests, turns ratio measurements, and inspection of accessories. They are performed relatively often and in the state of normal trouble-free operation. Some methods such as the measuring of partial discharges, in spite of their great importance for the assessment of the condition, are not usually used in determining the HI. The reason is possible financial losses resulting from the interruption of electricity supply that can be caused by unnecessary inspections. The advanced methods are used to assess the condition of ETs with developing defects or aged units, such as frequency domain

spectroscopy (FDS), frequency response analysis (FRA), advanced bushings, and on-load tap changer (OLTC) diagnostics, as well as measurement of partial discharges.

With the advance of prognostics and health management applications, it is possible to enhance traditional transformer health monitoring techniques. For instance, in estimating the remaining life of a transformer, besides the data of paper insulation condition, it is necessary to know the aging kinetics of the oil-impregnated cellulose insulation, which depends on the temperature and water content in the paper. AC conductivity of the composite of cellulose, mineral oil, and water nanoparticles was investigated in [2], while the relationships between the paper degree of polymerization and the furan content for dry and wet insulation were developed in [3]. The water content distribution along windings in transformers is given in [4]. To improve the accuracy of these methods, the dependence of the degree of polymerization of Kraft paper to 2-FAL content in the oil, corrected to a reference temperature of 20°C, is developed in [5], and the method converting experimental frequency dependence of the loss angle tangent measured by the FDS to the reference temperature is presented in [6].

As stated before, the advanced measurements are required only for aged ETs with developing defects, but for the vast majority of units, a practical condition index is required. This index should overcome the main problems of previous condition assessment approaches: (a) the rational aggregation of different ET components, (b) uncertainties, accuracy, and confidence of the inspection results, and (c) consistent grade assessment and weighting of different ET components. Recently, the concept of the transformer health index (HI) as an integral part of resource management was adopted for the condition assessment and ranking of ETs. HI calculation method that combines the impact of all available data and criteria based on the industry's common practices and technical standards is presented in [7], while Gorgan et al. [8] calculated HI based on the standard model of twenty-four diagnostic factors expanding the list with three factors (loss factor at very low frequency, conductivity factor, and polarization index). HI concept can be extended to other equipment, like in [9], where HI was determined for a number of around 2,000 secondary substations, each consisting of a MV switchgear, MV/LV transformer, and LV rack. The algorithm based on regularly conducted oil diagnostics and easily available maintenance data to enable estimation and update the device's health status in short intervals is proposed in [10]. A comprehensive study of previous research related to the transformer health index by using the mathematical equation/algorithm or expert judgment is given in [11], but very few research studies are dealing with the uncertainties, accuracy, and confidence of the inspection results.

Using machine learning techniques, the collected data can be used for the HI prediction in the future period. Various classification techniques have been investigated to reduce ET assessment complexities and decrease the number of features by extracting the most influential ones when determining the HI [12, 13]. Markov model has been developed in [14] to predict the state of health of a transformer and suggest a schedule for regular gas filtration. Markov model is also used in [15] for the determination of the future deterioration performance curve of the transformers. The conclusion is as test results are sometimes imprecise and even incomplete, a suitable evidence integration method is required to process the data. Furthermore, the technical condition of distribution equipment is facing uncertainties concerning the ambiental and operational condition in the future period. One of the solution is proposed in [16], where the methodology is based on discrete convolution of criteria probability distribution functions and OWA operators, modelling different types of criteria aggregation. In [17], a new methodology for the multicriteria risk assessment of the distribution network assets, based on influence diagrams and fuzzy probabilities, is proposed.

The evidential reasoning (ER) approach is a suitable method for dealing with the aggregation problem. The process developed on the basis of Dempster–Shafer evidence theory [18] and evaluation analysis model [19] can model various types of qualitative and quantitative uncertainties. With the introduction of the concepts of the belief structure [20, 21] and the belief decision matrix, it became possible to model various types of uncertainties in a unified format.

The methodology of how to transfer a transformer condition assessment problem into a multicriteria decision solution under an ER framework is presented in [22]. Subjective judgments are produced using various dissolved gas analysis (DGA) methods for all of the alternatives involved. Then, the concept of a preference degree was introduced to quantify these evaluation grades and subjective judgments with uncertainty. An interesting approach of usage of Dempster–Shafer theory for information fusion tasks combining the outcome of source classifiers through evidence combination strategies is presented in [23]. The study [24] presents an ER approach to transformer winding assessment based on frequency response analysis (FRA), but the degree of uncertainty, like in the previous study, relies only on the expert's judgment.

The integrated fuzzy and evidential reasoning model is presented in [25], with previous operation history, results of the latest inspection, and states of the on-load tap changer taken as evidence to assess the working state of the transformer. The fuzzy model is proposed for generating the original basic probability assignments for the second-level model. The testing data of indices are normalized according to the attention value on transformer tests and operation standards. Fuzzy variables are also used in [26], where the evaluation of the health status of a transformer using DGA, oil testing, and evidential reasoning criterion has been used. In the analysis, the dissolved gases and oil testing parameters are first normalized and then transformed into fuzzy variables using trapezoid membership function. Finally, an index assessing system, considering the main body, the bushing, and the accessory components, was established in [27]. A fuzzy evidence fusion method was represented to handle the fuzzy evidence fusion processes, but in this paper, like in the previous one, the complete state of nature is presumed to be known (the complete belief sum of all propositions within the recognition framework is equal to 1).

To overcome the problem of subjective treatment of old, dubious, and uncertain data, the hybrid model of ER and Markov chains is proposed in this paper. A basic tree structure necessary for ER assessment is developed based on the complete transformer model and individual HI of every component, and a general, multilevel evaluation process is used for dealing with multicriteria decision problems. The ET condition is represented as a probability distribution over all possible health states using the Markov chain model of component ageing. The confidence to the measurement results is calculated using evidential reasoning (ER) algorithm based on Dempster–Shafer theory. The contribution to the ER methodology is the calculation of the initial degrees of belief using Markov chains. The proposed methodology is tested on the real data for 110/35 kV transformer, and in the second case, compared to the sample of 30 110/x kV transformers with traditional HI calculation. The methodology is tested to the sample of 30 110/x kV transformers and compared with other HI calculation methods.

The rest of the paper is organized as follows. Section 2 briefly outlines the health index (HI) approach and how it works as a prioritization method. Section 3 explains the evidence reasoning algorithm. Section 4 provides data analysis and discussion, while Section 5 offers conclusion.

2. Transformer Modelling

2.1. Health Index Definition. In recent years, the numerical assessment (indexing) of the current state of an ET and other high-voltage equipment in plants assigning a health index (HI) emerges as a tool that could effectively provide a transition to condition-based maintenance. HI is a numerical value that can be used to estimate the overall condition of an ET. By individually evaluating the most representative key factors that are vital to the reliable operation of transformers and mathematically aggregating them into a quantitative index, this value provides information on the "health" of ET.

With this index, it will be possible to evaluate the state of a large population of distribution transformers and group them according to the state. Introducing this concept will increase availability and reliability while reducing maintenance costs. The assessment of the condition of the ET should include an assessment of the condition of the key parts: magnetic core and coil, solid insulation and insulating oil, bushings and voltage regulators, cooling system, transformer tank, expansion tank, and auxiliary equipment. The assessment is based on the results obtained by applying appropriate test methods in the field of chemical and electrical testing and visual inspection as well as evaluation of load histories [28]. For each of these parts, the health indices as well as the health index ET must be determined.

Given that the assessment of the condition of an ET is based on the following [29]:

(i) Results of electrical and chemical tests

(ii) Maintenance information

(iii) Work history—exploitation events

(iv) Condition of equipment: isolators, cooling system, transformer tank, expansion tank, and auxiliary equipment

(v) The estimated condition of the paper insulation

(vi) Expert opinion

HI represents the sum of these estimates. It is very important to view the health index as a variable parameter because by performing a multiparameter analysis of the condition, it changes over the life of the ET [30].

2.2. Weighting Factors of Examination Methods. Based on the previous analysis, the calculation of the transformer HI in the proposed methodology includes an assessment of the condition of its key parts listed in Table 1. Each part of the ET is assigned a weight factor W_d based on the impact it has on the overall condition of the ET. The impact of part of the ET was also estimated according to the current statistics of the place of occurrence of failure in the ET [31]. Weighting factors are given based on experience and can take the integer value from 1 to 5, as shown in Table 1. The source of weighting factor values for transformer components was the industry practice, established mostly by the experts of the Electrotechnical institute, "Nikola Tesla." The condition monitoring and assessment is performed for the long time period (more than 40 years in Electric Power Industry of Serbia), and the factors are the result of accumulated practice and experience, reflecting the local market characteristics and operating practice.

Different test methods are used to evaluate the condition of each part of the ET mentioned in Table 1. Some parts are joined by a group of appropriate test methods, each corresponding to a weight factor $W_m = (1–5)$, depending on how accurately the results of that method can describe the state of part ET (Table 2).

Since the DGA analysis of the transformer oil sample may indicate a problem of overheating or the occurrence of particles, but it cannot reliably define the location of the resulting fault, it is singled out as special. This limited its impact on the value of total HI but not on specific components, such as windings or cores.

2.3. Overall Health Index. The overall health index of a transformer can be calculated using the following expression:

$$\mathrm{HI} = \frac{\sum_i^n O_{di} \cdot W_{di}}{\sum_i^n W_{di}}. \tag{1}$$

In expression (1), n corresponds to the number of test methods for which there are applicable results and which assess the state of a given system. O_{di} is a grade for each individual i-th ET part in the range $0 \le O_{di} \le 3$ calculated in the following:

$$O_d = \frac{\sum_{i=1}^n O_{mi} \cdot W_{mi}}{\sum_1^n W_{mi}}. \tag{2}$$

Table 1: Weighting factors for different ET components.

No	ET component	Weighting factor (W_d)
1	Magnetic core	3
2	Geometry end electric contacts of windings	4
3	Insulation	4
4	Bushings	5
5	On-line tap changer	5
6	DGA analysis for the active part	5
7	Transformer oil	4
8	Transformer tank and auxiliary equipment	2
9	Work history	3

The estimation of the O_m method is given by an expert on the basis of the results of the last and previous tests, experience, and specificity of individual ETs and using the criteria given in the applicable standards and technical recommendations. The possible range is $0 \le O_m \le 3$. Alternatively, HI can be calculated with expression (3) using different weighting factors for the on-load tap changer or including the transformer loading history [7]:

$$\mathrm{HI} = A_1 \cdot \frac{\sum_{i=1}^{n=3} c_i \cdot \mathrm{DI}_i}{\sum_{i=1}^{n=3} 4 \cdot c_i} + A_2 \frac{\sum_{i=1}^{n=3} c_i \cdot \mathrm{DI}_i}{\sum_{i=1}^{n=3} 4 \cdot c_i}. \quad (3)$$

A_1 and A_2 represent the weighting factors for the transformer and load tap changer, respectively, while DI_i represents the diagnostic index of the ith ET component. The state estimates for electrical measurements are given in descriptive terms: "good condition," "moderately good," "moderately bad," and "poor." The corresponding estimates for the health index calculation are 3, 2, 1, and 0, as shown in Table 3.

The "moderately good" rating indicates dubious results but without major changes over time, e.g., comparing the last two to three trials and continuing the follow-up with more frequent testing. On the contrary, the rating "moderately bad" indicates a growing trend of deterioration of the transformer state, and it tightens control by more frequent testing, recommends additional testing, or emphasizes the need to plan for a specific intervention in the coming period.

Because of the irregular inspection period, it is hard to perform accurate yearly ET condition assessment. Some data may be several years old, and the main problem in interpretation is the lack of confidence of testing results. The validity of results can be treated by the similar grading system (from 0 for results older than the maximal inspection period and 3 for actual measurement results). The validity of the i-th transformer component V_{Ei} with n inspection methods is given in the following:

$$V_{Ei} = \frac{\sum_{j=1}^{n} V_{Mj}}{n}. \quad (4)$$

Then, the HI value composed of m components, calculated from equation (3), can be corrected with the validity of results (5):

$$\mathrm{HI}_v = \mathrm{HI} \cdot \frac{\sum_{i=1}^{m} V_{Ei}}{m}. \quad (5)$$

Because this treatment of old measurements is very simplified and not based on the complete transformer aging model, the ET condition must be represented as a probability distribution over all possible health states. In this paper, this distribution is determined using the Markov chain model of component ageing, and evidential reasoning is used for the quantification of different parameters. The integrated methodology is presented in the sequel.

3. Integrated Assessment Methodology

3.1. Evidential Reasoning Algorithm. To evaluate the state of a power transformer, large amount of qualitative and numerical information needs to be interpreted on different hierarchical levels. The ER approach is a suitable method for dealing with the aggregation problem, and the original ER model and algorithm, based on Dempster–Shafer theory [18], are described next.

In a two-level hierarchy of attributes with a general attribute at the top level and L basic attributes at the lower level e_i ($i = 1, \ldots, L$), it is possible to define a set of low-level attributes as follows:

$$E = \{e_i, \ldots, e_i, \ldots, e_L\}. \quad (6)$$

The weights of the attributes are presented by $\omega = \{\omega_1, \ldots, \omega_i, \ldots, \omega_L\}$, where ω_i is the relative weight of the ith lower-level attribute (e_i) with value between 0 and 1 ($0 \le \omega_i \le 1$). The evaluation grades are represented by the following:

$$\{H_1, \ldots, H_n, \ldots, H_N\}. \quad (7)$$

It is assumed that H_{n+1} is preferred to H_n.

The methodology for the evaluation grades for transformer components presented in Table 2 is given in [8]. For the sake of illustration, the grading of solid insulation is given in Table 4.

An assessment for the ith basic attribute e_i may be represented by the following distribution:

$$S(e_i) = \{(H_n, \beta_{n,i}), n = 1, \ldots, N\}, \quad i = 1, \ldots, L, \quad (8)$$

where $\beta_{n,i}$ denotes the degree of belief and $\beta_{n,i} \ge 0$, $\sum_{n=1}^{N} \beta_{n,i} \le 1$. If $\sum_{n=1}^{N} \beta_{n,i} = 1$, then assessment $S(e_i)$ is complete. In the opposite case, assessment $S(e_i)$ is incomplete. Equation (9) denotes a complete lack of information on e_i:

$$\sum_{n=1}^{N} \beta_{n,i} = 0. \quad (9)$$

Let H_n be a grade to which the general attribute is assessed with certain degree of belief β_n. The problem is to generate β_n by aggregating the assessments for all associated basic attributes e_i. For this purpose, the following algorithm is used.

Let $m_{n,i}$ be a basic probability mass representing the degree to which basic ith attribute e_i supports judgment that the general attribute y is assessed to the grade H_n,

Table 2: Weighting factors of different inspection methods.

ET component	Inspection method	Weighting factor (W_m)
Magnetic core	Open-circuit test/SFRA	5
Geometry end electric contacts of windings	Resistance testing	5
	Leakage inductance test/SFRA	5
Insulation	Insulation resistivity/tgδ and capacitance test	5
	PDC/RVM/FDS/water content in oil	4
	Furan derivative analysis	3
Bushings	tgδ and capacitance	4
On-line tap changer	Static/dynamic resistance testing	5
DGA analysis for the active part	Dissolved gas analysis (DGA)	4
Transformer oil	Physical and chemical oil characteristics	5
	Content of water in oil	4
Transformer tank and auxiliary equipment	Testing of cooling system and auxiliary equipment	2
	Visual inspection/leakage control	2
Work history	Loading and operation history	3

Table 3: Comparison of electrical and chemical test scores with appropriate numerical estimates for health index calculations.

Test results	HI
Good condition	3
Moderately good	$2 \le \mathrm{HI} < 3$
Moderately bad	$1 \le \mathrm{HI} < 2$
Poor	<1

Table 4: The evaluation grades for solid insulation.

Dielectric losses	Insulation state	H_n
tg$\delta \le 1\%$	Good condition	3
$1\% <$ tg$\delta \le 1.5\%$	Moderately good	2
$1.5\% <$ tg$\delta \le 2\%$	Moderately bad	1
tg$\delta > 2\%$	Poor	0

respectively; let $m_{H,i}$ be a remaining probability mass unassigned to any individual grade after all the N grades, concerning the e_i attribute, are considered. Next expression explains how basic probability mass is calculated:

$$m_{n,i} = \omega_i \beta_{n,i}, \quad n = 1, \ldots, N, \tag{10}$$

$$\sum_{n=1}^{N} \omega_n = 1. \tag{11}$$

Remaining probability mass is calculated as

$$m_{H.i} = 1 - \sum_{n=1}^{N} m_{n,i} = 1 - \omega_i \sum_{n=1}^{N} \beta_{n,i}. \tag{12}$$

Suppose that $E_{I(i)}$ is a subset of the first i attributes $E_{I(i)} = \{e_1, e_2, \ldots, e_i\}$, and according to that, $m_{n,I(i)}$ can be the probability mass defined as the degree to which all the i attributes support the judgment that y is assessed to the grade H_n. Also, $m_{H,I(i)}$ is the remaining probability mass unassigned to individual grades after all the basic attributes in $E_{I(i)}$ have been assessed. Probability masses $m_{n,I(i)}$ and $m_{H,I(i)}$ for $E_{I(i)}$ can be calculated from basic probability masses $m_{n,j}$ and $m_{H,j}$ for all $n = 1, \ldots, N$, $j = 1, \ldots, i$. Concerning all the above statements, the original recursive evidential reasoning algorithm can be summarized by the following expressions:

$$m_{n,I(i+1)} = K_{I(i+1)}\left(m_{n,I(i)} m_{n,i+1} + m_{n,I(i)} m_{H,i+1} + m_{H,I(i)} m_{n,i+1}\right), \quad n = 1, \ldots, N, \tag{13}$$

$$m_{H,I(i+1)} = K_{I(i+1)} m_{H,I(i)} m_{H,i+1}, \tag{14}$$

$$K_{I(i+1)} = \left[1 - \sum_{t=1}^{N} \sum_{\substack{j=1 \\ j \neq t}}^{N} m_{t,I(i)} m_{j,i+1}\right]^{-1}, \quad i = 1, \ldots, L-1, \tag{15}$$

where $K_{I(I+1)}$ is a normalizing factor so that $\sum_{n=1}^{N} m_{n,I(i+1)} + m_{H,I(i+1)} = 1$ is ensured. It is important to note that basic attributes in $E_{I(i)}$ are numbered arbitrarily and that initial values are $m_{n,I(1)} = m_{n,1}$ and $m_{H,I(1)} = m_{H,1}$. And finally, in the original evidential reasoning algorithm, combined degree of belief for a general attribute β_n is given by

$$\beta_n = m_{n,I(L)}, \quad n = 1, \ldots, N, \tag{16}$$

$$\beta_H = m_{H,I(L)} = 1 - \sum_{n=1}^{N} \beta_n, \tag{17}$$

while β_H denotes the degree of incompleteness of the assessment.

As explained in the introductory section, the hierarchical structure of an ER algorithm proved to be adequate for the condition-based maintenance of the power transformer [18–20]. However, although the process involves decision-making with multiple attribute with uncertainty, very little attention was paid to the determination of degrees of belief $\beta_{n,i}$. As the deterioration process from the last inspection can be easily modelled with the appropriate probability distribution, the methodology presented in this paper is using Markov chain modelling of component ageing for the assessment of this parameter. The single grade for the HI can

also be calculated using the concept of average expected utility [21]. The concept of expected utility is used to define equivalent numerical values. If $u(H_n)$ is the utility of the grade H_n with $u(H_n+1) > u(H_n)$ if H_n+1 is preferred to H_n, then the maximum, minimum, and the average expected utilities on y are given by

$$u_{\max}(y) = \sum_{n=1}^{N-1} \beta_n u(H_n) + (\beta_N + \beta_H) u(H_N),$$
$$u_{\min}(y) = (\beta_1 + \beta_H) u(H_1) + \sum_{n=2}^{N} \beta_n u(H_n), \tag{18}$$
$$u_{\text{avg}}(y) = \frac{u_{\max}(y) - u_{\min}(y)}{2}.$$

3.2. Markov Chain Modelling of Component Ageing. The process of transition from state to state can be represented by the diagram given in Figure 1. H_3 through H_0 represent the health status of the transformer according to the established health index. The λ_{ij} labels indicate the transition rates from state i to state j. If we assume that the transition rates are constant over a period of time, the time of transition from one state to another follows an exponential distribution, and the diagram would represent the Markov process. The same analysis is valid for the individual transformer component according to the analysis in the previous chapter.

The exponential probability distribution (19) is one of the most significant distributions in the reliability analysis:

$$F(X) = \begin{cases} 1 - \exp(-\lambda \cdot x), & x \geq 0, \\ 0, & x < 0. \end{cases} \tag{19}$$

The failure intensity of this distribution is a constant value, and the time to failure is independent of the operating time of the equipment being observed. By using Markov transition diagrams, degrees of belief in terms of ER methodology can be modelled in the following way. Let the measurement and inspection results indicate the health state Hi. After the period t since the last measurement, the probability that the component remained in the same state (P_{ii}) or transitioned to the state j (P_{ij}) can be represented by the following transition matrix:

$$P = \begin{bmatrix} P_{33} & P_{32} & P_{31} & P_{30} \\ 0 & P_{22} & P_{21} & P_{20} \\ 0 & 0 & P_{11} & P_{10} \\ 0 & 0 & 0 & 1 \end{bmatrix}. \tag{20}$$

An n-step transition probability $P(n)$ denotes the probability that n time units later the chain will be in state j given it is now in state i (21):

$$P(n) = P^n = P \times P \times \cdots \times P, \quad n \geq 1. \tag{21}$$

The intensity of leaving the state is equal to the sum of the transitions from the state to the other states of the system so that

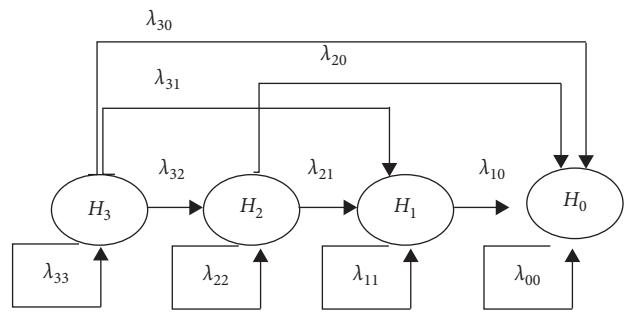

Figure 1: State transition scheme.

$$\lambda_{ii} = -\sum_{\substack{k=1 \\ k \neq i}}^{n} \lambda_{ki}. \tag{22}$$

λ_{ki} is the intensity of transition from state to state k and λ_{ii} is the intensity of leaving the state and with a negative sign.

Exponential distribution has one important feature that allows relatively simple modelling of systems with exponential residence time distributions in characteristic states. The probability that the system that is on state in t_1 is likely to transition to another state over a period of time (t_1, t_2) is

$$P\{(T \leq t_2) \mid (T > t_1)\} = 1 - \exp\left(-\int_{t_1}^{t_2} \lambda \mathrm{d}t\right) = 1 - \exp(-\lambda \cdot (t_2 - t_1)). \tag{23}$$

As can be seen from the previous relation, the considered probability depends solely on the length of time interval for which the probability is calculated and not on the length of stay in the previous state. If the time interval is very short, an approximate replacement of the exponential function is obtained from the previous relation:

$$P\{(T \leq t_2) \mid (T > t_1)\} \cong \lambda \cdot (t_2 - t_1). \tag{24}$$

Using the statistical data from the transformer history, the intensities of transition from state i to state j (λ_{ij}) are calculated based on the following relation:

$$\lambda_{ij} = \frac{1}{\sum t_{ij}/n_{ij}}, \tag{25}$$

where n_{ij} represents the number of transitions from state i to j, while t_{ij} represents the average number of years staying in state i before the transition to j.

The algorithm for the ET assessment can be presented in the following steps and graphically presented in Figure 2.

Step 1: define a set of L inspection methods (basic attributes) influencing the assessment of the ET component state (upper-level attribute)

Step 2: for each attribute, determine the transition probability matrix (22) for different health states

Step 3: depending on inspection accuracy and time, ε_i, and evaluation grade H_n, a degree of belief β_n is assigned for each attribute

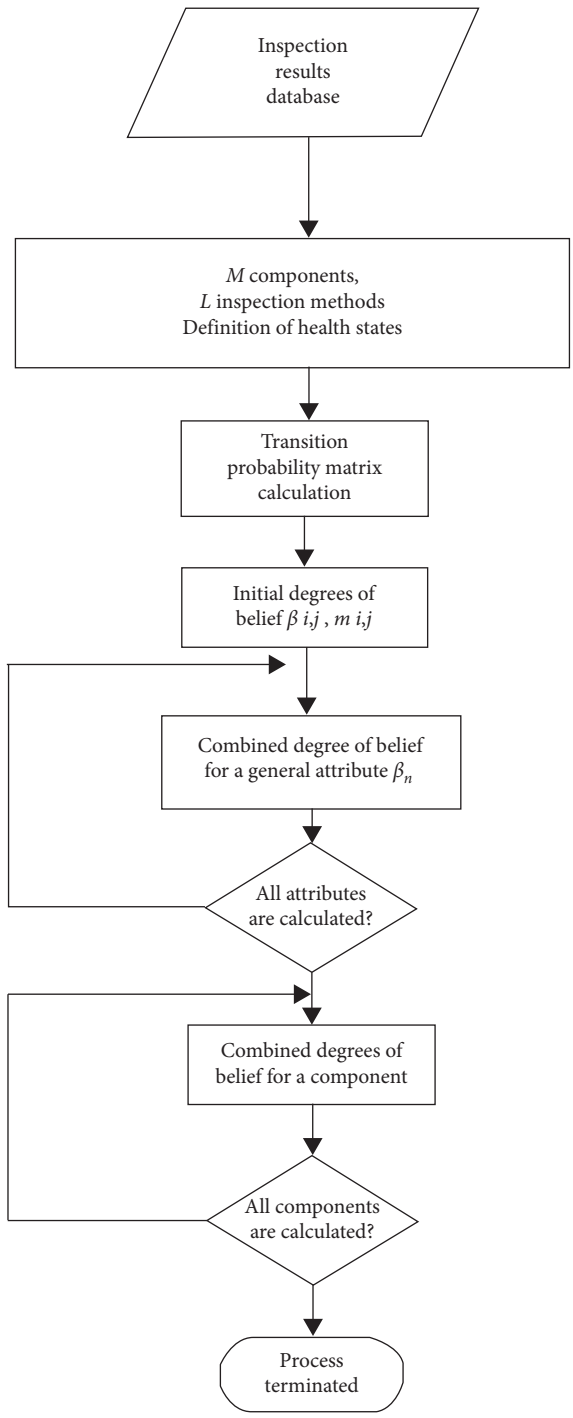

Figure 2: State transition scheme.

Step 4: $m_{n,i}$, a basic probability mass, representing the degree to which the ith inspection method ε_i supports a hypothesis that the health index is assessed to the nth evaluation grade H_n is calculated

Step 5: the combined probability masses are generated by aggregating all the basic probability assignments using the recursive ER algorithm

Step 6: calculate the combined degrees of belief for a higher-level property

The proposed methodology will be illustrated on individual transformer health estimation and on comparative estimation of 30 transformers operating in EPS (Electric Power Industry of Serbia).

4. Case Studies

The fleet of 344 transformers of 110 kV primary voltage operating in EPS was monitored during 10 years period

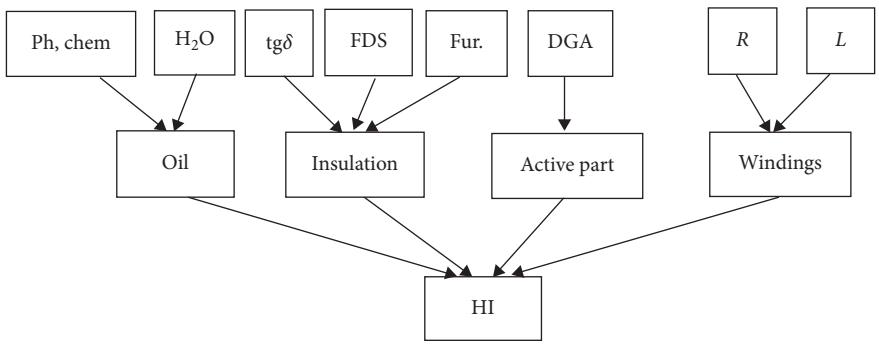

Figure 3: Hierarchical scheme for transformer HI assessment.

Table 5: Initial data for the degrees of belief calculation.

	Oil			Insulation		Active part	Windings	
W_d	0.24			0.24		0.28	0.24	
W_m	0.55	0.45	0.41	0.34	0.25		0.5	0.5
H_i	Phys, chem (β_i, 1)	H_2O (β_i,2)	tgδ (β_i,1)	FDS (β_i,2)	Furan (β_i,3)	DGA (β_i)	R (β_i,1)	L (β_i,2)
3	0.75	0	0	0	0.8	0	0.5	0.5
2	0.14	0.8	0	0	0	0.9	0.3	0.3
1	0.08	0.2	0.8	0	0	0	0	0
0	0.02	0	0	0	0	0	0	0

(2008–2018). Transition probabilities are derived from the measurement databases consisting of more than 10,000 measurements of 18 main transformer components. The proposed methodology will be illustrated on the individual transformer health assessment (Case 1) and the ranking of a sample of 30 transformers (Case 2).

4.1. Case 1. The methodology for the condition assessment will be applied to the existing transformer 110/35/10 kV, 20/20/10MVA. Starting from a complete model presented in Tables 2 and 3, a reduced model concerning only the main transformer parts without the on-line tap changer is presented in Figure 3.

Initial data with the available measurements, together with weighting factors for ET component (W_i) and testing method (W_m), are presented in Table 5. Starting from values in Tables 2 and 3, factors are normalized to fulfill condition (11). Because of different dates of inspection methods, different degrees of belief are presented in the table. The degree of belief denotes the source's level of confidence when assessing the level of fulfillment of a certain property. For instance, due to the lack of frequency domain spectroscopy (FDS) test, all belief values equal to zero. For the sake of illustration, the transition intensity matrix for the physical/chemical oil characteristics $\lambda_{P,C}$ (1/year) obtained from the 10-year period is given in the following:

$$\lambda_{P,C} = \begin{bmatrix} 0,75 & 0,14 & 0,08 & 0,02 \\ 0 & 0,82 & 0,17 & 0,01 \\ 0 & 0 & 0,8 & 0,2 \\ 0 & 0 & 0 & 1 \end{bmatrix}. \quad (26)$$

The physical/chemical characteristics have been inspected two years ago, and the state of oil has been graded as "good." Using expressions (23) and (24), the probabilities that the oil characteristics are in the states 3, 2, 1, and 0 are 0.75, 0.145, 0.08, and 0.02, respectively.

Recursively using equations (13)–(17) for the aggregation of probability masses for individual inspection method, probability masses for individual ET component are obtained and represented in Table 6. For instance, assessment of transformer oil for the grade H_3 = "good," H_2 = "moderately good," H_1 = "moderately bad," and H_0 = "poor," equals 0.17, 0.44, 0.045, and 0, respectively.

With the values calculated in step 3, we get the combined degrees of belief for H_3 = "good," H_2 = "moderately good," and H_1 = "moderately bad" which equal to 0.32, 0.175, and 0.08, respectively. The average HI, obtained from (19)–(21) is $\mathrm{HI}_{\mathrm{avg}} = 2.03$.

Using the traditional HI calculation method, using the data from Table 7 and equation (2), the grade O_d for oil, insulation, active part, and windings equals 2.56, 1.75, 2, and 3, respectively. Using equation (3), the value of the HI is given in the following:

$$\mathrm{HI} = \frac{\sum_1^4 O_{di} \cdot W_{di}}{\sum_1^4 W_{di}} = \frac{4 \cdot 2,56 + 4 \cdot 1,75 + 5 \cdot 2 + 4 \cdot 3}{17} = 2,3. \quad (27)$$

4.2. Case 2. The estimation of HI was performed on a sample of 30 distributive energy transformers. The complete transformer model with the elements in Table 2 is used. The first estimation was made by experts, who gave an assessment on the basis of existing electrical and chemical tests,

Table 6: The degrees of belief of the main transformer components.

	3	2	1	0	$m_{H,i}$
Oil	0.17	0.44	0.045	0	0.345
Insulation	0.062	0	0.14	0	0.8
DGA	0	0.252	0	0	0.748
Windings	0.153	0.07	0	0	0.777

Table 7: Transformer assessment using the traditional HI.

	Oil			Insulation		Active part	Windings	
W_d	4			4		5	4	
W_m	5	4	5	4	3		5	5
	Phys, chem	H_2O	tgδ	FDS	Furan	DGA	R	L
O_m	3	2	1	—	3	2	3	3

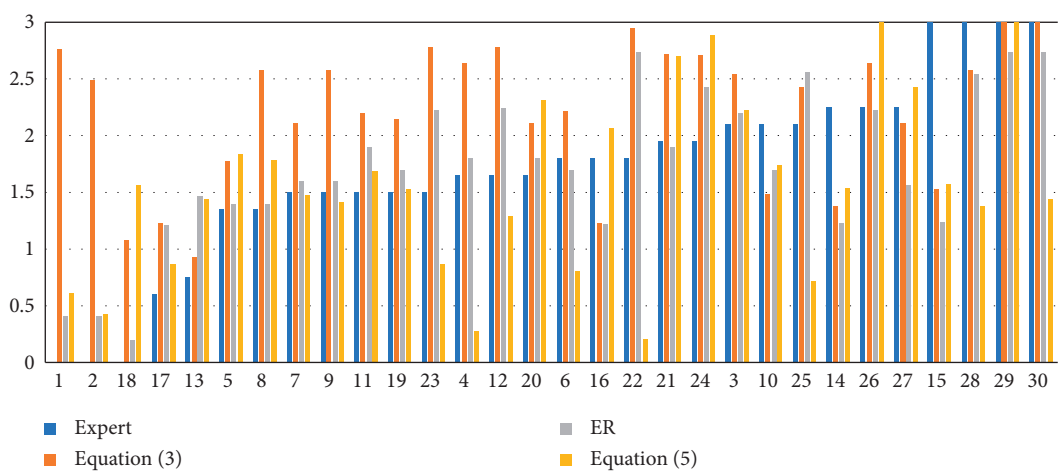

Figure 4: HI obtained by different assessment methods.

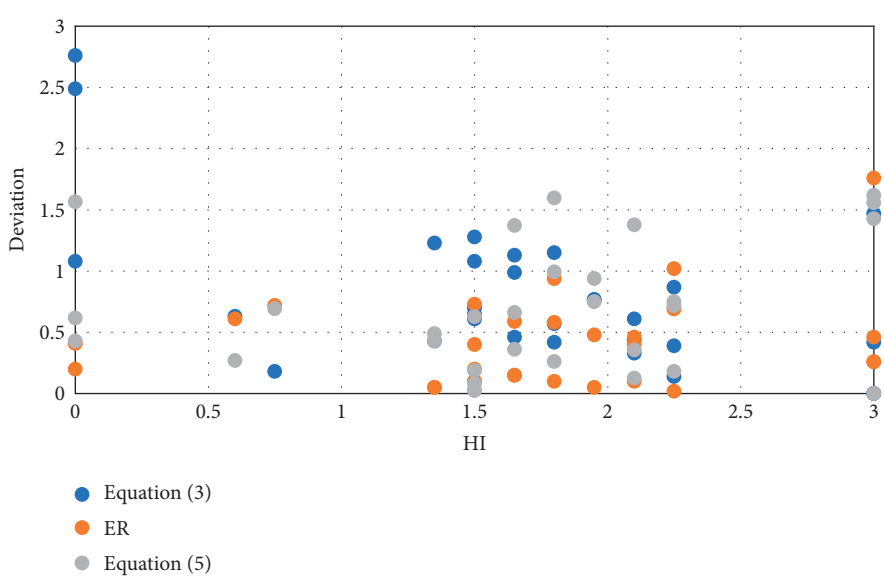

Figure 5: Deviations of the real health values from the HI obtained by the ER method.

Table 8: Inspection grades and assessment results.

		Magnetic core 3		Geometry end electric contacts of windings, 4		Insulation, 4		Bushings, 5		On-line tap changer, 5		Oil, 4		DGA, 5		Tank, 2		HI [0–3]	Total HI [0–100%]	Validity ažurnost	Expert	Equation (3)	ER	E 5	Dev equation (3)	Dev ER	Dev equation (5)
		HI	*V*	HI	*V*	HI	*V*	HI	*V*	HI	*V*	HI	*V*	HI	*V*	HI	*V*										
1	1983	3	10	2.5	10	3	6.67	0	10	3	10	1.44	10	3	10		0	**0.74**	**24.67**	**83.34**	0	2.76	0.41	0.616716	2.76	0.41	0.616716
2		3	5	1.5	2.5	3	6.67	0	0	3	0	3	10	3	10	3	10	**0.78**	**26**	**55.21**	0	2.49	0.41	0.430638	2.49	0.41	0.430638
18	1986	3	10	3	10	2.67	10		0	1	10	3	10	3	10	3	10	**1.79**	**59.67**	**87.5**	0	1.08	0.2	1.56625	1.08	0.2	1.56625
17	1979	3	10	1.5	5	3	6.67	3	10	3	0	3	5	3	0		0	**1.9**	**63.33**	**45.84**	0.6	1.23	1.21	0.87096	0.63	0.61	0.27096
13	1958	3	10	3	10	2	10		0	1	10	2	10	3	10	2.56	10	**1.65**	**55**	**87.5**	0.75	0.93	1.47	1.44375	0.18	0.72	0.69375
5	1969	3	10	3	10	3	10	3	10	1	10	3	10	3	10	3	10	**1.84**	**61.33**	**100**	1.35	1.78	1.4	1.84	0.43	0.05	0.49
8	1972	3	10	3	10	2.67	8.33	3	10	1	10	3	10	3	10	3	10	**1.82**	**60.67**	**97.91**	1.35	2.58	1.4	1.781962	1.23	0.05	0.431962
7	1968	3	10	2.5	10	2.38	6.67	1	0	3	10	3	10	3	10	3	10	**1.77**	**59**	**83.34**	1.5	2.11	1.6	1.475118	0.61	0.1	0.024882
9	1962	2	10	1.25	10	1.42	10		0	3	10	2	10	3	10	3	10	**1.62**	**54**	**87.5**	1.5	2.58	1.6	1.4175	1.08	0.1	0.0825
11	1978	3	10	3	10	3	10		0	3	10	3	10	3	10	1.22	10	**1.93**	**64.33**	**87.5**	1.5	2.2	1.9	1.68875	0.7	0.4	0.18875
19	1972	3	10	3	10	3	10		0	1	10	2.44	10	3	10	2.44	10	**1.75**	**58.33**	**87.5**	1.5	2.15	1.7	1.53125	0.65	0.2	0.03125
23	1989	3	10	1.5	5	3	6.67	3	10	3	0	3	5	3	0		0	**1.9**	**63.33**	**45.84**	1.5	2.78	2.23	0.87096	1.28	0.73	0.62904
4	1971		0	3	0	2.33	6.67	3	10	0	0	1.44	5	3	10		0	**0.7**	**23.33**	**39.59**	1.65	2.64	1.8	0.27713	0.99	0.15	1.37287
12	1988		0	3	5	3	6.67	3	10	3	10	3	5	2	0		0	**2.81**	**93.67**	**45.84**	1.65	2.78	2.24	1.288104	1.13	0.59	0.361896
20	2013		0	3	5	3	6.67	3	10	3	10	3	10	3	10	3	10	**3**	**100**	**77.09**	1.65	2.11	1.8	2.3127	0.46	0.15	0.6627
6	1968		0		0	3	5	3	5		0	1.44	10	3	10	3	5	**1.84**	**61.33**	**43.75**	1.8	2.22	1.7	0.805	0.42	0.1	0.995
16	1980		0	3	5	3	10	3	10	3	10	3	10	3	10		0	**3**	**100**	**68.75**	1.8	1.23	1.22	2.0625	0.57	0.58	0.2625
22	1971	0	10	0	10	0.58	6.67		0	3	10	3	5	0	0		0	**0.39**	**13**	**52.09**	1.8	2.95	2.74	0.203151	1.15	0.94	1.596849
21	1965	3	10	2.5	10	3	10	3	10	2	10	2.56	10	3	10	2.56	10	**2.7**	**90**	**100**	1.95	2.72	1.9	2.7	0.77	0.05	0.75
24	1968	3	10	3	10	2.67	10	3	10	3	10	2.44	10	3	10	3	10	**2.89**	**96.33**	**100**	1.95	2.71	2.43	2.89	0.76	0.48	0.94
3	1978	3	10	3	10	3	10		0	3	10	3	10	3	0	2.56	10	**2.97**	**99**	**75**	2.1	2.54	2.2	2.2275	0.44	0.1	0.1275
10	1982	3	10	1.5	5	2.67	10	3	10	3	10	2.56	10	3	10	3	10	**1.86**	**62**	**93.75**	2.1	1.49	1.7	1.74375	0.61	0.4	0.35625
25	1980	3	10	1.5	5	3	6.67	2	5	3	0	3	5	3	0		0	**1.82**	**60.67**	**39.59**	2.1	2.43	2.56	0.720538	0.33	0.46	1.379462
14	1954	3	10	3	10	1.46	6.67		0	3	10	2.44	10	3	10	3	10	**1.84**	**61.33**	**83.34**	2.25	1.38	1.23	1.533456	0.87	1.02	0.716544
26	1986	3	10	3	10	3	10	3	10	3	10	3	10	3	10	3	10	**3**	**100**	**100**	2.25	2.64	2.23	3	0.39	0.02	0.75
27	1974	3	10	3	10	2.58	10	3	10	3	10	3	10	2	10		0	**2.78**	**92.67**	**87.5**	2.25	2.11	1.56	2.4325	0.14	0.69	0.1825
15		3	10	2.5	10	3	3.33	3	10	3	10		0		0		0	**2.9**	**96.67**	**54.16**	3	1.53	1.24	1.57064	1.47	1.76	1.42936
28	1978	3	10	3	10	2.58	10		0	3	10	1.44	10	3	10		0	**1.84**	**61.33**	**75**	3	2.58	2.54	1.38	0.42	0.46	1.62
29	1978	3	10	3	10	3	10	3	10	3	10	3	10	3	10	3	10	**3**	**100**	**100**	3	3	2.74	3	0	0.26	0
30	1974	3	10	3	10	3	6.67	3	10	3	10	1	5	3	10		0	**1.87**	**62.33**	**77.09**	3	3	2.74	1.441583	0	0.26	1.558417

i.e., data on maintenance and load history. The results were rechecked during the next two-year period, and their assessment was accepted as the reference value for the benchmarking with two other HI calculation methodologies.

Figure 4 shows the condition estimation of the mentioned sample of 30 transformers obtained by different mathematical models.

The HI is calculated using the proposed ER methodology (denoted ER in Figure 4) and compared with the results obtained using equation (3) and adjusted HI index, taking into account the measurement period (equation (5)). The traditional approach to HI calculation gives the large deviations from the accurate health grades, especially for transformers in poor condition. Because of the lack of certain parameter values, (3) gives far more optimistic values (for transformers 1, 2, 8, and 18). On the contrary, integrated ER methodology gives the results much closer to accurate HI values. Transformers 14 and 15 are rated high with both expert's opinion and equation (3), but the ER methodology gave more pessimistic results, thanks to the lack of accurate data. Equation (5) gives better results than the traditional method, but great variations from the exact values are still present.

Deviations of all ER results from the accurate health state are presented in 5.

Maximal deviations from the exact values are obtained with equation (3). The problem with this methodology is that the nonexistent measurements are simply not taken into account in the calculation. Transformers 1, 2, and 18 have the high HI values although their real condition is alarming (the complete table with the inspection results is given in Table 8). Equation (5) methodology gives smaller deviations that are equally dispersed for all HI values. However, the deviations are still great (above unity) for greater number of transformers. ER methodology gives best results. Only two transformers (14 and 15) have the deviations from the exact values that are greater than 1 point. These transformers were ranked as "good" by the experts, which means that the ER methodology gives the security offset. The deviations for ETs that are ranked as "bad" are much more lower than for other two methods.

5. Conclusions

The main challenge in finding the relation between the HI and all the elements of the calculation is the lack of data. The regular, precisely defined dynamics of the full-scale testing is not present at all power distribution companies. Therefore, there is a difficulty in selecting a mathematical tool to calculate objective transformer state estimates in the absence of some parameters. The integration of evidential reasoning methodology with the Markov chain model of component ageing enables the more accurate estimation of transformer health. The proposed methodology takes the probability that the component remained in the same state or transitioned to another state in a quantitative way.

By calculating the HI for a fleet of transformers in the system, it is possible to rank them according to their current state or HI value. The traditional approaches to HI calculation give the large deviations from the accurate health grades, especially for transformers in poor condition. If the scope of the tests is small and the last tests were performed a long time ago, it is obvious the reliability of the HI is lower. However, the traditional HI methodologies did not give the quantitative evaluation of this reliability. The proposed methodology gives a clear signal that more accurate or full-scale testing should be performed to more accurately assess the current state of the unit. Further research will be focused on the more precise estimation of utility functions, concerning financial losses resulting from the interruption of electricity supply that can be caused by an ET failure or unnecessary inspections.

Data Availability

All the data were generated during the study realized for Electric Power Industry of Serbia. The derived data supporting the findings of this study are available upon request to Srdjan Milosavljevic via smilos@ieent.org.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] J. Schneider, "Asset management techniques," *Electrical Power and Energy Systems*, vol. 28, pp. 643–654, 2006.

[2] P. Żukowski, K. Kierczyński, T. N. Kołtunowicz et al., "Application of elements of quantum mechanics in analysing AC conductivity and determining the dimensions of water nanodrops in the composite of cellulose and mineral oil," *Cellulose*, vol. 26, no. 5, pp. 2969–2985, 2019.

[3] V. Vasovic, J. Lukic, J. Lukic et al., "Aging of transformer insulation - experimental transformers and laboratory models with different moisture contents: part I—DP and furans aging profiles," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 26, no. 6, pp. 1840–1846, 2019.

[4] V. Vasovic, J. Lukic, J. Lukic, D. Mihajlovic et al., "Aging of transformer insulation of experimental transformers and laboratory models with different moisture contents: part II—moisture distribution and aging kinetics," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 26, no. 6, pp. 1847–1852, 2019.

[5] V. Vasovic, D. Mihajlović, J. Janković, and J. Lukić, "Evaluation of paper insulation of power transformers based on the content of 2-furfural in mineral oil corrected to a reference temperature of 20°C," *Zbornik Radova Elektrotehnicki Institut Nikola Tesla*, vol. 29, pp. 45–56, 2019.

[6] P. Żukowski, T. N. Kołtunowicz, K. Kierczyński et al., "Dielectric losses in the composite cellulose–mineral oil–water nanoparticles: theoretical assumptions," *Cellulose*, vol. 23, no. 3, pp. 1609–1616, 2016.

[7] A. Jahromi, R. Piercy, S. Cress, J. Service, and W. Fan, "An approach to power transformer asset management using health index," *IEEE Electrical Insulation Magazine*, vol. 25, no. 2, pp. 20–34, 2009.

[8] B. Gorgan, P. V. Notingher, V. L. Badicu, and G. Tanasescu, "Calculation of power transformers health indexes," *Annals of*

the University of Craiova, Electrical Engineering Series, vol. 34, pp. 13–18, 2010.

[9] M. Vermeer, J. M. Wetzer, P. C. J. M. van der Wielen, E. de Haan, and E. de Meulemeester, "Asset-management decision-support modeling, using a health and risk model," in *Proceedings of the IEEE Eindhoven PowerTech*, Eindhoven, Netherlands, June 2015.

[10] P. Bohatyrewicz, J. Płowucha, and J. Subocz, "Condition assessment of power transformers based on health index value," *Applied Sciences*, vol. 9, no. 22, p. 4877, 2019.

[11] A. Azmi, J. Jasni, N. Azis, and M. Z. A. A. Kadir, "Evolution of transformer health index in the form of mathematical equation," *Renewable and Sustainable Energy Reviews*, vol. 76, pp. 687–700, 2017.

[12] A. Alqudsi and A. El-Hag, "Application of machine learning in transformer health index prediction," *Energies*, vol. 12, no. 14, p. 2694, 2019.

[13] K. Benhmed, A. Mooman, A. Younes, K. Shaban, and A. El-Hag, "Feature selection for effective health index diagnoses of power transformers," *IEEE Transactions on Power Delivery*, vol. 33, no. 6, pp. 3223–3226, 2018.

[14] A. Chatterjee, P. Bhattacharjee, and N. K. Roy, "Mathematical model for predicting the state of health of transformers and service methodology for enhancing their life," *International Journal of Electrical Power & Energy Systems*, vol. 43, no. 1, pp. 1487–1494, 2012.

[15] M. Yahaya, N. Azis, M. Ab Kadir, J. Jasni, M. Hairi, and M. Talib, "Estimation of transformers health index based on the Markov chain," *Energies*, vol. 10, no. 11, p. 1824, 2017.

[16] A. Janjic, Z. Dzunic, and V. Djordjevic, "Distribution network reinforcement planning in uncertain environment using stochastic multi-attribute utility analysis," *Electrical Engineering*, vol. 100, no. 4, pp. 2779–2788, 2018.

[17] A. Janjic, "Distribution network risk assessment using multicriteria fuzzy influence diagram," *Advances in Fuzzy Systems*, vol. 2018, Article ID 1087820, 10 pages, 2018.

[18] G. A. Shafer, *Mathematical Theory of Evidence*, Princeton University Press, Princeton, NJ, USA, 1976.

[19] Z. J. Zhang, J. B. Yang, and D. L. Xu, "A hierarchical analysis model for multi-objective decision making," in *Proceedings of the Analysis, Design and Evaluation of Man–Machine System*, pp. 13–18, Oxford, UK, 1990.

[20] J. B. Yang and M. G. Singh, "An evidential reasoning approach for multiple attribute decision making with uncertainty," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 24, no. 1, pp. 1–18, 1994.

[21] J. B. Yang and D. L. Xu, "On the evidential reasoning algorithm for multi-attribute decision analysis under uncertainty," *IEEE Transactions on Systems, Man and Cybernetics Part A Systems and Humans*, vol. 32, no. 3, pp. 289–304, 2002.

[22] W. H. Tang, K. Spurgeon, Q. H. Wu, and Z. J. Richardson, "An evidential reasoning approach to transformer condition assessments," *IEEE Transactions on Power Delivery*, vol. 19, no. 4, 2004.

[23] J. I. Aizpurua, B. G. Stewart, S. D. J. McArthur et al., "Prognostics & health management methods & tools for transformer condition monitoring in smart grids," in *Proceedings of the Advanced Research Workshop on Transformers*, vol. 6, Cordoba, Spain, October 2019.

[24] A. Shintemirov, W. H. Tang, and Q. H. Wu, "Transformer winding condition assessment using frequency response analysis and evidential reasoning," *IET Electric Power Applications*, vol. 4, no. 3, pp. 198–212, 2010.

[25] R. Liao, H. Zheng, S. Grzybowski, L. Yang, Y. Zhang, and Y. Liao, "An integrated decision-making model for condition assessment of power transformers using fuzzy approach and evidential reasoning," *IEEE Transactions on Power Delivery*, vol. 26, no. 2, pp. 1111–1118, 2011.

[26] G. K. Irungu, A. O. Akumu, and J. L. Munda, "Transformer condition assessment using dissolved gas analysis, oil testing and evidential reasoning approach," in *Proceedings of the 2015 Electrical Insulation Conference (EIC)*, Seattle, WA, USA, June 2015.

[27] F. Tian, Z. Jing, H. Zhao, E. Zhang, and J. Liu, "A synthetic condition assessment model for power transformers using the fuzzy evidence fusion method," *Energies*, vol. 12, no. 5, p. 857, 2019.

[28] E. Duarte, D. Falla, J. Gavin et al., "A practical approach to condition and risk based power transformer asset replacement," in *Proceedings of the 2010 IEEE International Symposium on Electrical Insulation*, June 2010.

[29] F. Scatiggio, A. Fraioli, V. Iuliani, and M. Pompili, *Health Index: the TERNA's Practical Approach for Transformers Fleet Management*, CIGRE, Paris, France, 2014.

[30] N. Dominelli, "Equipment health rating of power transformers," in *Proceedings of the 2004 IEEE International Symposium on Electrical Insulation*, pp. 163–168, Indianapolis, IN, USA, September 2004.

[31] CIGRE, *Life Management Techniques for Power Transformers*, CIGRE, Paris, France, 2003.