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A robust algorithm based on a failure-sensitive matrix for fault diagnosis of power systems: an application on power transformers

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Abstract: In this paper, a robust algorithm for fault diagnosis of power system equipment based on a failure-sensitive matrix (FSM) is presented. The FSM is a dynamic matrix structure updated by multiple measurements (online) and test results (offline) on the systems. The algorithm uses many different artificial intelligence and expert system methods for adaptively detecting the location of faults, emerging failures, and causes of failures. In this algorithm, all data obtained from the power transformer, which have various nonlinear input and output parameters, are processed using the parallel matrix structure of the FSM to reach a global solution quickly. The parameters of a power transformer are used to verify the algorithm under 4 operating conditions simulated in the MATLAB–Simulink program. The obtained results show that the algorithm is convenient for determining incipient failures of a system that consists of multiple parameters.

Key words: Failure–sensitive matrix, fault diagnosis, expert system, monitoring, transformer

1. Introduction

Diagnosis and early detection of faults in a system help to avoid the occurrence of abnormal events and to reduce production loss [1–4]. In recent years, there has been an increasing interest in fault detection, as a result of the increased degree of automation and the growing demand for higher performance, efficiency, reliability, and safety in industrial power systems. Most researchers have focused on finding incipient faults in the systems before they occur, and today's technology allows the monitoring of power systems through many different sensors. In industry, there is a lot of monitoring equipment developed specifically to detect incipient faults that can occur in the systems [5–8]. However, it is important to compose evaluations based on data obtained from the system through various sensors. For this purpose, various methods such as expert systems, heuristic algorithms, fuzzy logic, artificial neural networks, genetic algorithms, and their hybrid models are used to evaluate the obtained data for fault diagnosis and early detection [9–15].

On the other hand, complex industrial systems have many dynamic factors, such as various components, subsystems, the environment, and people. In these systems, any single fault may have multiple propagation paths, which could eventually lead to catastrophic accidents [9,12,16]. In these systems, monitoring data obtained from all systems should be evaluated quickly. According to the results, technical maintenance procedures must then be carried out to avoid any potential faults in the system and resulting economic costs, such as uneconomical operating conditions, unexpected equipment breakdown, unplanned outage, and high insurance

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premiums. In addition, the diagnosis system extends the life of the system by ensuring proper operation of and improvement in system performance and improved reliability, as well as plant availability.

However, early detection and diagnosis of incipient faults with their causes can be difficult, since complex industrial systems have a number of factors including output and input elements. For this purpose, an algorithm called a failure-sensitive matrix (FSM) has been developed using different mathematical rules to evaluate the various parameters and to accelerate the process of early fault detection. The algorithm also correlates between the parameters and the fault's symptoms using artificial intelligence (AI) and expert system (ES) adaptively.

In general, fault diagnostic methods can be classified into 2 categories, model-based and data-driven, as shown in Figure 1. In the model-based approach, fault detection and diagnostic systems can be classified as qualitative or quantitative. Quantitative models are expressed in terms of mathematical functional relationships between the input and output of the system. In contrast, in the qualitative model equations, these relationships are expressed in terms of qualitative functions centered on different units in a process [17–19]. In the data-driven approach, methods that do not assume any form of model information are used, and they rely only on previously processed data. The data-driven approach assumes only the availability of large amounts of previously processed data. The data can be transformed and entered as earlier information in a diagnostic system in different ways.

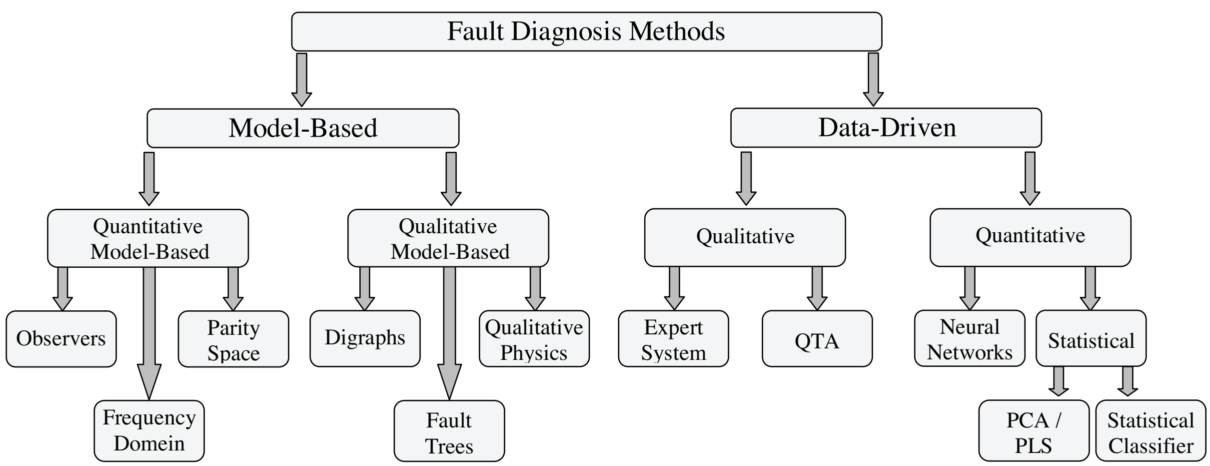

Figure 1. Classification of fault diagnosis method.

All fault diagnosis models have to adapt to a common system consisting of 3 subtasks: to detect the presence of faults in the system through monitoring, determine their locations, and estimate their severity. In general, the following definitions are expressed in the literature [20,21].

- Fault detection: To make a binary decision as to whether everything is fine (nominal) or something has gone wrong (off-nominal).
- Fault isolation: To determine the location of the fault, i.e. to identify which component, sensor, or actuator has become faulty.
- Fault identification: To estimate the severity, type, or nature of the fault.

A monitoring system is necessary to determine the relationship between failure and symptoms as described by Füssel and shown in Figures 2a, the physical system, and 2b, the diagnosis system, as well as to do condition-based maintenance [22]. The condition-based maintenance strategy monitors the condition of the equipment by measuring and analyzing key parameters for the purpose of detecting changes, which may indicate damage or degradation, and recommends optimal maintenance actions.

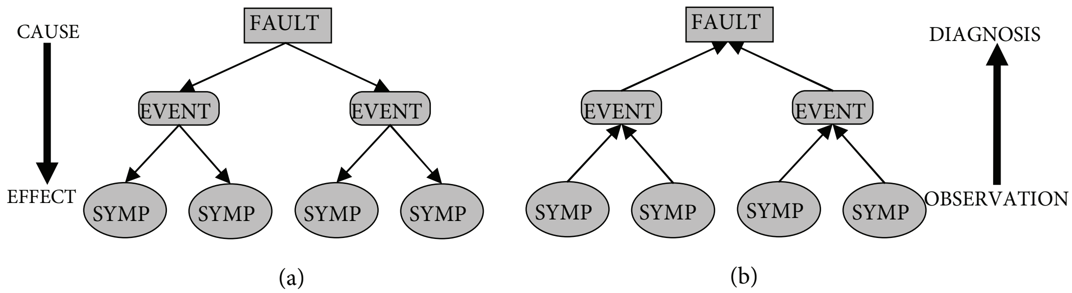

Figure 2. Fault–symptom relationship: (a) physical system, (b) diagnosis system.

Today's industrial systems have many nonlinear parameters related to multiple inputs and outputs. Therefore, evaluation and determination of a fault in these complex systems is not easy for experts. For this reason, different software programs based on monitoring and diagnosis algorithms have been developed by experts. The programs are widely and easily used by engineers to enter input data according to their experience and heuristic knowledge about the system. Various techniques have been reported for fault diagnosis and classification in industrial systems. Widely used techniques are the neural network approach, fuzzy approach, fuzzy neural network, expert systems, heuristic methods, and unique methods such as decision tree, fault tree, Petri nets, fuzzy Petri nets, and Bayesian networks. There are advantages and disadvantages to the methods specified in relation to each other depending on the application field such as data evaluation, fault identification, classification, forecasting, optimization, and planning process [23–32].

Today, the same methods are used together as hybrids to get robust results for fault diagnosis in industrial power systems. In large industrial power systems, the diversity and the complexity of problems are on a large scale. For this reason, the number of fault diagnosis methods used increases. In this case, the system is divided into subsystems and analyzed separately. This is an application that is time-consuming and difficult. In addition, fault probability results that are produced with the selected method(s) will be limited to good results related to the method(s), but will not cover the best global results for the whole system. The developed method, FSM, aims to eliminate such problems.

In this study, the algorithm was tested by various faults made to occur deliberately on a test transformer designed using a DAQ card and program interface. First, outputs of the system are defined according to the limit values, and then they are integrated into the FSM matrix, which combines different monitoring parameters evaluated by expert systems using an interface program. The proposed method and technical details are presented in the following sections. Power transformer prototype structure and instrumentation details are described in the Appendix.

2. The proposed method

In recent applications, mathematical algorithms have been combined with artificial intelligence techniques and methodologies to improve effective analysis. FSM opens a new dimension of fault diagnosis by evaluating multiinput and multioutput data obtained from large and complex industrial systems. The FSM is created by multiplying coefficient matrices and varies over time according to monitoring parameters in dynamic systems. A fault diagnosis algorithm based on the FSM is the common interface used to combine different monitoring parameters, which could be evaluated together by using selected AI and ES methods.

The characteristics of the monitoring systems are different, and some of the instruments have evaluation software using their own algorithms that need an expert system to interpret, test, and/or measure data [11,23]. Separate evaluation of all test and measurement (T&M) data is a disadvantage in large and complex systems, but evaluation of combined data obtained from all of the T&M systems on a single interface gives more effective results for detecting the location of faults, emerging failures, and causes of failures. For this reason, we developed a fault diagnosis algorithm based on the FSM that consists of 5 phases, as shown in Figure 3: a) online and offline data acquisition (T&M groups); b) expert system evaluations; c) creation of coefficient matrices; d) generation of the fault-sensitive matrix; and e) determination of defective components of the system. Both the data taken from the continuous system and the FSM are updated at time intervals. In addition, the processing time is fast due to the nature of the parallel computation caused by the matrix structures.

2.1. Failure-sensitive matrix

The FSM is the common interface for combining different data taken from monitoring equipment on the system and for evaluating all of it together. The FSM is a matrix created by sequential scalar multiplying of coefficient matrices and varies over time according to the monitoring parameters in dynamic systems. In Figure 3, the structure of the FSM is simply presented. Each matrix belongs to a test and measurement group. These submatrices consist of coefficients, and each coefficient row vector $[1 \times m]$ is created with an algorithm developed by human experts using AI and ES methodologies. Although coefficient vectors are similar to the fuzzy rule base, as a whole, the matrices should not be confused with it. Expert systems, fuzzy logic, artificial neural networks, heuristic algorithms, and their hybrid models can be used in the process of creating coefficient vectors. Each coefficient symbolized by C has a fault weight depending on the relationship between fault types and monitoring parameters. Decision vector $[1 \times m]$ means fault probabilities are according to only one test and/or set of measurement data. In this way, monitoring equipment will be used to detect ratings of failure for the other fault types in addition to its main function.

In the structure in Figure 3, the inception matrix size is set on the basis of maximum number of instruments in a T&M group (rows) and number of fault types (columns). In large and complex systems, due to the fact that the numbers of rows and columns depend on the number of components, the size of the FSM will be extensive. The matrices that are obtained from evaluation of the measurement data are multiplied element by element. Therefore, generated coefficients should be equal or greater than 1 $\{\alpha \propto C \Rightarrow \forall C \geq 1\}$. Alpha is $1 \leq \alpha$ and $\alpha \in \mathrm{N}^{+}, \mathrm{N}^{+} = \{1, 2, 3, \ldots\}$ a positive integer. Table 1 gives us the linguistic terms to determine relationships between monitoring parameters and fault types for all methods used in the data evaluation stages.

Table 1. Coefficient ranges.

Linguistic terms for all expert systems	Coefficient range
No relationship	$1\alpha = C$
Minimal relationship	$1\alpha < C < 2\alpha$
Less relationship	$2\alpha \leq C < 2.5\alpha$
Regular relationship	$2.5\alpha \leq C < 3\alpha$
Strong relationship	$3\alpha \leq C < 4\alpha$
Very strong relationship	$4\alpha \leq C < 5\alpha$

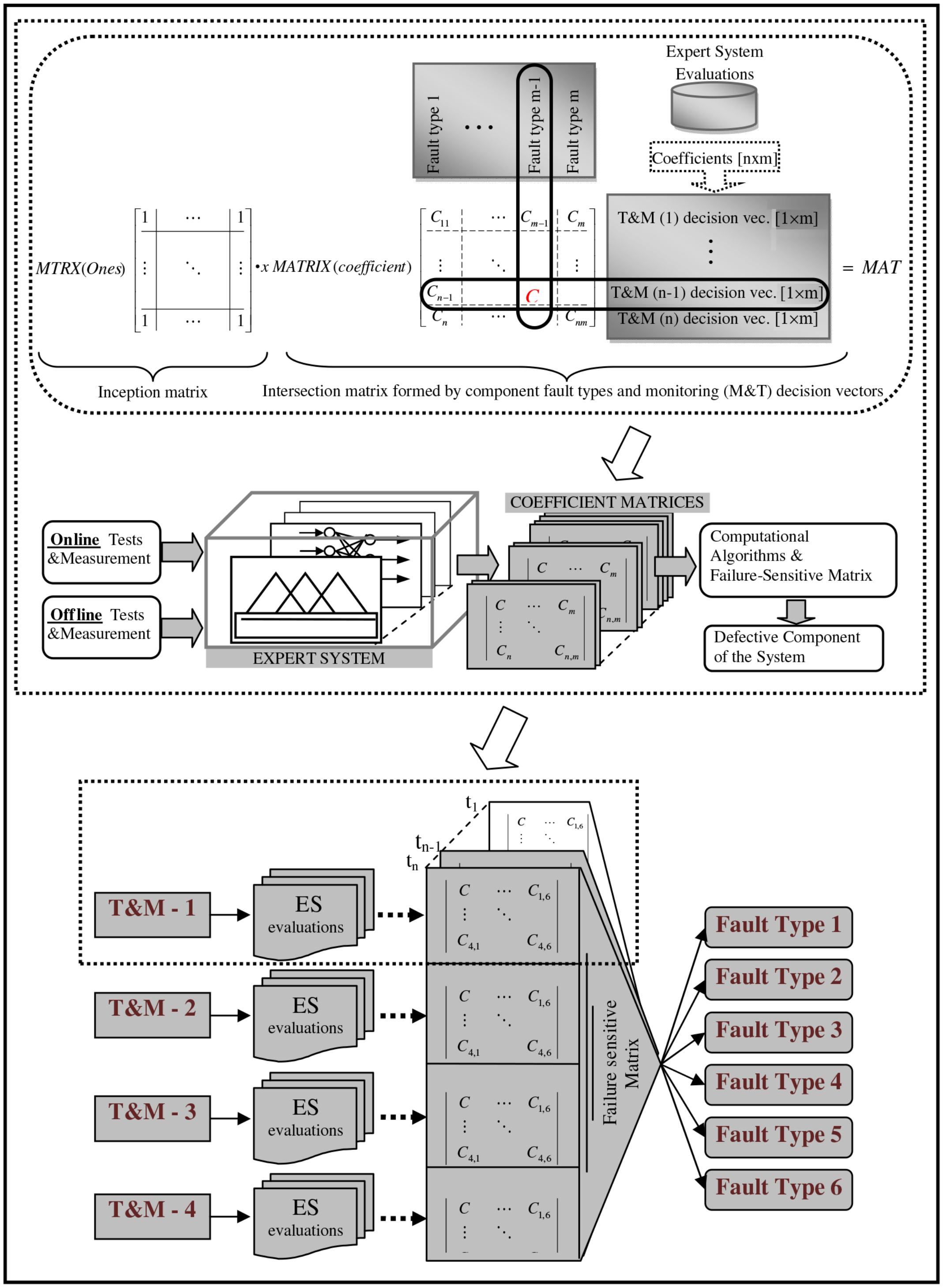

Figure 3. Fault diagnosis algorithm-based structure of failure-sensitive matrix.

The intersection matrix, which is formed by component fault types and monitoring (M&T) decision vectors $i = 1 \ldots n, j = 1 \ldots m$ and $i, j \in N^+ |MAT_k[i : \_] \perp MAT_k[\_ : j]| :\Leftrightarrow C_{ij}$, defines the relationship between T&M results and fault types of related components. Where MAT_k is the matrix consisting of rows

(n) and columns (m), each coefficient, C_{ij}, is weighted by the greatest value obtained in result evaluations according to the fault types. It cannot exceed the limit value, which is defined as in Eq. (1):

$$\left\{ C_{ij_{(k)}} \in MAT_k[nxm] : \forall C_{ij_{(k)}} < (5\alpha)^k \right\}, \tag{1}$$

where k is the number of scalar multiplications computed. The equation of subsensitive matrices consists of the number k, which is the same number as the T&M groups. The equations are written as follows:

$$\begin{gathered} MTRX(Ones)[nxm]. \times MATRIX(C_1)[nxm] = MAT(\mathrm{Pr}_1)[nxm] \\ MAT(\mathrm{Pr}_1)[nxm]. \times MATRIX(C_2)[nxm] = MAT(\mathrm{Pr}_2)[nxm] \\ MAT(\mathrm{Pr}_2)[nxm]. \times MATRIX(C_3)[nxm] = MAT(\mathrm{Pr}_3)[nxm], \\ \vdots \\ MAT(\mathrm{Pr}_{k-1})[nxm]. \times MATRIX(C_k)[nxm] = MAT(\mathrm{Pr}_k)[nxm] \end{gathered} \tag{2}$$

where $MTRX(Ones)[nxm]$ is an inception matrix and $MATRIX(C)[nxm]$ refers to the fault probability coefficient matrix consisting of decision row vectors. $MAT(\mathrm{Pr})[nxm]$ is the fault probability matrix created according to only one T&M group result. The last matrix, $MAT(\mathrm{Pr}_k)[nxm]$, is a failure-sensitive matrix including the effects of all monitoring data obtained from the complex system by the different T&M groups. Notation $(.\times)$ refers to scalar multiplication between matrices. Sometimes, the row numbers in the matrix cannot be equal to each other because of different numbers of T&M groups. In this case, the unit row vector requires equalization of the matrices.

Eq. (3) can be used to find the rating of fault probabilities after the scalar multiplications of the coefficient matrices.

$$Faults[1 \times m] = \left| \sum_{i=1}^{n} MAT_{(k_1)}\ [i:1], \sum_{i=1}^{n} MAT_{(k_2)}\ [i:2], \cdots, \sum_{i=1}^{n} MAT_{(k_m)}\ [i:m] \right| \tag{3}$$

Here, $Faults[1xm]$ is a vector and consists of the cumulative totals of each column related to fault type. The vector gives us all the probabilities of current fault types. The occurrence of all failures is not possible at the same time and/or at an equal rate. Therefore, Eq. (4) is used to find the maximum probability of faults ($Cfj\%$) in the system.

$$Cf_j\% = \left[\left(\frac{\max(Faults\,[1xm]\,)_j}{[TpV]_j} \right)^{1/(k-Cr_j)} \right] \times 100 \tag{4}$$

Here, TpV is a value of maximum probability for the jth fault type, and Crj is an exponential correction coefficient of the jth fault type, which is defined as $\{Cr_j \in \mathrm{N} : 0 \le Cr_j \le k\}$. In case of the absence of significant relationships between T&M results and fault types, the coefficient values are defined as 1 ($Cij := 1$). The exponential correction coefficient Crj is used to correct the result in these situations.

3. Modeling and verification of the algorithm

In order to verify and show the robustness of the algorithm, power transformer equipment has been preferred as a complex system in the power industry. Power transformers used in power plants can be monitored and examined in aspects such as loadability, life extension, aging, dielectric degradation, dielectric breakdown, arcing, discharges, contact failures, cooling performance, etc. At this stage, T&M systems that will be used for related applications have been chosen, and their input parameters have been modeled in MATLAB. The T&M systems should be grouped according to the degree of closeness when considering the fault types. In Figure 3, there are 4 groups of T&Ms, which have different main tasks. The task of each T&M group and the evaluation method used to calibrate the coefficients of FSM are described. T&M methods and related parameters have been evaluated by considering the fault types. In the case of continuous operation of the algorithm, all the T&M parameters would be continuously variable. However, to assess the current processing performance of the algorithm, the parameters that take a certain time (t_n) are used in this section, as shown in Figure 3. In application, the obtained data are updated for certain periods. Thus, when the system is out of service, the last FSM results in memory can be accessed.

As shown in Figure 4, the data are obtained using National Instrument DAQ-16 with 1.25 MS bit/s resolution from the system, which has different outputs. Because the DAQ card has a 0–10 V analog input range, the outputs must be normalized for the range of value. For this purpose, a precircuit card is designed to amplify and to normalize the electrical signal transferred to the DAQ card. Before creation of the FSM matrix, to determine the limit value of the each input and considering the faults, expert systems, fuzzy logic tools, program loops, and a fault tree are used.

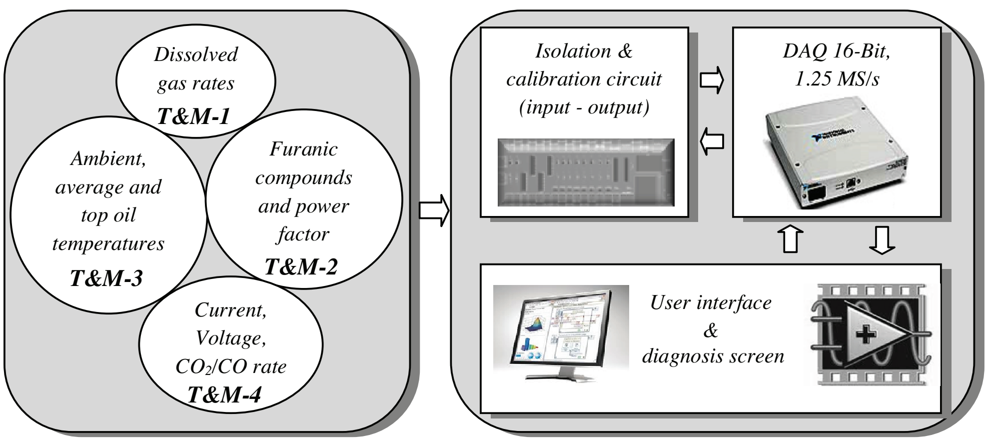

Figure 4. T&M system application and evaluation interface using the FSM.

T&M-1: Dissolved gas rates: Dissolved gas analysis (DGA) is the most important tool in determining the condition of a transformer. The DGA is carried out on the aged samples to predict the incipient faults and can identify deteriorating insulation and oil, overheating, hot spots, partial discharge, and arcing [33–38]. The expert systems combined with the fuzzy logic incorporate the expertise and experience of the diagnostic experts into the systems in the form of 'if–then' rules. The knowledge or diagnostic criteria extensively used by the utilities, such as the key gas method, Duval triangle, and the Dornenburg and the Rogers gas ratio methods, in accordance with the standards IEC 60599 and IEEE C57.104, have served as the framework of the expert diagnosis system [39–41].

T&M-2: Current, voltage, CO_2/CO rate: Loadability of the transformer is continuously monitored with SCADA systems in modern power technologies. Loadability gives the same information as power transformers, such as power demand and life loss information over time. Some evolving faults may be caused by overloading, but to know that, other symptoms should be closely monitored. In this context, the second

T&M group (CO_2/CO rate measurement) gives the information about isolation conditions, aging acceleration, temperature, loadability, etc. IEEE Standard C57.104 gives status conditions based on the accumulated values of CO_2 and CO [40]. Artificial neural networking is the most appropriate method for evaluation of T&M-2 data.

T&M-3: Temperatures (ambient, average, and top oil temperatures): One of the most important parameters governing a transformer's life expectancy is the hottest-spot temperature (HST) value. Hot-spot insulation temperature represents the most important factor that limits a transformer from loading [42]. The hot-spot temperature has to be under a prescribed limit value. A cumulative effect of insulation aging, depending on time change of hot-spot temperature, should be less than a planned value. That is why it is important to know the hot-spot temperature at every moment during real transformer operations under the conditions of variable loads and ambient air temperature [43–46]. The generally accepted relationship of thermal aging properties of insulation material is described by the Arrhenius reaction rate law [47]. The IEEE C57.91-1995 and IEC60076-Part.7 standards give an expression for the loss of life of mineral-oil–cooled power distribution transformers [48–50]. Artificial neural networks are presently established as a useful and very promising tool, in particular those of a nonlinear dynamic system model [38,51].

T&M-4: Furanic compounds and power factor: Power factor testing is important to determine the insulation condition of transformers because it can detect the insulation integrity in the winding, bushing, arrester, tank, and oil [52]. Transformer insulation is universally made from a combination of cellulose paper or pressboard, fully impregnated with insulating oil. Overheating, oxidation, acids, and decay caused by high moisture with oxygen accelerate the destruction of insulation and form furanic compounds. Normal deterioration of paper is characterized by the rate of furan evolution as 50–90 ppb. However, large amounts of furans can be generated when the temperature is above 120–130 °C [53]. Furanic compound analysis reveals the rate of insulating paper degradation of the equipment, and it directly projects the expected life [53,54]. Another test, called the power factor, is an effective way to detect defective electrical equipment insulation. The results of the overall power factor tests on power transformers reflect the insulation conditions of the windings, barriers, tap changers, bushings, and oil. The power factor is the ratio of the capacitive or 'charging' current (measured in volt-amperes) to resistive or 'leakage' current (measured in watts) [52,55]. In this section, the fuzzy-rule–based approach is used for the evaluation of input data.

Fault types have been categorized as follows:

Fault type 1: Overloading, high power loss,

Fault type 2: Partial discharge,

Fault type 3: Breakdown, arcing,

Fault type 4: Insulating degradation, aging,

Fault type 5: Cooling problem,

Fault type 6: Component fault, connection failure.

In Table 2, for the verification of the algorithm, the conditions of 4 different instances are considered. These conditions are based on T&M, regardless of the fault types. The fault in the system has already been cleared as a cooling problem, as stated in conditions I, II, and III, but not condition IV. However, T&M data obtained from the system or interpretation of sensor information might not be reliable. On this basis, conditions II, III, and IV have been prepared for testing the robustness of the algorithm. All conditions and decision vectors are shown in Table 2.

In this examination of the fuzzy method, the rule-based approach and artificial neural networks are

Table 2. Momentary evaluation (t_n) and determination of the fault probabilities.

Test & Measurement Groups	Expert System Evaluations and Generated Fault Probability Coefficient																	
	Condition I [Decision vectors]						Condition II / III [Decision vectors]						Condition IV [Decision vectors]					
Four test group that have different number are composed	*Fault type 1*	*Fault type 2*	*Fault type 3*	*Fault type 4*	*Fault type 5*	*Fault type 6*	*Fault type 1*	*Fault type 2*	*Fault type 3*	*Fault type 4*	*Fault type 5*	*Fault type 6*	*Fault type 1*	*Fault type 2*	*Fault type 3*	*Fault type 4*	*Fault type 5*	*Fault type 6*
Group (1) *T & M (1)*	1.02	1.89	1.41	1.15	4.15	1.08	2.02	4.23	3.41	3.24	3.07	2.75	1.02	1.89	1.41	1.15	1.74	1.08
T & M (2)	1.54	1.07	1.21	1.13	3.97	1.24	1.54	1.07	1.21	1.13	3.97	1.24	1.54	1.07	1.21	1.13	1.57	1.24
T & M (3)	1.06	1.51	1.73	1.37	4.67	2.11	1.06	1.51	1.73	1.37	4.67	1.11	1.06	1.51	1.73	1.37	1.62	2.11
T & M (4)	1.22	1.18	1.15	1.10	3.66	1.19	1.22	1.18	1.15	1.10	3.66	1.19	1.22	1.18	1.15	1.10	1.46	1.19
Group (2) *T & M (1)*	1.16	2.33	1.71	1.25	4.26	1.74	1.16	2.33	1.71	1.25	4.26	1.74	2.67	4.71	2.59	3.84	3.95	2.52
T & M (2)	1.22	1.47	1.43	1.57	3.79	1.03	1.22	1.47	1.43	1.57	3.79	1.03	2.57	3.97	3.28	3.56	3.27	3.39
T & M (3)	1.31	1.18	2.03	1.45	3.98	1.53	1.31	1.18	2.03	1.45	3.98	1.53	3.12	2.51	2.83	4.35	2.41	1.96
	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Group (3) *T & M (1)*	1.71	1.09	1.51	1.41	3.73	1.23	1.71	1.09	1.51	1.41	3.73	1.23	1.71	1.09	1.51	1.41	1.33	1.23
T & M (2)	1.45	1.25	1.75	1.11	3.20	1.05	1.45	1.25	1.75	1.11	3.20	1.05	1.45	1.25	1.75	1.11	1.22	1.05
T & M (3)	2.04	1.31	1.42	1.45	2.67	2.13	2.04	1.31	1.42	1.45	2.67	2.13	2.04	1.31	1.42	1.45	1.49	2.13
	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Group (4) *T & M (1)*	1.54	1.72	1.86	1.88	4.54	1.71	1.54	1.72	1.86	3.46	2.66	1.71	1.54	1.72	1.86	1.88	1.68	1.71
T & M (2)	1.59	1.94	1.74	1.93	4.56	1.29	1.59	1.94	1.74	3.84	2.15	1.29	1.59	1.94	1.74	1.93	1.36	1.29
	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

: *Circle of conspicuous fault probability value\s belonging to a fault type* **(reliable)**

: *Circle of conspicuous fault probability value\s belonging to a fault type\s* **(not reliable)**

: *Pointer of decision vector belonging to a T&M group*

recommended for determining the coefficients according to the T&M parameters. Generated coefficients, which are shown as a row vector determined by a preferred expert system, are combined as only one matrix structure in Table 2. The T&M group numbers are not equal to each other, so in this case a command can be written as "MAT $(n, :)$ =1" for the equalization of a related matrix in MATLAB. Matrix sizes should be equal to the matrix belonging to the largest T&M group, as shown in Equation (5).

$$FSM\,[4\times 6] = \left| \left[\left[\left[MAT_{(1)} \begin{bmatrix} C & \cdots & C_{1,6} \\ \vdots & \ddots & \vdots \\ C_{4,1} & \cdots & C_{4,6} \end{bmatrix} \cdot \times MAT_{(2)} \begin{bmatrix} C & \cdots & C_{1,6} \\ \vdots & \ddots & \vdots \\ C_{4,1} & \cdots & C_{4,6} \end{bmatrix} \right] \right. \right. \right.$$
$$\left. \left. \left. \cdot \times MAT_{(3)} \begin{bmatrix} C & \cdots & C_{1,6} \\ \vdots & \ddots & \vdots \\ C_{4,1} & \cdots & C_{4,6} \end{bmatrix} \right] \cdot \times MAT_{(3)} \begin{bmatrix} C & \cdots & C_{1,6} \\ \vdots & \ddots & \vdots \\ C_{4,1} & \cdots & C_{4,6} \end{bmatrix} \right] \right] \right| \qquad (5)$$

Actually, each matrix indicates fault probabilities specifically related to the T&M group. All T&M systems should be considered as a whole to get the most accurate result of fault diagnosis. The last matrix, the FSM, is formed through scalar multiplications of submatrices to ensure this validity. The FSM is stated in an algorithm as $MAT(\mathrm{Pr}_k)$, and to determine any fault probabilities in the system, the command should be written confirming Eq. (3) in the algorithm. All procedures according to these results are shown as bar graphs, and all bar graphs indicated by 'last graph (d)' indicate the last matrices that were created by the recent scalar multiplication, in the algorithm for all of the figures.

$$Faults[1 \times 6] = \left| \sum_{n=1}^{4} FSM_{4_{(1)}}[n:1], \sum_{n=1}^{4} FSM_{4_{(2)}}[n:2], \ldots, \sum_{n=1}^{4} FSM_{4_{(4)}}[n:6] \right| \tag{6}$$

Hence, Cf_j gives the greatest fault probability in Equation (7). In this example, *Crj* is taken as zero ('0') because all T&M information has a certain number of relationships by fault types.

$$Cf_j\% = \left[\left(\frac{\max(Faults\,[1x6]\,)_j}{[TpV]_j} \right)^{1/(4-Cr_j)} \right] x\,100 = Faultprobability\% \tag{7}$$

All results produced by FSM are interpreted by the specific levels of bandwidth. When the fault probability value is *0%* $< f_j <$ *40%*, the system can be assumed to be in the secure region. If the value is *40%* $< f_j <$ *60%*, the system should be observed. If the value is *60%* $< f_j <$ *100%*, the system is operating dangerously, and an operation may be required.

The data obtained from the system using sensors are normalized and graded from best to worst considering fault types. The outputs of the sensors are different from each other. For instance, water content of the paper less than 0.5 ppm is the expected value, 0.5–2 ppm is permissible, and values higher than 2 ppm are unacceptable. The other important parameter of the power transformer is temperature, which has limit values according to the IEEE standards, such as hot-spot temperature being 110 °C and planned overloading temperature being 130 °C. Therefore, the obtained data are normalized using the same base value and 5 different risk levels, as shown in Figure 5.

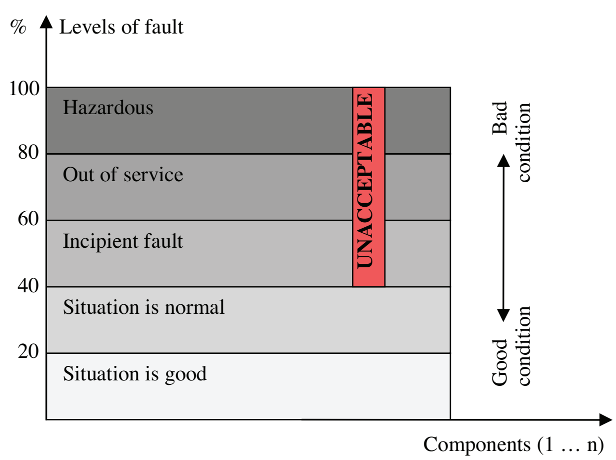

Figure 5. Fault levels of components.

In this study, the algorithm was tested and verified by various failures caused intentionally in the laboratory. In addition, operations of the sensors located in the application circuit are checked during the experiments.

Generally, result graphs show the fault probabilities as a percentage, and while the red bar indicates the maximum possible faults, the blue bar indicates incipient failures. In addition to this, it may indicate a defect in the T&M system or evaluation process. If all the graphs indicate only one fault possibility, the result is good and reliable. However, sometimes the results of T&M may be defective, or an expert's know-how/database may not be enough to write the correct algorithm related to the T&M group. The FSM is consistently reliable against such disturbances. Even if some evaluation results in the matrices indicate different fault possibilities contrary to others, the FSM can discover the correct result on a global level; these situations are shown in Table 3. The FSM results of the overall fault situations are determined in a range, as shown in Table 4. These evaluation results are valid for the continuous case of each fault condition. For this reason, the results vary in a certain bandwidth according to the severity of the fault/s.

Table 3. Condition definitions and FSM results according to Table 2.

Conditions	Power system situation	T&M reliability	Reliability of the algorithm	FSM results	Operation
I	Cooling problem	Completely reliable T&M groups	Reliable	80% probability	Needed
II*	Cooling problem	Only one T&M in the group is not reliable	Reliable	67.5% probability	Needed
III*	Cooling problem	A group of T&Ms is not reliable	Reliable	67.5% probability	Needed
IV	No problem	A group of T&Ms is not reliable	Reliable	39% probability	Not needed

∗These conditions occurred at the same time.

Table 4. The FSM results for the continuous-case situation of related fault(s).

Power system situation	T&M reliability	Reliability of the algorithm	FSM results (min–max values)	Operation
Overloading, high power loss	Completely reliable T&M groups	Reliable	60 $<$ probability % $<$ 100	Needed
Partial discharge	Completely reliable T&M groups	Reliable	60 $<$ probability % $<$ 100	Needed
Breakdown, arcing	Completely reliable T&M groups	Reliable	60 $<$ probability % $<$ 100	Needed
Insulating degradation, aging	Completely reliable T&M groups	Reliable	60 $<$ probability % $<$ 100	Needed
Cooling problem	Completely reliable T&M groups	Reliable	60 $<$ probability % $<$ 100	Needed
Component fault, connection failure	Completely reliable T&M groups	Reliable	60 $<$ probability % $<$ 100	Needed

Condition I: As mentioned in Table 3, the cooling system is faulty on the power transformer, and in reality, this fault is possible under all conditions except condition IV. The data obtained from the system using T&M systems and evaluations of these data are reliable. Thus, the obtained results that are shown in Figure

6 are reliable, too. Fault type 5 has emerged, which is shown as a red bar in Figure 6. The probabilities of the fault types according to the processing of the first, second, and third T&M groups are indicated in Figures 6a–6c, respectively. Figure 6d shows the results of the fault probabilities according to the processing of the last matrix, FSM.

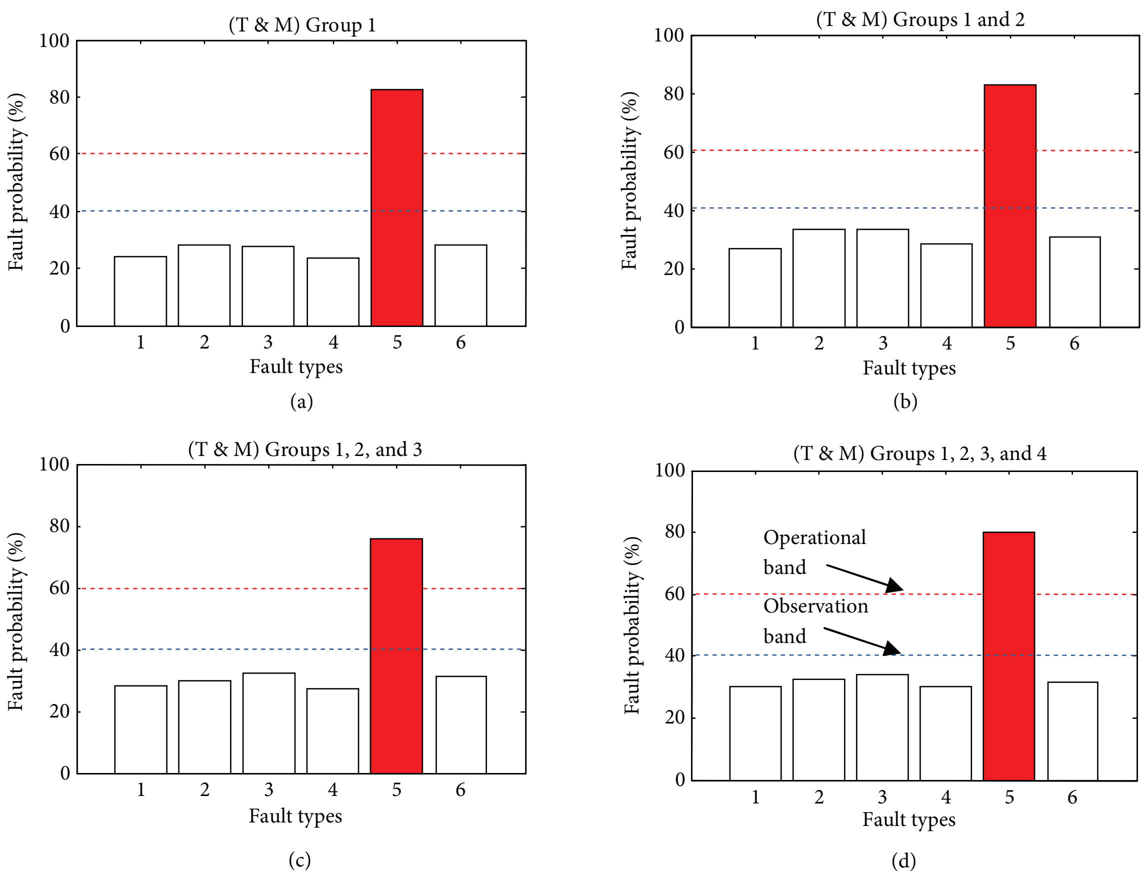

Figure 6. Fault probabilities graphs based on the FSM according to evaluation of groups for condition I: (a) Group 1; (b) Groups 1 and 2; (c) Groups 1–3; (d) Groups 1–4.

Conditions II and III: Conditions II and III indicate that the T&M system is faulty. In condition II, only one T&M of the group is not reliable or data evaluation is not correct. In condition III, a group of T&M are not reliable. In addition to the actual fault, shown by the red bar, the other fault probability, shown by the blue bar, which is not correct, is shown in Figures 7a–7d, respectively. The algorithm has discovered the actual fault using the FSM approach. The type 2 fault should be observed because of the higher level of security. The functioning of the algorithm could be controlled by the experts. Figure 7b is different from 7a, 7c, and 7d in terms of fault type 2. In this examination, it is clear that the T&M system appears to be faulty or data evaluations are not correct. This is an advantage of the algorithm: it can determine if the T&M equipment is faulty. It is important to develop the evaluation process for the fault diagnosis system.

Condition IV: Condition IV indicates that the T&M system or data evaluations are as shown in Figures 8a–8d, respectively. There is a faulty situation, because the power transformer systems do not have any actual fault. Excluding Figure 8b, the others provide reliable results. However, the algorithm still reaches a global outcome as shown in Figure 8d.

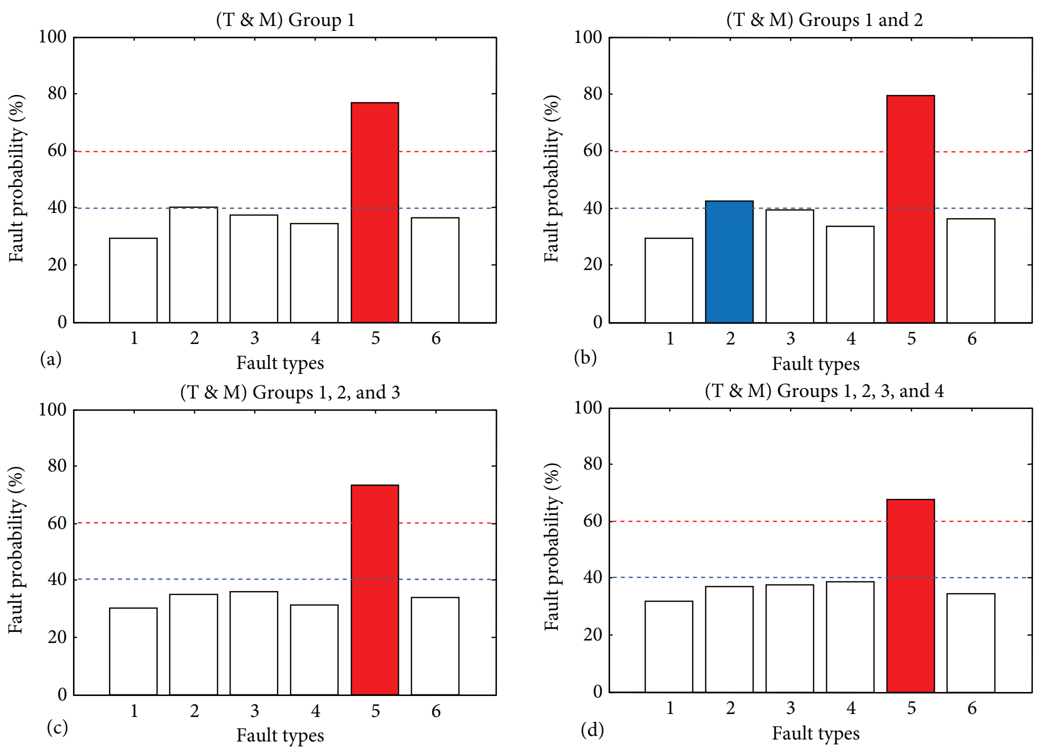

Figure 7. Fault probability graphs based on the FSM according to evaluation of groups for conditions II and III: (a) Group 1; (b) Groups 1 and 2; (c) Groups 1–3; (d) Groups 1–4.

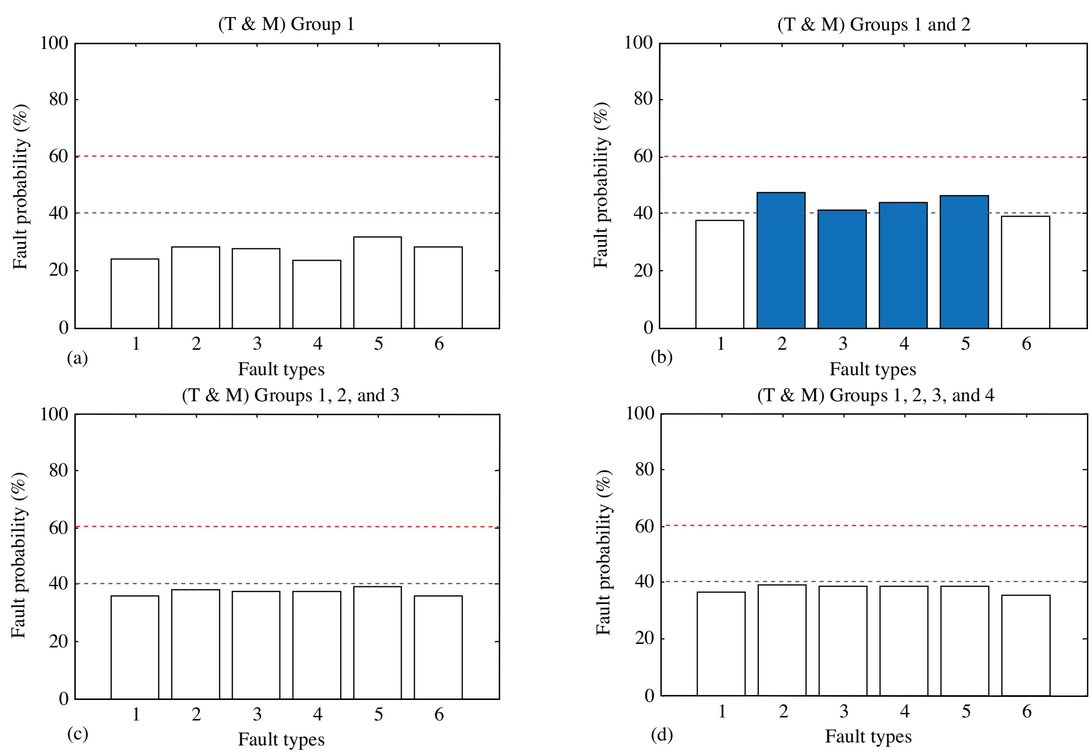

Figure 8. Fault probability graphs based on the FSM according to evaluation of groups for condition IV: (a) Group 1; (b) Groups 1 and 2; (c) Groups 1–3; (d) Groups 1–4.

4. Conclusions

In this study, a robust fault diagnosis and evaluation algorithm based on the FSM structure was presented. The most important advantage of the FSM is that it is an interface that works with ES and AI. For this reason, most suitable ES and AI applications for the system can be used without any restrictions. The processing times of the FSM and expert system are evaluated separately since they is affected by the expert system. Therefore, the FSM has a matrix structure and is designed to be different from the expert system, to obtain rapid response.

Thus, it is possible to get a valid evaluation from the data obtained. The FSM is not affected negatively when the number and type of T&M are increased. On the contrary, these increases provide more accurate and reliable results for FSM. This results in an increase in the utility of fault diagnoses based on the FSM in large and complex systems. Since data obtained from T&M systems and evaluation results of specialist systems are processed in a parallel manner through use of the matrix structure of the FSM, the operation time is fast (almost the time of a matrix multiplication). The FSM can be defined as a hybrid interface that is a part of the algorithm to combine the results produced by different expert systems. Four different conditions have been prepared in the laboratory environment for testing and fault detection of the algorithm. The FSM method can detect and define faults at close to 100% under all conditions. In addition, this method provides information to the user about the degree of the fault with the probability of failure.

In the construction stage of the FSM-based evaluation algorithm, expert knowledge and experience are important, along with historical databases of the system. The performance of the algorithm depends on them, as well as selected ES and AI applications. However, the FSM-based algorithm is robust against local distortions due to both measurements and evaluation results of the system; it can still reach correct conclusions on a global level. In this model, distortions on algorithms or measurement systems can be found easily by pursuing submatrices of the FSM, and it can be improved continuously in accordance with current knowledge.

Appendix

The test system consists of a prototype (bar-winding heating transformer powered in the line voltage) whose physical characteristics, such as thermal, aging, cooling performance, and liquid and solid insulation characteristics, are similar to those of a power transformer, as shown in Figure 9. The other components of the system are online and offline test and measurement instruments, as listed in Table 5. Multiple data acquired from the prototype are transferred to the algorithm via the converter circuits and DAQ card.

In this study, Nytro Lyra X (IEC 60296) is used as liquid insulation and a pressboard is used as solid insulation. Additionally, normal life time is considered as 20.55 years in accordance with the IEC 60076-7 standard.

Figure 9. Prototype and test system environment.

Table 5. System components.

DAQ card, terminal mass / NI-USB 6251-16 bits	Input: 1.25 MS/s, Output: 2.00 MS/s
Output normalization and amplifier card for the sensors and transmitters	0–10 V / 0–5 V
Current and voltage transducers	50 A / 500 V
Kelman Transport X portable offline DGA device	9 gases
Hydran M2 Online DGA device	H_2
EE36 Series; water content	Water content 0–100 ppm / 0–5 V
redLINE temperature adjustment heating oven	800 W
PH, acidity, salinity, conductivity, particle quantity measurement device	Series 86505
Pyrometer (surface temperature measurement/portable)	Measuring range: –30 / +500 °C
Supply units	0–12 V, +5 / –5 V, +12 / –12 V
Variac	Power: 3500 VA (0%–100 %)
Prototype: bar-winding heating transformer	Power: 2500 VA
Cooling fans	100–1500 rpm
Oil circulation pump	650 L/h
External heating furnace	Power: AC 220 V / 1500 W
Temperature control relay (on–off control)	Measuring range: –55 °C to +125 °C
Temperature control relay (PID control)	Inputs : TC, RTD, mV, V, mA
Pressure control valve	1–16 Bar
Boiler safety valve	1–10 Bar
Manometer	Measuring range: 0–10 Bar
PT100	–50 °C to +400 °C
J-type thermocouple	–200 °C to 800 °C
Liquid level transducer (transmitter)	Output:4–20 mA/Reed switch
Transformer hot spot copper coil and wrapped in pressboard	Pressboard: IEC 60554
Liquid insulation type	Nytro Lyra X (IEC 60296)

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