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Classification of Events in Power Transformers Using Wavelet Packet Transform and Fuzzy Logic

Hermes M. G. C. Branco · Daniel Barbosa · Mário Oleskovicz · Denis V. Coury

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Abstract A monitoring algorithm based on wavelet transform and fuzzy logic was developed in this paper to perform event classification in power transformers. These events were observed in an electrical power system simulated using the alternative transients program software. It should be emphasized that the modeled system presented transformers connected in parallel, which allowed the study of specific operational events, including sympathetic inrush. The proposed algorithm presented a satisfactory performance to many situations, identifying the causes of the differential currents, either caused by faults or other operation conditions.

Keywords Power transformers · Event classification · Wavelet packet transformer · Fuzzy logic · ATP—alternative transients program.

1 Introduction

Power transformers are important equipment for the operation and interconnection of the power grid, implying the need for special care and monitoring of all their operating conditions. Thus, reliable information must be recorded, processed, and interpreted, making it possible to characterize and analyze the operation of the power transformer and the system as a whole. The differential protection applied to power transformers is based on the principle of comparing the currents of the equipment's terminals protected with predetermined thresholds. Some limitations in this procedure have been observed, since there are operating conditions of transformers that can cause misoperation. The main situations that affect the operation of the differential logic in transformers are: inrush, over-excitation, saturation of current transformers (CT), and sympathetic inrush (Barbosa et al 2011).

With the aim of improving the performance of the protection systems applied to power transformers, new techniques and methodologies based on intelligent tools are constantly being developed and proposed in the literature, such as the use of artificial neural networks (Baran and Kim 2006; Tripathy et al 2010) and fuzzy systems (FS) (Shin et al 2003; Saleh and Rahman 2005; Delshad and Fani 2007). Wavelet transforms (WT) (Faiz and Lotfi-Fard 2006; Valsan and Swarup 2008; Vahidi et al 2010) and wavelet packet transforms (WPT) (Saleh and Rahman 2005) should also be highlighted as tools that may be successfully used in the pre-processing of information, since they provide an efficient representation of the signal for the widest variety of cases. In addition, they provide speed and accuracy in the detection and discrimination of the phenomena under consideration.

It should be noted that the objective of protection methodologies proposed in the correlated literature is to obtain a robust and reliable algorithm, capable of correctly distinguishing fault situations from other operational situations that may cause trip. Accordingly, the main focus of these methodologies is on the speed and reliability of the protection algorithm, with no real concern in characterizing as to which phenomenon did or did not cause the trip of the protection.

H. M. G. C. Branco (✉)· M. Oleskovicz · D. V. Coury
Department of Electrical and Computer Engineering, São Carlos School of Engineering, University of São Paulo/USP, Av. Trabalhador São Carlense, 400, Centro, São Carlos, SP 13.566-590, Brazil
e-mail: hermescb@usp.br

M. Oleskovicz
e-mail: olesk@sc.usp.br

D. V. Coury
e-mail: coury@sc.usp.br

D. Barbosa
Salvador University, Alameda das Espatódeas, 915, Caminho das Árvores, Salvador, BA 41.820-460, Brazil
e-mail: daniel.barbosa@pro.unifacs.br

In this context, it is important to remember that many power quality (PQ) events are associated with operational situations of transformers, such as inrush, over-excitation (Santoso et al 2000; Zheng et al 2004; Khederzadeh 2010) or the occurrence of internal short circuits. This fact justifies the interest in identifying and classifying the operational situation of power transformers by means of a continuous diagnostic algorithm, as already pointed out by Branco et al (2009).

Given the above, the main objective of this work is classifying the operating events in power transformers. Through information available from monitoring currents in the power transformers, it is possible to establish a procedure to determine and classify the events, providing support for decision-making in the substation environment. It is important to note that the main benefits provided by the proposed methodology are: to enable an analysis of the relationship of PQ events highlighted in the electrical system and the operational situation of the transformer, and to diagnose the reason behind a trip or failure of the differential protection associated with the protected equipment.

The algorithm proposed in this paper uses the WPT in conjunction with a FS to classify the operational situation faced by the transformer. This approach will enable a refinement of the analysis of the currents passing through the equipment, and, consequently, improve feedback and facilitate the recording of the responses obtained from the protection system, in addition to permitting future studies, for example in the context of power quality and fault diagnosis. It should be stated that the tests and the validation of the proposed technique were performed with data from an electrical system modeled using real parameters in the alternative transients program software. Several operational and fault situations were simulated. It should equally be highlighted that the processing time of the proposed algorithm is compatible with the activation times of the differential protection, which provides an application in real time simultaneously to the protection algorithm adopted.

2 Basic Concepts of the Tools Used

2.1 Wavelet Packet Transforms

The basic concept of the WT is centered on the use of small waveforms (wavelets) those are located in time. These waveforms are manipulated through processes of translations (movements of the signal being analyzed) and dilations, or contractions. Through these manipulations, an input signal is transformed into another waveform with “doubling” in time and scales (levels). Therefore the WT, in its continuous form, is the correlation of the input signal with a set of wavelets of different widths (dilated or contracted) translated through

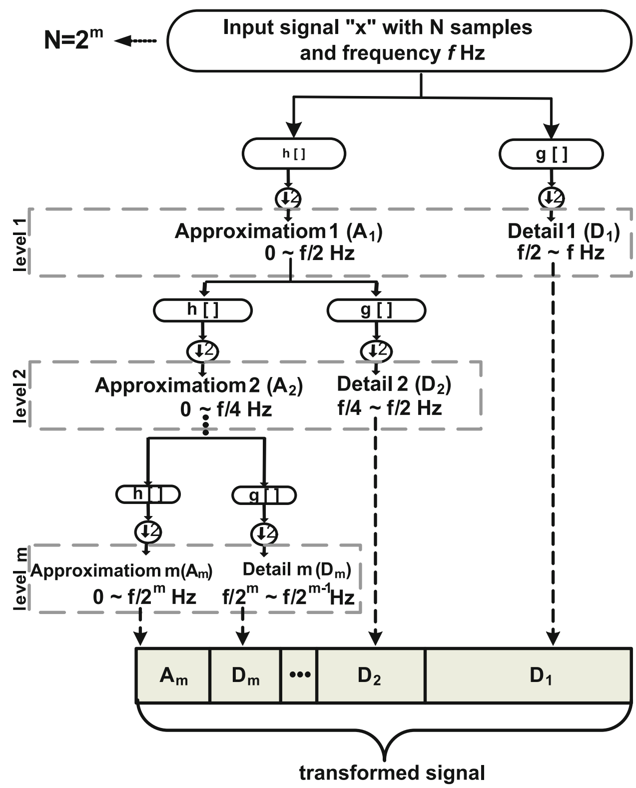

Fig. 1 Decomposition of a signal by the WT.

this input signal (Addison 2002). The application of the WT can be achieved by implementing a bank of filters, given that, from the practical point of view, the discrete wavelet transform (DWT) is a digital filtering process in the time domain, via discrete convolution, accompanied by downsampling by a factor of 2 (Jemse and Harb 2000).

Figure 1 illustrates various levels of decomposition of a signal through the use of the DWT. As the figure shows, a signal is filtered by a low-pass filter (h) and a high-pass filter (g), and then the downsampling operator is applied at the output of each filter. The output of the low-pass filter is the approximation of the signal. The response of the high-pass filter however, is provided by the detail of the original signal. This process may be successively applied to the approximations to obtain different levels of the decomposition, where each level in the frequency band is divided in half after the passage of the signal through the filters. The signal resulting from the filtering is given by the concatenation of the approximation of the last level with the details.

The WPT consists of a generalization of the WT, in which the filters are applied to the approximation of the signal and to the detail, resulting in the complete development of the tree of coefficients (Jemse and Harb 2000). This approach results in better resolution in the frequency domain, making it possible to isolate frequency ranges adequately within the spectrum under analysis, and for this reason it was adopted in this work.

It should be noted that there are several wavelets which can be used for processing signals and the choice of the best wavelet to be used in a particular application depends, both on the nature of the signal, and the requirements of the analysis to be undertaken (Addison 2002). The literature indicates, for example, the Daubechies family is usually a good choice for most situations encountered in an EPS, since they are generally better at identifying the phenomena and decays with rapid oscillations, in addition to transients, typical characteristics of these events (Baran and Kim 2006). It is also confirmed that wavelets with less support (filters with few coefficients) are ideal for locating phenomena in time. Yet again, for better resolution in the frequency domain, wavelets with a greater number of coefficients are the most recommended (Jemse and Harb 2000).

2.2 Fuzzy Systems

People are capable of dealing with fairly complex processes, based on imprecise or approximate information, and the decision-making strategy they adopt is also imprecise (Zimmermann 2001). It is in this context that the theory of fuzzy sets proposed by Zadeh (1965) enters, enabling the processing of information of an imprecise or vague nature in computer systems. According to Zimmermann (2001), fuzzy inference systems allow the processing and manipulation of uncertain and imprecise information, which is represented by a family of fuzzy sets. Such inference systems enable the modeling of processes that have their information provided in a qualitative way. The fuzzy inference mechanism is comprised of linguistic variables which are associated by means of connectives to form rules. Each rule implies a fuzzy output variable, which is also a linguistic variable. Finally the fuzzy outputs of each rule need to be combined, so that, at the end of the inference process, only one fuzzy output is provided.

The main advantage of a FS is the ability to represent expert knowledge in terms of variables and linguistic rules. This advantage affords greater robustness to the decision system, endows it with enhanced fault tolerance and permits the manipulation of information subject to imprecision and uncertainties. These characteristics are very encouraging for the use of FS in EPS, since the quantities under analysis involve a certain degree of uncertainty. Furthermore, transducers are also susceptible to faults that may cause measurement errors.

3 The Proposed Algorithm

As previously stated, the proposed algorithm was developed with the use of WPT and a FS, increasing the robustness and reliability of the proposed approach. The WPT is applied due to its efficiency when used in analyzing events which are aperiodic, noisy and with the presence of transients (Addison 2002), while FS is used to properly evaluate the uncertainties and inaccuracies in the input data (Mendel 1995). Thus, advantages are obtained in the extraction process of features of the phenomena studied and possible errors due to measurement or distortions in the shapes of secondary waves of the CT are decreased.

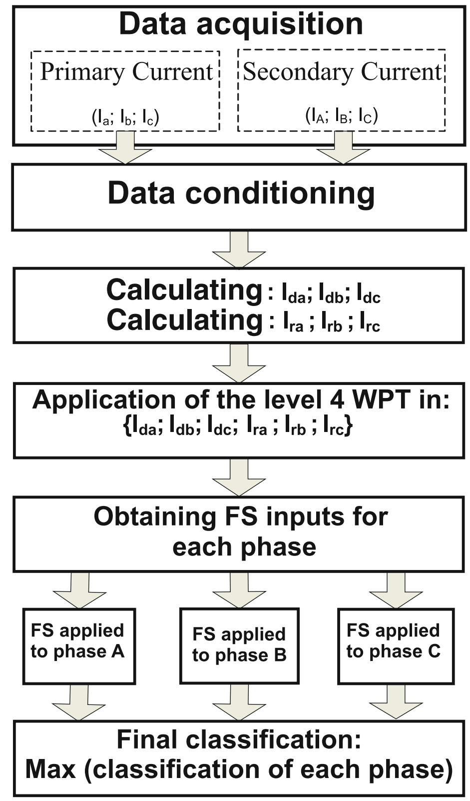

Fig. 2 Flowchart of the proposed algorithm.

Figure 2 shows the flowchart of the proposed algorithm with the sequence of procedures used. The steps illustrated in the flow chart will be described below.

3.1 Acquisition and Conditioning of Input Data

The data acquisition is performed through a windowed function on a cycle of the signal under analysis and with fixed step displacement of a sample. In this way, all the processing of the algorithm on the currents measured in the primary and secondary of the transformer will be performed through a data window containing 16 samples (960 Hz), respecting the available time frame for processing, which will be quantified by provision of a new sample (approximately 1 ms). The chosen sampling rate is sufficient to allow for adequate representation of phenomena to be classified, as these have signatures characterized by the presence of low-order harmonics, especially the second and fifth harmonics (Coury et al 2007).

It is important to point out that the currents are obtained and conditioned in a manner similar to that observed in commercial equipments. Therefore, the following steps were implemented computationally and included in the proposed algorithm: anti-aliasing filtering (assuming a cutoff frequency of 480 Hz); re-sampling; lag-angle correction; the CT ratio correction and elimination of the zero sequence (IEE 2008).

3.2 Calculating the Differential and Restriction Currents

After conditioning the signals, they undergo WPT to extract the fundamental and harmonic components, of both the differential currents (I_d) and the restriction currents (I_r) of the monitored transformer. The I_d and I_r currents were calculated by Eqs. (1) and (2):

$$I_\mathrm{d} = i_\mathrm{ps} + i_\mathrm{ss}, \tag{1}$$

$$I_\mathrm{r} = \frac{i_\mathrm{ps} - i_\mathrm{ss}}{2}, \tag{2}$$

where, i_ps and i_ss are the phase currents in the primary and secondary transformer, respectively.

It is important to note that these components will be used in the discrimination process of the operating conditions of the equipment, since each situation has a particular signature.

3.3 Application of the WPT to Obtain Information About The Harmonic Components

As noted in the related literature, the WPT can be used successfully for analyzes related to the harmonics in an EPS (Barros and Diego 2006). Figure 3 illustrates the decomposition tree deriving from the application of the level 4 WPT on a data window with 16 samples. The frequency bands delimited by each of the resulting leaves is of interest for this application (highlighted in Fig. 3), and the number of samples in each leave, is shown in Table 1.

The leaves of the WPT to be used in the proposed algorithm were determined by frequency bands of interest which, in this case, involves the second and fifth harmonics, given that these are characteristic of the events studied. To illustrate, it can be seen that the leaves $D_{2,4}$ and $A_{3,4}$ were selected to provide information regarding the second harmonic since these encompass the frequency of 120 Hz (Table 1). Considering the decomposition depicted in Fig. 3, the determination of the effective value of the harmonic current of second and fifth order is obtained by the Eqs. (3) and (4), respectively:

$$I_2 = \sqrt{\frac{(D_{2,4})^2 + (A_{3,4})^2}{2}}, \tag{3}$$

$$I_5 = \sqrt{\frac{(D_{5,4})^2 + (A_{6,4})^2}{2}}. \tag{4}$$

In turn, the effective value of the fundamental frequency component (60 Hz), is obtained by Eq. (5):

$$I_\mathrm{F} = \sqrt{\frac{(D_{1,4})^2 + (A_{2,4})^2}{2}}. \tag{5}$$

It should be stressed that the accuracy in the estimation of harmonics in this methodology depends on the wavelet used, which in this application was the *Db*20 (Daubechies twentieth order), since this was the one that showed the best performance among a number of candidates tested (Daubechies16, Daubechies18, Daubechies20, Daubechies22, Daubechies24, Beylkin18, and Vaidyanathan 24 and Coiflet24).

At each moving data window, the contributions to the fundamental component of the differential and restriction current, as well as the components of the second and fifth order of the differential current (I_d2 and I_d5) are obtained. The values of the harmonic components calculated by Eqs. (3) and (4) are, then, normalized with respect to the effective value of the fundamental frequency component.

The operating current ($I_\mathrm{dF}/I_\mathrm{rF}$) was obtained by means of Eq. (6):

$$I_\mathrm{dF}/I_\mathrm{rF} = \frac{I_\mathrm{dF}}{I_{\mathrm{rF}_\mathrm{MAX}}}, \tag{6}$$

in which, I_dF corresponds to the root mean square (RMS) value of the first order harmonic of the differential current in each phase, and $I_{\mathrm{rF}_\mathrm{MAX}}$ corresponds to the RMS value of the harmonic of first order of the restriction current of the highest value of the three phases, obtained by the application of Eq. (5) to the fourth level decomposition of a window of I_d and I_r, Eqs. (1) and (2), respectively.

3.4 Applicaton of FS and the Classification of the Operating Condition

To diagnose the operating condition of the transformer, a FS was developed with three inputs, eight inference rules, and an output. The knowledge base was defined on the spectral content usually found in the different situations analyzed. The adjustment of the membership functions was carried out using the knowledge of the harmonic composition present in the events studied, strongly characterized by the presence of the second and fifth harmonics. Initially, a first adjustment was made, based on the information available in the

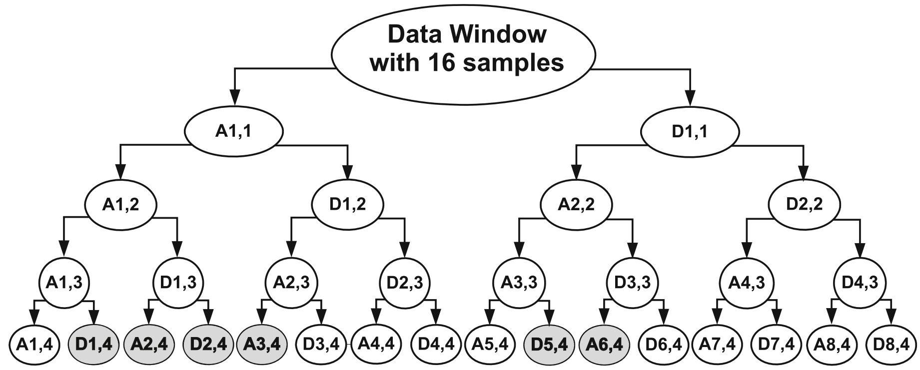

Fig. 3 Tree decomposition of the WPT (level 4).

Table 1 Frequency bands in leaves after application of WPT level 4

Leaf of WPT	No. of samples	Frequency band (Hz)
Original signal	16	0–480
$D_{1,4}$	1	30–60
$A_{2,4}$	1	60–90
$D_{2,4}$	1	90–120
$A_{3,4}$	1	120–150
$D_{5,4}$	1	270–300
$A_{6,4}$	1	300–330

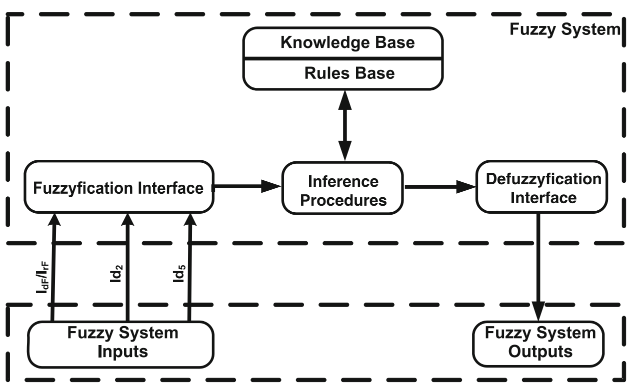

Fig. 4 Structure of the FS used.

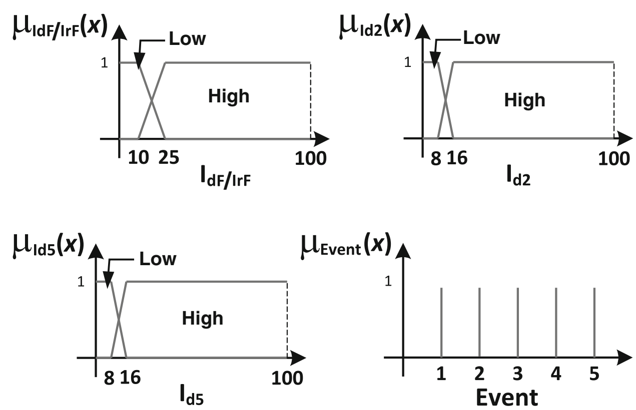

Fig. 5 Membership functions of the linguistic variables modeled in the FS.

literature, as found in Coury et al (2007). Subsequently, fine tuning (with small modifications) of the membership functions was undertaken using various tests and observations of the responses obtained.

Figure 4 depicts the structure of the modeled FS, illustrating the procedures for fuzzification, inference, and defuzzification.

In order that the data collected may be used by FS, the process of fuzzification is carried out, which converts discrete variables into fuzzy linguistic variables.

Figure 5 illustrates the FS linguistic variables input (I_{dF}/I_{rF}, I_{d2} and I_{d5}) and the fuzzy output variable ($Event$) used. It can be seen in the figure that the fuzzy input variables are composed of two fuzzy terms: Low and High, membership functions of which are trapezoidal. While the output variable consists of five unitary fuzzy sets (singletons) that define the operating condition to be classified. The singleton set with value equal to 1 represents the normal operation (NO); the singleton with value equal to 2 represents the inrush class, the singleton with value equal to 3 represents the sympathetic inrush class, the singleton with value equal to 4 represents the over-excitation class and the singleton with value equal to 5 represents the transformer internal fault class (IF).

		I_{d2} Low	I_{d2} High
I_{d5}	Low	NO	SI
I_{d5}	High	OE	SI

For I_{dF}/I_{rF} Low

		I_{d2} Low	I_{d2} High
I_{d5}	Low	IF	IN
I_{d5}	High	OE	IN

For I_{dF}/I_{rF} High

Fig. 6 Summary of rules modeled in the FS.

The FS uses the inference step to map the knowledge between the inputs in the intelligent system and their respective output by means of a limited number of fuzzy rules in the typical "IF-THEN" pattern, such as:

IF $I_{\mathrm{dF}}/I_{\mathrm{rF}}$ is Low **and** I_{d2} is Low **AND** I_{d5} is Low
THEN Event *Normal Operation*

In this context, the proposed technique uses eight fuzzy inference rules which relate the three inputs with a respective output, as shown in Fig. 6.

The composition of the inferences was performed by means of the Max–Min operator, since it presents less computational effort and affords rapid and efficient processing, essential to making the application of the algorithm viable.

The defuzzification procedure informs the numerical value of the output of the fuzzy system, which will be used to determine the operating condition of the transformer being monitored. To that end, the last maximum technique was applied, which provides in response the highest value of the domain with maximum membership of the output set. The numerical values associated with the operating conditions analyzed are illustrated in Fig. 5. Considering the method of defuzzification adopted, care was taken to position the membership function associated with the class of internal fault at the end of the universe of discourse of the output variable. Thus, assuming a conservative position, in the case of doubt between a situation of internal fault or any other operational situation encountered, a situation of internal fault will be flagged.

After obtaining the outputs of the FS, a distinction is made between the diagnosis of an internal fault and an energization with fault (EF). Whenever the FS flags the occurrence of internal fault, the energy of the first detail of the WT in the current of the secondary of the transformer will also be calculated. If the calculated energy assumes the value zero, the algorithm will classify the situation as energization with fault, and will assign the value six (6) to its output. Equation (7) shows how the energy of the signal is calculated (Oppenheim et al 1997):

$$\text{Energy} = \sum_{n=0}^{N} x_n^2, \tag{7}$$

where N is the total number of samples and x_n is the nth sample of the analyzed signal.

It is important to point out that although an FS is applied to each phase independently, the diagnosis of the event to which the transformer is subjected is indicated by the output with the highest numerical value among the phases analyzed, which is computed at the end of the algorithm. It is noteworthy that experiments were performed considering a sixth membership function in the output variable, representing the energization with fault class. However, the results obtained were not satisfactory, since, owing to the manner in which it was implemented, the classifier confused this event with other events. Therefore, we chose to make this distinction after the classification presented by the FS. With respect to the input variables and the membership functions of the linguistic variables, it is worth stating that different experiments were conducted, in which fuzzy systems were tested with more input variables (for example, third, and fourth harmonics, and the DC component), in addition to variables with up to four membership functions. However, no improvements were observed in the results, merely adding to the system's computational effort.

4 The Electrical System Used

Figure 7 illustrates the electrical system used to simulate the operating conditions of the transformers and evaluate the performance of the proposed technique.

The electrical system consists of a synchronous generator of 13.8 kV (60 Hz), with 90 MVA, a three-phase induction motor of 4.0 kV and 1,582 HP, three transformers (as shown in Fig. 7 as TR1E, TR2E and TR3E) with ratios of 13.8/138 kV and 25 MVA (these were modeled taking into consideration the saturation curves); transmission lines with lengths ranging from 50 to 100 km; three step-down transformers (indicated in Fig. 7 as TR1A, TR2A and TR3A) and loads characterized by an inductive power factor of 0.92 and 25 MVA.

In addition to the equipment shown in Fig. 7, the CTs and voltage transformers were modeled taking into account their saturation curves so as to obtain the voltage and current signals in question. The dynamic speed control system for hydraulic systems, as well as the automatic voltage control were also simulated. Further information about the electrical system used in this work may be found in reference (Barbosa et al 2011).

The simulated situations on the EPS include the following operating conditions:

- Internal faults (short circuits) to the TR2E and TR3A transformers;
- Over-excitation of the transformer TR2E;

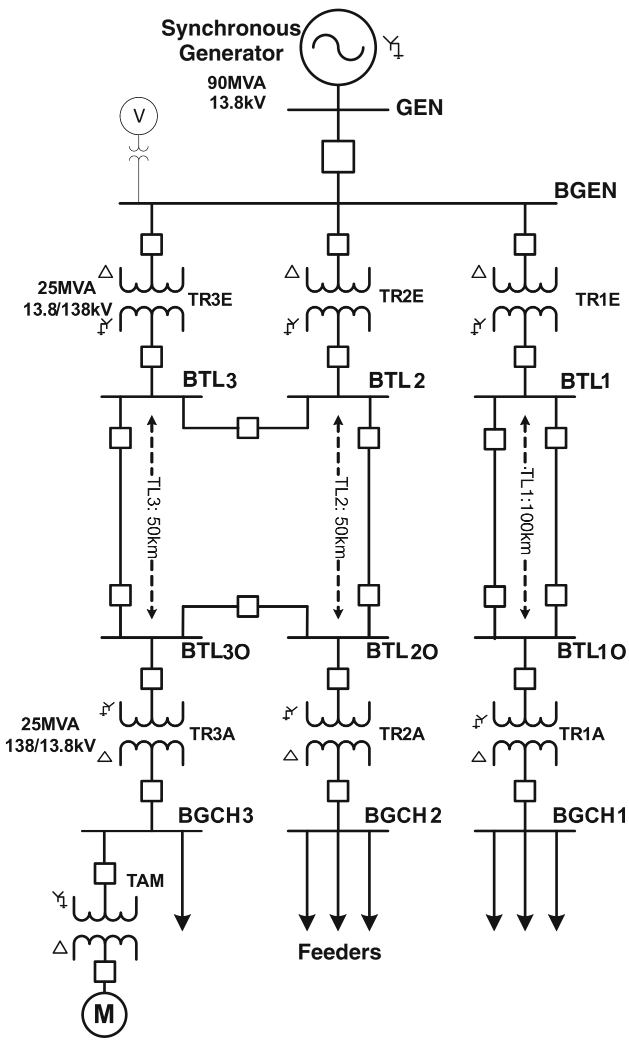

Fig. 7 The EPS analyzed.

– Inrush of the transformer TR2E; and
– Inrush of the transformer TR2E in internal short circuit.

The results from the algorithm implemented will be discussed in the next section.

5 Tests and Results

This section presents the results obtained using the proposed algorithm for the different situations simulated in the EPS represented by Fig. 7.

5.1 Internal Short Circuits to TR2E and TR3A Transformers

In order to test the efficiency of the proposed algorithm to indicate the occurrence of an internal fault in the transformer,

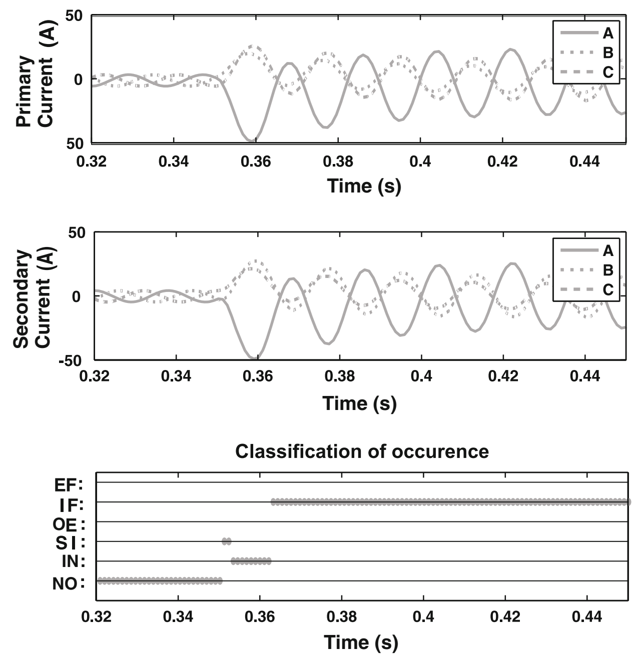

Fig. 8 Output of the algorithm facing the occurrence of an internal fault in the TR2E transformer.

507 situations of internal faults were simulated on the TR2E and TR3A transformers. The situations were applied in both the primary and the secondary of the transformers, varying the percentages of the windings involved between 5 and 80 %, the inception angle of the fault between −90° and 90° and the type of fault (phase-phase, phase to ground and inter-turn).

Figure 8 illustrates the response of the algorithm upon the occurrence of an internal fault in the TR2E transformer. This situation was characterized by a fault involving 80 % of the winding of phase *A* and ground, with inception angle of 60°. It is possible to verify in the figure the waveforms of the currents measured in the primary and secondary of the protected transformer, as well as the classification of the event. It may be noticed that from the very start of the fault, the algorithm is sensitized, although, there is no indication of internal fault, which only occurs 11 ms after the onset of the situation illustrated.

Table 2 shows the response of the algorithm to situations of internal faults applied to transformers TR2E and TR3A. Observing this table, it is found that the algorithm correctly highlighted the occurrence of almost all the situations evaluated. However, this indication always had a slight delay in relation to the instant the fault arose in the transformer. The average delay was about 12.5 ms. During this period, the samples were classified as over-excitation or inrush, due mainly to the transient behavior on the begining of the fault.

The algorithm failed to identify 14 situations of internal faults. These situations were characterized by phase-to-ground faults involving 5 % of the winding and faults

Table 2 Outputs provided by the algorithm facing internal short circuits in transformers TR2E and TR3A

Transformer in fault	Number of cases	Success (%)	Average time (ms)
TR2E	299	97.3	12.5
TR3A	208	97.1	12.5
Total	507	97.2	12.5

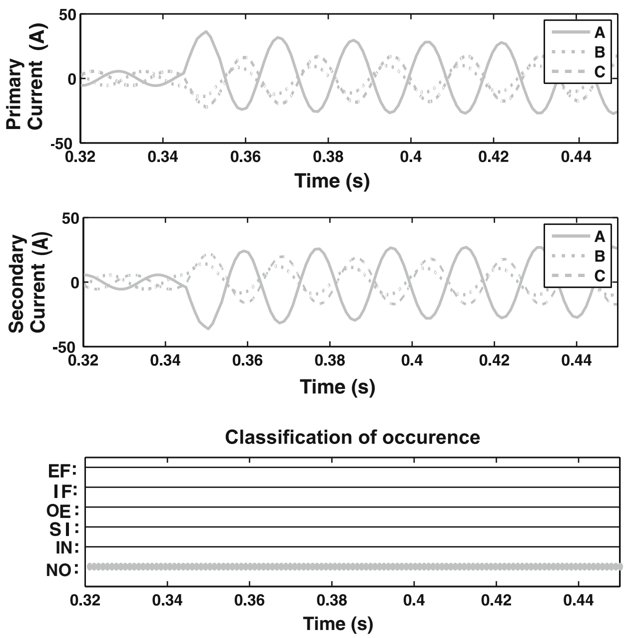

Fig. 9 Output of algorithm applied to transformer TR3E facing an internal short circuit in TR2E.

between turns also involving small portions of the winding. It is considered that the algorithm was successful in the task of identifying situations of internal faults since it was able to identify 97.2 % of the situations presented. For situations where it failed to identify the presence of a internal fault, it may observed that virtually no changes in the waveforms occurred, since the fault impedance was characterized by a minimum value.

The differential philosophy states that a situation of an external fault should not sensitize the protection associated with this equipment. However, this situation may occur when, for example, there is an internal fault in a transformer connected in parallel to another operating normally. Figure 9 illustrates the situation described, in which TR3E is monitored during the occurrence of the internal fault detected in TR2E and illustrated by Fig. 8. For this situation the output of the algorithm indicates that TR3E is operating normally, in steady state (NO).

For every situation of internal faults in TR2E and TR3A presented to the algorithm, the analysis of the waveforms

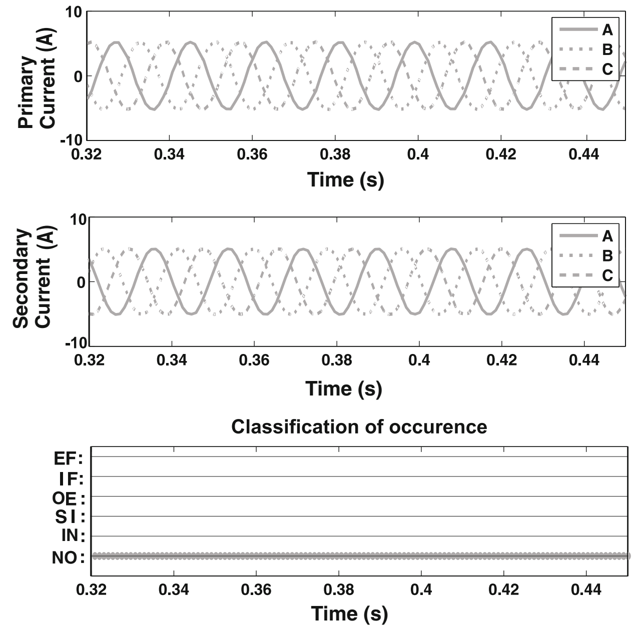

Fig. 10 Output of the algorithm facing an elevation of the nominal voltage to 1.18 p.u.

Table 3 Outputs provided by the algorithm facing over-excitation of the TR2E transformer

Transformer	Nominal voltage (p.u.)	Number of cases	Output
TRE2	$V_n < 1.25$	15	Normal operation
TRE2	$V_n \geq 1.25$	45	Over-excitation

from the other transformers connected to the system indicates that they are operating in steady state.

5.2 Over-Excitation of the TR2E Transformer

For the tests in situations of over-excitation, the nominal voltage of the EPS was increased from 1 to 1.7 p.u., in steps of 0.1 p.u. Through these values in steady state, it was possible to characterize the over-excitation of the power transformers. Figure 10 illustrates the output of the algorithm facing an elevation of the rated voltage to 1.18 p.u. In this figure, it can be seen that practically no alterations occurred in the waveforms of the primary and secondary currents of the transformer. Therefore, the algorithm indicates that the transformer is operating in steady state.

It is feasible to verify that when the transformer is subjected to less severe overvoltages, the differential currents are not significant. This may be explained by the fact that saturation of the transformer core does not occur until a certain voltage level is reached. Thus, in situations where the nominal voltage is less than 1.25 p.u., the algorithm indicated that transformers were operating in steady state, as can be seen in

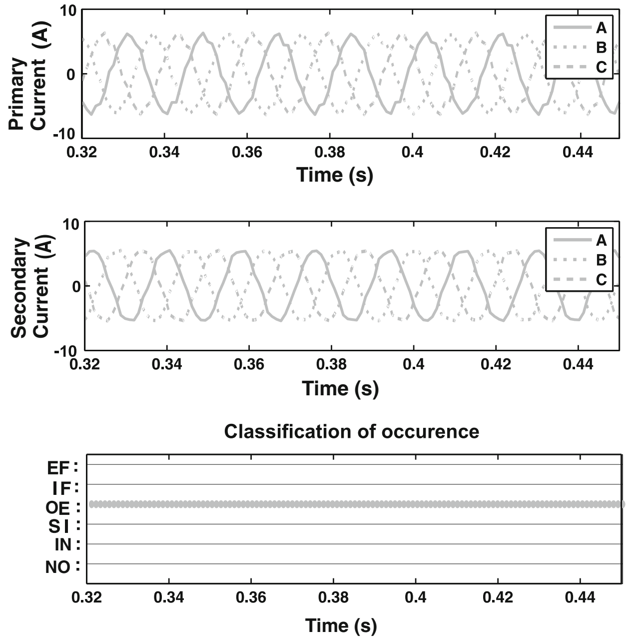

Fig. 11 Output of the algorithm facing an elevation of the nominal voltage to 1.28 p.u.

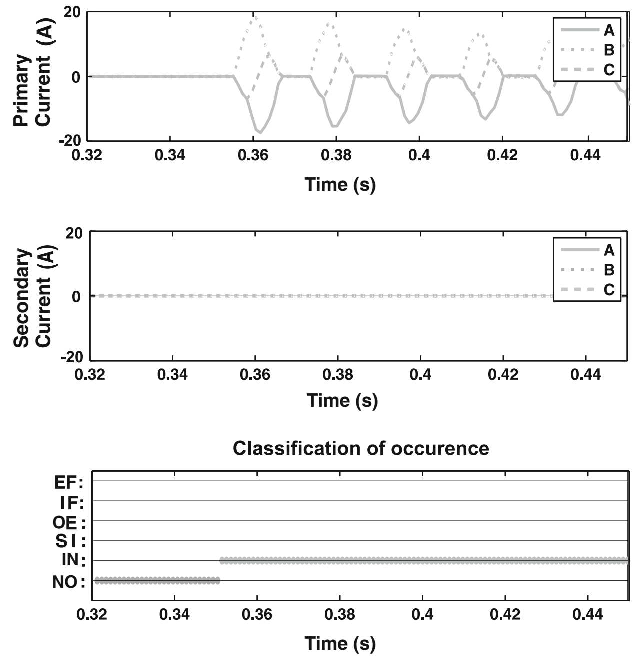

Fig. 12 Output of the algorithm facing an inrush in transformer TR2E with an inception angle of inrush of 15°.

Table 3. However, for situations where the nominal voltage of the system was above 1.25 p.u., the algorithm indicates that the transformer was operating in over-excited mode, as set out in Table 3. For these situations there was evidence of significant quantities of differential currents, as well as the presence of harmonic components, primarily of the fifth order, in the current waveforms. Figure 11 illustrates the currents observed in a situation of overvoltage of 1.28 p.u., as well as the algorithm's response to this situation, indicating that the transformer is working in an over-excited state.

5.3 Energization of the TRE2 Transformer

This subsection presents the results observed for the situations of inrush in the transformers. To undertake the tests, several inrush situations in the TR2E transformer were simulated, varying the angle of onset of the inrush from −90° to 90°, in steps of 15°. For each of the situations where the TR2E transformer was energized, in addition to observing the operating condition of this equipment, the operating condition of the TR3E transformer, which was operating in parallel to TR2E at the moment of inrush, was also observed.

The typical behavior of the algorithm in situations of inrush can be illustrated by Fig. 12. This figure shows the response of the proposed methodology given an inrush in transformer TR2E with an angle of inrush of 15°, highlighting the effectiveness of the methodology in correctly identifying this operating condition.

Table 4 shows the results obtained by the proposed algorithm for the inrush situations considered. It is noteworthy that all situations were indicated correctly. Table 4 also presents the results obtained by applying the algorithm to the analysis of TR3E during the situation of inrush in TR2E.

As shown in Table 4, it can be seen that the algorithm was unable to identify all the situations of sympathetic inrush. The errors occurred because, although the inrush in one transformer affected the waveforms in the other equipment operating in parallel, this alteration does not always imply differential currents with significant amplitudes (Wang et al 2008).

In this sense, it needs to be clarified that the algorithm was unable to identify the occurrence of sympathetic inrush for energization at angles close to −90° and 90°. Figure 13 illustrates a situation where the algorithm was unable to detect the sympathetic inrush.

Table 4 Output of the algorithm facing an inrush in transformer TR2E with sympathetic inrush in TRE3

Transformer observed	Output desired	Number of cases	Success (%)	Average time (ms)
TR2E	Inrush	13	100	3.5
TR3E	Sympathetic inrush	13	77	86

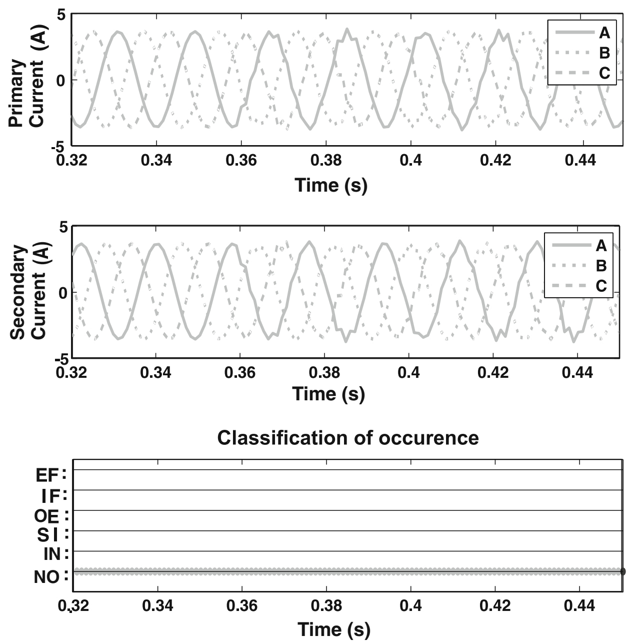

Fig. 13 Output of the algorithm facing an inrush in transformer TR2E in which the algorithm was unable to identify the occurrence of sympathetic inrush in TR3E.

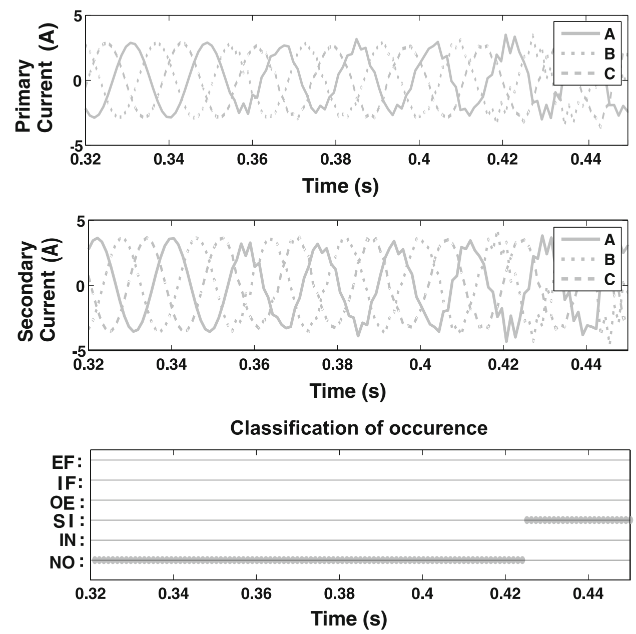

Fig. 14 Output of the algorithm facing an inrush in transformer TR2E in which sympathetic inrush was detected in TR3E.

However, as the angle of inrush in the transformer approaches 0°, the influence of this operation increases in the currents observed in the transformer connected in parallel to the one being energized. In these cases the algorithm managed to detect the events of sympathetic inrush. This took on average 86 ms (5.15 cycles of the fundamental frequency) to perceive such an event. It was found that the differential current characterized in the transformer connected in parallel to the one being energized increases significantly throughout the inrush process, which may also be observed in studies conducted by Wang et al (2008). This explains the delay of the algorithm in detecting sympathetic inrush, since this will only be detected when characterized by input variables with values capable of activating the fuzzy rules. In Fig. 14, an example is given of how the currents behave in situations that the proposed algorithm should detect, as well as the algorithm's response to such situations.

It is important to mention that the correct identification of the occurrence of sympathetic inrush facilitates the analysis regarding the poor performance of the differential protection, since this phenomenon is pointed out as a possible cause of misoperation of the differential protection (Bronzeado et al 1996).

5.4 Energization of the TRE2 Transformer with Internal Short-Circuit

Another important situation defined for the tests was the energization of the TRE2 transformer with internal fault. For these tests, inrush situations were simulated identical to those undertaken in the previous subsection. However, for this step, the transformer displayed an internal fault at the moment of inrush. These faults were considered both in the primary and in the secondary of TR2E. In addition, the equipment that was being energized was observed and the operating condition of TR3E was also analyzed via occurrences in TR2E.

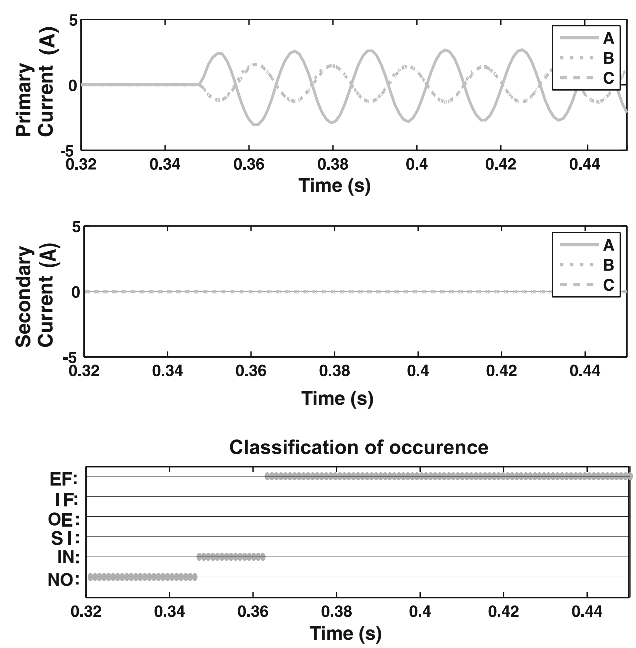

Fig. 15 Output of the algorithm facing a situation of inrush with internal fault.

Table 5 Output of the algorithm facing situations of energization of the TRE2 transformer with internal short-circuit

Side in fault	Number of cases	Success (%)	Average time (ms)
Primary	130	100	16
Secondary	182	100	16
Total	312	100	16

Table 6 Summary of outputs of the algorithm applied to TR3E facing energizing the transformer TR2E under internal fault

Side under fault	Angle ϕ of inrush	Cases	Output	Average time (ms)
Primary	–	130	Normal operator	-
Secondary	$-45° \geq \phi < 45°$	84	Normal operator	-
Secondary	$\phi < -45°$ and $\phi \geq 45°$	98	Inrush under fault	86.5

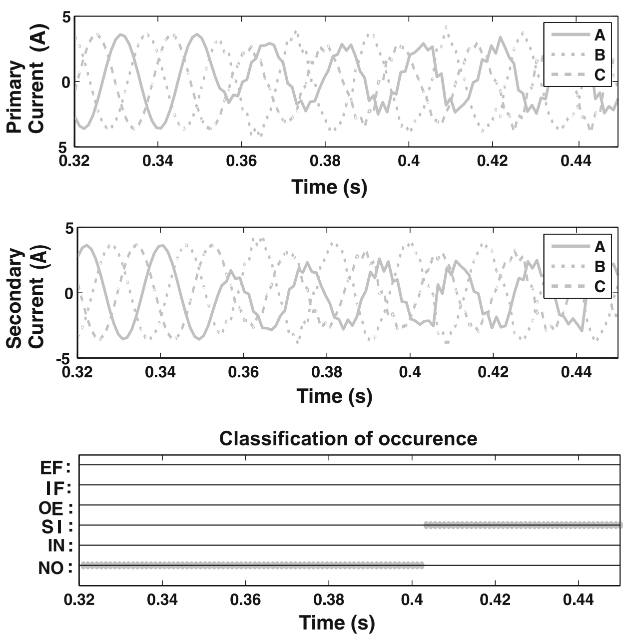

Fig. 16 Output of the algorithm for analyzes of TR3E facing a situation of energizing TR2E under internal fault in the secondary.

Figure 15 illustrates the output provided by the algorithm for a situation of inrush with internal fault. As can be seen, the algorithm correctly indicated that the transformer was subjected to a situation of internal fault facing the energization procedure. However, just as in situations in which only an internal fault occurred, the start time of the correct indication was affected due to the harmonic content at the begining of the fault. For energization situations under fault, the algorithm takes a little longer to identify the presence of internal fault because of the even harmonics characteristic of the situation. The algorithm goes on to indicate correctly the inrush under internal fault, on average, 16ms after it starts. Table 5 sets out the situations of energization under internal fault that were presented to the algorithm.

When the TR2E transformer is energized under internal fault condition, the influence of this event is observed in TR3E. Since the main event that occurs in TR2E is the internal fault, the ideal would be for differential currents not to occur in TR3E. Therefore, the algorithm would have to point out that this was operating under normal conditions. What was expected was confirmed in every situation of inrush in TR2E with internal fault in the primary. However, when the inrush occurred with the internal fault in the secondary of the transformer, in several situations the algorithm proceeded to indicate that TR3E was experiencing a sympathetic inrush, as can be seen in Table 6.

The behavior of the classifier, when excitation under internal fault in the secondary of the transformer occurs, is similar to that presented when a real sympathetic inrush occurs, caused by a power transformer connected in parallel, as can be seen in Fig. 16. This happens because during the energization under fault in the secondary, the current becomes reflected on the secondary side of the transformer, characterizing the process of inrush, and only then begins to feed the fault. In this way, the saturation of the transformer core occurs, in the same way at it occurs during an energization procedure without fault. Thus, the distortions generated during this procedure are reflected in the transformer that operates in parallel with the one being energized under a fault.

6 Conclusions

This article proposed a monitoring algorithm that uses an FS, with the input variables preprocessed by the WPT, to diagnose the operating conditions of power transformers. The results show that the algorithm developed was capable of discriminating, with good accuracy, the various kinds of phenomena concerning operation and fault which might occur in a power transformer.

Emphasis is given to the analysis of situations involving the parallelism between transformers, which allowed the characterization and study of sympathetic inrush, as well as its consequence for the protection of transformers. It was found that the influence of the phenomena stemming from parallelism depends on its inception angle and that this variation directly influences the impact of the phenomenon observed in the operation of the equipment in parallel.

Based on these results, it appears that the use of the proposed methodology and subsequent analysis of events allow a better understanding of operational situations to which a power transformer may be subjected. Thus, the gains achieved by the application of the technique can be directed both towards the protection analysis of this equipment as well as for studies related to PQ. With the output coming from the monitoring algorithm it is possible to correlate a phenomenon of PQ in the EPS with the operational situation of the transformer. Furthermore, the monitoring algorithm helps in the understanding of the causes of trip of the differential protection, reducing the downtime of the equipment due to misoperation.

In general, the use of the proposed technique proved to be very efficient, since it presented a correct classification of the events studied and indicated precisely the start of the events evaluated.

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