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An Expert System Based Approach for Diagnosis of Occurrences in Power Generating Units

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1. Introduction

Nowadays power generation utilities use complex information management system, as new monitoring and protection equipment are being installed or upgraded in power plants. Usually these devices can be configured and accessed remotely, thus, companies that own several stations can monitor their operation from a central office. This monitoring information is crucial in order to evaluate the power plant operation under normal and abnormal situations. Specially in abnormal cases, like fault disturbances and generator forced shutdown, the monitoring system data are used to evaluate the cause and origin of such disturbance.

As the data can be accessed remotely, in general the analysis is performed at a specific department of the utility. The engineers at this department spend, on a daily basis, a substantial amount of time collecting and analyzing the data recorded during the occurrences, some of them severe and others resulting from normal operation procedures. Example of a severe occurrence is the forced shutdown of a loaded generator due to a fault (short-circuit). Concerning normal occurrences, examples are the energization and de-enegization procedures and maintenance tests.

The main data used to analyze occurrences are disturbance records generated by Digital Fault Recorders (DFRs) and the sequence of events (SOE) generated by the supervisory control and data acquisition (SCADA) system. Usually this information is accessible through distinct systems, which complicates the analyst's work due to data spreading. The analyst's task is to verify the information generated at the power stations and to evaluate whether an important occurrence has occurred. In this case, it is also needed to identify the cause of the disturbance and to evaluate whether the generators protection systems operated as expected. Although this investigation is usually performed off line, it has become common in case of severe contingencies to contact the DFR specialist to ask for his advice before returning the generator to operation. Thus the importance to perform the analysis as quickly as possible (Moreto et al., 2009).

The excess of data that needs to be analyzed every day is a problem faced in most analysis centers. It is of fundamental importance to reduce the time spent in disturbance analysis as more and more data become available to the analyst as the power system grows and technology improves (Allen et al., 2005). In practice, engineers can't verify all the occurrences because of the number of records generated. It should be pointed out that a significant percentage of these disturbance records are generated during normal situations. This way, the development of a tool to help the analysts in their task is important and subject of several studies. Using such a tool, the severe occurrences can be analyzed in first place and an automated analysis result leading to a probable cause of the disturbance would greatly reduce the time spent by the analyst and improve the quality of the analysis. The remaining records corresponding to normal situations can be archived without human intervention.

To obtain a disturbance analysis result, specialized knowledge is necessary. Interpretation of the operative procedures of distinct power units, familiarity with the protection systems and their expected actions are just a few skills that the analyst should dominate. Thus, this task is suited for application of expert systems. The focus of this chapter is on the application of a set of expert systems to automated the DFR data analysis task using also the SOE.

The DFRs are devices that record sampled waveforms of voltage and current signals, besides the status of relays and other digital quantities related to the generator circuit. The DFR triggers and the data is recorded when a measured or calculated value exceeds a previously set trigger level or when the status of one or more digital inputs changes. Thus, when a disturbance is detected a register containing pre-disturbance and post-disturbance information is created in the DFR's memory, (McArthur et al., 2004).

Fig. 1 shows the typical quantities monitored by a DFR. The currents on the high voltage side of the step-up transformer ($I^{tf}_{A,B,C}$), the generator terminal voltage ($V_{A,B,C}$), the loading current ($I_{A,B,C}$), the neutral current/voltage (I_N, V_N) in addition to the field voltage and current (V_f, I_f) lead to a total of 13 analog quantities per generation unit that should be verified at each occurrence.

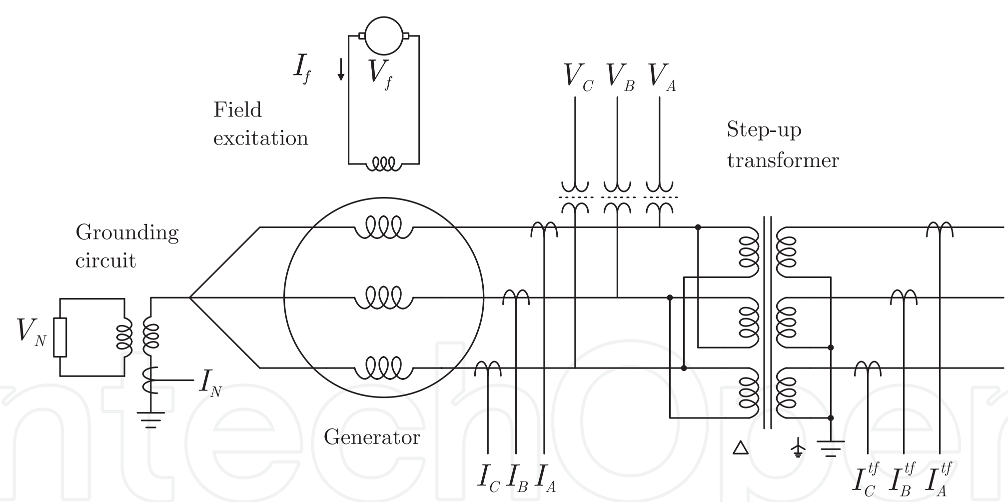


Fig. 1. Typical quantities monitored by DFRs in a power generation unit.

Several papers have been published in technical journals and conferences proposing and testing schemes to automate the disturbance analysis task. However, the majority are designed for fault diagnosis in transmission systems and for power quality studies, not considering the characteristics of generation systems.

Davidson et al. (Davidson et al., 2006) describe the application of a multi-agent system to the automatic fault diagnosis of a real transmission system. Some agents, based on expert systems and model based reasoning, collect and use information from the SCADA system and from DFRs.

Another paper (Luo & Kezunovic, 2005) proposed an expert system (ES) that makes use of data from DFRs and sequence of events of digital protection relays to analyze the disturbance and evaluate the protection performance. Expert systems are also employed in PQ studies as in Styvaktakis (Styvaktakis et al., 2002). In this paper the disturbance signal is segmented into stationary parts that are used to obtain the input data for the ES.
When applied to automated disturbance analysis of power systems, computational intelligence techniques are normally used in conjunction with techniques for feature extraction. The most common ones are the Fourier Transform (Chantler et al., 2000), Kalman Filters (Barros & Perez, 2006) and the Wavelet Transform (Gaing, 2004).
In this chapter we propose a scheme to automatically detect and classify disturbances in power stations. Two sources of information are used: disturbance records and sequence of events. The first objective of this scheme is to discriminate the DFR data that do not need further analysis from the ones resulting from serious disturbances. To do this the phasor type of disturbance record is used. The SOE is used in the scheme to complement the result obtained by the DFR data. Examples of incidents that do not require further analysis are: DFR data resulting from a voltage trigger during normal energization or de-energization of a generator; a protection trigger during maintenance tests of relays while the generator is off-line; or a trigger coming from another DFR without any evidence of fault on the monitored signals. The second objective is to classify the disturbance, using the waveform record, providing a diagnosis to help the analysts with their task.
The proposed methodology has been developed with collaboration from a power generation utility and a DFR manufacturer. The module which analyses the phasor record was validated using hundreds of DFR records generated during real occurrences in a power plant over a period of four months while the waveform record module was tested with simulated records and a real fault record.
Section 2 of this chapter presents a brief description of the sources of data used: Digital Fault Recorders and the SCADA system (responsible for generating the SOE). In Section 3 an overall view of the proposed scheme is shown. Sections 4 and 5 describe the two main modules proposed to diagnosing the disturbances that use phasor and waveform records. Some results and comments about the performance of the system are discussed in Section 6. Finally, some general conclusions are stated in Section 7.

2. Data sources

Currently most power utilities have communication networks that allow remote monitoring and control of the system. These networks make possible to access disturbance records and supervisory data in a centralized form. Next subsections will describe these data (disturbance records and sequence of events), which are used by the proposed scheme to automatically classify disturbances.

2.1 Digital fault recorders

Digital fault recorders are responsible for generating oscillographic data files. An oscillography can be viewed as a series of snapshots taken from a set of measurements (like generator terminal voltages and currents) over a certain period of time. Usually these records are stored in COMTRADE format (IEEE standard C37.111-1999)(IEE, 1999), when the DFR is triggered by one of the following situations:

- The magnitude of a monitored signal reaches a previously defined threshold level.

- The rate of change of a monitored signal exceeds its limit.
- The magnitude of a calculated quantity (active, reactive and apparent power, harmonic components, frequency, RMS values of voltage and currents, etc.) reaches the threshold level.
- The rate of change of a calculated quantity for instance, active power, exceeds its preset limit.
- The state of the DFR digital inputs change.

When the DFR triggers by some of the above situations, all digital and analog signals are stored in its memory, including the pre-fault, fault and post-fault intervals. Because the thresholds (also called triggers) are set at aiming to detect every fault, DFRs may also be triggered during normal situations. Examples of these situations are energization and de-energization of the machine and tests in protective relays while the generator is disconnected.

One of the main advantages of modern DFRs is their ability to synchronize their time stamp with the global position system (GPS) time base. Thus, in addition to synchronized waveforms, these devices are able to calculate and store a sequence of phasors of the electrical quantities before, during and after the disturbance. In general, one phasor is stored for each fundamental frequency cycle. Because of this lower sampling rate, a phasor record, also called "long duration record" may store several minutes of data, while the waveform record, called "short duration record" only records for a few seconds.

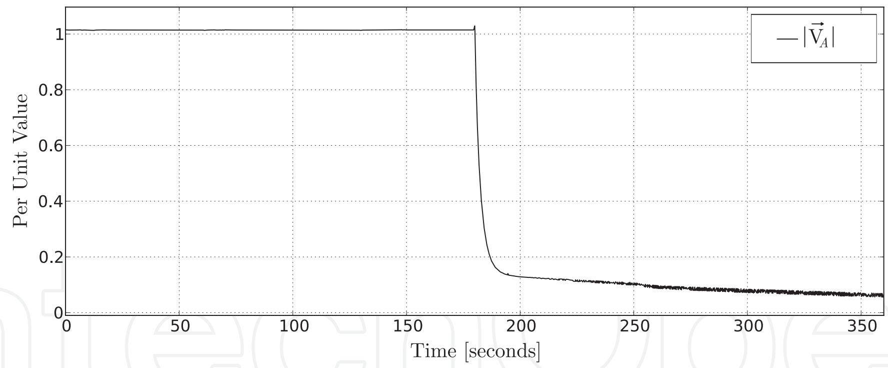
The approach described in this chapter uses the long duration record to pre-classify the disturbance and the waveform record to analyze the occurrences tagged as "important". The main reason for this choice of using firstly the phasor record is that in large generators the transient period of disturbance signals can be considerably long (dozens of seconds or even minutes). Short duration records usually do not cover the entire occurrence in these cases. This is particularly true in voltage signals, as in Fig. 2. The two signals depicted were recorded during the same disturbance, although they do not share the same time axis scale in this picture. The zero instant of Fig. 2(b) is located approximately at 175 seconds on Fig. 2(a).

As can be seen in Fig. 2(a), the transient lasts for approximately 20 seconds, several times longer than the duration of a typical waveform record (usually 4 to 6 seconds). This is clear in the waveform record shown in Fig. 2(b). In this case, using the waveform record, it is not possible to know whether the voltage will stabilize at a peak value of 0.5pu or decreases further to zero.

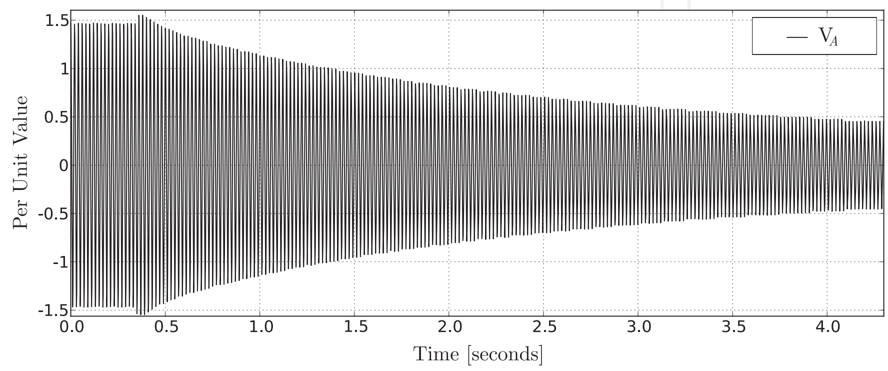
2.2 Supervisory system

The supervisory system is responsible, among other things, for registering the sequence of events in the utility's database. The SOE is a series of messages recorded every time the state of a digital input monitored by a Remote Terminal Unit (RTU) changes. The states monitored by RTUs are generally auxiliary contacts of protective devices, circuit breakers (CB) and switches. Typically, the following information is associated with each event stored in a SOE file:

- The time stamp and date of the event, usually with a degree of accuracy to within milliseconds and synchronized with GPS
- An indication of the substation or power plant where the event was recorded
- An indication of the circuit or equipment related to the event
- A unique tag associated with the digital input that originates the event



(a) Phasor record



(b) Waveform record

Fig. 2. A disturbance in phasor and waveform record.

- A description of the event.

The listing bellow shows an example of three SOE messages.

```
 Time stamp  Stat. Date  Eq.           Description
19:13:58.088 UTCH Jun25 GT04 Reverse power relay 32G change to trip
19:13:58.104 UTCH Jun25 GT04 Generator lockout relay change to trip
19:13:58.137 UTCH Jun25 GT04 Main GT04 circuit breaker change to open
```

3. The proposed scheme

In the proposed scheme the first data to be processed is the phasor data recorded by the DFR. This first module is detailed in (Moreto & Rolim, 2011). It is composed of an expert system reasoning over the characteristics of the symmetrical components calculated using phasor records divided into pre- and post-disturbance segments. Regardless of the DFR analysis conclusion, the SOE from SCADA system is analyzed by a second expert system. Finally the results of both analysis (DFR and SOE) are correlated in order to achieve the final conclusion. The phasor record analysis can be interpreted as a filter where the serious disturbances (like those resulting from short-circuits) are separated from the other situations, thus, fulfilling the first objective of this work. These serious cases are then submitted to the second step of the proposed scheme where the waveform record is used because of its higher sampling rate. The goal is to detect if a short-circuit occurred and where (in the generator terminals or in the nearby power grid) and classify it according to its type like phase-to-graund fault, phase-phase fault and so on. This step is derived from the second objective stated at the introduction. The overall structure of the proposed scheme is depicted by Figure 3.

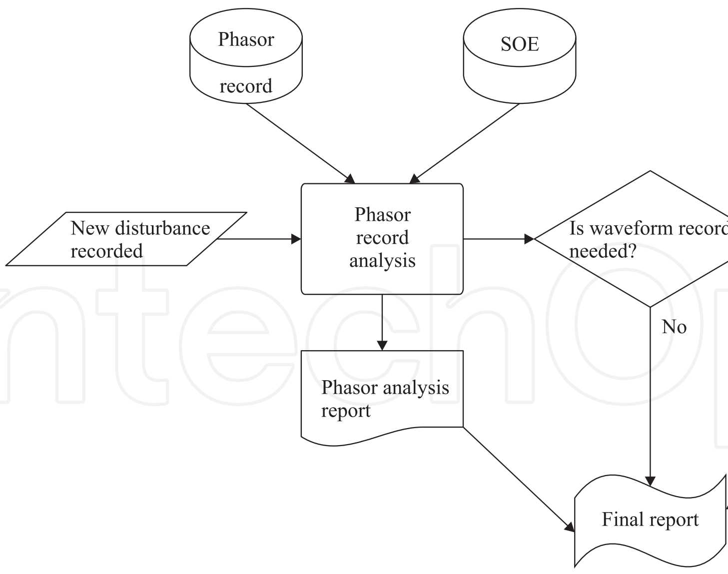


Fig. 3. Structure of the proposed scheme.

The phasor record analysis and waveform record analysis are described in the next sections.

4. Phasor record analysis

The phasor analysis is started when a new disturbance record is available at the analysis center. The phasor record along with the SOE are then analyzed by the proposed scheme. The disturbance record and SOE data are read from the DFR and SCADA databases available at the utilite's office. Only the SOE recorded during the disturbance record time lapse is used. Fig. 4 shows the structure of the proposed scheme. The disturbance record is firstly preprocessed and segmented into pre- and post-disturbance parts. For each of these parts the mean values are calculated composing the feature set used by the decision making expert system.

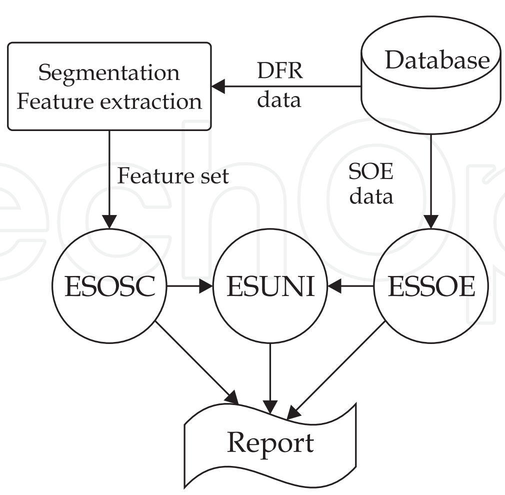


Fig. 4. Structure of the proposed phasor analysis scheme.

The decision making process is made by three expert systems: ESOSC uses the features calculated from the disturbance record to achieve a result concerning the DFR data; ESSOE uses the sequence of events to obtain a complementary result and ESUNI correlates the results

from both expert systems. All the messages and conclusions achieved during the decision making process are included in the phasor record analysis report.
The following subsections give an overview of the functional blocks of Fig. 4. A detailed description of each block can be found in (Moreto & Rolim, 2011).

4.1 Segmentation and feature extraction

The segmentation and feature extraction process is represented by the block diagram in Fig. 5 where indexes ABC and 012 denote the three electrical phases and three symmetrical components (zero, positive and negative) respectively. The operator $(|.|)$ is the absolute value and $(\vec{.})$ represents a vector quantity.

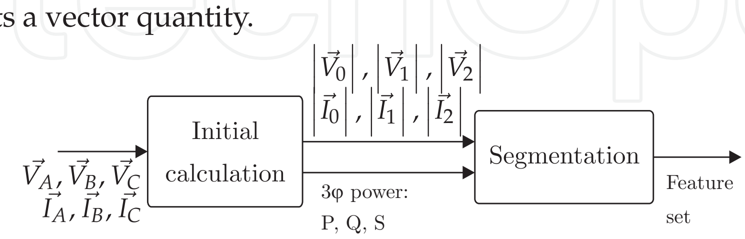


Fig. 5. Segmentation and feature extraction.

The recorded quantities are initially normalized to *per unit* (*pu*) values followed by the calculation of the symmetrical components (Grainger & Stevenson, 1994) and complex power. The segmentation process is applied to these calculated quantities in order perform a feature extraction in each segment. The signals are split into parts before and after the transient.
In (Moreto & Rolim, 2008), the authors propose a detection index that is suitable to segment phasor records that contain slower disturbances as observed in large power generators. This index is calculated using Equation 1.

$$di(n) = \sigma_\Delta(n) = \frac{1}{\Delta - 1} \sum_{i=n}^{n+\Delta} (|\vec{y}(i)| - \mu_\Delta)^2 \tag{1}$$

Where n is the sample index, $|\vec{y}(i)|$ is the absolute value of the considered phasor quantity at sample i, Δ is the window width, σ_Δ is the standard deviation calculated over this window and μ_Δ is the mean value of the data window. In this chapter, the chosen Δ was 480 samples (8 seconds).
When $di(n)$ exceeds a certain threshold δ, point n belongs to a disturbance segment. Consequently the first point where $di(n) > \delta$ indicates the beginning of a disturbance interval which ends after the last point where $di(n) > \delta$.
Fig. 6 presents an example of the segmentation process. The magnitude of the voltage phasor record is segmented according to the gray bar. The calculated detection index is also shown in the picture.
The mean value of the samples before and after the detected disturbance interval are stored in the ESOSC facts data base.

4.2 ESOSC: Expert system for oscillographic analysis

This expert system is responsible for analyzing the data provided by the segmentation procedure. Based on the pre- and post-disturbance data, ESOSC can classify the long term oscillographic record in several categories.
ESOSC is represented by the diagram in Fig. 7. It is composed of 19 rules that will be described in the following paragraphs.

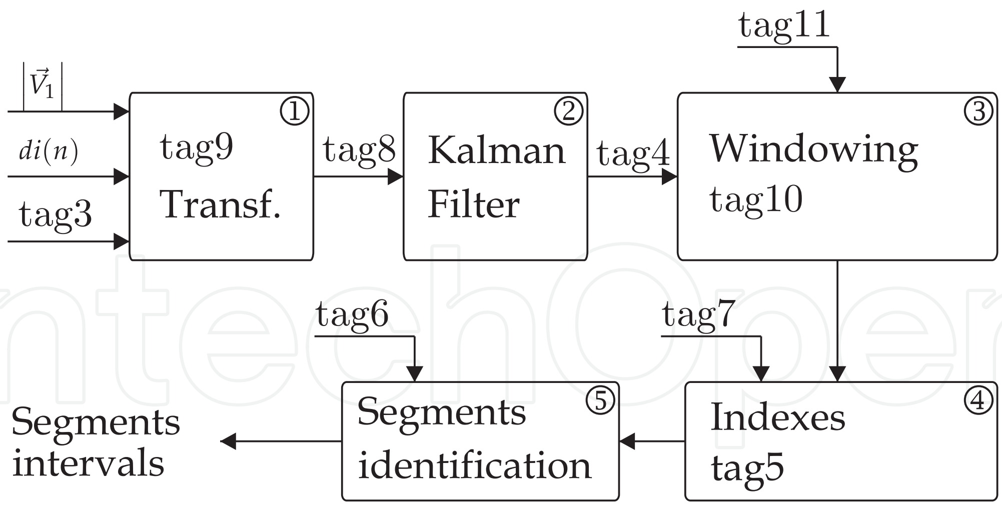


Fig. 6. Example of data segmentation and proposed detection index.

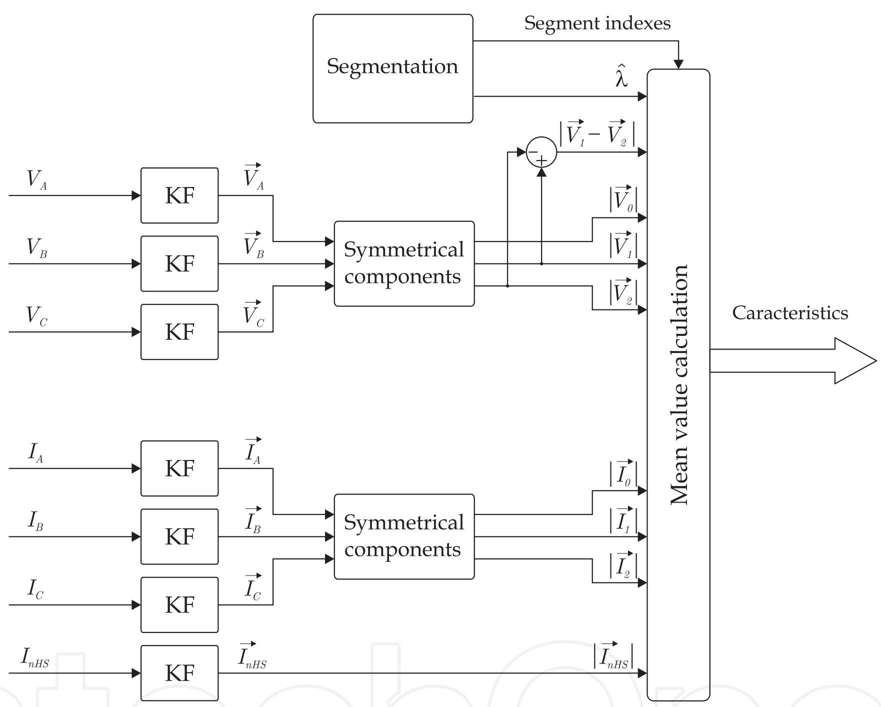


Fig. 7. ESOSC representation.

The ESOSC implementation is based on the CLIPS expert system shell with the facts being created using CLIPS' template objects. Each input fact contains three slots:

- Name: String with the processed quantity, such as I_0, I_1, I_2, V_0, V_1, V_2 or P.
- PreValue: Mean value of the named quantity calculated over the pre-disturbance segment.
- PostValue: Mean value of the named quantity calculated over the post-disturbance segment.

The ESOSC knowledge base is composed of two sets of rules. The set called *Characteristics identification rules* uses the input facts as premises. According to the pre-disturbance and post-disturbance values of each quantity, these rules create a new type of fact called *Characteristic fact* which stores information about the characteristic identified in each quantity.

Table 1 shows the premises of each characteristics identification rule and the type *characteristic fact* obtained (conclusion of the rule).
Each row of Table 1 corresponds to a rule. Some of these rules have a third premise about the difference between the pre- and post-disturbance values of the quantity being evaluated.

Rule conclusion	*Pre* [*pu*]	*Post* [*pu*]	Additional premise
Step-up from 0	< 0.05	> 0.05	
Step-down to 0	> 0.05	< 0.05	
Step-up	> 0.05	> 0.05	$(Post - Pre) \geq 0.1pu$
Step-down	> 0.05	> 0.05	$(Pre - Post) \geq 0.1pu$
No variation			$\text{abs}(Pre - Post) \leq 0.1pu$

Table 1. ESOSC: Premises and conclusions of characteristics identification rules

Depending on the values of the pre- and post-disturbance segments of a quantity one of the rules in Table 1 is fired and a new *characteristic fact* is created. These facts are composed by the following information slots:

- Name: String with the processed quantity, such as *I0*, *I1*, *I2*, *V0*, *V1*, *V2* or *P*.
- Type: A string indicating the characteristic type. The values can be: Step-up from 0, Step-down to 0, Step-up, Step-down and No variation.
- Value: The value associated with each characteristic. Normally the difference between the pre and post-segments mean values. In the case of the *No variation* rule, this value is the post-disturbance mean value.

Another set of rules was created to reason about the *Charateristic facts*. These rules correlate the characteristics identified in different quantities for example, between positive sequence voltages and currents. They also provide a conclusion about the disturbance generating a *Result fact*. Table 2 shows the premises of each rule of this set which is called *Characteristic relation rules*. The logical operators used to associate multiple premises are also indicated.
The rules in Table 2 conclude about the occurrence based on the disturbance record. In some cases the oscillographic record is not enough to obtain a definitive conclusion (Moreto & Rolim, 2011) and the SOE can be used to complement the result. The SOE analysis is performed by the Expert System for SOE analysis (ESSOE).

4.3 ESSOE: Expert system for SOE analysis

ESSOE has two objectives: the first is to complement the ESOSC analysis (when it is inconclusive) and the second is to provide an independent analysis, which is confronted with the ESOSC.
Prior to the execution of the ESSOE, the sequence of events recorded during the oscillography time lapse is selected. This selection is then classified and stored in a structured way as shown in Fig. 8.
The events which refer to the generation unit under analysis are picked up from the SCADA database and classified according to the four classes of Fig. 8:

- Protection Relays: The tripping events of protective relays are in this class. For each event the data read are time stamp of the event (date and hour with millisecond precision), state of the event (operated or normal), a code indicating the function of the relay according to the ANSI classification and a description of the event. Usually, when the protection device returns to its normal state another event is generated.

Rule	Quantity	Characteristic type	Characteristic value
Energization	and { V^+	Step-up from 0	$> 0.9pu$
	or { I^+	Step-up from 0	
	I^+	No variation	$< 0.05pu$
De-energization	and { V^+	Step-down to 0 or step-down	$> 0.8pu$
	or { I^+	No variation	$< 0.05pu$
	P	No variation	$< 0.1pu$
Isolated unit	and { V^+	No variation	$> 0.9pu$
	I^+	No variation	$< 0.05pu$
Synchronism	and { V^+	No variation	$> 0.9pu$
	I^+	Step-up from 0	
Normal operation	and { V^+	No variation	$> 0.9pu$
	I^+	No variation	$> 0.05pu$
Out of service	V^+	No variation	$< 0.05pu$
Forced shutdown	and { V^+	Step-down to 0	
	I^+	Step-down to 0	
	P	Step-down to 0	
Load increment	and { V^+	No variation	$> 0.9pu$
	or { I^+	Step-up	
	P	Step-up	
Load decrement	and { V^+	No variation	$> 0.9pu$
	or { I^+	Step-down	
	P	Step-down	

Table 2. ESOSC: Premises and conclusions of characteristics relation rules

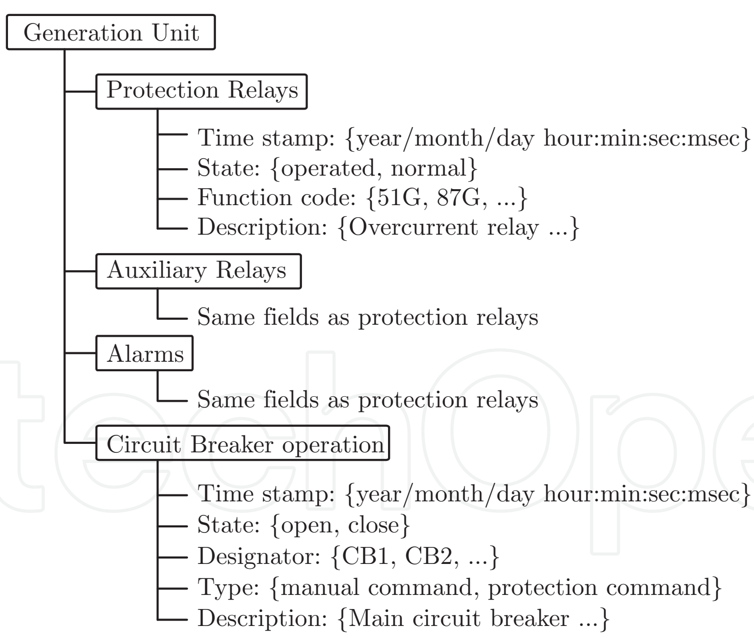


Fig. 8. Structure of sequence of events data.

- Auxiliary Relays: This class is used to represent the auxiliary relays, such as lockout relay (86), circuit breaker opening relay (94) and any other auxiliary device. The information fields are the same as the protection relays class.
- Alarms: All the events that are only informative (they do not represent any protective action) are grouped in this class.

- Circuit Breaker operation: This represents the events of opening and closing Circuit Breakers (CB).

Among these classes each event is classified according to its function for instance, overcurrent relay (ANSI 51), lockout relay (ANSI 86), main circuit breaker, manual opening of the circuit breaker and several other functions. The classification of the events is carried out performing a previous configuration of the system where the user informs the associations of SCADA monitored events with the classes.
Fig. 9 shows a representation of the sequence of event analysis that is based on the ESSOE whose input facts are the classified events and their status read from SOE database.

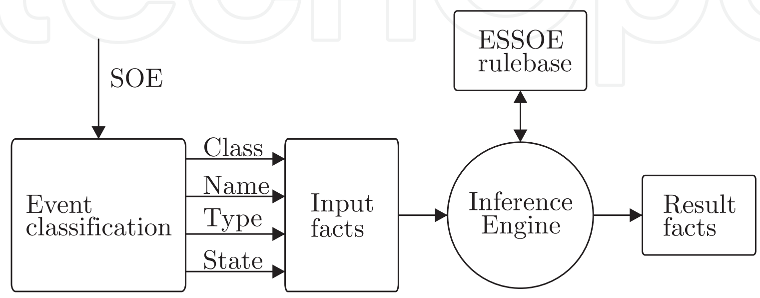


Fig. 9. ESSOE representation.

The knowledge base is formed by a set of rules obtained from the protection scheme of every generation unit with the collaboration of protection specialists. It is necessary to know which protective devices trip the circuit breakers, which ones are the auxiliary relays and their actions, the energization and de-energization procedures of the unit and other relevant characteristics or procedures associated with each generation unit. From these studies it is possible to write several rules. The ESSOE has 8 rules for the following situations: *de-energization*, *reverse power de-energization*, *isolated unit de-energization*, *protection testing* (maintenance), *generator lockout*, *synchronization* of unit, *forced shutdown* and the *no events*. (Moreto & Rolim, 2011).
The SOE analysis and oscillographic analysis should be correlated in order to obtain a final conclusion about the occurrence (Moreto & Rolim, 2011). This is the objective of the Expert System for generation Unit analysis (ESUNI).

4.4 ESUNI: Expert System for Unit analysis

The ESUNI is responsible for correlating the results from oscillograph (ESOSC) and sequence of events (ESSOE) analysis providing a diagnosis about the generation unit. It consists of an expert system with a set of simple rules that compares each result. These rules, listed in Table 3, represent a set of possible final results from the phasor record and sequence of events analyses (Moreto & Rolim, 2011).
A “no result” is obtained when none of the Table 3 rules is satisfied. The most common causes of “no result” conclusion are:

- Failures in the data collection system, such as missing events in the SOE
- Synchronization failure between the oscillographic records and the SOE
- Spurious events in SOE due to noise at RTU inputs
- Wrong connections of current or voltage transformers with the DFR

When the conclusion is “no result” or “fault”, a subsequent analysis is needed, using the waveform record in order to detect and classify possible faults.

ESUNI conclusion	ESOSC	ESSOE
Normal operation	Normal operation	No events
	Load increment	No events
	Load decrement	No events
Out of service	Out of service	No events
Reverse power de-energization	De-energization	De-energization with 32G
Normal de-energization	De-energization	De-energization
Energization	Energization	Generator lock-out
	Energization	Synchronism
Protection system tests	Out of service	Protection testing
Isolated unit operation	Isolated unit	No events
Synchronism	Synchronism	Synchronism
	Isolated unit	Synchronism
	Normal operation	Synchronism
Fault or forced shutdown	Forced shutdown	Forced shutdown

Table 3. ESUNI rule set.

5. Waveform record analysis

The structure of the waveform record analysis scheme is composed by the following processing blocks that are executed in sequence (Fig. 10): Data acquisition; data segmentation; data feature extraction; and decision making (expert system based).

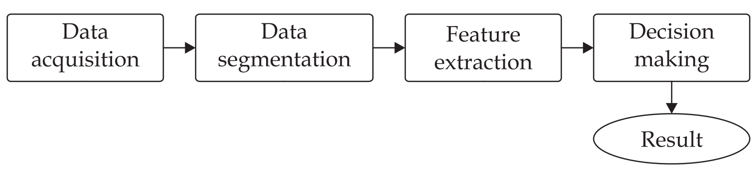


Fig. 10. Processing blocks of the waveform analysis scheme.

Data acquisition is the process of reading and interpreting the data stored in DFR records. These data are the sampled waveforms of voltages and currents acquired at the generator terminals. The segmentation block is responsible for detecting transients in the acquired data, resulting in a set of pre-fault, fault and post-fault segments. An Extended Complex Kalman Filter (ECKF) is used for this purpose (Nishiyama, 1997). For each detected segment a feature extraction is performed and those features will be used as inputs to the decision making process. Parameters of the signal estimated by the ECKF and also by linear Kalman Filters (KF) are used to calculate the input features of the expert system.

The occurrence analysis based on the DFR waveform records is also performed by an expert system. The input facts are the calculated features and the output fact is the type of disturbance. Development of the rule set was made based on several simulations of a power generating unit bay composed a hydraulic turbine, a synchronous machine, a speed regulator, a voltage regulator and a step-up transformer. In the simulated system this unit is connected to an slack bus which represents a bulk power system.

The processing blocks of Fig. 10 will be discussed in detail in the following subsections.

5.1 Data segmentation

Segmentation consists of splitting a disturbance record that is not stationary into a series of segments that can be considered stationary (Bollen & Gu, 2006). Through a segmentation process, traditional tools like Fourier analysis can be applied to each segment without the errors that would occur when such tools are employed in non-stationary signals. An example of segmentation is shown in Fig. 11.

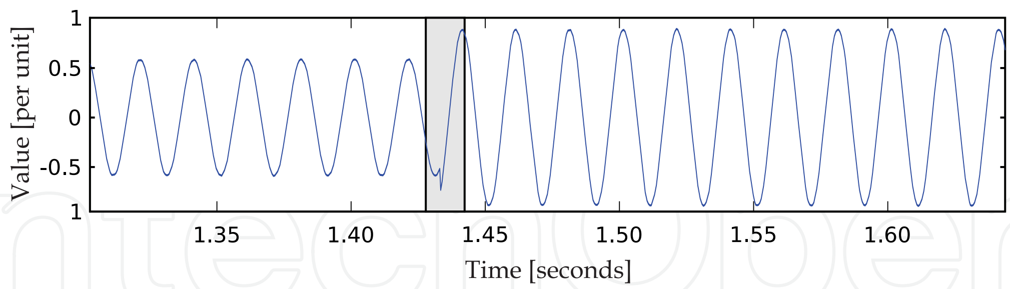


Fig. 11. Exemple of waveform record segmentation.

Several signal processing tools can be employed in the segmentation process. The most common ones are the Short Time Fourier Transform (STFT) (Gu & Bollen, 2000), the Wavelet Transform (Silva et al., 2006; Ukil & Zivanovic, 2007) and adaptive filters like Kalman Filters (Bollen & Gu, 2006; Styvaktakis et al., 2002). The segmentation schemes proposed in the literature are not appropriate for power generation units, because they have not been designed for segmenting slow transients like the example of Fig. 2(b). To overcome this limitation a new segmentation scheme is proposed in this chapter. This scheme is based on an extended complex Kalman filter (ECKF). Before the explanation of the signal model used and the segmentation algorithm, a brief introdution to Kalman filters is presented.

5.1.1 Kalman filters

The Kalman filter (KF) is a recursive and efficient estimation process that minimizes the mean square error of a signal model based on measured values. The process uses a observation variable obtained from the measurements (DFR data) to estimate the state variables. In its basic formulation, the relation between the states and the measurements and the relation between the actual states and previous ones are assumed to be linear. This implies that the model to be estimated can be written as state variables where all Matrix elements are constants (Bollen & Gu, 2006):

$$\text{State equations:} \qquad \mathbf{x}_{k+1} = \Phi_k \mathbf{x}_k + \mathbf{w}_k \tag{2}$$

$$\text{Observation equations:} \qquad y_k = H_k \mathbf{x}_k + \mathbf{v}_k \tag{3}$$

where $\mathbf{x}_k$ is the state vector at instant k; Φ_k is the state transition matrix that provides the relation between instants k and $k+1$ and H_k is the observation matrix that relates the states with the measurements y_k. $\mathbf{w}_k$ and $\mathbf{v}_k$ are vectors representing the noise of the model and the measurements respectively. It is assumed that both are white noise, non correlated, with zero mean and covariance matrix $Q_k = E\left\{\mathbf{w}_k \mathbf{w}_k^T\right\}$ and $R_k = E\left\{\mathbf{v}_k \mathbf{v}_k^T\right\}$ where E is the expected value operation.

The recursive calculation of the Kalman filter starts from an initial estimation of the state vector $\hat{\mathbf{x}}_0$ and the error covariance matrix $\hat{P}_0$. With these values the Kalman gain K_k is calculated for sample k:

$$K_k = \hat{P}_{k-1} H_k^{*T} \left[H_k \hat{P}_{k-1} H_k^{*T} + R \right]^{-1} \tag{4}$$

where the operations denoted by * e ^{T} are the complex conjugate and transposition, respectively. R is the covariance of the measurement noise, assumed constant and acts as a speed adjustment parameter of the filter.

With the updated gain, the covariance matrix is also updated,

$$\hat{P}_k = \hat{P}_{k-1}\left(I - K_k H_k\right) \tag{5}$$

as well for state vector, using the new measurement y_k to correct it:

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_{k-1} + K_k\left(y_k - H_k\hat{\mathbf{x}}_{k-1}\right) \tag{6}$$

The term between parenthesis in Equation 6 is called innovation or residual. I is the identity matrix.
Finally a projection of the states and covariance matrix is calculated:

$$\mathbf{x}_{k+1} = \Phi_k \mathbf{x}_k \tag{7}$$

$$\hat{P}_{k+1} = \Phi_k \hat{P}_k \Phi_k^{*T} \tag{8}$$

With the projected values, the k index is incremented and a new iteration begins with the application of Equation 4. The process continues until $k = N$, where N is the total number of samples.
If the relations of the state equations and observation equations are non-linear, the extended Kalman filter (EKF) is more adequate. In EKF the matrix operations of Equations 2 and 3 are replaced by nonlinear functions:

$$\mathbf{x}_{k+1} = \phi_k\left(\mathbf{x}_k\right) + \mathbf{w}_k \tag{9}$$

$$y_k = \mathbf{h}_k\left(\mathbf{x}_k\right) + \mathbf{v}_k \tag{10}$$

To apply the EKF, the non-linear model (Equations 9) and the output equation (Equation 10) are linearized using the first term of the Taylor series. As a result, Equations 4, 5, 6 and 8 become (Girgis & Hwang, 1984):

$$\Phi_k = \left.\frac{\partial \phi_k\left(\mathbf{x}_k\right)}{\partial \mathbf{x}_k}\right|_{\mathbf{x}_k = \hat{\mathbf{x}}_k} \tag{11}$$

$$H_k = \left.\frac{\partial \mathbf{h}_k\left(\mathbf{x}_k\right)}{\partial \mathbf{x}_k}\right|_{\mathbf{x}_k = \hat{\mathbf{x}}_{k-1}} \tag{12}$$

5.1.2 Signal model

In this chapter the parameters of the signal model are estimated by a extended Kalman filter. The proposed model, expressed in Equations 13 to 15 is a complex sinusoid with a damping coefficient:

$$y_k = z_k + v_k \tag{13}$$

where:

$$z_k = e^{\lambda t_k} A_1 e^{j(\omega_1 t_k + \varphi_i)} \tag{14}$$

$$\omega_1 = 2\pi f_1, \qquad t_k = k\Delta t \tag{15}$$

The term A_1 represents the sinusoid magnitude, φ_i the phase angle and f_1 the system's fundamental frequency (usually 50Hz or 60Hz). The exponential damping coefficient is given by λ, and Δt is the sampling period.

This model can be written in state variable form (Nishiyama, 1997):

$$\begin{bmatrix} x_{k+1}(1) \\ x_{k+1}(2) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & x_k(1) \end{bmatrix} \begin{bmatrix} x_k(1) \\ x_k(2) \end{bmatrix} \tag{16}$$

$$y_k = \begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} x_k(1) \\ x_k(2) \end{bmatrix} + v_k \tag{17}$$

where:

$$x_k(1) = e^{\lambda\Delta t + j\omega_1 \Delta t} \tag{18}$$

$$x_k(2) = A_1 e^{\lambda k \Delta t + j(\omega_1 k \Delta t + \varphi_1)} = z_k \tag{19}$$

As the model is non-linear, the equations of the EKF have to be used. It should be pointed out that the measured signals are complex quantities, obtained from the three phase components using the $\alpha\beta$ transform as in (Dash et al., 1999; Hase, 2007).
With the estimated states it is possible to estimate of the fundamental frequency ($\hat{f}_{1k}$), exponential damping coefficient ($\hat{\lambda}_k$), fundamental component magnitude ($\hat{A}_{1k}$) and phase angle ($\hat{\varphi}_{1k}$) using the following relations:

$$\hat{f}_{1k} = \frac{\omega_{1k}}{2\pi} = \frac{1}{2\pi\Delta t}\text{Imag}\left(\ln\left(\hat{x}_k(1)\right)\right) \tag{20}$$

$$\hat{\lambda}_k = \frac{1}{\Delta t}\text{Real}\left(\ln\left(\hat{x}_k(1)\right)\right) \tag{21}$$

$$\hat{A}_{1k} = |\hat{x}_k(2)| \tag{22}$$

$$\hat{\varphi}_{1k} = \text{Imag}\left(\frac{\hat{x}_k(2)}{|\hat{x}_k(2)|\,\hat{x}_k(1)^k}\right) \tag{23}$$

5.1.3 Segmentation algorithm

The overall scheme of the proposed segmentation algorithm is shown in Fig. 12.

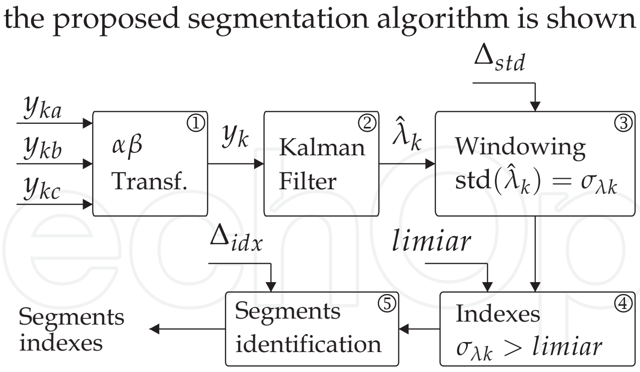


Fig. 12. Proposed segmentation scheme.

Each block in Fig. 12 is described in the following paragraphs:

5.1.3.1 ① Complex signal calculation

The measured complex signal y_k is obtained from the three phase measurements contained in the disturbance record (y_{ka}, y_{kb} and y_{kc}) using the $\alpha\beta$ transform (Hase, 2007) of Equations 24 and 25.

$$\begin{bmatrix} y_{k\alpha} \\ y_{k\beta} \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} y_{ka} \\ y_{kb} \\ y_{kc} \end{bmatrix} \tag{24}$$

$$y_k = y_{k\alpha} + j y_{k\beta} \tag{25}$$

5.1.3.2 ②Kalman filter calculation

The extended complex Kalman filter is applied to y_k and the parameter $\hat{\lambda}_k$ is estimated. This signal is used to segment the disturbance record.

5.1.3.3 ③Detection index calculation

The signal $\hat{\lambda}_k$ is submitted to a windowing procedure where at each window of length Δ_{std} the standard deviation is calculated. The result of the sliding windows calculations is the detection index $\sigma_{\lambda k}$, similar to the detection index applied for the phasor record segmentation.

5.1.3.4 ④Threshold comparison

A new segment is identified as the period when the detection index exceeds a given threshold. Thus, the threshold detection gives the beginning and the ending of the segments.

5.1.3.5 ⑤Segments identification

The segments identified at the previous step are analyzed in such a way that those considered close enough are grouped in a single segment. The parameter Δ_{idx} correspond to the minimum time interval between two consecutive segments. The time instants of the beginning and ending of each segment are used to calculate the features that will be used by the expert system.

5.2 Feature extraction

The process of feature extraction is based on the fundamental frequency phasors of each monitored quantity, obtained through a set of linear Kalman filters. The signal model used is the number 1 of (Kennedy et al., 2003). From these calculated phasor parameters, the symmetrical components are calculated. Finally, a mean value of each symmetrical component magnitude is calculated in each segment. This process is depicted in Fig. 13.
The inputs are the voltages (V_A, V_B and V_C) and currents (I_A, I_B and I_C) at the terminals of the generator and the neutral current at the high side of the unit's step-up transformer (I_{nHS}). These quantities are usually monitored by the DFRs at power stations.

5.3 Decision making

An expert system is the core of the waveform analysis. This tool is suitable to this application, due to its ability to represent the knowledge applied by the specialist to solve the problem. The facts knowledge base of this expert system is composed of facts containing the calculated quantities stated in the previous subsection for each segment identified. The fields that compose these facts are described in Table 4.
The fields “Disturb.” and “Classific.” are used during the reasoning process to store the results of the analysis. That is, their content shows the classification of each disturbance segment.
By defining the facts structure, the rule base can be described. These rules can be grouped in sets to facilitate the explanation process, but they coexist simultaneously at the expert system knowledge base. The defined sets are:

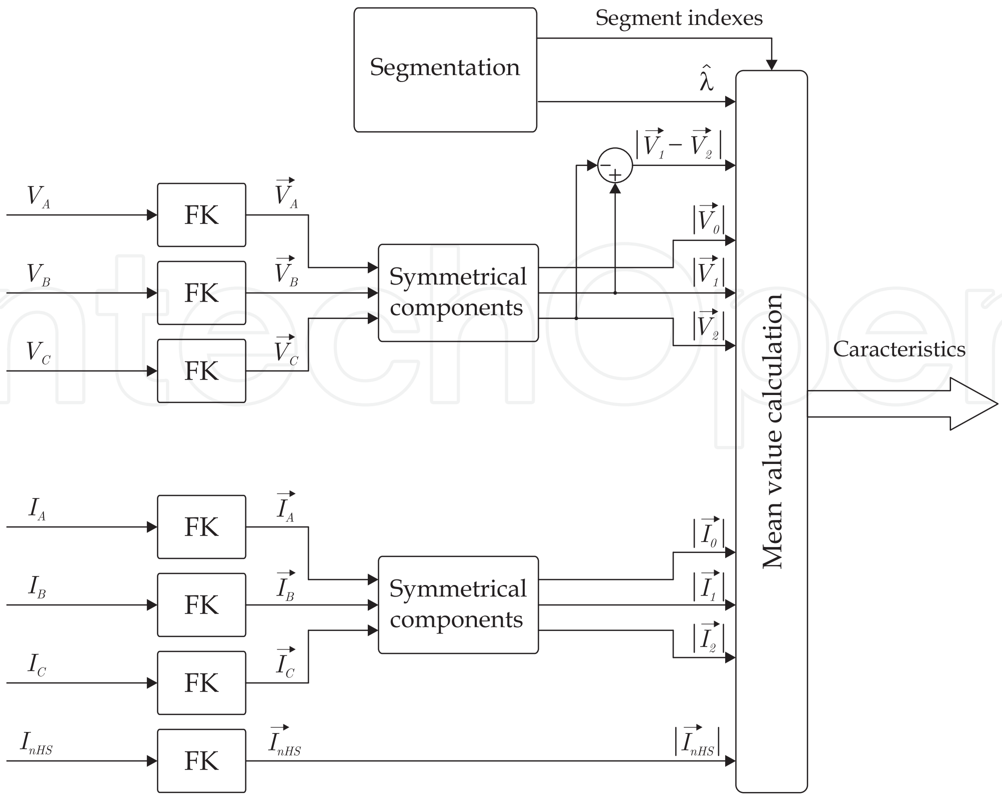


Fig. 13. Feature extraction process.

Field or slot	Description
Num	Number of the segments
V0m	Mean value of the zero sequence voltage modulus
V1m	Mean value of the positive sequence voltage modulus
V2m	Mean value of the negative sequence voltage modulus
I0m	Mean value of the zero sequence current modulus
I1m	Mean value of the positive sequence current modulus
I2m	Mean value of the negative sequence current modulus
InATm	Mean value of the high side neutral current modulus
CexpVm	Mean value of the damping coeficient $\hat{\lambda}_k$
ModV12m	Mean value of $\vec{V}1 - \vec{V}2$ modulus
Disturb.	Type of identified disturbance
Classific.	Classification of the disturbance

Table 4. Fact contents of the waveform analysis expert system.

- Fault detection rules.
- Classification of normal situations rules.
- Fault classification rules.

Each rule set is described below.

5.3.1 Fault detection rules

The objective of this set of rules is to determine if a segment shows characteristics of a short circuit (balanced or unbalanced) or represents a normal operative situation. These rules are

mainly based on the values of negative sequence voltages and currents, which indicate an imbalance between the three phases.
The conclusion of the rules is the fulfillment of the field “Disturb.” with a corresponding code. When rule-based expert systems are build in CLIPS platform, this modification is equivalent to the redefinition of the fact in the knowledge base.
Table 5 summarizes de fault detection rules. The symbol $\Leftarrow$ is used to denote a field modification within in the fact. The premises column shows the thresholds used to detect each type of disturbance and also the logical operators “and” and “or”.

Rule conclusion	Action	Premises
Normal operation	Disturb.$\Leftarrow$“normal”	V2m $< 0.1pu$ and I2m $< 0.07pu$ and I1m $< 1.1pu$
Unbalanced fault	Disturb.$\Leftarrow$“unbalanced”	V2m $> 0.1pu$ or I2m $> 0.07pu$
Balanced fault	Disturb.$\Leftarrow$“balanced”	V2m $< 0.1pu$ or I2m $< 0.07pu$ and I1m $> 1.1pu$

Table 5. Premises of fault detection rules.

5.3.2 Classification of normal situation rules

These rules are responsible for classifying the segment were “normal” operative situation have been detected in, for instance: de-energization, normal operation, generator unloaded, generator shutdown and so on. The rules for classifying normal situations are presented in Table 6.

Rule conclusion	Action	Premises
Normal operation with load	Classifi.$\Leftarrow$“normal load”	V1m $> 0.9pu$ and I1m $> 0.05pu$ and Disturb. = “normal”
Normal operation without load	Classifi.$\Leftarrow$“normal no load”	V1m $> 0.9pu$ and I1m $< 0.05pu$ and Disturb. = “normal”
Shutdown	Classifi.$\Leftarrow$“shutdown”	V1m $< 0.1pu$ and I1m $< 0.05pu$ and Disturb. = “normal”
De-energization	Classifi.$\Leftarrow$“De-energization”	0.1 $<$V1m$<$ $0.9pu$ and I1m $< 0.05pu$ and CexpVm < -0.2 and Disturb. = “normal”

Table 6. Premises and actions of the rules to classify normal situations.

In this rule set, the premises are based on the positive sequence values, but they will not fire if an acceptable imbalance or overload situation is detected as a *Disturb. = “normal”* condition is needed. The classified operative conditions are: normal operation with load (nominal voltage and current), normal operation without load (nominal voltage and no current), generator shutdown (no voltages and currents) and de-enegization (voltage at intermediate levels with exponential decrease and no current).

5.3.3 Fault classification rules

These rules a used to classify those cases when an imbalance condition is detected. Their premised are based on the relations between the symmetrical components values obtained by short circuit analysis theory (Grainger & Stevenson, 1994). These relations are stated below for two phase faults.

$$\vec{I}1 \approx -\vec{I}2 \tag{26}$$

$$\vec{V}1 \approx \vec{V}2 \tag{27}$$

$$\vec{V}0 \approx \vec{I}0 \approx 0 \tag{28}$$

Concerning two phase to ground faults, the relations are the following:

$$\vec{I}1 \approx -\vec{I}2 - \vec{I}0 \tag{29}$$

$$\vec{V}1 \approx \vec{V}2 \approx \vec{V}0 \tag{30}$$

And for single phase to ground:

$$\vec{I}1 \approx \vec{I}2 \approx \vec{I}0 \tag{31}$$

$$\vec{V}1 \approx \vec{V}2 + \vec{V}0 \Rightarrow -\vec{V}1 + \vec{V}2 + \vec{V}0 \approx 0 \tag{32}$$

The relations mentioned are valid in the faulted point of the system. If a fault occurs in the nearby system (like in the power plant substation), they will be influenced by the distance to the fault and by the connections of the power transformer. Most of the step-up transformers employed in generation units have Δ-Y configuration. This way, a single phase to ground fault at the transformer high voltage side is "seen" as a two phase fault at the generator terminals. In order to discriminate ground faults and phase faults at the transformer high voltage side the neutral current I_{nHS} is used. The presence of this current indicates a ground fault in the high voltage side. Table 7 shows the set of rules used to classify the disturbances.

The classification of each segment, along with the messages generated by each rule, are stored sequentially (using the same order of the segments) in the waveform analysis report. In the event of a fault, the analysis conclusion is its classification otherwise it is the normal operation classification. The expert engineer can then check the report where all the information needed is condensed, which result in less time spent and an improvement of the quality of the analysis.

6. Results

The approach explained in the previous section, has been tested using real data from a coal fired thermal power plant in Brazil. This power plant has four 24 MVA turbogenerators. The DFR monitors the terminal voltages and load currents from the four turbogenerators (G1 to G4).

The scheme is implemented as a standalone application written in *python* language. The expert systems have been implemented in CLIPS and interfaced with the routines in python.

Some results of phasor and waveform record automatic analyses are presented in the following subsections.

Rule conclusion	Action	Premises
Double phase fault at terminal	Classifi.$\Leftarrow$"fault dP term"	V0 $<$ 0.05pu and ModV12 $<$ 0.2pu and Disturb. = "unbalanced"
Double phase to ground at terminal	Classifi.$\Leftarrow$"fault dPg term"	V0 $>$ 0.05pu and ModV12 $<$ 0.2pu and Disturb. = "unbalanced"
Single phase to ground at terminal	Classifi.$\Leftarrow$"fault Pg term"	V0 $>$ 0.05pu and $-0.1 <$(-V1+V2+V0)$<$ 0.1pu and Disturb. = "unbalanced"
Ground foult at high side	Classifi.$\Leftarrow$"ground fault high"	V0 $<$ 0.05pu and InHS $>$ 0.2pu and Disturb. = "unbalanced"
Double phase fault at high side	Classifi.$\Leftarrow$"dP high side"	V0 $<$ 0.05pu and InHS $<$ 0.2pu and ModV12 $>$ 0.2pu and Disturb. = "unbalanced"

Table 7. Premises and actions of fault classification rules.

6.1 Phasor record analysis

An oscillograph database corresponding to four months of registered occurrences was used to test the proposed phasor analysis scheme. The results for the four generation units are stated in Table 8. This table shows the conclusions achieved by the proposed methodology.

Specialist's diagnosis	Correct result	No result	Total
Normal operation	170	0	170
Normal operation: load increase	3	0	3
Normal operation: load decrease	7	0	7
Out of service	129	0	129
Reverse power de-energization	11	6	17
Normal de-energization	1	4	5
Energization	2	4	6
Isolated unit	3	1	4
Synchronism	1	1	2
Fault	1	1	2
Totals:	328	17	345

Table 8. Phasor record results (Moreto & Rolim, 2011).

The classification shown in the first column of Table 8 was provided by the specialist responsible for the task. The results summarized in this table show that the diagnosis provided by the automatic tool were correct in more than 95% of the cases. They also show that the majority of the occurrences came from oscillographies recorded during normal situations or when the generators were out of service. Therefore, for most cases, the manual analysis by a specialist is not necessary. With the proposed scheme the engineer should only check the fault cases and the cases where there is no result from the automated analysis module. As a result, less time is spent in selecting, downloading and opening oscilographic records and SOE data, and engineer may focus his attention on the important cases.

It is important to point out that the automatic system never presented a wrong diagnosis and the number of cases that should be verified by the specialists or the waveform analysis module was reduced from 345 to 17.

6.2 Waveform record analysis

The development and testing of the proposed waveform analysis scheme was made using simulated cases. This is motivated by the fact that the number of fault occurrences in power generation units are much smaller in comparison with normal situation records. Thus, there are not enough cases involving all the fault types in order to fully validate the scheme with real data. In order to overcome this problem, a simulated model is employed. This model consists of a hydroelectric generation unit with the corresponding voltage and speed controllers connected through a Δ-Y step-up transformer to a slack bus which represents the bulk power system. The model used is the *Power turbine* demonstration system distributed along with the *SimPowerSystems* blockset of the Matlab/Simulink© program.
In order to show the performance of the methodology with real data, a case study of a short circuit is also presented.

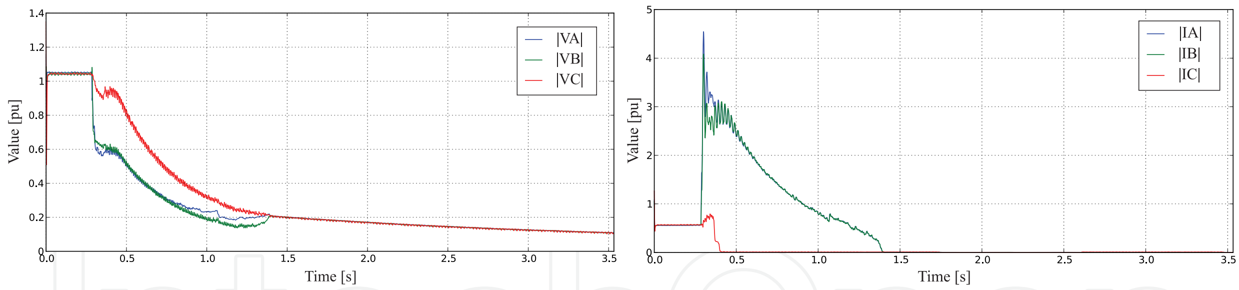
6.2.1 Simulation results

In order not to extend excessively the length of this text with tables and figures of each fault type, the simulation results are presented in a descriptive form. Several simulations were carried out with the variation of different parameters for each fault type: single phase to ground, two phase to ground, two phase and three phase. The faults were applied at the generator terminals and at the high voltage side of the transformer. A discussion of the results is presented in the following items:

- Fault resistance variation: the four fault types were simulated considering fault resistances of 0.01Ω, 0.1Ω, 0.5Ω, 1Ω and 5Ω. The scheme classifies correctly the fault segments with resistance 0.01Ω and 0.1Ω. In the cases with resistance higher than 0.5Ω the scheme is able to correctly detect the fault, but the classification is compromised due to the small increase in currents (around 1.5 pu for the worst case) during the fault. Although the classification was not obtained, the fault was correctly detected in all cases, which is enough to signal the analyst that that record should be manually verified. For faults at the high voltage side, the fault resistance limit that compromises the classification is 1Ω due to the same reason.
- Variation of the involved phases: The scheme makes no distinction of which phase is involved with the fault (phases A, B, C, AB, BC or AC). In other words, the results do not change with the variation of these fault characteristics.
- Incidence angle: For the cases with fault resistance of 0.01Ω the incidence angle was varied in ± 5 milliseconds that correspond to approximately 1/3 of a fundamental frequency cycle of 60 Hz. No influence of this parameter was observed in the results.

6.2.2 Case study

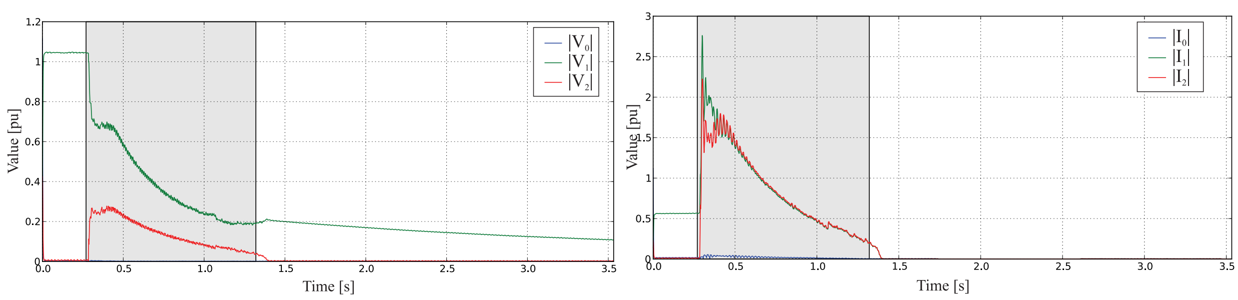
This case study uses data from a real occurrence where a failure of a surge arrester on phase B resulted in a solid (fault resistance near zero) single phase to ground fault at the high voltage side of the step-up transformer.
Figs. 14(a) and 14(b) show the estimated magnitudes of voltages and currents during the segmentation process. As can be seen, there is an expressive overcurrent and a significant voltage drop until the fault is extinguished.
The symmetrical components of voltages and currents are presented in Fig. 15. The gray bar represents the fault segment identified by the segmentation process. The calculated characteristics (described by Table 4) obtained in each of the 3 segments can be seen in Table 9. When the characteristics are applied to the expert system, the rule activations stated bellow is obtained:



(a) Phase voltages (b) Phase currents

Fig. 14. Fundamental frequency estimated magnitudes of phase quantities during the occurrence.

⇒Segment 0: Fault detection rule - normal operation
⇒Segment 0: Normal situation classification - Normal operation with load
⇒Segment 1: Fault detection rule - unbalanced fault
⇒Segment 1: Fault classification rule - **Ground fault at high voltage side**
⇒Segment 2: Fault detection rule - normal operation
⇒Segment 2: Normal situation classification - De-energization



(a) Sequence voltages (b) Sequence currents

Fig. 15. Fundamental frequency estimated magnitudes of the symmetrical components during the occurrence.

	Mean value in the segments:		
Feature	0	1	2
V0m	0.011	0.001	0.001
V1m	1.038	0.392	0.151
V2m	0.011	0.137	0.003
I0m	0.025	0.020	0.002
I1m	0.559	0.870	0.006
I2m	0.013	0.837	0.006
InHSm	0.020	0.629	0.001
CexpVm	0.041	-1.709	-0.249
ModV12m	1.035	0.469	0.150

Table 9. Feature extraction result.

The waveform analysis scheme has correctly classified the disturbance, identifying the situation in each segment. During the first segment (0) the generator is under normal operation with nominal voltage and approximately 0.6 pu of load. During the fault period (segment 1) the characteristics indicate a high voltage side ground fault. After the fault end (segment 2) the generator voltage continues to reduce exponentially, characterizing a de-energization process.

7. Conclusions

This chapter described a scheme that combines signal processing routines with expert systems for diagnosing occurrences of power generation units. The approach consist in a two level methodology. The first level is responsible for a pre-classification, using the digital fault recorder phasor records and sequence of events. The analyses are executed independently. So, if one source of information fails, the conclusion will be *no result*, starting the second level that provides a classification of the occurrence using the waveform record. In case of an abnormal operation, the engineer has to manually verify the data.
The results attested that the proposed scheme can significantly help the analysts by providing a classification of each occurrence. The system was able to identify common situations when the oscillographic data may be automatically archived with a high percentage of success. Therefore the engineers may focus their attention on the most important cases, such as, faults or forced shutdowns. For these cases the waveform record analysis is performed in order to determine whether the record corresponds to a fault case and to provide a fault classification. The knowledge base of the expert systems have been built based on extensive studies about the generator protection philosophy and operational procedures of the power plant. The knowledge base of the expert system responsible for analyzing the sequence of events should be reevaluated for each power plant, as their protection schemes and monitored events can be different. The expert system for phasor record analysis does not need to be changed from one power plant to another.
The waveform analysis scheme was developed using a simulation model. Several simulation parameters were changed and the proposed methodology was able to detect the fault in all cases. The case study with real data showed that the scheme is suitable to be used in practice in order to facilitate the task performed by the engineer at the analysis center.
This chapter also presented a new segmentation procedure for waveform records based on the exponential damping coefficient, suitable for being applied to data from power generation systems that shows slow transients, like the de-energization case.

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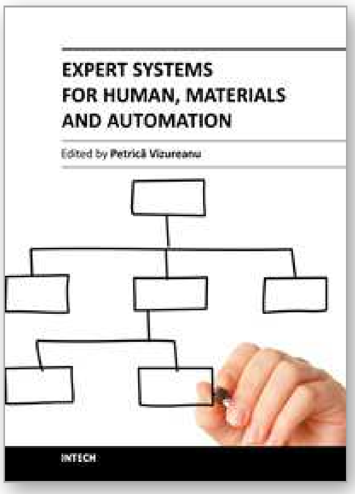

Expert Systems for Human, Materials and Automation
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The ability to create intelligent machines has intrigued humans since ancient times, and today with the advent of the computer and 50 years of research into AI programming techniques, the dream of smart machines is becoming a reality. The concept of human-computer interfaces has been undergoing changes over the years. In carrying out the most important tasks is the lack of formalized application methods, mathematical models and advanced computer support. The evolution of biological systems to adapt to their environment has fascinated and challenged scientists to increase their level of understanding of the functional characteristics of such systems. This book has 19 chapters and explain that the expert systems are products of the artificial intelligence, branch of computer science that seeks to develop intelligent programs for human, materials and automation.

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