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On-line analysis of fault events in power transmission systems using SOE, fuzzy logic and expert systems

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Abstract

The aim of this paper is to present an integrated model to perform an on-line faults analysis in power transmission systems and more specifically in high voltage transmission lines using SOE records from SCADA. In order to do that, the proposed solution divides the problem in two parts. The first one is the faults detection from SOE and the selection of the corresponding useful information; the second one is the analysis itself that gives as result the event sequence and equipments operations such as protective relays. For these two parts two corresponding modules were designed. The first one uses a fuzzy inference system that monitors SOE in sliding windows to determine the possible occurrence of events. The second one uses a rule based expert system to infer what happened during those events. Both modules were implemented on a software application and successfully validated with real SOE records collected within the Colombian transmission system, specifically from Interconexión Eléctrica S.A. E.S.P.-ISA company.

Keywords: on-line fault analysis, power transmission systems, fuzzy inference systems, rule based expert systems.

Análisis en línea de eventos de falla en sistemas de transmisión de electricidad usando SOE, lógica difusa y sistemas expertos

Resumen

El objetivo de este artículo es presentar un modelo integrado para realizar el análisis en línea de fallas en sistemas de transmisión de energía y más específicamente en líneas de alto voltaje usando registros de SOE desde SCADA. Para lograr esto la solución propuesta divide el problema en dos partes. La primera consiste en la detección de fallas desde el SOE y la selección de la correspondiente información útil; la segunda consiste en el análisis como tal, el cual da como resultado la secuencia del evento y la operación de los equipos tales como los relés de protección. Para estas dos partes, se diseñaron dos módulos correspondientes, el primero usa un sistema de inferencia difusa que monitorea el SOE en ventanas deslizantes para determinar la posible ocurrencia de eventos mientras que el segundo usa un sistema experto basado en reglas para inferir que ocurre durante esos eventos. Ambos módulos fueron implementados en una aplicación de software y fueron validados exitosamente con registros de SOE reales recolectados del sistema de transmisión Colombiano, específicamente de la empresa Interconexión Eléctrica S.A. E.S.P.-ISA.

Palabras clave: análisis de fallas en línea, sistemas de transmisión de electricidad, sistemas de inferencia difusos, sistemas expertos basados en reglas.

Introduction

Faults diagnosis in any productive process is a mandatory task for those who are responsible of its operation and maintenance and, in some cases (particularly in large industries), they have to deal with huge amounts of information like alarms, operation signals, equipments manuals, etc. which must be processed sometimes on-line and with a little error margin. A clear example is a power transmission system that consists in the transportation of electricity power from generation plants to consumption places through high voltage nets (115, 230, 500 or 750 kV) that mainly consist in of substations, transmission lines and power transformers. All these elements make up the Power Transmission System-PTS. The equipments of the PTS are monitored and operated from control centers using SCADA (Supervisory Control And Data Acquisition) systems that allow connecting or disconnecting the equipments; monitoring several measures like power and voltage; receiving the event alarms due to protections and circuit breakers operation in a record known as SOE (Sequence Of Event); among others. Also, they must help to coordinate control functions in order to improve the efficiency, quality and availability of power supply [1, 2].

When an event, i.e., an electric perturbation, is produced in the PTS, operators in control centers must use SCADA information in order to guarantee trustworthiness of the service. In order to do that, they must analyze large information blocks from these sources using specialized engineering knowledge. Such analysis is made most of the times in an uncertainty environment due to information problems. In addition to this panorama they must deal with the pressure of providing a high quality diagnosis in a short period of time because the decisions they made must look for the safety restoration of the service in the shortest time possible.

In this paper a model that considers several Artificial Intelligence techniques is proposed to assist operators in the events diagnosis task using only the on-line information of SOE that come from the equipments of the PTS. Such model consist in two modules: the first module detects when an event is produced and selects the relevant information to analyze it; the second module uses the results of the previous one to realize an analysis that gives as result the event sequence as well as the equipments operations, mainly protective relays.

The rest of the paper is organized as follows: In the next section a brief background about faults diagnostics within transmission lines is presented as well as a review of the state of the art in the automation of this task. Later a module to detect events and select data from SOE using a Fuzzy Logic approach is described, followed by a section that shows the module that is in charge of performing the analysis using a multi level rule-based Expert System. In both cases validation examples are presented in order to show the fitness of such modules. The final section concludes the paper giving some final remarks.

Fault diagnostics in power transmission systems

When facing an electric fault in a transmission line, the circuit breakers must open in the order given by the protections which detect the fault. This operation produces some alarms that are reported in the SOE, locally in the corresponding substation, and remotely in the control center through SCADA. An example of a typical SOE block is presented on Table 1, names of substation and lines where altered and some columns where hidden.

With this SOE and other information from SCADA database and Fault Recorders, operators must perform a preliminary analysis in a short period of time (minutes), but there are two issues that must be considered. First, according to the fault features like involved substations and their configurations, fault cause, fault type, etc., the amount of signals may vary from some few, to hundreds or even thousands. Second, in an ideal situation all the alarms from all the equipments that are involved with the fault must arrive to the consolidated SOE; however it is not rare to find some limitations in the information such as loss of signals due to problems of data transfer, incorrect or incomplete information, false operation of protections, lack of synchronization of the signals, wrong operation of protections, among others. These two problems: huge amount of data

Table 1
Example of SOE record

Hour	SubEst	Line	Alarm	Action
04:29:50,512	X	X-Y	PL2 21 ZONE 2 START	ACTIVE
04:29:50,518	X	X-Y	PL2 21 PHASE B START	ACTIVE
04:29:50,521	X	X-Y	PL2 CARRIER TRANSFER	ACTIVE
04:29:50,522	X	X-Y	PL1 CARRIER TRANSFER	ACTIVE
04:29:50,522	X	X-Y	PL2 21 ZONE 1 TRIP	ACTIVE
04:29:50,522	X	X-Y	PL1 21 GENERAL TRIP	ACTIVE
04:29:50,529	X	X-Y	PL2 21 GENERAL TRIP	ACTIVE
04:29:50,549	X	X-Y	PL1 21 PHASE B TRIP	ACTIVE
04:29:50,549	X	X-Y	PL1 21 ZONE 1 TRIP	ACTIVE
04:29:50,550	X	X-Y	PL2 21 ZONE 2 ACCELERATED TRIP	ACTIVE
04:29:50,553	X	X-Y	PL2 21 PHASE B TRIP	ACTIVE
04:29:50,555	X	X-Y	79 IN-PROGRESS RECLOSE	ACTIVE
04:29:50,564	X	X-Y	PL2 CARRIER RECEIVE	ACTIVE
04:29:50,566	X	X-Y	PL1 CARRIER RECEIVE	ACTIVE
04:29:50,569	X	X-Y	PHASE B CIRCUIT BREAKER	OPEN
04:29:50,575	X	X-Y	PL2 21 ZONE 1 TRIP	DISACTIVE
04:29:50,577	X	X-Y	PL2 21 ZONE 2 START	DISACTIVE
04:29:50,588	X	X-Y	PL2 CARRIER TRANSFER	DISACTIVE
04:29:50,588	X	X-Y	PL2 21 PHASE B START	DISACTIVE
04:29:50,599	X	X-Y	PL2 21 PHASE B TRIP	DISACTIVE
04:29:50,600	X	X-Y	PL2 21 GENERAL TRIP	DISACTIVE
04:29:50,606	X	X-Y	PL1 CARRIER TRANSFER	DISACTIVE
04:29:50,608	X	X-Y	PL1 21 ZONE 1 TRIP	DISACTIVE
04:29:50,608	X	X-Y	PL1 21 GENERAL TRIP	DISACTIVE
04:29:50,610	X	X-Y	PL1 CARRIER RECEIVE	DISACTIVE
04:29:50,610	X	X-Y	PL2 CARRIER RECEIVE	DISACTIVE
04:29:50,612	X	X-Y	PL1 21 PHASE B TRIP	DISACTIVE
04:29:50,615	X	X-Y	PL2 21 ZONE 2 ACCELERATED TRIP	DISACTIVE
04:29:51,339	X	X-Y	PHASE B CIRCUIT BREAKER	CLOSE

and uncertainty, make the analysis task very hard and jeopardize companies that are responsible for operation and control of the PTS which may suffer monetary penalties if the analysis is delayed or inaccurate.

Since the 90's considerable efforts have been made to develop computational tools for the automatic diagnosis of faults in PTS. Many of them have used classical or fuzzy expert system approaches with good results [3-6]. Others have used different types of Petri Nets – PN to monitor transmission lines and to diagnose faults: stochastic PN [7], temporized PN [8], PN with coding theory [9]. There are inclusive some approaches that combine several techniques. In [10] for example, authors propose a method for on-line faults diagnosis in PTS by a combination of PN and fuzzy logic, where the diagnosis process is dominated by a fuzzy reasoning mechanism. In [11] a fuzzy logic within a Markov model is used, whereas in [12] a combination of fuzzy logic and probabilistic load is proposed and in [13] a combination of fuzzy sets with Monte Carlo simulation is implemented.

Later researches have focused their attention in improving the performance of the kind of systems mentioned above, especially in the handling of uncertainty by false or incomplete information, its on-line performance and its mechanism of learning from new experiences.

Event detection and data selection

For the on-line fault diagnosis, it is fundamental to detect when an event occurs (when does it start and end) and to extract the useful information about it. These two tasks are quiet difficult to solve by conventional programming techniques using SOE because any algorithm would consider hardly all the cases and exceptions that may be present: loss of information, false signals, signals that are result of external disturbances to the analyzed system, etc. According to this, events detection is carried out under uncertainty, and in many cases it is solved by operators using some vague heuristics like: "if there are too many signals in a SOE block and there is a little timing difference among them, then there is a high probability that an event has happened" and "if the signals within the block have a good level of importance more surely a electric fault happened in the supervised system".

These issues made us think on using fuzzy logic to solve these tasks. Fuzzy logic was developed from the basic theory of fuzzy sets, established for the first time in an article of Zadeh [14]. The scope of this paper does not consider a description of the theoretical basis of this technique; however as a short description, and in agreement with Mendel [15], it could be said that a fuzzy logic system is, in general, a nonlinear mapping of a input data vector inside a scalar output using rules with vague (fuzzy) concepts. In order to do that, the basic structure of a fuzzy inference system consists of three elements: a set of membership functions for the input and output variables, a set of IF … THEN … rules that relates these variables, and a reasoning mechanism that executes the inference process.

The selected fuzzy inference system in this paper was a Mamdani in which the set of rules is constructed from expert knowledge and defines the relation that would be expected from the combination of all the possible values of the input variables and the output variable. The considered input variables were: *amount of SOE signals*, *mean time difference* among them and *importance of the signals*. These three variables are measured in a sliding window of 1 second from SOE when the module detects that an update to the corresponding file has been made. The size of such window was selected according to typical duration of an event and signals delay. The range and shape of the fuzzy sets for each one of these variables were defined according to the experts' knowledge. In the case of the *amount of SOE signals* the membership functions were defined thanks to the estimative of an experts crew considering a one second time window for a transmission line as shown on Table 2.

In the case of the *mean time difference* among SOE signals, experts considered the instantaneous operation of the protections during a fault (0-5 ms), the circuit breakers tripping (5-100 ms) and the backup protection settings (200-1000 ms). In the case of the *importance of the signals* experts determined an importance value for a set of signals that may be indicators of the events occurrence, so in each window the

Table 2
Estimation of the *amount of SOE signals* versus fault type

Fault type	Estimate amount of signals in 1 second for a transmission line
No fault	0-4
Extern fault	4-10
One element fault	20-200
Several elements fault	100-500

module search for these signals and sums all the values. The resulting modeling for the three input variables is shown on Figure 1.

By the other hand the output variable, defined as the *possibility of event* was modeled as shown on Figure 2 and is calculated in the fuzzy inference system by means of the defuzzyfication using the centroid method. In few words, this method provides the crisp (numeric) value of the result as the center of mass of the resulting surface when the fuzzy rules are applied. It is important to highlight that output variable refers to possibility instead of probability because it tries to quantify expert expectations.

The rules matrix of the inference system is presented on Table 3 and represents the combination through AND operator of the input variables and the corresponding output using IF-THEN rules.

For instance, R12 may be interpreted as: "When there are many signals in a SOE block AND the mean difference time among them is very short AND the kinds of signals that are appearing are very relevant with respect to the events, THEN it may be concluded that the possi-

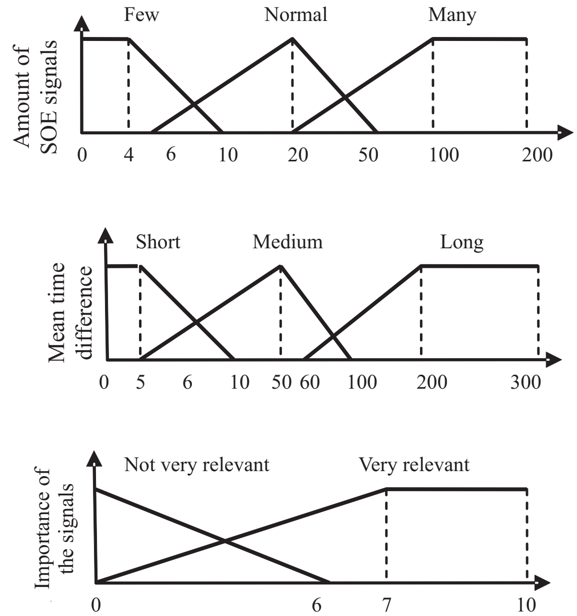

Figure 1. Fuzzy sets for input variables.

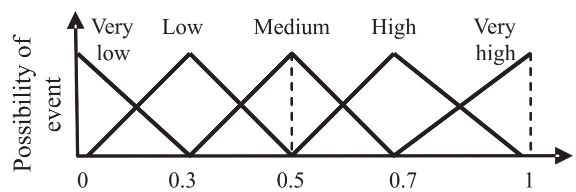

Figure 2. Fuzzy sets for output variable.

Table 3
Fuzzy rules matrix

Importance of the signals	Mean time difference	Amount of SOE signals		
		Few	Normal	Many
Not very relevant	Short	Low (R1)	Medium (R2)	Medium (R3)
	Medium	Very low (R4)	Low (R5)	Medium (R6)
	Long	Very low (R7)	Very low (R8)	Low (R9)
Very relevant	Short	High (R10)	Very High (R11)	Very high (R12)
	Medium	Medium (R13)	High (R14)	Very high (R15)
	Long	Medium (R16)	Medium (R7)	High (R18)

bility that a fault has happened in the supervised element is very high".

This way, when the module detects that an update to the SOE file has ocurred, it runs the fuzzy inference system in each time window. If the output of a time window states that the possibility of an event is high, the module determines the beginning of the event, selects the signals and analyzes the next time window. If the event continues (if the possibility of event is also high in the next window), that window is attached to the selected signals, and the process goes on. For each group of selected signals where there is a high possibility of event, the module extracts interesting data like: time of the first and the last signal (beginning and end of the potential event), amount of signals, involved substation and lines.

As a validation example, the SOE of Colombian PTS in a specific day was selected. When running the module, 2664 registries were analyzed. As result, 4 potential events were detected and 813 registers of such SOE (useful signals) were selected. The comparison of the effectiveness of the module with regard to the solution given by an expert is presented on Table 4.

During this validation, the module detected 4 events in the same way that expert did. The events identified by 2 and 2* are part of the same event but they came from unsynchronized substations. The events in which the fuzzy system exceeded the amount of signals are not considered unsatisfactory since this issue does not imply any difficulty for the diagnosis, as a misdetection of the beginning of the event or a signals omission may be. With respect to the lack of synchronization problem due to the clocks in the different substations, we propose to complement the solution using heuristic rules for identifying these cases based on teleprotection signals.

As conclusion, the proposed fuzzy inference system turned out to be successful for identifying the beginning of the event in the cases in which a good correlation between the considered input variables is clear. This situation may be considered as typical in transmission lines faults because elements of the PTS have one or more protections that operate when facing such faults generating the required SOE signals. Another feature of the module is that it allows to suitably handle the uncertainty that occurs with the SOE information. This is demonstrated with its success in the identification of the event and selection of useful information even with losses of signals like circuit breakers position or loss of substations supervision. This data missing would seriously affect detection methods that are based exclusively on the circuit breakers state changes or the signals by substation and not by the complete system.

Table 4
Validation example results of the first module

	Events	Signals (Expert)	Signals (Module)
1	02:18:27,310	201	213
2	02:20:34,495	67	67
2*	02:21:35,033	42	51
3	13:42:09,206	378	392
4	16:57:47,171	125	127

Event analysis

As it was mentioned before, the main goal of the event analysis is to obtain its sequence and to determine the functioning of the involved equipments. In order to do that the proposal presented in this paper consist in a module that uses the selected SOE signals (that results from the previous module) as inputs for a multi-level rule based expert system. In such system the consequents of a level are used as antecedents for the later one in a sort of chained reasoning. In this way, the antecedents of first level consist only in SOE signals, equipments settings and system structure, whereas antecedents in the last levels are made from the hypothesis that are result of the previous ones. As summary, the goal of each level is to determine the next reasoning (in that order):

1. Detection of tripping conditions, their relation with tripping orders, their origin and causes
2. Detection of tripping orders and their relation with openings
3. Detection of re-closing conditions and their fulfillments

4. Detection of potential failed elements and phases
5. Valuation of the certainty in the potential failed element diagnosis, failed phases and tripping conditions
6. Comparison of diagnosis results among similar protections in potential failed elements
7. Comparison of diagnosis results among opposite protections in potential failed elements

To represent the rules of each level, logical diagrams were used. It is important to highlight that using this type of diagrams was quiet helpful because they facilitate rules reading compared with the syntax that rule based languages like LISP or CLIPS provide. Such representation also became a useful bridge between domain's experts (mainly electrical engineers), knowledge engineers (mainly computer science engineers) and programmers. The notation of such diagrams is quite simple, AND, OR and NOT operators are presented using the common digital logic representation. A temporizer is represented as a box with a diagonal to represent activation and deactivation conditions. The value in the upper left corner of the box represents the time in which consequent is activated after antecedent is activated (how long must it wait), meanwhile the value in the lower right corner represents the time in which consequent remains activated after antecedent is deactivated. As example, Figure 3 presents a simplification of some rules that relates what happens in an event (actual SOE signals) and what is expected. Doing this, it is possible to determine if there was a normal evolution of the event and if the equipments operated properly.

The whole knowledge database consists in more than 150 rules whose detailed description is beyond the scope of this paper. Readers are invited to review [16] for further details. As final result of diagnosis, the module determines the sequence of the event, the failed elements, the disconnected elements and their causes (acted protections) and a list of problems or potential anomalies. As a validation of this module, the SOE presented on Table 1 was analyzed, and some of the conclusions that were made by this module are presented on Table 5.

Conclusions

In this paper, a system that uses several artificial intelligence techniques to solve the problem of the on-line fault diagnosis in electric power systems using SOE records is described. In order to do that, the proposed solution divides the problem in two parts: the first one is the events detection and its corresponding useful data selection, and the second one is the analysis of such data in order to determine event sequence as well as equipments operations. The first part

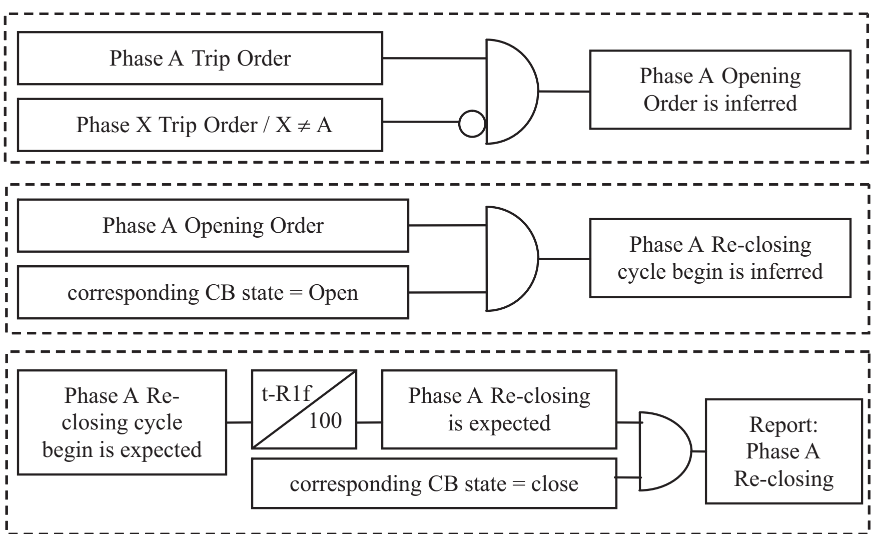

Figure 3. Example of an expert system's part.

Table 5
Validation example results of the second module

Module's output	1. (report (event_ID 1) (initial_time 04:29:50,518) (final_time 04:29:50,577) (substation X) (element_ID Y230BL1) (relay 999) (protection_ID PL2) (situation FaultDetected) (phase "B")) 2. (report (event_ID 1) (initial_time 04:29:50,549) (final_time 04:29:50,599) (substation X) (element_ID Y230BL1) (relay 888) (protection_ID PL1) (situation TripOrder) (phase "B")) 3. (report (event_ID 1) (initial_time 04:29:50,569) (final_time 04:29:51,339) (substation X) (element_ID Y230BL1) (situation Reclosing) (phase "B")) 4. (report (event_ID 1) (initial_time 04:29:50,522) (final_time 04:29:50,610) (substation X) (element_ID Y230BL1) (relay 888) (protection_ID PL1) (situation CarrierTransferReceiveZ1)) 5. (report (event_ID 1) (initial_time 04:29:50,521) (final_time 04:29:50,610) (substation X) (element_ID Y230BL1) (relay 999) (protection_ID PL2) (situation CarrierTransferReceiveZ1))
Translation	1. Fault in phase B within X-Y 230BL1 line at 04:29:50 2. Monophase trip in phase B of X-Y line, inside X substation after 31 milliseconds 3. Succesfuly monophase re-closing in phase B of X-Y line, inside X substation at 827 milliseconds 4. PL1 and PL2 operated correctly in zone 1 with transfer and receive carrier

was solved using a fuzzy inference system that monitors the SOE in a sliding window and uses as input variables the amount of SOE signals, the mean time difference among them and its importance (regarding faults evidence). The second one was solved using an expert system that handles several levels of reasoning.

Both modules were successfully validated using real SOE records collected within the Colombian transmission system and produced very encouraging results. In most of the cases the first module was able to detect the beginning and ending of the events, as well as the useful information of them. In the same way, the inferences given by the second module were similar to experts' analyses, except in some occasions were significant signals loss was presented.

As an important result, the two modules of the proposed solution are general enough to be applied in other PTS. The first one because the shape of the membership functions of each input variable may be calibrated with the features of the PTS and the corresponding experts knowledge, and the second one because such a module uses general signals and concepts that can be translated easily to specific SOEs.

In spite of the good results that the proposed solution showed, there are still some difficulties in the analyzed problem that hinder the automation of diagnosis: the lack of synchronization among signals from different substations, and the loss of information in the SOE due to several causes. Even if the proposed solution deals partially with these issues, it can not assure that diagnosis is always correct, so the assistance of an expert is still required to validate or complement it. Other important issue about the proposed solution is that it only considers signals of distance protective relays in transmission lines. Even if such kind of signals represents the major part of relevant SOE information during faults, it remains to incorporate other kinds of line protections as well as other equipments besides protections.

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