

A Real Time Expert System for Decision Support in Nuclear Power Plants

Andressa dos Santos Nicolau, João P. da S.C Augusto, Claudio Márcio do N. A. Pereira, Roberto Schirru

Abstract—In case of abnormal situations, the nuclear power plant (NPP) operators must follow written procedures to check the condition of the plant and to classify the type of emergency. In this paper, we proposed a Real Time Expert System in order to improve operator's performance in case of transient or accident with reactor shutdown. The expert system's knowledge is based on the sequence of events (SoE) of known accident and two emergency procedures of the Brazilian Pressurized Water Reactor (PWR) NPP and uses two kinds of knowledge representation: rule and logic trees. The results show that the system was able to classify the response of the automatic protection systems, as well as to evaluate the conditions of the plant, diagnosing the type of occurrence, recovery procedure to be followed, indicating the shutdown root cause, and classifying the emergency level.

Keywords—Emergence procedure, expert system, operator support, PWR nuclear power plant.

I. INTRODUCTION

DURING the normal operation, no special attention is required to monitor and maintain the reactor. When an emergency occurs, quick and efficient diagnosis and treatment of the problem are essential. The process of accidents and abnormal events diagnoses for most PWR NPPs is currently established in written procedures, which must be followed by operators during the occurrence of any abnormal events. Facing a large amount of information, including spurious sensor signals, lack of knowledge for diagnosis, complexity of the plant, the shortage of time and other factors, which affect human reliability, operators may have difficulties to make their judgment in available time or may make mistakes in their judgments.

In order to support NPP operators in distinguishing the accident quickly and accurately, several methodologies of artificial intelligence have been proposed in the literature over the past 30 years. Artificial Intelligence involves neural network [1]-[3], genetic algorithm [4], particle swarm optimization [5], quantum-inspired algorithms [6], expert system [7]-[10] and others, where the main characteristic is to simulate the human abilities thought process.

Nicolau, A. S. is with the Federal University of Rio de Janeiro, Rio de Janeiro, Brazil (corresponding author, phone: +55 21 3936-0399, fax: +55 21 3938-8069, e-mail: andressa@imp.ufrj.br).

João P. da S. C Augusto is with the Engineering Program, Polytechnic School, Federal University of Rio de Janeiro, Brazil (e-mail: jpsca1293@imp.ufrj.br).

Claudio Marcio, N. A. P. is with Nuclear Institute – IEN, Rio de Janeiro Brazil (e-mail: cmnap@ien.gov.br).

Schirru, R. is with Federal University of Rio de Janeiro, Rio de Janeiro Brazil. He is now with the Nuclear Engineering Program, Rio de Janeiro, Brazil (e-mail: schirru@imp.ufrj.br).

Expert system is a computer program that uses knowledge and inference procedures to solve problems that are ordinarily solved through the human expert. It can deal with a large amount of information in a very short time and has high reliability in a specific domain of knowledge. The main components of expert system are KB, inference engine, and user interfaces. An expert system's knowledge is obtained from expert sources and coded in a form suitable for the system to use in its inference or reasoning processes [11].

In this paper, we present a Real Time Expert System (RTES). This approach consists of two real-time modules that explore two knowledge representation approaches: rule and logic trees. It is composed by information of two-emergence procedure and SoE of known shutdown of a Brazilian PWR NPP. The results show that each module is separately capable of monitoring, inferring, and exposing the operator to the information on these processes at the interface, decreasing the cognitive workload and analysis of the operators and increasing the response time and decision-making in case of emergency.

The remaining of this article is organized as follows: Section II explains how a generic expert system works and how the human knowledge in a specific topic can be codified into a computer. Section III presents the computational method used in the diagnose system proposed. It explains knowledge representation, how it is inputted into the system and which rules are used by the expert system during the signal processing. Section IV shows real applications of the RTES. Finally, Section V discusses the conclusions.

II. EXPERT SYSTEMS

Expert systems (ESs) [12] were developed in the 60s by the Stanford Heuristics Programming Project as a new intelligent method to find solutions for complex problems as a disease diagnosis. Feigenbaum, widely known as the father of ESs, defined it as “an intelligent computer program that uses knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solutions”. In the other words, an ES is a computational system that emulates the decision ability of a human expert in any topic.

A basic concept of ES is composed by a KB (KB) where the intelligence of the system is stored, and an inference machine that processes current facts based on the knowledge to generate new ones and conclusions. Fig. 1 illustrates how a basic ES works.

The most relevant advantage in using ES is the independency between the KB and the inference machine. The

KB can be changed or adapted to a new knowledge without the need of remodeling the inference engine. This capability makes this type of system a significant tool to handle diagnosis problems of many different types of power plant.

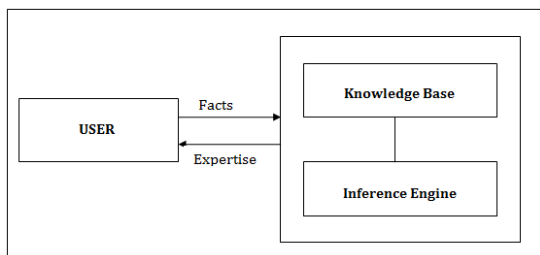


Fig. 1 ESs

ESs are classified based on the paradigm in which information is represented in its KB. The information can be represented in many forms; usually rules but also logic trees and logical framework and others. If the KB is rule-based, its information is coded as IF-THEN rules. On the other hand, the same information could be written in a logic tree model. Therefore, the KB model should be chosen based on the closest representation to the real problem or the most descriptive way.

There are two main types of inference machine used in the knowledge based systems: forward and backward inference. A forward inference starts with known facts and uses the knowledge in the KB to create new facts and conclusions or to take actions. A backward inference starts with an initial assumption and tries to prove it using the knowledge in the KB [12]. The main difference between these two approaches is the guidance: a forward inference is guided by data and a backward is guided by an objective.

III. THE PROPOSED RTES

The RTES was developed for Angra1 NPP and aims to: a) classify the emergency level according to PEA03 procedure (Area Emergency Procedure), b) Monitor the actions of the PO-E0 procedure (Reactor Shutdown Procedure or Safety Injection) and, indicate to another Manual/Operating Procedure, c) Make TRIP (reactor shutdown) analysis.

The RTES consists of two real-time modules: a) emergency situation diagnostic module (ESDM) and b) TRIP diagnostic module. Both modules were developed in the Python 2.7, give their ease of working with recursive rule sets and logical trees [13]. All the information necessary for the operation of the RTES comes from three sources: SoE of the plant, real-time variables from the Integrated Computer System (SICA), and information provided by the operators about variables not monitored by SICA.

Fig. 2 shows the structure of the RTES and the interrelationship between its components: Facts Base (Working Memory - WM), Rule Base and Inference Engine is presented. The ES knowledge consists of the data from SICA and the data provided by the operator. Once the WM is completed, the system selects the rules that can be applied to

the facts during a specific processing. In front of the selected rules, the inference engine applies a selection criterion to evaluate when and which rule best fits the facts in that context, selecting the rule that will be effectively applied. This cycle repeats as long as there are rules that can be applied to the WM.

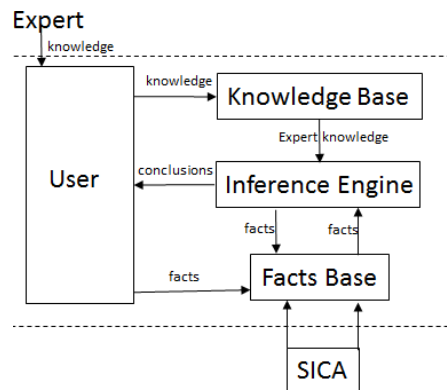


Fig. 2 Structure of RTES

A. Emergency Situation Diagnostic Module (ESDM)

The ES knowledge in the ESDM was developed using information's of PEA03 and POE0 procedures, it is based on IF/THEN rules and forward inference.

The PEA03 consists of several categories of hazard recognition caused by the plant or that may reach the plant and may affect its physical safety. The classification of the emergency level is determined from five recognition categories where the main objective is to mitigate damages caused, such as radiological releases. The recognition categories are A (Abnormal Radiation Levels / Radiological Effluent), D (Poor Function in Cold Off or Recharge Systems), S (Poor System Function), R (Risks and Other Conditions Affecting Plant Safety), and F (Fission Product Barrier Degradation).

Each recognition category is represented by an emergency situation classification diagram that relates, through logical operators, a set of signals and limiting values to an emergency classification of the plant depending on the given conditions. Each block of the diagram is equivalent to antecedents of rules whose consequence, together with the value of the previous block, is the classification of the emergency situation of the plant. The emergency level is given depending on plant state and plant situations. The plant can classify into five emergency level: 1) Normal Condition, 2) Unusual Event - ENU, 3) ALERT, 4) Area Emergency and 5) General Emergency. Fig. 3 presents the structural of the PEA03 procedure.

The information of the procedure can be translated in IF/THEN rules, where CLASS1 means the classification of the emergency situation of the plant, as follows:

- 1) IF A1 OR A2 OR A3 THEN A Block = TRUE
- 2) IF B1 OR B2 OR B3 THEN B Block = TRUE
- 3) IF C1 OR C2 THEN C Block = TRUE
- 4) IF D1 OR D2 THEN D Block = TRUE

- 5) IF A Block == FALSE THEN CLASS1 = NORMAL
- 6) IF A Block == FALSE THEN CLASS1 = NORMAL
- 7) IF A Block AND B Block == FALSE THEN CLASS1 = ENU
- 8) IF B Block AND C Block == FALSE THEN CLASS1 = ALERT
- 9) IF C Block AND D Block == FALSE THEN CLASS1 = Area Emergency
- 10) IF D Block THEN CLASS1 = General Emergency

Each emergency level is shown in the RTES interface in different colors: Normal Condition – green color, 2) ENU - yellow, 3) ALERT - orange, 4) Area emergency - pink and 5) General Emergency – red and purple for operator answer. On the other hand, the ESDM using POE0 procedure is responsible for determining actions to be followed by the operators, in order to preserve the integrity of the plant in case of reactor shutdown. POE0 procedure is described by 41 items

structured in form of actions, as shown in Fig. 4. One of the action of POE0 is the indication of others procedures, such as: RF-S 1 (Response to Nuclear Power Generation / ATWS, item 1), PO-ECA 0.0 (BLACKOUT, item 1), PO-ES 0.1 (Response to reactor shutdown, item 1), RF-F 1 (Cold Source Loss Response, item 1), PO-A 28, PO-E 1 (Loss of the Reactor Coolant or Secondary, item 1), PO-E 2 (Insolation of Steam Generation Fault, item 1), PO-E 3 (Steam generator rupture tubes, item 1), PO-ECA 1.2 (Loss of coolant out of contention, item 1). In this case, the ESDM is responsible for supporting the operators in following the actions of each item of the procedure. To accomplish that, each action is classified into three types of colors: green (indicates that the actions is ok), purple (indicates that the system is waiting for an operator information) and red (indicates that the actions have not been ok). Thus, the system only turns on the other item when the previous item receives green color.

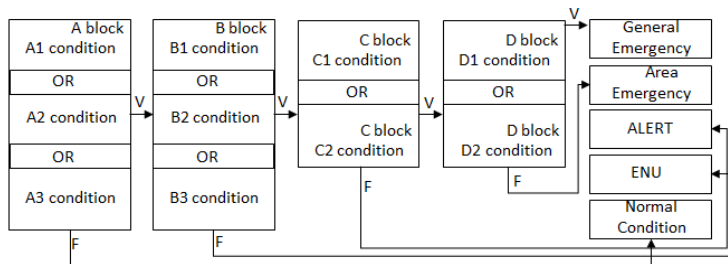


Fig. 3 Structure of the PEA03 procedure

| Items | Action/Expected answer | Answer not obtained |
|--|------------------------|--|
| Note | | |
| Items 1 to 5 are immediate action | | |
| The Criteria page should be open | | |
| 1 Check reactor shutdown: | | Do: |
| <ul style="list-style-type: none"> • Bars indicators light on the bottom – on • Main circuit breakers and by-passes of shutdown reactor - open • Neutrons flow - decreasing | | <ul style="list-style-type: none"> a. Unload manually the reactor through the reactor panel key or safety panel key. b. If the reactor does not turn off Then insert the control rods continuously and turn off 1B1A and 1B2A bars. And turn on after. c. If the reactor don't turn off Then go to RF-S1 procedure. |

Fig. 4 Example of the structure of the POE0 procedure

B. Trip Diagnostic Module (TDM)

The main objective of the TDM is to support the shutdown root cause analysis. For this, the ES knowledge - accident information is represented by logic trees. The tree knowledge representation was chosen due to its similarity with a “Fault Tree”, a well-known structure in a power plant operation environment.

In this approach, the current SoE is the track record of alarms in a plant, usually with a time accuracy of milliseconds. The SoE is provided by SICA and is analyzed backwards by the diagnosis system from the shutdown alarm until about 5 or 10 minutes before the event. It is analyzed by a similarity algorithm that starts from the top of the tree – the shutdown alarm until it finds a root alarm or the similarity between the known accident and the current event stops. In the

last case, the diagnostic will be shown as a partial similarity with the event selected.

The diagnosis in the similarity algorithm starts with searching for trees in the KB that matches the top alarm. Then, each tree selected is followed through, branch per branch, from the top to the bottom matching nodes with events logged in the SoE, depending on its logic operator. The matched events determine which branch or branches that the similarity algorithm will then follow. Fig. 5 shows how the similarity algorithm works. In the experimental SoE represented in Fig. 5, the shutdown alarm represented by A is the top node of the tree. From this point, the SoE is processed backwards checking if the alarms match the accident tree. Consequently, C is chosen due the second rule pointed above, leading to the alarm D where root-cause is F and G (fifth rule). In Fig. 5, TRASH is the events not directly related to TRIP, for example, door open sensor, valves or pumps not directly related to TRIP and so on.

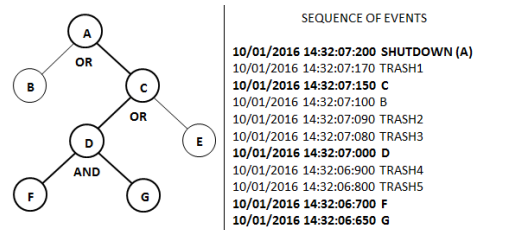


Fig. 5 Example of the structure of the POE0 procedure

The matching process of the similarity algorithm involves protocol rules based on expert knowledge of the control room operator and a validation time between alarms in the SoE:

- Alarms, where the time difference between its current date-time and its cause event(s) date-time are higher than a KB pre-determined validation time, do not match.
- In the case of logic operator OR, the path chosen is the path that shows the lowest time difference between the alarm current date-time and its cause events.
- In the case of logic operator OR, if the rule above shows a conflict; in the other words, two cause alarms present the same time difference, the similarity algorithm stops.
- In the case of logic operator AND, all cause alarms must be valid and must be present in the SOE.
- In the case of logic operator AND, if all cause events are valid and present in the SOE, then all tree branches are followed by the algorithm.
- In the case of logic operator EQ, the cause event must be present in the SOE.
- Else, the similarity algorithm stops.

Finally, after analyzing all possible trees, the diagnostic is the event where the sequence of alarm reached its root-cause or the one that shows the highest depth of similarity. In addition, the inference engine can also answer “I don’t know” if no previous knowledge matches the current SoE. It is worth mentioning that the diagnosis capability is as good as the knowledge inputted in the system.

The TDM is triggered every time that a shutdown alarm is detected. At this point, the SoE is analysed by the algorithm described above that will choose the trees which represent the event. The selected tree or trees are processed by the inference engine making the diagnosis. Finally, the diagnosis is sent to the human-machine interface – user.

IV. APPLICATION AND RESULTS

Here, we first present knowledge representation of both modules: ESDM and TDM were inserted in the KB interface. Then, we present the main system interface and how the RTES works.

A. ESDM

This module is composed of rule blocks that represent the PEA03 and POE0 procedures. Within the KB, there is a block structure and a specific location for the addition each logic. Fig. 6 shows the KB interface for PEA03 procedure, it is the same for POE0 procedure.

Each rule takes the IF/THEN format and is composed by variables collected in real time by SICA. Fig. 7 shows an example of insertion rule of PEA03 procedure; it is the same for POE0 procedure.

Once all knowledge is inserted and distributed to the RTES, it can classify the emergency situation using ESDM. So, the RTES interface presents the results of the ES knowledge. Fig. 8 shows the RTES interface of ESDM – PEA03. In addition, it is noted in Fig. 8 that each class is shown with different colors. This is an indication of each emergency level: Normal Condition – green color, 2) ENU - yellow, 3) ALERT - orange, 4) Area Emergency - pink and 5) General Emergency – red and purple for operator answer.

By clicking on the desired category, one can also observe the classification of the emergency situation for each diagram, as shown in Fig. 9.

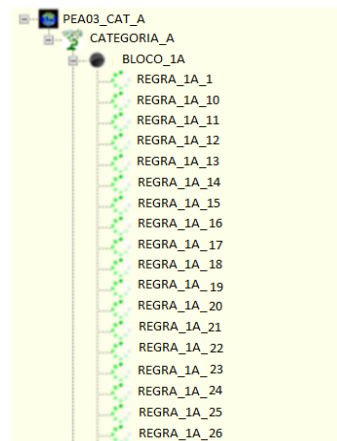


Fig. 6 Example of the KB interface for PEA03 procedure

Fig. 7 Example of rule insertion for PEA03 procedure



Fig. 8 RTES Interface of ESDM - PEA03



Fig. 9 Class classification

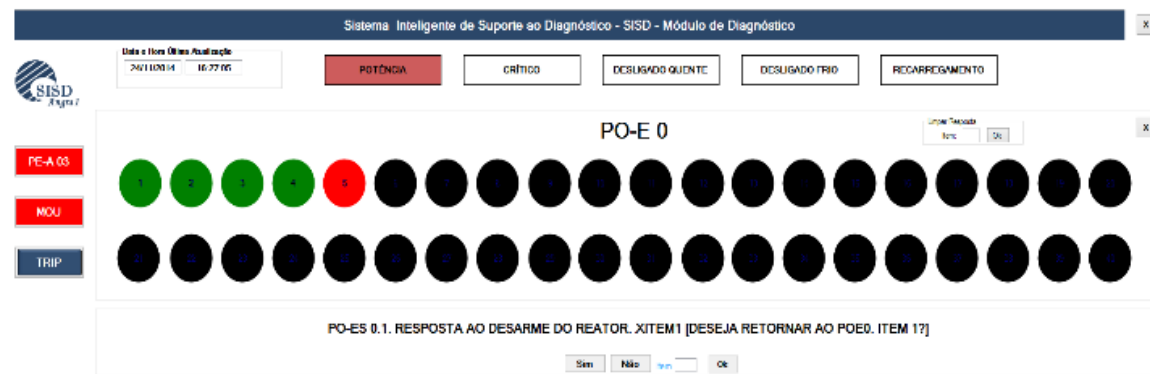


Fig. 10 RTES Interface of ESDM – POE0

Fig. 10 shows the RTES interface of ESDM – POE0, where each item is represented by a circle and color. The color green indicates that the actions are OK, purple indicates that the system is waiting for an operator information, and red indicates that the actions have not been OK.

It should be remembered that since the system acts in real time, the classification and operator response issues may change automatically without interaction with the system.

B. TDM

The KB of the TDM is composed of logical trees, which means that logical relationships between alarms and/or parameters activate the safety shutdown of the power plant. Thus, the information about such relations is inserted in the

KB and later distributed to the SE. Fig. 11 shows an example of the knowledge interface.

An interface was developed to insert the information about father nodes, their respective child nodes and temporal relationship. Fig. 12 shows this interface.

Once all knowledge is inserted and distributed to the RTES, the TDM is triggered every time that a shutdown alarm is detected and delivers to the RTES interface the response of the diagnostic. Fig. 13 shows the RTES interface result of TDM.

The results displayed on Fig. 13 are not necessarily the root cause of shutdown of the plant, but they can be used as a guide for operators to reach the possible cause.

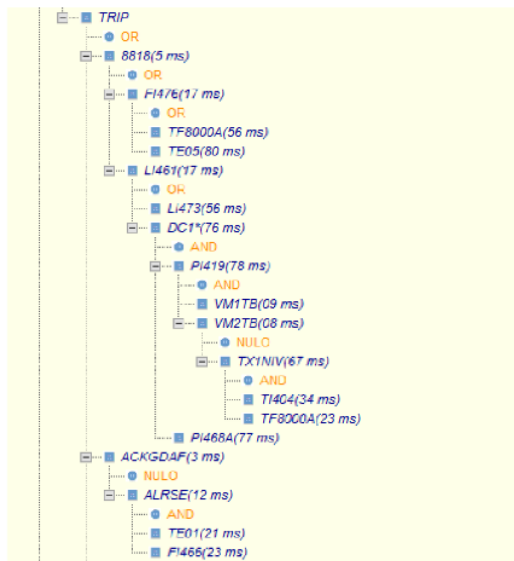


Fig. 11 Example of KB interface of TDM

| Referência | Tempo |
|------------|-------|
| TRIP | |
| 8818 | 5 |
| ACKGDAB | 3 |
| 8811A | 2 |
| | |
| | |
| | |
| | |
| | |
| | |
| | |
| | |

Fig. 12 Logical and temporal relationship interface

Fig. 13 RTES Interface of TDM

V. CONCLUSION

The results show that the system is able to classify the response of the automatic protection systems, as well as to evaluate the conditions of the plant, diagnose the type of occurrence, and the recovery procedure to be followed. In addition, it is able to indicate the shutdown root cause and to classify the emergency situation level. The results show that system can be used in any type of NPP and can decrease the operator’s cognitive workload. The knowledge interface is clear and easy-to-use by any operator or expert.

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Andressa dos Santos Nicolau has a degree in Physics from the University of the State of Rio de Janeiro (2007), a Masters in Nuclear Engineering from the Federal University of Rio de Janeiro / COPPE (2010) in the Human Factors Engineering area and a PhD in Nuclear Engineering at the Federal University of Rio de Janeiro January / COPPE, in the area of Human Factors with emphasis on research in the identification and diagnosis of accidents / transients in Nuclear Power Plants of the PWR type, with the use of Artificial Intelligence methods. Currently, she works as a researcher in the Laboratory of Project Monitoring (LMP / UFRJ / PEN), being a FAPERJ / CAPES postdoctoral Fellow. He has experience in Nuclear Engineering, working mainly on the following topics: identification of transients / nuclear accidents, diagnostics of nuclear accidents, artificial intelligence, alarms system, optimization algorithms and quantum inspiration in MATLAB and FORTRAN platform.