AN EXPERT SYSTEM FOR FAULT DIAGNOSTICS IN CONDITION BASED MAINTENANCE

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Abstract. *The main idea of Condition Based Maintenance (CBM) is to monitor the health of critical machine components and system almost in real time during operation and support the maintenance decisions based on the assessed condition. Correctly implemented CBM has the benefits such as reducing catastrophic failures, minimizing maintenance, operational and logistical cost, maximizing system security, availability and improving platform reliability. A CBM system developed has seven functional layers, data acquisition, signal processing, condition monitor, health assessment, prognostics, decision support and presentation. Among them, diagnostic and prognostic are the most important enabling technologies. The diagnostic process consist in detect faults and show suggestions to the operation and maintenance team. This paper presents a fault diagnostic method based using expert system. The implemented of the seven layers process and the rules using JESS (Java Expert System Shell) is described in detail. Also is show a comparison of maintenance indicator before and after the expert system installation. Finally, satisfactory fault diagnostics has been verified in the SIMPREBAL (Predictive Maintenance System of Balbina) system installed in the hydroelectric power plant of Balbina.*

Keywords: *Condition Based Maintenance, Expert System, Fault Diagnostics, OSA-CBM.*

1. INTRODUCTION

Nowadays, many companies are reducing their production costs continuously. One of the main expenditure items for these companies is maintenance cost which can reach 15-70% of production costs, varying according to the type of industry (Bevilacqua and Braglia, 2000). Coetzee (2004) declare that maintenance cost can represent as much as 15 to 50% of the total production cost. A consensus of the above-mentioned percentages is, thus, that maintenance costs represent more than 15% of the total production cost. Wireman (1990) reported that as much as one-third of the total maintenance cost is spent unnecessarily because of circumstances such as bad planning, overtime costs, poor usage of work order systems, and limited or misuse of preventive maintenance. According with Wireman (1990), it becomes clear that 5% or more of the total production cost is spent unnecessarily due to bad maintenance. As a consequence, actually, most companies are searching for means to control and reduce machine failures. These companies already understand that an excellent maintenance is key driver for competitively and sustainability in a global market.

Good maintenance in theory is when very few corrective maintenance actions are undertaken and when as little preventive maintenance as possible is performed (Cooke & Paulsen, 1997). Continuous maintenance would lead to decreased availability and high direct and indirect maintenance costs in terms of lost production, rework, scrap, labor, spare parts, fines for late orders, and lost orders due to unsatisfied customers (Moore and Starr, 2006). This demands great skills in planning proper preventive maintenance.

Artificial intelligence (AI), in particular, knowledge-based systems (KBSs) represents a relatively new programming approach for effective fault diagnosis and trouble shooting in machines of industrial plants. AI is being used in maintenance programs of industrial plants from common malfunctions to rarely emergency situations (Angeli, 2008). The AI approach is promising for this domain as, it captures efficiency of problem solving expertise from the domain experts; guides the human operator in rapid fault detection; explains the line of reasoning to the human operator and supports modifications; and refinement of the process knowledge as more experience is gained.

Fault diagnosis has become increasingly important for industrial automation and a variety of fault detection and diagnosis techniques have been developed for the diagnostic problem in industrial plants. These techniques include model-based approaches, knowledge based approaches, qualitative simulation based approaches, neural network based approaches, and classical multivariate statistical techniques.

Fault diagnosis that uses AI has been researched by Chan and Christine (2005), Pierre *et al.* (1998) and Yang *et al.* (2004). Reports on expert systems (ESs) for fault diagnostics have also been frequently published in the last decade by Liao (2005) and Jian-Zhong & Qing-Feng, (2008). For expert diagnosis systems are capable of utilizing human knowledge and tracing the complex relations between various signals and possible results as experts do, successful diagnosis applications based on knowledge processing have often been reported.

In this paper, is developed an ES for fault detection applied to the HPP (Hydroelectric Power Plant) of Balbina. The implementation is a rule base knowledge system applied to the condition based maintenance that use a seven layer of OSA-CBM (Open System Architecture for Condition Based Maintenance) model reference.

The rest of this paper is organized as follows: Section 2 presents the condition based maintenance architecture; Section 3 describes the ES development approach, showing how the ES was developed; Section 4 presents the system developed, it is the condition based maintenance system; and finally Section 5 concludes the paper.

2. CONDITION-BASED MAINTENANCE ARCHITECTURE

Many machine do not have a clear and visible wear-out devices and are thus not applicable for scheduled overhauls. Condition based maintenance (CBM), with condition monitoring are introduced as one solution for some of these potential failures (Bengtsson, 2007). CBM is defined by Bengtsson (2007) as: "Preventive maintenance based on performance and/or parameter monitoring and the subsequent actions". Condition monitoring can be performed using different levels of technology. The purpose of condition monitoring of a machine is to collect condition data to make possible detect incipient failure, so that maintenance tasks can be planned at a proper time.

CBM is applied in order to give input to decide maintenance actions dynamically. According to Mobley (2002), CBM is performed to serve two purposes: (1) to determine if a problem exists in the monitored item, how serious it is, and how long the item can be run before failure, and (2) to detect and identify specific components in the items that are degrading and diagnose the problem.

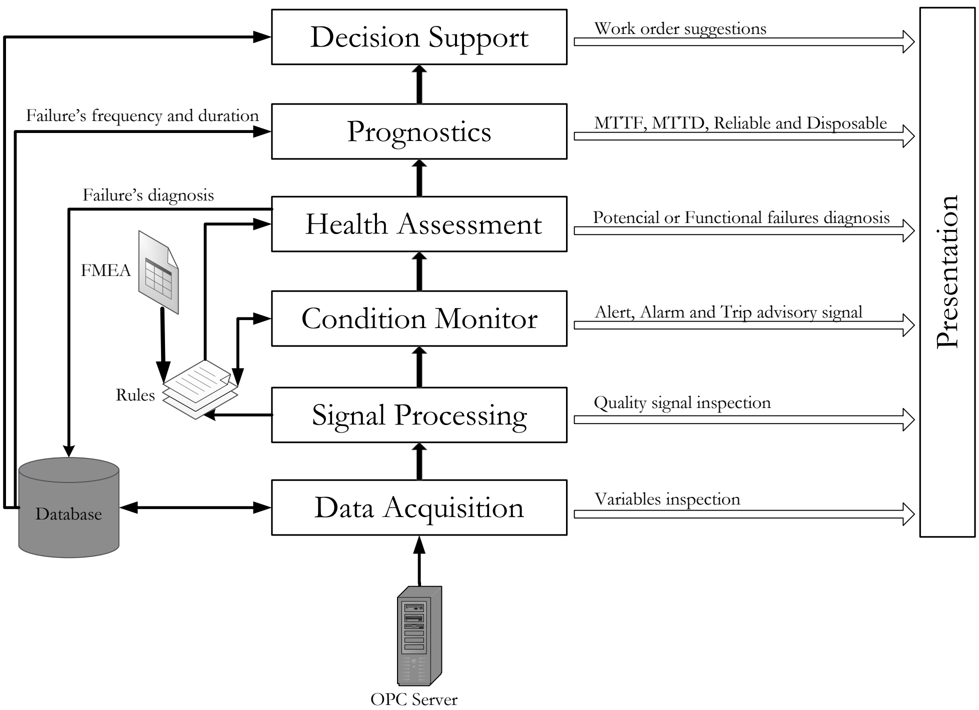

Figure 1. Condition based maintenance architecture.

The CBM system architecture used in this paper is based on OSA-CBM model. This model was used by Amaya *et al.*, (2007b), Thurston (2001) and Lebold *et al.* (2003). This architecture contains seven layers as show in the Figure 1: data acquisition, signal processing, condition monitoring, health assessment, prognostics, decision support, and presentation. Each layer is explained as follow:

Data Acquisition - Information collected from sensor, transmitter or another data source. With this signal the system capture the dynamic effect caused by the incipient failure. This layer is developed using the standard IEEE 1451 (Bengtsson, 2004) and provides to the CBM system with digitized information.

Signal processing - The purpose of signal processing in diagnostic applications and CBM is: (1) remove distortions and restore the signal to its original shape, (2) remove sensor data that is not relevant for diagnostics, and (3) transform the signal to make relevant features more explicit (Bengtsson *et al.*, 2004).

Condition Monitor - This layer compares on-line data with its expected values. The condition monitor should also be able to generate alerts based on preset operational limits. The condition monitor could be developed using the standard ISO 13373-1 (Bengtsson, 2004).

Health Assessment - The primary focus of the health assessment layer is to prescribe if the health of the monitored item has degraded. The health assessment layer should be able to generate diagnostic records and propose fault possibilities. The diagnosing should be based upon trends in the health history, operational status and maintenance history. According with Bengtsson (2004), this layer could be developed using the standard IEEE 1232 and ISO 13373-1.

Prognostics - This layer require data from the previous layers. The primary focus of the prognostic module is to calculate the future health of an asset. Thurston and Lebold (2001) present a proposal for a generic prognostic module in which input requirements cover historic data in the form of health, failures, mission, maintenance history, model information, and spare part assets.

Decision Support - The previous layer should be integrated into a decision support for the best possible solution. The primary function of decision support is to provide recommended maintenance actions. Additional information such as production scheduling and labor should be applied.

Presentation - The presentation layer receives data from the previous layers. The most important are data from the health assessment, prognostic and decision support layers. The presentation module could be built into a user interface.

There are many documents written on failures, potential failures, faults, etc. According to Soderholm (2005), failure is defined as: "Termination of the ability of an item to perform a required function". A fault, on the other hand, is defined as: "State of an item characterized by inability to perform a required function, excluding the inability during preventive maintenance or other planned actions, or due to lack of external resources". Therefore, a failure is an event, while a fault is a state. Failures in industrial plants can generate many inconveniences. Todinov (2006) lists the possible problems resulting from system failure, all of which can incur massive costs: lost production, time, volume of lost production, mass of harmful chemicals into the environment, lost, customers, warranty payments, cost of mobilization of emergency resources, and insurance cost.

3. EXPERT SYSTEM DEVELOPMENT APPROACH

Early recognition of failure modes represents the most efficient way to reduce the probability of equipment failure. However, a major obstacle to the assessment of component failure modes in industrial plants is the inability to provide industrial practitioners with the necessary knowledge concerning preventive maintenance analysis. One possible solution to overcome this obstacle is the use of computer assisted systems such as ESs. ESs are computer programs that use numerical or non-numerical information to solve problems.

The objective of this research is to develop a web-based ES to assess the potential failure effects of the equipments in a HGU (Hydroelectric Generator Unit). This research aims to develop an ES that diagnosis the fault causes quickly and displays measures to correct them. For the development of this ES, the standardization of a failure code classification, the list of the equipments in the plant and the creation of decision codes were first performed. Through of the failure history analysis, maintenance manuals, and the expert knowledge, the rule base has been constructed using CLIPS (C Language Integrated Production System) programming language. The goal of the system is provide to the non-experts in industrial maintenance with a list of possible failure modes, decisions to be adopted.

A CBM system was developed to incorporate the knowledge contained in the equipment evaluation documents, machine failure modes and knowledge from experts in maintenance. This knowledge encapsulation process was carried out systematically to consider all the different key factors in the analysis according to the Figure 2. The first step consisted of the identification of all possible failure modes for the most commonly used equipment in the HPP. The knowledge obtained was then organized and analyzed. From this analysis, the system architecture was defined, and the initial set of inference rules was constructed.

3.1 The knowledge engineering phase

There are five HGU in the HPP of Balbina. However, all HGU are very similar, if not identical. The knowledge engineering phase of this research involved the identification of the different main components and corresponding failure modes for the three systems of the HGU, electric generator, bearing system and hydraulic turbine. These systems have equipments associates as show in the Table 1. Through extensive research, relevant data were collected of all the possible failure modes that may prevent the selected pieces of equipment from operating properly. Such data were recorded on reliability centered maintenance analysis FMEA (Failure Mode and Effect Analysis) sheets. An example of FMEA is illustrated in the Table 2. As noted in the Table 2, the sheets contain information about the machine, equipments and associated failure modes. In the Table 3 can be observed the numeric parameters like: Severity (S), Occurrence (O), Detection (D) and risk priority number (R), given for each failure modes and applied to the five HGU. In the Eq. (1) is show the calculus of the risk priority number.

$$R = S * O * D \qquad (1)$$

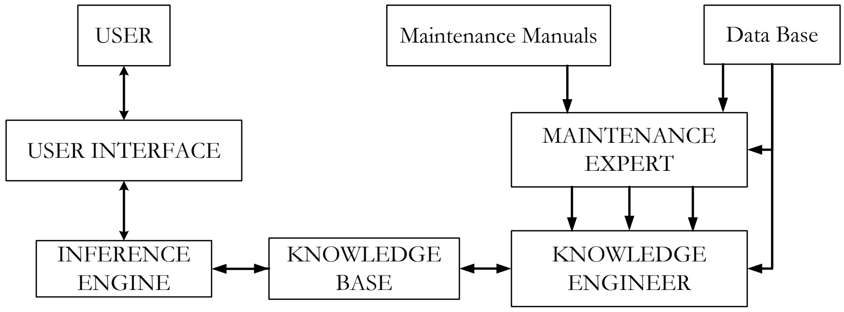

Figure 2. Developed of the knowledge base.

Knowledge acquisition was conducted primarily during interviews with experienced workers, field visits, service order, manuals, technical documentations and actual operations. During the interview process, conversations were recorded in detail and then we transformed it into acceptable format for diagnosing rules. This knowledge consists of concepts, objects, relationships and inference rules. An expert knowledge represented by statements in a natural language, by proposition or by predicates. For Prootiapas & Kaminaris (1990) the problem-solving knowledge of an expert is often represented in terms of: IF <Situation> THEN <Action> RULE.

The general framework that is being used is the rule-based ESs. In such systems, expertise of an expert are encoded in the form of inference rules of the form (Bose, 1988): IF S1, S2, S3 ,..., Sn, then A. Where Si's are the situations and A is the action for these situations. The set of rules constitute the knowledge base of the rule-based ES. Another important component of a KBS is inference engine that uses the given knowledge base in the solution of a problem. Expert maintenance engineers besides of using test procedures and maintenance manuals, use their intuition or heuristics and understanding of how the system works to solve the problems. Based on years of experience, maintenance engineering develops a intuitive understanding of how the system will behave when a certain subsystem fails (Grigoriu & Phillip, 1988).

Table 1. Systems and equipments considered.

System	**Equipment**
Electric generator	Coil stator Temperature Core stator Temperature Cold air Heat exchanger Hot air temperature Coil excitation temperature
Bearing system	Metal Guide Temperature Oil Guide temperature Oil tank level Oil tank pressure Oil tank temperature Oil injection pressure Oil flow Oil density Water flow Water temperature
Hydraulic turbine	Water flow Water pressure Water temperature Oil regulation temperature

3.2 Software and hardware considerations

During the preliminary system design process, several system requirements were identified to achieve the objectives of the project. Among them, programming language, friendliness of the user interface, and ability to connect with OPC (OLE - Object Linking and Embedding - for Process Control) servers, database and handle with ES shell were regarded as necessary for the success of the final system. Such system requirements or specifications determined the choice of the software and hardware platform needed for this project. The ES was developed using JESS (Java Expert System Shell) as a rule engine. JESS uses an enhanced version of the Rete algorithm to process the ES rules. Rete is a very efficient mechanism for solving the difficult many-to-many matching problem (Friedman-Hill, 2003). All maintenance system was developed in Java in client-server architecture, integrated with OPC Server and databases.

Table 2. FMEA worksheet.

System in Analysis: Guide bearing cooling and lubrication system
Function: To dissipate heat on the guide bearing and lubrication their components

Component	Function	Failure mode	Effects	Cause	Control
1. Pumps	Oil pump	1.1. Low pressure operation (<2bar)	-Turn off the priority pump and turn on the alternative pump in low pressure. -Lubrication and cooling failure.	-Oil leaks by the mechanical seal. -Coupling damage -Corrosion by contamination Oil -Cavitations by presence air in oil	Oil pressure transmitter in the pump out
		1.2. High pressure operation (>6bar)	-Turn off the priority pump and turn on the alternative pump in high pressure. - Pump failure risk. - Crack tubes and leaks -Lubrication and cooling failure.	-Incorrect adjustment	Oil pressure transmitter in the pump out
		1.3. Abnormal sound	-Pump failure risk	-Bearing wear -Bad bearing lubrication	Sound inspection
2. Heat exchanger	To cool the oil	2.1. Insufficient cool of oil	-Lost oil's physic-chemist characteristics -Cooling failure	-Plate pack with noise	Temperature transmitter
		2.2. Oil leaks	-Oil contamination risk -Lost oil's physic-chemist characteristics -cooling failure	-Stud bolt wear -Plate pack connections slack	Oil flow transmitter
		2.3. Water leaks	-Cooling failure	-Slack tubes connections of water	Water flow transmitter

Table 3. Critic failure analysis.

System in Analysis - Guide bearing cooling and lubrication system.

	HGU-01				HGU-02				HGU-03				HGU-04				HGU-05			
ID	**S**	**O**	**D**	**R**	**S**	**O**	**D**	**R**	**S**	**O**	**D**	**R**	**S**	**O**	**D**	**R**	**S**	**O**	**D**	**R**
1.1	4	1	1	4	4	5	1	20	4	3	1	12	4	1	1	4	4	3	1	12
1.2	4	1	1	4	4	3	1	12	4	1	1	4	4	1	1	4	4	1	1	4
1.3	3	1	5	15	3	3	5	30	3	1	5	15	3	1	5	15	3	1	5	15
2.1	2	6	1	12	2	6	1	12	2	5	1	10	2	7	1	14	2	9	1	18
2.2	7	1	1	7	7	1	1	7	7	3	1	21	7	1	1	7	7	2	1	14
2.3	3	1	1	3	3	3	1	9	3	4	1	12	3	1	1	3	3	2	1	6

4. THE SYSTEM DEVELOPED

The system developed named SIMPREBAL (Predictive Maintenance System of Balbina) emulates the job of an maintenance expert in HPP. The major SIMPREBAL functions is get pertinent information from online and historic sources, computing the faults of each equipment considered in the analysis, and displaying suggestion of maintenance actions. Its structure involves the seven OSA-CBM layers adapted to a client-server computational framework. The project of this computational system in UML (Unified Modeling Language) was presented by Amaya *et al.* (2007a). This system has been introduced to a Kaplan HGU in the HPP of Balbina located on Uatuma River in Presidente Figueredo city, Amazonas state, Brazil. There are five HGU, the rated output power is 250 MWh, the rated descriptive rotary speed is 105.88 rpm and the rated water head is 21.85 m.

4.1 Systems and Equipments

The first step in the developed of the system was to identify all the systems and equipments in each of the five HGU. In the Table 1 is show the list of the assets into one HGU. It is divided in electric generator, bearing system and hydraulic turbine system. Each system have incorporated foundation fieldbus transmitters in their equipments. The transmitters are connect to an H1 network of 31.25 Kbps. In order to communicate the information from the H1 network to the HSE (High Speed Ethernet) network of 100 Mbps is used the DFI (Distributed Field Interface). The instruments in each HGU are organized with DFI bridges, through of these DFI, the instruments are capable to send their information to an OPC server.

4.2 System inputs

The SIMPREBAL collect information through the data acquisition layer, online and historic variables from OPC server and database respectively. The SIMPREBAL collect data from the OPC server using the JOPCClient library, this library is implemented in Java. The database is accessed using JDBC (Java Database Connectivity) and is used to storage failures, variables related to failures and decisions. The database also includes maintenance and operation personnel information. The system is foresee for communicate to another database in order to have in the future an integrated system with ERP (Enterprise Resource Planning) system, MES ((Manufacturing Execution Systems) and others systems.

4.3 System processing

In this section is described the methods to be adopted for process the information collected from the data acquisition layer. The knowledge base storage in rule files that will be process in the signal processing, condition monitor and health assessment layers. These rules were implemented using the CLIP language and processed through of JESS.

Signal processing - In this layer the system tests the connectivity of the SIMPREBAL with the DFI, OPC server and database. The connectivity test with the DFI and OPC server is realized using the PING command, with this command is verified the connectivity in the IP (Internet Protocol) level sending messages and waiting for the response of the ICMP (Internet Control Message Protocol). The variable value change is tested in periodical cycle, if the variable value don't change means that the system stopped their function. In this layer is processed information about the OPC and fieldbus signal quality. The method of representing the monitoring variables for signal quality processing is explained in the Figure 3. Each process variable (i.e. coil stator temperature) is composed for two items (VALUE and STATUS). The first load the variable value and information about the quality of the item obtained through OPC server. The last have information about the signal quality transmitted by foundation fieldbus instrument. With this information is constructed the TAG object that is used in the next layers. The rules of this layer is show in the Table 4. The rules detect the signal quality in the OPC server and foundation fieldbus instrument.

Condition Monitor - This layer receives as information the TAG object. The value of the TAG object is compared with the values established previously. The rules showed in the Table 4 verify the relationship between the variables values and machine operational limits. The out of this layer is the state of the equipment operation. There are four states that characterize the condition monitor.

NORMAL - The values are inside of the normal equipment operation .

ALERT - In this state the monitored values show an incipient default in the equipment. This state was established to find any alteration of the normal condition.

ALARM - This state was previously established by the maintenance, operator and automation managers of the HPP. This state indicates the risk situation of the equipment monitored. When is arrived to this state is require to take preventive actions in order to prevent achieve to a failure stage that will produce unexpected stops.

TRIP - Values in this state is considered inacceptable in the equipment operation. When is achieved to this state as a security measure is turned off the equipments.

Health Assessment - This layer uses the FMEA tool in order to find relations between the monitored variables and the equipment faults. The operation and maintenance personnel contributed to indentify the maintenance problems in the

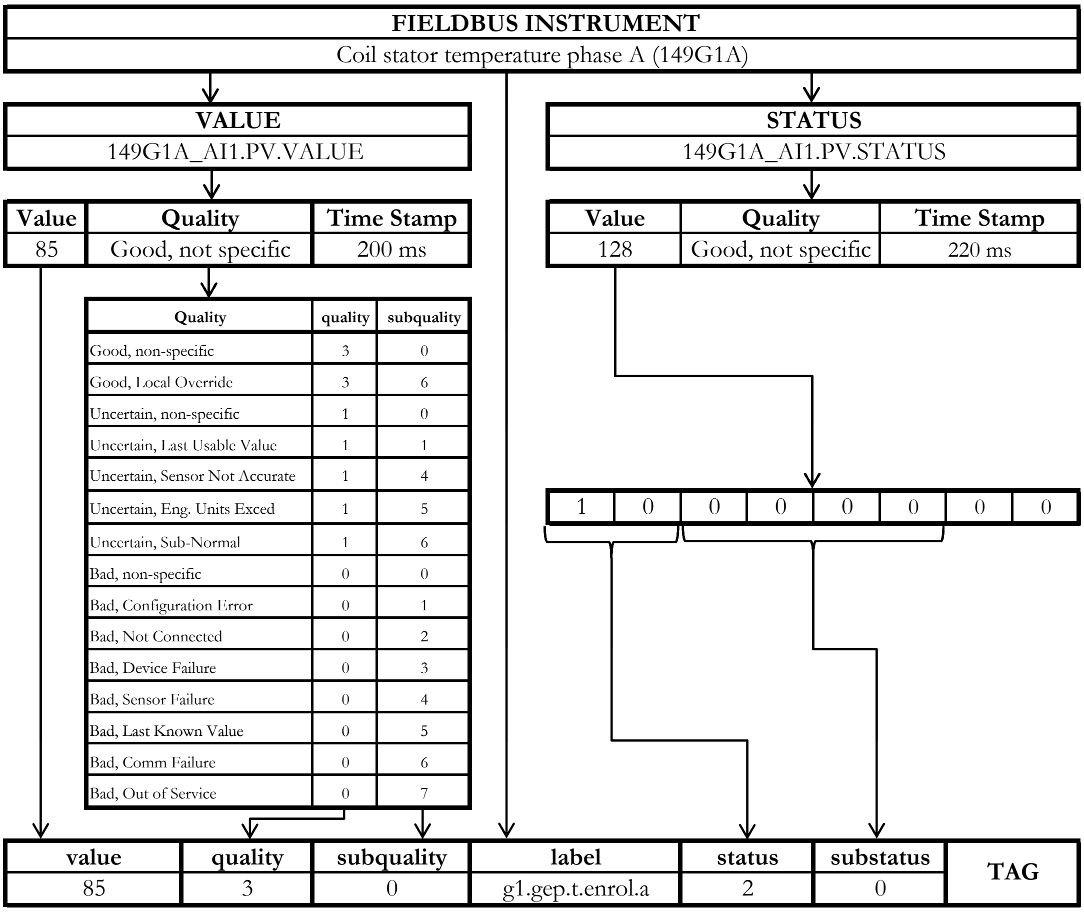

Figure 3. Tag object construction for coil stator temperature.

HPP. Also were used documents like TOI (Technical Operation Instructions), TMI (Technical Maintenance Instructions) and MPA (Maintenance Planning Autonomous), the documents contain functional description of the equipments. Other documents used are maintenance service order from the 2004 to 2008 year, in this case was analyzed in detail the failures occurrence and the maintenance procedure realized. With all this information was elaborated a complete analys of the possible FMEA (i.e. see the Table 2). The following problems are identified: oil contamination, heat exchanger overheats, oil leaks, coil overheats, mechanical looseness, bearing problems, etc. The rules developed from FMEA are about failure diagnostic of the condition monitor.

Prognostics - The failure prognostics are the mean estimation between failures calculated through the process model using Markov chain. For the prognostic calculus is necessary to get from the SIMPREBAL database the ALERT, ALARM and TRIP registers. Another important informations are the initial and final time, information like frequency, MTTD (Mean Time To Dignose) and MTBF (Mean Time Between Failures). There are others AI techniques that can be implemented, a theory proposition of prognosis using fuzzy ARTMAP model was presented by Amaya (2008).

Decision Support - The decision support is a maintenance service order developed from the FMEA. All the decision associated to an eventual failure diagnostic was previously storage in the SIMPREBAL database. This layer send their information to the presentation layer.

4.4 System output

The presentation layer is the client side of the client-server architecture. This client was conceived to be a web application make available through of the HPP intranet. This application was developed in HTML pages into of this is inserted an applet Java, JavaScript and PHP structures. This layer presents the information of the previous layers. When the system detects one fault, information about the type of fault is send to the user through email, storage in database and advisory in the synoptic window. The database tables containing relevant information on the pieces of equipment considered by the knowledge base. The window, as shown in the Figure 4 display the HGU, each one display the fault and failure in its components. This screen contains explanatory messages intended to inform the user about faults advisory in the five HGU.

Table 4. Layers rules implementation

Layers	Rules
Signal Processing	- IF (quality == 3) THEN (COM-GOOD) ELSE (COM-BAD) - IF (COM-GOOD and (status == 2 or status == 3)) THEN (signal-GOOD) ELSE (signal-BAD)
Condition Monitor	- IF (signal-GOOD and value $\leq$ 105) THEN (condition-NORMAL) - IF (signal-GOOD and value > 105 and value $\leq$ 130) THEN (condition-HIGH) - IF (signal-GOOD and value > 130 and value $\leq$ 155) THEN (condition-ALARM) - IF (signal-GOOD and value > 155) THEN (condition-TRIP)
Health Assessment	- IF (condition-HIGH) THEN (code-G149H and color-YELOW and email-OPERATORS) - IF (condition-ALARM) THEN (code-G149A and color-RED and email-ELECTRICIANS) - IF (condition-TRIP) THEN (code-G149T and color-RED and email-ENGINEERS)

4.5 Results

Where there are specific maintainability requirements or goals, which must be obtained for a system, then there is a need to determine the system's quantitative maintainability characteristics. This could be represented in terms of a % success, MTTR and MTBF. In the past the analysis was made by the operational personnel, nowadays the system send maintenance suggestion and the operator decide if the suggestion will be adopted. The system was installed in march 2008, considered an analysis period of 500 days. The total failures in the HGU 01 is 23, the failure detected by the system is 16, using the Eq. (2), we have that a sucess is 69.57 %.

$$\%\text{Success} = \frac{N^\circ failures\, detected}{N^\circ failures} \tag{2}$$

The MTTR in hours changed from 18 to 42 for the system managed by the operators and by the ES respectively. This calculus was made for the period 2008 – 2009 ausing the Eq. (3).

$$\text{MTTR} = \frac{Total\, time\, of\, the\, component\, repair}{N^\circ of\, repairs} \tag{3}$$

The MTBF indicator was calculated using the Eq. (4) have as a result 34 days managed by the operator and 45 days managed by the ES.

$$\text{MTBF} = \frac{Operational\, period}{N^\circ failures} \tag{4}$$

5. CONCLUSIONS

Intelligent ES software for fault detection applied to HPP of Balbina has been developed. The benefits of this system include: reduction in machine down time, reduction in skill level for maintenance activities, ease of maintenance, speedy response and affordable cost. The reliability of diagnosis is highly dependent on the accuracy information from online and historic sources. This study dealt with the design and development of a knowledge-based system for the evaluation

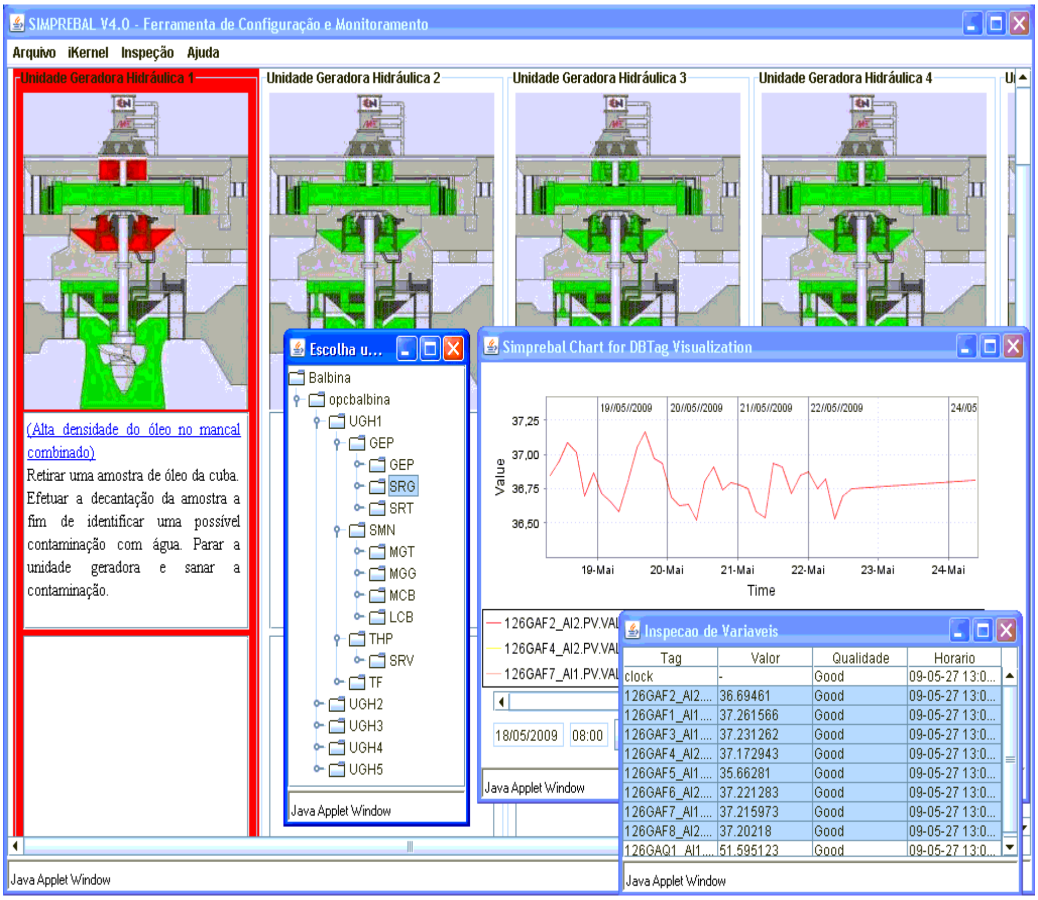

Figure 4. Presentation layer of the SIMPREBAL.

of industrial equipment in terms of fault diagnosis. The first phase of the project consisted of a comprehensive knowledge engineering effort to identify the major failure modes associated with the five HGU and equipment used in the HPP. The final product of the research was a user-friendly ES named SIMPREBAL. The system is computer based, and was developed in Java environment. The OSA-CBM model reference used to develop the SIMPREBAL can be implemented in modular way, the distributed processing architecture is easily scalable. Another system potentially capable of rapid deployment would be a generic OSA-CBM module that can be programmed via a model or process description. After the analysis of the % success, MTTR and MTBF indicator, we conclude that the system with ES is better than the operators except in the % success, because is assumed that the operator expert in maintenance have 100 % of success. A future work is to develop a prognosis layer using AI techniques that calculate the RUL (Remaining Useful Life) of the equipments.

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8. Responsibility notice

The authors are the only responsible for the printed material included in this paper