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Expert Alarm System for Prediction of Chemistry Faults in a Power Station

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ABSTRACT

The integration of rule based techniques in traditional real-time systems is a promising approach to cope with the growing complexity of real-world applications. Real-time expert systems are on-line knowledge-based systems that combine analytical process models with conventional process control to monitor complex industrial processes and to assist in problem identification. Intelligent system for alarm diagnosis and root cause analysis and operator guidance in process plants is an important area for which the real time expert system is being used. Fault monitoring and prediction is of prime importance in a Power Plant. This paper proposes an expert system to aid plant operation engineers in diagnosing the cause of abnormal water / steam parameters in a Fossil fuel Power station. The diagnostic decisions are written in the form of fault trees. Fault trees fare developed or all steam water cycle parameters. This system enables the operator to take preventive measures in time, avoiding costly outages, in turn increasing the plant availability and efficiency. The proposed system has been successfully implemented in a thermal power plant on PI Process book environment of OSI soft and is written in Microsoft Visual Basic.

Keywords: Decision tree, distributed control system, expert system, power station, alarm alert, chemistry faults.

Mathematics Subject Classification: 68T35

Computing Classification System: I.4

1. INTRODUCTION

Knowledge Based System (KBS) has an important role to play, particularly in fault diagnosis of process plants, which involve lot of challenges starting from commonly occurring malfunctions to rarely occurring emergency situations. KBS address issues such as intelligent alarm processing for fault diagnosis and operator guidance. Power Plants use Intelligent Decision Support Systems as a tool for monitoring and managing process. Decision Support Systems (DSS) are computerized tools derived from decision theory used to enhance user ability to make decisions efficiently. They are not intended to offer the final solution, but rather to explore and seek alternative solutions. The ultimate decision is left to the user. Intelligent Decision Support Systems (IDSS) add intelligence to existing systems to enhance problem solving ability and help maintain a broad range of knowledge about a particular domain.

Early prediction of faults is of prime importance in electric power stations. Faults are defined as adverse events (situations) with significant impact on the system status (Narayanswamy et al., 1998; Tsumoto, 2003). Faults may cause a meaningful shift in the system operations even when the values of the individual parameters are acceptable. Generally, any process remains normal most of the time, whereas faults usually make up a small fraction of the operating range (Narayanswamy et al., 1998). Accurate prediction of faults is difficult due to unbalanced volume of data for normal and faulty states. In an extreme case, no prior fault data could be available.

Water and Steam are the crucial components of any Power Plant and proper chemistry control is critically important to plant operation and reliability. Improper plant chemistry management can lead to various chemistry related issues which can be detrimental and can directly affect plant availability. Some of the common issues are boiler tube failures, turbine and boiler tube wall depositions. Operating power plants efficiently is very important in the economics of power generation (Buecker, 1997). This requires that all the systems function at their peak performance over long term operation. SWAS helps power plants to function efficiently and keeps them in continuous operation for optimal performance. Recognition of the role of steam and water analysis system (SWAS) in efficient power plant operation is growing as and this paper proposes integration of expert system in SWAS for betterment of power plant efficiencies. The quality of steam that is used by these power plants is of utmost importance – it is like monitoring cholesterol in human body. Various contaminants that might exist in steam can prove very harmful to the turbine, to the boiler, to the piping, etc. SWAS effectively monitors these parameters (such as pH, conductivity, silica, sodium, phosphates, dissolved oxygen etc.) and thus helps in maintaining healthy operation of a power plant. In all power plants in India that work with more than 90% efficiency a well engineered, well maintained SWAS is established. A typical SWAS comprises of

- a Sample Conditioning System (some call it Sampling System) where the Temperature, Pressure & Flow of sample if conditioned and regulated, and
- an analyzer panel where all the on-line analyzers are located. The sensors of these analyzers receive the sample conditioned by the sample conditioning system and send signals to analyzers. The analyzers in turn send these signals to respective parameters in 4 to 20mA signal which is finally delivered to the plant DCS.

In this paper, a hierarchical decision-making approach is proposed to generate alarms. The background of the steam and water analysis system (SWAS) faults commonly called as water chemistry faults (WCF) and the fault literature are presented in Section 2. A brief functioning of data acquisition system (DAS) is presented in Section III, the general configuration for the development of the expert system for fault prediction is presented in Section IV, and the decision trees are presented in Section V. The proposed approach has been demonstrated to predict faults due to water chemistry problems at a commercial power plant and the application is presented in Section VI. The conclusions are discussed in Section VII.

2. BACKGROUND

A power plant involves various systems, e.g., coal/fuel feeder system, condenser system, turbine system, and feedwater system. The fuel (coal) is fed into the boiler by the coal feeders to generate heat that is conducted through the boiler walls to water (boiler water system) flowing through the boiler tubes. The water becomes steam flowing to a turbine system where the heat energy is converted into electrical energy. The used steam flows through the secondary heaters either to heat the steam flowing to the turbine or to preheat the water flowing into the boiler. From the secondary heaters, the steam is condensed in a cooling tower and then converted back into water.

This water is then checked for impurities before feeding (feedwater system) it back into the boiler system. There is a loss of water during the cycle, which is substituted by river water. The river water is initially treated to maintain acceptable levels of impurities. A fault in any of these systems may lead to temporary shutdowns and, in some cases, may have catastrophic consequences. Thus, monitoring various systems to predict impeding problems is of importance. A 500 MW power plant overview is shown in Figure 1.

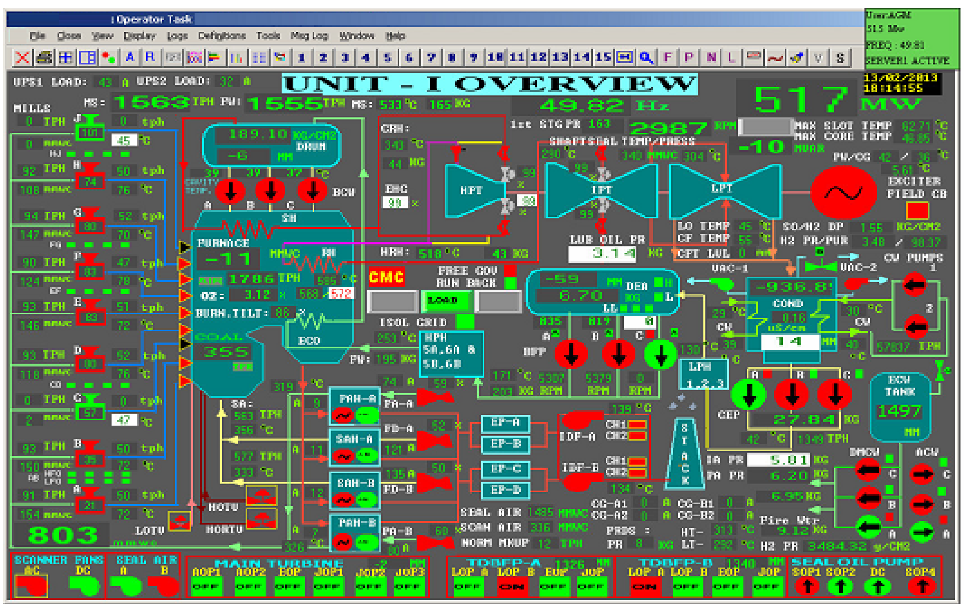

Figure 1. Overview of a 500 MW unit.

Water-treatment regimes control the steam purity, deposits, and corrosion to produce high-quality steam (Charles, 2003; Shvedova et al., 2002; Sopocy et al., 1991). The water contains impurities such as dissolved gases (e.g., oxygen, carbon dioxide, and nitrogen), sand, silt, particles of organic matter, and ions of dissolved mineral impurities (e.g., bicarbonate, carbonate, manganese, sodium, silica, chloride, iron, *phosph*ate, and sulfate) (Charles, 2003). The temperature and pressure at which the boiler operates affect the behaviour of various impurities, leading to the formation of scales (calcium carbonate, magnesium hydroxide, magnesium silicate, iron oxide, calcium phosphate, magnesium phosphate, and calcium sulfate), corrosiveness, and saturation. The water impurity can lead to rapid degradation of the equipment, lower availability, inefficient operations, and other unwanted events (Bruce et al., 1989). The parameters collected for the feedwater system are dissolved oxygen, feedwater pH, oxygen scavenger concentrations, conductivity. Typically, the data for the feedwater system are collected at condensate pump discharge, condensate polisher outlet, deaerator inlet and outlet, and economizer inlet. The data points for the boiler water system are phosphate concentrations, silica concentrations (Choi et al., 1995), boiler water pH, and so on. Water pH imbalances can severally hamper the boiler operations causing corrosion, scales, and water tube damages (Charles, 2003). Appropriate water-alkalinity levels will ensure proper chemical reactions and hence normal operations of the boiler. The feedwater pH is generally maintained at slight alkalinity (pH in the range of 8.3–10), whereas the boiler water pH is more alkaline (pH in the range of 9–11) to prevent acidic outbreaks. Oxygen reacts with magnetite (Fe_3O_4, a protective coating) or cuprous oxide (Cu_2O) to form ferric oxide (i.e., rust) or cupric oxide. The corrosive effect of the dissolved oxygen in the boiler operations is undesirable [15]. At higher temperatures, nodules of corrosion products and sites are formed on the boiler tubes. The depositions inhibit heat transfer across the tube boundaries and reduce the efficiency of the boiler. Deaeration is a mechanical process used to remove the dissolved oxygen. It is followed by the addition of chemical oxygen scavengers such as hydrazine (N_2H_4 or N_2H_6CO), chelant, and carbohydrazide. The performance of hydrazine (Shvedova et al., 2002) is enhanced at increased temperature and pH, but excessive hydrazine may lead to the formation of ammonia, a by-product that aids corrosion process. A phosphate treatment is commonly used to remove dissolved mineral impurities (Charles, 2003; Choi et al., 1995). The phosphate ion in trisodium phosphate (Na_3PO_4) is extremely effective for conditioning the boiler water in an alkaline pH range. Phosphate reacts with scale-forming compounds to form soft sludge that is easier to remove. The requirements for satisfactory steam purity, minimum corrosion, and minimum deposition are interlinked, forming a multiobjective function. In addition, the chemicals added to prevent the WCF might interact with each other or exhibit different properties at different operating conditions. Consequently, the development of an optimal water treatment plan involves a tradeoff. Thus, the monitoring of all the water chemistry parameters (Charles, 2003; Sai et al., 2014) is imperative not only in terms of their individual operating ranges but also in their interactions. Traditionally, water samples are retrieved three to five times a day from the water systems and tested for various impurities as well as pH values (Bruce et al.,1989). This system monitors the trends but not in real time. For in-process intervention, continuous monitoring of the water chemistry parameters is essential. Unscheduled shutdowns are costly, because productivity is lost, and, thus, a system that can predict in advance the developing WCF is needed. The main sources of impurities in the boiler are condenser leak, faulty demineralization and corrosion products from improperly treated feed system.

2.1 The Basic Chemistry of the Effect of Impurities and Remedies

***Calcium & Magnesium salts*:** These salts present in impure water causes hard scale formation, overheating of tubes and reduce efficiency of the boiler. If these salts are left untreated may form corrosive hydrochloric acid. Phosphate dosing is done to combat the effect of these salts. Conductivity is measured to analyse the amount of salts present in different stages of water steam cycle (Buecker et al., 1997).

***Dissolved Gases*:** Carbondioxide and Oxygen mainly contribute for the degradation of boiler material. CO_2 gas forms a weak carbonic acid which attacks the metal. O_2 forms iron oxide on steel. Hydrazine dosing is done to control the dissolved oxygen. If the amount of O_2 is restricted, a thin film of iron oxide forms on the metal surface which is not so fully oxidized as the red iron oxide, and is more dense, thus tending to resist further corrosive attack. In water of increasing alkalinity, this oxide film becomes gives more protection to the steel, but until a definite alkalinity is reached, after it still tends to break down in selective areas, where pits will develop. So the measurement and maintenance of the pH which is the indicator of water acidity or alkalinity is a must. Excess dosing may also lead to pH changes. Proper dosing is to be monitored as shown in the flowcharts.

***Silica*:** One of the soluble impurities carried forward in the steam is silica. Silica is more soluble and when the scale formed is a mixture of silica, calcium and magnesium salts, it is very hard. The deposits of silica are extremely hard to remove on turbine blades. The silica levels are reduced by reducing boiler pressure and operating Blow down.

***Carryover*:** When water is converted into steam in a boiler, a small proportion of any impurities in the water are carried forward with the steam and deposited in the super heater or turbine blades. A very small deposit of sodium hydroxide or sodium chloride cause stress corrosion and may lead to failure in tubes.

2.2 Application necessity in a power plant

- Corrosion and erosion are major concerns in thermal power plant operating on steam. The quality of production of steam in the boiler depends upon the Water chemistry maintained in the inlet of the boiler. The steam reaching the turbines need to be ultra-pure and hence needs to be monitored for its quality.
- Timely action with respect to the steam and water quality is required for continuous generation of a power plant without any breakdowns.\
- Many parameters are targeted for a single problem. So experts advice from previous experience rather than theoretical approach is the fast and practical solution for a deviation faced.
- The proposed application provides knowledge capturing in turn framed to rules.

3. DEVELOPMENT OF REAL TIME EXPERT SYSTEM

The developed expert system (ES) for power plant and its architecture are shown in Figure. 2. This ES mainly concentrates on capturing the so-called Experts experience. Here the experts are the people who were continuously working on the system for years together having sound practical knowledge to provide the inputs for a sustainable solution. The basic components of the system are Customizable Data Interface, Event Processor, Inference Engine, Knowledgebase, Knowledge base Editor and Web based GUI for providing Operator guidance. Stability analysis method for fuzzy control systems dedicated controlling nonlinear processes (Tomescu et al., 2007), fault detection, isolation and estimation for Takagi-Sugeno nonlinear systems (Ichalal et al., 2014), Fuzzy rule interpolation based fuzzy signature structure in building condition evaluation (Molnárka et al., 2014), classification of HIV-1 mediated neuronal dendritic and synaptic damage using multiple criteria linear programming (Zhang et al., 2004) are the popular methods having interesting applications of expert systems, knowledge-based including fuzzy systems.

The model is developed by coding the basic math and logical functions in a visual basic form.

The system design details are presented here. The control system software controls the main process of power plant. Hence any expert systems to be build on the system needs to take care of security and integrity. Any minor mistake in these terms may hamper the process and thereby creating a huge loss to the industry. Hence any external communication to the system is to be through a series of security measures. The real time data from the control system is available to the external world via a standard protocol called OPC (OLE for Process Control where OLE stands for Object linking and embedding). The OPC is DCOM (Distributed COM) object which uses multiple ports for its communication. A specific port cannot be fixed in a fire wall for secured transfer of data in this protocol. For the communication to happen securely, an integrated OPC client with socket data transfer through a single port is developed using visual studio. This data is being collected in an enterprise data server called PI server. This real time data is being used by Exert Alarm software developed in PI process book. The PI process book is a frontend software used to design the graphics using data from PI enterprise data server. But the expert alarm software development requires the data analysis, rules framing and rules validating. The VB scripting is done to populate the alarms in the Process book. The VB script collects the real time data every 5 seconds and validates the condition of the process. Depending upon the process condition and rule base logic, an alarm is displayed on the screen. The rule framing is configurable to the user. Any new advice can be simply configured by using the math and logical functions in the configuration file.

Knowledge Base (KB): The system uses a hybrid knowledge base, the main components of which are Meta Rules, Rules & Frames. The KB can be built with domain specific information using the web based, user friendly Knowledge Base Editor GUI. Rules are used to keep the experiential knowledge captured or extracted from the Plant Expert. Frames are used to hold the deep knowledge regarding systems, process and equipments. Besides Rules & Frames, Temporal information from DCS is also used for root cause analysis of faults. The various parameters required for alarm diagnosis including on line DCS data are stored in a database (Subrahmanian, 1994).

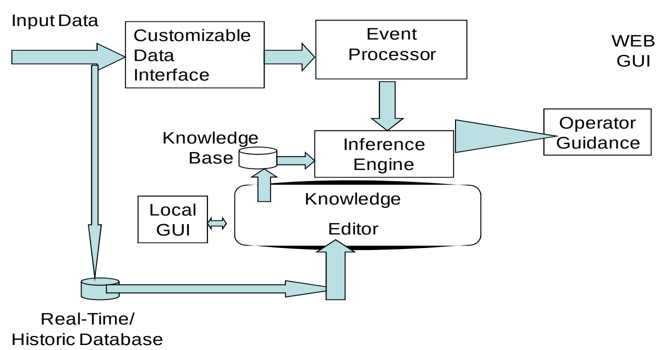

Figure 2. Architecture of expert system.

Meta Rules are of “IF Complaint THEN Hypothesis” form Rules and mainly used to control the inference mechanism. Meta rules decide what domain rules should be applied next or in what order they should be applied. Meta rules thus help in increasing the efficiency of the system. Use of Frames enables to build knowledge based models of plants or any other target area. A frame is a data structure with typical knowledge about a particular object or concept. A frame provides a means of organising knowledge in “slot-value pair” to describe various attributes and characteristics of the object.

Knowledge Base Editor (KBE): It provides facility to input different rules of an application by the domain expert using user-friendly GUI. Rules and other application specific attributes will be represented using Frames and Production rules. Knowledge base consists of domain specific information that is fed into the system through GUI. This information is used to interpret and diagnose real-time data received from controllers and sensors.

Customizable Data Interface (CDI): It is application dependent, which pre-processes the input data and feed to the Event Processor module. It is a plug-in module for interfacing with other systems. CDI is an OPC client utility with alarm configuration facility. The Customizable Data Interface interfaces with the external DCS and reads the tag data using OPC connectivity in this implementation. The online data are logged into a database. The Event Processor module takes the real-time data output of CDI for processing and triggering inference in Expert System. This module processes different types of alarms in real time, classifies and sorts the alarms based on priority. These alarms are used for triggering the Inference Engine.

Inference Engine: The Inference Engine is the heart of ES. Since this ES is intended for diagnosis of faults, a Backward Chaining inference strategy is preferred. This inference engine will use knowledge stored in Production Rules and Frames for arriving at a conclusion or a goal while performing a fault diagnosis using backward reasoning method. The Backward Chaining engine is triggered when it gets a high priority alarm from the Event Processor Module. Backward chaining involves, working back from possible conclusions of the system to the evidence, using the rules and frames. Thus backward chaining behaves in a goal driven manner. The expert system developed below is integrated seamlessly with existing DCS .Expert systems have been developed primarily as job performance aids. Expert systems used to assist in job performance usually include a knowledge base and an inference engine. The details of configuration from plant DCS to expert system is shown in Figure 3.

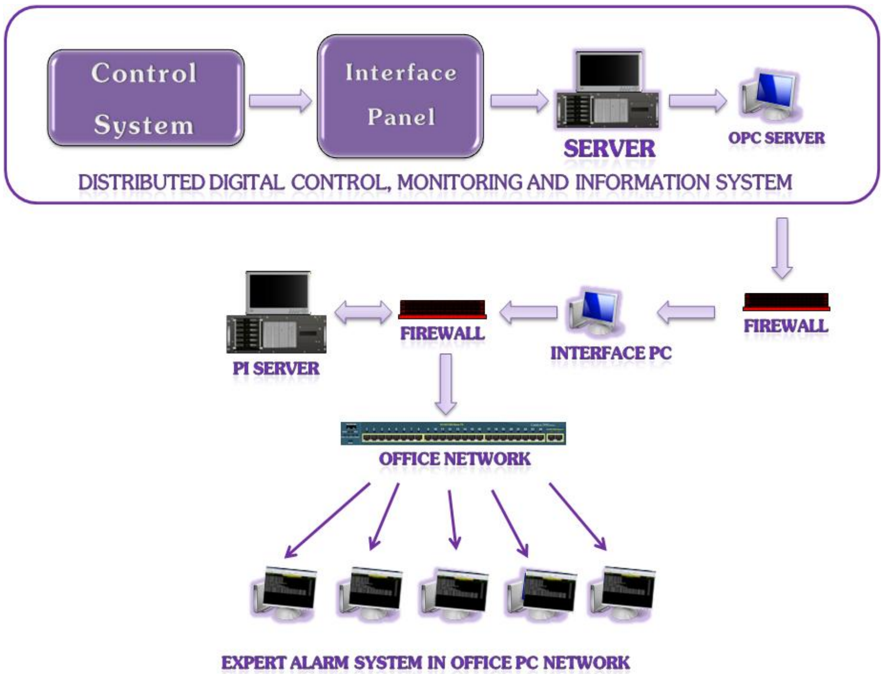

Figure 3. DCS integration to expert system.

4. DATA ACQUISITION

The process starts with collection of plant data from distributed control system (DCS). The expert system is a PC based software system that is passively connected to DCS (Zhang et al., 2003). The Expert system receives the plant data along a one way highway and has no interaction with DCS. DCS deals with various water/steam parameters measured at eleven sampling nodes in a 500 MW power plant, as shown in Figure 4.The DCS provides a huge amount of data related to the chemistry parameters. However there is a need to convert this data into useful and meaningful information where domain expertise of plant chemists and operation engineers can be used (Bruce et al.,1989). To this end an expert system is developed which can use the real time data and manage plant chemistry in a more efficient manner. Rule-based systems are generally more robust than analytic ones. Hence, they should be used in a support role, with the objective of bringing a plant to a safe condition should the analytic controller fail for some reason, such as loss of a sensor. One of the disadvantages to the analytic approach is that human operators do not think in terms of formalized control laws and, therefore, may not understand the behaviour of an automated system (Kusiak, 2000). Rule based technology could be employed to provide the reasoning behind a particular analytic control decision. In summary, the rule-based and analytic approaches should not be viewed as competing technologies but to be used in tandem to create truly robust control systems. The following online process parameters are the parameters of the expert system:

Boiler Water – pH , Boiler Water – Specific Conductivity, Boiler Water – Silica, Boiler Water – Phosphate, Boiler Water – Chloride, Deaerator Outlet – Dissolved Oxygen, Feed Water – Hydrazine, Feed Water – pH, Feed Water – Specific Conductivity, Feed Water – Cation Conductivity, Make-up Water – Specific Conductivity ,Make-up Water – Cation Conductivity, Main Steam – Specific Conductivity, Main Steam – Cation Conductivity, Main Steam – pH, Main Steam – Silica, Condensate Polisher Outlet – Sodium, Condensate Polisher Outlet – Silica, Condensate Polisher Outlet – Sp. Conductivity, Condensate Polisher Outlet – pH, Condensate Polisher Outlet – Cation Conductivity, Hotwell Condensate Left– Sp. Conductivity, Hotwell Condensate Right– Sp. Conductivity, Condensate extraction pump (CEP) Discharge – Cation Conductivity, CEP Discharge – Sodium, CEP Discharge – Dissolved Oxygen , CEP Discharge – pH, Saturated Steam – pH, Saturated Steam – Sp. Conductivity, Saturated Steam – Cation Conductivity, CEP Drives status, Unit Load, Superheated and reheated Steam temperatures & presseures, Feed water temperatures & Pressures.

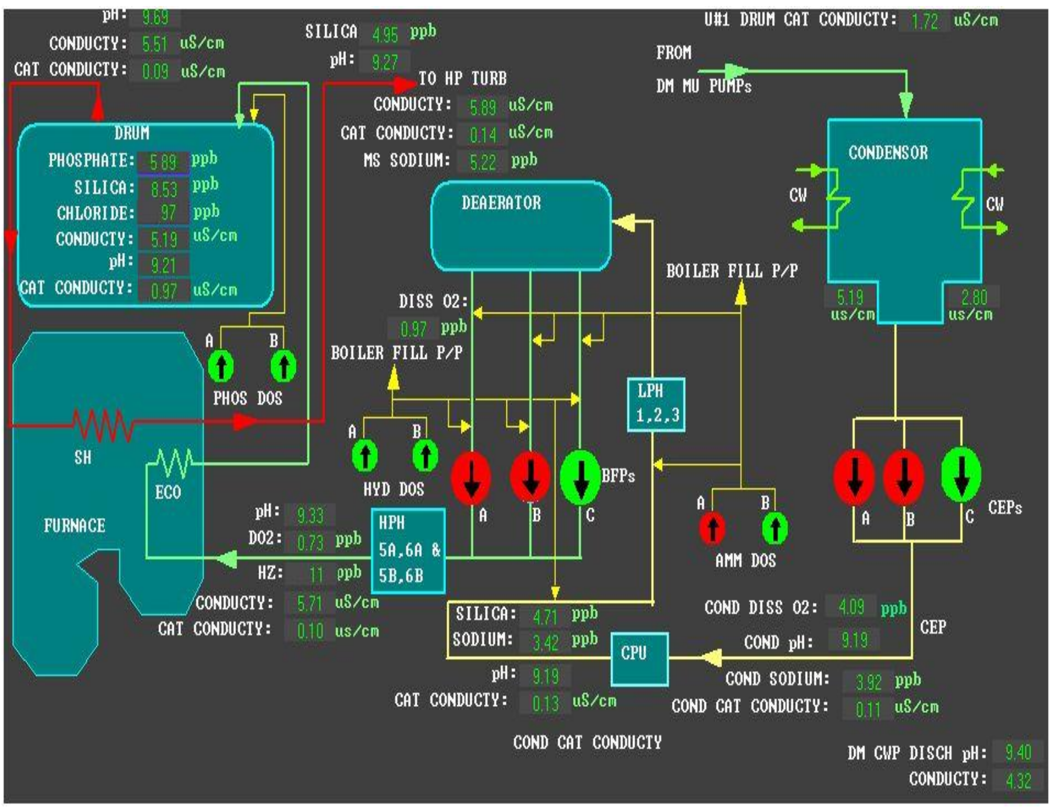

Figure 4. SWAS system and overview of used DCS.

5. DECISION TREES

A decision tree (DT) is a decision support tool that uses a tree-like graph to breakdown a complex decision–making process into a collection of simpler decisions thereby providing an easily interpretable solution (Brown, 2002). DT are a simple, but powerful form of multiple variable analysis. DT are developed for all Steam Water cycle parameters in the power plant as given in Figures 5 to 14. The DT are self explanatory based on the above explained theory. The fault trees given the optimized chemical dosing and optimized operation for the maintaining the SWAS parameters of the power plant within limits. This helps the operator in reducing the forced outages and increases the plant efficiency.

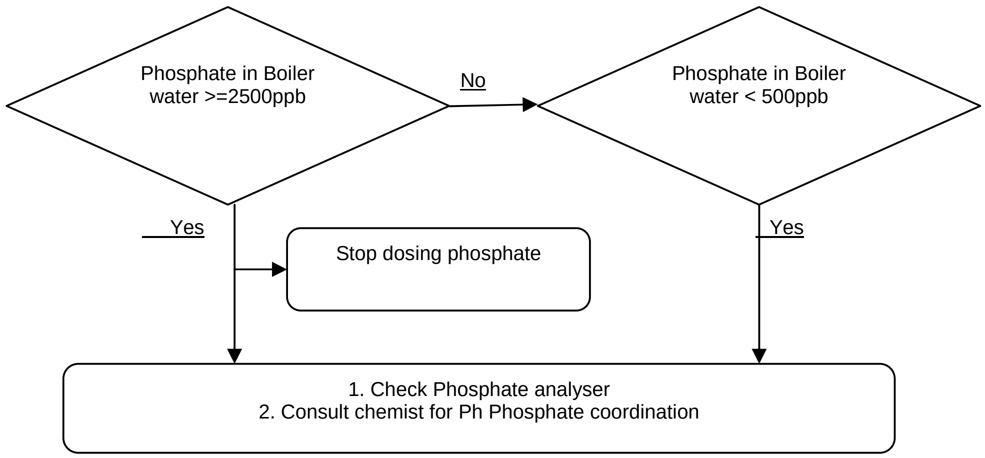

Figure 5. Boiler Water Phosphate.

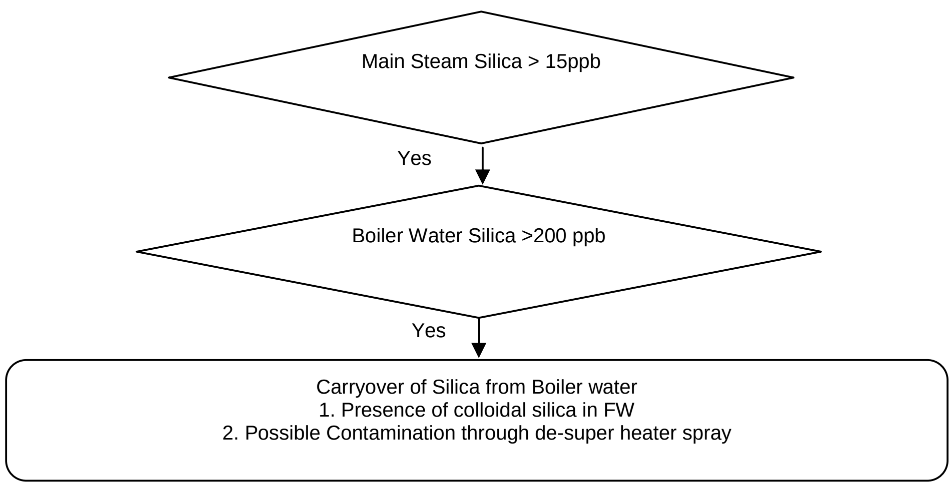

Figure 6. Main Steam Silica.

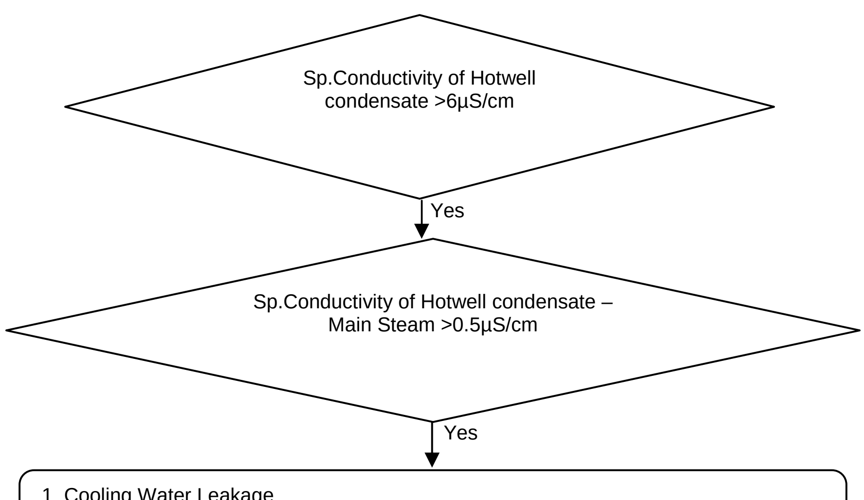

Figure 7. Hotwell Conductivity.

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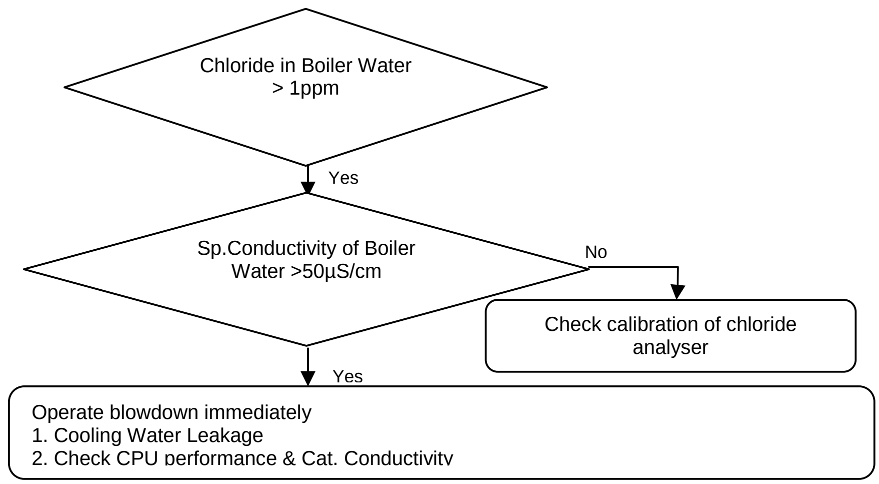

Figure 8. Boiler Water Chloride.

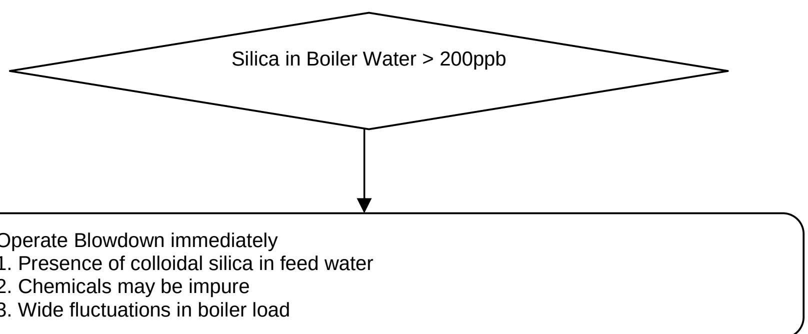

Figure 9. Boiler Water Silica.

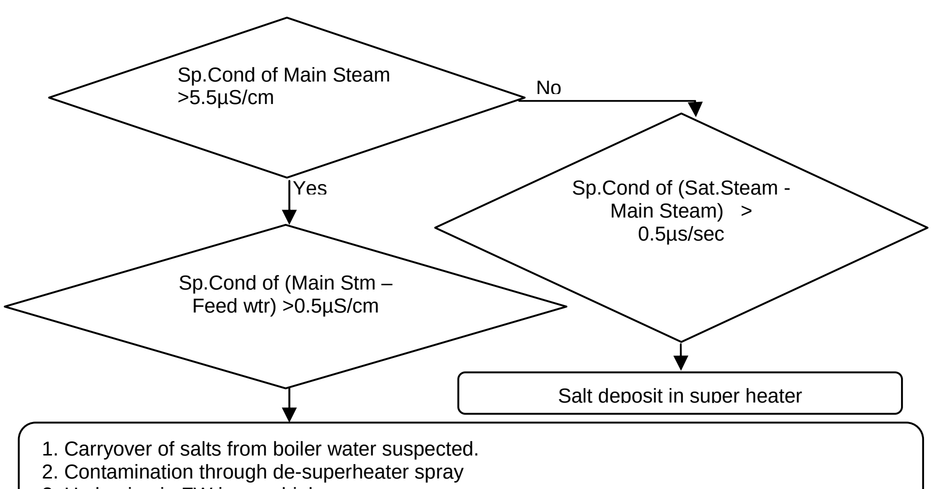

Figure 10. Main Steam Specific Conductivity.

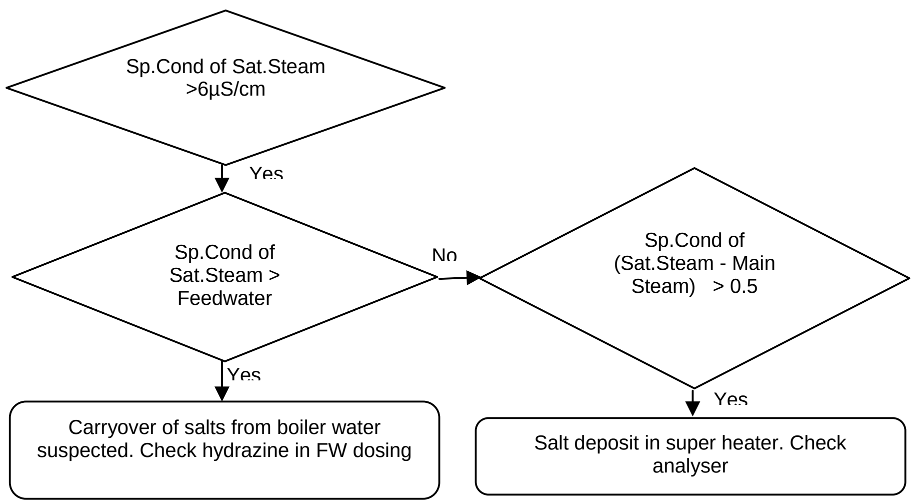

Figure 11. Saturated Steam Specific Conductivity.

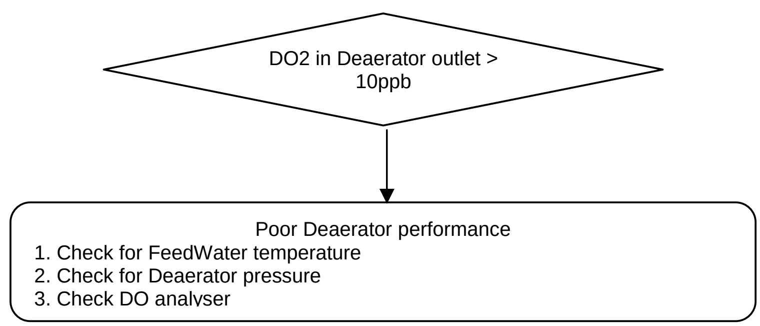

Figure 12. Deaerator Outlet Dissolved Oxygen

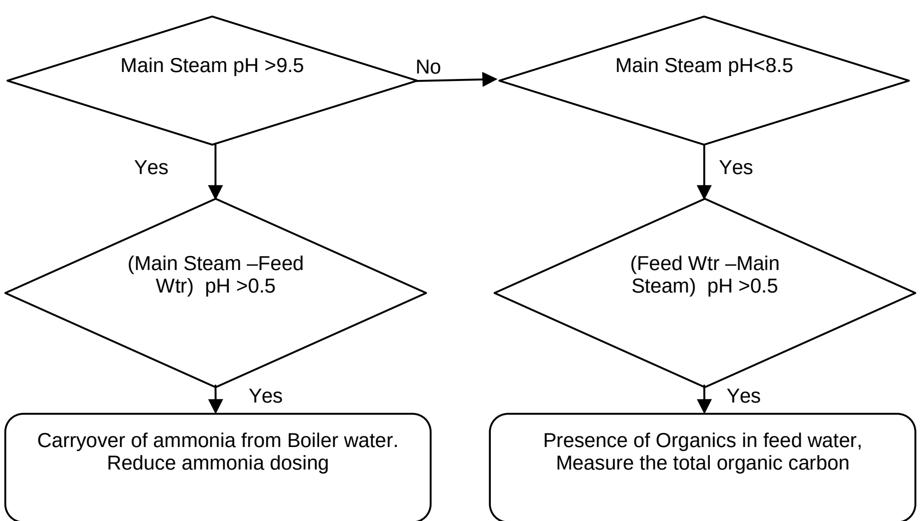

Figure 13. Main Steam pH.

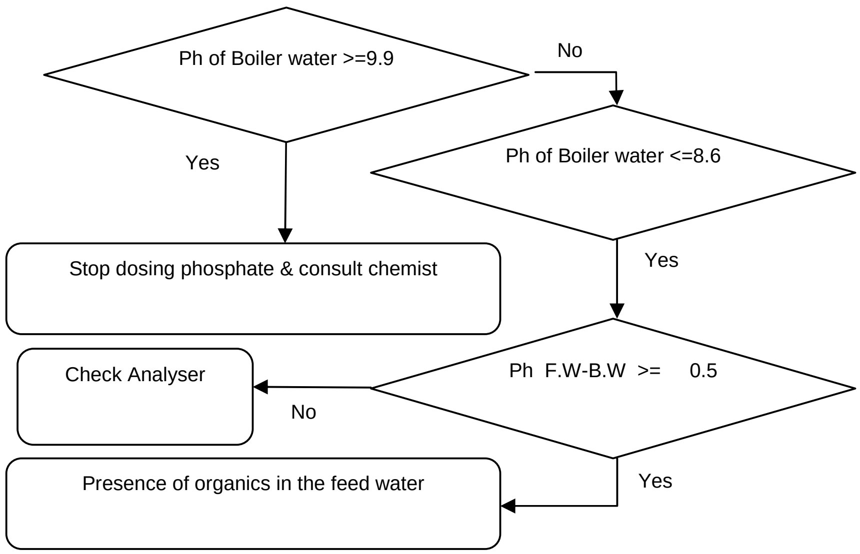

Figure 14. Boiler Water pH.

6. APPLICATION

The decision trees are implemented on PI Process book environment of OSI soft and the code is visual basic script integrated with in the PI process book. As we are having four units of 500MW each, a common application for the entire station is implemented. As an example, the alarms implementation of the decision tree no. in Figure 14 is given in Table 1.

TABLE 1: Alarm implementation of a decision tree.

	Alarm-1	Alarm-2
Logic	**If BoilerWater PH>9.9** Display "**Stop the dosing of phosphate & Consult Station Chemist coordination"**	**If [BoilerWater PH<8.6] AND [(FeedWater PH - Boiler Water PH)>0.05]** Display **"Presenceof Organics in FeedWater"**
Script for U#1	UNIT#1 BW Ph HIGH >9.9- Stop the dosing of phosphate & Consult Station Chemist: '$01HAD01CQ101_QX04'>9.9	UNIT#1 BW Ph LOW >9.9- possible Presenceof Organics in FeedWater: '$01HAD01CQ101_QX04'< 8.6 & '$01HAC10CQ103_XQ04'- '$01HAD01CQ101_QX04'>0.05:

The logic is implemented written as a script in alarmconfig.ini file as shown in Figure 15, from which the query is executed and alarm is displayed in the PI Process book. The Screenshot of the Code is shown in Figure 16.

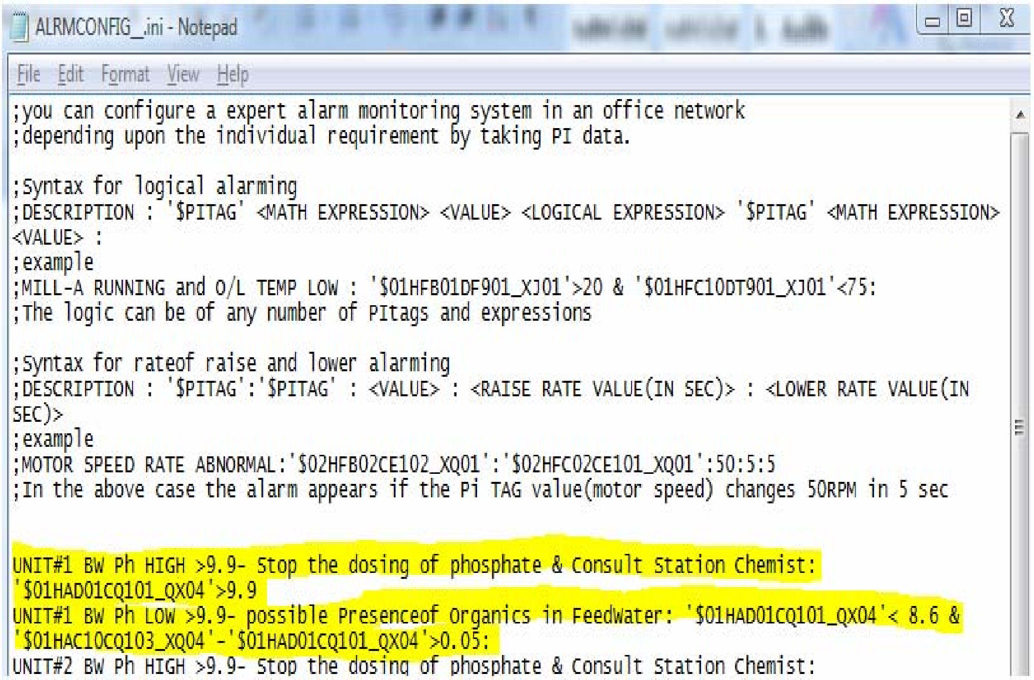

Figure 15. Screenshot of configuration file.

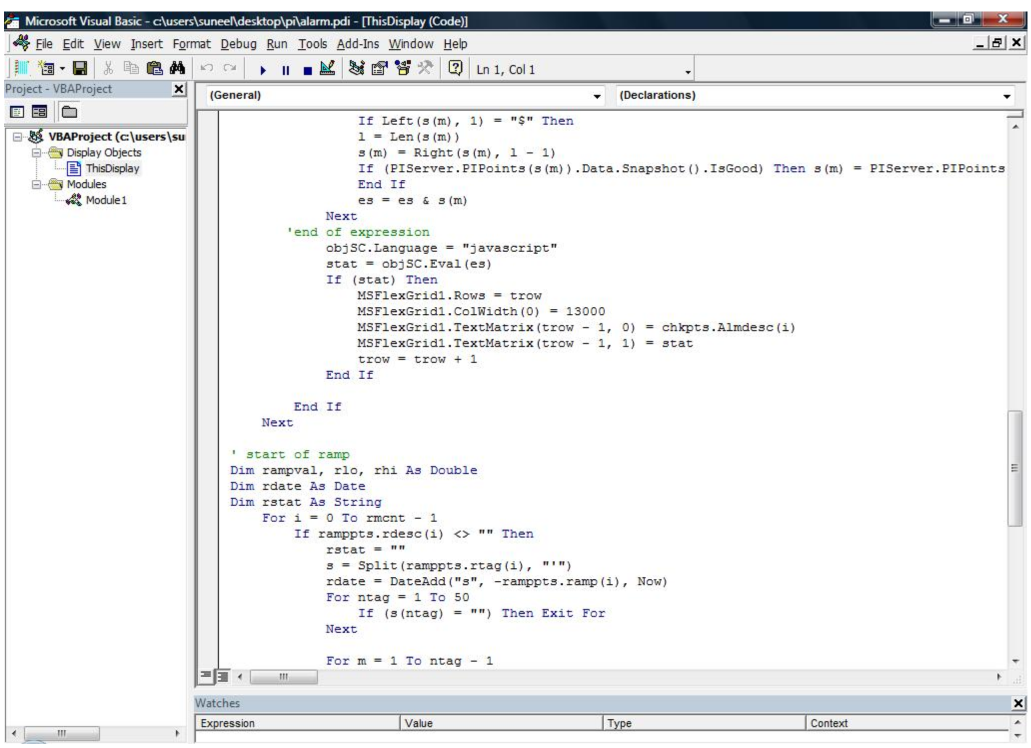

Figure 16.

Figure 16. Screenshot of VB code.

An alarm diagnostic station will provide the messages as shown in Fig.17 for any deviation in the process related to decision trees. The alarm disappears on the screen when the condition resets.

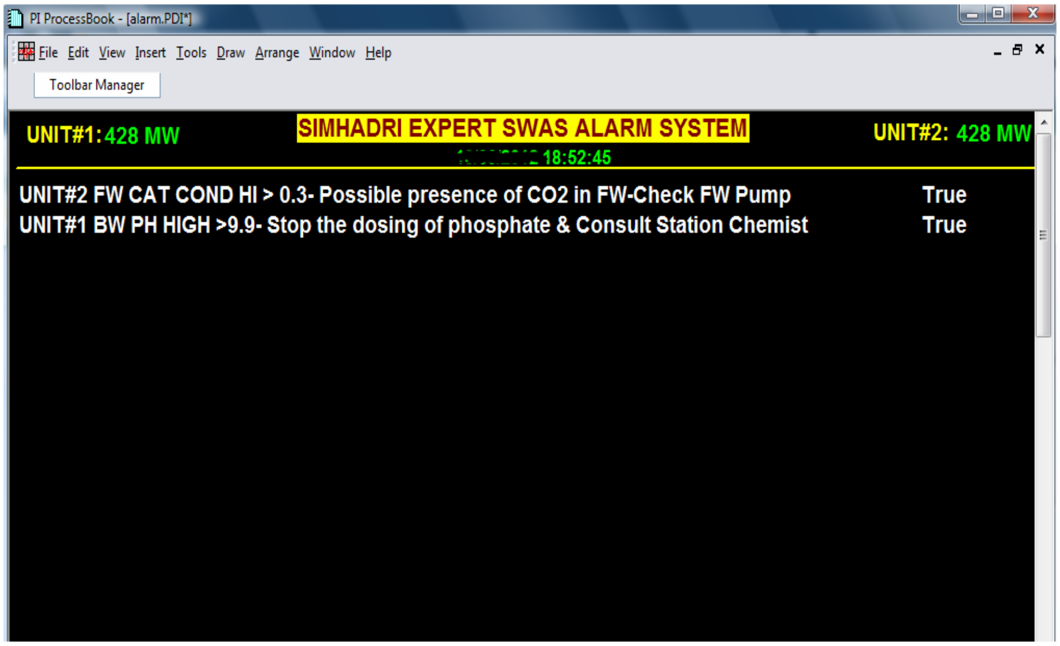

Figure 17. Alarm System Screen Shot.

7. CONCLUSIONS

This paper has presented the development of expert system application using a data driven approach to the development of separate decision support systems for chemistry faults in a power plant. A simple, robust, and real-time expert system for early prediction of faults due to unbalanced water chemistry was developed. Decision trees produced easy-to-interpret multiple rule sets, which were employed by the hierarchical decision making algorithm to predict faults. The developed approach is effective despite the sparse fault data and allows for controlling the granularity of the required inputs and predictions (*n* inputs, i.e., decision parameter values, and can predict *m* outcomes, i.e., the system status and alarms. The alarm system was successfully applied to the data from a thermal power plant to monitor WCFs. The system effectively identified normal and faulty operating conditions. Independent test data sets were used to validate the developed system.

The expert system developed using the decision trees are validated by the domain expert. This shall help in identification, rectification and restoration of the systems in a power plant. This application can further be implemented for all domains in the process Power plant. This will ensure the expertise is no longer hidden and educates the inexperienced human resources. Expert systems can be customized and utilized for different purposes such as efficiency improvements, process optimizations and to maintain the equipment health. This system was developed and tested in a 500 MW power plant in India.

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