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A Review on Expert System Applications in Power Plants

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Article Info	ABSTRACT
	The control and monitoring of power generation plants is being complicated day by day, with the increase size and capacity of equipments involved in power generation process. This calls for the presence of experienced and well trained operators for decision making and management of various plant related activities. Scarcity of well trained and experienced plant operators is one of the major problems faced by modern power industry. Application of artificial intelligence techniques, especially expert systems whose main characteristics is to simulate expert plant operator's actions is one of the actively researched areas in the field of plant automation. This paper presents an overview of various expert system applications in power generation plants. It points out technological advancement of expert system technology and its integration with various types of modern techniques such as fuzzy, neural network, machine vision and data acquisition systems. Expert system can significantly reduce the work load on plant operators and experts, and act as an expert for plant fault diagnosis and maintenance. Various other applications include data processing, alarm reduction, schedule optimisation, operator training and evaluation. The review point out that integration of modern techniques such as neural network, fuzzy, machine vision, data base, simulators etc. with conventional rule based methodologies have added greater dimensions to problem solving capabilities of an expert system.

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1. INTRODUCTION

Power generation plants play a major role in the economic development of a country. A power plant converts energy from nonelectrical to electrical form. Based on the type of energy transformation the plants are classified as fossil, nuclear, solar, geothermal, hydro, wind etc. A plant comprises of numerous complex machines including turbine, generator, transformers, protection units, control units etc. Power plant control and operation has become complicated with the increase in size of power generating units and increase in plants capacities. The safe and reliable operation of power plant is in the hands of human experts. These experts must be able to take decisions based on logic, heuristics, experience and non formalized knowledge, such as intuition. Lack of adequate experts is one of the major problems faced by power industry, which forced the industry to adopt the modern techniques for the management and control of power generating plants. With the fast advancement of computer and information technology, computer aided tools and data collection techniques have been widely utilized for power plant operation management. Artificial Intelligence is a widely accepted method adapted to automise and reduce the manpower requirements in power plants. Artificial Intelligence involves Fuzzy Logic, Genetic Algorithms, Neural Networks and specially, Expert Systems, whose main characteristic is to simulate the human expert thought process.

An Expert System is a computer program that uses knowledge and inference procedures to solve problems that are ordinarily solved through the human expert [1]. The main components of expert system are knowledgebase, 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 [2]. Major techniques used in expert system development are production rules, frames, fuzzy, genetic algorithms, neural networks, semantic nets and object oriented techniques. Using an expert system, besides increasing productivity and decreasing the error rate, will allow for formalization of the knowledge and will make it easier for this knowledge transference to occur.

Over the past thirty years numerous expert systems have been developed for power plant control and monitoring. Fault diagnosis is one of the main areas where the expert system technology excels, as it mimics the problem solving characteristics of an expert plant operator. Other application areas include power plant design, alarm processing, data analysis, plant maintenance, fault prediction, operator training and evaluation.

Successive sections uncover the different technologies and methods used by expert system developers in the case of power generation plants. The review mainly focused on various application areas and technologies used by expert system.

2.   FAULT DIAGNOSIS EXPERT SYSTEM

One of the most important application areas of power plant expert system is fault diagnosis. During fault conditions expert system acts as a human expert itself. It gives directions to the operator to diagnose the fault and explains how corrective actions can be taken to restore the system operations as early as possible. For such expert system knowledge base is acting as the backbone structure. Based on the knowledge representation techniques fault diagnosis expert system can be broadly classified into rule based, fuzzy based and hybrid expert system.

2.1. Rule Based Expert System

First generation Expert system used heuristic rules in which knowledge collected from plant experts, manuals and books were stored in the form of *if then* rules. Inferencing techniques such as forward, backward and hybrid reasoning on the knowledge base helped in arriving at proper conclusions. If the knowledge rule base is complete and concise then the conclusions made by the expert system will be accurate.

REACTOR developed by William Nelson is one of the earliest expert systems in the case of power plants [3]. The main aim behind its development was to avoid nuclear reactor accidents. Reactor Simulation Environment (RiTSE) was another widely discussed nuclear power plant expert system developed for predicting reactor trip events [4]. It has used one thousand and two hundred frame based rules and was able to respond in real time. Programming language LISP was used for making rules in the case of REACTOR and RiTSe.

Knowledge Scoring Engine (KSE), an operator support tool to monitor electrical power supply in nuclear power plant proposed by Ancelin et al. illustrated how expert system concepts can be integrated with real time architecture [5]. Its architecture was based on a two-level structure, design/off-line expert system and an application/real-time expert system. The real time functions include event processing based on sensor values and non real time expert system objective was to give step wise directions to the maintenance staff to reduce the time requirement.

Chou et al. developed an expert system called Thermal Performance Diagnostics Expert System (TPDES), which serve as a powerful tool in diagnosing the heat rate degradation problems found in nuclear power plants [6]. It used rule based architecture to store the diagnostic trees of each component of the plant into a number of rule sets. TPDES contains both plant monitoring system and fault diagnosis system. Plant monitoring system uses online sensor data and fault diagnosis system is based on previously stored rule base. The inferencing technique used by TPDES is mainly rule -based deduction which is performed by searching the rule sets. TPDES illustrated how rule base can be constructed from diagnostic fault trees normally used by maintenance experts of the power plants. It is difficult to construct normal computer programs that can take into account the complex data processing involved in the power plant process monitoring. Knowledge base techniques have evolved as a powerful alternative with the development of REACTOR, RiTSE, KSE and TPDES.

2.2. Fuzzy Based Expert System

One of the major bottlenecks in the development of a rule based expert system is the acquisition of the expert's knowledge about the problem. Typically an expert's knowledge is elicited through the questionnaires, interviews, protocol analysis or combination of some of these. But in some cases it is difficult

to build correct and complete knowledgebase of the system under study due to uncertainty. Fuzziness of information is caused by appearance of noise, caused by observations (especially on bounds of intervals of working parameters), incompleteness of description of states classes and fuzziness of bounds between states classes and classes of its diagnostic features [7]. In order to consider incorrect and uncertainty factors several reasoning techniques such as fuzzy logic theory was suggested by researchers. They suggest inference process using fuzzy relations. Many expert system developers successfully integrated fuzzy logic and expert system technology to deal with incomplete rule base. Here each rule contains a certainty factor which is obtained through the application of fuzzy relationships.

The Diagnostic Expert System for Turbo (DIGEST) machinery developed in Germany, by the Siemens Power Generation Group illustrated the potential of integration of the fuzzy logic technology with rule based architecture [8]. This system used a three-level hierarchical design. The lowest level represent measured data acquisition and conditioning, the middle level represents module-specific analysis and mathematical diagnostics such as vibration analysis, detection of insulation faults conditions or diagnosis of generator hydrogen leaks etc. Logical reasoning is performed by a central expert system at the top level which uses fuzzy logic based rule base. The system includes a common data base for storing various data and a modern graphical user environment, which guarantees uniform appearance and operation. The use of fuzzy based rules made it possible to solve the fault diagnosis problem in the same way as done by plant experts and this has given wide acceptance to the DIGEST implementation concepts.

Power transformer fault diagnosis system proposed by Falqueto et al., used a three level fuzzy rule architecture [9]. It mainly consisted of a fuzzification module, a defuzzification module and an inference engine. The inference engine uses the fuzzified set values of the numeric input data to fire the corresponding rules rather than crisp values as in the case of a purely rule based system. The defuzzification module finally transforms the fuzzy values again into crisp values. The prototype model is developed mainly to reduce the maintenance cost of complicated equipments in power plants such as power transformers.

Shaw et al. through his work demonstrated how fuzzy reasoning method can be used for the development of an intelligent relay protection setting system [10]. The expert system deals with relay setting parameters, which overcome the limitations of precise reasoning and make the system more comprehensive and intelligent.

To deal with uncertainty and time a novel idea of Fuzzy Temporal Network (FTN) was presented by the developers of expert system shell called System for Analysis and Diagnosis of Events and Disturbances (SADEP) [11]. SADEP can be used to recognize the significance of events and state variables in relation to current plant conditions and predict the future propagation of disturbances. The system is developed as a prototype model to assist operators in fossil fuel power plant. The main advantageous of using SADEP is early detection of faults that could lead to plant shutdown.

Power plants are characterized by number of complex non linear proceses and interacting process variables. Fuzzy rules can effectively model the uncertaniy factor among non linear variables. But system performance becomes unpredictable during novel fault cases for which no rules exists. Artifical Neural Network (ANN) is a widely accepted technique that can handle novel fault situations if properly trained [12]. But neural networks reasoning technique canot be eaily explained. Expert systems interfaces can easily explain their reasoning process. A proper integration of these two techniques could improve the total system performance considerably.

2.3. Hybrid Expert System

A hybrid expert system integrating the neural network and rule based architecture was developed and tested by Kraft et al. [13] for thermal plants. The fully recurrent neural network is trained with data obtained from various sensors connected to plant equipment to learn time series behavior. Rule based expert system tests the deviation of actual recorded measurements from the predicted neural network output. Deviation from normal conditions triggers rules to suggest corrective action. It is developed for boiler fault monitoring in a fossil fuel power plant. The modeling of complex time dependent behavior of plant parameters is done effectively with the help of neural networks.

A prototype expert system using neuro fuzzy hybrid integrated approach for inspecting steam generator tubes of nuclear power plants was developed by Jae et al. [14]. The system successfully incorporated modern techniques such as machine vision, robotics, distributed computing, remote monitoring and artificial intelligence techniques. For the prototype about 600 rules were used as a knowledge base. Test result shows that one third of original time and number of experts are only required if inspection is done with the help of expert system.

Nabeshima et al. [15] and Molina et al. [16] through their work presented the results of integrating ANN with rulebased expert system. Expert system with the help of knowledge base analyses process variables in as static way, it cannot take into account the non linear relationship between variables which is effectively handled with the help of neural networks. All type of plant data audio, video and internal process

variables are collected by the system and used for ANN training and current state detection. It is difficult to get data related to plant abnormal condition, so artificial training data also created using rule oriented technique.

Fault diagnosis expert system developed by Gazzana et al. integrated Discrete Fourier Transform (DFT), fuzzy logic and ANN. The fuzzy System is generalist and identifies only the local of fault, whereas, ANN is qualified to indicate the related circuit breaker. Widely used simulation transient program Alternative Transient Program (ATP) models are used to simulate various fault conditions and which is used for ANN training, fuzzy membership creation and hybrid expert system testing.

Combining expert system with real time data collection systems such as Supervisory Control and Data Acquisition Systems (SCADA) and distributed control system and plant data bases etc. has given new dimensions to the expert system technology. Knowledge base of the expert system can be connected to the plant database containing entire plant sensor data values. The inference engine combines heuristic reasoning with algorithmic methods based on data analysis to reach at final conclusions.

For solar power plant fault diagnosis an expert system was developed by Guo et al. integrating the rule base, fuzzy and neural network and data base connectivity [17]. An expert system approach put forward by Zhan et al. for leakage control for air preheat in power plant, in which method of combining the database and knowledge of controller rules are used [19]. Zeng et al. developed a real time expert system for the maintenance of hydro generator excitation system [20]. The system is integrated with SCADA database. Twenty five maintenance related parameters are observed by the system and these are optimised trough automatic on line tuning. The system incorporates self learning techniques and online knowledge base modification.

Rodrigo et al. showed how the expert system concept can be used to detect faults in the refrigeration system of a hydraulic power station [21]. This system gives valuable information to the operator about the fault location and their type. Its knowledge base contains production rules obtained by simulating the dynamic behavior of the process. The knowledgebase is interfaced with SCADA system database. The system shows a 96% of detection effectiveness under different operational conditions.

Yaolin et al. developed an expert fault diagnosis and monitoring system for wind power plants generating units. Based on Controller Area Network (CAN), a new generation of open broadcast-network communication protocol, real time data is collected from various parts of the machinery [22]. Remote monitoring host receives the raw data through communication computer and processes the raw data using neural networks, wavelet transform, fuzzy rules, fractal method and expert system to diagnosis the fault and make analysis decision.

Khadir et al. through his work presented how domain ontology concept of knowledge extraction can be used for the development of an expert system for power plant steam turbine maintenance [23]. Ontology's have been used to represent knowledge and help knowledge inference in the industrial field. Ontology is a formal specification of a "shared conceptualization" [24]. The expert system is developed as a two step process. First the domain ontology of the system is constructed using the existing databases, and then an expert system is developed using ontology as a reasoning basis. Java Expert System Shell (JESS) is used to develop the system [25]. JESS is a rule based reasoning engine that can use with the ontology instances. The integration of new techniques reduces the time and manual processing involved in the maintenance system development.

A Predictive Maintenance System of Balbina called SIMPREBAL project was developed as a real time fault diagnosis system and predictive maintenance system for hydroelectric plants [26]. Sensor data are collected from power plant equipments and with use of all this information an intelligent system is developed. Knowledge rules in the proposed system are obtained from the experienced experts and operators of the hydroelectric plant. The expert system was developed using JESS as a rule engine.

Todorovic et al. pointed out that knowledge base concepts and algorithmic concepts can be integrated together to design an expert system that can give better results [27]. To detect the fault and to isolate coal shortage in thermal power plants, a two layer expert system strategy is employed. The first layer implements a statistical data analysis based Fixed Size Sampling algorithm (FSS) and a fuzzy rule based expert system. The FSS is easy to implement, but it is based upon several assumptions, so alone they are not suitable for the real time plant implementations. So in addition, a fuzzy rule based expert system using the process data is employed and both of these are running in parallel. The residuals generated by first layer are presented to the second level Residual Evaluation Expert System (REES) which gives final results.

A real time expert system for vibration fault diagnosis of large steam turbine generator set is suggested by Yang et al. [28]. This diagnosis system consists of two parts, data acquisition system and fault diagnosis expert system. The data acquisition system is responsible for collecting vibration signals for primary treatment. The fault diagnosis expert system receives data from the data acquisition, analyzes the data and diagnoses the problem using knowledge base and inference techniques. Rule based expert system is

developed which uses rule based hybrid reasoning techniques and creditability theory [28]. Credibility theory is a method to calculate the risk by combining the individual risk experience with the class risk experience, and confidence is used to describe the truth degree, which is based on the experience. Credibility theory will be used to resolve conflict when a symptom matches much knowledge. This will increase diagnostic accuracy when some minor symptoms have not been input, and the hybrid inference will remedy the disadvantage of forward inference and backward inference. Table 1 summarizes the fault diagnosis expert system developments based on methodologies s used.

Table 1. Fault Diagnosis Expert System

Expert System	Plant	Purpose	Methodology
Nelson et al. [3], 1982	Nuclear	Avoid Nuclear Reactor Accidents	Rule Base
Nelson et al. [4], 1986	Nuclear	Predict Reactor Trip Events	Rule Base
Ancelin et al. [5],1991	Nuclear	Electrical Power Supply Monitoring	Rule Base
Chou et al. [6], 1994	Nuclear	Thermal Performance Diagnosis	Rule Base
Muller et al. [8], 1993.	Hydro	Turbine Generator FDS	Fuzzy Base
Falqueto et al. [9], 2007	Hydro	Power Transformer Fault Diagnosis	Fuzzy Base
Sha et al. [10], 2009	Hydro	Relay Protection Setting	Fuzzy Base
Figueroa et al.[11], 1998	Thermal	Generator Fault Diagnosis	Fuzzy Base
Kraft et al. [13], 1991.	Thermal	Boiler Fault Diagnosis	Rule Base, ANN
Jae et al. [14], 2002	Nuclear	Steam Generator Tube Inspection	Rule Base, ANN
Nabeshimaet al. [15], 2002	Nuclear	Nuclear Reactor Monitoring	Hybrid
Molina et al. [16], 2000	Hydro	Power Plant Management	Hybrid
Guo et al. [17], 2009	Solar	Equipment Fault Diagnosis	Data Base, Rule Base
Gazzana. et al. [18], 2010	Thermal	Power plant Substation FDS	DFT, Fuzzy, ANN
Zhan et al. [19], 2008	Thermal	Leakage Control for Preheat air	Hybrid
Zeng et al. [20], 2008	Hydro	Excitation System FDS	Hybrid
Rodrigo et al. [21], 2008.	Hydro	Refrigeration Process FDS	Hybrid
Yaolin et al.[22], 2008	Wind	Wind Plant Management	Hybrid
Khadir et al. [23],2009	Thermal	Steam Turbine FDS	Domain Ontology
Amaya et al .[26],2010	Hydro	Hydro Generator Machinery FDS	Hybrid
Todorovic et al. [27], 2010	Thermal	Coal shortage Isolation & Detection	Hybrid
Yang et al. [28], 2011	Hydro	Vibration Fault Diagnosis	Hybrid

3.   OPERATOR SUPPORT EXPERT SYSTEM

The power plant operators have to deal with large amount of information coming from various sensors, bar charts, computers and other data collecting equipments. Many times operators are overwhelmed with large volumes of data flowing from various parts of the complex machinery. Expert systems play very important role in analysing the data and supporting the operators with optimised data values. There are many other fields such as design, schedule optimisation, overload clearing and load forecasting where expert knowledge based programming can be helpful for the operators. Some of the important fields where expert system acts as operator support other than fault diagnosis and maintenance are summarized below.

3.1. Expert System for Design

To demonstrate the viability of expert system technologies in the design process of power applications, Pnttgen et al. developed a prototype expert system called Auxiliary System Design and Evaluation Program (ASDEP) [29]. Knowledge extracted from standard manuals and expert operators were stored in the knowledge base as production rules. ASDEP was written using the LISP and PASCAL programming languages. The reusability of the expert system rule base for similar type of plant design can be pointed out as one of the important advantage.

3.2. Schedule Optimisation

Power plant start-up schedule optimisation techniques are aimed at minimizing the start up time while limiting maximum turbine-rotor stresses within an acceptable level [30]. The start-up scheduling problem is a highly non linear problem and involves the interaction among complex process variables. It is difficult to make accurate mathematical models for solving these types of problems. Researchers suggest that artificial intelligent techniques can be used along with different technologies for solving start up schedule optimization problem [30] [31] [32].

Matsumoto et al. has developed two expert systems for power plant start up schedule optimisation, one for fossil fuel power plant [30] and other for combined cycle power plant under Nox emission regulation

[31]. The speed-up and load-up pattern of the plant is automatically optimized through an iterative process. Plant dynamics models representing quantitative knowledge and fuzzy rules representing qualitative knowledge are alternately used in the optimization process to modify the schedule parameters. The rules represent expertise on causal relations between modification rates of the schedule parameters and operational margins for constraints. Fuzzy reasoning based expert system minimizes the start up time automatically. Only disadvantage pointed out by developers is large size of the fuzzy rule table.

Kamiya et al. proposed a novel expert system based scheme for the start up schedule optimisation process showing how expert system concepts can be integrated with soft computing techniques such as genetic algorithms and reinforced learning neural networks to solve such highly nonlinear problems [32].

A knowledge based expert system was proposed by Hidalgo et al. for the scheduling of an Energy Storage System (ESS) installed in a wind-diesel isolated power system [33]. The program optimizes the cost of operation by determining the diesel generation and the charging/discharging cycles of the storage system from the wind and load profiles one hour ahead. The rules created aim to minimize the use of the dump load associated with diesel operation.

3.3. Overload Clearing and Load Forecasting

It is the duty of power plant operators to reduce the magnitude and time of overloads on the systems. The overload clearing is a process that cannot be accurately represented mathematically. It requires the skill and experience of operators. Negnevitsky et al. shows the development of an online rule based expert system to enhance the decision making capacity of the operators by providing appropriate control actions [34]. A method employing the network sensitivity factors is used to determine appropriate control actions and amount of corrections required to clear overloads. The proposed system gives directions within minutes or even seconds to meet the real time operating conditions of the plant.

Delfino et al. developed an expert system that can be used as tool to prepare lookup load-shedding tables online [35]. Offline validation of the proposed load shedding is then operated by static and/or dynamic simulation. With this operator support aid, the load shedding process became more flexible and was possible to maintain continuity of the process.

Damousis et al. developed a fuzzy expert system that forecasts the wind speed at a wind energy conversion system (WECS) site and the electrical power that will be generated [36]. The system implements wind speed and direction measuring stations that are installed around and in the WECS site. The stations send measurements via wireless modems to a central computer running the fuzzy expert system, which exploits any spatial correlation existing among the measuring stations' wind speed time series. For the training of the fuzzy expert system two genetic algorithm implementations were used and compared. Binary coded genetic algorithm with 5000 training patterns is used by the system. The training period is large and is almost three hours. Trained fuzzy logic expert system can be used to make forecast within one minute.

3.4. Data Processing and Analysis

Expert System for Performance Evaluation and Diagnosis (ESPD) is an intelligent system that has been developed to support operators in nuclear power plants to improve plant performance and to enhance operating flexibility [37]. In the case of nuclear power plants, it is estimated that more than 4000 parameters are monitored using various sensors, meters, strip-chart recorders, and indication lamps as well as computer print-outs. It is a burden on the operators to analyse these much volume of data and decide about optimal plant conditions. ESPD has selected thirty four major plant parameters related to steam turbine generator set at design stage. The performance evaluation module of the expert system processes the major parameters by meta facts stored in the rule based expert system with query operation and derives eight performance monitoring parameters based on real data.

An expert system for analysing the data obtained from oscillographic records of Digital Fault Recorders (DFR) and Sequence of Events (SOE) from supervisory systems is developed by Moreto et al. [38]. Normally all these records are analysed by experienced plant operators, who can identify the fault conditions and these fault records are finally used by maintenance team. But tedious manual processing is involved in it. To automise the data analysis process expert system technology is proposed and tested. Three different expert systems were designed, one for ocillographic data analysis, one for SOE analysis for the same time period and the results generated by both expert systems are compared by the final expert system. Final conclusion and results are generated by this expert system. As a test case about 140 cases have been analysed and only three are classified as faults or shut downs. This result shows that for most of the records manual analysis was not required. Table 2 summarizes the various operator support expert systems and their application areas.

Table 2. Operator Support Expert Systems

Expert System	Plant	Purpose	Methodology
Pnttgen et al. [29], 1988	Thermal	Electrical Auxiliary System Design	Rule Based
Matsumoto et al.[30] 1993	Fossil Fuel	Start Up Schedule optimization	Rule Base
Matsumoto et al.[31],1996	Thermal	Start Up Schedule optimization	Rule Base
Kamiya et al. [32], 1996	Thermal	Start up Schedule Optimization	Rule Base, Soft Computing
Hidalgo et al. [33], 2009	Wind	Optimal Scheduling	Algorithmic, Rule Base
Negnevitsky et al. [34], 2009	Thermal	Overload clearing	Data base, Rule Base
Delfino et al. [35], 2001	Fossil Fuel	Load Shedding	Database, Rule Base
Damousis et al. [36], 2001	Wind	Speed Forecasting	Algorithmic, Rule Base
Kang et al. [37] ,1992	Nuclear	Data Analysis	Rule Base
Moreto et al. [38], 2011	Thermal	Data Processing	Rule Base, Database

4.   ALARM PROCESSING EXPERT SYSTEM

Alarms are typically generated in power system control centers any time when an analog value measured by a transducer passes a limit or a digital value changes state. In addition alarm messages may be generated by application programs within the control center or by other computers that are connected to the control center computers [39]. According to the report prepared by the Power System Control Centers Joint Working Group there is definitely a problem of excessive alarms especially during emergency conditions [40]. The alarm-processing problem is to interpret a large number of alarms under stress conditions, such as faults or disturbances, by providing summarized and synthesized information instead of a flood of raw alarm data [41]. Almost all modern SCADA systems use intelligent alarm processing techniques such as prioritization, filtering etc. Despite variety of proposed solutions, operators still have a strong need for a better way to monitor the system than what is provided by the existing alarm processing software. Expert systems are well suited technology for alarm processing problems due to the symbolic nature of reasoning involved in it.

An expert system for thermal power plant alarm processing was developed by Huaazhong University of China using C language [42]. The system detects the location of equipment faults, types of faults and possible malfunctions of the protection system and will give explanation if required. Expert System for Alarm Processing and Diagnosis called ESPD based on object oriented concepts was developed by Se Woo Cheon and Soon Heung Chang [43]. Mainly it assists operators to identify primary alarms from multiple fired alarms. The developers identified that many times alarms are produced as a consequence of other alarms. Filtering of alarm is done to reduce the number of alarms presented to operator by using the alarm processing meta rules and the alarm processing frames in the knowledge base. They have also developed online fuzzy based Expert system named Alarm Filtering and Diagnosis System (AFDS) [44]. For reliable diagnosis in spite of insufficient or uncertain alarm information, fuzzy expert system technique is utilized. AFDS uses dynamic alarm prioritization techniques to filter alarms based on current plant state by analysing the knowledge stored using expert system concepts, the relationship between the alarms are identified and priority is set accordingly.

Korea Atomic Energy Research Institute (KAERI) has developed an Alarm and Diagnosis-Integrated Operator Support (ADIOS) system for intelligent process monitoring, alarming, and diagnosis as an operator aid [45]. The system tries to reduce the unwanted alarm messages produced by sensor failures or hardware failures in the system. The designed system uses object oriented knowledge base containing logic diagrams and alarm response procedures.

Gwi-sook Jang et al. presented a procedure using data mining techniques to suppress unwanted alarms in a nuclear power plant [46]. Association rule mining techniques are used for extracting useful rules from the alarm database. Obtained rules are used for automatically reducing the alarms. Fault diagnosis and recovery measures can be effectively be done with the help of reduced alarm lsit.

Table 3. Alarm Processing Expert System

Expert System	Plant	Purpose	Methodology
Cheng et.al [42] 1991	Thermal	Alarm Processing	Rule Base
Choi et al. [43] 1993	Nuclear	Alarm Reduction	Rule Base
Choi et al. [44], 1995	Nuclear	Alarm Processing	Fuzzy Rule Base
Kim et al.[45], 2001	Nuclear	Alarm Reduction	Object Oriented and Rule Base
Jang et al.[46], 2008	Nuclear	Alarm Reduction	Rule Base, Data mining

5.   OPERATOR TRAINING

Scarcity of well experienced and trained operators is one of the major problems faced by the power industry. Newly joined operators though qualified, create problems due to lack of experience and knowledge on the complex power system machinery. Surveys depict that power plant accidents are caused by the wrong actions taken by the plant operators due to their lack of knowledge about the situation. This emphasises the need for training the inexperienced operators.

Generally, operator training is done by human experts in the fields. They share their plant experience and teach the operators about the type and working of the system. More than two decades computer based simulators are also used for training purpose. They help the operators in simulating the situations that may take place during plant operations. They are very well used and adapted technology, but economically not attractive. Researchers are going on in the direction towards the application of artificial intelligence techniques in the operator training field.

Pack et al. developed an Expert Training System (ETS) by modifying the existing power plant operator assistance system for operator training [47]. Existing expert system for power plant operational assistance is enhanced with several modules to develop the ETS. The system in addition to knowledge base and inference engine contains the model of an expert trainer and a trainee also. Number of trainer functions such as analysing learning needs, conducting training, showing examples, getting feedback, getting reviews etc is included in the system. The trainee model contains information about the knowledge level of trainee, the preferences of interaction, evaluation of his/her performance during training etc. The interaction among trainer and trainee module is used for giving individual instructions.

Motoiu et al. purposed an expert system training tool for thermal power plant operators [48]. The developed application simulates the behavior of high-pressure steam reducing valves used in Romanian 50 MW thermal power plants. The main goal of the simulation programme is to train the plant personnel so as to determine the causes that generate abnormal situations. Turbo Pascal is used for program development and expert system contains knowledge base, inference engine and fact base. With the rules stored in the knowledge base, the system automatically generates maintenance strategies to be followed by the operators during abnormal conditions.

Power plant training simulators along with expert systems act as a powerful tool in training operators [49] [50]. The simulator programs are normally developed as independent software's and they are not tailor made for each and every power plant. If expert system can be embedded within the simulator program the system can be made plant oriented by incorporating the knowledge of domain experts.

Table 4. Operator Training Expert System

Expert System	Plant	Purpose	Methodology
Pack et al.[47], 1988	Nuclear	Operator Training	Rule Base
Motoiu et al.[48],1998	Thermal	Operator Training	Rule Base
Arjona et al. [49], 2003	Fossil Fuel	Operator Training	Simulator, Rule Base
Tavira et al[50], 2010	Fossil Fuel	Training and Evaluation	Simulator, Rule Base
Zhou et.al [51], 2011	Nuclear	Operator Evaluation	Fuzzy Rule Base
Hassan Qudrat-Ullah [52], 2012	Nuclear	Operator Training	Rule Base

Mexican Electric Utility implemented an expert system called Intelligent Tutoring System (ITS-TS) for power plant operator training purpose along with already running Turbine simulator system (TS) [49]. Normal TS training requires an instructor, but ITS -TS can run independently. A real time expert system is embedded within the main sequencer of the simulator. The expert system is responsible of tracking the status of the simulation to determine the group of rules that should be fired. The expert system implements a group of functions to train and evaluate the trainees in theoretical and practical aspects of the simulated process. The rule based approach was selected to knowledge representation. The instructors can also interact with the expert system to evaluate the operator performance. The expert system is based on the C Language Integrated Production System (CLIPS), which is a widely used tool to build expert system by government, industry and academia.

A fuzzy based expert system named Nuclear Power Plant Operator Evaluation Expert System (NPPOEX) is one of the latest expert system which shows the use of expert system techniques in the personal evaluation process [51]. This expert system provides an interactive environment, where all the human factors related to operator performance is collected. It is then evaluated by the inference program using the fuzzy rule based production rules stored in the knowledge base. The system gives evaluation result in the form of crisp values within the range 0-1 along with a certainty factor and it also gives explanation about the result.

QUES-SHELL is an expert system developed for training operators to diagnosis the fault conditions of nuclear power plants using rule based methodology [52]. With the help of this system it is possible to learn all fault conditions if symptoms are given as queries.

6. CONCLUSION

This paper presents a review on various expert system applications in power generation plants. The review features the key role of expert system technology in power plant management. A well designed expert system can prevent accidents due to wrong decisions taken by unskilled operators. It can considerably reduce the manpower requirements for plant control. Earlier expert systems centered on rule based technology had various limitations. Later developers incorporated fuzzy logic, neural network, real time databases and algorithmic processing along with the rules to improve the decision making capability of expert systems. Single methodology as such is not suitable for the development of modern expert systems because of the complexity and non linearity of processes involved in the power plant management. Integration of various artificial intelligence and learning methodologies can highly improve the performance of expert systems. Secure and flexible power plants can be visualised with the help of knowledge base systems along with modern computer networking and information system developments.

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