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FAULT DETECTION AND DIAGNOSIS METHODS IN POWER GENERATION PLANTS - THE INDIAN POWER GENERATION SECTOR PERSPECTIVE: AN INTRODUCTORY REVIEW

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ABSTRACT: The power sector in India is the most significant component of the social overhead capital that effects directly Indian economic through growth of GDP. Since last four decades industrial growth has been increasing significantly, so also power requirements also increasing rapidly. As a result there is low levels of tolerance towards performance degradation in power generation plants (PGPs). Abnormalities or potential faults in power generation plants (PGPs) lead. To situations like low productivity, loss of production, human safety, and environmental hazards. To avoid undesirable conditions and to supply uninterrupted power to industry and other users, power generation industry has started using Fault Detection and Diagnosis (FDD) methods in conventional and renewable energy power generation plants (PGPs) like Nuclear Power Plants (NPPs), Solar Power Plants (SPPs) and Thermal Power Plants (TPPs) to improve reliability and availability of power plants. The paper discusses about different faults related to nuclear power plants (NPPs), thermal power plants (TPPs), and solar power plants(SPPs) and their performance monitoring, instrumentation or sensor calibration, system dynamics, system faults, sensor faults, equipment monitoring, reactor and furnace monitoring, and transient monitoring. The uses of model-based and model-free FDD methods are explained some recent FDD methods are also examined. The popularity of FDD applications is continuously increasing as safety and reliability are significant requirements for different power generation sector. The paper discusses the model-based and model-free FDD methods in NPPs, TPPs, and SPPs types of power generation plants (PGPs).

KEYWORDS

Fault detection, Fault diagnosis, Model-based, Model-free, Nuclear power plant, Thermal power plant, Solar power plant

Introduction

Indian Energy Scenario

India is one of the largest consumers of energy in the world. However, more than 70 percent of its primary energy needs are being met through imports, mainly in the form of crude oil and natural gas. Power generation in the country uses mainly two types of energy sources: conventional and non-conventional energy sources. The use of non-conventional energy sources are increasing since last two decades for power generation because of its inherent advantages of transportation and certainty of availability. However, the conventional energy pollutes the atmosphere to a great extent.

Power generation capacity in India using non-conventional energy (renewable energy) sourcing depicted in Fig. (2) till 30th November, 2017 as per data available in the Ministry of New and Renewable Energy (MNRE) (All India Installed Power Capacity of Power Stations Information, 2017). It must also be noted that India has increased installed power capacity from a more 1362 Megawatts (MW) to over 3,30,860 Megawatts (MW) since independence and electrified more than 500,000 villages. NP electricity consumption in India is expected to rise around 2.28.

Megawatts hour (MWh) by 2021-22 and around 4.50 Megawatts hour (MWh) by 2031-32 (Pankaj Kumar et al., 2016). Therefore complex, instrumentation, and automation are required in the current power generation plant (PGPs) of India for producing more power with higher efficiency and less operating expenses. In that performance degradation. This is where the role of Fault Detection and Diagnosis (FDD) algorithms became very important.

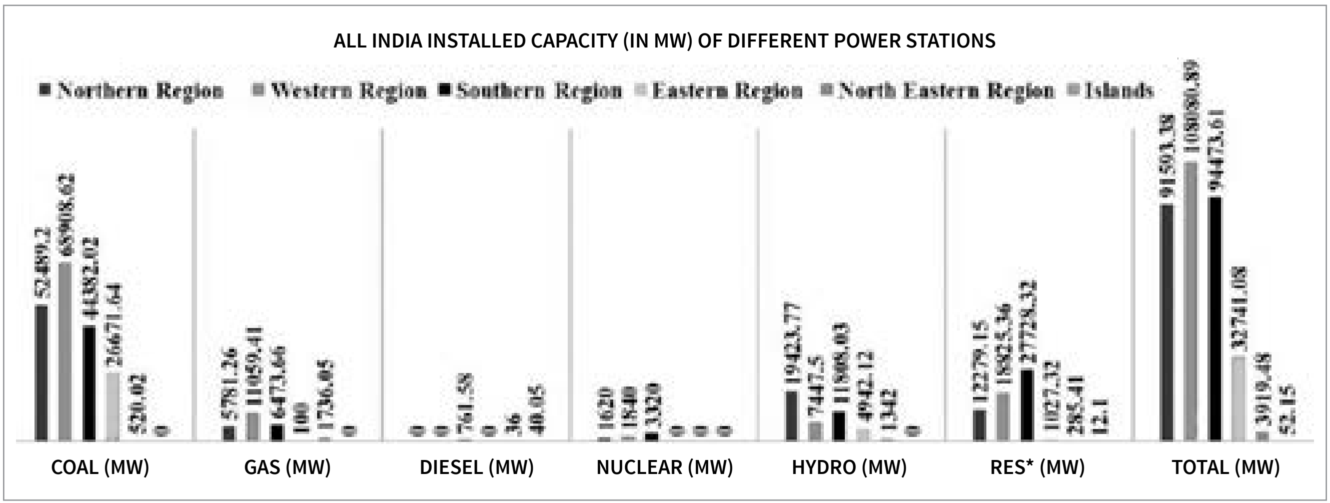

FIGURE 1. Shows total installed power capacity with respect to different regions pertaining to India and conventional and non conventional energy wise (central electricity Authority of India, 2017). All India installed power capacity in (MW) region and type of power generation Wise (Source – The Ministry of New and Renewable Energy (MNRE) as on 30th November, 2017).

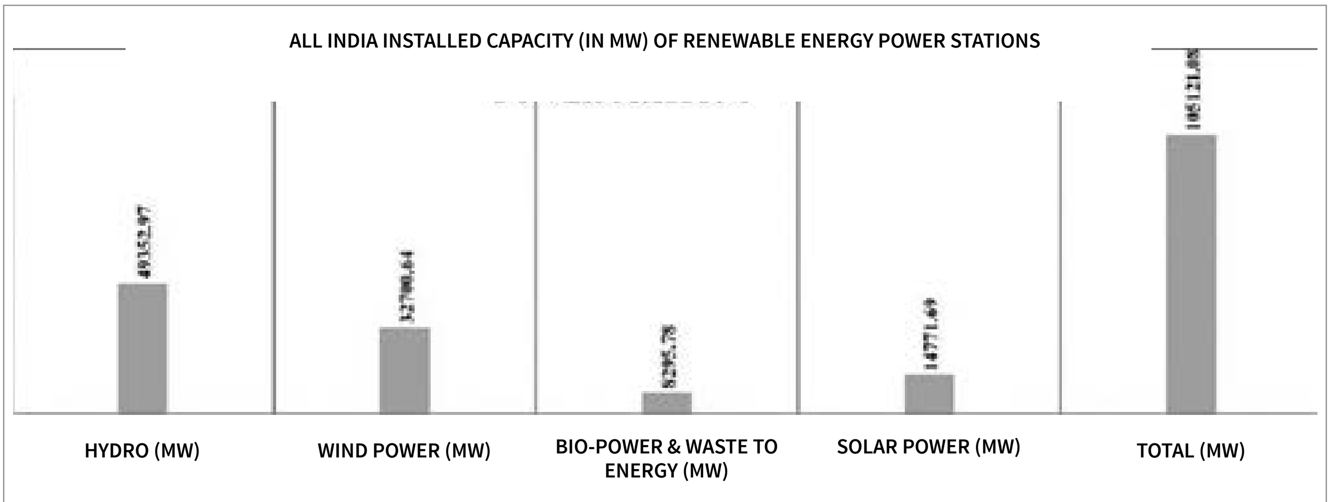

FIGURE 2. All India installed power capacity in (MW) using non-conventional energy. (Source – The Ministry of New and Renewable Energy (MNRE) as on 30th November, 2017).

Model-based methods	**Model-free methods** **Data-driven methods**	**Signal-base methods**
Parity equations Observers	Artificial neural networks (ANN) Multivariate state estimate technique (MSET)	Spectrum analysis Time-frequency analysis (TFA)
Kalman filters Parameter estimation	Principal component analysis (PCA) Partial least squares (PLS) Auto associative kernel regression (AAKR)	Wavelet transform (WT) Autoregressive (AR) signal model Control charts

TABLE 1. Classification of FDD methods.

Fault detection and diagnosis for power generation plants (PGPs)

In a critical system such as PGPs, safety is of major importance. To improve safety, reliability, and capacity factors in PGPs even, preventive actions are desirable. Generally fault is defined as unpermitted deviation or change in characteristics from the desired ones in the system. A failure is a permanent interruption of a system ability to maintain desired performance (Isermann & Balle, 1997). Different faults and failures can occur in instruments, equipment, and systems of PGPs, which can have significant impact on plant performance and productivity. For example, in /(NPPs) can reduce power up to 3% drift in steam generator (SG) (Chan & Ahluwalia, 1992).To enhance efficiency certain PGPs employ heat recovery steam generator (HRSG) to capture energy from the hot combustion gases exhausted from the turbine. Therefore, efficiency of HSRG plays very vital role in improving the efficiency of PGPs. The design in the thermal measurement system for fault detection within a power generation system improves SPPs productivity (Chillar et.al, 2015). Measuring yields by automatic supervision, analyzing the losses, and faults in the present system using automatic fault detection in grid connected PV systems will improve maximum efficiency Power Point Tracking (MPPT) of PV standalone module in diverse climate conditions and will improve power productivity of SPPs,(Silvestre et al., 2013; Joshi Siddharth et al., 2017). Using life cycle and maintenance cost of the wind turbine would be beneficial as this improves efficiency (Walford, 2006; Hastiemian et al., 2006; Hameed et al., 2009). Antonio et al., (2015) proposed that active and reactive power strategies using peak current limiting during the grid faults. Therefore, DG power plants can avoid over current tripping helping to mitigate the adverse effects of grid faults.

Fault detection and diagnosis (FDD) is an advance algorithm to detect, isolate, and identify faults in the system. The first process in fault detection identifies whether a fault occurs in the system. Second fault isolation process implies determination of fault location and, The third most important process identifies the magnitude and time variant behavior of the faults in the system(Isermann and Balle, 1997). The fault diagnosis processes are a combination of two fault detection and fault isolation processes. FDD methods can be applied to monitor a system continuously during operation, which is often referred to as on-line monitoring (OLM). As shown in Table 1. FDD can be classified in abroad spectrum in the model-based methods and model-free methods. Thereafter FDD can be further divided into data-driven methods (multivariable, artificial intelligence based, and signal based methods (single variable, pattern recognition). In model-based methods, a mathematical model is used to represent the ideal or normal behavior of the system. Fault in a system can be detected by checking consistency between predicted output and observed output of the model. The limitation of model-based method is the difference to find out an accurate model that is always hard for every practical system. Data-driven methods rely on correlated measurements of normal/healthy conditions and faulty conditions. Hence the relationship can be formulated by the implicit way by training an empirical model through analysis of fault free training data obtained during normal conditions. The empirical model is used to find out new measurements for faulty conditions, and the fault is detected and fault diagnosis is done by evaluating the residual values statistically. In signal-based methods signal is monitored and exerted (e.g., spectrum) from the measured value with respect to the desired limit. Thereafter FDD decision can be made from the actual signal with standard baseline values. Signal-based and data-driven methods are extensively used for various industries (Chiang et al., 2001; HenryYue & JoeQin, 2001; Venkatasubramanian et al., 2003; Hines and Davis, 2005; Zhang and Dudzic, 2006; Pengand Chu, 2004; Rehorn et al., 2006; Sejdic et al., 2009).

Since the last four decades, various FDD methods are applied in different power generation plants like, NPPs, TPPs, and SPPs etc.(Hashemian & Feltus, 2006;Uhring & Hines, 2005;Ajami & Daneshvar, 2012;Chouder & Silvestre, 2010; Ma, & Jiang, 2011; Jianhong et al., 2015).Especially data-driven and signal-based methods are extensively used in these systems. Applications of FDD methods to solve the problems related to power generation plants (PGPs), presented in Table 2 are briefly summarized in Table 3. These applications lead to safe and efficient plant operations.

Faults	Examples	Impact on an NPP, TPP, and SPP
	NPPs	
Instrument steady state performance degradation	Sensor drift Sensor bias	Reduced reactor power output Substantial operation and maintenance (O&M) cost, Radiation exposure to personnel
Instrumentation channel dynamic performance degradation Faults in equipment	Pressure measurement slow response due to sensing line blockage Damaged machine bearing Motor winding faults Poor lubrication	Affect system reliability technical specifications not met Reactor trip/scram Plant transients and safety system actuation substantial O&M cost
Loose parts in reactor coolant system (RCS) Plant transients	Detached RCS structures External objects Control rod ejection Loss of normal feed water flow	Potentially affect safety functions and expensive to repair Reactor trip actuation of safety systems
	TPPs	
Steam Turbine Health Monitoring and Control Design fault	Bearing temperature sensor fault Leak fault in lube oil system and turbine shaft axial position proximity switch fault	Reduce efficiency of the steam turbine hence decreasing the overall efficiency of the TPPs.The hazardous situation may occur
Combustion Control Mechanism and Flue Gas Heat Recovery Fault Change in calorific value of the fuel	Actuator or leak faults occur in pipe line which carries the coal and air to the boiler Fuel quality for TPPs	Combustion efficiency reduces and thereafter the insufficient amount of superheated stem to the turbine. Reduce efficiency of the plant
Faults in boiler feedwater control System (Leak) fault	During the load variation actuator fault which carries water in boiler and sensor transients Leakage in pipes containing water, steam or fuel	Affects the boiler safety and efficiency Potentially affect safety functions also trip the turbine system due to the leak of superheated steam
	SPPs	
Constant energy loss Changing energy loss Total blackout Failure in solar PV module	Degradation, soiling, module defect and string defect Shading, grid outage, high losses of low power, power limitation, MPP-tracking, hot inverter and high temperature Defect inverter and defect control devices Yellowing and browning, delamination, bubbles in the solar module, cracks in cells, defects in anti-reflective coating and hot spots caused by the panel acting as a load	Potentially affect safety functions and reduce the efficiency of the plant Permanent failure in control and inverter devices so reduce system reliability Permanent failure in PV module, reduce efficiency and system reliability

TABLE 2. Potential Faults and their impacts on Power Generation Plants (PGPs).

From the view point of NPPs, TPPS, and SPPs, safety and reliability, one the benefits of included in the paper, but are not limited to following:

a. Reduced expose are of radiation to mankind: FDD can lead to improved scheduling of maintenance and repair work for plant and equipments. Therefore, radiation expose are to the nearby mankind can be minimized.

b. Improves instrumentation reliability: Using plant OLM continuously checks the condition of the various plants and equipment. These early warnings or detection of the incipient faults in the plant allows for the corrective action before the critical situation occurs.

c. Avoid actuation of safety/interlocks system: Fault detection is an early stage warming system for detecting a fault in the system. So it prevents any unplanned events (e.g. plant shutdown) in the plant with potentially safety significance.

d. Correct and timely Decision making: On the one part to detect incipient fault detection reduces the chanceof any unwanted situation and helps in diagnosing the fault, and to take corrective action in right time.

e. Improves safety margins: Using different FDD methods monitor and diagnoses the plant operations and helps to avoid uncertainties (e.g, in NPPs core monitor, in TPPs furnace monitor and in SPPs monitor PV modules and grid stability).

From the viewpoint of plant economics, benefits of FDD in various power plants, among other things are as follows:

a. Optimize the maintenance schedule: The correct method and time for maintenance are the major limitation for power generation plants (PGPs) (Hines and Seibert, 2006;Eicker et al., 2005). Condition or OLM based maintenance of instruments and equipment can be accepted.

b. Improves plant reliability: FDD can improve plant reliability for various reasons: first, FDD can do early detection and diagnose incipient faults and avoid unexpected breakdown. Second by it helps to schedule correct plant down-time efficiently and manage the maintenance time. And finally, FDD application helps to improve plant performance, by reduction in various system or plant and sensor faults.

c. Escape from converging a minor problem to major problem: FDD is an advance application which can detect and diagnose the faults early before any dangerous situation happens. FDD is prevents faults from developing into the more critical situation.

d. Power production and system life extension: Using better plant performance monitoring and aging management, production of power is increased and plant life is increased through application of FDD.

Applications	**Data-driven methods**	**Signal-base methods**
Instrument calibration monitoring, Sensor faults	Sensor output estimation	--
Instrumentation channel dynamic performance monitoring, System/ Component fault	(e.g., ANN, MSET, PCA AAKR)	Analysis of measurement noises (e.g., power spectral density (PSD), AR model)
Equipment monitoring, Failure in solar PV module	Sensory data estimation (e.g., ANN, MSET)	Analysis of vibration, motor current, and acoustic emission (AE) signals (e.g., PSD, WT, TFA)
Loose part monitoring, Actuator/ Final control element fault	--	Analysis of structural borne acoustic signals (e.g., spectrum analysis, TFA)
Transient identification, Changing energy loss (Abrupt fault)	Pattern recognition (e.g., ANN)	--

TABLE 3. Applications of Model-free FDD methods in PGPs.

With progress in FDD theory, and its applications on power generation plants (PGPs), and developments in instrumentation and control (I&C) technologies, there is increasing interest in power plant industry to apply FDD. To meet the requirements of safety and economy in power I&C systems more plant data needs to be available for the analysis using advanced FDD methods. Real-time and historical plant data can be analyzed for N performance monitoring of the plants, so as to avoid the critical situations. The power generation industry has also started using wireless communications, which makes cost-effective OLM increasing by feasible (Hashemian,2011;Hashemian et al., 2011b;Kadri et al., 2009).

This paper, reviews model and model-free FDD methods and their applications in NPPs, TPPs, and SPPs. One of the objectives of this paper is to review FDD method and applications on various power plants. Due to the focus of this paper, on model and model-free FDD methods, technical details were kept in the references. The rest of the paper is organized as follows: section 2 presents an introduction to FDD methods on the basis of a survey in terms of model-based, data driven, and signal based methods. Principles of three FDD methods are explained and characteristics of number of a popular techniques are summarized in Table 3 gives an overview of the different applications and Table 5 summarizes data-driven FDD methods and applications related to power generation plants (PGPs), Section 3 includes applications of FDD in TPPs with possible faults summarized in Table 7.Also addressed are some popular techniques for the various faults in TPPs. Section 4 gives a brief summary and subsequently detailed dismission is conducted.

Review Of FDD Methods

Model-based FDD methods

Analytical redundancy is key concepts for most of the modelbased FDD methods. (Willsky, 1976;Chow and Willsky, 1984) In model-based FDD methods normal behavior of the system is represented by a mathematical model of the physical system. Sensor measurements are estimated analytically by other correlated measurements using the model that describes their relationship. The difference between analytical estimated value and actual measured values are labeled as residuals. Any non-zero values of the residuals identify the faults in the system. By analyzing the residual values statistically, faults can be determined (Gertler, 1988;Isermann, 2006). Fault diagnosis methods vary by model structure. However some popular methods improved residuals (Gertler & Singer, 1990;Li & Shah, 2002;Li & Jiang, 2004; Gertler, 2015;Beard, 1971; R. N. Clark, 1978; Frank, 1990;Isermann, 1992; Jia & Jiang, 1995;Isermann, 1993). The model-based FDD methods are divided into three following process: residual generation, fault detection, and identification which are based on the residual evaluation and fault diagnoses by residual analysis (Fig. 3).

As shown in Table 4, system models used for the model-based FDD incorporate both the state space and input-output models. Distinguishing characteristics of the model-based FDD methods are summarized in Table 5. The model-based FDD methods are capable and designed to detect multiple faults and diagnoses simultaneously (Clark, 1978). However, an accurate model is required for the physical system, which can be difficult to obtain for complex systems. The challenging is that, all the faults not considered at the modeling stage may not be detected at all. Further, robustness required against model uncertainty and disturbances (Chow & Willsky, 1984; Lou et al., 1986; Frank & Ding, 1997; Patton & Chen, 1997). To summarize model-based FDD methods are still inadequate at present.

States space model	Input-output model
$X(t) = Ax(t) + Bu(t)$ $Y(t) = Cx(t) + Du(t)$ Where, t is time, X is state vector, A,B,C, and D are system matrix, input matrix, output matrix and D direct transmission matrix with proper dimensions. D matrix is zero in the normal case.	$Y(t) = \varphi^T(t)\theta$ Where, θ consists of model parameters and φ^T (t) contains system past inputs and outputs (Isermann, 1993).

TABLE 4. System models for model-based FDD methods.

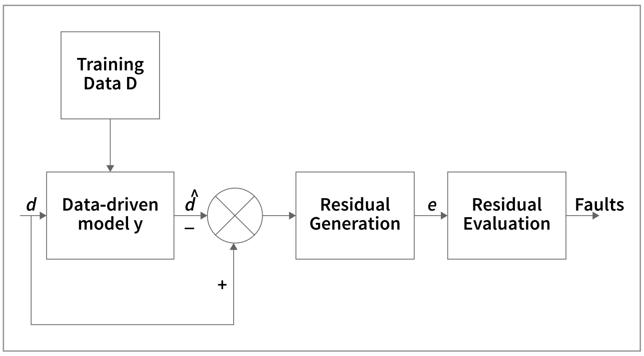

FIGURE 4. Schematic diagram of data-driven FDD methods

Methods	Equations	Comments
Parameter estimation	$\theta = [\varphi^T \varphi]^{-1} \varphi^T Y$ Where, θ is estimation of system parameterθ and φ is a matrix consists of φ^T (t)	Advantage in multiplicative faults[a] Physical coefficients may be recovered for fault diagnosis On-line computation increases costs.
Diagnostic observer	$X\hat{}(t+1) = Ax\hat{}(t) + Bu(t) + K(y(t) - Cx\hat{}(t))$ $e(t) = y(t) - Cx\hat{}(t)$ Where, X is an estimate of X, K is observer feedback gain matrix	Advantages for additive faults for estimation purpose
Kalman filter	$X\hat{}(t+1) = Ax\hat{}(t) + Bu(t)$ $X\hat{}(t+1) = x\hat{}(t-1) + K'(t)e(t)$ $e = y(t) - Cx^{t-1}$ Where, K' (t) is kalman gain	Advantages for additive faults for a system with stochastic disturbances
Parity equations	$e(t) = G(z)u(t) - H(z)y(t)$ Where, e(t) is residue	Advantages for additive faults[b]

TABLE 5. Model-based FDD methods and their characteristics.

[a]An multiplicative faults such as final control element chock up, surface contamination or sludge accumulating on the tank bottom side reflects the change in plant parameters, hence residue leads to depending on system variable.

[b]An additive faults such as sensor bias and system leak faults which leads to a residue that is not depending on system variable.

Various data-driven methods have been developed such as Artificial neural network (ANN) (Anderson, 1995; Watanabe et al., 1989;Venkatasubramanian et al., 1990), principal component analysis (PCA) (Wise and Gallagher, 1996; Dunia et al., 1996; Kaistha and Upadhyaya, 2001), Multivariate state estimation technique (MSET) (Bockhorst et al., 1998; Nela Zavaljevski and Gross, 2000), Partial least squares (PLS) (MacGergor and Kourti, 1995) (Wise and Gallagher, 1996), auto associative kernel regression (AAKR) (Garvey and Hines, 2006), Independent component analysis (ICA) (Hyvarinen, 1999) and Cross-calibration and their modifications (Kramer, 1991; Qin & McAvoy, 1992; Dong & McAvoy, 1996; Scholkopf et al.,1998; Ji-Hoon et al., 2005). Those methods have been extensively applied in various industries.

In various power plants (e.g., NPPs, TPPs, and SPPs), data-driven methods have been studied for different applications like instrumentation calibration, equipment monitoring, reactor core monitoring, transient identification, and furnace monitoring. Amongst the data-driven methods, PCA is the most appropriate and used method due to the fact that is simple and adjustable. There are two methods widely used for applications in NPPs: MSET and ANN, particularly the auto associative neural network (AANN) (Kramer, 1991; Hines et al., 1998). A technique- based on MSET and ANN is used for the smart signal system (Hines and Davis, 2005; Smart Signal, 2010) and process evaluation and analysis by neural operators (PEANO) system (Fantoni et al., 2003) (Fantoni, 2005) developed for OLM in NPPs. ANN has also been studied in power generation plants (PGPs) for transients identification (Bartlett & Uhrig, 1992) (Embrechts & Benedek, 2004), and to estimate important parameters for reactor core monitoring (Dubey et al., 1998) (Souza & Moreira, 2006). Features of PCA, MSET, and ANN methods are categorized in Table 6. Recently, kernel-based machine learning techniques (Cristianini, & Shawe-Taylor, 2004) have been used for pattern-recognition (Vapnik, 1995; Burges, 1998) and fault detection (Lee et al., 2004; Widodo & Yang, 2007; Mahadevan & Shah, 2009; Ma & Jiang, 2010) in various industries. Their applications in different power generation plants have not yet been fully explored.

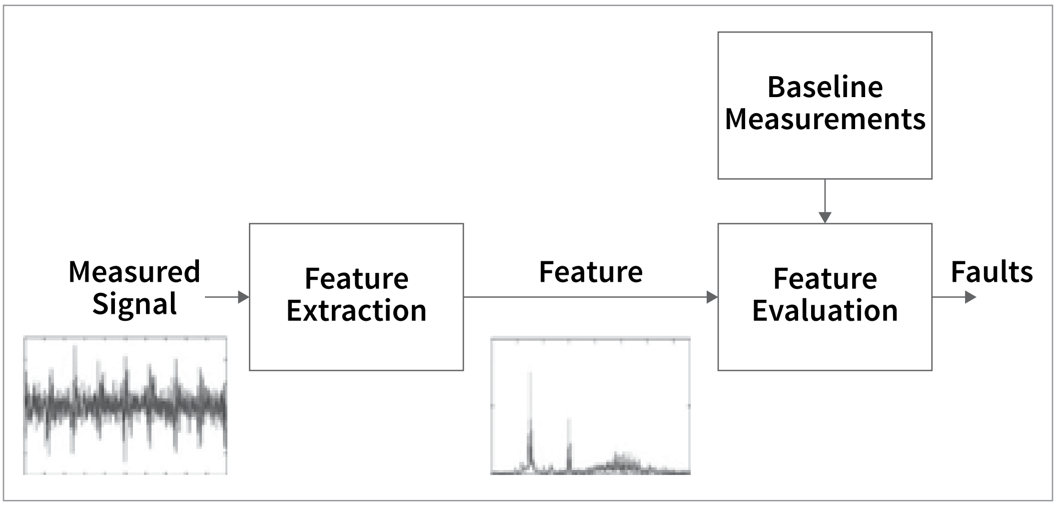

FIGURE 5. Schematic diagram of signal-based FDD methods.

Signal-based FDD methods work by comparing two signals; one is feature extraction from measured signal and the second one for base line characteristics that are considered to be normal operation. Features in terms of frequency domain and time domain have been used, (Fig. 5). Signal-based methods do not rely on the analytical relationship between measured variables. Spectrum analysis is the most used method in signal-based FDD. The spectrum of the measured signal can be obtained using Fast Fourier Transform (FFT). Spectrum analysis is used for NPP instrumentation, equipment, and processes. Time-frequency Analysis (TFA) (Cohen, 1989 ; Hlawatsch & Boudreaux-Bartels, 1992 ; Stockwell et al., 1996) and Wavelet Transform (WT) (Qian, 2002) are extensions of spectrum analysis.

Methods	**Equations**	**Characteristics**	**Power generation plants (PGPs) applications**
PCA	$\hat{d} = \sum_{i=1}^{n} m q_i q_i^T$ Where, q_i is the eigenvector of the correlation matrix of D corresponding to i^{th} largest value and n is the retained principle components.	Simple in use and flexible Linear TPP, SPP	Instrument and equipment monitoring
MSET	$\hat{d} = D \cdot (D^T \odot D)^{-1} (D^T \odot d)$ Where, $\odot$ is a nonlinear kernel operator and D is correlation matrix.	Nonlinear Popular for specially NPP	Instrument and equipment monitoring
ANN	$\hat{d} = F\left(\sum_i w_i h_i(d)\right)$ Where, F is a function for, w_i are weights, h_i are other function which calculate outputs using weights, subject to function F.	Nonlinear Popular for specially NPP Popular for pattern recognition Black-box model	Instrument and equipment monitoring, transient identification reactor and furnace monitoring

TABLE 6. Data-driven FDD methods: Characteristics and Application to (PGPs).

Process information using tools such as if-then rules are also used in FDD methods. These qualitative methods can process incomplete information to make FDD decision. Two popular techniques are fuzzy logic and expert systems. Fuzzy logic (Zhang and Morris, 1994), Expert systems (Nelson, 1982;Bernard & Washio, 1989), Genetic algorithms (Holland, 1992), and ANN are the most used techniques in the computational system. Application of the computational intelligence methods in various power generation plants include sensor validation, equipment monitoring, and core or furnace surveillance. Such applications are reviewed in Uhring & Tsoukalas, 1999. Some recent studies and reviews (Na et al., 2001 ; Maeseguerra et al., 2003 ; Gueli, & Mongiovi, 2006 ; Embrechts & Benedek, 2004 ; Zio & Baraldi, 2005 ; Souza & Moreira, 2006 ; Razavi-Far et al., 2009 ; Zaferanlouei et al., 2010). Other qualitative methods studied in the literature include qualitative reasoning (De Kleer & Brown, 1984 ; Weld & De Kleer, 1990; Kuipers, 1994 ; Iwasaki, 1997), signed directed graph (Iri et al., 1979 ; Umeda et al., 1980 ; Kramer & Palowitch, 1987), and case-based reasoning (Aamodt & Plaza, 1994 ; Watson & Marir, 1994). However applications of such methods in NPPs, TPPs, and SPPs are relatively limited at present.

Applications of FDD methods in TPPs

In the thermal power plants (TPPs) it is a fact, that maintenance cost of the TPPs is goes up to 30% of the total production cost of the electricity (Ulrich,2004). According to the script by U.S Department of Energy (DOE) The costs of Combined Heat and Power Installation Database (Technology characterization – steam turbine by US EPA, 2015), for a typical steam turbine the may fall by 0.004 $/kWh-year. For the study combined cycle power plant, it is reported that the maintenance cost may to amount to 17% of the plant life cycle cost (Boyce, 2006). In fig. 9 percentage wise costs are given during the plant life cycle for a combined cycle power plant.

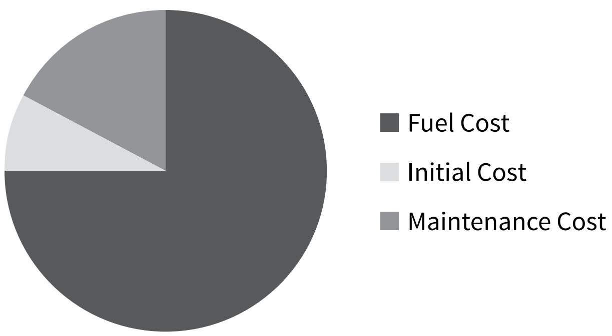

FIGURE 9. Plant life cycle cost for a combined cycle power plant (Jerome, R, 1989).

From the various heads for the plant life cycle cost, the main and controllable head is maintenance cost. In the light of data, it can be said that any improvement in the performance of the existing maintenance practice leads to significant cost savings. This reflects into less production cost of the electricity and economic benefits for the customers. Indeed, a study by Rosen (Jerome, R, 1989) has revealed that a saving of about 30% in maintenance cost can be achieved by simply changing from preventive maintenance to Condition Based Maintenance (CBM) in which a Fault Detection and Diagnosis (FDD) system plays a major role. Advancement into FDD algorithm, therefore, would mean significant improvement in the CBM capacity.

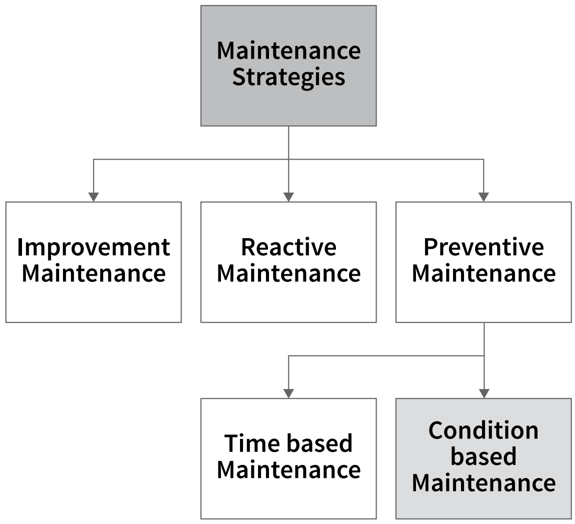

FIGURE 10. Types of Maintenance Strategies.

There are three types of maintenance strategy, (Fig. 10). The first one is Improvement Maintenance (IM) that deals with maintenance considerations at the manufacturing stage of the equipment itself. The intention of this strategy is to do away with any maintenance requirement, due to the limitation of the material properties and manufacturing method, and design the parts and equipment for finite life. It is however, difficult to implement this strategy practically. The second one is called Corrective or Reactive Maintenance (CM). In this kind of approach parts are replaced when they fail (It is adoptable when the frequency of the failure of parts is high. It however causes unnecessary down-time leading to production losses. The third type is known as Preventive Maintenance (PM).Further PM is divided into Time-Based Preventive Maintenance (TBM) and Condition Based Maintenance (CBM). TBM schedule is predefined and applied to the plant or equipment to prevent failure before it occurs. Unlike TBM, CBM is a proactive strategy in the sense that it is recommended based on existing conditions of the plant. The advantage of the CBM strategy is that it reducing unnecessary shut-down and maintenance costs.

For improving efficiency of the TPPs and reducing the production costs CBM strategy is employed in TPPs. CBM involves three steps: data acquisition, data processing, and decision making (Jerome, 1989). For the successful application and execution of the CBM scheme state-of-the-art scheme is used like FDD.

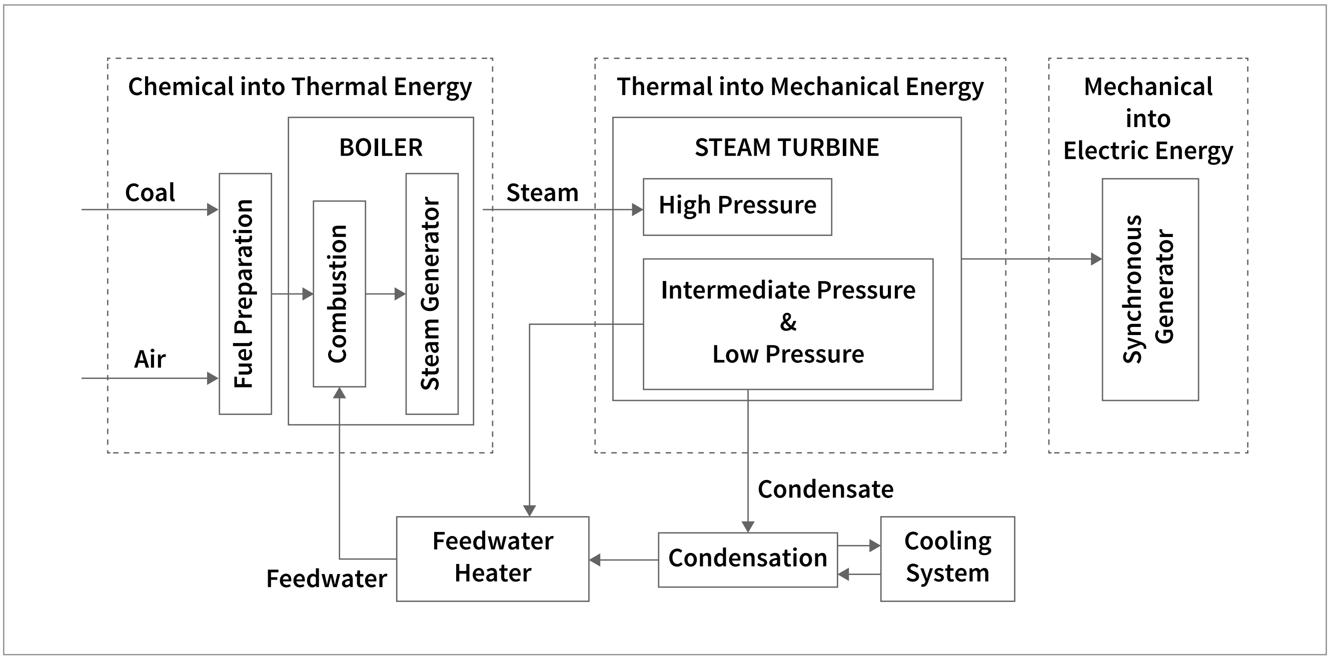

FIGURE 11. Energy Cycle in TPPs.

Thermal Power Plant (TPP) in Brief

Thermal Power Plants (TPPs) deliver electricity that could be either from natural gas or coal. The typical three forms of energy conversation in different steps of TPPs is illustrated in Fig. 11. To convert chemical energy into electrical energy in any TPPs, several closed loop controls are used. To improve the overall efficiency of the plant,all the closed loops should be closely monitored and precisely controlled. In every closed loop system in the plant there are three type of fault. The first being system fault in which the mechanical structure of the system or component is prone to damage (i.e. leak fault in pipe lines or in the tank). The second one is actuator fault in which the characteristic of the actuator changes due to mechanical wear and tear(i.e. in pneumatic actuator faults incorrect pressure supply, diaphragm leakage, plug aging etc.)This may drastically change the system behavior, resulting in degradation or even instability. The third fault is sensor fault in which measured value may be high or low from the actual one (i.e. sensor accuracy, miss calibration etc.). All three types of fault in any closed loop system represents in fig. 12. By applying FDD methods into closed loop system incorporating effective maintenance schedule, gives optimum efficiency of the overall plant. Improving efficiency and reliability of the TPPs depend upon the steam turbine controls.

Detailed working flow diagram and possible faults and failures in TPPs are demonstrated for TPPs in fig. 15.

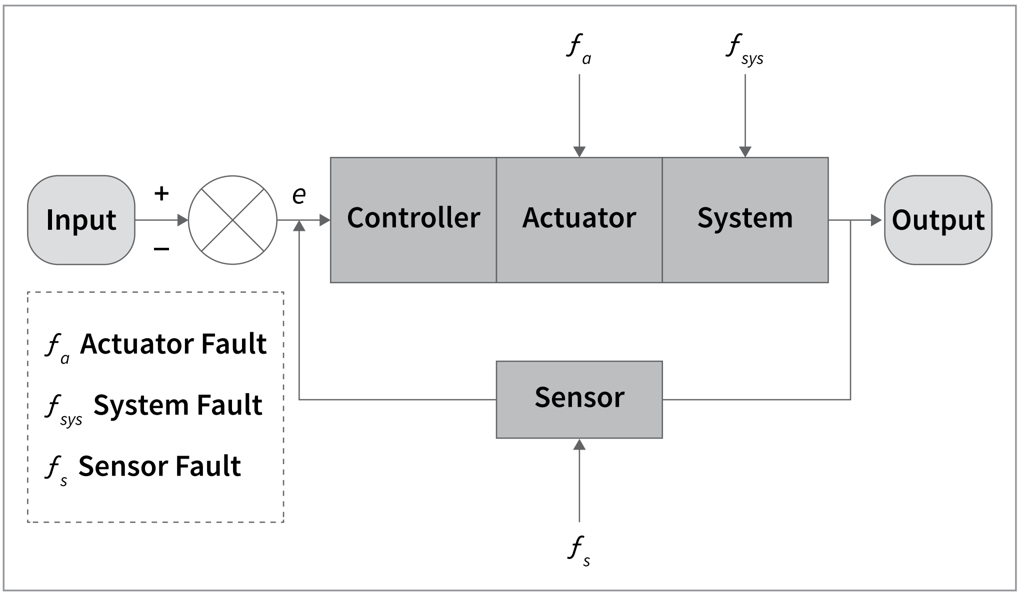

FIGURE 12. Potential faults in any closed loop system.

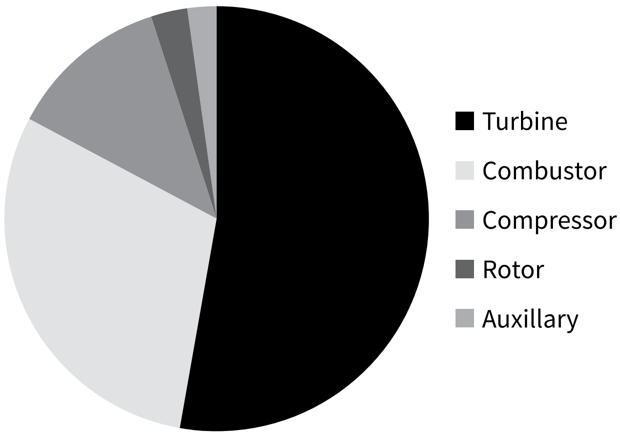

FIGURE 13. Major failure in a steam turbine for low capacity less than 220 MW TPPs. (Jerome, R, 1989).

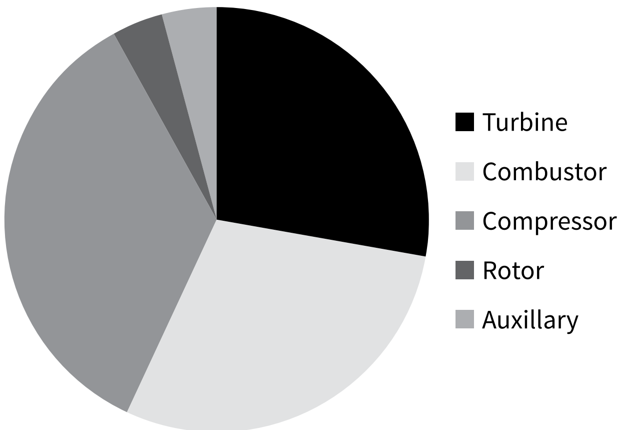

FIGURE 14. Major failure in a steam turbine for high capacity more than 220 MW TPPs (Jerome, R, 1989).

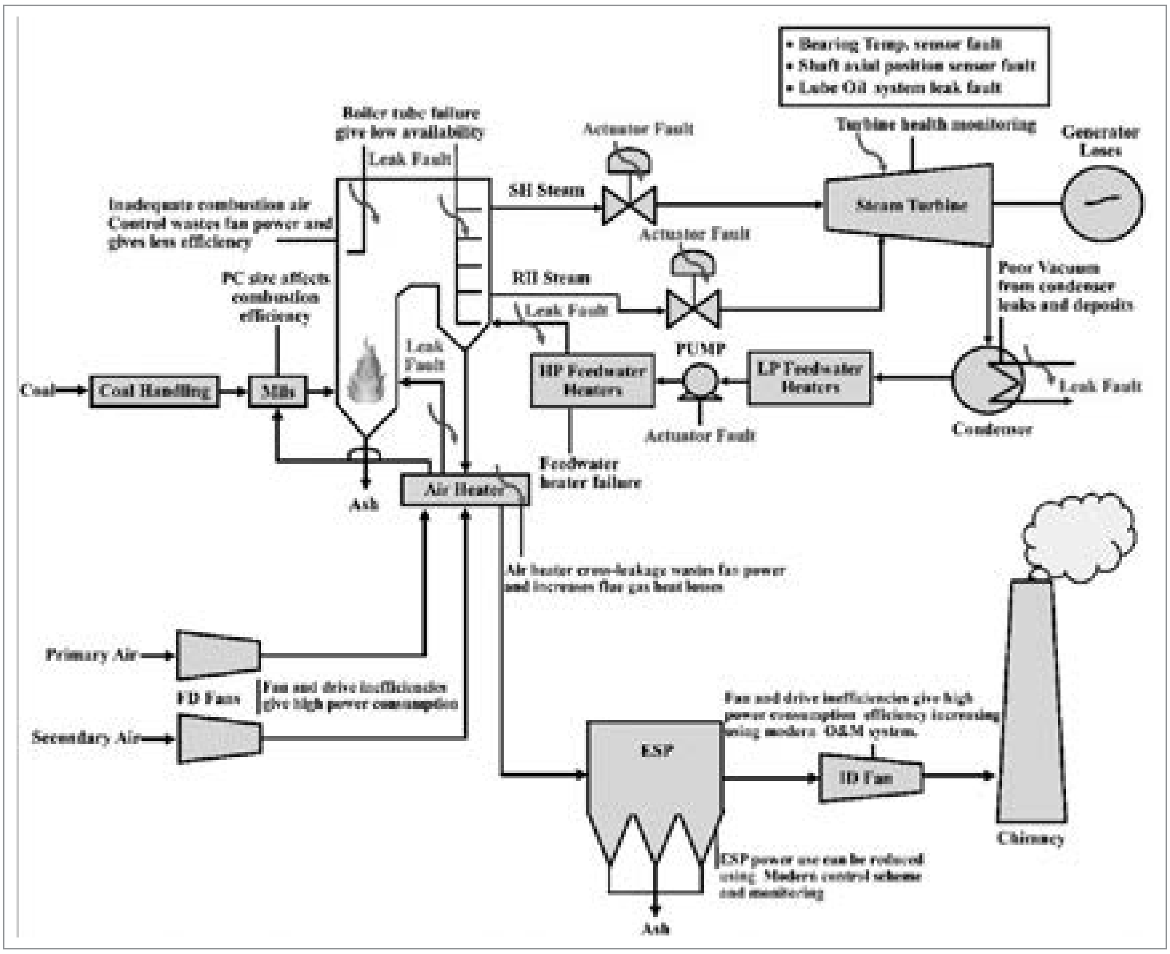

FIGURE 15. TPPs working flow with possible failure and faults.

Possible Faults in TPPs	**Description**	**Remarks**
Steam Turbine Health Monitoring and Control Design	Indeed, turbine health monitoring and control is an essential part in the thermal power plants (TPPs) to improving efficiency. However fault occurs (i.e. sensor, actuator and system faults) during the operation of the turbine. Increasing steam turbine efficiency and output, various FTC strategies have been applied.	The steam turbine in TPPs may cause major losses in terms of efficiency and maintenance. It is major equipment in any TPPs. Maintenance cost leads to significant change in the efficiency of TPPs.
Combustion Control Mechanism and Flue Gas Heat Recovery	Combustion controls adjust coal and air flow to optimize steam production for the steam turbine/generator set. In TPPs, steam reheater or super heater pipe leakage may reduce combustion efficiency, steam temperature, furnace slagging and fouling, and NOX formation.	For proper combustion control in boiler,continuously provide sufficient amount of air and fuel, System fault occurs in stem heater, super heater and reheater and fuel pipe line, dropping the combustion efficiency. Heat recovery is important for utilizing maximum energy from the flue gases. Leaks faults leads to in heat recovery cycle occurs energy losses.

Possible Faults in TPPs	Description	Remarks
Boiler Feedwater Control	The drum water level control is essential in boiler control. Due to increasing and reducing demand of the steam drum water level must be controlled precise, by Actuator faults, lead to the hazardous situations which may be due to an insufficient amount of water in the boiler drum.	Actuator fault occurs in the power plant system reduce efficiency of turbine due to an insufficient amount of superheated steam produced by the boiler.

TABLE 7. Possibly Potential faults in TPPs with a brief description.

Heat Recovery steam Generator (HSRG) is a part of TPPs. The HSRG has a steam drum, water drum, water-walls, economizer, pre-heater, and feed-water pumps as sub units. The prominent performance related faults common in the units include malfunction in the feed-water pump (actuator) (i.e. damaged seals and erosion of impellers), tube leaks (system fault), and fouling in the remaining critical components. Fouling in the HSRG causes the exhaust gas exit temperature to increase, and exhaust gad pressure and steam production to decrease (Port & Herro (1991). Possible faults in TPPs are summarized with a brief description in table 7. The steam turbine fault is a major fault in TPPs from the perspective of economic

losses due to failure or lack of maintenance of the steam turbine. Maintenance expenses in the TPPs is fora steam turbine. So,detecting an early fault in turbine and diagnosis is mandatory for reliability of the power plant. Several researchers have focused on various FDD methods that are applied to the turbine for TPPs(Dhinietl., 2017; Karlsson, 2008 ; Bin, 2012 ; Changfeng, 2009 ; Zwebek & Pilidis, 2003). The other major faults are small function insensor in the TPPs. The sensor is an essential part of any closed loop system for measured variable, and a malfunction in sensor results in deviate the controlled variable significantly, and hence affects the plant efficiency. The various FDD methods are applied to prevent sensor faults (Toffolo, 2009; Kusiak, & Song, 2009) (Mehranbod, 2005;Mehranbod & Soroush, 2003; Cho, 2004). The third important fault is actuator fault.Plays.Failure to control variable would degrade the quality and further to dangerous situations. If the actuator fails or of a fault occurs,in boiler drum water level control, the superheated steam quantity reduces drastically and affects the efficiency of the turbine Low levels of water in tubes damage due to overheating by the superheated steam. If combustion control fail affects the combustion efficiency. To overcome the effect of the actuator fault in a system various FDD methods discussed are(Dhini, 2017; Bin, 2012;Changfen, 2009; Karlsson et al., 2008; Karlsson et al., 2008; ZwebekPilidis, 2003).

Summary and Discussion

In this paper, an overview of FDD methods is presented in the field of different power generation plants (PGPs). Vibration monitoring and loose part monitoring, noise analysis have beenextensively applied with success in various PGPs. It is recognized that on-line monitoring of instruments andequipment in power plant industry brings benefits to plant availability and results in better economy. Some commercial products have been developed and are increasingly used in power plants. Encouraging results have been obtained for reactor core monitoring in NPPs, furnace temperature monitoring in TPPs, and transient identification. Application of FDD in NPPs, TPPs, and SPPs (PGPs) will become more beneficial as I&C technologies and FDD methods theory progress. Application of model-based FDD methods are very because of complex plants like NPPs. Signal-based FDD methods have been proven useful for instrumentation channel dynamics performance monitoring, and equipment vibration monitoring. Transient identification is basically a pattern recognition problem, with ANN dominating in this area. Emerging pattern recognition methods have not yet been explored. For the TPPs various faults are considered and appropriateFDD methods are discussed.

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