

Chapter 2

Literature Review

2.1 Introduction

This chapter is intended to discuss the FDD methods in the area of power plants. However, apart from covering the methods applied to CCPs, it zooms into thermal systems in a wider perspective. The main benefits from this chapter is that it reveals possible research directions that reaffirm our choice of a specific method in Chap. 1. Further more, candidate areas for possible further research are also enumerated.

A power plant may experience abnormal or faulty state. This state could be a manifestation of a freezed sensor outside the control loop or a result of unrecoverable problem such as erosion of the turbine casing or the rotating blades. In some cases it could be a combination of two or more problems that happen to demonstrate similar symptoms, e.g. compressor fouling and VIGV drift. Regardless of the condition of sensors, however, we rely on sensor information to conduct fault detection and diagnostics. The presence of a sensor fault invalidates the calculation intended for optimization, supervisory control, and FDD. Hence, the ideal version of FDD system needs to take into account the expected conflicting situations, both in terms of fault combinations and availability of sensors for measurement and diagnostics.

The design of a fault detection and diagnostics system is affected by many factors: (i) detectability and isolability of the fault, (ii) the type of signals available for measurement, (iii) the state of the sensing element, (iv) the threshold assigned to the detection step, (v) richness of the diagnostic knowledge base, and (vi) adequacy of the inference system. Several approaches have been suggested to design a fault detection and diagnosis system.

2.1.1 Basic Definitions

In this book, the meaning for key technical words and phrases related to FDD follow the definitions as provided by the SAFEPROCESS Technical Committee (International Federation for Automatic Control) [1].

Fault: *An un-permitted deviation of at least one characteristic property or parameter of the system from the acceptable/usual/standard condition.*

Failure: *A permanent interruption of a systems ability to perform a required function under specified operating conditions.*

Malfunction: *An intermittent irregularity in the fulfilment of a systems desired function.*

Fault detection: *Determination of the faults present in a system and the time of detection.*

Fault isolation: *Determination of the kind, location and time of detection of a fault. Follows fault detection.*

Fault diagnosis: *Determination of the kind, size, location and time of detection of a fault. Follows fault detection. Includes fault isolation and identification.*

2.1.2 Available Signals Versus Faults

Addressing the issue of fault categories in relation to the process model, signals accessible for system monitoring and time dependence of the faults themselves is worthwhile to the subsequent detail literature review. In connection to this, consider a controlled plant described by a block diagram given in Fig. 2.1. In general, a plant is characterised by input sensors, output sensors, controller, and actuators. The state of the plant is monitored by means of input signal $x(t)$, output signal $y(t)$, signals

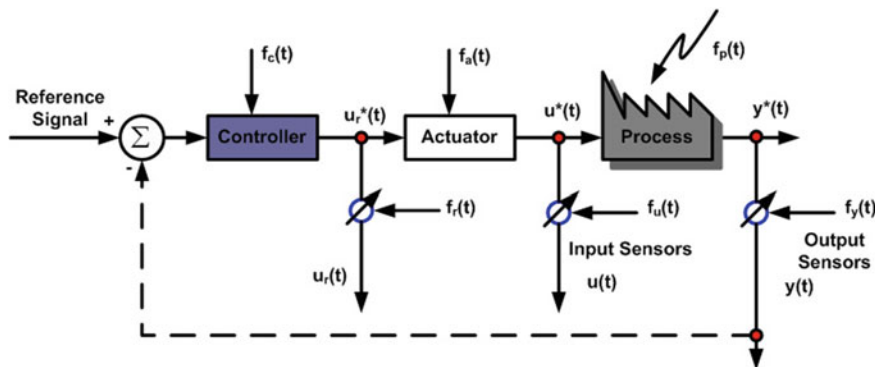


Fig. 2.1 A controlled system and fault topology

Table 2.1 Time dependence of faults

Types of fault	Relation	Examples
Abrupt	$f(t) = \hat{f}$, for $t \geq t_s$	Freeze sensor, FOD in compressors
Incipient	$f(t) = a_{11}(t - t_0) + a_{10}$	Fouling, Erosion and Corrosion
Intermittent	$f(t) = \hat{f}_i$ for $t = t_i$	Outliers

from the controller $u_r(t)$, and signals outside the control loop. The actual plant inputs $u^*(t)$ and outputs $y^*(t)$ are not directly available. The same is true for the controller output $u_r^*(t)$. Sensors are used to acquire these quantities. The feed back controller gets the output signal through an output sensor. In ideal case the output measured by these sensors are equal to the actual values. In reality, the measurements are affected by the characteristics of the sensing element and disturbances. Noise is the first thing that can not be avoided (true for output sensors). Besides that, for different reasons, e.g. stuck sensor, the output could be offset in a certain direction.

It can be inferred from Fig. 2.1 that a fault in the system can be of a controller fault $f_c(t)$, an actuator fault $f_a(t)$, a process fault $f_p(t)$ or a fault linked to the measurement sensors $f_u(t)$ or $f_y(t)$.

In relation to the process models, faults on inputs and outputs sensors, respectively, are often modelled either as additive type, $u(t) = u^*(t) + f_u(t)$, or multiplicative type, $f_u(t) = \delta u^*(t)$. Where the vector $f_u(t) = [f_{u1} f_{u2} \dots f_{u,nu}]^T$ describes a specific fault signature and δ is the multiplier. Including the effect of measurement noise, $\tilde{u}(t)$ and $\tilde{y}(t)$, with the assumption that they are white, zero mean and uncorrelated Gaussian processes, faulty sensor signals can be modelled as

$$\begin{cases} u(t) = u^*(t) + \tilde{u}(t) + f_u(t) \\ y(t) = y^*(t) + \tilde{y}(t) + f_y(t) \end{cases} \quad (2.1)$$

Additive faults manifest themselves as offsets of sensors where as multiplicative faults appear as parameter changes within the process – e.g. fouling in a heat exchanger or compressor. Faults are also distinguished based on their time dependence as abrupt fault (stepwise), incipient fault (drift like), and intermittent fault, Table 2.1.

So far we have focussed on those signals involved in the control loop only. In real application, there are also signals outside the control loop and used for the purpose of condition monitoring. A good example is to consider an industrial gas turbine, Fig. 2.2. The pressure drop on the suction side of the compressor is monitored to make sure that the air filter at the inlet of the duct is not dust clogged excessively. The other signals available for measurement range from lube system temperatures and pressures, turbine enclosure temperature, vibration signals at the shaft supporting bearings, generator winding temperatures, and acoustic signals to lube oil sampling.

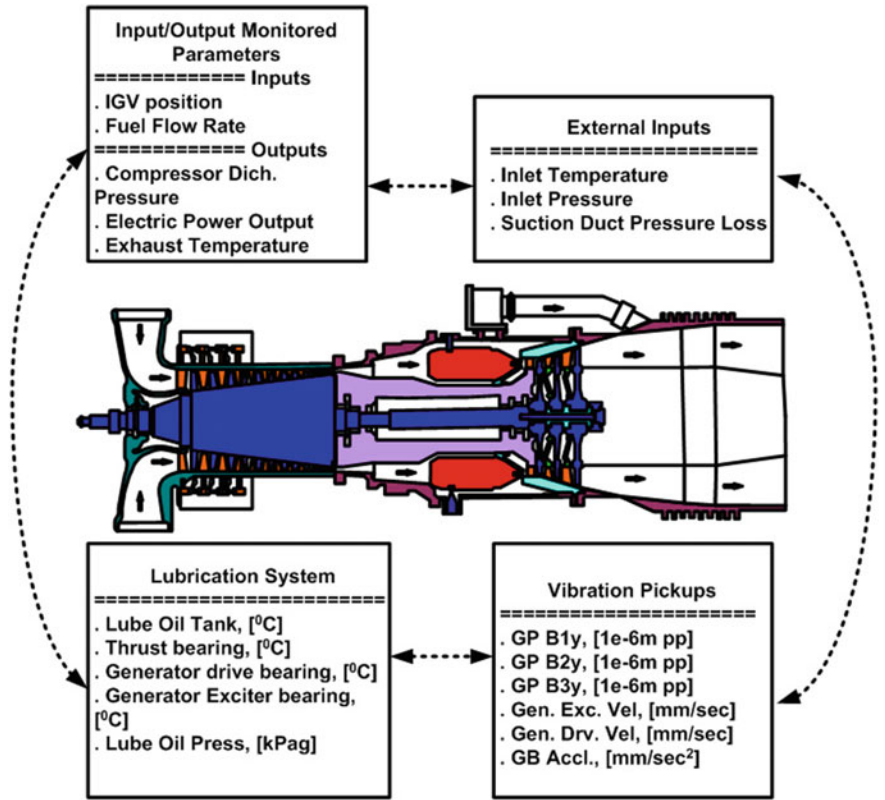


Fig. 2.2 Measurable signals for a single-shaft industrial gas turbine

Heuristic information is another source of monitoring signal. Human observations in the form of noises, colours and smells contribute to this group. Past maintenance history is also another source of heuristic information.

2.1.3 *Classification of Fault Detection and Diagnosis (FDD) Methods*

The classification of the fault detection and diagnosis techniques follows the signals available for measurement, the techniques used for signal processing and the type of inference system. Literature reviews on the different approaches are available in conference papers [2, 3], journal papers [1–12], and books [13, 14].

The first grouping for FDD is as fault detection and fault diagnosis, Table 2.2 and Fig. 2.3. Detailing the fault detection a little bit, the general classification emerges as model-free and model-based. While model-based approaches rely on a mathematical

Table 2.2 Time dependence of faults

Objective	Method	Examples
Fault diagnosis	Classification based	<ul style="list-style-type: none">• Statistical based• Pattern recognition• Neural networks• Fuzzy logic
	Reasoning based	<ul style="list-style-type: none">• Forward reasoning• Backward reasoning
Fault detection	Model free	<ul style="list-style-type: none">• Hardware redundancy• Signal based
	Model based	<ul style="list-style-type: none">• Quantitative model based• Qualitative model based

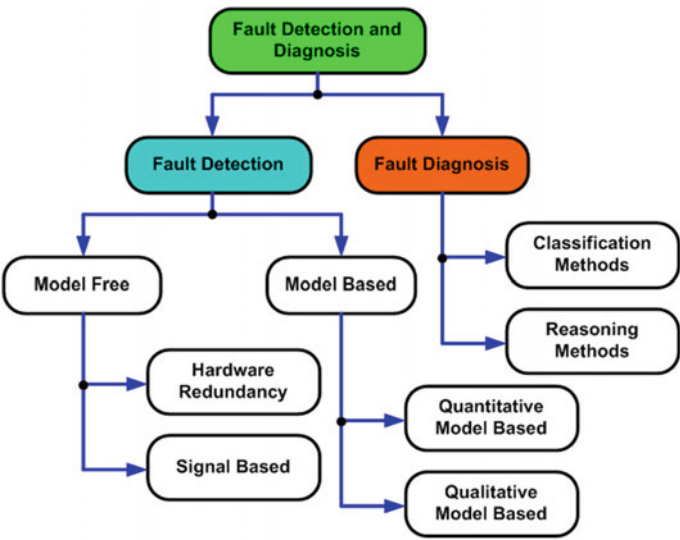


Fig. 2.3 Classifications of fault detection and diagnostics methods

model developed either from fundamental laws or based on measured input-output data, model-free approaches often make use of direct analysis of the collected signals.

There are several methods as model-free approach. These include physical redundancy, special sensors, limit checking, spectral analysis [15] and logical reasoning. In hardware redundancy design [16, 17], multiple sensors are used to measure a variable and voting techniques are used to decide on the faulty measurement. The drawback to this method is the extra cost to the system. Limit checking [17, 18] on the other hand works by comparing the real time data with the threshold that is preset by the operator. Though it is simple, it is not accurate enough for the thresholds are calculated not taking into account the effect of other variables in the system.

In fact, this makes it identical to a univariate statistical technique. Limit checking lacks sensitivity and robustness as it ignores spatial and serial correlations among the observations and variables. Some signals could have special frequency spectrum in normal and faulty conditions. In that case, spectral analysis can be used for fault detection and diagnosis. Logical reasoning takes the symptoms from the other methods and applies structured approaches in an expert style or without the involvement of the human operator.

A model based fault detection system doesn't need extra equipment or there is no voting involved. The method simply works making use of the discrepancy between actual output and model output of the system. The model can be developed employing either qualitative techniques or quantitative methods, Table 2.2.

Fault diagnosis is the determination of the time of detection, location, type and size of a fault. The available signals are translated into suitable symptom vectors and classification or diagnostic reasoning strategies are applied to reach to diagnostic decisions. Classification methods statistical based [19], pattern recognition methods [20], neural networks [21], and fuzzy systems [22–24] are used in cases where there are no available knowledge about fault-symptom causalities. Most of the time partial information is known for a system. If it is so, diagnostics reasoning strategies play a major role.

2.2 Model-Based Fault Detection and Diagnosis Techniques

The general classification on the model based approaches towards fault detection is given in Fig. 2.3. The main step in all the cases is the generation of fault symptoms by comparing a reference or normal operation model with actual data. The difference in the approaches lies on the way the symptoms are generated. But, all use models developed in either online or off-line mode. The model based approach is broadly classified as qualitative model based and quantitative model based. The general structure of a model based fault detection and diagnosis system is given in Fig. 2.4. To make diagnostic decisions possible, a residual $r(t) = y(t) - \hat{y}(t)$ featured by an offset from the threshold $th(t)$ is further processed by a classifier or a diagnostic reasoning strategy (Fig. 2.5).

2.2.1 Quantitative Model Based Methods

Analytical Methods (Observers, Parity Relations, Parameter Estimation Techniques, and Kalman Filters)

Models in this group use mathematical representations of the system derived from first principle concepts and are applicable to information rich systems, mostly linear. They are often referred to as analytical based approaches. Output observer

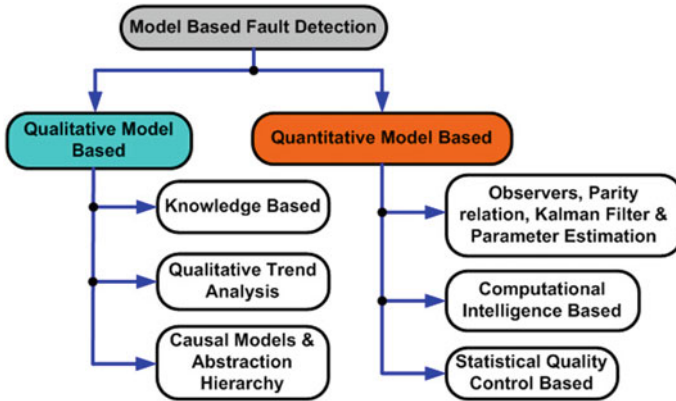


Fig. 2.4 Classifications of model based fault detection and diagnostics methods

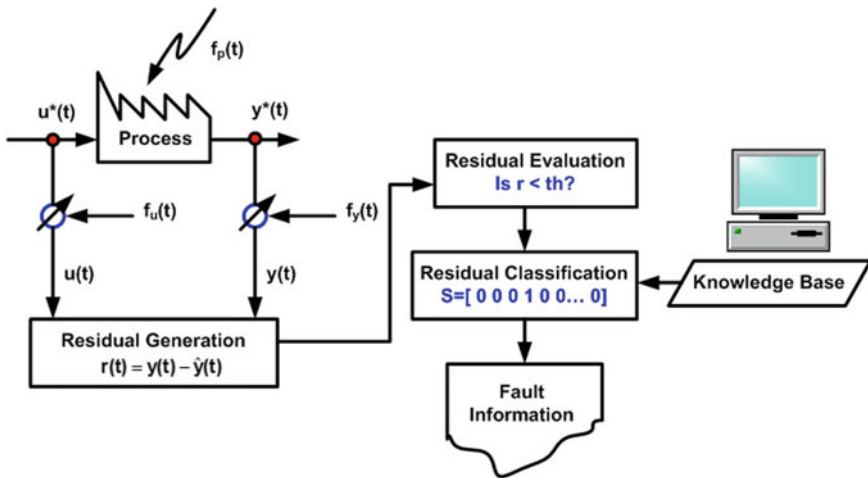


Fig. 2.5 Structure of a model based fault detection and diagnosis system

(Luenberger observers) [25, 26], and Unknown Input Observer (UIO) based fault detection methods make up the first group. The design structure corresponding to the two methods features each output modelled as a function of all the inputs and each input modelled as functions of all inputs and outputs except the input under consideration.

In the dedicated observer scheme, the output observers are designed for each output sensor assuming that the state of the system is observable from the measured quantities. Changes in the estimated states are used as fault indicators. The necessary condition for this approach is that the observers need to be designed in such a way that they converge to zero under normal operating conditions. The drawback in this

approach is the requirement for a mathematical model and the need for a number of observers as there are number of outputs.

The first use of observers for fault detection and diagnosis is dated back to the early 1970s. Beard [27] at Massachusetts Institute of Technology (MIT) was the first to apply observer-based fault detection models. Since then different observers have been applied to sensor fault detection of steam generators [28], power plants [29], turbofan engines [30], heat exchangers [31, 32] and coal mills [33].

One difficult task prior to designing the decoupled observers is the calculation of system matrices. Simani, Fantuzzi et al. [34] investigated the used of model identification techniques (ARX, and EIV models) to obtain the system matrices in the design of input observers and output observers for an industrial gas turbine. The data used for the identification process is obtained from simulation of a MatLab/simulink model of the system.

Belonging to the same group of model based approaches is parity equations [35–38]. In this case, while the model is developed applying first principles, the model is simulated in parallel with the actual system and a residuals are calculated as difference between the model outputs and outputs from the plant. Through a comparison of the magnitude of the residuals to preset thresholds, the state of the system is identified. Good side of the parity approach is simplicity. However, for a Single Input Single Output (SISO) system, the residual will not be enough to isolate between different faults.

The other class of analytical model based approach for fault detection is parameter estimation [39, 40]. In this case, the technique is based on the hypothesis that faults may be reflected in the system parameters. For an actual system, physical parameters are seldom known. In parameter estimation method, the parameters are estimated from measured input and output signals, $u(t)$ and $y(t)$. In real time application, it mostly uses Recursive Least Squares (RLS) method.

De la Fuente and Vega [41] tested RLS and neural networks for fault detection in a water treatment plant. Belle and Isermann [42] applied RLS and local linear fuzzy models to detect and diagnose faults in an industrial scale thermal plant. The fuzzy models are used to capture the parameters during normal operation of the system. Abidin, Yusof et al. [43] used RLS with fuzzy inference system to diagnose faults in DC motors. Other related investigations using this approach include research works by Weyer, Szederknyi et al. [44], Kumar, Sinha et al. [45], and Yoshida, Kumar et al. [46].

The last approach in this category is Kalman Filter (KF) technique. In this case, structure of the detection device is similar to output observers. The major difference id, KF recursively estimates model matrices assuming that the measurement noise is white and Gaussian.

KF based observer design has been used by Tylee [47], Usoro [48], Li [49], Hines [50], Simani [51, 52], Zhang [53], and Ryerson [54]. KF is mostly applied for signals whose noise to measured signal ratio, $\|y^*(t)\|^2/\|\tilde{y}(t)\|^2$ and $\|u^*(t)\|^2/\|\tilde{u}(t)\|^2$, are relatively low.

In summary, all the analytical approaches are mostly applicable to systems with limited number of inputs and outputs, in fact to linear systems. For large scale systems, it is difficult to apply the methods given the cross-coupling between system variables. With analytical models it is also difficult to accurately consider the effect of model uncertainties caused by disturbances and noise. Robust fault detection and diagnosis strategies could improve the latter effect but even then it would be at the expense of delayed result in the detection of incipient faults.

Multivariate Statistical Methods

Multivariate statistical methods are qualitative model based techniques. All of them in this category are derived directly from measured process data. In this class, we find Principal Component Analysis (PCA), Partial Least Squares (PLS), Fisher Discriminate Analysis (FDA), and Canonical Variate Analysis (CVA). In the following, we only consider the PCA method.

In PCA approach, the data is mapped to a reduced dimension space making use of Singular Value Decomposition (SVD) on the covariance matrix defined by the input-output data. If the data matrix is $\mathbf{Z} \in R^{N_d \times (n_x + n_y)}$ then, when written in terms of parameters from the projected or lower dimensional space

$$\mathbf{Z} = \sum_{i=1}^k \mathbf{t}_i \boldsymbol{\vartheta}_i^T + \mathbf{E} \quad (2.2)$$

where, \mathbf{E} is the residual matrix, $\boldsymbol{\vartheta}_i$ is the loading vector eigenvectors of the covariance matrix $\mathbf{Z}^T \mathbf{Z} / (N_d - 1)$ and \mathbf{t}_i is the projection of \mathbf{Z} in the direction of $\boldsymbol{\vartheta}_i$. N_d , n_x and n_y are number of data, number of inputs and number of outputs, respectively. The number of loading vectors k considered for the projection is determined either by proportion of trace explained method or SCREE test [55]. For fault detection using PCA, Hotelling's T^2 and Q-statistic are used as condition measuring criteria while contribution plots are used to isolate the variables responsible for the fault. Extensions of the classical PCA method are available in different forms: Moving PCA (MPCA), adaptive PCA, exponential weighted PCA [56]. The application of PCA for fault detection and diagnosis can be found in the area of air handling units [57, 58], centrifugal chillers [59–61], steam generator of a nuclear reactor [61, 62], gas turbines [64, 65], and Heating Ventilation and Air-Conditioning (HVAC) [19, 66, 67]. In Xu, Xiao et al. 2008 [61], the PCA based fault detection is enhanced by pre-processing the measured data by Discrete Wavelet Transform (DWT). PCA is also combined with other approaches like Hidden Markov Chains [68], and neural networks [69] to exploit dimension reduction capability of PCA. For a comparison between PCA and Adaptive Neuro-Fuzzy Inference System (ANFIS), refer to the paper by Maghsooloo, Khosravi et al. [70]. It demonstrated how PCA out performed ANFIS in terms of fault detection ability.

One advantage of this group of methods is that they don't need first principle model. Instead, they only rely on the input-output data. The other advantage is that they provide dimension reduction. The drawback of PCA, however, is that it assumes

the projected data follows Gaussian distribution, which is rarely true. Besides, it doesn't take into account serial or self correlation. In fact, this property is shared by PSA as well. Some research works suggested Independent Component Analysis (ICA) to deal with the non-Gaussian condition, [71]. The next section will focus on computational intelligence based fault detection techniques.

Computational Intelligence Based Methods

CCPs reside to nonlinear systems. When the effect of measurement noise is significant and the system is featured by uncertain operating parameters, FDD users rely on computational intelligence techniques: neural networks, fuzzy logic and meta-heuristics.

Neural networks are computing elements inspired by the behaviour of nerve cells in the brain. They are well known for their function approximation and classification abilities. A neural network having one hidden layer is capable of approximating any nonlinear function [72]. They are also chosen over the other approaches for their characteristics to generalize from a given training data set, tolerance to measurement noise and fast execution time once they are trained. The drawback of a neural network, however, is lack of transparency of the resulting model in human understandable terms.

Reviewing the application of CI methods to fault detection and diagnosis were the subject of many research [3]. Neural networks are used in two ways regarding process fault detection and diagnosis in power plants. The first use is as residual generator [21, 73–77] in the sense that neural networks are employed to capture Normal Operating Condition (NOC) of the system. The second application is as fault isolator or classification technique [17, 51, 78–82]. Some researchers also applied neural network as One Step Diagnostician (OSD) [83–87]. In this case, detection and isolation of faults are performed from available measurements without the need for prior generation of intermediate signals as residuals. In the report by Chun-ling [86], Radial Basis Function (RBF) networks trained by Genetic Algorithms (GAs) are used to formulate the OSD for such units as steam generator, steam turbine and condenser. Group Method of Data Handling (GMDH) neural network, [63, 88–91], is one design from the same class used for developing a fault detection and diagnosis system.

Neural networks are also used together with other methods. Sreedhar et al. [92] investigated the use of neural networks and sliding observers for fault detection in a thermal power plant. In some cases PCAs are also used for dimension reduction in the process of model identification through neural networks [69, 93]. A research work by [94] addressed the use of Kohonen Self-Organizing Maps (SOM) to reduce the training data size prior to using the data for formulating the neural network model. Simani, Fantuzzi et al. [95] and Simani [96] used Kalman filters and neural networks for fault detection and diagnosis, respectively, in an industrial gas turbine. Leger, Garland et al. [17] examined the feasibility of using neural networks combined with statistical control charts (CUSUM) for fault detection and diagnosis. Pattern recognition techniques are also combined with neural networks in developing dedicated models for different operating regions of a power plant [97]. Neural networks are

also integrated with expert systems in the work of [98]. While the neural network is used for fault detection, the expert system is applied for fault diagnosis.

One special type of neural networks is the Auto-Associative Neural Network (AANN). First proposed by Kramer [99], the network has five layers with the middle layer called bottleneck layer. The network is suitable to formulate nonlinear principal component analysis on a given data set. Other than image processing, the network has been used by some researchers for sensor fault detection in gas turbines [100–102].

Fuzzy logic is another class of computational intelligence group. In fuzzy logic, the classical crisp description of concepts is generalized to fuzzy sets whose membership now assuming partial belongingness or full membership to a given set. Fuzzy logic was designed originally to describe vague linguistic concepts. A good example is temperature high, very high, low, very low, medium etc. As compared to neural networks, fuzzy approach is more appropriate for fault isolation. Fuzzy logic allows integration of human knowledge into the diagnosis process. One drawback of fuzzy modelling is its complexity and time consuming modelling procedure.

Similar to the neural networks, fuzzy systems can be used either as residual generator or pattern recognition technique. The latter use of fuzzy systems is common for cases where there is no prior knowledge about fault-symptom causal relationship in the design of a fault detection and diagnosis system. Some of the fault detection and diagnosis approaches exploiting fuzzy concepts include works by Diao [103] and Ogaji [104] both in the area of gas turbines.

Observers combined with fuzzy logic, in a serial way, are used for fault detection and diagnosis in high pressure pre-heaters [105]. The observers are applied to generate the residuals while the fuzzy logic is used to process the residual for fault isolation reasons. Upadhyaya, Zhao et al. [63], and Zhao and Upadhyaya [106] examined the use of Adaptive Fuzzy Inference System (ANFIS) for fault detection in a nuclear power plant.

Evolutionary computing techniques genetic algorithm, genetic programming and evolutionary strategies are derivative free global optimization tools. In fault detection and diagnosis design, they are used to estimate neural network weights [86] and fuzzy model parameters. Guo and Uhrig [94] applied genetic algorithm searching strategy to determine optimum number of inputs to a neural network model. In their work, SOM was adopted to reduce the data size.

Computational intelligence techniques, when they are implemented as stand alone design, cannot efficiently model complex systems even if they provide better performance as compared to first principle modelling approaches. Distributed fault diagnosis system design is the suggested approach to alleviate the drawback. One such design was suggested in Koppen-Seliger, Kiupel et al. [105]. They reported residuals considered all together during fault isolation only. Multi-agent based fault diagnosis design that uses neural networks for modelling sub-systems of a complex plant is discussed by Heo and Lee [107]. A similar approach is also proposed by Arranz, Cruz et al. [108]. Hierarchical and decentralised neural network based approach is investigated by Ogaji and Singh [109]. A two step decentralized approach using Petri nets for the first steps and neural networks for the second is also suggested by Power

and Bahri [110]. The neural networks are used to indicate the exact location of a fault in a certain section of the power plant.

Neural networks have learning abilities while fuzzy systems are capable of representing knowledge as sets of if-then rules. The combined use of neural networks and fuzzy systems possesses the advantages of both. There are several ways to combine neural networks and fuzzy systems [111–117]. One way is to create a fuzzy neural model using fuzzification block to map the measured data to a different scale and feed the result to a neural network system [118]. In the other design, Self-organising Maps (SOM) can be used to pre-process data, e.g. clustering or noise removal, for fuzzy systems. In the other design the fuzzy model can be adopted in the neural network allowing the parameters to be estimated using neural network learning algorithms.

Palade, Patton et al. [111] used NF networks for fault diagnosis in an industrial gas turbine. They used simulated data generated with the inlet guide vane position and fuel flow rate considered as inputs. Actuator faults and compressor contamination faults are among the cases considered in their study. NF networks representing Mamdani models were used for fault isolation. Zio and Gola [119] investigated the use of NF approaches to fault classification on the gland seals of pumps of the primary heat transport system in a nuclear reactor.

Uppal, Patton et al. [120] applied NF approach to develop a fault diagnosis system for a process featured by multiple operating points. For assumed number of faults and operating points, the method suggests number of decoupled observers extracted from the NF models. The method was tested using the data from DAMADICS valve benchmark problem [121]. Robust fault detection scheme based on NF networks was developed by Korbicz and Kowal [122]. They used bounded-error assumption to define model confidence intervals. The approach was tested by experimental data for a flow control valve. Tan, Rao et al. [123] presented the combined use of fuzzy systems and Adaptive Resonance Theory (ART) networks to the detection and diagnosis of faults in the cooling system of a power generation plant. The same system was previously studied by Chen, Lim et al. [124] applying fuzzy neural networks integrated with rule extraction scheme.

Razavi-Far et al. [125] investigated the use of NF networks for fault diagnosis in a U-Tube Steam Generator (UTSG) that is part of a nuclear power plant. They trained the models based on a data from UTSG simulator. The NF for residual generation was trained by a Locally Linear Model Tree (LOLIMOT) algorithm while the NF model Mamdani type for fault isolation was trained by Genetic Algorithm (GA). Applications of ANFIS to model identification and fault isolation can be found in Zhao and Upadhyaya [106]. NF approaches as applied to pattern classification for the purpose of fault isolation is presented by [119].

In the other use of combined approaches, Evsukoff and Gentil [126] have tested neural network models feed forward and recurrent designs whose inputs are fuzzified simulated data. The resulting models have been used for fault detection and isolation in nuclear reactors.

2.2.2 *Qualitative Model Based Methods*

The group in this section entails knowledge based systems (cause effect graphs and expert systems), Qualitative Trend Analysis (QTA), and causal models and abstraction hierarchy.

The expert system can be of a shallow-knowledge expert system, deep-knowledge expert system, or a combination. In the shallow-knowledge approach, the algorithms are developed based on knowledge from the experience of humans. The knowledge in the expert system is represented using one of such techniques as predicate calculus, production- rules, frames, scripts or semantic networks. As a searching strategy, all Artificial Intelligence (AI) techniques use forward chaining or backward chaining scheme. For a large searching space, the depth-first and breadth-first searches are applied.

Expert systems have been applied to boiler feed water systems [127], acetic acid extraction process [128], turbo-generators [129], and refrigeration process of a hydraulic power plant [130]. The drawback in these methods is the difficulty to apply the methods to large scale systems for they require large amount of effort. Often, the design is customized to specific application.

Causal analysis is based on fault-symptom relationships. Signed Directed Graph (SDG) is one approach that uses causal relationships. Symptom-Tree Model (STM) also resides to the same group. SDG has been applied to air-conditioning [131], and de-aerator system of a power plant [132, 133].

Model Based Diagnosis (MBD) that is based on logical statements and relying on detail modelling of the system also belongs to this group.

2.3 Fault Detection and Diagnosis Techniques as Applied to CCP

Conroy et al. [134] used symptom tree approach for fault diagnosis. Shallow knowledge systems and deep level approach was also tested. The case considered was a combined heat and power unit. A monitoring and diagnostic approach based on multiple aspect modelling and model interpretation is described in [135] by considering a cogeneration plant.

In [136], they discussed a real-time fault diagnosis system for a cogeneration plant. They relied on hierarchical fault propagation models to deal with non-interacting multiple faults. The nodes at each level are attached to causal relations describing failure modes between subsystems. The approach includes fault propagation probabilities and fault propagation time-intervals. Their method has resemblance with the works of Conroy [134] and Sztipanovits [135] for they used multiple-aspect modelling approach Hierarchical Process Model (HPM), Hierarchical Component Model (HCM) and Hierarchical Fault Model (HFM) that takes into account the component structure and functional structure of the plant.

Kumamaru, Utsunomiya et al. [137] has carried out fault diagnosis in district heating and cooling plant. Used were cause-effect tree diagrams to find the causes of faults e.g. reduced capability, pressure malfunction etc. and an analytical method for judging the malfunction rate. It handled a system comprised of vapour compression chiller, thermal storage tank and the associated pump network. Interesting part of their work is that dialogue style expert system is employed for fault diagnosis and the technique of adaptive adjustment of the threshold level is applied to realize sensitivity in early detection of operation anomalies. However, with the method being ad-hoc, limited numbers of faults are considered and the case of multiple faults is not considered at all.

Perryman and Perrott [138] and Perryman [139] reported on an intelligent control and monitoring system developed for a stand-alone combined heat and power plant. Artificial neural network is used to describe Normal Operating Conditions (NOCs). A residual calculated between the actual operation data and the NOC model output is used to detect if the performance is going to the unwanted region. In their extended work, they have also used Multilayer Perceptron (MLP) to normalize the operation data before it is feed to the residual calculation block.

Renders et al. [140] investigated the application of Radial Basis Function (RBF) networks to a nuclear power plant. Data from simulation model of the plant is used to train the neural networks. Input variables to the neural network are decided based on first principle concepts and applying such criteria as availability, completeness, minimality and sensitivity of the state variable to faults. Guglielmi et al. [79] tested the effectiveness of using multilayer feed forward and radial basis function networks in the heater section of a power plant. Data generated by a simulated model of the plant was used to train and test the approaches. Leaks in the feed water pipes, malfunction of a draining valve and malfunction of a sensor are the cases considered in their study. Batanov and Cheng [141] developed fault diagnosis expert system for ethylene distillation plant; they used shallow knowledge and deep knowledge of the process. Their work and Convroy et al. [134] work resemble each other as they use qualitative model based approaches (see Sect. 2.2.2).

Bonarini and Sossaroli [142] studied fault diagnosis in a steam-turbine driven plant based on opportunistic models models with different levels of abstraction. Munoz and Sanz-Bobi [143] developed incipient fault detection system based on probabilistic radial basis function approach. They considered condenser of a power plant as a case study. In their work degree of significance of the residual signal is estimated based on the input data adaptive residual calculation. As an optimization tool, they used low-memory quasi-Newton method.

Abu-el-zeet and V.C. Patel [144] developed a data based power plant condition monitoring system using K-means clustering, Euclidian distance calculation and Vector Quantization.

Biagetti and Sciubba [145] depicts a description of an expert system capable of monitoring the performance of a cogeneration plant. They developed performance indicators based on the real-time data. A hybrid semi-quantitative monitoring and diagnostics system for the same system is given in [146]. Though the approaches

are simple both of them consider limited number of faults and the cases of multiple faults are not included.

In a different model based design, Valero, Correas et al. [147] and Lazzaretto and Toffolo [148] have used thermo-economic and exergetic approaches to detect and diagnose faults in a Combined Heat and Power (CHP) plant. The techniques describe operation anomalies in terms of additional irreversibility. Akin to the other methods, though, their approach requires a reference model and actual operation data.

Thomson et al. [149] showed the use of Statistical Quality Control (SQC) to fouling detection in a CHP plant. Their method is designed to work with flow rate measurements as an input. Prediction of heat transfer coefficients by Exponentially Weighted Moving Average (EWMA) method with suitable control charts allowed them to successfully monitor the plant.

Flynn et al. [150] focused on a Combined Cycle Gas Turbine (CCGT) plant and investigated the use of PCA and PLS for fault detection and diagnosis. The two tools are applied for monitoring the system with the PLS extended by incorporating neural networks. The neural network is incorporated to cover nonlinear operating conditions. Structure wise, they applied multi-block approach to effectively handle critical components of the plant. Niu et al. [151] developed a reformative PCA-based fault detection method for a thermal power plant. K-means clustering (for classifying the data under different operating regions) and fuzzy partitions are also used to supplement the method. Odgaard et al. [33] considered power plant coal mills fault blocked inlet pipe. They compared the optimal input observer approach with a data-driven approach based on dynamic PCA and PLS. In the end, they proposed a hybrid model data driven methods used to drive the optimum unknown input observers.

Odgaard and Mataji [152] used optimal unknown input observer approach to detect faults in a coal mill. The linearized model is developed from a nonlinear model of the mill. Hines, Don et al. [153] performed a study on analytical redundancy and neural network based Fault Detection and Isolation (FDI) system for a nuclear power plant. Their work was targeted at solving the problem of formulating a single FDI system covering the whole system and avoiding the problems coming due to coupling problems. Multilayer feed forward neural network with three alternative training algorithms (back-propagation with momentum, conjugate gradient method and Levenburg Marquardt algorithm) were tested.

Korodi and Dragomir [154] developed a mobile fault detection and diagnosis module. The case considered was a Geothermal Power Plant (GPP). Correlations derived from simulation results of the mathematical model for GPP is the reference to formulate the strategies. Their study focused on only on the stationary operating regions.

Fast and Palme [155] recently applied ANN to condition monitoring of CHP plants. While they use the method to capture NOCs, they included the calculation of production cost. According to their work, they have integrated it in a Graphical User Interface (GUI) with the option of linking to the CHP computer system. In fact the addition of GUI put their work to the same level with the work of Abu-el-zeet, Z. H. and V. C. Patel [144], and Arranz et al. [108]. Except the addition of cost calculation and GUI, the method is similar to the work of Szczepaniak [74].

2.4 Summary

The purpose of this chapter has been to explore the FDD technologies as applied to thermal systems in general and to CCP in particular. While considering different techniques in terms of design structure, advantages and drawbacks it was our main objective to reveal clear research directions and possible areas where new contributions could be made. The outcomes are summarized as follows:

In general, a CCP involves integrated operation of auxiliary systems and varieties of signals available for measurement. While there is a need for high fidelity model to investigate how the system responds to different operating conditions, the development of such a model is complicated by availability of limited design point data. In most of state of the art FDD methods, quantitative model-based techniques designed relying on historical data are frequently used. Even then, rigorous treatment of gas-path, lube system, generator coils are hardly available. The same is true with the combined handling of GTG, HRSG and SAC.

Nonlinear relations govern the mechanism of energy exchange in the CCP. While the uses of analytical methods are often ruled out for such systems, we have witnessed few cases where linearization around a certain region is used to formulate representative linear models. As compared to analytical methods, multivariate statistical methods gained wide spread application. Nevertheless, the latter method overlooks serial correlation, which makes it not flexible enough to deal with variable operating conditions. In large scale and dynamic systems, the use of PCA is mostly seen as dimension reduction technique.

The review has also revealed that there is hardly a single method capable of demonstrating all the characteristics needed for designing a successful fault detection and diagnosis system for a CCP. Many of the available approaches tend to apply hybrid techniques. In terms of accommodating nonlinearity of the processes, tolerance against uncertainty caused by disturbances and measurement noise, and ability to represent knowledge in human understandable forms, hybrids of neural networks and fuzzy systems seems to be gaining more attention. However, the use of the hybrid approach in context of multiple auxiliary systems functioning together is not investigated well yet.

Models based on the use of Computational Intelligence (CI) techniques have been found falling in one of the three basic structures, Fig. 2.6. The first method is using either the neural network or the fuzzy system used as a classification tool, Fig. 2.6a. In this case, all the input-output data are feed to the model and fault index delivered as an output. While this method works for simple systems with limited number of output features, it tends to be troublesome as the parameter size increases and if the process is featured by multiple operating conditions. In the second design, the intelligent model is still used as a classifier but the inputs are calculated by another algorithm, Fig. 2.6b. In this case, the numbers of inputs are limited to the number of states being monitored. A good example is the research work by Simani, Fantuzzi et al. [95]. The last approach is to use the intelligent system as modelling technique, Fig. 2.6c. In all the cases, curse of dimensionality seems an issue that is yet to be solved.

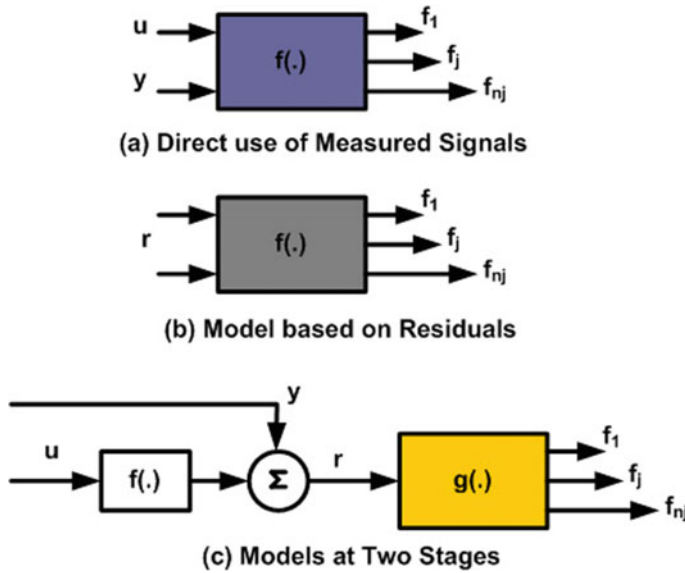


Fig. 2.6 Basic application oriented structures of CI based FDD

In dealing with a power plant featured by multiple operating regions, two approaches have been suggested. One is to develop dedicated neural network based models for each region [97] and the other is developing a neuro-fuzzy model covering the whole region but the result of NF model converted into a number of observers as there are operating regions [120]. Another approach that may go with the afore-said points is reducing the size of a training data using clustering techniques. In this case cluster centres, rather than the real data, are used as an input to the neural network [94].

One important outcome of the literature review is that, in all the models featured by the prediction of current output based on past inputs and past outputs, the model order is decided by minimizing Euclidean norm of the modeling error using optimization algorithms. This, however, while resulting in fairly accurate prediction, may not guarantee model parsimony. Recently, the use of Orthonormal Basis Functions (OBFs) in model predictive control showed that parsimonious models could be developed if the models are constructed in the framework of OBFs. The use of OBF in the design of FDD systems is, therefore, one area that deserves detail study.

Finally, in light of the findings discussed so far, while designing the planned FDD system, we intend to concentrate on the following key areas:

- Dynamic models in the framework of GOBFs, CCP
- Multi-agent based design of the FDD system with a scope that covers main components of the,
- Semi-empirical models for the GTG and HRSG that could be used to generate data under implanted faults,

- Issue of multiple operating conditions, and
- Integrating fuzzy diagnostics procedure with adaptive fault detector.

In the next chapter, the development of nonlinear models using CI techniques is presented.

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