Fault Detection Methods: A Literature Survey

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Abstract - Fault detection plays an important role in high-cost and safety-critical processes. Early detection of process faults can help avoid abnormal event progression. Fault detection can be accomplished through various means. This paper presents the literature survey of major methods and current state of research in the field with a selection of important practical applications.

I. INTRODUCTION

Increasing demands on reliability and safety of technical plants require early detection of process faults. Methods are developed that enable earlier detection of process faults than conventional limit and trend checking based on single process variable. These methods encompass information from not just one process variable but also include nonmeasurable variables as process state, parameters and characteristics quantities, [1,2,3]. Some methods require accurate process models while others rely primarily on available historical process data.

In this brief review paper is outlined introduction to the field with major methods and literature references.

II. BASIC TERMINOLOGY

It is of importance to define terminology of a field: fault, failure and malfunction, types of faults and fault detection.

A. Faults

A fault is an unpermitted deviation of at least one characteristics property (feature) of the system from the acceptable, usual, standard condition [1,2].

B. Failure

A failure is a permanent interruption of a system's ability to perform a require function under specified operating conditions [1].

C. Malfunction

A malfunction is an intermittent irregularity in the fulfillment of a system's desired function, [1].

Development of events "failure" or "malfunction" from a fault is illustrated in Fig. 1, [1].

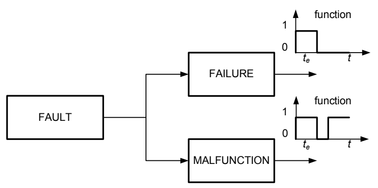

Figure 1. Progression of fault toward failure or malfunction

D. Types of Faults

- Based on the faulty component: actuator faults, plant component faults and sensor faults, Fig. 2, [1,2].

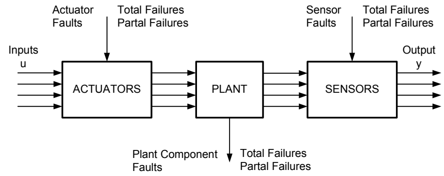

Figure 2. Fault models based on faulty component

- Based on the faulty form: abrupt (stepwise), incipient (drift-like) and intermittent faults (with interrupts), Fig. 3, [1,2].

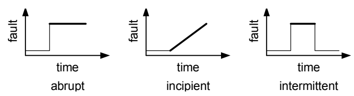

Figure 3. Fault models based on faulty form

- Based on the form in which he fault is added: additive and multiplicative, Fig. 4, [1,2].

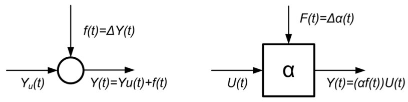

Figure 4. Additive and multiplicative fault models

Additive fault, variable $Y_u(t)$ is changed by addition of fault $f(t)$.

$$Y(t) = Y_u(t) + f(t) \quad (1)$$

Multiplicative fault is given by:

$$Y(t) = (a + f(t))U(t) \quad (2)$$

Additive faults often appear as offsets of sensors, whereas most common multiplicative faults are parameter change within a process, [2].

E. Fault Detection

Fault detection determines the occurrence of fault in the monitored system. It consists of detection of faults in the processes, actuators and sensors by using dependencies between different measurable signals. Related tasks are also fault isolation and fault identification. Fault isolation determines the location and the type of fault whereas fault identification determines the magnitude (size) of the fault. Fault isolation and fault identification are together referred as fault diagnosis, [4]. The task of fault diagnosis consists of the determination of the type of the fault, with as many details as possible such as the fault size, location and time of detection, [1].

III. FAULT DETECTION METHODS

There exist several overlapping taxonomies of the field. Some are more oriented toward control engineering approach, other to mathematical/statistical/AI approach. Interesting divisions are described in [1-12]. The following division of fault detection methods is used in this paper:

A. Data Methods and Signal Models

- Limit checking and trend checking
- Data analysis (PCA)
- Spectrum analysis and parametric models
- Pattern recognition (neural nets)

B. Process Model Based Methods

- Parity equations
- State observers
- Parameter estimation
- Nonlinear models (neural nets)

C. Knowledge Based Methods

- Expert systems
- Fuzzy logic

IV. DATA BASED METHODS AND SIGNAL MODELS

Data based methods exploit only available experimental (historical) data.

A. Limit Checking and Trend Checking

Two limit values, thresholds, are present, a maximal value Y_{max} and a minimal value Y_{min}. A normal state is when

$$Y_{\min} \leq Y(t) \leq Y_{\max} \tag{3}$$

This method can be also applied to first derivative (called trend checking)

$$\dot{Y}_{\min} \leq \dot{Y}(t) \leq \dot{Y}_{\max} \tag{4}$$

Big advantage of limit checking is its simplicity and reliability, however they are able to react after relatively large change of feature [1,2]. The distribution of normal condition (non fault) data is not always Gaussian, in such cases Gaussian Mixture Models can be used, [13].

B. Fault Detection with Principal Component Analysis

Principal component analysis (PCA) uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables called principal components. It is defined by linear transformation matrix $\mathbf{P}_{[m \times r]}$, $r < m$ (its determination requires several matrix calculation steps), which transforms matrix of input data $\mathbf{X}_{[N \times m]}$ in a group of orthogonal data $\mathbf{T}_{[N \times r]}$ (principal component scores),[1].

$$\mathbf{T}_{[N \times r]}=\mathbf{X}_{[N \times m]}\mathbf{P}_{[m \times r]} \tag{5}$$

PCA reduces dimensionality of a data set considering a large number of interrelated variables, while retaining as much as possible of the variation present in a data set. This makes processing and monitoring of large dimensional data possible [1,7,14,15,16]. Fault detection is accomplished by application of change detection on transformed data **T** considering acceptable means μ_j and variances σ^2_j, Fig. 5. The extension of PCA to tackle dynamic systems is suggested in [16].

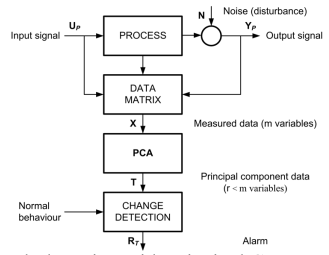

Figure 5. Fault detection with Principal Component Analysis

C. Fault Detection with Signal Models

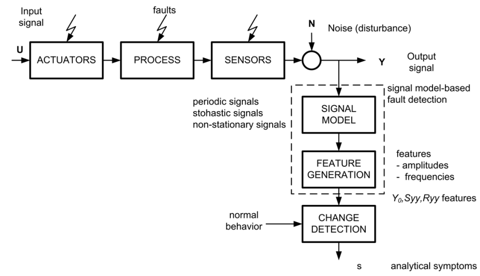

Figure 6. Fault detection with signal models

When changes in signal are related to faults in a process, a signal analysis can be applied [1,2]. By assuming mathematical models for the measured signal, suitable features are calculated (e.g. amplitudes, phases, and spectrum). A comparison with the observed features for normal behavior provides changes of the features that are considered as analytical symptoms, Fig. 6, [2].

- Spectrum Analysis

The extraction of fault-relevant signal characteristics can be restricted to the amplitudes or amplitude densities within a certain bandwidth of the signal. An efficient algorithm Fast Fourier transform (FFT) can be used to calculate frequency content of signal $x(t)$. During normal operation components A_i fall within particular range:

$$x(t) = A_0 + \sum_{i=1}^{N} A_i \sin(\omega_i t + \theta_i) \tag{6}$$

$$A_{i,\min} \leq |A_i| \leq A_{i,\max} \tag{7}$$

- Parametric Signal Models

Parametric signal models like ARMA (autoregressive moving average) can also be used, [1,2]. ARMA(p,q) refers to the model with p autoregressive terms φ_i and q moving average terms θ_i, constant c and error terms ε_t, ε_{t-i}:

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{8}$$

Parametric models are very sensitive to small frequency changes.

D. Pattern Recognition

- Neural Networks

Neural networks have been successfully used for pattern recognition and as such are suitable for fault detection, [1,7,17,18,19,20]. In supervised training input-output pairs, both for normal and faulty conditions, are presented to the network. If not enough faults are available in training data, additional training samples can be produced by artificial fault injection. For supervised training a feedforward network is the most common architecture, Fig. 7, usually trained with some variant of backpropagation algorithm. If unsupervised learning is

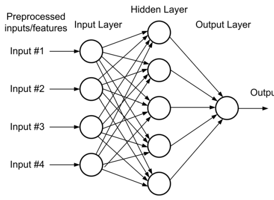

Figure 7. Feedforward neural network

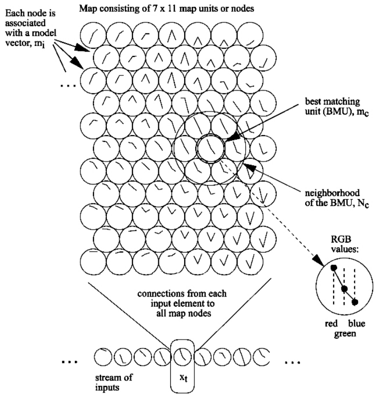

Figure 8. Self-organizing map (SOM), from [17]

required (training data without labeled input-output pairs) Kohonen selforganizing network is a choice, Fig. 8, [17]. The neurons of the competitive net learn to recognize groups of similar input vectors, in such a way that each neuron competes to respond to an input vector $\mathbf{x}_t$, the neuron whose value $\mathbf{m}_c$ is closest to $\mathbf{x}_t$ get the highest net input and therefore wins the competition and outputs one, all other neurons output zero. Non fault and fault conditions are represented as different subsets of neurons within a map, [17,18,19]. Among other statistical classifiers, the common is the k-Nearest Neighbor rule as nonparametric supervised classification method [1, 7].

V. PROCESS MODEL-BASED FAULT DETECTION

Model based methods are based on concept of analytical redundancy, [4,5]. The essence of this concept is the comparison of the actual outputs of the monitored system with the outputs obtained from a (redundant. i.e. not physical) analytical mathematical model, Fig. 9, [1,2,3,4,5,10,12]. It involves two stages: residual generation and residual evaluation.

This approach assumes that that the structure and the parameters of the model are precisely known. Faults can be modeled as state variable changes. Limiting consideration to linear systems, the actual system may be given in continuous time by state equations, (9) and (10):

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) \tag{9}$$

$$\mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) \tag{10}$$

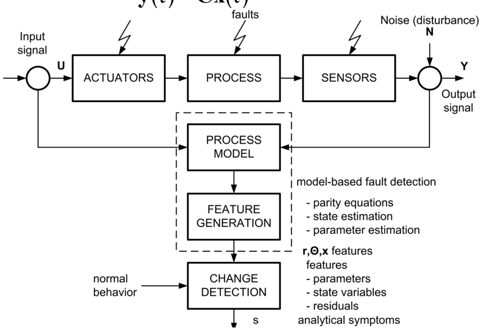

Figure 9. Process model based fault detection

where $\mathbf{A}$, $\mathbf{B}$ and $\mathbf{C}$ are known matrices. Output $\mathbf{y}$(t) is a

$$\mathbf{y}(t) = f(\mathbf{u}(t), \omega(t), \mathbf{x}(t), \theta(t)) \tag{11}$$

function, (11), where $\mathbf{u}$(t) denotes measurable outputs and inputs, $\mathbf{x}$(t) and $\boldsymbol{\omega}$(t) represent (mostly unmesurable) state variables and disturbances, and $\boldsymbol{\theta}$ are the process parameters. Process faults cause changes in state variables and model parameters. Based on a process model one can estimate $\mathbf{x}$(t) or $\boldsymbol{\theta}$(t) by observed $\mathbf{y}$(t) and $\mathbf{u}$(t). Residual evaluation is accomplished by threshold logic and decision function. Beside fixed thresholds, advanced robust adaptive residual evaluators exist, [22].

A. Fault Detection with Parity Equations

This method compares the process behavior with a process model describing nominal, i.e. non-faulty behavior. The key idea is to check the parity (consistency), [12], of the mathematical equations of the system (analytical redundancy relations) by using the actual measurements. The difference of signals between the process and model is expressed by residuals, Fig. 10.

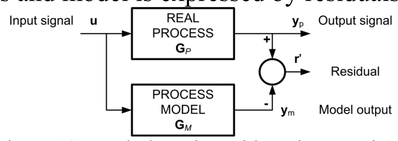

Figure 10. Fault detection with parity equations

The process is described by transfer function $G_p(s)$ and the process model by $G_m(s)$, [2]. A straightforward model-based method is to take fixed model G_M and run it in parallel to the process, thereby forming an output error

$$r'(s) = [G_p(s) - G_M(s)]u(s) \tag{12}$$

B. Fault Detection with State Observers and State Estimation

Changes in the input/output behavior of a process lead to changes of the output error and state variables [1,2]. The basic idea of the observer approach is to reconstruct the outputs of the system from the measurements with the aid of observers using the estimation error, or innovation, as residual for the detection of the fault, [12].

a) State observers

State observer can be applied if the faults can be modeled as state variable changes Δx_i. The configuration of linear full order state estimator is shown in Fig. 11, [2]. It consists of a parallel model of a process, (13), (14), with the feedback (matrix $\mathbf{H}$) of the estimation error $\mathbf{e}$, [12].

$$\dot{\hat{\mathbf{x}}}(t) = \mathbf{A}\hat{\mathbf{x}}(t)\mathbf{B}\mathbf{u}(t) + \mathbf{H}\mathbf{e}(t) \tag{13}$$

$$\hat{\mathbf{y}} = \mathbf{C}\hat{\mathbf{x}} \tag{14}$$

$$\mathbf{e}(t) = \mathbf{y}(t) - \mathbf{C}\hat{\mathbf{x}}(t) \tag{15}$$

$$\mathbf{r}(t) = \mathbf{W}\mathbf{e}(t) \tag{16}$$

$\mathbf{e}$ from (15), is used for calculation of the residual, $\mathbf{r}$, (16), for the purpose of fault detection (eg. by threshold logic).

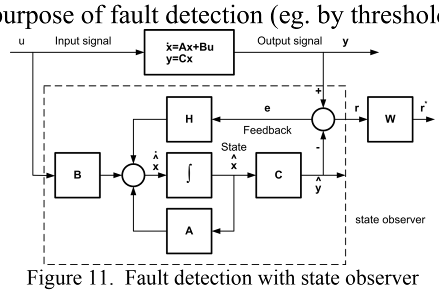

Figure 11. Fault detection with state observer

b) Output observers

The task of state observers is to reconstruct the states of a process. However, there is generally no such need for diagnostic purpose. It is possible to use output observers if the reconstruction of the state vector **x**(t) is not of interest. A linear transformation with matrix $\mathbf{T}_1$ leads to new state vector ξ(t), [2]. Output observers reconstruct the outputs in order to create redundancy, Fig. 12, [2].

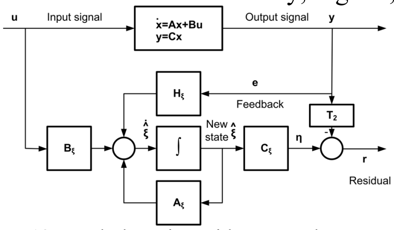

Figure 12. Fault detection with output observer

Observer equations now change to:

$$\dot{\hat{\xi}}(t) = \mathbf{A}_\xi \hat{\xi}(t) + \mathbf{B}_\xi \mathbf{u}(t) + \mathbf{H}_\xi \mathbf{y}(t) \quad (17)$$

$$\eta(t) = \mathbf{C}_\xi \hat{\xi}(t) \quad (18)$$

$$\xi(t) = \mathbf{T}_1 \mathbf{x}(t) \quad (19)$$

$$\mathbf{r}(t) = \mathbf{C}_\xi \xi(t) - \mathbf{T}_2 \mathbf{y}(t) \quad (20)$$

$$\mathbf{C}_\xi \mathbf{T}_1 - \mathbf{T}_2 \mathbf{C} = 0 \quad (21)$$

Parity equations method and state observers have similar equations, but differ in filtering of a residual.

C. Fault Detection with Parameter Estimation

In most practical cases the process parameters are partially not known or not known at all. They can be determined with parameter estimation methods by measuring the input and output signal if the basic model structure is known. Faults of a dynamical system are reflected in physical parameters (friction, mass, resistance, capacitance, inductance etc.). The idea of the parameter identification approach, Fig. 13, [1,2,3,5,12] is to detect the faults via estimation of the parameters of the mathematical model due to following procedure, [12]:

1. Choice of parametric model of a system
2. Determination of relationship between the model parameters θ_i and physical parameters p_i
$$\theta = f(\mathbf{p}) \quad (22)$$
3. Identification of model parameter vector **θ** using the input **u** and output **y** of the actual system
4. Determination of physical parameter vector **p**
$$\mathbf{p} = f^{-1}(\theta) \quad (23)$$
5. Calculation of vector deviations, $\Delta\mathbf{p}$, from its nominal value taken from the nominal model
6. Decision on a fault by exploiting the relationships between faults and changes in the physical parameters, Δp_i

The symptoms are deviations of the process parameters.

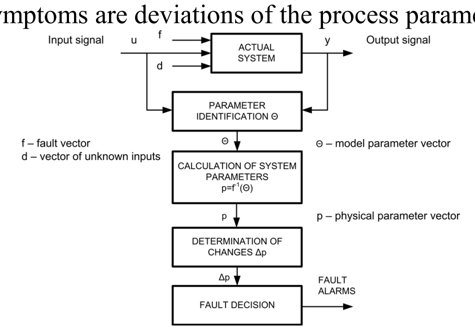

Figure 13. Fault detection with parameter estimation

D. Nonlinear Models and Neural Networks

Many industrial processes are not suitable to conventional modeling approaches due to the lack of precise, formal knowledge about the system and strongly nonlinear behavior. In cases when mathematical process models G_P are not available, a nonlinear model can be employed to generate residuals, Fig. 14. One way to build a nonlinear model G_{NM} is to use neural networks [1]. Neural networks do not require specific knowledge of process structure. They can serve as black-box models of general nonlinear, multivariable static and dynamic systems.

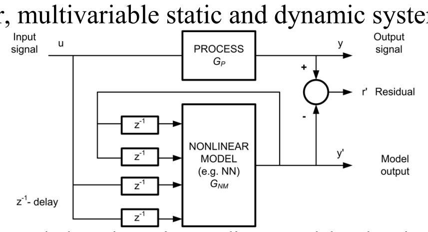

Figure 14. Fault detection using nonlinear model and parity equations

Neural networks contain many parameters, but these parameters are generally not suitable for physical interpretation of the modeled system. However, once the process modeling is completed, fault detection with parity equations can be implemented.

$$r'(s) = [G_P(s) - G_{NM}(s)]u(s) \quad (24)$$

Use of neural network for model based fault detection with parity equations is described in [23].

Neural networks for pattern recognition can also be combined with various process models and used for residual evaluation (often after some residual preprocessing), [18].

E. Fault Detection of Control Loops

Control systems must include automatic supervision of closed-loop operation to detect malfunctions as early as possible. For larger plants with hundreds of control loops it is practical to have automatic fault detection for control loops. Control loop faults lead to oscillations; hence automatic detection of different kinds of oscillations is of importance. Methods are signal based (variance), detection of oscillations and model based, [1].

VI. Knowledge Based Methods

In recent time there is a trend towards knowledge based and artificial intelligence methods [6,7,24,25,26].

A. Expert Systems

Rule-based expert systems have a wide range of applications for diagnostic tasks where expertise and experience are available, but deep understanding of the physical properties of the system is either unavailable or too costly to obtain. This approach offers efficiency for quasi-static systems operating within fixed set of rules. Main components of this approach are knowledge base and inference engine, Fig. 15. Knowledge is represented in form of production rules. Knowledge acquisition is always considered as one of the biggest difficulties in designing an expert system. The main knowledge source is the experience of domain specialists, including the experienced engineers and operators of industrial plant. Main advantages of expert system are following: rules can

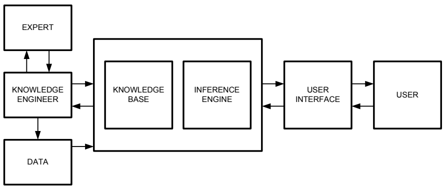

Figure 15. Main components of expert system approach

be added or removed easily, explanation of the reasoning process, induction and deduction process is easy. Disadvantages are: lack of generality, poor handling of novel situations, inability to represent time-varying phenomena, inability to learn from their errors and development and maintenance is costly, [25].

B. Fuzzy Logic

The output of fault detection system needs not to be an alarm that takes two values, fault or no fault. Instead of simple binary decision fault/no-fault, fault severity of the system is provided to operators as the output of fuzzy controller. A linguistically interpretable rule-based model is formed based on the available expert knowledge and measured data, [1,26,27]. Block diagram of fuzzy logic controller is shown in Fig. 16, [26].

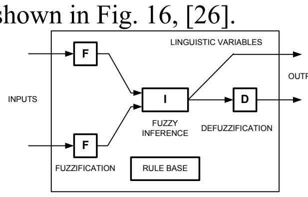

Figure 16. Fuzzy logic controller

Fuzzy inference process involves following steps:

- Fuzzification

Inputs to a controller pass through the fuzzification process using membership functions. The membership function is a graphical representation of the magnitude of participation of each input. The shape of some membership functions is shown in Fig. 17.

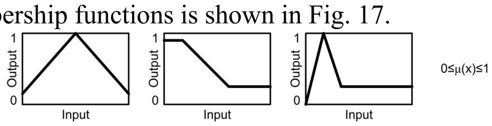

Figure 17. Examples of membership functions

- Rule Based Inference

All rules are evaluated in parallel using fuzzy reasoning. The process of fuzzy inference use membership functions, logical operations and if-then rules, Fig. 18.

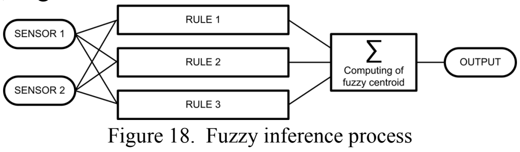

Figure 18. Fuzzy inference process

- Defuzzification

Converting the fuzzy information to crisp is known as defuzzification. It is accomplished by combining the results of the inference process and computing the "fuzzy centroid" of the area, x^* is defuzzified value, $\mu_i(x)$ is the aggregated membership function, x is the output variable:

$$x^* = \frac{\int \mu_i(x) x dx}{\int \mu_i(x) dx} \tag{25}$$

Fault detection of hydraulic plant using combination of nonlinear observer and fuzzy logic is given in [27].

VII. APPLICATIONS

Until early 1990s most research and development in fault detection was limited to nuclear power plants, aircraft, process plants, the automobile industry and national defense. Today fault detection is established in many industries. Major categories of applications are, [1]:

A. Machines and Engines

Signal analysis technique for internal combustion engine using ANN is given in [28], engine cylinder fault detection in [29], marine diesel engine monitoring in [30].

B. Electrical Motors

Electrical motor fault detection is described in [31] and fault detection of induction motors in [32].

C. Pumps

Fault detection for centrifugal pumps combining neural networks and neuro-fuzzy approach, is described in [33].

D. Steam turbines

Fault detection for steam turbine is described in [34]

E. Manufacturing

Fault detection is an essential part in automated electronics manufacturing systems, particularly in semiconductor manufacturing, [35]. Reliable detection of faults is an important for maximization of productivity.

F. Bearings and Machinery

Fault detection in hydraulic system is given in [27], use of neural nets in rotating mechanical systems in [20].

G. Aircraft

Fault detection systems have great application in a field of flight critical aero engine control systems, [36], in order to achieve high degree of reliability. Fault detection of flight critical systems is described in [37]. Solution to fault detection of aircraft fuel system is given in [38].

H. Automotive Systems

Model-based fault detection is adding functionality to existing engine electronic control unit of internal combustion engine. Fault detection for the injection, combustion and engine-transmission is described in [39]. Fault detection of faulty components in railway suspension is described in [40].

I. HVAC (Heating, Ventilation, Air Conditioning)

Review of methods for HVAC&R is in [8,9]. Fault detection system for HVAC Systems is described in [41].

J. Chemical Processes

The performance of chemical processes degrades due to deterioration of process equipment and components. An application to wastewater plant is given in [15], fatty acid fractionation [21], esterification in [42] and refinery in [43].

VIII. CONCLUSION

Early fault detection can minimize plat downtime, extended equipment life, increase the safety and reduce manufacturing costs. Number of issues must be considered when choosing particular fault detection method. Most important are: type of failures, description of process structure, process dynamics, available process signals, process complexity, available amount of process input-output data and process suitability for description in terms of rules. Simplest approach is direct limit checking of measurable variable. Large scale processes (e.g. chemical plants) can benefit from multivariate statistical analysis, particularly PCA. Some processes generate periodic or stochastic signals that can be used for fault detection if changes in signal models are caused by process faults. When large amount of process input-output data can be obtained, but process structure is unknown or too complex to be modeled, pattern recognition methods (neural nets and k-NN) can be used. Process model based fault detection includes process dynamics and nonmeasurable state variables, but requires accurate models and is easier to apply for well defined processes such as electrical and mechanical then for thermal and chemical processes. If basic relationship between faults and symptoms is known in form of rules knowledge based methods are the choice.

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