Fault Diagnosis Methods in Dynamic Systems: A Review

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Abstract—**This paper reviews the contemporary approaches adopted for the diagnosis of faults in dynamic systems. It also takes into account the limitations of the age-old techniques like limit checking. The model-based methods of parameter estimation, parity space and other such approaches are discussed. The earlier methods, employed the age-old technique of monitoring the process variables like temperature, pressure, etc. and generated alarms. Generally, such an observation is possible only when the process has progressed in an advanced stage. This paper reviews the basic concepts starting from its infancy onto the mature facets involved in fault diagnosis.**

Index Terms—**fault diagnosis, fault types, FDI system, observers, parity relations, residuals, redundancy, supervision**

I. Introduction

Present day industrial processes require sophisticated and complex arrangement of different types of controllers, actuators, sensors along with other safety equipment. This is done, largely, to account for the offset of parameter variations and disturbances, occurring therein. Although, the controllers are well capable of balancing many of the differences, they are inefficient, when it comes to nullifying the after-effects, brought about in the system. The faults, affecting the system, may manifest in one the following forms: problems associated with actuator, variations in process parameters, disturbances at various ends in a system and measurements recorded through the sensor. A fault can be described as any kind of malfunction in the actual dynamic system.

Whereas fault detection helps to recognize that a fault has happened, fault diagnosis facilitates finding the cause, nature and location of fault. Early detection and diagnosis of faults present in the plants can minimize the downtime, render the plant safer, and thus result in economic operation by bringing down the production cost [1]-[3].

This paper gives a bird's eye view of the different developments made so far in the field of fault diagnosis. It discusses the different techniques employed for the diagnosis of faults occurring in the system. At the outset, there is a brief description of the rationale behind the study of fault diagnosis. Subsequent sections deal with the different areas of fault diagnosis. The conclusion gives a formal summary of the finer points discussed. The paper winds up with the citations enlisted in the reference section.

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II. Fault Diagnosis System

A system that combines the capabilities of detection, isolation and identification or classification of faults is termed as a fault diagnosis system.

All real-world systems exhibit a common adverse attribute - they are susceptible to faults, malfunctions at some point of time during the operation and therefore, depict abrupt modes of behaviour. This rationally justifies the need of reliable and continuous monitoring systems that employ effective fault-management of fault-diagnosis strategies. This explains the important role that fault diagnosis plays in the operation of effective and efficient control systems. The Fig. 1 on the next page depicts the different stages of fault diagnosis [4]-[6].

III. Fault Classification

Faults can be classified on the basis of location (within the plant) and on the basis of their individual behaviour.

A. Based on Location

Actuator faults: These faults represent the partial or total loss of the system function. Alternatively, these can be observed as any fault in the system that actuates the system e.g. a malfunction of the pneumatic system in a plant. In a plant, actuator represents the final control element that gets activated, due to a malfunction and can drive the whole system into a state of fault [1].

Component/Process faults: These faults are said to occur when some changes brought about in the system force it to an invalid dynamic relation between its different physical variables [1].

Sensor faults: These can be visualized as some serious variations in the measurements made in the system and appear in the form of discrepancies between the actual and measured values of process variables [1], [7].

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B. Based on Behaviour

Abrupt fault: This fault occurs due to sudden change in the values of variables. Generally, a variable value remains constant throughout the operation of the plant. But on the occurrence of fault, this value suddenly assumes a new magnitude. Consequently, the system state is modified.

Incipient fault: This fault varies gradually and slowly develops to an enormously large value. If a component is slowing degrading in operation, this can be observed as an incipient fault.

Intermittent fault: A fault is intermittent if fault occurs and then suddenly disappears and this process continues to happen in a repeated manner, over a period of time. [6].

For maintaining healthy system operation, it becomes necessary to isolate the fault as early as possible.

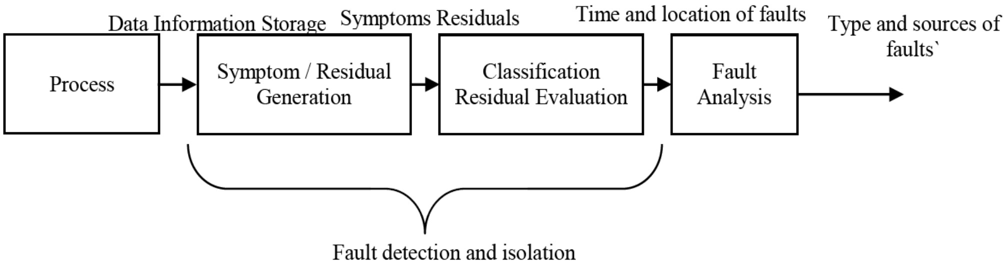

Figure 1. Fault diagnosis procedure

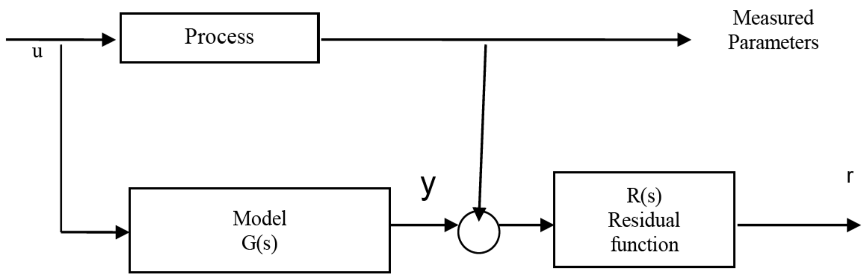

Figure 2. Fault isolation method

IV. Fault Isolation

Fault isolation comes into effect after the fault is detected in the system with the motive of finding the type and location of the fault. In case, where there are different fault modes, fault isolation implies the decision making process, associated with choosing, under which fault mode the process is being driven. Fault isolation is established by careful comparison of non-zero residuals with pre-computed fault vectors. For fault to be isolated from the system residuals generated in system should be fault-sensitive and they should respond differently depending on the type of fault. In other words, they should be endowed with the capability of distinguishing among different kinds of faults. The Fig. 2 above shows the means to accomplish isolation of faults. Following two methodologies are used for fault isolation:

1) Directional Residual Method: Here residual vectors are generated along a specific direction in the residual space according to a particular fault kind. Here the problem of fault isolation is re-shaped into a problem of establishing the direction of residual vector.
2) Structured Residual Method: Here the vectored residuals are characterized such that they are sensitive to a single fault or to a class of similar faults for which the residuals observed are in closer proximity and unresponsive to others. Any two faults having nearly same fault behaviour may not be isolated from each other. Every fault isolation approach should take into account and properly weigh all the permutations and combinations of the different errors before arriving at a definitive conclusion. [9]-[16].

V. Fault Detection Methods

Through fault detection significant data is derived in the form of signal values from fault, process, and signal models, based on the different methods that can be invariably be applied on a plant undergoing varied processes. Combining a judicious mix of fault detection methods, the undue abrupt rise of signal values can be detected and subsequently the anomalies can then be worked upon [17]-[19].

A. Parity Space Method

This model-based approach relies on a test that is conducted to verify the consistency of the parity equations which are system equations modified using the measured signals of the given process. This is done in order to facilitate the decoupling of the residuals from the system as well as faults so that they could be easily distinguished from each other. The inconsistency arising in the parity equations gives rise to residuals that further helps to sense the faults to which the residuals observed are in closer proximity [20].

Fig. 3 depicts the generation of residual function R(s) after comparison of measured parameters of the process with that of the model G(s).

This method checks the deviations arising between the governing equations of the system and the model [21]-[23].

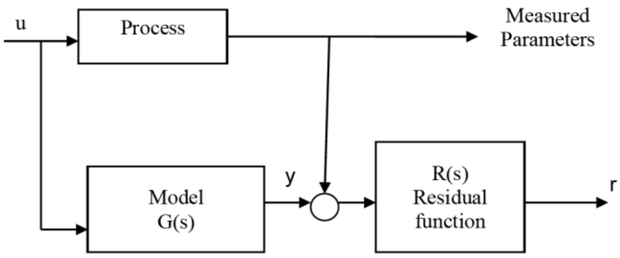

Figure 3. Parity space method

B. Generation of Residuals

The value of these residuals is generally zero under no-fault conditions. They attain non-zero values only under the effect of noise and model errors. In case, the faults are found in the system, the residuals attain high values. This necessitates the making of thresholds and requires that residuals be tested against them. The Fig. 4 below shows the process being subjected to inputs, faults and disturbances (unknown inputs), where model is acted upon by the inputs, which could be different set of process variables. The process outputs are then evaluated against the model outputs, to obtain residuals [24]-[26], [19], [27].

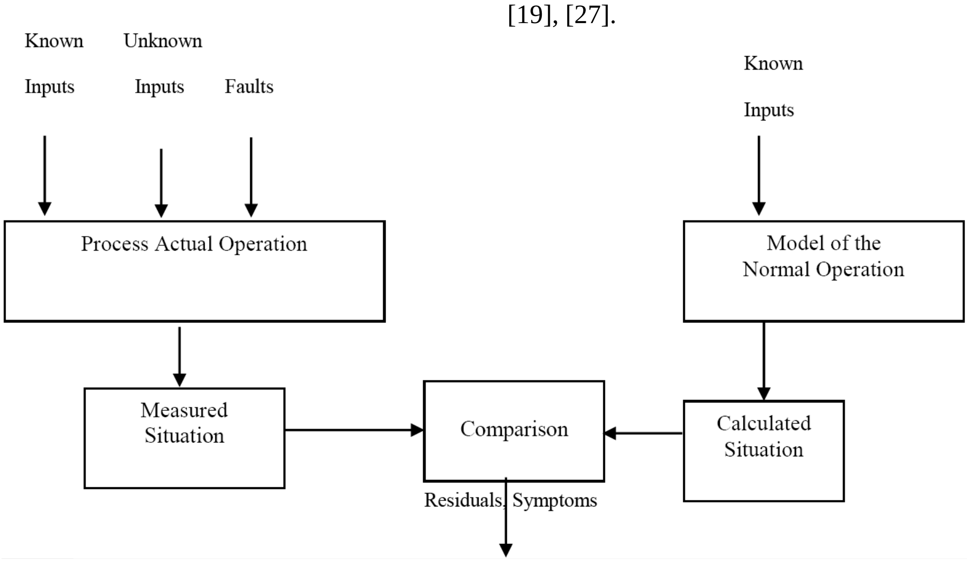

Figure 4. Process subjected to inputs, faults and disturbances (P. M. Frank. 1996)

C. State Observers

This approach tries to restructure the system using the system output and input signals, with the help of observers. The difference between parameters measured from the system and those estimated serve as residual vector. This method of residual generation relies on restructuring the system outputs using observers or Kalman filters. A diagnostic observer in the form of output observer can be designed in the frequency domain, which does not need the application of state-space theory. The objective behind the design of such observers for residual generation is that modified residuals or directed vectors in such a manner that each fault assumes a different direction. This aids in decoupling of each fault. Each observer is made robust to the effect of unknown inputs (read fault) and is capable of handling efficiently a particular type (of fault). These observers are sensitive enough to react differently to each fault [28], [20].

D. Algebraic Observers

Fault diagnosis approaches have been employed for the solution of non-linear systems. These are generally based on differential geometric methods and usually involve observation of fault dynamics, often referred to as the uncertain inputs. The fault diagnosis problem is therefore an observation problem and the procedure rests its foundation on algebra. The observers can be constructed and implemented using principles of differential algebra. For the construction of an observer, based on fault diagnosis, a function is defined. This function comprises of the fault, description of which is given in terms of states, other known faults and inputs, as well as certain extra states that are unknown [29]-[31].

E. Limit Checking

This is a traditional method involving the measurement of output variable. This method tries to put a ceiling on the values of output variables to ensure that these lie within preset limits, known as thresholds. There are two maximum and minimum values, between the ranges of which, the output is expected to remain for the healthy flow of process. For monitoring the process trend, the derivatives of the change in output with respect to a suitable variable, generally chosen as time, are checked for limits. For early fault detection, signal prediction is done using polynomial regression and least square methods. This aids in early detection of threshold crossing and prevents the generation of false alarms. This classical limit-value method is helpful in the detection process only when the change in the process variable is significantly large. This generally happens either in case of large sudden fault or continuous gradual-increasing fault. A serious problem imposed by this method is the concurrent triggering of alarms, resulting in utter confusion related to the cause of the fault [6].

F. State Estimation

The process of state estimation involves either giving class labels or drawing real-valued description in terms of parameters, for time or space-varying processes. The states estimated from the system are then evaluated against those obtained from the model, to finally generate the residuals [32], [33].

G. Adaptive Filtering Technique

This technique is applicable to discrete-time linear stochastic systems and takes into account the abrupt jumps in the values of state variables that are used to model the system behaviour. The proposed system comprises of a Kalman-Bucy filter, capable of sensing a jump in the state variables and based on generalized likelihood ratio (GLR) hypothesis testing. This filter can adjust to jump detections in the following three ways: (i) the value of state estimates can be increased using parameter estimates, (ii) covariance of the estimation error can also be increased using GLR testing data and adjust the Kalman filter to adjust to the new position of jump, and (iii) both error covariance and estimates can be used for adjusting the value of the Kalman-Bucy filter. This method is found to be useful in the failure detection applications [3], [34].

H. Parameter Estimation

This method assumes that the faults manifest themselves in the form of physical parameters such as resistance, capacitance, inductance, friction, mass, damping force etc. These parameters are concurrently being monitored, estimated on-line by employing different estimation methods and subsequently the results are matched with parameters of the fault-free reference model. Any inconsistency or mismatch is indicative of process change and hence a fault is said to be occurred. The procedure for process estimation involves estimating the mathematical parameters and their subsequent transformation into the physical parameters. An edge over its counterparts, it produces the amount of deviation from the normal or fault-free conditions. Its limitation lies in constant updations of parameters for calculation of estimates [5], [6], [18], [34]. It is supposed to be one of the most powerful ways of implementing the FDI approach. The following steps need to be taken for working with this method:

1. Define the linear system by a regression-based input-output equation.
2. Detect faults in the system by correspondingly measuring the inputs and outputs.
3. Estimate the parameters of system model based on the above.
4. Model fault as additive term in the in the parameter vector.
5. On-line estimation can then be done using popular recursive algorithms.
6. The parameters of the model should co-relate with the system parameters, otherwise it’s intricate to strike a difference between fault and variation of model parameter [35]. The error ensuing as difference between the process output and model output can further be employed as a substitute for estimating the faults in the system. The idea fundamental to this method is obtaining of estimates of input/output or any other quantifiable signals [36]-[38].

I. Auxiliary Signal Fault Detection

Recently, a new definition of ‘active’ systems has emerged, which is different from the conventionally used term ‘active’ that implies those taking action for accommodating the faults in a system. Such systems are in close interaction with the system by making use of a test signal, which helps to unravel the abnormal performance of the system. For excitation, a test signal, called auxiliary signal, is injected into the system, either at repeated intervals or when safety of the system seems to be critical [1].

VI. Fault Detection Tools

There are different methods using which the fault detection strategies can be implemented. Of these, some employ mathematical procedures while rely on modelling and subsequent programming [39]-[42]. These are discussed in the subsequent sub-sections:

A. Soft Computing Approaches to Fault Detection

Going by the trends of available different fault detection methods, it has been observed that development of automatic supervision can take place if it is possible to detect the fault early in the process. Certain fault detection methods alarm the system against a fault when it has progressed in an advanced state. This necessitates going for new methods of predicting and striking a balance for faults. At this juncture, there is a need of a possibly combining the modelling-based mathematical procedures with the artificial intelligence techniques. The following methods are in vogue, and in tune with the present times.

1) Neural Networks
2) Fuzzy Logic
3) Fuzzy-Neural Networks [6]

B. Principal Component Analysis (PCA)

This approach can be applied on matrices containing raw data. This raw data can be further analyzed to evaluate the importance of individual variables. This technique facilitates the transformation of original variables into sequence of new variables, having a definitive order. The variables thus generated, called the new variables, are termed as ‘principal components’ and can be approximated using the eigenvectors of the covariance matrix drawn from the original variables. This is a multivariable statistical method, employed for the fault detection. It helps to compress large sets of variables and deduce features of a dynamic system. It assumes linearity in the system. Its application is easy and it generates certain non-linear features from the observations, taken from the system. This approach is used in wide applications varying from face recognition, data compression, image analysis, visualization apart from fault detection [29], [32], [43], [44].

C. *Monte Carlo Simulation*

This approach derives its name from a term coined by S. Ulam and Nicholas Metropolis with regard to a famous game of attraction in the place of Monte Carlo in Monaco. These methods, also known as particle filters, when applied, can prove to be very effective. This method relies on the use of random numbers and probabilistic distributions for the solution of a wide array of problems. The approximation is done in a recursive manner with the help of probabilistic distributions of the system states using random measures consisting of particles and weights. This method is known as particle filtering as the different distributions are approximated using a properly weighed particles. Each such particle represents a system moving through a trajectory in the state space. The weight pertains to the probability of the trajectory with regard to the measured data. Monte Carlo methods have the capable of giving accurate probabilistic error descriptions for finite length of identification data. Due to its widespread use, it has become an accepted numerical method that can deal in some of the most intriguing problems of today [39], [45], [46].

D. *Intelligent Supervisory Systems*

The growing complexity among present-day process plants and ever-increasing demands of quality, cost-effectiveness, reliability, stability and system safety are some of the critical issues that have led to the emergence of intelligent supervisory systems (ISS). Such systems incorporate the features of control engineering and artificial intelligence techniques. The ISS systems shall have the capability of achieving intelligent objectives in the presence of uncertainties, disturbances and fault conditions, thus obviating the need of human intervention. [47]-[49].

VII. Approaches to Fault Diagnosis

In the fault diagnosis parlance, the methods of application could be categorized into two parts: model-based and model-free. These methods help to make a correct estimate of the diagnosis of the system. The diagnosis approach assesses the current system condition after taking into account of symptoms and observations of the system. This methodology helps predict the remaining working life of a system [42].

A. *Model-Free Methods*

These methods do not rely on general mathematical procedures adopted to develop the system model. Model-free methods need signal-based information, obtained from conduction experiments on the system itself. The range of such methods is from physical redundancy, use of sensors for limit checking, to spectrum analysis and logical reasoning [35], [50].

B. *Model-Based Methods*

These methods rely heavily on the rigorous mathematical techniques for developing the system model. The basis of fault detection methods lies in the use of redundancy relations among the process variables. The robustness of any fault detection methodology is, therefore, dependent on the reliability of redundancy relations [51]. The need for enhancement in the reliable and safe operation of the plant necessitates the advancement in the methods of fault detection and diagnosis. As a consequence, these have become an important and almost indispensable for the development of fail-safe systems like aircrafts, trains, automobiles and industrial plants. The classical methods lacked foresight and hence gave birth to the development of model-based methods of parameter estimation, parity equations or state observers. The fault models tend to identify the faulty modes of operation of the components of the system [7]. The system diagnosis done using model-based approach suffers from being sensitive to errors in the process model. These errors can arise from simple model structure, process variations, noise and possible irregularities in the plant model [52]-[54].

VIII. Problems with Fault Detection and Diagnosis

There are different bottlenecks experienced during the application of fault diagnosis to practical arena [6].

1) Necessity of Prior Knowledge: In some cases, some prior knowledge may be present, while in others it may be necessary to obtain the quantitative relationships between the physical variables defining the process. These can then be formulated in terms of model. In certain situations, it becomes imperative to formulate a functional relationship between the physical and model parameters. Any prior information about the occurrence of faults can prove to be helpful in defining the structure of the system.

2) Depiction of Knowledge: The kind of diagnosis method dictates the type of knowledge one can represent:

(i) Analytic: This can be gained through the study of the physical law or from measurements taken from the model, or by observation. This acts as an input for the developing fault-symptom relation or building rule-based inference methods.

(ii) Heuristic: Such knowledge is implicit, in the sense, that it cannot be stated directly as the analytic knowledge. It has to be gained through trial-and-error approach. It is generally acquired, after long years of experience of working on a particular system. The actual behaviour of a system, how shall it respond in a particular condition, is one phenomenon that cannot be known in a single day. Such knowledge is difficult to embed in a system. But, if present, can prove to beneficial for the system, as a whole.

3) Statistical Distributed Nature of Symptoms: In case, experimental data is made use of, in developing a system, then that data may follow a defined statistical pattern. This needs to be considered carefully. The symptoms in such a system can stem from:

(i) Variations in model parameter estimated

(ii) Digression of measured parameters from normal [6]

The system must be able to withstand the presence of faults, for coping with malfunctions that occur for short periods of time. The systems with such a property are termed as fault-tolerant systems.

IX. Conclusion

The study of different fault diagnosis methods points towards the paradigm shift from the traditional signal-based methods to the more precise model-based methods that employ the analytical-based methods. An effort is made to develop a unified theory from amongst the various methodologies that have been outgrown so far since the past four decades. Owing to extensive research ongoing in this field, it is not possible provide a comprehensive representation of every minute facet in the field of fault diagnosis.

This paper attempts to discuss the different approaches adopted so far in the field of fault diagnosis. But the treatment is not exhaustive, rather it is extensive. This is so because from the perspective of fault diagnosis, various techniques have been discussed. The different methodologies presented in this paper reflect the type and depth of research done so far in this field.

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