Volume 1, 2025, Pages 129-139 *Journal of Computer and Communication Networks*
| Regular Article | Open Access

Integrating Model and Signal Based Methods for Efficient Fault Diagnosis

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Article Info
Journal of Computer and Communication Networks
https://www.ansispublications.com/journals/jccn/jccn.html

https://doi.org/10.64026/JCCN/2025013

Received 02 March 2025
Revised from 30 April 2025
Accepted 25 May 2025
Available online 30 June 2025
Published by Ansis Publications

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Abstract – Fault diagnosis is a well-defined process that involves identification and isolation of abnormalities, or defects within a system. The system can work at its best in terms of speed and reliability by providing prompt identification and correction of the errors. It involves systematically identifying the abnormalities in the expected behavior and analyzing their root causes so that effective management and rectification can be made. These diagnostic processes are described in this article, and they range from traditional hardware redundancy to the current signal-based and model-based diagnostics. Diagnostics is one of the critical activities of the system maintenance process that involves identification, localization, and analysis of the defects, which enables the provision of the structure with reliability and efficiency. The paper categorizes fault diagnosis methodologies into hardware redundancy, signal processing and model-based approach and provides clear description of what they entail and how they are used. Notably, it stresses the use of model-based method, which is a software-based process model that eliminates the need for hardware duplication. This technique examines the critical parts, such as residual generation and observer-based fault detection. In addition, the research focuses on the probabilistic and deterministic techniques and signal-based approaches with the aim of detecting faults. These methods include those that address the strategies, which analyze the indicators in the domains of time, and time thresholds.

Keywords – Fault Diagnosis, Signal-Based Fault-Diagnosis Methods, Signal Processing-Based Fault Diagnosis, Model-Based Fault Diagnosis Methods, Hardware Redundancy-Based Fault Diagnosis.

I. INTRODUCTION

The primary aim of fault diagnosis is to determine, isolate, and detect the faults in the system including the identification of the occurrence and time of the faults and their position. It is a method of managing errors with reference to the analysis of test results, knowledge of faults and symptoms of error. Fault diagnosis is categorized into two types namely the analytical model-based and the data-based diagnostic techniques [1]. Analytical model-based techniques often build residual signals using observable input and output signal processing together with precise mathematical frameworks of the structure. In fault diagnostic, the residual signal may serve as a reflection of differences among the actual and expected states of the structure. A precise mathematical framework of the structure under diagnosis is essential to the effectiveness of analytical model-based techniques. It is challenging to create a precise mathematical model of a system, particularly for complex systems. The model-based approach is no longer relevant in this situation. However, as information technology has advanced, a lot more system operating data is now able to be recorded and examined, leading to the development of data-based problem diagnostic techniques. Artificial intelligence models [2] are used in data-based approaches to analyze system operation process data, enabling problem detection to be performed without the need to know the exact analytical model of the system.

Fig. 1 illustrates a generic framework for model-based fault diagnostics. Typically, fault diagnosis is accomplished by a two-step procedure. Initially, a signal known as residual is created by using the existing input-output data obtained from the system being analyzed. When the system is functioning without any faults, the residual should ideally be zero or very near to zero. Conversely, when a problem is available, the residual should be dissimilar from zero. The residual may either be a scalar indicator that carries data about a single defect or a vector signal that carries data about numerous failures. The residual generator might range from a systematic mathematical framework to a black-box framework of the structure. In the decision-making process, the residuals are analyzed to determine the probability of defects. The decision-making method might range from a basic threshold to more advanced statistical techniques.

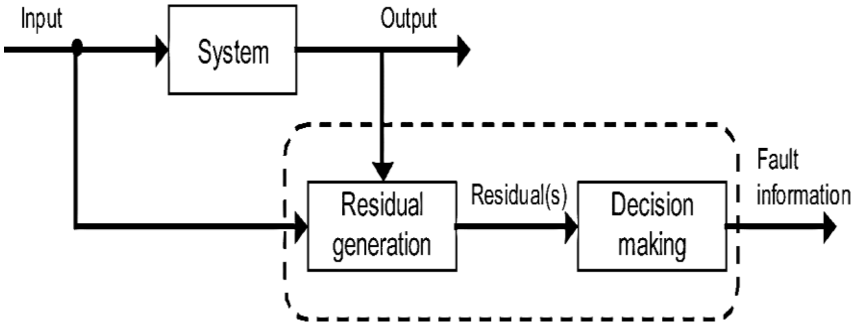

Fig 1. Overall Framework of Model-Based Fault Diagnosis.

Presently, the use of artificial intelligence technology, namely intelligent fault detection, in essential equipment to support advanced intelligent maintenance is more encouraging. An intelligent maintenance system anticipates and averts possible machine failure by using sophisticated data analysis and decision-making tools or algorithms. Intelligent maintenance might be designed and developed more efficiently and consistently with the help of model-driven engineering, particularly with the use of model-based dependability analysis approaches [3]. In [4], authors integrated model-based reliability study techniques with conventional preservation technologies and introduced a framework for intelligent preservation of systems based on models. To accomplish model-based system maintenance, this framework integrates model-based system reliability analysis techniques with more conventional theories of maintenance, like Reliability-Centered Maintenance (RCM) [5]. This research proposes many Artificial Intelligence (AI)-based defect diagnostic approaches to advance the analytical presentation of the framework. Approaches for fault diagnosis may be grouped into single-based and model-based methods.

The subsequent sections of the article have been arranged in the following manner: Section II provides a discussion of the basic components of fault diagnosis, which include hardware redundancy, and signal processing. Section III reviews model-based fault diagnosis approaches, such as probabilistic methods (arithmetic test, and Bayesian approach) and deterministic methods (integrated detector and controller design, and guaranteed fault analysis). Section IV discusses signal-based fault diagnosis techniques (time-domain signal-based techniques, frequency domain signal-based techniques, and time-frequency signal-based techniques. Lastly, Section V provides a summary to the discussions in this paper.

II. BASIC COMPONENTS OF FAULT DIAGNOSIS

The fundamental components of fault diagnosis integrate three imperative tasks:

- *Fault recognition:* identifying the presence of faults in the efficient units of the procedure that result in undesirable behavior of the entire structure;
- *Fault separation:* pinpointing and categorizing dissimilar faults;
- Fault identification or analysis: determining the nature, extent, and root cause of the fault.

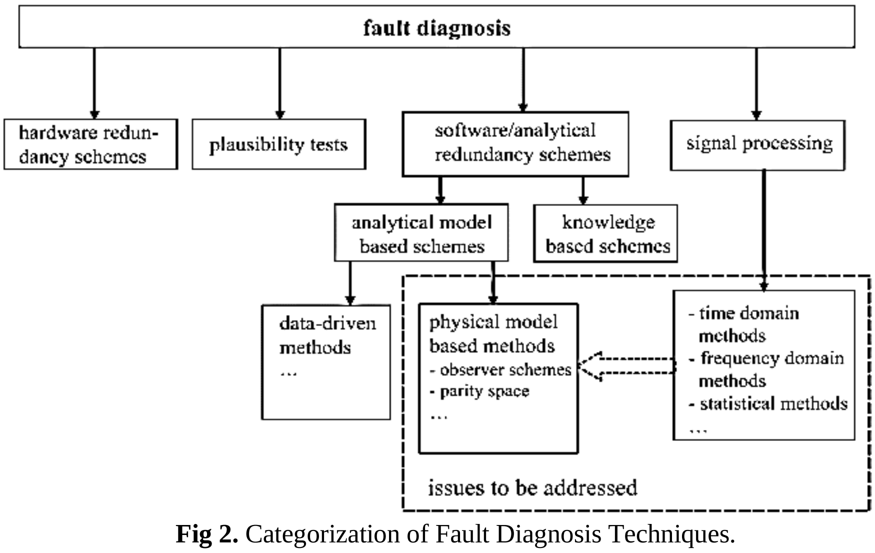

Fig 2. Categorization of Fault Diagnosis Techniques.

The outputs of a fault verdict system can be categorized as FDI (for Fault Detection and Isolation), FD (for Fault Detection), or FDIA (for Fault Detection, Isolation and Analysis), depending on the structure`s performance. The outputs can be alarming indicators indicating when faults have occurred, categorized alarm indicators to indicate which fault has arisen, or data of distinct types that provide data about the magnitude or type of the failed component. As a new area of study within the technical fault diagnostic subfield of classical engineering, model-based fault diagnosis is gaining momentum quickly and is getting a lot of attention right now. Before diving into the core concepts of the framework-based fault verdict method, it is helpful to have a quick look at some classic fault diagnosis schemes and how they relate to the framework-based approach. **Fig. 2** provides a classification of procedural fault diagnosis methods.

A Fault Diagnosis Based on Hardware Redundancy

The key aspect of this system, shown in **Fig. 3**, is reconstructing the procedure elements using identical hardware elements. A defect in the procedure element is recognized when the output of the procedure element differs from that of its redundancy. The primary benefit of this method lies in its exceptional dependability and the capability to separate faults directly. The use of superfluous hardware leads to elevated expenses, therefore limiting the implementation of this strategy to a select few crucial components.

Signal Processing-Based Fault Diagnosis

A fault diagnosis may be accomplished by appropriate signal processing if particular process signals include relevant information about the specific defects and convey this information as symptoms. In the time domain, common symptoms include magnitudes, limit values, arithmetic or quadratic means, arithmetic moments of the amplitude circulation or envelope, and so on. In the frequency domain, common symptoms include frequency spectrum lines, spectral power densities, centrum, and the like. The signal dispersion-based approaches are mostly used for steady-state processes. However, their effectiveness in detecting defects in dynamic structures, which have a broad effective range owing to potential variations in input indicators, is significantly restricted. **Fig. 4** depicts the fundamental concept of the signal processing techniques.

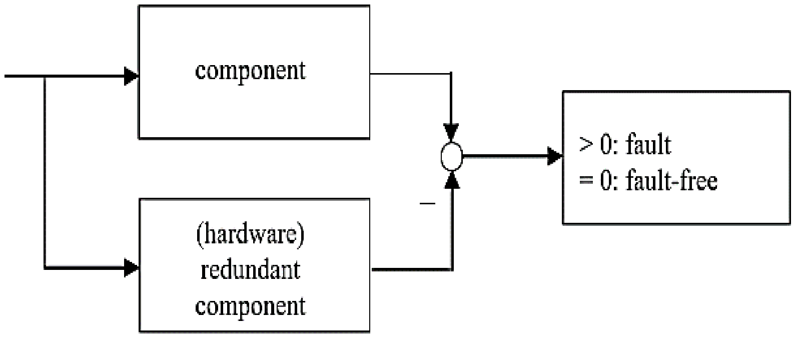

Fig 3. Overview of the Hardware Redundancy Approach.

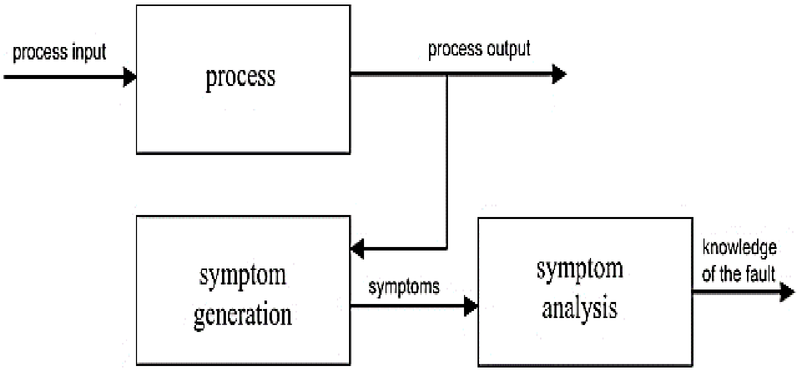

Fig 4. Illustrative Depiction of the Approach Using Signal Dispensation Techniques.

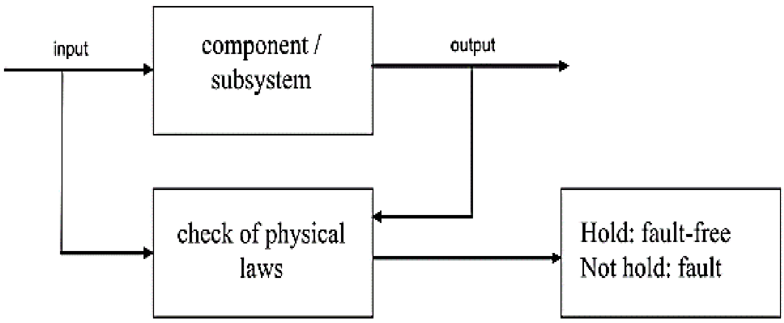

Fig 5. Overview of the Plausibility Test Approach.

As seen in **Fig. 5**, the plausibility test relies on the examination of basic corporeal rules that govern the functioning of a process component. If we assume that a defect will result in the loss of plausibility, then by evaluating the plausibility, we may get data about the problem. The plausibility test has restricted efficacy in discovering defects in a complicated process or isolating errors. The fundamental concept behind the framework-based fault diagnostic approach is to substitute hardware redundancy with a software-based process framework that is executed on a computer. A procedure framework is a description, either qualitative or quantitative, of the dynamic and stable behavior of a process. This description is generated using a well-established approach for process modeling. By using software redundancy, we may effectively restore the process behavior in real-time, in conjunction with the idea of hardware redundancy. Software redundancies are sometimes referred to as analytical redundancies.

In the context of software redundancy, the process framework will operate simultaneously with the process and be controlled by the same inputs, similar to hardware redundancy systems. It is fair to anticipate that the recreated procedure variables provided by the procedure framework will closely align with the relevant actual procedure variables under normal operating conditions and exhibit a noticeable deviation in the presence of a process defect. To get this information, we will compare the observed procedure variables (output indicators) with their corresponding estimations provided by the process framework. The residual is the discrepancy among the measured procedure variables and their estimations. In essence, a residual signal contains the crucial information necessary for effectively diagnosing faults: if residual 6= 0 then fault, otherwise fault-free.

The process of generating estimates for the outputs of a method and calculating the alteration among the actual outputs and their estimations is referred to as residual initiation. The residual generator is constructed by the comparison unit and the process modeling. **Fig. 6** presents a schematic representation of the defect diagnostic technique based on a model. A description of the input-output process is used to indicate plausibility, and remanent generation can be thought of as an extended version of that test. Consequently, the plausibility check may be substituted by an evaluation between the actual outputs of the process and their estimations. Due to the inability to accurately simulate technical processes and the presence of unknown disturbances, the fault message in the remanent signal is affected by both model errors and unknown disturbances. Furthermore, the procedure of fault isolation and identification necessitates a further examination of the residual produced to differentiate the effects of various faults. An inherent challenge in implementing model-based fault detection techniques is effectively filtering and retrieving the necessary data about the specific problems of interest from the residual indicators. Two distinct tactics have been devised for this purpose:

- Developing a residual generator that effectively separates the fault of attention from other faults, and framework concerns.
- The fault data of interest is obtained by analyzing the residual signals via post-processing. The process is referred to as residual assessment.

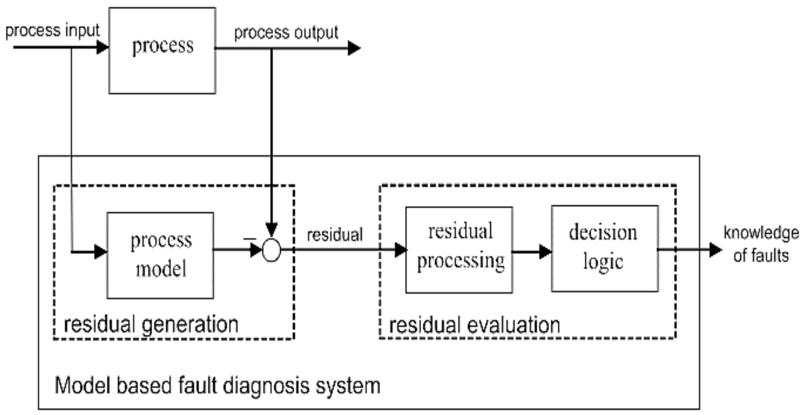

Fig 6. Overview of the Defect Diagnostic Technique Based on a Model.

Many study groups working on framework-based fault diagnostic approach have extensively pursued the first option [6, 7, 8]. The fundamental concept underlying the advancement of the observer-based fault diagnosis technique is to substitute the procedure framework with an observer that can provide dependable estimations of the process outputs. Additionally, this technique allows the designer to have the necessary flexibility in achieving the target decoupling using reputable observer theory. Within the context of residual assessment, the use of indicator dispensation algorithms represents the most advanced and current approach. Statistical approaches and norm-based assessment are often used evaluation systems for achieving effective post-processing of residuals produced by an observer. Both of these assessment approaches have the common feature of establishing a limit, known as the threshold, that encompasses all potential model uncertainties, unknown inputs, and irrelevant flaws. If the threshold is surpassed, it signifies a malfunction in the process and will trigger an alert signal. The observer-based fault diagnostic approach and state-of-the-art model is shown by the integrated use of both techniques, as seen in **Fig. 4 and Fig. 6**.

III. MODEL-BASED FAULT DIAGNOSIS METHODS

Leveson and Stephanopoulos [9] introduced model-based failure detection in 1971 as a way to replace hardware redundancy with analytical redundancy. This approach has been extensively documented in well-written publications, such as references

[10, 11, 12]. Model-based approaches need the availability of models for practical systems or industrial processes, which may be acquired via the use of physical values or structures identification methods. The fault diagnostic networks are designed based on the model to check the constancy among the observed outputs of practical structures and the projected outputs of the model. This section provides an overview of model-based fault diagnostic approaches, which are categorized into two groups: probabilistic and deterministic methods.

Probabilistic Methods

Probabilistic approaches operate on the assumption that uncertainties may be represented by random variables that have well-defined possibility density purposes. The approaches may be categorized into two groups: those which employ statistical tests without previous knowledge, and those that adhere to the Bayesian model.

Statistical Test

If the structure being monitored is characterized by a stochastic framework, the residual indicator is a stochastic procedure that is expected to exhibit changes when a defect occurs. Many fault detection approaches operate under the assumption that the model without any faults is accurate. These methods use a sequential statistical test to identify any changes in the model when it becomes faulty. This test is conducted on the residual signal. The duration of the testing interval cannot be predetermined and is contingent upon the samples of the residual signal, since the consecutive arithmetic tests collect data until a dependable conclusion can be reached. Heirung and Mesbah [13] presented a design for the auxiliary input signal that decreases the average recognition latency of the successive possibility ratio test while distinguishing among numerous ARMAX frameworks.

In a study conducted by Saad, Prokhorov, and Wunsch [14], the focus was on reducing the average recognition latency while ensuring that the mean time among false alarms remains above a specified frequency. It has been shown that the best auxiliary input indicator in an open loop system should focus all of its power on a single frequency. Using linear feedback to create a closed loop auxiliary input signal for the CUSUM test is covered in the paper by Niemann [15]. The supposition that the parameters of the defective model are totally known was partly eliminated in a study conducted by Rigdon [16]. Specifically, the user is aware of the direction in which the parameter will change, but does not have information on its exact magnitude. Additional relaxation, which permits the consideration of unknown directions, was included in a study by Bydder et al. [17].

Bayesian Approach

The Bayesian technique offers a methodical manner to revise prior knowledge by incorporating measured data in order to acquire posterior information. It is essential to employ the predicted possibility density values of the output habituated by various frameworks as likelihood functions in order to produce judgments. Hence, the fundamental concept is to use an auxiliary input signal to reduce the overlap between these extrapolative possibility density functions, as seen in **Fig. 7** for both the fault-free and defective models. The degree of overlap among the PDFs may be quantified using several methods that are linked to the penalization of inaccurate judgments. It should be noted that if all random variables have a limited range of potential values, it is feasible to achieve an assured finite deviation. However, the majority of donations operate under the assumption of unlimited support, resulting in a constant chance of making an erroneous choice.

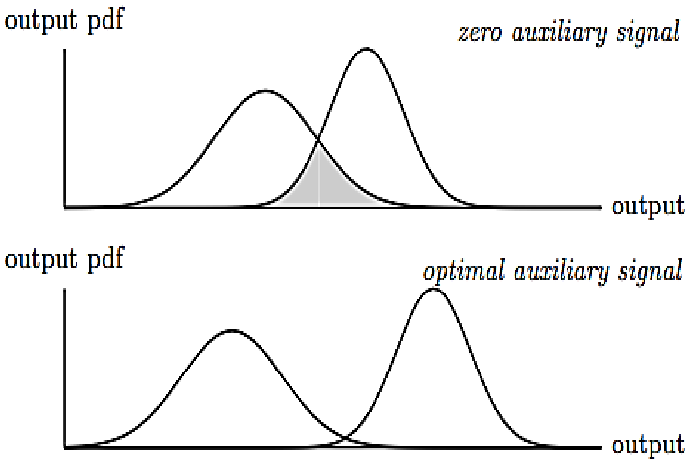

Fig 7. Probability Density Function of the Output Divided into Fault-Free Model and Defective Model.

Adams et al. [18] presented an open loop strategy for auxiliary input signal in framework discrimination. This design minimizes the detection criteria while ensuring that the control principle remains below a predetermined frequency, and vice versa. This concept was expanded to nonlinear systems that permit state feedback linearization. A concise overview of this method for active fault identification and control was presented by Shraim, Awada, and Youness [19]. In [20], a closed loop auxiliary input indicator generator was examined to distinguish between two models. Solving a linear matrix inequality problem led to the specifications of an affine feedback auxiliary input signal generator. Schenkendorf, Xie, and Krewer [21] used polynomial chaos theory to address the propagation of uncertainty and successfully resolved the issue of discriminating across models.

The ideal input signal generator for a finite-time prospect is often a time-changing structure that poses challenges in terms of implementation and design. Hence, the concept of an infinite-time horizon has garnered significant attention due to the possibility of finding a more straightforward asymptotic solution [22]. The first phase was the reformulation of the issue, which led to the emergence of a problem with perfect state data. The **Fig. 8** block diagram depicts the supervised system together with an estimator that generates useful data. The data are then used to create decision d and supplementary input signal u. The study assumed nonlinear frameworks with a directly observable constant component of the state. Additionally, an auxiliary input signal generator was built utilizing the approximation value iteration process across an infinite-time horizon. In [23], the standardized policy iteration technique was used to decrease the processing requirements of the auxiliary input signal generator. The incorporation of noisy dimensions of the constant component of the state into linear models was achieved by using informative information, as shown by De Valpine and Hastings [24]. In [25], the auxiliary input signal generator was trained with simulated data using machine learning techniques. The user's text is empty. The extension of this method to nonlinear models was shown in [26].

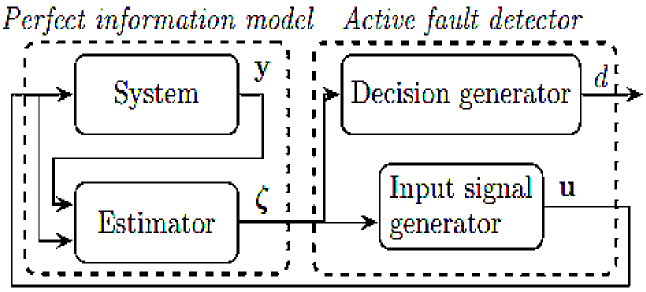

Fig 8. The Block Scheme of AFD with the Perfect State Data Framework.

Deterministic Techniques

The deterministic approaches presuppose that the disturbances affecting the monitored structure may be represented as deterministic indicators constrained by a certain norm.

Integrated Detector and Controller Design

The active method to fault detection for deterministic structures originated from the algebraic component of linear control stability, as discussed by Wu and Hadjicostis [27]. Lozoya et al. [28] presented a controller with four parameters and examined the inherent trade-offs of integrating the detector and controller design. **Fig. 9** shows a block model of the structure being watched, which is shown by the four-parameter controller, and the transfer function matrix S, which is shown by the transfer function matrices C_{22}, C_{21}, C_{12}, and C_{11}. While C_{11} and C_{12} provide a residual generator, the controller is signified by the transfer function matrices C_{22} and C_{21}. In addition, the block diagram delineates the connections among the residual signal r, system input u, system output y, and reference signal r_y.

The standard robust control architecture was used to redefine the four-parameter controller [29]. This step not only facilitated the use of computational methods for robust control in integrated design, but it also enhanced the ease of analyzing the link among the residual controller and generator. It has been determined that the residual controller and generator may be developed separately for the nominal framework due to the existence of a separation principle in this scenario. When dealing with an uncertain model, it is essential to use integrated design to get the ideal solution. In [30], an adapted four parameter controller was designed using a hybrid H_2 and H_∞ approach. This approach was chosen because it is more effective to employ separate norms for assessing control and discovery performance. The parting concept was shown to be applicable to this adapted four parameters controller even in the nominal situation. While the combined design successfully balanced the control and detection performance, it did not consider the explicit production of an auxiliary input indicator that enhances the quality of FD. The modified four parameter controller was augmented with an intentionally created auxiliary input indicator to enhance the identification of parametric defects. This configuration is shown in **Fig. 10.**

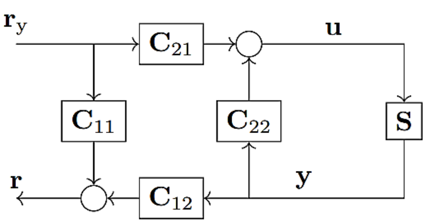

Fig 9. The Four-Parameter Controller's Block Diagram.

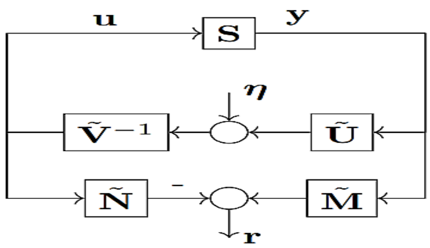

Fig 10. An Adapted Four-Parameter Controller Including an Auxiliary Input Indicator.

Guaranteed Fault Analysis

Another set of deterministic techniques concentrates on devising an auxiliary input indicator that may provide assured fault detection under the premise of limited disruptions. With a few exclusions, the early studies mostly used a multiple model that consisted of just two alternative linear frameworks: a fault-free framework and a defective framework. A valid auxiliary input indicator is an indicator that allows for the differentiation among the two frameworks by ensuring that the sets of all potential outputs under the fault-free and defective models do not overlap, as shown in **Fig. 11**. The ideal auxiliary input indicator u is determined offline as the appropriate auxiliary input indicator with the least norm.

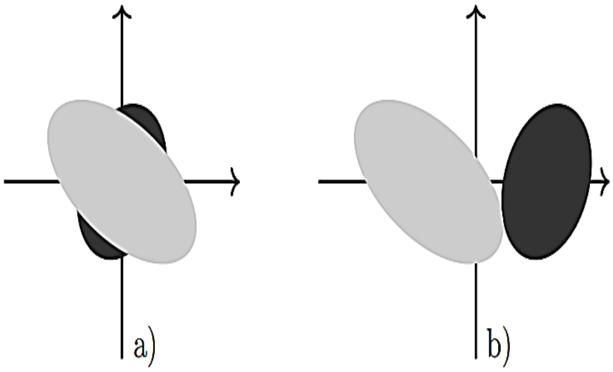

Fig 11. The Sets of Potential Outputs Under a Fault-Free Framework Are Shown by a Black Ellipse, While the Sets of Potential Outputs Under a Faulty Model are Represented by a Gray Ellipse. This Applies to Both the Scenario with Zero Auxiliary Input Signal (A) and the Scenario with an Ideal Auxiliary Input Signal (B).

IV. SIGNAL-BASED FAULT DIAGNOSIS METHODS

Rather than using explicit input-output models, signal-based techniques employ observed signals to detect faults. By assessing the symptoms and drawing on what is known about symptoms in healthy systems, a diagnosis may be obtained after measuring the signals, which show the process faults. From these, features can be derived. The use of signal-based fault detection methods allows for the real-time monitoring and diagnosis of mechanical system components such as induction motors, power converters, and others. Simplified signal-based fault diagnostics are shown in **Fig. 12**. To analyze symptoms or patterns, one may employ feature signals that are either time-realm (like root mean square, magnitudes like peak, slope, phases, standard deviation, trends, and mean,) or frequency-realm (like spectral). Thus, time-realm, threshold-realm, and time-threshold signal-based fault diagnosis techniques are the three primary categories.

Time-Domain Signal-Based Methods

To efficiently track a continuous dynamical procedure, it is important to derive time-realm properties to identify defects. A defect detection approach was advanced for power converters of switching disinclination motors in [31]. This approach included examining the variations in the root-mean-square recent features that were observed under various scenarios, such as single or open circuit or dual transistor short circuit and then comparing them to the normal settings. In two converters of PMSG (permanent magnet synchronous generators) drivers for wind turbine usage, the fault indication that identified several open-circuit failures was the absolute value of the derivative of the Park's vector phase angle, as shown in [32]. In [33], a technique for diagnosing short and open circuit switch problems in non-separated DC-DC converters was proposed. The technique involved tracking the steepest rate of change of the induction current as it responded to time. This approach was tested in an investigational configuration with a field programmable gate array (FPGA) modern target for practical application.

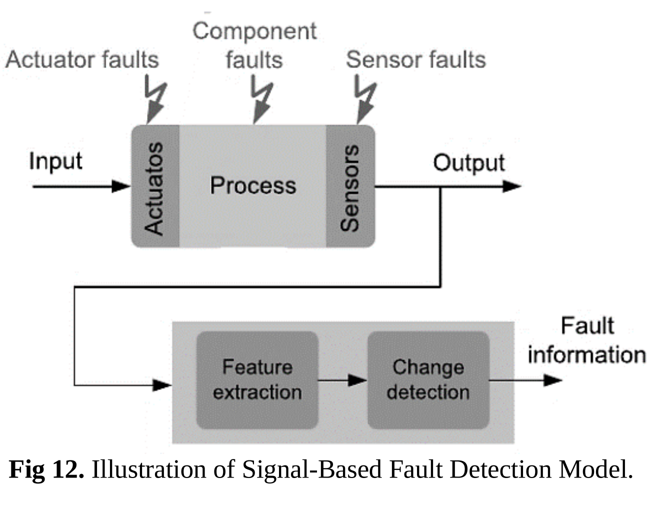

Fig 12. Illustration of Signal-Based Fault Detection Model.

In [34], a real-time method was recommended to identify and locate various open circuit faults in power switches of inverted-fed AC motor drives. This approach employed the stage currents measured on the motor and the constant reference pointers on the currents. According to the findings in [35], when the supply voltage is evenly distributed, the magnitude and phase angle of the zero- and negative-pattern currents may be used as dependable signs of stator issues in induction motors. A mathematical approach was presented in [36] to sense abrupt sensor failures in flight control systems. This method used the covariance of the sensing data to derive pertinent characteristics. A novel diagnostic methodology using time-domain signals was recently devised in [37] for the purpose of monitoring gear problems. This method utilizes the Fast DTW and CK approaches in combination. The quick Dynamic Time Warping (DTW) technique was used to restore the periodic instinct innervations caused by the broken gear tooth. Subsequently, the obtained signal was resampled using the CK technique for diagnostic analysis. The CK algorithm utilizes the periodic nature of the geared flaws to precisely recognize the specific position of the local gear failure inside the gearbox's mechanism.

In contrast to fault recognition and diagnosis methods that utilize properties of the measured indicator in a one-dimensional realm, a novel approach was introduced in [38]. This approach involves translating the vibration signal into a two-dimensional image and extracting local characteristics from images based on SIFT (scale invariant feature transform) framework. These derived features are then utilized for fault isolation and detection within a pattern organization network. A recent study [39] introduced a two-dimensional method for diagnosing faults in induction motors. In this approach, vibration indicators from the motor during operation were initially transformed into grayscale images. From these images, distinctive texture features were extracted using the local binary patterns (LBP) method. The textural characteristics that were gathered were ultimately used for fault identification with the assistance of a classifier. When signals are converted into pictures, the presence of additional noise causes changes in the lighting of the image. Due to their illumination invariance capabilities, both the SIFT methodology and the LBP operator can handle background sounds well, as shown in the defect detection techniques given in [40].

Frequency-Domain Signal-Based Techniques

Spectrum data tools, like discrete Fourier transformation (DFT) are utilized by the frequency-realm signal-based technique, to identify changes or defects. A very effective method for detecting motor problem is known as MCSA (motor-current signature analysis). It involves analyzing the frequency spectrum of the stator current to identify rotor faults such as mechanical imbalances and broken rotor bars. The MCSA technique has garnered significant interest, as seen by its thorough assessment in [41], without the need for vehicular access. Information on the latest advancements in fault diagnosis using current based spectral signature analysis may be found in [42]. The examination of the vibration indicators is one of the most common diagnostic techniques used for assessing the condition of mechanical equipment, including gearboxes. This is because the noise made by the machine is useful in determining the status of the machine at any given time.

The auditory defect detection technique for gear box was presented in [43], which used an enhanced frequency domain blind de-convolution method. In a recent study performed in [44], the authors relied on the demodulated spectra and Fourier spectrum of amplitude envelope to locate and diagnose diverse gear issues in planetary gearboxes. The MSD approach, which is explained in [45], is therefore used to decompose a given signal into different smoothed and detailed signals. The MSD approach decomposes the discrete-time signal x[n] into two components: Smoothing of the indicator in the time domain is represented by $C_1[n]$ while $D_1[n]$ represents the detailed indicator in the threshold realm. This decomposition is dependent on the wavelet coefficient at scale 1. It might be continued until the approximation is disintegrated again, and again, and again, and the whole initial indicator is disintegrated into several elements of lower resolution. The implementation of the MSD approach may be achieved using cascaded Quadrature Mirror Filter (QMF) banks [46]. The selection of the decomposition level must be such that it effectively targets the frequency range produced by the issue.

Table 1 displays the frequency ranges associated with each degree of decomposition with a sample rate of 10 kHz. The frequency range of [416 - 833] Hz is prominent during a short-circuit problem, as shown by Bovik, Clark, and Geisler [47]. The 4th level detail coefficient, as shown in [48], is the optimal choice for accurately identifying and localizing the desired frequency. A collection of compact orthogonal wavelets known as Daubechies wavelets are very useful for examining short-lived, quick transients. Wavelets of different orders are provided, as seen in **Fig. 13**. The ideal wavelet for the fault recognition utilization is the one with a central frequency that fits the fault sequence.

Table 1. Frequency Band at Each Disintegration Level

Decomposition level	**Frequency band (Hz)**	
	Approximation	Detail
1	0 – 2.5k	2.5k – 5.0k
2	0 – 1.25k	1.25k – 2.5 k
3	0 - 625	625 – 1.25k
4	0 – 312.5	312.5 - 625
5	0 – 156.25	156.25 – 312.5

Another option is to choose the best wavelet by calculating the Pearson product moment association constant among it and the fault outline, as shown in $r = \frac{\sum_{i=1}^{n}(X_i-\bar{X})(Y_i-\bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i-\bar{X})^2(Y_i-\bar{Y})^2}}$, where the data sets for the wavelet Y_i and the fault signal X_i are averaged to form $\bar{X}$ and $\bar{Y}$, respectively. As shown in **Fig. 13**, X_i represents the fault indicator, and Y_i is the selected

Daubechies mother wavelet. In **Fig. 14**, we can see the calculated correlation constants among the Daubechies mother wavelet and the fault signal of different orders (db2 − db9). Among these choices, db3 is determined to be the most suitable for the given fault pattern.

Time-Frequency Signal-Based Techniques

When machines are not carrying any load, or when the supply voltages are imbalanced, or when the load or load torque is fluctuating, the measured indications often exhibit dynamic and transient behavior during the relevant time interval. Consequently, it might be challenging to identify flaws using either a time-realm or frequency realm method while analyzing stationary numbers in some instances. In order to efficiently monitor and diagnose faults in real-time, it is necessary to use time-frequency decomposition methods that can handle the changing frequency spectrum of transient signals. Time-frequency analysis is a useful method for deriving feature data from non-stationary indicators. It may detect the threshold components of a signal and expose their time-varying characteristics. This analysis has proven to be beneficial in monitoring and diagnosing faults. Several time-threshold examination techniques have been suggested and used for the purpose of equipment failure identification. The most often utilized procedures among the temporal frequency techniques are the Hilbert-Huang transform (HHT), Wigner-Ville distribution (WVD), wavelet transformations (WT), and short-time Fourier transform (STFT).

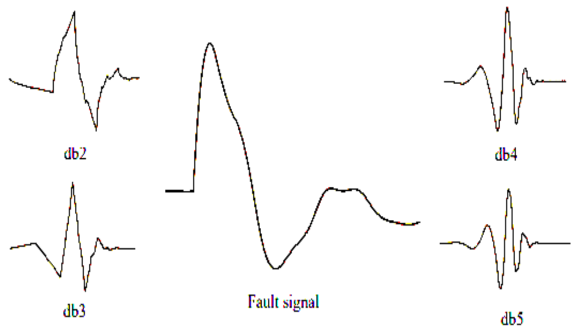

Fig 13. Daubechies Wavelet (db) and Fault Signals of Varying Orders.

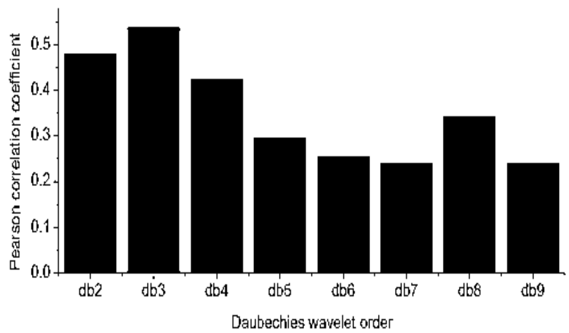

Fig 14. Correlation Constant Among Fault Indicator and Daubechies Wavelet.

The STFT approach is used to analyze the threshold components of small parts of a signal as it varies over time. This method has been extensively used to identify defects in both the stator and rotor of inductor motors [49]. Nevertheless, the STFT approach incurs a significant computational burden when aiming to achieve a high level of resolution. The WT based method, as a linear decomposition, offers high temporal tenacity for high-threshold elements and high frequency resolution for low-threshold elements. This method has been proven effective in stalking fault threshold elements in non-stationary states [50]. The integration of the STFT and discrete WT was used to achieve early prognosis and detection of anomalies in the monitored industrial systems [51]. STFT and WT may exhibit various restrictions. For example, determining the appropriate window dimension in STFT is necessary, although it is often not known in advance. The choice of the fundamental wavelet purpose in wavelet transform (WT) directly impacts the ability to accurately detect transient components that are concealed inside a time-varying signal.

However, the HHT technique is not limited by the indefinite constraints on frequency and time resolutions that other time-threshold methods like STFT and WT suffer from. This is because the HHT method analyzes the immediate resonances consequential from the inherent-mode parameters of the indicator being examined. This technique has shown promising performance in evaluating fault severity. The WVD approach is characterized by its cheap computing high resolution and cost. It utilizes the complete signal to calculate the energy at each time-threshold bin. This method has been effectively used in fault detection, current analysis, and vibration analysis [52]. A built-in limitation of the classic Wigner-Ville distribution (WVD) paradigm is the circulation of cross terms in the artifact, which tends to make WVD approaches impractical. A new improved WVD based fault analysis network was proposed in [53] by integrating notch FIR filters with the conventional WVD technique. This algorithm can effectively reduce cross terms and generate smooth high-verdict time threshold plots which can be used to assess rotor unbalance and deviation in the initiation machines that are directly link to the grid even in worst case scenarios. In [54], a self-oriented Wigner-Ville distribution (WVD) has been introduced by using local mean disintegration. This method is especially effective in the erasing of the cross terms of the WVD, which results to better identification of the faults.

V. CONCLUSION

This article presents a detailed overview of defect diagnostic methods and begins with the fundamental idea of hard ware redundancy and ends with the modern framework based and signal-based approaches to diagnosis. Fault analysis is very useful for complex systems because it enables one to identify the root of the problem and correct it as soon as possible to enhance the dependability and effectiveness of the system. The division of the fault diagnostic techniques into those that involve hardware superfluity, signal processing and model-based procedures is crucial in understanding the approaches used in handling system defects. The model-based method is also most striking because instead of relying on redundant hardware, it employs process models embedded in software, which can prove to be more beneficial in terms of flexibility and cost effectiveness. The versatility and sophistication of the current fault diagnosis techniques are well illustrated in areas like observer-based fault diagnosis, probabilistic and deterministic methods within the model-based framework, and the residual generation. In addition, the discussion on signal-based fault detection methods including time-threshold, frequency-realm, and time-realm methods show that there are many approaches used for identification of the characteristics of the system and detection of faults. This article enhances our understanding of fault diagnostic procedures by explaining the ideas behind such techniques and their advantages and disadvantages. Lastly, it highlights the importance of the constant development of research and new ideas in such a significant area.

CRediT Author Statement
The author reviewed the results and approved the final version of the manuscript.

Data Availability
The datasets generated during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interests
The authors declare that they have no conflicts of interest regarding the publication of this paper.

Funding
No funding was received for conducting this research.

Competing Interests
The authors declare no competing interests.

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ISSN: 3080-7484