DISTINGUISHING SENSOR FAULTS FROM SYSTEM FAULTS BY UTILIZING MINIMUM SENSOR REDUNDANCY

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Received February 2017, Accepted May 2017
No. 17-CSME-16, E.I.C. Accession 4052

ABSTRACT

Automated Fault Detection and Diagnosis (FDD) systems depend entirely on the reliability of sensor readings. This paper fills an important gap in the literature by pinpointing the distinction between sensor faults and system faults in the monitoring process. The proposed methodology determines the minimum degree of sensor redundancy necessary to achieve this. A priori knowledge of physical relationships between monitored variables is used to check the credibility of sensor observations. The generalization reveals that for serially connected systems if the number of sensors is greater than 1.5 times of the number of monitored variables, the task of distinguishing between sensor and system faults can be accomplished with certainty, as long as serial causality is valid between the monitored variables. This is verified using a system of interconnected multi reservoirs and control valves.

Keywords: sensor fault; system fault; sensor redundancy; fault localization; fault diagnosis; reliability.

DISTINCTION DES DÉFAILLANCES DU CAPTEUR EN RAPPORT AUX DÉFAILLANCES DUES AU SYSTÈME PAR L'UTILISATION DE LA REDONDANCE MINIMALE DU CAPTEUR

RÉSUMÉ

Le moteur de détection et de diagnostic de défaillance (FDD) dépend entièrement sur la fiabilité des relevés du capteur. La présente recherche vient combler un vide important dans la littérature en exposant le problème de distinction entre les défaillances dues au système comme tel dans les procédés de contrôle. La méthodologie proposée détermine le degré minimal de redondance du capteur nécessaire pour faire cette distinction. On utilise la connaissance à priori des relations physiques entre les variables surveillées pour vérifier la fiabilité des observations du capteur. En général, on constate que pour les systèmes connectés en série, la tâche de distinguer entre les défaillances du capteur et celles du système peut être réalisée avec certitude aussi longtemps que le lien de causalité sérielle est valide entre les variables surveillées. Ceci est validé en ayant recours à un système interconnecté de multi réservoirs et des soupapes de contrôle.

Mots-clés : défaillance du capteur; défaillance du système; redondance du capteur; localisation de la défaillance; diagnostic de défaillance; fiabilité.

1. INTRODUCTION

Fault detection and diagnosis (FDD) is a key element of operation and management of automated systems to increase reliability and safety. There is a high demand for the development of diagnostic systems that are capable of autonomous detection of the presence of anomaly as well as localization of the faults that may occur in different components of a complex dynamic system while in operation. Most of the existing FDD approaches can be divided into computational intelligence-based and model-based methods [1, 2]. The former approach employs quantitative historical data or qualitative information on the system. While in the latter, the mathematical model of the system is being utilized as an *a priori* source of information on the monitored system. In the area of automatic control, the most powerful, reliable and accurate diagnostic approaches are model-based schemes.

A *fault* in a model-based scheme is defined as the deviation of measurement from the model output. An unanticipated inconsistency in a sensor's readings from its expected values under specific operating conditions may not necessarily be a fault in the sensor mechanism itself, but it can be a symptom of a more serious potential fault in the monitored system. Hence, system and sensor faults might be manifested with the same symptoms. Present FDD schemes only consider either the malfunction of the system, assuming that the sensing system is functioning normally, or sensor failure while the system is fault-free. The ability to identify the source of faults is crucial in the monitoring of a system, as different corrective actions or compensatory responses are required in case of sensor or system faults, attributed to the diagnostic decision. There is an abundance of literature on fault detection and diagnosis for both sensor and system individually. Despite the importance of the practical application of diagnostic schemes, distinguishing between sensor and system faults does not appear to have received a substantial prior attention in the monitoring and diagnosis literature.

1.1. Sensor Fault vs. System Fault

When a sensor produces an output measurement signal proportional to the physical input stimulus, within an acceptable amount of deviation as dictated by the sensor physics, resolution, accuracy, application requirements, etc., it is considered 'healthy'. This deviation is called 'noise'. However, the effects of faults are manifested as *undesirable deviations* in the sensor output such as drift, bias, loss of effectiveness, and hard failure. Such phenomena may occur intermittently or steadily over a period indicating the development of gradual sensor degradation. In the extreme case, there may be a complete loss of information from a sensor due to an abrupt failure of the sensing element or power/signal transmission lines, connectors, and faults in the onboard signal processing circuits [3]. In the cases where the readings are used for feedback control purposes, it may lead to undesirable system behavior if the sensor measurement readings become faulty, unavailable or invalid. Hence, we can conclude that the presence of faults in sensors may result in inefficient and/or inaccurate control.

The system faults are usually represented as cases where some condition changes in the system, which make the nominal dynamic equation of the system invalid. System faults are dependent on the sub-systems and actuators being monitored. Some examples include but not limited to lock-in-place or freezing, float, hard-over-failure and loss of effectiveness in electromechanical or electromagnetic actuators such as valves, gearbox, and robotic arms [4]; leakage in a tank in chemical systems; accumulation of debris and clogging in hydraulic cylinders [5]; bearing faults in rotational equipment such as engines [6], etc. System faults may have minor to extremely severe consequences. For example, an unexpected failure of the aircraft engine components may cause significant economic as well as fatal losses [7]. Thus, it is extremely crucial to diagnose these faults at early stages of component degradation in order to avoid catastrophic consequences. Mathematical representation or modeling of these faults is sometimes very arduous, and extensive experimentation may be needed before constructing a model. In general, system faults can be represented by a

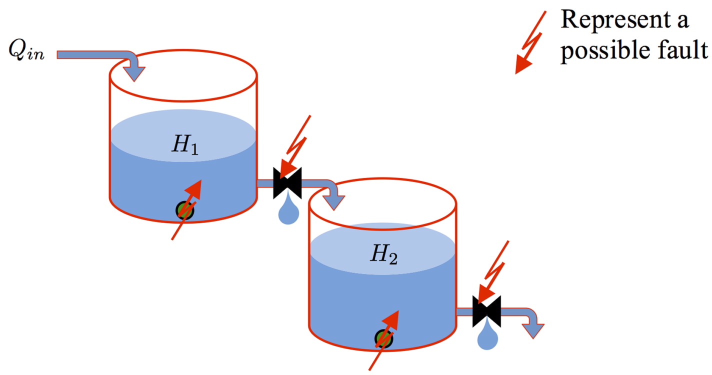


Fig. 1. Schematic view of the potential sensor/system faults in a multi-reservoir process.

change in the system's state equation [1]. Without any knowledge of the system status, in some cases, the discrepancy of sensor readings from the system model may erroneously be interpreted as potential faults in the monitoring sensors.

1.2. Example of Interconnected Multi Reservoirs System

Throughout this paper, the multi reservoirs process (commonly known as Continuous Stirred Tank Reactors (CSTR) in chemical industries) is exemplified to explain the definitions and later, in order to show the effectiveness of the proposed diagnostic method and sensor placement algorithm for the distinction of sensor and system faults. This is a well-known example in the area of control engineering [8]. The liquid heights in each reservoir are described as controllable outputs, which are regulated by control valves, equipped with electrical actuators. It is assumed that the valves resistances are set in a way that the height of liquid in each reservoir is proportional to the required flow rate [9]. The system consists of a series of reservoir (tanks), control valves and liquid level sensors. It is noted that no other variable is monitored in this system. Reservoirs can have different architectures in their connections. However, the type of connection makes no difference in causality modeling. The detailed dynamics of the process is derived in [10], and only relationships between heights are important here.

1.2.1. Potential faults in the operation

As schematically shown in Fig. 1, the system fault and sensor fault, which may occur during the operation of the process include:

- *Valve fault*: A fault in the valve (such as leakage) results in a change in the input flow rate of the descendent tank without a corresponding adjustment in the control signal.
- *Sensor fault*: A fault in the liquid level sensor introduces a deviation into the measurement. For example, a bias in sensor reading causes the actual flow rate to be maintained at a level below the set point.

2. PROBLEM STATEMENT

System fault detection based on sensor observations and measurements is valid only when it is guaranteed that all sensors are working properly and are fault-free. A system fault should be detected and isolated immediately. On the other hand, sensor faults, which lead to incorrect measurements, can be detected and diagnosed, assuming that anomaly and inconsistency are not from the system. Both the system faults and the sensor faults may have similar symptoms in sensor observations or mask each other in the worst case.

The consequence of similar symptom or masking in these two faults leads to an inability to differentiate between them. The essence of this distinction is due to the fact that either has a different corrective action or compensatory response:

- In the case of sensor faults, the sensors can be replaced physically; redundant sensors can be deployed, or the measurement can be mathematically compensated temporarily. As an instance, a faulty reading of air speed in an aircraft can be counterweighted by flight crew until the end of the flight.
- System faults on the other hand, often require immediate attention, which might range from a simple diagnostic alarm to notify the operator, to severe cases, where full shut down of the operation is inevitable, as soon as it becomes safely possible. For example, a leakage in an aircraft engine, need immediate action, such as emergency landing before it leads to fatal consequences.

2.1. Literature Review

The idea of using banks of dedicated observers is frequently used for detecting individual predefined faults; each one is assigned to be sensitive to a certain fault while remaining invariant to other predefined faults [2]. This scheme brings isolability for different faults from each other. However, a differentiation between system and sensor faults cannot be achieved, since the design does not consider the two types of faults in a unified framework [11]. The residuals are still computed using the measurements from the sensors, and a faulty measurement leads to breaching the threshold in either case. Hayes et al. in 2008 [12], Hajiyev et al. in 2000 [13], and Xue et al. in 2007 [14] used fault specific threshold selection to achieve isolation for some *known* sensor/actuator faults by robust Kalman filtering and statistical analysis of innovation sequence.

Krysander et al. in 2005 [15] and 2008 [16] and Rosich in 2012 [17] proposed the sensor placement algorithm for detectability and isolability of different known faults based on structural models. Bhushan and Rengaswamy addressed the problem of sensor location assignment for optimal fault observability based on graph theoretic approaches [18]. It is noted that many researchers have also investigated the concept of distinguishing between disturbances and faults using hardware redundancy in the chemical process [19].

Distinguishing between sensor and system faults does not appear to have received a substantial amount of prior attention. The existence of this issue has been acknowledged in a large number of publications [20]. However, only a few has tried to tackle this problem. Xu and Feng [21] looked explicitly into this problem via data-driven and statistical methods. They investigated a hydraulic tank and pressure line with Principal Component Analysis (PCA) and concluded that these faults are indistinguishable without employing hardware redundancy. Krishnamoorthy [22] has also introduced a framework based on Bayesian Belief Networks to detect and isolate multiple faults. The foundation of this method is a probabilistic inference, which allows for incorporating and propagating uncertainties. The shortcoming of this approach is that belief updating takes place upon knowing where the fault (discrepancy) is injected. It has also been reported that the method has no efficacy on all edge nodes.

Having this in mind, to the best of the authors' knowledge and literature surveyed, presently there appears to be no way of knowing which of these faults causes the triggering of the diagnostic alarm, using the current fault diagnosis schemes.

2.2. Necessity of Redundant Information

Through the course of this research, a number of approaches such as observers and filters, Bayesian Belief Networks and Neural Networks on different applications such as wood drying kiln and hydraulic systems have been implemented and examined. None of these methods showed a promising solution for the distinction between sensor and system faults since this issue is one step ahead of conventional FDD and requires redundant and *a priori* knowledge of the system and its components. Basically, making a decision regarding this issue has an analogy with solving one equation with two unknowns.

Table 1. Modeling a two-tank process with causal network and its analogy.

Causal Network Model	Equivalent in Multi Reservoirs System
Node A	Liquid level in tank 1 (H_1)
Node B	Liquid level in tank 2 (H_2)
Link $A \rightarrow B$	Valve (v_1)

Some qualitative database of knowledge rules can narrow down this problem; however, it can be realized in the extreme cases. For instance, in a wood drying kiln, when the controller set point is on 70°C, if a sensor indicates a reading of $\ll 70$°C or very low temperatures (lower than the outside temperature), it would be a strong indication of sensor fault rather than a fault in the actuators (heaters) of the system. However, these rules are highly application dependent and require expert's knowledge. These rules are only valid in the extreme cases and not conclusive during most of the operation cycle of the kiln.

3. UTILIZING SENSOR REDUNDANCY

Before explaining the proposed methodology, some definitions are described for modeling purposes.

3.1. Causal Networks

A causal network is a graphical and intuitive model presentation based on physical principles, which can assist users to realize the model. The use of causal networks is common in the modeling of real system as well as fault diagnosis and fault propagation [23, 24]. In this study, the causal networks are used to illustrate the monitored variables and their physical relations. In essence, a causal network represents the underlying *first principle* relationships between the different variables that represent the monitored parameters in the system. The graphical framework of causal networks provides an intuitive understanding of the system variables being modeled. A causal network is shown as a graphical structure that consists of a set of nodes that represent the variables related to the physical domain of interest. These nodes are connected by a set of directed links, which explicitly represent the dependencies between the variables. The lack of a link between two nodes represents their independence. The structure is referred to as a Directed Acyclic Graph (DAG) [24]. If a node A and a node B are connected by a directed link as $A \rightarrow B$, then B is said to be dependent on A.

3.1.1. Representation of sensor and system on causal network

A and B correspond to some physical variables and measurables, using appropriate sensors. The link $A \rightarrow B$ between the two nodes denotes that they are causally related i.e. $B = f(A)$ and thus represents the 'system AB'. To make this point clear, we may refer to the connected reservoirs. The analogy of components of this process to a two-node causal network is given in Table 1.

3.1.2. Serially connected causal network

In the case of a serially connected causal network, there is only one path between any two nodes in the network as shown in Fig. 2. Only this architecture illustrated in is useful for modeling of the system in the proposed methodology. Alternatively, other types of causal networks (multiply connected and tree network) can be truncated to several serially connected causal networks. This point is further discussed in Section 3.7.

Among all variables of a system, a certain subset is required to be monitored to make the system detectable. This subset is the minimum number of variables, which makes it possible to isolate the system faults from each other. The necessary (but not sufficient) condition is that the system should be observable. The criteria for detectability of the system and isolability of faults from each other are addressed in [15, 16]. Once the minimum subset of variables is defined, which clearly must be observable, each of the variables

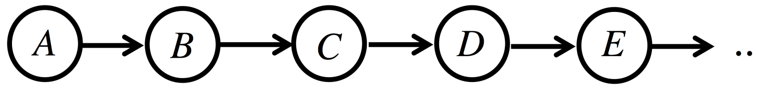


Fig. 2. A serially connected causal network, for modeling a multivariable system.

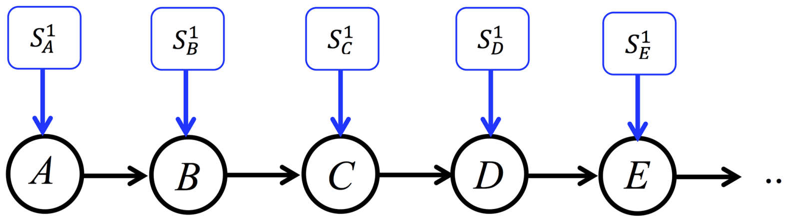


Fig. 3. A set of variables in the system equipped with a single sensor for monitoring.

should be equipped with a proper sensor in the design phase for the purpose of monitoring. In Fig. 3, the sensors are shown as boxes corresponding to each variable.

Many papers discuss the issue of sensor placement for fault detection and isolation [15–17]. This is the necessary configuration (but not sufficient) to detect and isolate faults. However, relying only on the detected fault after the detection procedure, no decision can be made at this point regarding the origin of the fault, i.e. system or the sensor itself. Since monitoring this subset is the necessary condition for detection of faults, the lesser number of sensors will result in an inability to detect and isolate faults. The magnitudes of faults and handling the uncertainties, e.g. noise and unmodeled parameters have a substantial role in correctly detecting the faults. Since the purpose of this research is crisp distinguishing of sensor and system faults, the issue of uncertainty is not considered for explaining the methodology.

3.2. Duplication of Sensors

Based on the definition of fault, the aforementioned configuration of sensors will provide the grounds for detecting faults with model-based detection techniques (either sensor or system). However, no firm decision is conclusive on the origin of the detected fault with a single sensor on each variable. Some studies suggested following statements regarding the isolability of sensor faults [16, 17].

- A fault of a sensor placed to solve the detectability problem is only detectable.
- A fault of two sensors placed to aid the detectability problem is always isolable between them.

These statements implicitly describe the criteria for distinguishability of sensor faults from system faults. In our methodology, the following assumption is made: *The probability of the occurrence simultaneous faults in the redundant sensors is statistically close to zero*.

While the probability of individual faults in each sensor is not zero, this point is statistically true, since the essential and redundant sensors are installed in parallel, which makes the probability of concurrent faults next to zero. Assuming this, in the presence of a redundant sensor S_i^2 for the essential sensor S_i^1, a sensor fault in either S_i^1 or S_i^2 is isolable between them. Notation S_i^j corresponds to the sensor of ith variable and superscript j denotes the number of sensor installed on the variable.

While both sensors S_i^1 and S_i^2 monitor one variable, if the readings at a particular instant have discrepancy (i.e. larger than the defined threshold for consideration of measurement noise), it is a strong indication of a fault in either sensor. Since handling uncertainty is discussed later, for convenience, we consider that in fault-free condition, the readings from both sensors are equal.

In a model based fault diagnosis environment, if the sensors are duplicated, any fault can be isolated, and the origin can be identified (localized) from the discrepancy of sensor readings. Typically, one sensor indicates the model output and the other deviates. On the other hand, a system fault leads to deviation of both sensors and the deviation from the model results in successful detection of the fault. The significance of reading for both sensors S_i^1 and S_i^2 is exactly the same; therefore, there is no privilege between them even if they are of different type.

3.3. Difficulties Associated with Sensor Redundancy

There are several downsides related to sensor redundancy. These factors include but are not limited to additional costs; weight, space, electrical/power and installation constraints; increased complexity; and finally, the sophistication associated with redundant data from measurements. Given these limitations with redundant sensors, there is a reluctance to add sensors in order to fully satisfy the duplicated configuration subset. Therefore, in order to successfully perform the task of sensor/system fault differentiation, we should minimize the sensor set, while producing enough redundant analytical substitutions using functional relationships to either confirm or reject the measurement data from existing sensors.

Henceforward, the problem of distinguishing sensor and system faults will be addressed as 'what *degree of redundancy* is sufficient to perform a crisp decision on the differentiation of the aforementioned faults?'

3.4. Mitigation of Sensor Redundancy

Strict duplication of sensors will result in crisp distinguishability of sensor and system faults. The diagnostic methodology described in this section is based on minimizing the sensor redundancy and knowledge utilization, without compromising the distinguishability and diagnosability of the system. Hence, by using physical relationships between the monitored variables, we can reduce the degree of redundancy from strict duplications. Functional relationships represent the physical interactions between the variables, which are described in a mathematical form. It basically models the first principle relationships between variables, e.g. mass balance. The form of mathematical equation can vary from linear to highly nonlinear, temporal, etc., as long as there is a closed form solution between the two variables. Given the form of the causal model, these functional relationships can generate analytical values to check the credibility of sensor readings in neighboring nodes.

Definition 1. We call the values generated by functional relationships using the readings from the sensors *Analytical Computational Substitutions* (ACS). Generation of ACS could be computationally expensive, depending on the form of the functional relationships; however, they should be calculated in real-time at each evaluation instant of the monitoring procedure.

Definition 2. Logic set consists of all system/sensor state possibilities, which are called *System Behavioral Modes*. It is designed offline with a set of knowledge-based rules (e.g., IF symptom AND symptom THEN conclusion). The parametric design of the logic set allows on-line decision-making by comparing the generated ACS and sensor readings at the sampling point. Now we use the definition of ACS and logic set to eliminate a number of redundant sensors from the fully duplicated configuration. Removing a duplicated sensor from a particular variable is effective, only if neighboring nodes can generate the values of it, i.e. ACS. Hence, a sufficient subset must at least contain three nodes.

Definition 3. We define a window, which covers three nodes at a time, as it traverses through the nodes of the system as shown in Fig. 4. This window is referred to as *Moving Monitoring Window* (MMW).

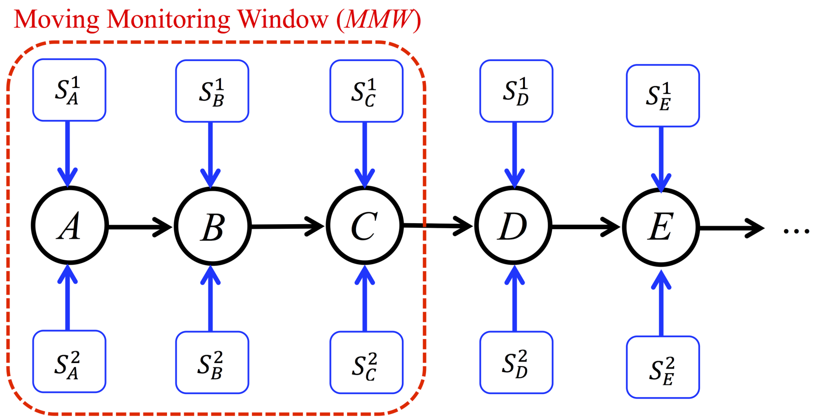
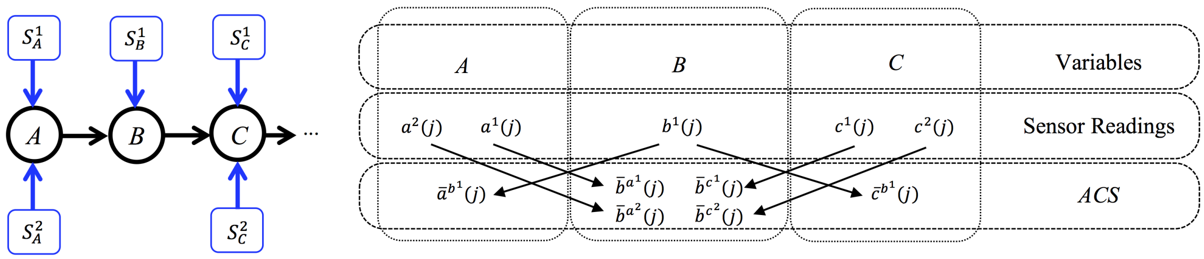


Fig. 4. MMW considers three variables in a step of monitoring.



(a) (b)

Fig. 5. (a) Configuration of optimal minimum redundancy. (b) Variables, sensor readings, and ACS at time (j).

Given three variables (nodes) in one MMV, there are three permutations of sensor culling available for mitigation of redundancy. It should be noted that the significance of S_i^1 and S_i^2 are the same; therefore removing either of them will have the same consequence. The effects of culling permutations are fully described in [10]. Only removing the duplication on middle node (B) is effective, since it is possible to use ACS from nodes A and C to check the credibility of sensor on B. As shown in Fig. 5(a), by using this configuration, in each MMW we will have three variables and five sensors, which are placed in a way that middle variable (node) is bordered by variables (nodes) with duplicated sensors. Indeed, by removing this sensor from full duplication configuration, we lose some state possibilities of the system, and the lack of these states appear detrimental to distinguishing procedure for a few of the fault modes. The sensors will provide five measurements from three variables, at each sampling time. On the other hand, functional relationships between variables yield six ACS corresponding to the variables, as shown by arrows in Fig. 5(b). At any sampling point, j, two measurements from sensors S_A^1 and S_A^2, ($a^1(j)$ and $a^2(j)$) can provide two ACS for variable B ($\bar{b}^{a^1}(j)$ and $\bar{b}^{a^2}(j)$). Similarly, S_C^1 and S_C^2 provide two ACS for variable B. Measurement of S_B^1 provides one ACS for A and one for C using the functional relationships ($\bar{a}^{b^1}(j)$ and $\bar{c}^{b^1}(j)$, respectively). These six values and five measurements enter the logic set unit for further processing.

3.4.1. Structure of the logic set unit

This unit contains all possible states and combinations of measurements and values and decides based on a bank of knowledge-based rules (behavioral modes). In addition to detection of faults and anomalies, this unit can act as the distinguisher and differentiate between sensor faults and system faults, and generate signals for corrective actions or compensatory responses. The parametric structure of the logic set allows comparing and further processing of sensor measurements and corresponding ACS. Table 2 lists all thirty state possibilities of behavioral modes and corresponding diagnosis.

3.4.2. Multiple faults

When the number of concurrent faults in an MMW exceeds two or three, practically, the operation of the system should be halted. As shown in Table 2, some diagnoses are 'Shut Down'. This means that the number of faults in either sensor or system is more than the case that we can distinguish the origin of it, due to the missing information on corresponding state possibilities, which is the consequence of removing a sensor from full duplication configuration. This is also practically not feasible to have a high number of faults at the same time unless another underlying issue causes it. In these situations, the system should be shut down immediately to stop the catastrophic consequences. However, in all other cases, the diagnostic system is able to handle multiple faults successfully, while maintains the ability to distinguish and locate sensor and system malfunctions.

3.4.3. Sensor fault-tolerance strategy

This diagnostic methodology is capable of deciding on this issue and utilizing either the sensor reading or the 'analytical computational substitution (ACS)'. Subsequently, it has the capacity to tolerate some sensor faults temporarily; however, the malfunctioning sensor(s) should be fixed or replaced as soon as possible. For example, in the case that the diagnosis is that S_B^1 is faulty and all other component are healthy, the ACS from node A or C can be substituted for monitoring node B. Hence, $\bar{b}^{a^1}$, $\bar{b}^{a^2}$, $\bar{b}^{c^1}$ or $\bar{b}^{c^2}$ can cover the reading of S_B^1. However, this substitution is not sustainable and may not be valid after some sampling points; hence the fault tolerance cannot be guaranteed for large time spans. In this situation, the system works in a *degraded mode*.

A fault in either sensors A or C can be tolerated by using the validated measurement from its corresponding sensor. For example, if S_A^1 is faulty, the validated reading from $S_A^2(a^2)$ is used as the correct measurement of node A. Since it is for a single fault, we call that sensor fault tolerant of degree one. The system is also capable of sensor fault tolerance of degree two, which means that two sensor faults can be tolerated. For instance, a fault in S_A^2 and a fault in S_B^1 can be tolerated at the same time with the aforementioned logic. It should be noted that the probability of concurrent faults in duplicated sensors is zero, hence, S_A^1 and S_A^2 cannot be faulty at the same time.

3.4.4. Structure of proposed diagnostic system

Figure 6 depicts the structure of the proposed diagnostic system with a minimum number of redundant sensors. To re-iterate, measurements are used to generate ACS. Then measurements and ACS enter the logic set unit to make a decision on the status of the system, based on the predefined behavioral modes. If the system is unable to continue operation, it will be shut down. Moreover, if the system is able to operate in the presence of a fault, the diagnostic system runs the fault isolation procedure, commands the system to operate in a degraded mode and temporarily initiates the sensor fault tolerant strategy. It can be concluded that:

When a variable (node) is bordered with two nodes with duplicated sensors, one sensor is sufficient for the task of distinguishing sensor fault from system fault, since the ACS generated by neighboring measurements can provide redundant values in order to check the credibility of reading of the single sensor installed on the middle node. Removing any more sensors leads to an inability to localize and differentiate between sensor and system faults, due to the lack of adequate behavioral modes for diagnosis decision-making.

Table 2. Logic set.

State of Behavioral Modes	System Fault	Sensor Fault	Diagnosis
$a^2 = a^1, \bar{b}^{a^1} = b^1, \bar{c}^{b^1} = c^1 = c^2$	NO	NO	$S_A^1, S_A^2, S_B^1, S_C^1, S_C^2, AB, BC$ OK
$a^2 = a^1, \bar{b}^{a^1} = b^1, c^1 \neq c^2, \bar{c}^{b^1} = c^1, \bar{c}^{b^1} \neq c^2$	NO	YES	$S_A^1, S_A^2, S_B^1, S_C^1, AB, BC$ OK S_C^2 Faulty
$a^2 = a^1, \bar{b}^{a^1} = b^1, c^1 \neq c^2, \bar{c}^{b^1} \neq c^1, \bar{c}^{b^1} = c^2$	NO	YES	$S_A^1, S_A^2, S_B^1, S_C^2, AB, BC$ OK S_C^1 Faulty
$a^2 = a^1, \bar{b}^{a^1} = b^1, c^1 = c^2, \bar{c}^{b^1} \neq c^1, \bar{c}^{b^1} \neq c^2$	YES	NO	$S_A^1, S_A^2, S_B^1, S_C^1, S_C^2, AB$ OK BC Faulty
$a^2 = a^1, \bar{b}^{a^1} \neq b^1, c^1 = c^2, \bar{b}^{c^1} = b^1, \bar{b}^{c^1} \neq \bar{b}^{a^1}$	YES	NO	$S_A^1, S_A^2, S_B^1, S_C^1, S_C^2, BC$ OK AB Faulty
$a^2 = a^1, \bar{b}^{a^1} \neq b^1, c^1 = c^2, \bar{b}^{c^1} \neq b^1, \bar{b}^{c^1} = \bar{b}^{a^1}$	NO	YES	$S_A^1, S_A^2, S_C^1, S_C^2, AB, BC$ OK S_B^1 Faulty
$a^2 = a^1, \bar{b}^{a^1} \neq b^1, c^1 = c^2, \bar{b}^{c^1} \neq b^1, \bar{b}^{c^1} \neq \bar{b}^{a^1}$	YES	YES	SHUT DOWN
$a^2 = a^1, \bar{b}^{a^1} \neq b^1, c^1 \neq c^2, \bar{b}^{c^2} = b^1, \bar{b}^{c^2} \neq \bar{b}^{a^1}$	YES	YES	$S_A^1, S_A^2, S_B^1, S_C^2, BC$ OK S_C^1, AB Faulty
$a^2 = a^1, \bar{b}^{a^1} \neq b^1, c^1 \neq c^2, \bar{b}^{c^2} \neq b^1, \bar{b}^{c^2} = \bar{b}^{a^1}$	YES	YES	S_A^1, S_A^2, S_C^2, BC OK S_B^1, S_C^1, AB Faulty
$a^2 = a^1, \bar{b}^{a^1} \neq b^1, c^1 \neq c^2, \bar{b}^{c^2} \neq b^1, \bar{b}^{c^2} \neq \bar{b}^{a^1}$	YES	YES	SHUT DOWN
$a^2 = a^1, \bar{b}^{a^1} \neq b^1, c^1 \neq c^2, \bar{b}^{c^1} = b^1, \bar{b}^{c^1} \neq \bar{b}^{a^1}$	YES	YES	$S_A^1, S_A^2, S_B^1, S_C^1, BC$ OK S_C^2, AB Faulty
$a^2 = a^1, \bar{b}^{a^1} \neq b^1, c^1 \neq c^2, \bar{b}^{c^1} \neq b^1, \bar{b}^{c^1} = \bar{b}^{a^1}$	YES	YES	S_A^1, S_A^2, S_C^1, BC OK S_B^1, S_C^2, AB Faulty
$a^2 = a^1, \bar{b}^{a^1} \neq b^1, c^1 \neq c^2, \bar{b}^{c^1} \neq b^1, \bar{b}^{c^1} \neq \bar{b}^{a^1}$	YES	YES	SHUT DOWN
$a^2 = a^1, c^1 = c^2, \bar{b}^{a^1} \neq b^1, \bar{b}^{c^1} \neq b^1, \bar{c}^{b^1} \neq \bar{b}^{a^1}$	YES	NO	SHUT DOWN AB, BC Faulty
$a^2 \neq a^1, \bar{b}^{a^2} = b^1, \bar{c}^{b^1} = c^1 = c^2, \bar{c}^{b^1} = \bar{b}^{a^2}$	NO	YES	$S_A^2, S_B^1, S_C^1, S_C^2, AB, BC$ OK S_A^1 Faulty
$a^2 \neq a^1, \bar{b}^{a^2} = b^1, c^1 \neq c^2, \bar{c}^{b^1} = c^1, \bar{c}^{b^1} = \bar{b}^{a^2}$	NO	YES	$S_A^2, S_B^1, S_C^1, AB, BC$ OK S_A^1, S_C^2 Faulty
$a^2 \neq a^1, \bar{b}^{a^2} = b^1, c^1 \neq c^2, \bar{c}^{b^1} = c^2, \bar{c}^{b^1} = \bar{b}^{a^2}$	NO	YES	$S_A^2, S_B^1, S_C^2, AB, BC$ OK S_A^1, S_C^1 Faulty
$a^2 \neq a^1, \bar{b}^{a^2} = b^1, c^1 = c^2, \bar{c}^{b^1} \neq c^1, \bar{c}^{b^1} \neq c^2$	YES	YES	$S_A^2, S_B^1, S_C^1, S_C^2, AB, BC$ OK S_A^1, BC Faulty
$a^2 \neq a^1, \bar{b}^{a^2} \neq b^1, c^1 = c^2, \bar{b}^{c^1} = b^1, \bar{b}^{c^1} = \bar{b}^{a^1}$ (then $\bar{b}^{a^1} = b^1$)	NO	YES	$S_A^1, S_B^1, S_C^1, S_C^2, AB, BC$ OK S_A^2 Faulty
$a^2 \neq a^1, \bar{b}^{a^2} \neq b^1, c^1 = c^2, \bar{b}^{c^1} = b^1, \bar{b}^{c^1} \neq \bar{b}^{a^1}$	YES	YES	SHUT DOWN
$a^2 \neq a^1, \bar{b}^{a^2} \neq b^1, c^1 = c^2, \bar{b}^{c^1} \neq b^1, \bar{b}^{c^1} = \bar{b}^{a^1}$ (then $\bar{b}^{a^1} = b^1, \bar{c}^{b^1} \neq c^1$)	NO	YES	$S_A^1, S_C^1, S_C^2, AB, BC$ OK S_A^2, S_B^1 Faulty
$a^2 \neq a^1, \bar{b}^{a^2} \neq b^1, c^1 = c^2, \bar{b}^{c^1} \neq b^1, \bar{b}^{c^1} \neq \bar{b}^{a^1}$	YES	YES	SHUT DOWN
$a^2 \neq a^1, \bar{b}^{a^2} \neq b^1, c^1 \neq c^2, \bar{b}^{c^1} \neq b^1, \bar{b}^{c^1} \neq \bar{b}^{a^1}$	YES	YES	SHUT DOWN
$a^2 \neq a^1, \bar{b}^{a^1} = b^1, c^1 = c^2, \bar{c}^{b^1} = c^1, \bar{b}^{c^1} = \bar{b}^{a^1}$	NO	YES	$S_A^1, S_B^1, S_C^1, S_C^2, AB, BC$ OK S_A^2 Faulty
$a^2 \neq a^1, \bar{b}^{a^1} = b^1, c^1 \neq c^2, \bar{c}^{b^1} = c^1, \bar{b}^{c^1} = \bar{b}^{a^1}$	NO	YES	$S_A^1, S_B^1, S_C^1, AB, BC$ OK S_A^2, S_C^2 Faulty
$a^2 \neq a^1, \bar{b}^{a^1} = b^1, c^1 \neq c^2, \bar{c}^{b^1} = c^2, \bar{b}^{c^2} = \bar{b}^{a^1}$	NO	YES	$S_A^1, S_B^1, S_C^2, AB, BC$ OK S_A^2, S_C^1 Faulty
$a^2 \neq a^1, \bar{b}^{a^1} \neq b^1, c^1 = c^2, \bar{b}^{c^1} = b^1, \bar{b}^{c^1} \neq \bar{b}^{a^1}$	YES	YES	SHUT DOWN
$a^2 \neq a^1, \bar{b}^{a^1} = b^1, c^1 = c^2, \bar{b}^{c^1} \neq b^1, \bar{b}^{c^1} = \bar{b}^{a^2}$	NO	YES	$S_A^2, S_C^1, S_C^2, AB, BC$ OK S_A^1, S_B^1 Faulty
$a^2 \neq a^1, \bar{b}^{a^1} = b^1, c^1 = c^2, \bar{b}^{c^1} \neq b^1, \bar{b}^{c^1} \neq \bar{b}^{a^2}$	YES	YES	SHUT DOWN
$a^2 \neq a^1, \bar{b}^{a^1} = b^1, c^1 \neq c^2, \bar{b}^{c^1} \neq b^1, \bar{b}^{c^1} \neq \bar{b}^{a^2}$	YES	YES	SHUT DOWN

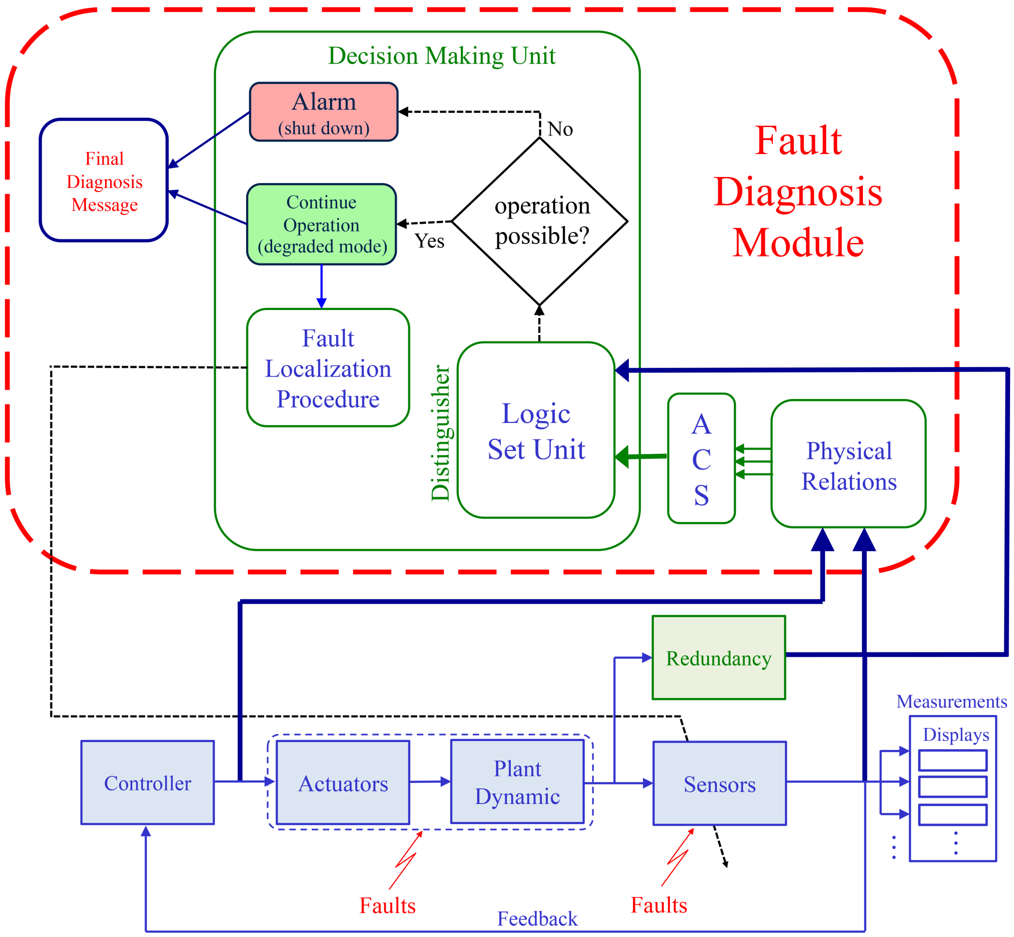


Fig. 6. The structure of the proposed diagnostic system.

3.5. Generalization by Deduction

We discussed the concept of MMW, which monitors three variables and then traverses in the direction of causality to monitor the next proper set. If the system is modeled with only three variables, there is no need to move the window. However, for the systems with larger number of variables, the redundancy configuration methodology has two strategies. It is noted that edge nodes must always have duplicated sensors. As shown in Fig. 7, for a system with four variables, since the first and fourth nodes are edge nodes, they must have full sensor duplication. There are two subsets with three nodes, $\{A,B,C\}$ and $\{B,C,D\}$ that MMW can cover. Considering Fig. 7(a), MMW first monitors subset $\{A,B,C\}$, where B has only one sensor. Since D has sensor duplication, there is no need to move MMW and monitor subset $\{B,C,D\}$. Alternatively, as shown in Fig. 7(b), MMW can first monitor subset $\{B,C,D\}$, where C has only one sensor. There is no fundamental difference between these two solutions and they show that by having four variables, instead of eight sensors, we can perform fault localization with seven sensors.

For a system with five variables, we have three subsets of $\{A,B,C\}$, $\{B,C,D\}$ and $\{C,D,E\}$, when MMW moves in the direction of causality. Since A and E are edge nodes, they must have duplicated sensors. As schematically shown in Fig. 8(a), when MMW covers subset of $\{A,B,C\}$, the node B is a single-sensor. Moving MMW in the direction of causality to monitor $\{B,C,D\}$, since edge node B is not duplicated, monitoring of this subset is not effective. Then by covering subset $\{C,D,E\}$, the node D can be a single-

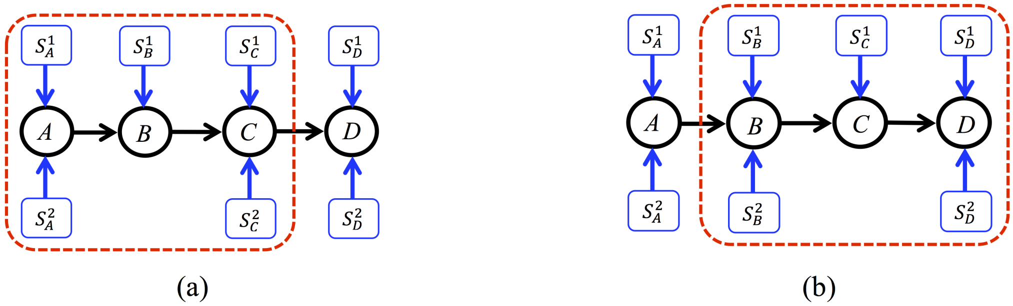


Fig. 7. A system with four variables (nodes), (a) node B is single-sensor; (b) node C is single-sensor.

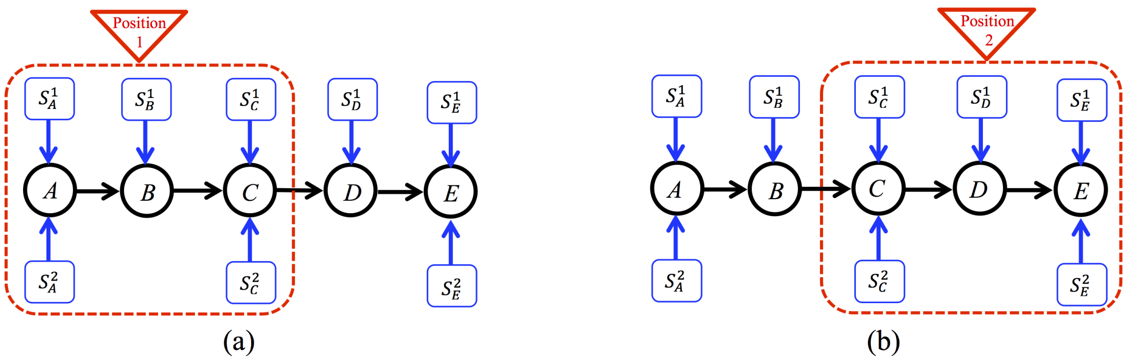


Fig. 8. A system with five variables (nodes), MMW moves from position 1 in (a) to position 2 in (b).

sensor, since it is bordered by two sensor-duplicated nodes. Hence, the MMW is at position 1 at first to check $\{A,B,C\}$, and then moves to position 2 and performs the same action on $\{C,D,E\}$, as shown in Fig. 8(b). The nodes B and D are dominated by two nodes, which have duplicated sensors. Therefore, one sensor is enough for each of them, and then ACS, provides redundant values. For a five-variable system, eight sensors are sufficient to perform the fault localization task.

For a system with six variables, the condition is similar to the system with four variables. There are four subsets of $\{A,B,C\}$, $\{B,C,D\}$, $\{C,D,E\}$, and $\{D,E,F\}$. Given the sensor duplication of edge nodes, covering the subsets $\{B,C,D\}$ and $\{D,E,F\}$ by MMW is not effective. Hence, as shown in Fig. 9(a), MMW starts with subset $\{A,B,C\}$ and then moves to position 2, to monitor subset $\{C,D,E\}$. Since F, as an edge node, has duplicated sensors, there is no need to move MMW toward that. In this configuration, by having six variables, ten sensors are adequate to distinguish sensor and system faults.

For a larger number of variables, the process is analogous; they are either similar to a system with five variables or six variables. When the number of variables in a causal model is odd, the situation is similar to the system with three or five variables. On the other hand, when the number of variables is even, the case is similar to the system with four or six variables. By *deduction*, the methodology remains analogous. Therefore, we can define the number of required sensors, which can perform the defined fault localization task. By extending of the pattern of sensor placement, it is evident that the function, which shows the number of required sensors, depends on whether the number of variables in the causal model is even or odd.

Let us define m as the number of variables to be monitored, and n_d as the number of sensor required for the crisp distinguishing of sensor fault and system fault. By deduction:

$$\left.\begin{array}{l}\text{if } m \in \text{odd} \Rightarrow n_d = 1.5 \times m + 0.5 \\ \text{if } m \in \text{even} \Rightarrow n_d = 1.5 \times m + 1\end{array}\right] \Rightarrow n_d > 1.5 \times m \tag{1}$$

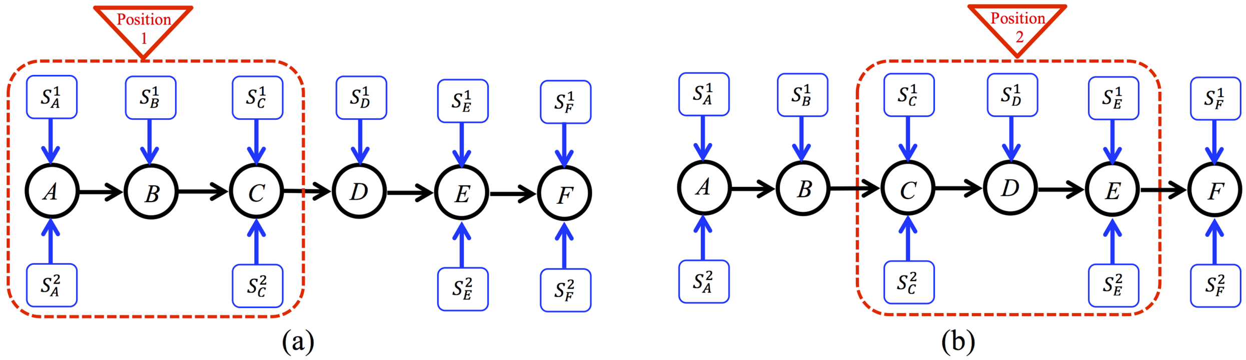


Fig. 9. A system with six variables (nodes), MMW moves from position 1 in (a) to position 2 in (b).

It should be noted that for the purpose of control or model-based fault detection, having at least m sensors is sufficient. The generalization is established on deduction since the methodology works for any number of variables. This means that if the system can be modeled as serially a connected causal network, the number of the required sensors to distinguish sensor faults and system faults should be at least greater than one and half times the number of variables. Without this number of sensors for the serial configuration, full localization of sensor and system faults is inconceivable.

3.6. Features and Applications of the Method

Basically, any dynamical system amenable to serially causal modeling can be monitored with this method, and consequently, its sensor and system faults can be distinctly identified. Multi-reservoirs plants for liquids, transmission pipelines with several output valves, interconnected gas containers, etc. are examples of systems that have several variables to be monitored, and these variables have physical (first principle) relationships with each other. Therefore, these systems can be modeled as serially connected causal networks within the framework of the proposed diagnostic method. This approach is capable of detecting faults, distinguishing between the sensor and system faults, and localizing them.

Once an appropriate number of sensors is determined through the methodology presented here by tracking the faulty sensor signal based on the approaches similar to that described in [25], it possible to identify the type of the occurred sensor fault. For instance, statistical analysis of a sensor signal (mean and variance) may reveal bias, drift or loss of effectiveness of the sensor.

3.7. Extension to Non-Serially Connected Systems

While many real-world systems can be described as serially connected causal models [26], it is noted that where the model cannot be defined as a serially connected causal network, the method cannot be directly used. At any branching node of a combined serial-parallel network, the sensors of the corresponding nodes should be duplicated in order to comply with the task of distinguishing. As shown in Fig. 10(a), the sensors for the nodes B, C and $\bar{C}$ are duplicated.

However, if we can find a branch in the causal network that has more than three nodes itself, the concept of MMW can be used to eliminate the duplication of the sensor for the middle node of this branch. For instance, in Fig. 10(b), the branch with the subset of $\{\bar{C}, \bar{D}, \bar{E}\}$ can be considered as a separate serially connected causal network, hence MMW can cover it. Given this, the node $\bar{D}$ can be single sensor, while the fault distinguishing capability is maintained. By considering this argument, the non-serially connected causal networks (tree and multiply connected) can also be decomposed to serially connected causal networks. Then the methodology can be applied to each branch individually. Although the number of sensors will not

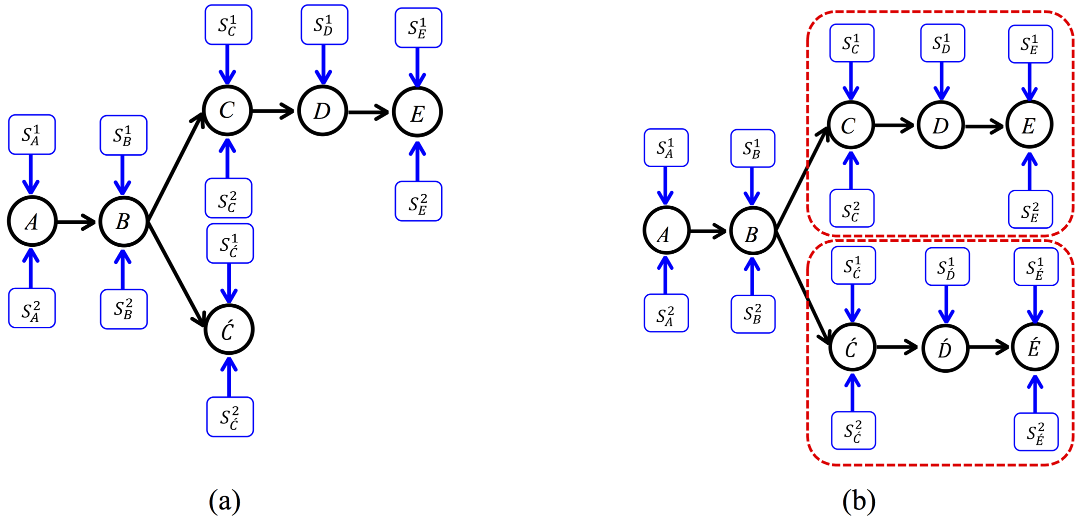


Fig. 10. Extension for non-serially connected causal networks.

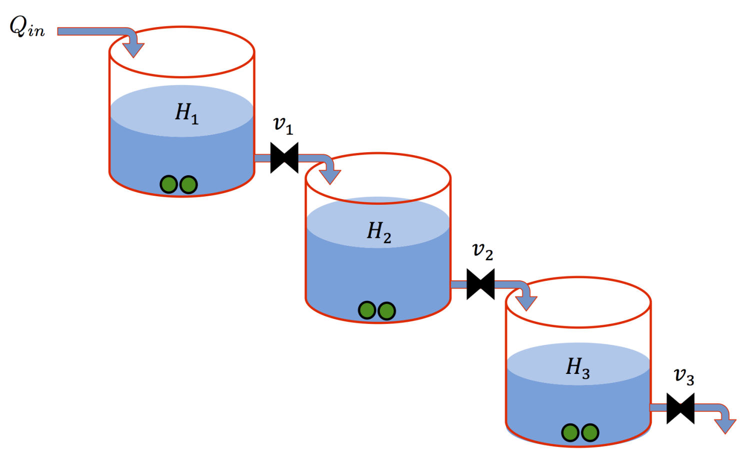


Fig. 11. A system of three interconnected liquid reservoirs with duplicated height level sensors.

be minimized as before, it can be reduced from strict duplication configuration, but the minimum number of sensors required is configuration-dependent.

4. APPLICATION FOR INTERCONNECTED MULTI RESERVOIRS

4.1. Modeling of Interconnected Multi Reservoirs with Causal Networks

Multi reservoirs can be modeled by causal networks since the level of liquid in each tank is proportional to the flow rate from the valves. The flow rate in valves is also a function of the height of the liquid in the tank before the valve. The serially connected tanks architecture satisfies the serially connected causal network modeling requirement, which is described in the methodology. The liquid levels in the tanks are represented by nodes in the causal network, and the valves are the links between the nodes. Now, we consider a system with a different number of interconnected tanks and apply the methodology. For a system with one or two tanks, the number of permutations for behavioral modes is not sufficient to reduce the degree of redundancy from duplication. We consider a system with three interconnected tanks and duplicate

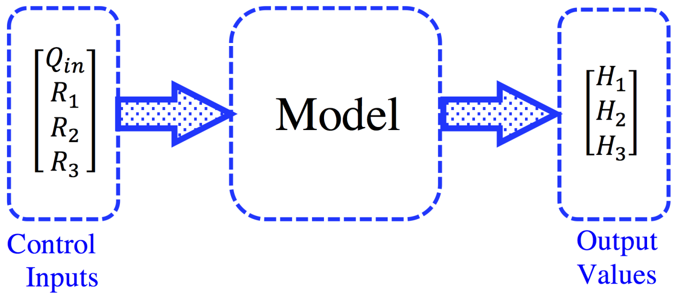


Fig. 12. Relationships between inputs and outputs.

all height-level measurement sensors as shown in Fig. 11. This configuration will provide a ground to fully distinguish sensor and system faults.

According to the methodology, the only optimal redundancy mitigation solution is to remove one of the sensors in tank 2. Therefore, tank 1 and 3 are monitored by duplicated sensors, and tank 2 has only one sensor. This configuration has a sufficient number of sensors to comply with the conditions of the procedure. The known control inputs are: $Q_{in}(k)$, $R_1(k)$, $R_2(k)$, $R_3(k)$, which are input flow to the tank 1, and resistance of valves v_1, v_2 and v_3, respectively. The variables to be monitored and measured are $H_1(k)$, $H_2(k)$ and $H_3(k)$ at sampling time k. Based on causality, we can define the relationships between the heights of the tanks as $H_2 = f(H_1)$ and $H_3 = g(H_2)$. By having the control inputs and model of the system, the output can be generated (or estimated), as shown in Fig. 12.

In the process of diagnosis and distinguishing for this system based on the methodology, at each sampling time, we have five measurements from sensors, corresponding to three variables, as shown in Fig. 12. The sensor readings are:

- h_1^1 and h_1^2 corresponding to H_1,
- h_2^1 corresponding to H_2,
- h_3^1 and h_3^2 corresponding to H_3,

where the superscript indicates the sensor that has been used for measurement and subscript corresponds to the variable. Additionally, we have three equations relating to the physics of the problem. Each equation computes the variation of height in a tank:

$$\dot{H}_1(k) = \frac{Q_{in}}{A_1} - \frac{H_1(k)}{A_1R_1(k)} \quad \text{(for tank 1)} \tag{2}$$

$$\dot{H}_2(k) = \frac{H_1(k)}{A_2R_1(k)} - \frac{H_2(k)}{A_1R_2(k)} \quad \text{(for tank 2)} \tag{3}$$

$$\dot{H}_3(k) = \frac{H_2(k)}{A_3R_2(k)} - \frac{H_3(k)}{A_3R_3(k)} \quad \text{(for tank 3)} \tag{4}$$

Having the initial conditions for these relationships, the measurements can be used to obtain ACS. By substituting each measurement in the relationships, the ACS from one tank to adjacent tank is determined. Using five measurements and three equations, six values in total can be derived.

In Table 3, $\bar{h}_p^q$ shows the analytical value (ACS) derived from physical relationships. Here, index p denotes the variable number corresponding to ACS, and q denotes the sensor reading that has been used to generate ACS. As shown in Table 3:

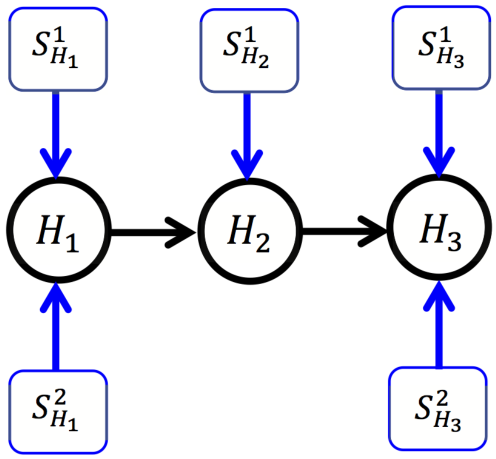


Fig. 13. The causal network and sensor configuration for liquid tank process.

Table 3. Variables, sensor readings, and ACS for the three-reservoir system.

Variable	H_1	H_2		H_3
Sensor measurements	h_1^1 , h_1^2	h_2^1		h_3^1 , h_3^2
ACS	$\bar{h}_1^{h_2^1}$	$\bar{h}_2^{h_1^1}$ $\bar{h}_2^{h_3^1}$	$\bar{h}_2^{h_1^2}$ $\bar{h}_2^{h_3^2}$	$\bar{h}_3^{h_2^1}$

- Variable H_1: two measurements, one ACS.
- Variable H_2: one measurements, four ACS.
- Variable H_3: two measurements, one ACS.

This configuration will result in 30 distinct behavioral modes in the system including all state possibilities, derived from the system model, which are designed off-line similar to Table 2. The logic set contains the knowledge base parametric rules (e.g., IF symptom AND symptom THEN conclusion). These parametric values in this configuration are sufficient to construct a logic set. The logic set contains 30 statements, which represent all distinctive behavioral modes of the process.

4.1.1. Fault emulation

It was shown in Section 3.4.1 that by having measurements from sensors and online generated ACS, a table similar to Table 4 can be composed. After constructing the logic set, any faults in the valves or liquid level sensors can be detected and then localized. It is clear that in fault-free case, $h_1^1 = h_1^2 = \bar{h}_1^{h_2^1}$, $h_2^1 = \bar{h}_2^{h_1^1} = \bar{h}_2^{h_1^2} = \bar{h}_2^{h_3^1} = \bar{h}_2^{h_3^2}$ and $h_3^1 = h_3^2 = \bar{h}_3^{h_2^1}$. This means that the level measurements and corresponding ACS for each monitored height are equal. Any discrepancy between these values is indicative of a fault. To avoid replication, only five scenarios of a single fault in various sensors/components of liquid reservoirs are given in Table 4. Then in each scenario, the corresponding behavioral mode, which leads to the distinction of sensor and system faults, is presented. The first two scenarios represent the cases where the system is faulty (i.e. control valves are leaking). The next three scenarios characterize the cases where sensor faults

Table 4. Fault scenarios in different components of reservoirs system and corresponding behavioral modes.

Fault type	Fault location	Corresponding Behavioral Mode
System fault	Control Valve 1 v_1	$h_1^1 = h_1^2, \bar{h}_2^{h_1^1} \neq h_2^1, h_3^1 = h_3^2,$ $\bar{h}_2^{h_3^1} = h_2^1, \bar{h}_2^{h_3^1} \neq \bar{h}_2^{h_1^1}$
System fault	Control Valve 2 v_2	$h_1^1 = h_1^2, \bar{h}_2^{h_1^1} = h_2^1, h_3^1 = h_3^2,$ $\bar{h}_3^{h_2^1} \neq h_3^1, \bar{h}_3^{h_2^1} \neq h_3^2$
Sensor fault	Sensor 1 in tank 2 $S_{H_2}^1$	$h_1^1 = h_1^2, \bar{h}_2^{h_1^1} \neq h_2^1, h_3^1 = h_3^2,$ $\bar{h}_2^{h_3^1} \neq h_2^1, \bar{h}_2^{h_3^1} = \bar{h}_2^{h_1^1}$
Sensor fault	Sensor 1 in tank 1 $S_{H_1}^1$	$h_1^1 \neq h_1^2, \bar{h}_2^{h_1^2} = h_2^1,$ $\bar{h}_3^{h_2^1} = h_3^1 = h_3^2, \bar{h}_3^{h_2^1} = \bar{h}_2^{h_1^2}$
Sensor fault	Sensor 2 in tank 3 $S_{H_3}^2$	$h_1^1 = h_1^2, \bar{h}_2^{h_1^1} = h_2^1, h_3^1 \neq h_3^2,$ $\bar{h}_3^{h_2^1} = h_3^1, \bar{h}_3^{h_2^1} \neq h_3^2$

are responsible for the discrepancy between measurement and ACS values. Only three sample sensor faults amongst all permutations of five liquid level sensors in the tanks are given here. The rest of the faults including multiple faults cases can be similarly diagnosed and localized.

4.1.2. Extension for a larger number of reservoirs

The procedure is extendable for systems with more tanks (and consequently more variables), by traversing MMW in the direction of causality between liquid levels in the tanks. Similar to the procedure given in Section 3.5, the methodology can be applied to a process with any number of serially connected tanks. This configuration can be applied to a parallel but independent variable in the system as well. For example, if the temperature is also monitored in the tanks, while the number of temperature sensors is greater than 1.5 times the number of tanks (considering the placement configuration), the temperature sensor faults and system faults (e.g. heaters in the tanks) are both distinguishable.

4.2. Remarks on Presence of Uncertainty

The first principle models (physical relationships) used in this methodology are deterministic. Once we decide the degree of sensor redundancy for distinguishing sensor and system faults in a deterministic case, we can incorporate uncertainty models as add-ons to the procedure. The important issue of robustness to uncertainty is not the subject of the present research and has been addressed by many researchers. Usually, the uncertainty representations for estimation and detection are extensions of the deterministic model. Indeed, introducing noise as well as using detection techniques leads to a number of missed and/or false alarms in the diagnostic procedure. This part is concerned with 'detection' of faults, whereas establishing the minimum number of sensors, described in this paper, results in crisp distinguishing of all detected faults. In other words, if we install the required minimum number of sensors in the configuration, the origin of any detected fault (sensor or system) can be determined via modified logic set rules. Readers are referred to [10] for accommodating uncertainty in the methodology.

5. CONCLUSIONS AND FUTURE WORK

This study sheds light on better understanding the criteria needed for differentiating sensor faults from system faults in a controlled system, in order to make an attributable diagnostic decision with respect to the type of the fault. We developed a framework to address this problem for a certain class of systems, which have serial causality between their variables. In this way, *a priori* knowledge of the physical relationships (functional redundancy) between monitored variables is used to check the credibility of existing sensor observations. By defining the concept of MMW and the logic set the minimum degree of sensor redundancy has been established. This research is the first step in perspective on effective distinguishing of sensor fault from system faults. It has opened a new area for exploration in the field of fault diagnosis prospect. There are many ways to improve the proposed framework. In future works, the methodology can be extended in the following directions:

1. Investigation and extension of the method for non-serial networks.

2. Theoretical evaluation of distinguishability criteria.

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