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Effective Fault Detection & Isolation using Bond Graph-based Domain Decomposition

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Abstract— **The problem of fault detection and isolation in complex chemical/biochemical plants can be effectively addressed by a hierarchical strategy involving successive narrowing of the search space of potential faults. A bond graph network is one means of achieving a decomposition based on a separation of the physical domains such as mechanical, electrical, etc. In this work, bond graph theory is used with a three-stage procedure to fulfill the tasks of fault detection and isolation. First, the multivariate statistical method of principal component analysis is used to remove outliers and reduce the data dimensions. Second, the discrete wavelet transform is applied to the resulting scores to abstract the dynamics at different scales. In the third and final step, the Mahalanobis distance is applied to the results found in step two to calculate the confidence level. Based on the degree of violation from the nominal probability level, the detection of a potential fault is concluded to be true. Following a conclusion of true, fault isolation is achieved by comparing the time scale at which the violation of the nominal probability level occurred to the time scale associated with each physical domain. Two examples are presented to demonstrate these concepts.**

I. INTRODUCTION

The complete reliance on human operators to cope with process faults is increasingly difficult due to several factors. Primary among these are the complexity and the size of process. Furthermore, the unreliability of human operators adds to inefficient, unreliable fault management. Without an effective response to faults, minor local faults may evolve to plant-wide failures, emergency shut-down, and sometimes an environmental disaster with large economical losses and occupational injuries. Effective and rapid fault detection and isolation (FDI) is the first step in developing a successful fault management system.

Majority of the past efforts on developing a fault management systems focused on solving the problem as a two-stage procedure, detection and isolation. The various methods proposed can be divided into two categories according to the extent of prior process knowledge, model and data-based approaches. The former utilizes a mathematical model (often based on conservation laws) to formulate the diagnostic conclusion. While the latter relies on historical operating data and evidential observations.

Most approaches on FDI are proposed at a single level of abstraction. These non-hierarchical methods require sufficient details to resolve faults at the unit level. For today's complex plants, the cost to develop high resolution models and collect data can be extremely expensive. Also non-robust fault management systems may become unacceptably inefficient because of the large plant scale and simultaneous large search space. Finch and Kramer suggest that a multi-tiered, hierarchical approach to FDI may be more suitable for large or complex processes [1]. Thus, a modeling formalism is needed to describe processes at an appropriate level of abstraction for rapid early-stage FDI. One example of a model formalism is one that abstracts and represents the complex and integrated system as subsystems that correspond to the physical groups or functional behavior.

Bond graph [2], a graphical modeling language, provides a model formalism that decomposes the process into subsystems that map to the physical connections. The resulting subsystems are essentially physical fields including mechanics, electronics, hydraulics, and chemistry. The time granularity for these domains are usually distinct. For instance, the dynamic response for a mechanical pump is usually on the scale of milliseconds when compared to the consumption or generation of a chemical species (usually on a scale of minutes or greater). Thus, in this work, we propose a multi-scale analysis based on the time features of the phenomena for the purpose of an innovative FDI corresponding to the process decomposition based on bond graph theory. It is expected that by narrowing the search space to locate the fault, the response to correct the fault will be improved. Further, the proposed approach is developed to detect single/multiple fault(s) either intermittent or slow drift type. This multi-scale analysis is accomplished by incorporating techniques such as principal component analysis (PCA) and discrete wavelet transform (DWT)to enhance the resolution of fault feature analysis.

The paper is organized as follows. In section II, the concepts of fault are introduced. In section III the necessary theory on bond graphs is reviewed. In section IV, the concept of a hierarchical FDI is introduced as the process decomposition is developed based on its bond graph. The procedures involved with detection & isolation, PCA and DWT are introduced in section V. The detailed approach for on-line detection and isolation is presented in section VI with two examples to demonstrate the approach. Lastly, in section VII a summary of the findings and some recommendations are presented.

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II. FAULT DETECTION & ISOLATION

Simply stated, a fault is a malfunction of the system because of some unexpected change. The malfunction disturbs normal operation and if unchecked may further deteriorate the system performance. The underlying cause(s) of the fault, such as failed equipments or drifting process parameters is (are) defined as the root cause(s). It is noteworthy to compare *fault* and *failure*. The term *fault* is usually used to indicate a malfunction that may be tolerable at the present time, while *failure* suggests a complete breakdown of a function. If a fault cannot be detected and resolved, it is highly probable that the fault may evolve into a failure.

As a fault is defined as an unpermitted deviation of at least one characteristic property of a variable from its acceptable range, the time dependency of a fault can be distinguished as an abrupt fault, a drifting fault, or as an intermittent fault [3]. An abrupt fault is rare, in contrast, the other two types of faults frequently occur but are usually not readily detected because of masking by process and measurement noise.

The task of responding to a fault event involves timely detection, isolating the causal origin of the fault, estimating the degree of the fault, and finally taking the necessary steps to bring the process back to normal. This work will concern itself only with detection and isolation.

A. Fault Detection

Fault detection usually involves making a binary decision, either that something has gone wrong or that everything is within normal accepted ranges. The outcome is simple, but never the procedure to arrive at the outcome. For a single variable not within its normal range, limit checking may be enough to make a decision. But most industrial processes consist of monitoring and collecting hundreds of process variables. Moreover, process and measurement noise are unavoidable and may contribute to false alarms. Thus, robust detection must be a feature in the design of an effective fault detection algorithm. Depending on the prior process knowledge available for detection, the proposed approaches can be broadly classified into two categories: first-principle and historical-data approaches [3].

B. Fault Isolation

Also called fault localization, fault isolation locates the possible root causes for the detected fault. Previous research on fault isolation methods can be classified as either quantitative or qualitative. Quantitative approaches, such as analytical redundancy [4] and parity space [5], were proposed to combine FDI as a one step procedure. In contrast, qualitative methods, such as digraphs, focused on constructing and searching using causal models.

There are several issues about isolation but perhaps of primary importance is resolution. Resolution indicates the depth of isolation, which determines the effort required for fault recovery. With a finer resolution, such as at the component level, the fault origin is clearly targeted but may be too time consuming to be effective. On the other hand, a coarser resolution, such as at the unit level, while more rapid (smaller search space) may not reveal the true fault origin.

III. BOND GRAPH

Bond graph is an explicit graphical tool for capturing the structures among the physical systems into an energy network based on power exchanges [6]. Others [7]–[9] have extended the bond graph concept to represent phenomena such as chemical kinetics and to extract causal models and control structures from the bond graph networks.

Power is the common variable among the different physical domains. Indeed, the product of variables such as voltage (V) and current (A), pressure (N/m^2) and flowrate (m^3/s) is power. In bond graph theory, these variables are referred to as *effort* (e) and *flow* (f). Table I gives some examples of effort and flow in different physical domains. The elements of a system to be modeled in the bond graph framework are called *nodes*. *Bonds* connect nodes and *ports* connect bonds to nodes. The bond denotes the energy transferred between nodes. The direction of the transfer of energy and the associated flow between nodes is based on the orientation of a half arrow ($\rightharpoonup$) added to the bond. The bond graph of a system reflects the physical structure in which the effort and flow variables are used to construct a path between nodes to track power exchanges and the dynamics associated with power conversions.

TABLE I

POWER VARIABLES FOR DIFFERENT PHYSICAL DOMAINS.

Variables	Electronic	Hydraulic	Mechanic (translation)	Mechanic (rotation)
Effort (e)	Voltage	Pressure	Force	Torque
Flow (f)	Current	Flowrate	Velocity	Frequency

Bond graph theory provides a series of standard elements to model the flow of power among heterogeneous domains. Each element can be mapped to a specific physical device within a given domain [10]. A graphical representation of a process using bond graph elements is defined to be a bond graph network (see Fig. 2).

A. Basic elements

The basic bond graph elements provide mappings for fundamental physical phenomena in various fields. Resistance ($\rightharpoonup$R) is introduced to represent power dissipation by imposing a constitutive relationship between effort and flow,

$$e = Rf \qquad\qquad f = e/R$$

The R-element is analogous to electrical resistors, mechanical dampers or dashpots, porous plugs in fluid lines and other passive power elements. The concepts of a capacitor ($\rightharpoonup$C) and inductance ($\rightharpoonup$I) also are basic bond graph elements. Both are power storage element, by imposing a time integral relationship between two power variables,

$$e = C \int_0^t f\,dt \qquad\qquad f = I \int_0^t e\,dt$$

A capacitor can be the idealization of springs in a mechanical system, a tank in a hydraulic system or reactants in a chemical system. An inductance is used to represent physical elements with inertial effects such as the mass in a mechanical domain (see Fig. 2).

B. Converting between domains

Power variables from different domains cannot be connected without some conversion. The transformer (TF) and the gyrator (GY) bond graph elements provide this conversion capability. Both TF and GY assure that power is conserved. The TF element has the property that the ratio of the efforts is the inverse of the ratio of the flows ($e_i/e_j = f_j/f_i$). For example, the boundary between the mechanic and hydraulic domains in Fig. 2 is denoted by TF which represents a pump that converts mechanical motion into hydraulic motion. In the case of the GY element, the flow at one port is dependent on the effort at the other. In some cases, information rather than power is the link between domains, for instance, hydraulic flow carrying reactants imposes a modulating effect on the chemistry. In the bond graph network, a dashed line is used to represent this non-energetic interaction (see Fig. 2 - dashed line from the hydraulic to the reaction domain.) By identifying TF and GY elements and information bonds from the physical system, the boundaries among the physical domains are naturally inherited by the resulting bond graph network.

C. Representing measurement devices

In a bond graph network, either effort or flow within their respective domain is measurable. To capture this concept of sensing in a bond graph network, the bond graph elements *De* and *Df* are used for effort and flow detection, respectively (see Fig. 2). Thus, the location and type of measurement are made explicit by the bond graph network. The real sensor and its corresponding representation by effort or flow is necessary to represent a measurement in a bond graph. The procedure depends on the type of real measurements. In case of a direct map between the physical sensor and the effort or flow variable, the conversion is essentially to classify the sensor as *De* or *Df* as well as the domain it belongs to. On the other hand, if the sensor to either effort or flow is not a direct map, a conversion is necessary to arrive at the corresponding effort or flow variable.

With a complete representation of the system by a bond graph network, it is claimed that the tasks of detection and isolation can be done more efficiently. For example, if the fault is due to a single equipment malfunction, it will not be difficult to detect and isolate the equipment due to the domain separation achieved by the bond graph network. With the bond graph elements, these errors are isolated explicitly in the bond graph network.

IV. PROCESS DECOMPOSITION

A. Hierarchical FDI

Since the tasks of fault detection & isolation are complicated by the high dimensionality search space of the process it is not unreasonable to consider a hierarchical approach to narrowing the search space. Here a procedure is proposed in which the isolation focus is rapidly narrowed from an initially broad scope to a restricted, feasible space. In the first pass, the faulty subsystems are isolated. The resolution may be coarse but the tradeoff is efficiency. Then, detailed fault identification can be applied about the isolated space in question.

B. Domain decomposition

There are at least two distinct dimensions of decomposition, a structural dimension corresponding to the physical groupings of components, and a functional dimension relating the purpose of the equipment. In many instances, it is not easy to discern functional from structural features of a fault. In contrast, the domain decomposition natural to a bond graph network is a hybrid between structure and function of the process.

One disadvantage of functional decompositions is the non-unique correspondence between the inspected fault and candidate units. Frequently, a single unit may perform two or more functions, while several units are collectively responsible for the performance of a single function. For example, hydraulic tubing in a continuous process may be used for fluid conductance, heat transfer, and/or material holdup. In contrast, the process of heat transfer requires hydraulic tubing and a heat exchanger. This makes narrowing the search space for the root cause inefficient due to overlap among multiple subsystems. Similar disadvantages exist for a structural decomposition.

The domain decomposition provided by bond graph theory resolves conflicts by imposing clear boundaries among the physical domains with a unique mapping from the bond graph elements to the physical units of the system. Consider the hydraulic tubing mentioned above, the functions that the hydraulic tubing performs are represented by one element in the hydraulic domain for fluid conductance and another in the thermal domain for heat transfer. Thus, by isolating the origin of the fault to within distinct domains, the search space for the following procedures is definitely restricted to within a scope that has no overlap with other subsystems.

V. PROCEDURES

We propose an on-line approach to address fault detection and isolation based on a domain decomposition provided by an application of bond graph theory. We will apply Principle Component Analysis (PCA) to reduce the data size and to remove multivariate outliers. Next, an application of Discrete Wavelet Transform (DWT) to the score representation of the data signals to arrive at a multiple time scale decomposition. At the final step, the Mahalanobis Distance (MD) is applied to the results of the DWT. The steps in the on-line procedure are illustrated in Fig. 1. Calibration is done off-line to

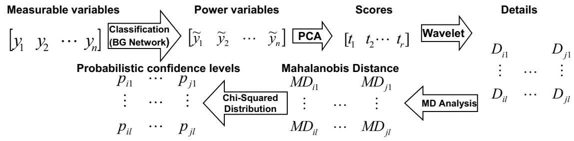

Fig. 1. Scheme of the FDI procedure

provide a reference for on-line FDI. Based on the degree of violation from the nominal probability level, the decision that a potential fault(s) exists is made. It then follows that fault isolation is accomplished by comparing the time scales at which the violation of the nominal probability level occurred to the time scales associated with each physical domain in the bond graph network.

A. *Multivariate process monitoring*

Multivariate statistical analysis methods such as principal component regression (PCR) and PCA are developed to assist in the identification of process correlations [11].

Theoretically, PCA is based on an orthogonal decomposition of the covariance matrix of the measured variables along directions that explain the variability in the data. Let $\hat{\mathbf{X}}$ represent a matrix of m sample data points of n variables. Assume that $\hat{\mathbf{X}}$ can be normalized to $\mathbf{X}$ such that each variable has a zero mean and unit variance. The application of PCA, $\mathbf{X} = \mathbf{TP}' + \mathbf{E}_x$ produces a set of projection vectors or eigenvectors $\mathbf{P}'$ of size $r \times n$ with $r < n$ and a set of scores $\mathbf{T}$ of size $m \times r$ (projection of $\mathbf{X}$ onto $\mathbf{P}$). The residual $\mathbf{E}_x$ is a measure of error in the fit. The columns of the $\mathbf{T}$ matrix are orthogonal and represent linear combinations of the data variables. The first column of $\mathbf{P}$ is the first eigenvector and corresponds to the direction with the largest variability. The second column describes the next dominant direction of variability and so on. Determination of the number of eigenvectors can be established by several techniques, such as cross validation. Once a calibration model of normal variations is established, it can be used to classify new data points. That is given $\mathbf{x}$(k), $\mathbf{t}$(k) can be determined from $\mathbf{t}_k = \mathbf{x}_k'\mathbf{P}$. The new scores can be compared against expected scores using different statistical measures.

B. *Multi-resolution analysis using wavelet transform*

The wavelet transform has been used to identify events that are localized in time and space [12]. The wavelet transform is essentially an alternative to the classical windowed Fourier transform (WFT). Whereas the WFT uses a single analysis window, wavelet transform uses short windows at high frequencies (small time resolution) and long windows at low frequencies (large time resolution). Basically, the wavelet transform is a signal decomposition onto a set of basis functions, called wavelets that are generated from a single basic wavelet (*mother* wavelet). The family of wavelets are generated by stretching (dilation), compressing, and shifting (translation) the mother wavelet [13]. Similar to the Fourier concept there are continuous, discrete and series wavelets.

In the case of a DWT, the signal is processed using a band pass filter (highpass: $\mathbf{g}= [g_m, g_{m-1} \ldots g_2, g_1]$ and a lowpass: $\mathbf{h}= [h_m, h_{m-1} \ldots h_2, h_1]$). The results are two sets of coefficients, one describing the details of the signal, and the other describing a smooth approximation to the signal. Application of the band pass filter can be done iteratively to any number of scales by recursively applying the filter to the smooth approximation at the previous scale. There are corresponding reconstruction filters. Thus, the original signal can be reconstructed without loss of information. Alternatively, it is possible to construct a variant of the signal using different combinations of the highpass and lowpass filtered signals.

C. *Off-line calibration procedure*

(1) Convert the process sensors into bond graph elements *De* or *Df*, based on sensor type and sensor location.
(2) Obtain a calibration model about the nominal historical data using PCA.
(3) Apply DWT to each score. The number of filtered passes is dependent on the slowest dynamic time constant.
(4) Reconstruct the reference signals for on-line FDI using the highpass filter results at each scale.

D. *On-line FDI procedure*

(1) Find the score vector $\mathbf{t}$(k) that corresponds to the new measurement vector $\mathbf{x}$(k) using the calibration model found off-line.
(2) Apply DWT to a window of score data whose length is based on the slowest time constant but also includes the most recent score data. If there are r scores then there are r datasets to be analyzed.
(3) Perform DWT on the first window of score data and reconstruct the signal at each scale. Using the DWT of the reference score set, calculate the MD for the reconstructed data at each scale. Violation of MD about a pre-specified probability level at any scale is classified as a fault. In this work, the level is set at 0.01. If a fault is detected in the most dominant score data, the fault is classified as an intermittent fault. This work excludes abrupt faults.
(4) Repeat step 3 using the second dominant score data, and so on if no violation is found within the first dominant score data. If a fault is found with a less dominant score data, it can be classified as a slow drift. In the case of no faults the process is proclaimed to be fault free.
(5) Isolate the location of the fault by comparing the time resolution at which a violation is found to the natural time constants in the domains of the bond graph network. Depending on the complexity of the domain, the resolution of the isolation may be coarse, but the search space has been narrowed to that domain.

Remark: The defining feature between an intermittent and a slow drifting fault is their temporal characteristics. The former is characterized by sharp pulses over a short duration of time, thus a technique such as PCA can readily pickup the variability in the dominant score set. In contrast, the variability found with a slow drifting fault is more likely to be captured in the less dominant score set.

VI. Case Studies

A. Continuous-stirred tank reactor (CSTR)

A schematic of the CSTR is shown in Fig. 2. The chemical reaction consumes incoming reactant A and produces the product B. The reaction is occurring in a mixed solution system of which the inlet stream of solution A is delivered by a pump, and the outlet flowrate is controlled by a ball valve. Three process variables, the pump speed ω, hydraulic pressure P at the bottom of the CSTR, and the product concentration C_B at the outlet, are measured with a sampling interval of 15 seconds. The dynamic time constant of the reaction domain is approximately 120 minutes. To abstract the slow dynamics from the original data requires dilation of the wavelet. Nine applications of the DWT provide a time scale of up to $0.25(2^9)$ min = 128 min, to represent the slowest dynamic time constant.

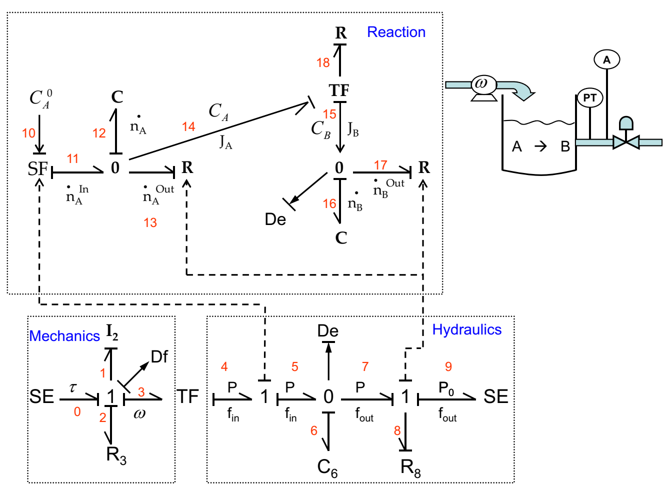

Fig. 2. CSTR. Left: Bond graph network. Right: Schematic.

Following the procedures presented in [14], a bond graph network is developed (Fig. 2). A transformer element, TF, indicates the boundary between the mechanic and hydraulic domains, while only the dotted signal bonds link the hydraulic and reaction domains. Process measurements are converted into *De* and *Df* to represent the measured effort and flow variables.

1) Single slow drift: The friction coefficient of the pump's motor is decreased from its nominal value at t=200 min with a slope of -5%/min for two minutes. In the bond graph network there will be a change in the value of element R_3. Applying the aforementioned procedures an indication of a fault is found in the analysis of the second score data at t=201.25 min. From the DWT analysis (Fig. 3), with a moving window size of 2^9, a violation of the MD is found at the first two filtered scales. The time resolution of these scales corresponds to that found in the mechanical domain ($\sim$30 seconds). The fault feature is captured in the second score data set, t_2, which is less dominant when compared to t_1, indicating that the fault type is a slow drift.

2) Single intermittent fault: An intermittent fault is introduced to the pump by decreasing the friction coefficient

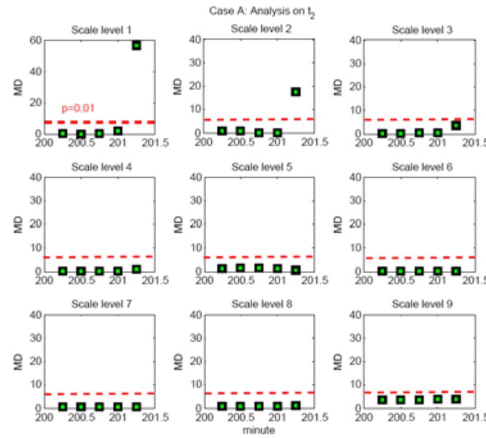

Fig. 3. Single drift fault - CSTR.

of the motor at t=200 min is a pulse disturbance applied onto element R_3. As shown in Fig. 4, detection of the fault is found in the first score data (conclude that the fault is intermittent) at t=201.75 min. The origin of the fault can be isolated to the mechanical domain because the violation shows up at scale levels 1 and 2. It is worth pointing out that because fault propagation is based on the interactions among domains, the interpretation of a single fault may indicate that the root cause covers a wide range of time granularity from multiple domains. For instance, in Fig. 4, a noticeable violation is observed at scale level 4 that may lead to the conclusion that the root cause is in the hydraulic domain.

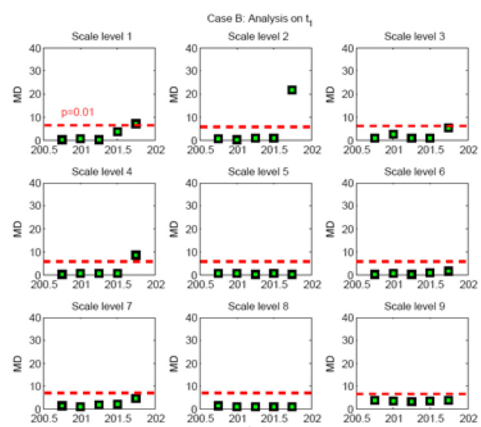

Fig. 4. Single intermittent fault - CSTR.

B. Biochemical wastewater treatment process (WWTP)

Consider a WWTP whose primary unit operations are a packed bed (PB) bioreactor in series with a set of tubular (TR) bioreactors. A full description of the system can be found in [15]. Positive displacement pumps move the fluid through the hydraulic loop. The mechanical domain consists of the pumps, and the hydraulic domain includes the piping and the tanks. The PB reactor is represented in the bond graph network by a CSTR, while the TR is approximated by a series of CSTRs [16] (Fig. 5).

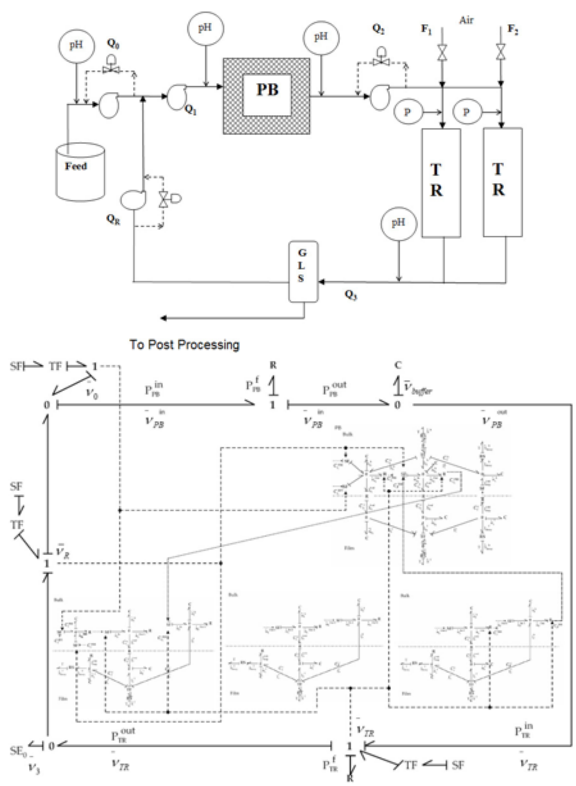

Fig. 5. Top: Schematic of the WWTP. Bottom: Bond graph network of the WWTP.

1) Multiple faults: Two faults with distinct origins are introduced. Fault A imposes a slow drift (decrease) in the friction coefficient of the feed pump at t=200 min while fault B is a slow drift (increase) in the feed composition at t=160 min. The result of applying the proposed FDI method is shown in Fig.6. Both faults are detected at different scales from an analysis of the second score data. The first fault is located in the mechanical domain because the MD violation occurs at scale levels 1 and 3. The other is identified from a violation at scale levels 7 to 9 with a corresponding time resolution of $\sim$ 60 minutes, which points to the reaction domain.

VII. SUMMARY

This work described and developed an efficient approach to the FDI task. The approach is efficient because it is based on a domain decomposition that is inherited from a bond graph network of the process. The approach makes use of data reduction by PCA and multiscale analysis by wavelets. Two case studies were presented. The slow drift and the intermittent fault are found through abstraction of the features. The search space to locate the fault origins is isolated explicitly due to the corresponding physical domain decomposition natural to the bond graph network. Future work focuses on a probability based FDI based on Bayesian network, to consider the fault propagation and uncertainty together [17].

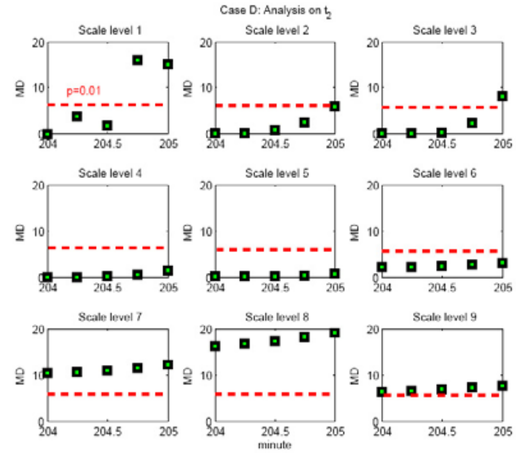

Fig. 6. Multiple faults - WWTP.

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