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Fault Detection and Isolation of a Three-tank System Using Analytical Temporal Redundancy – Parity Space/Relation Based Residual Generation

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ABSTRACT

This paper investigates the fault detection and isolation technique in measurement datasets from a three-tank system using analytical model-based temporal redundancy. It is based on residual generation using a parity equations/space approach. The paper further briefly outlines other approaches of model-based residual generation. The basic idea of parity space residual generation in temporal redundancy is a dynamic relationship between sensor outputs and actuator inputs (input-output model). These residuals were then used to detect whether or not the system is faulty and indicate the location of the fault when it is faulty. The method obtains good results by detecting and isolating faults from the considered measurement datasets generated from the system.

Key words: Fault Detection, Fault Isolation, Disturbing Influences, System Failure, Parity Equation/Relation, Structured Parity Equations.

1 INTRODUCTION

With the continuous automation of the present day industrial processes, Automatic control system is becoming more and more important because it ensures that certain system parameters assume specific constant values recognized as safe operating conditions or are kept constant in relationship to other system variables [1]. Hence, the task is to bring these parameters to certain desired set points and maintained them constant against certain disturbing influences and sudden system failures. Obviously, this task involves a large number of complexities which are not very common at first glance. Moreover, the control algorithms relating to these specialized tasks are becoming more sophisticated with the current state of the art technology development. Thus far, several studies have been conducted which have led to the development fault detection and isolation (FDI) concept, Chow and Willsky [2], Frank [3], Gertler [4] Patton *et al.* [9], Sainz *et al.* [10], Theilliol *et al.* [11] and Witzak [13].

A longitudinal study of fault diagnosis in dynamic systems using analytical and knowledge based redundancy by Frank [3] reports that a fault is fully apprehended as any kind of malfunction in the actual dynamic system, the plant that leads to a dissatisfactory aberration in the overall system efficiency. Such malfunctions may occur either in the sensors (instruments), or actuators, or in the components of the process. Regardless of where the fault can occur, one distinguishes between instrument fault detection (IFD), actuator fault detection (AFD) and component fault detection (CFD) [3]. In the same vein, Gertler [4] found that fault detection is the indication that something is going wrong in the monitored system. Fault isolation is the determination of the exact location of the fault (the component which is faulty). Together these studies indicate that, fault detection and isolation is a technique in the field of control engineering that is usually employed to identify when a fault occur, and if it has occurred, determine its location of occurrence (isolation).

Several techniques exist for fault detection and Isolation (FDI) and these include physical redundancy, analytical knowledge - based redundancy and analytical model - based redundancy. For more details and comprehensive understanding of these techniques, we refer to Chow and Willsky [2] and Frank [3]. However, the focus of this paper is on fault detection and isolation technique upon the basis of analytical model – based redundancy (temporal, because it relates the input- output model for a part of the dynamics of the system for actuator and sensor fault detection and isolation) is adopted. The work is motivated by the fault diagnosis consideration of Sainz, *et al.* [10] and Theilliol, *et al.* [11] for a three tank system.

Nevertheless, however, residual generation and decision making process are the major components that for the basis of FDI technique and it is necessary here to clarify exactly what is meant by these components. Residuals are according to Gertler [4] quantities that are nominally zero in the absence of fault and any deviation away indicates the presence of fault. Hence, the effect of failure on the residuals is called the fault signature. In the decision making process, however, the residuals are examined for fault signatures through a simple threshold test on the sliding window (moving averages) of the residuals. This view was supported by Chow and Willsky [2].

Several lines of evidence suggest numerous methods/approaches of residual generation. One of which includes the diagnostic observer approach such as the Luenberger observer and innovation based approach [3][6-7]. The procedure in this approach is to reconstruct the outputs of the system from the measurements through the use of the diagnostics observers using error estimation technique or the Kalman filters using the innovative technique as a residual for the detection and isolation of the faults. Numerous studies have considered this approach (For example, Frank [3]; Kalman [5]; Luenberger [6-7]; Maybeck [8]; Welch and Bishop [12] and Witczak [13]). Yet, another alternative approach to residual generation is parameter estimation based on state estimation. This approach relies on the fact that faults of a dynamic system are reflected in the physical parameters of the system. The technique was further explicitly explained by Frank [3] and Maybeck [8]. More importantly, the parity relation/space approach which involves parity check for consistency of the mathematical equation – parity relations of the system by using the actual measurements, thus any deviation declares the occurrence of a fault in the system [3]. The parity space/relation approach is the approach adopted in this paper and consequently, it will be discussed and outlined in subsequent section of the paper.

This paper is divided into sections. The next section is section 2 which provides an insight into the parity relation/space – analytical redundancy approach to FDI. The subsequent section briefly describes the three tank system and presents the model of the dynamic system which is the basis of fault detection and isolation in this paper. Section 4 and 5 discusses the FDI using parity relations respectively. Section 6 presents the linearisation of the system through simulation about the operating points. Finally, conclusion drawn from the investigation was outlined in the last section.

2 PARITY RELATION/SPACE- ANALYTICAL REDUNDANCY

Chow and Willsky [2] states the basis for residual generation is analytical redundancy which essentially takes up two forms: Direct redundancy and temporal redundancy. The direct redundancy relates the instantaneous outputs of sensors and this limits its application to failure detection of sensors whereas the temporal redundancy relates the histories of sensor outputs and actuator inputs (Sliding window or the moving average process) thus, making it useful for both sensor and actuator fault detection. These relationships make the comparison of the different sensor outputs at different times. The residuals resulting from these comparisons can then be used to measure the differences between the observed sensor outputs and the behavior that could result under fault free conditions (i.e parity check for consistency). The temporal redundancy parity relation was adopted in this paper. To explain the temporal redundancy parity relations of the dynamic system as generalized by Chow and Willsky [2], we consider mathematical model of the system given by the linear discrete state equations of Equation (1) and (2) respectively.

$$x(k+1) = Ax(k) + Bu(k) + EP(k) \tag{1}$$

$$y(k) = cx(k) + Du(k) + FP(k) \tag{2}$$

Where x is the $n \times 1$ state vector, u is the $m \times 1$ actuator input vector, y is the $q \times 1$ sensor output vector, and A is $N \times N$. EP represents the actuator faults whereas FP is the sensor faults. A, B, C and D are the nominal matrices of the system and of appropriate dimension and the faults are primarily reflected in changes of A, B, C as well as modeling errors are considered by P associated with proper choice of E and F.

Let us define L, such that $L = \begin{bmatrix} c \\ cA \\ \vdots \\ . \\ cA^t \end{bmatrix}$ $t = 0, 1, 2, \ldots$

We take the transpose of L, i.e L^T and then compute the singular value decomposition of the resulting operation. This operation yields [x y z] of singular values. y is a matrix of the same dimension as L^T with non-negative diagonal elements in decreasing order, and x and z are unitary matrices. So that $L^T = x*y*z^T$. Therefore, z is defined as the subspace of $(t+1)q$ dimensional vectors such that:

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$$P = z^T \begin{bmatrix} c \\ cA \\ : \\ . \\ cA^t \end{bmatrix} = \tag{3}$$

Equation (3) is called the parity space of order *t* which form the basis of fault detection at any instant *k*, using the below equation;

$$\mathrm{r}(k) = z^T \left[\begin{bmatrix} y(k-t) \\ y(k-t+1) \\ : \\ . \\ y(k) \end{bmatrix} - M \begin{bmatrix} u(k-t) \\ u(k-t+1) \\ : \\ . \\ u(k) \end{bmatrix} \right] \tag{4}$$

$$\text{Where } M = \begin{bmatrix} 0 & 0 & 0\ 0\ 0\ \ 0 \\ cB & 0 & 0\ 0\ 0\ 0 \\ cAB & cB & 0\ 0\ 0\ 0 \\ . & & \\ . & & \\ . & & \\ cA^{t-1}B & \ldots\ \ldots & cAB\ \ cB\ \ 0 \end{bmatrix} \tag{5}$$

Equation (4) is known as the generalized parity vector or parity equation/relation. The Right hand side of Equation (4) is called the parity function. *r(k)* is non-zero under fault free condition and Equation (3) must be satisfied for it to qualify as residual capable of detecting a fault. Z^T in Equation (3) is called the residual generator and has to meet the requirement of Equation (3). The choice of *t* should always influence the solvability of Equation (3). For the ideal solution, an upper bound is generally given by $t \leq n$, where *n* is the dimension of $x(k)$.

3 THE THREE TANK SYSTEM: SET - DESCRIPTION

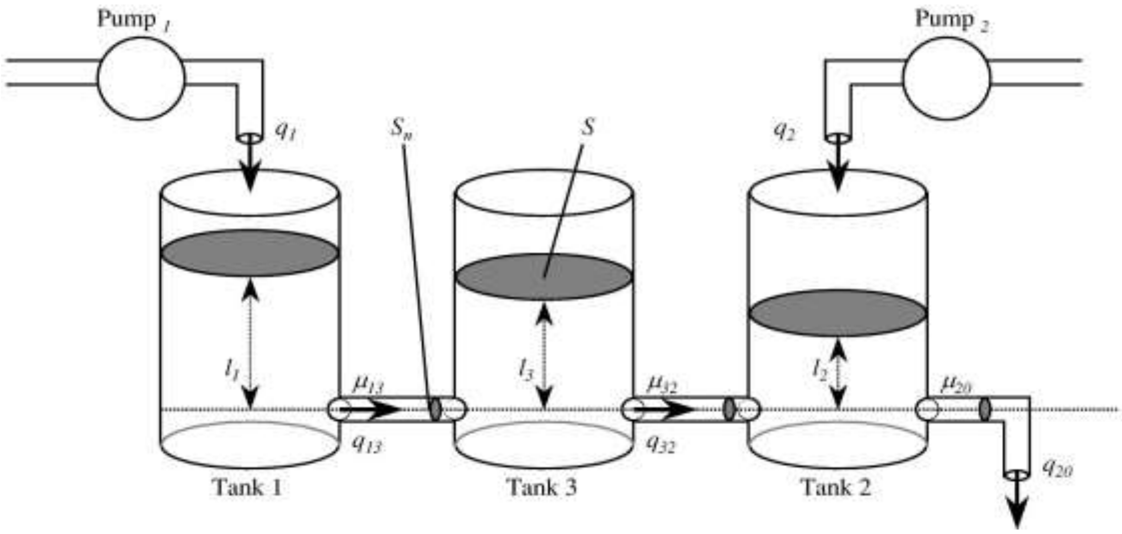

Figure 1: The three tank system schematic (source; Theilliol, *et al.* [11])

Theilliol, *et al.*[11] describes the three tank system as pilot plant composed of three identical cylindrical tanks with a cross section *S* as shown on the schematic diagram on Figure 1 above. The tanks are coupled by two connecting cylindrical pipes with a cross section S_n and an outflow coefficient $\mu_{13} = \mu_{32}$. The nominal outflow is located at tank 2; it has an outflow coefficient of μ_{20}. In the experimental setup, communication of the plant sensors and actuators is achieved via data acquisition card (DA6214) with a personnel computer. Tanks 1 and 2 were supplied by the two pumps driven by dc motors. Pump flow rates Q_1 and Q_2 are defined by the calculation of flow per rotation. Two D/A converters with a voltage range from – 10 to + 10 V are used two control the pumps. Piezoelectric differential pressure sensors carry out the necessary level measurements which deliver a voltage signal between – 10 to + 10 V. The three measured outputs: L_1, L_2, L_3 gives the level of fluid within each of the tanks and each measurement is sampled with a period T = 1s. The plant is linearised about the following operating point:

$$\bar{u} = \begin{pmatrix} Q_1 \\ Q_2 \end{pmatrix} = \begin{pmatrix} 0.350 \\ 0.375 \end{pmatrix} \text{ x } 10^{-4}\ [\mathrm{m}^3/\mathrm{s}] \tag{6}$$

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$$\bar{x} = \begin{pmatrix} \overline{L_1} \\ \overline{L_2} \\ \overline{L_3} \end{pmatrix} = \begin{pmatrix} 0.400 \\ 0.200 \\ 0.295 \end{pmatrix} [\mathrm{m}] \tag{7}$$

The resulting model is thus;

$$y_k = x_k, \qquad x_{k+1} = \begin{pmatrix} 0.9880 & 0.0001 & 0.0109 \\ 0.0001 & 0.9778 & 0.0114 \\ 0.0109 & 0.0114 & 0.9776 \end{pmatrix} x_k + \begin{pmatrix} 64.576 & 0.0014 \\ 0.0014 & 64.212 \\ 0.3571 & 0.3721 \end{pmatrix} u_k$$

Where y_k are the measurements, x_k are the states and u_k are the inputs at the *kth* sample.

$$x_k = (L_1\ L_2\ L_3)^{\mathrm{T}},\ u_k = (Q_1\ Q_2)^{\mathrm{T}}$$

A proportional controller with full state feedback has been added to the system to regulate the tank levels and has the following form:

$$Q_1 = \bar{Q}_1 + 5\ x\ 10^{-6}\ x\ (0.4 - L_1) \tag{8}$$

$$Q_2 = \bar{Q}_2 + 5\ x\ 10^{-6}\ x\ (0.895 - L_1 - L_2 - L_3) \tag{9}$$

Four data sets were generated using measurement from the system and these were used for the investigation of the fault in this paper.

4 FAULT DETECTION

Fault Detection (FD) is a technique used to identify faults when they occur in a system, and in which part of the system. This view has been supported by Sainz *et al*. [10]. This was achieved by generating residuals by means of parity equations in Equation (4) which is expected to be zero under fault-free conditions in the absence of disturbances, uncertainties and noise. And residuals with non-zeros provide an indicative violation of these conditions and may indicate a fault. A MATLAB program code was developed to generate the parity equations for each data set. For dataset 0, the fault was detected at a measurement instance of 240s and above because it was at that instance the parity equations have a non-zero value. This is depicted in Figure 2.

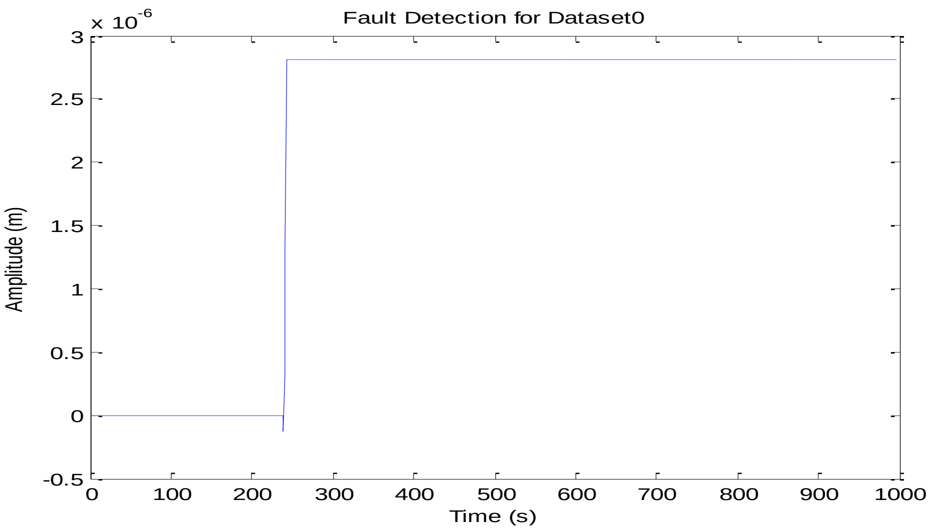

Figure 2: Fault detection for dataset 0

For dataset 1, the parity equations have a non- zero at instance of 240s and above which evidences the detection of fault at that point. The Figure 3 below depicts it;

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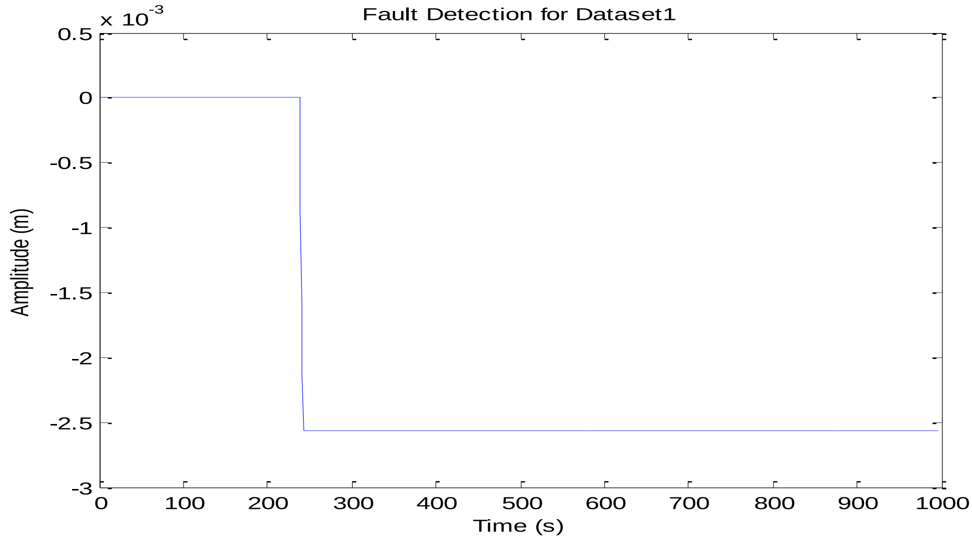

Figure 3: Fault detection for dataset 1

For dataset 2, the parity equations have a zero value, which indicates a fault-free condition throughout in the measurement dataset. This is depicted in Figure 4.

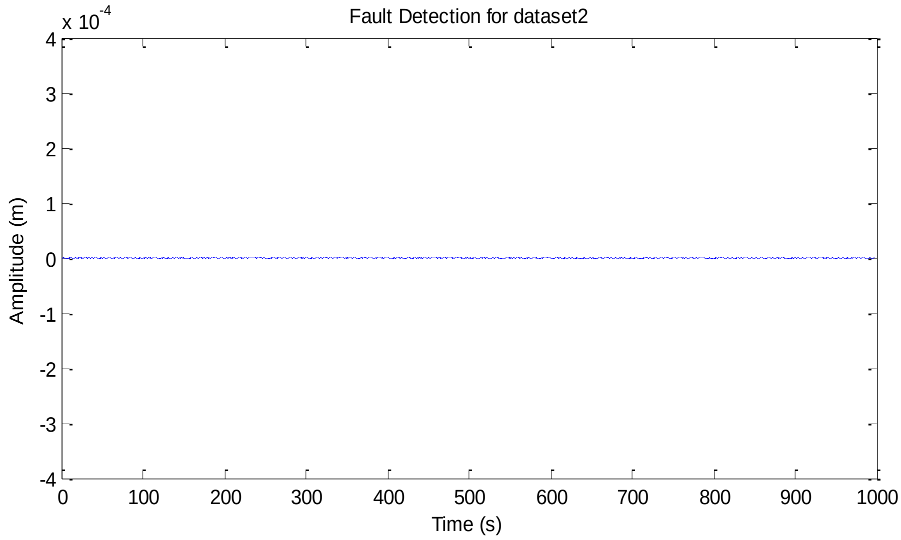

Figure 4: Fault detection for dataset 2

And for dataset 3, the fault was detected at a measurement instance of 240s because it was at that instance the parity equations have a non-zero value. This is depicted in Figure 5.

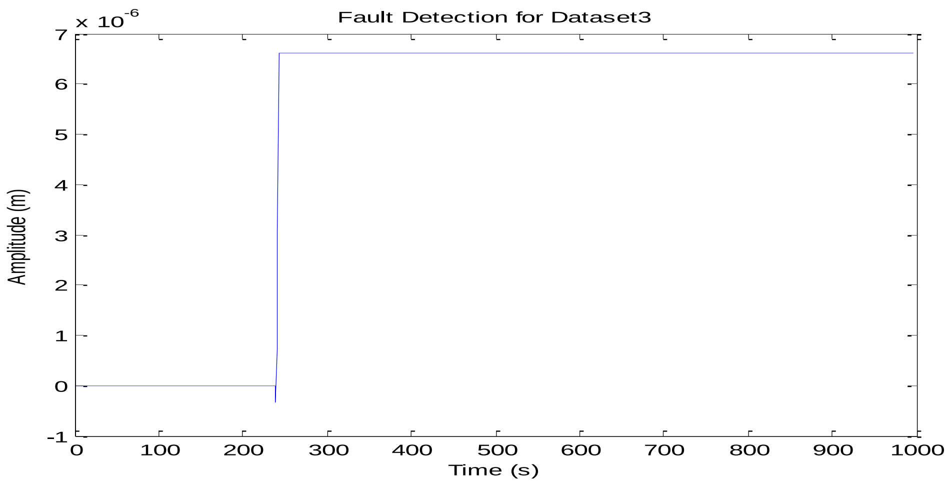

Figure 5: Fault detection for dataset 3

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5 FAULT ISOLATION

Fault Isolation (FI), is to determine the location of the faulty component. Contrary to the detection of a fault in a system which was achieved using a single residual, the isolation of the fault requires enhanced residual sets. Two major enhancement techniques have been developed as presented in Gertler [4]. These are the structured residual sets and the fixed direction residuals. The former is adopted in this study. Enhancement of the residuals using the structured residual sets technique is such that the generated residual vector *r(k)* in Equation (4) in response to a particular sensor or actuator fault, only a fault-specific subset of the components is non-zero i.e it will be confined to a subspace of the residual space (Parity space). Such residual-sets are said to be structured, which thus implies that each residual is completely unaffected by a different subset of faults. The advantage of this is that the diagnostics analysis is resorted to determining which of the residuals are non-zero. Thus, the procedure involves performing a threshold test for each residual, which consequently yield a Boolean decision for each with “1” representing a fired test. Transformation of these bits into binary vector yields the fault code or fault signature and the set of the possible nominal fault codes forms the coding set. This view has been supported by Gertler [4].

Further on Gertler [4] states that for the detection of all faults, no nominal fault code should contain all zero elements. A minimum requirement for fault isolation is that all nominal fault codes be distinct. Coding sets satisfying these two requirements are called weakly isolating. In noisy environment or when modeling errors, weak isolation may not be sufficient. Setting the thresholds high produces a fault of moderate size which may cause some “1”s to be replaced by “0” (i.e degraded fault code). The procedure should be such that no degraded fault code is identical with a valid code in order to avoid mis-isolation in that case. The resulting coding set is said to be strongly isolating code. An easy way of making the coding strongly isolating implies a column canonical set; in such a set, each nominal fault code contains the same number of zeros, each in a different pattern [4].
A fault code beta (β) chosen to achieve the isolation in this paper has the shape given below with *BT* corresponding to each of the sensors and actuators.

$$BT = \begin{bmatrix} 1&0&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0 \\ 0&0&0&1&0&0&0&0 \\ 0&0&0&0&1&0&0&0 \\ 0&0&0&0&0&1&0&0 \\ 0&0&0&0&0&0&1&0 \\ 0&0&0&0&0&0&0&1 \end{bmatrix} \qquad (10)$$

$$\text{Beta } (\beta) = [BT\ BT\ BT\ BT\ BT] \qquad (11)$$

To achieve this FI, we again recall the form of Equation (1) and (2) for the system and thus we define;

$$D = \text{zeros } (3, 2 \qquad (12)$$

$$E = [A\ B \text{ zeros } (3, 3)] \qquad (13)$$

$$F = [C\ D\ C] \qquad (14)$$

$$N = [F \text{ zeros } (3, 32);\ CE\ F \text{ zeros } (3, 24);\ CAE\ CE\ F \text{ zeros } (3, 16);\ CA^2E\ CAE\ CE\ F \text{ zeros } (3, 8);\ CA^3E\ CA^2E\ CAE\ CE\ F] \qquad (15)$$

$$\text{wt} = Z^T\ (7{:}14, :) \qquad (16)$$

$$G = pinv\ (wt{*}N) \qquad (17)$$

$$\alpha = \beta{*}G \qquad (18)$$

The resulting structured residual sets are given in Equation (19) below;

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$$r^*(k) = \alpha^* wt\left[\begin{bmatrix} y(k-t) \\ y(k-t+1) \\ \vdots \\ y(k) \end{bmatrix} - M\begin{bmatrix} u(k-t) \\ u(k-t+1) \\ \vdots \\ u(k) \end{bmatrix}\right] \quad (19)$$

Equation (19) was coded using MATLAB code so as to achieve the isolation of the fault for each of the datasets. For dataset 0, the fault is located at the location (5, 1) which corresponds to the position of the input u_2 from the second actuator in the fault vector. This is shown in Figure 6 below;

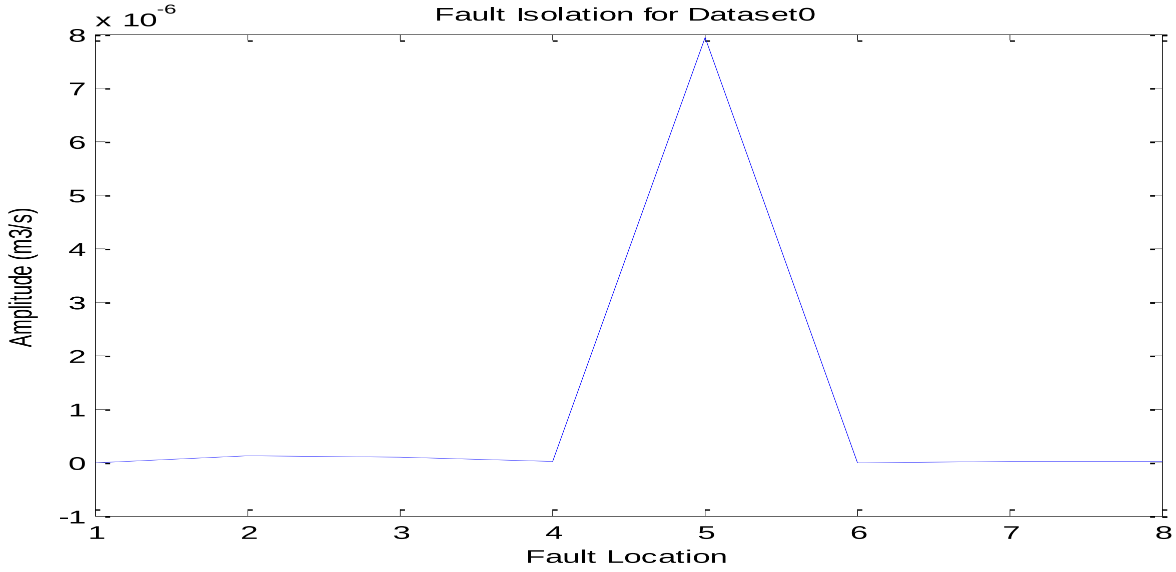

Figure 6: Fault isolation for dataset 0

Similarly, for dataset 1, the fault is located at the location (3, 1) which corresponds to the position of the state x_3 in the fault vector. This is shown in Figure 7 below;

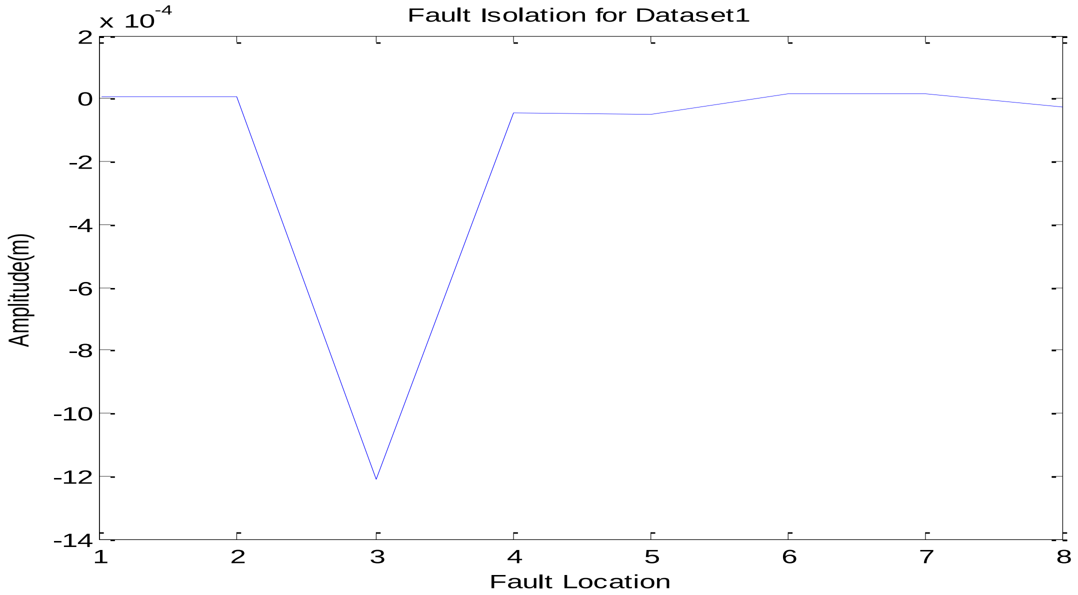

Figure 7: Fault isolation for dataset 1

For dataset 3, the fault is located at the location (4,1) which correspond to the position of the input u_1 from the first actuator in the fault vector. This is shown in Figure 8 below;

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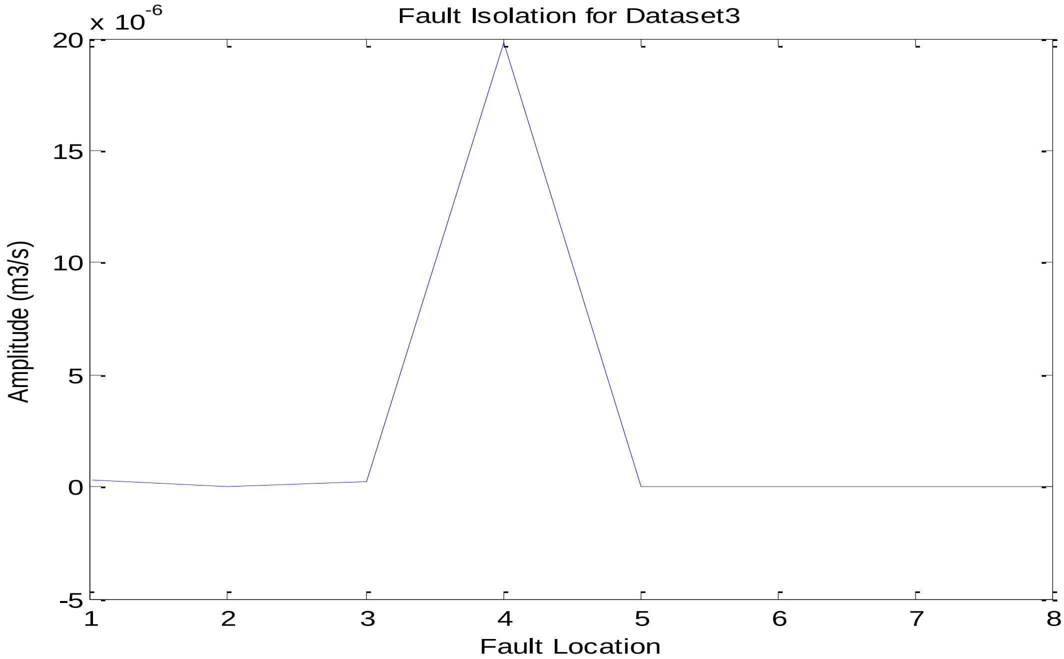

Figure 8: Fault isolation for dataset 3

6 CONCLUSION

In this paper, the method of fault detection and isolation has been presented which involves a three tank system. The method was based on analytical temporal redundancy using parity space/relation as the basis for residual generation. Moreover, other techniques of residual generation were briefly introduced. A computer program using MATLAB codes was used to implement this method. The technique obtains good results by detecting and isolating faults in the given measurement datasets (i.e datasets 0, 1 and 3) generated from the system.

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