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Intermittent Fault Detection on an Experimental Aircraft Fuel Rig: Reduce the No Fault Found Rate

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***Abstract*— In the context of aircraft engineering and maintenance, No Fault Found (NFF) is a chain of events that develops from a pilot experiencing a system malfunction with post-flight maintenance failing to reproduce the reported symptoms. Without any repair being undertaken, the malfunction may be experienced again on subsequent flights. This present significant cost impacts to the industry that includes financial, reduced operational achievement, airworthiness challenges and potential flight safety issues. One of the major causes identified for NFF occurrence within electronic, mechanical and hydraulic products are faults that are intermittent in nature. This makes it difficult to use systematic fault detection techniques effectively, as system are subject to unknown disturbances and model uncertainties. The philosophy behind this criterion is that the designed model-based Fault Detection (FD) observer should be robust to disturbances but sensitive to intermittent faults where the occupance of intermittent faults can be alarmed by the use of an adaptive threshold. The aim of this paper is to demonstrate the development of such methodologies and to examine its performance in a real-world test bed. The test bed consists of an aircraft fuel system simulation rig which simulates by hardware the components of an aircraft fuel system.**

I. INTRODUCTION

A fault within a system is described as an external input that causes the behavior of a system to deviate from a pre-defined performance threshold [1]. Faults are generally categorized according to whether they have developed slowly during the operation of a system usually characteristic of gradual component wear (incipient fault); arisen suddenly like a step change as a result of a sudden breakage (abrupt faults); or accrued in discrete intervals attributed to component degradation or unknown system interactions (intermittent faults). Intermittent faults can manifest in any system, mechanical or electronic, in an unpredictable manner. If these are left unattended over time they will evolve into serious and persistent faults. This unpredictability of an intermittent fault means that it cannot be easily predicted, detected nor is it necessarily repeatable during maintenance testing, However, an intermittent fault, which is often missed during standardized maintenance testing, by its very definition will reoccur at some time in the future. The intermittent fault case therefore poses an ever increasing challenge in the maintenance of electronic, mechanical and hydraulic equipment. Thus faults of this nature raise many concerns in the realm of through-life engineering of products [2]. A substantial portion of malfunctions attributed to intermittent faults will test ”OK” and will be categorized as No Fault Found (NFF) [3].

A much simplified maintenance process within an organization can be observed in Figure 1, which separates the rectification process into three key levels within an organization. Here it is important to understand the concept of how NFF instances can manifest themselves at various levels. When an operator records a system error, maintenance personnel are notified, who will attempt to investigate the reason for the system malfunction. For the most part, faults are diagnosed, isolated and rectified. However, when bench test do not reveal any reported faults perfectly working components are replaced and tagged as ”NFF”, Figure 1.

There may be various reasons that contribute to this overall process, however, recent publications have highlight intermittent faults within the system to be a major cause, [3]. This highlights the need for revisiting testability requirement that are capable of detecting an intermittent fault.

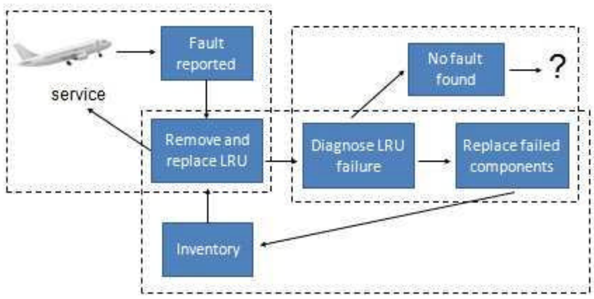

Fig. 1: The NFF phenomena.

In general, intermittent fault typically tend to worsen with time, until eventually becomes substantial enough that it can be detected with conventional test equipment [4]. Hence, developing the capability for early detection and isolation of the intermittent fault will help to avoid major system breakdowns [6]. Faults can occur in the actuators, process components or the sensors. Sensor faults are of particular importance. The impact of sensor faults causes the system fails to perform its function, or results in a catastrophic mechanical failure [5]. For years, several methods have been introduced for detecting possible issues in dynamic systems to guarantee normal functionality of the system. In practice,

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the designer selects one out of several Fault Detection (FD) methods, based on the specifications of the system and the nature of possible faults. Some methods are more suitable for off-line FD test. One example is subspace-based detection method, introduced in [7] and [8]. The method is used for health monitoring of mechanical structures, such as bridges. Other methods aim at detecting faults online. Among all the methods for online fault diagnosis, one of the particular interesting techniques is the observer-based FD approach.

In observer based FD methods, the designers usually need to construct an observer that will be robust to the disturbance impacting the system but sensitive to the faults, and then a residual is constructed based on the output of the observer. One can determine whether the system has suffered from some fault or not by comparing the residual with a fixed or adaptive threshold. The method to flag the fault occurrence by observing the residual is called residual-based FD. Nevertheless, finding systematic design methods for systems subjected to unknown disturbances and model uncertainties has been proven to be difficult [9]. Since both disturbances and faults contribute to the residual generated by the FD observer, some small faults cannot be detected for a predesigned threshold. A perfect or ideal FD observer should aim at minimizing the maximal undetectable fault size in the worst case as its goal. However, this criterion is not adopted for FD observer design directly. The philosophy behind this criterion is that a FD observer should be robust to disturbances but sensitive to faults [10] and [11].

In this paper, the aim is to study the robust FD problem of the considered system when a nonlinear observer is provided and is asymptotically stable. The FD consists essentially of two steps, residual generation and residual evaluation. The purpose of the first step is to generate a signal, the residual, which is supposed to be nonzero in the presence of intermittent fault and zero otherwise. However, the residual is almost always nonzero due to disturbances and model perturbations, even if there is no fault. The purpose of second step of the FD algorithm is thus to evaluate the residual and draw conclusions on the presence of a fault. This is done by comparing some function of the residual to a threshold. This paper is organized as follows: Section II presents the mathematical description of the nonlinear system of interest to this paper. Modeling the aircraft fuel rig is addressed in Section III. The observer design along with the residual and appropriate adaptive thresholds are designed in Section IV while the numerical example and simulation results are provided in Section V. The conclusions are given in Section VI.

II. System Description

Consider the class of nonlinear systems defined by the state-space form:

$$\begin{aligned} \dot{x}(t) &= h_x(x,u,\boldsymbol{\mu},g_s,f_i) \\ y(t) &= h_y(x,f_s) \end{aligned} \qquad (1)$$

If the nonlinear function $h_x(x,u,\boldsymbol{\mu},g_s,f_i)$ is differentiable with respect to the state $x(t)$, then this class of the system may be expressed in terms of a linear unforced part, and nonlinear state dependent controlled part [12] and [13]:

$$\begin{aligned} \dot{x}(t) &= Ax(t)+Bu(t)+D\boldsymbol{\mu}(t)+Sg_s(x,u,t)+K_i f_i(t) \\ y(t) &= Cx(t)+K_{ss} f_s(t) \end{aligned} \qquad (2)$$

where $x(t) \in \mathbb{R}^n$, $u(t) \in \mathbb{R}^m$, $\boldsymbol{\mu}(t) \in \mathbb{R}^m$ and $y(t) \in \mathbb{R}^p$ represent the state, input, unknown input (disturbance) and output vectors respectively. $A \in \mathbb{R}^{n\times n}$, $B \in \mathbb{R}^{n\times m}$, $D \in \mathbb{R}^{n\times m}$, $C \in \mathbb{R}^{p\times n}$, $S \in \mathbb{R}^{n\times s}$, $K_i \in \mathbb{R}^{n\times r}$ and $K_{ss} \in \mathbb{R}^{p\times i}$ are known matrices, f_i and f_s present the intermittent and sensor faults respectively. This paper considers general nonlinearities that depend on unmeasured states, but for illustration, a nonlinearity of the form $g_s(x,u,t) \in \mathbb{R}^s$ has been included in the design procedure.

To illustrate the application of the results obtained in sections II-V, the authors aim to take a relative simple fuel system, to illustrate the key steps of the intermittent fault diagnostic analysis which meets the initial fault detection and isolation requirements. A schematic diagram of the fuel system is presented in Figure 2. The fuel system contains a motor driven external gear pump with internal relief valve, a shut off valve, one filter, two tanks (main tank and sump tank, the last one emulating the engine), non-return valve, three-way valve to switch between recirculation and engine feed mode, variable restrictor to simulate engine injection and back pressure when partially closed. The fuel system is representative of a small UAV engine feed. The diagnostic analysis will focus on the filter, pump, shut-off valve, pipes and nozzle failure modes. Five failure modes that are emulated on the rig are: filter clogging from foreign matter, pump degradation, valve stuck in a midrange position, leak in the main line, and a clogged nozzle.

The fuel rig can accommodate various faults with different degrees of severity. When a filter clogs, the flow through the filter reduces and the pressure difference measured across the filter increases. The filter failure was emulated by replacing the filter component with a Direct-acting Proportional Valve (DPV1). Valve position fully open is equivalent to a healthy filter; partially closed being equivalent to a clogged filter with a particular degree of severity. Various degrees of severity of this fault can be simulated by varying the DPV position. In this manner, incipient, slow progression, cascading, abrupt and intermittent types of faults can be simulated on the rig and the ability of the functional approach to model and address such conditions can be assessed. The physical implementation of the fuel system test bed is depicted in Figure 3.

Pipes' length and diameter, pump characteristics, loss coefficient versus valve opening characteristics, shut-off valve pressure drop when fully opened, tank's capacity have been identified within the design phase by carrying out various scenarios in a controlled simulation environment. Volumetric flow rates in the main line and pressure rates at five different locations were calculated using the physical model.

For the healthy state of the fuel system, the direct acting proportional valves were set as follows: DPV1 - fully open,

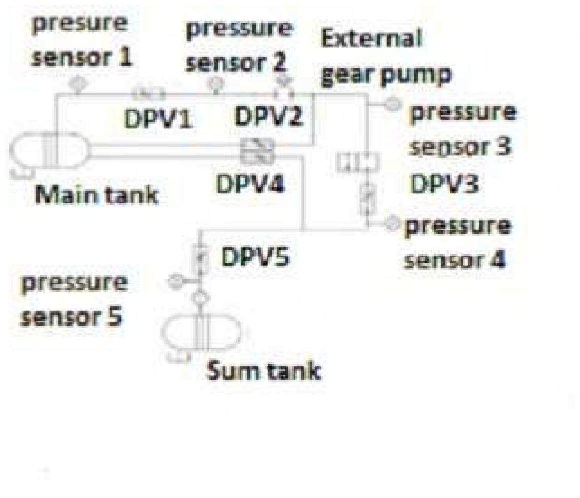

Fig. 2: IVHM Centre fuel system demonstrator

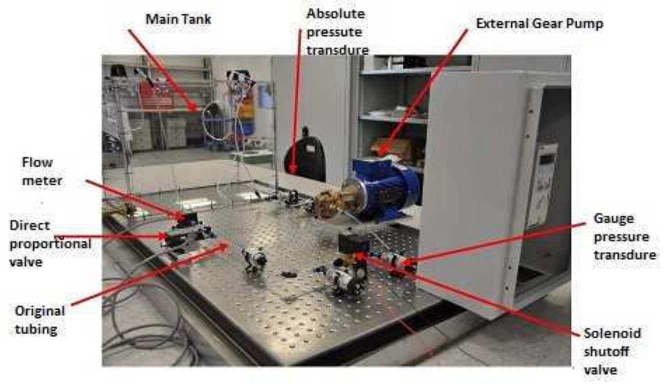

Fig. 3: Fuel system test bed.

DPV2 - fully closed, DPV3 - fully open, DPV4 - fully closed and DPV5 - fully open. Pressure and flow rates for the healthy condition were recorded for a period of 6 minutes in order to have a good estimation and pump rotational speed was set at 400*rpm*. The feedback loop of the pump control unit was active, so the pump speed was constant for the entire testing session.

III. System Modeling

The modelling will focus on the fluidic side of the rig and the approach used is mechanistic/physical modelling based-on the hardware of the fuel rig and the fluid properties. On the rig, the main tank supply fluid by means of pump with an array of valve connected to the pump (Figure 2).
Each element in this figure is modeled as a subsystem and the overall model consists of all such models to represent the system shown in Figure 2. It should be noted that whilst some of the pipes depicted are very short they are included in the model of the system to make the overall model equations solvable.

A. Tank Model

The height and pressure of the fluid in the tank are defined by equation (3) and equation (4). The equations provide a pressure output for a given height which in turn is dependant on the flow in and out of the tank.

$$h(t) = \frac{\int (Q_{in} - Q_{out})dt}{A_t} \tag{3}$$

$$P_t = \rho g h(t) \tag{4}$$

Substitute equation (3) into (4) where $Q_{in} = 0$, will give:

$$\dot{P}_t = C_t Q_{out} \tag{5}$$

With $C_t = -\frac{\rho g}{A_t}$. Q, A_t, h, ρ, P and g represents volumetric flow $(\frac{m^3}{s})$, tank cross-section (m^2), height (m), density $(\frac{Kg}{m^3})$, pressure (Pa) and gravity $(\frac{m}{s^2})$ respectively.

B. Valve Model

The valve equation below gives the volumetric flow rate from the valve for a given pressure differential across the valve.

$$Q(t) = C_v A_v \sqrt{\frac{2}{\rho}\Delta P} \tag{6}$$

where Q, ρ, ΔP, C_v and A_v represents volumetric flow $(\frac{m^3}{s})$, density $(\frac{Kg}{m^3})$, pressure difference (Pa), valve conductance (m^2) and proportional valve opening respectively. The equation (6) for fast opening valves is nonlinear and could be rewritten as

$$\Delta P = RQ^2 \tag{7}$$

where $R = \frac{\rho}{2C_v^2 A_v^2}$.

C. Pump Model

The pump, motor and gearbox are represented in the model based on results found by practical experiment. The ramp of pump time is equal to valve transition time. It means that the pump will reach the maximum voltage when the valve reach it's state. The pump is also required to validate the pipe and valve model as it is the only physically measurable input signal available to drive the pipe and valve subsystem models.
For a pump with positive displacement,

$$\begin{aligned} Power_{in} &= \tau\omega \\ Power_{loss} &= f(friction,\ viscous,\ effects,\ \cdots) \\ Power_{out} &= \Delta P \times Q. \end{aligned} \tag{8}$$

where τ and ω represent nominal displacement and rotational (shaft) speed respectively. $\tau\omega$ is considered as input speed of the pump in (rpm).
Equations (8), could be represented as follows

$$Power_{out} = \eta_m Power_{in} \tag{9}$$

where η_m is the pump volumetric efficient and typically gear pumps have efficiencies around 85% . Hence the following equation is obtained for pressure difference around the gear pump:

$$\Delta P = \frac{\eta_m \tau\omega}{Q} \tag{10}$$

D. Pipe Model

The defining equation for the pipe subsystem model is based on the compressibility of fluid in the system due to the pressure acting upon it, defined by the bulk modulus and is shown in equation (11).

$$P = \frac{E_\nu}{V_0}\int (Q_{in} - Q_{out})dt \qquad (11)$$

where Q, E_ν, P, and $V_0 = A_p \times \Sigma L_p$ represents volumetric flow $(\frac{m^3}{s})$, Bulk modulus (Pa), pressure (Pa) and original volume of pipe (m^3) respectively. The time derivative of (11) is presented as

$$\frac{dp}{dt} = I_p \frac{d(Q_{in} - Q_{out})}{dt} \qquad (12)$$

where $I = \frac{E_\nu}{V_0} = \frac{\rho L_p}{A_p}$. L_p and A_p are the length and cross-section of the corresponding pipe respectively.

E. Overall System Model

When constructing the overall model the subsystems are simply parameterized and connected together to represent the complete system. For parameterizations of the component models, information was taken from measurement, data-sheets and based on experiment. In our model we assume that the fuel temperature is constant during operations. The fuel pressure dynamics can be calculated by suitably combining the continuity equation, the momentum equation and Newton's motion law. consequently the system state can be represented by the pressure in each control volume. We also neglect fluid dynamic phenomena connected to flows through pipes.

Equations (3) to (11) can be rewritten in a state space form, assuming the pressures as state variables and the pump speed, as inputs. With the following positions:

$$x = \begin{bmatrix} P_1 & P_2 & P_3 & P_4 & P_5 \end{bmatrix}^T, \qquad (13)$$

where P_i for $i = 1,\cdots,5$, presents the outputs of the i^{th} pressure sensor respectively .

The global system equation may have the following form:

$$\begin{aligned}
\dot{x_1} &= x_2 \\
\dot{x_2} &= \frac{1}{I_1C_t}x_1 \\
\dot{x_3} &= x_4 \\
\dot{x_4} &= -\frac{R_1C_t}{I_1}x_4^2 - \frac{1}{I_1C_t}x_3 \\
\dot{x_5} &= x_6 \\
\dot{x_6} &= -\frac{R_1C_t}{(I_1+I_2)}x_6^2 - \frac{1}{(I_1+I_2)C_t}x_5 + \frac{K_u}{(I_1+I_2)C_t} \\
& \quad U(t) \\
\dot{x_7} &= x_8 \\
\dot{x_8} &= -\frac{(R_1+R_2+R_3)C_t}{(I_1+I_2)}x_8^2 - \frac{1}{(I_1+I_2)C_t}x_7 \\
& \quad + \frac{K_u}{(I_1+I_2)C_t}U(t) \\
\dot{x_9} &= x_{10} \\
\dot{x_{10}} &= -\frac{(R_1+R_2+R_3+R_4)C_t}{(I_1+I_2+I_3)}x_{10}^2 - \frac{1}{(I_1+I_2+I_3)C_t} \\
& \quad x_9 + \frac{K_u}{(I_1+I_2+I_3)C_t}U(t) \qquad (14)
\end{aligned}$$

The intermittent fault, $f_i(t)$, is considered as a fault in $DPV3$. $f_i(t)$ is defined as a time varying function of the form $f_i(t) = dd_i y_{n_c}(t)$, where dd_i, the maximum fault amplitudes, are constant and y_{n_c} is the designers's choice of output. Hence the intermittent fault, $f_i(t)$, could be generated as combination of impulses at different amplitudes which will occurred in discrete intervals. We could model the fault as follows

$$f_i(t) = \begin{cases} 0 & for \quad 0 \le t < 30s \\ f_{i_1} & for \quad 30s \le t < 40s \\ 0 & for \quad 40s \le t < 100s \\ f_{i_2} & for \quad 100s \le t < 160s \\ 0 & for \quad 160s \le t < 200s \\ f_{i_3} & for \quad 200s \le t < 260s \\ 0 & for \quad 260s \le t < 280s \\ f_{i_4} & for \quad 280s \le t < 360s \end{cases} \qquad (15)$$

where $dd_1 = 0.0020$, $dd_2 = 0.0035$, $dd_3 = 0.0050$ and $dd_4 = 0.080$ are constants, $n_c = 1,\cdots,5$ is the choice of output and t indicates the time in seconds.

IV. Intermittent Fault Detection

To avoid the consequences caused by the failure of the elements in the control systems, it is critical to monitor the health situation of the plant and to detect and identify any possible faults at the earliest stage.

Not all the states $x(t)$ can be directly measured (as is commonly the case), therefore an observer is designed, $\hat{y}(t)$ to estimate them, while measuring only the output $y(t)$. The observer is basically a model of the plant; it has the same input and follows a similar differential equation. An extra term compares the actual measured output $y(t)$ to the estimated output of the observer $\hat{y}(t)$; minimising this error will cause the estimated states $\hat{x}(t)$ to tend towards the values of the actual real-system states $x(t)$. It is conventional to write the combined equations for the system plus observer using the original state x(t) plus the error state [14],

$$e(t) = x(t) - \hat{x}(t). \tag{16}$$

For more details on the nonlinear observer design for the system and it's error stability see [15]. In general the fault detection system consists of two parts, 1) residual generation, 2) residual evaluation [17].

A. Residual Generation

While a suitable observer is chosen for every case, if the error system stability is satisfied, then the following scalar observer-based residual can be generated for each output to detect the intermittent faults

$$r_s(t) = (y(t) - \hat{y}(t)) = \zeta Ce(t) + \zeta K_{ss} f_s(t) \tag{17}$$

where $\zeta \in \mathbb{R}^{n \times p}$, is a suitable weighting matrix to be designed.
The problem can be stated as finding ζ, such that the following aims are achieved [18]:

- The effect of unknown input and disturbance signals on the residual signal are as small as possible while the effect of fault signal is as large as possible.
- The effect of parametric uncertainties on residual signal are as small as possible.
- The fault detection system is robust stable in the presence of exogenous signals and uncertainties.

The object is to show that the residuals are differing from zero when faults have occurred; however, the residual tends to zero in "no fault" situation.

B. Residual Evaluation

A common choice of evaluation signal is the 2-norm:

$$r_{s_{eval}} = \|r_s\|_2 \triangleq \sqrt{\int_0^\infty |r_s(\tau)|^2 d\tau}. \tag{18}$$

Since the evaluation function (18) can not be realised exactly, because the value of $\|r_s\|_2$ is not known until $t = \infty$, and it is reasonable to assume that faults could be detected, if they occur over finite time interval. Therefore equation (18) could be modified to

$$r_{s_{eval}} = \|r_s(t)\|_2 \triangleq \sqrt{\int_0^t |r_s(\tau)|^2 d\tau} \tag{19}$$

where τ is the time window and it is finite [16].

C. Adaptive threshold

For the evaluation signal (19), the occupance of faults can be alarmed if

$$r_{eval} > T_r \Longrightarrow A\ fault\ is\ detected$$

and

$$r_{eval} \leq T_r \Longrightarrow No\ fault\ is\ detected.$$

Hence the value of threshold gives an explicit bound on in the fault free case and thus provides a valuable guideline for robust threshold selection ([17], [19]).

T_r, the threshold, is obtained based on the residual dynamics in fault-free case. To design the adaptive threshold for nonlinear system (2) and evaluation signal (19) redefine the residual $r(t) = \xi C\bar{\omega}e_x(t)$ as follows:

$$r(t) = r_e(t) + r_{f_i}(t), \tag{20}$$

where $r_e(t) = r(t)\mid_{\mu(t)=0, f_i(t)=0}$ and $r_{f_i}(t) = r(t)\mid_{\mu(t)=0}$ are the residuals due to the error and intermittent fault

Finally according to the obtained results the designed residual and adaptive thresholds are able to detect the intermittent faults while occurred (see [2]).

V. Simulation Results

The model has been implemented and simulated in the MATLAB/Simulink environment. To assess the model performance, simulation results have been compared with experimental data obtained on a fuel rig system.
Some simulation results, which highlight the modeling capability, are illustrated in following figures.

Figure 4 shows the pressures outputs from all five sensors, the main and sum tank flows and the intermittent fault. The intermittent fault has been injected manually. It was considered as shutoff valve is getting clogged gradually with some rest periods in betweens. Eventually the shutoff valve will be 80 percent clogged approximately. Based on Figures 5 and 6, it can be seen from the residual responses that the observers perform as expected and the state estimation errors do tend to zero asymptotically as expected. They also show that the intermittent fault has been detected using the designed adaptive threshold accurately for the chosen outputs.
Figure 5 also shows that the output of the sensor located right after the faulty valve, P_3 has been affected by stronger intermittent fault in compare with first output P_1, Figure 6.
The simulation results also demonstrate that the proposed design approach minimising the effect of the unknown inputs (uncertainties) to the state estimation errors and will give a straightforward way to design a robust observer for intermittency fault detection where the bounded uncertainties are existed.

VI. CONCLUSIONS

This paper presents a mathematical model of a fuel rig system. The model equations are obtained by resorting to physical laws regulating the main fluid-dynamic and mechanical phenomena. The proposed model is validated by comparing simulation results with both experiments and the outputs of an accurate fluid-dynamic model. A robust nonlinear observer has been designed for a class of nonlinear systems with bounded unknown inputs (uncertainties). The authors also show that the existing error dynamics between the estimated and actual states are stable. In this method, the non-unique design matrix, ζ, has been used to provide extra degrees of freedom to the user to design the residual. The main advantage of the proposed method is the possibility to diagnose the intermittent faults by generating a residual and an adaptive threshold which is highly sensitive to faults and insensitive to any bounded uncertainties. An adaptive threshold, as employed in this paper, makes the difficult intermittency fault detection an easier task for the considered class of nonlinear systems.

Finally, the effectiveness of the technique is illustrated by the help of a numerical example. The simulation results show that the designed residual and adaptive threshold can indeed detect the intermittent faults regardless of the bounded unknown inputs (uncertainties).

The next key issue is how to deal with the intermittent faults in prognosis and how to balance the decision making strategy. To deal with this issue a Bayesian Network (BN) will be obtained to predict the intermittent failure probability by designing a safety limit threshold. By monitoring the operations data the BNs for failure prediction can be driven and hence the performance warning when the predicted failure probability meets the threshold of safety limit will be provided. Hence by predicting the intermittent fault the huge reduction in NFF rate will be obtain.

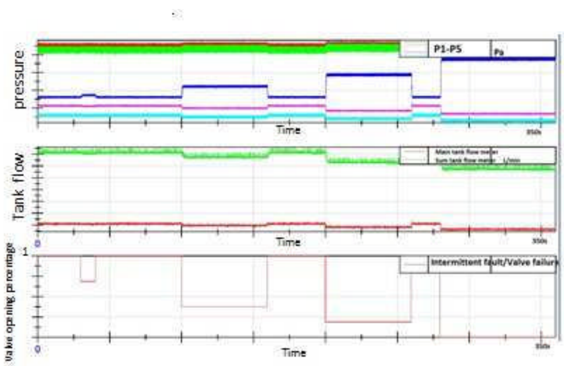

Fig. 4: The experimental sensors, tank flows and intermittent fault.

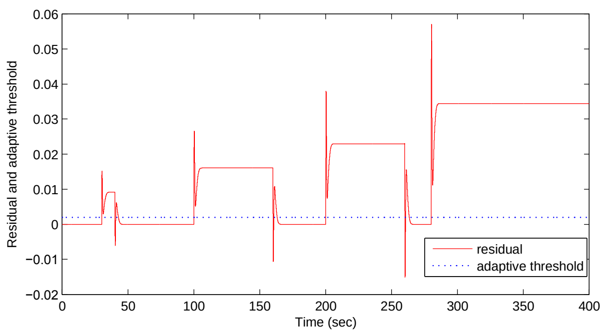

Fig. 5: The observer-based residula and adaptive threshold responses, third choice of output, $y = P_3$.

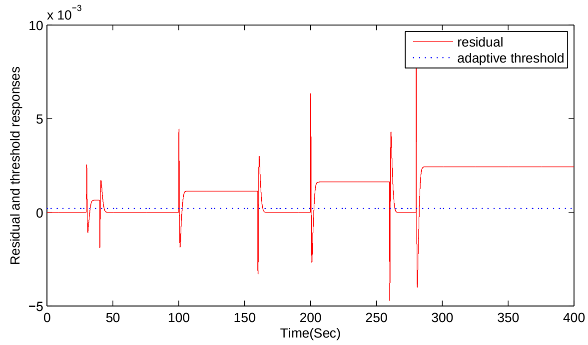

Fig. 6: The observer-based residula and adaptive threshold responses, first choice of output, $y = P_1$.

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