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A FAULT DETECTION AND IDENTIFICATION SYSTEM FOR TESTING LIQUID ROCKET ENGINES

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Abstract. *This work deals with the fault detection and identification (FDI) problem for a liquid rocket engine in a test bench. The approach adopted uses a Kalman filter residual-based hypothesis testing. A simple dynamic model, with 17 continuous states and 11 measurements of the engine, is developed and typical failure modes of the engine and sensors are inserted into the model in order to simulate the development of a fault. The strategy adopted regarding the faults is to identify the presence of a fault and assess whether it is a fault in the engine/test bench, i.e., a system fault, or a fault in a sensor. In the case of a system fault, the test must be stopped at once, but, in the case of a sensor fault, it is more interesting to simply ignore the failed sensor readings and continue with the test. The proposed FDI system also estimates unknown parameters in the engine dynamics, without any effect in the filtering scheme. In order to validate the designed FDI system, several Monte Carlo simulations are made and the results indicate that the approach is effective for all the tested fault modes.*

Keywords: *Fault detection and identification system, Liquid rocket engine, Engine testing, Kalman filtering, Hypothesis testing*

1. INTRODUCTION

Liquid Rocket Engines (LRE) are very complex machines whose development is firmly based on test results. These tests are performed in massive test stands, fully equiped with various sensors, electronic equipment as well as considerably large propellant tanks in most cases. However, in the early stages of development, is is not unusual that some faults, originated from the engine or from the integration of the engine with the test bench, manifest themselves during the test. If unattended, some of these faults may result in catastrophic damage for the engine and/or for the test stand. Since LREs can be shut down during operation without the complete destruction of the engine, it is very interesting, in terms of reducing overall life cycle cost, to be able to detect and identify the development of system faults. With this capability, the engine can be shut down before any major damage takes place.

On the other hand, there are also significant costs incurred by stopping an LRE test for any reason. In fact, ignition procedures involve purging and cooling down propellant lines, when cryogenic propellants are in use, and changing pyrotechnic igniters, among several other required procedures. Additionally, LREs are manufactured for a limited number of ignitions. Therefore, shutting down limits their life significantly. Thus, unnecessary interruption of a test in course, for instance, due to a minor sensor fault, is extremely undesirable. For those reasons, Fault Detection and Isolation (FDI) is a very important concern for LREs in the development stage. An adequate FDI system, for a LRE in the test bench, should be able to properly detect any faults and decide, with minimum error probability, if the test must be stopped or not.

Some FDI approaches employ somewhat rudimentary techniques, in which all the measured variables are compared with minimal and maximal (fixed) bounds. Whenever any measurement is out of bounds, the FDI system shuts down the engine (Johnson, 1990). This procedure main setback is that a single sensor fault might trigger the (unnecessary) interruption of the test in course. Other model-free techniques use physical hardware redundancy and basic statistical tools such as median filters (Wu, 2005). More sophisticated possibilities use model-based fault detection and identification, well explored by many textbook authors, such as Gertler (1998), Basseville and Nikiforov (1993) and others. This general approach comprises several different techniques, such as Direct Fault Parameter Estimation (Duyar *et al.*, 1994), Detection via Neural Networks (Whitehead *et al.*, 1990; Luce and Govind, 1990), "if–then" rules-based expert systems (Bickmore and Bickford, 1992), and others. Some existing engine health monitoring systems employ combinations of two or more of the above methods, such as those implemented for the Space Shuttle Main Engine (Musgrave *et al.*, 1992) and the Long March Main Engine (Zhang *et al.*, 1998).

2. DYNAMIC MODEL OF THE LRE AND FAULT MODELS

The proposed FDI scheme is applicable to any system well-modeled by a dynamically coupled set of state equations. In the present work, the system is illustrated by a simple model of an open-cycle, turbopump-fed, LRE. In particular, a model for the L75 engine, currently under development at IAE, is used. The model has 17 continuous states, such as:

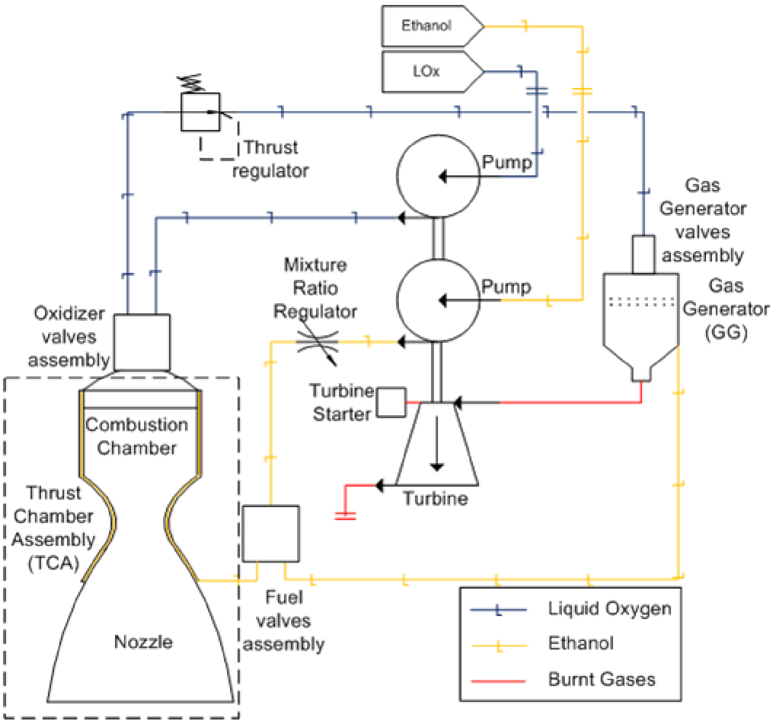

Figure 1. Diagram of the L75 Engine.

thrust chamber, referred to as Thrust Chamber Assembly (TCA), pressure; gas generator, referred to as GG, pressure; oxidizer and fuel pump outlet pressure; turbopump, referred to as TurboPump Assembly (TPA), axis rotational speed; turbine outlet pressure and temperature; pressure in numerous hydraulic chambers along the propellant feed lines; as well as position and speed of the spool in the thrust regulating valve. Figure 1 shows an overall scheme of the engine.

For the sake of brevity, not all the state equations are shown here, since they are based in simple mass and energy conservation laws. The references used for constructing the models are Belyaev *et al.* (1999) and Barbosa (1999). The following concise model will be used to refer to the engine dynamics:

$$\dot{x}(t) = f(t, x(t), u(t)) \ . \tag{1}$$

Here, t is the time, $x(t)$ is the vector of engine states and $u(t)$ is the input for the engine, which is the thrust regulator command.

Eleven (11) of these 17 states are measured by pressure, temperature, and rotational speed transducers placed in the engine. Since the measurements only become available for processing by the computer at discrete sampling times, they are modeled by discrete time equations. Hence, the measurements available at discrete time, k, are represented by z_k, a vector of length 11 in the simulations for this work, which is related to the states according to

$$z_k \ = \ H \, x_k \ + \ n_k \ . \tag{2}$$

Here, $x_k = x(t_k)$, and n_k is a Gaussian, white noise sequence accounting for measurement noise. It is assumed that $n_k \sim \mathcal{N}(0, R)$, where R is the known covariance of the measurement noise. The H matrix rearranges the states, since each measurement corresponds to only one state.

Some model parameters are unknown *a priori*, i.e., cannot be measured or determined accurately without proper testing. Pumps and turbine efficiencies, for example, are modeled by polynomial equations whose coefficients depend on the actual composition and temperature of the working fluids; therefore, these coefficients are predetermined by "cold tests" (tests with different fluids, such as water or nitrogen gas), but must be corrected for the real conditions in the engine. Other parameters include equivalent passage area for oxidizer and fuel injectors, friction coefficient for the turbopump axis, among others.

In order to overcome these problems, the "uncertain parameters" are introduced in the dynamic equation of the engine as

$$\dot{x}(t) = f(t, x(t), u(t), \pi) \ . \tag{3}$$

In this equation, $\pi \sim \mathcal{N}(0, \Pi)$ is the vector of uncertain parameters, modeled by a random vector of constants, *i.e.*, it is assumed that π does not vary with time. The uncertain parameters covariance, Π is a diagonal, positive-definite matrix accounting for the actual degree of uncertainty in each parameter.

The faults on the engine are divided between system faults and sensor faults. System faults are defined by sudden and significant variations on engine parameters, e.g., a rise in equivalent oxidizer or fuel injector area, representing a leak in the injector head; or a jamming in the spool of the thrust regulating valve. In order to account for the system faults, the state equation is modified as

$$\dot{x}(t) = f(t, x(t), u(t), \pi, \xi(t)) \ , \tag{4}$$

where $\xi(t)$ are the system fault parameters, which, by convention, are zero in the absence of faults. It is important to mention that the *a priori* statistics of the faults or failures are not known. In fact, these are caused, for instance, by mistakes in engine assembly or manufacturing processes, structural failure, or the presence of impurities in the propellants, for which there is no reliable data. Therefore, it is decided to avoid unrealistic modeling and, hence, to model the function $\xi(t)$ as deterministic, but unknown.

Sensor faults, on the other hand, are deviations on sensor readings greater in absolute value than the measurement noise previously adjusted. Therefore, the measurement equation is modified:

$$z_k = Hx(t_k) + n_k + \mu_k \tag{5}$$

where μ_k are the sensor fault parameters, which, also by standardization, are zero in the absence of faults. Once again, considering the lack of statistical information concerning sensor faults, the function μ_k is modeled as deterministic and unknown.

3. FAULT DETECTION AND ISOLATION

As mentioned before, the following FDI algorithms work for a variety of systems. So, in order to avoid unnecessary loss of generality, the number of states is N, the number of uncertain parameters is p, the number of measurements is M.

3.1 Overview of the FDI Scheme

In accordance with basic fault detection, isolation and identification literature (Gertler, 1998), the proposed FDI scheme is organized in layers, as shown in Fig. 2. The FDI "main function" manages the status of failed sensors and

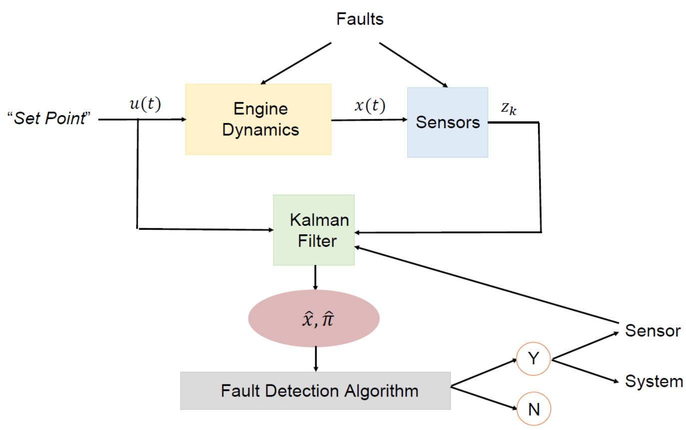

Figure 2. Architecture of the proposed FDI scheme.

the conditions for terminating the test. In the bottom level lies an Extended Kalman Filter, designed for the mathematical model of the engine in the absence of faults, *i.e.*, Eqs. (2) and (3). The Detection Algorithm is based on the outputs of the Kalman Filter and, in case of detection, both the Isolation Algorithm and the Sensor Recovery Algorithm run simultaneously.

3.2 Kalman Filtering

The Extended Continuous-Discrete Kalman Filter (ECDKF) is the first level of the FDI system. It provides optimal state estimates for all the engine states, by assuming absence of faults in the engine or its sensors, as well as playing the part of a residual generator. The basic ECDKF scheme is now briefly explained. Readers interested in the derivation of the equations are referred to Anderson and Moore (1979).

The Kalman Filter is an algorithm for obtaining optimal state estimates $\hat{x}_{k|k}$ given the measurements $\{z_i;\ 0 \leq i \leq k\}$. In the case of the current filtering scheme, both the states and the uncertain parameters have to be estimated; this is done by considering the uncertain parameters as additional "static states", i.e., with no associated dynamics. The covariance of the estimation errors is given by:

$$P_{k|j} = E\left[\begin{bmatrix} x_k - \hat{x}_{k|j} \\ \pi - \hat{\pi}_{k|j} \end{bmatrix} \begin{bmatrix} x_k - \hat{x}_{k|j} \\ \pi - \hat{\pi}_{k|j} \end{bmatrix}^T\right] \tag{6}$$

The equations for propagating the state estimate, $\hat{x}$, and the uncertain parameter estimate are given by:

$$\begin{cases} \hat{x}_{k|k-1} = f_k\left(\hat{x}_{k-1|k-1}\right) \\ \hat{\pi}_{k|k-1} = \hat{\pi}_{k-1|k-1} \end{cases} \tag{7}$$

where $f_k(\xi)$ is the solution of $\dot{x} = f(t, x(t), u(t))$ with initial conditions $x(t_{k-1}) = \xi$, evaluated at $t = t_k$. For propagating the covariance of the state estimation error, usually, the CDEKF proposes integrating a non-linear matrix differential equation. It is decided, however, to propagate a linear equation provenient from direct linearization of the state equation.

At the correction step, on the other hand, the state and uncertain parameters estimates are improved by incorporation of measurements available at that time step. The equations for correction of state and uncertain parameter estimates, and covariance of the estimation error, respectively, are given by:

$$\begin{bmatrix} \hat{x}_{k|k} \\ \hat{\pi}_{k|k} \end{bmatrix} = \begin{bmatrix} \hat{x}_{k|k-1} \\ \hat{\pi}_{k|k-1} \end{bmatrix} + K_k \zeta_k \tag{8}$$

and $P_{k|k} = (I - K_k H) P_{k|k-1}$, where K_k is the Kalman gain and

$$\zeta_k = z_k - H\hat{x}_{k|k-1}\,, \tag{9}$$

is referred to as the *innovations sequence*, and it plays a major role in the Fault Detection Algorithm.

3.3 Detection Algorithm

As proposed by Gertler (1998), the Detection Algorithm is a hypotheses test based on the *scalar residual*, which in turn is given by $r_k = \zeta_k^T Z_k^{-1} \zeta_k$, where $Z_k = HP_{k|k-1}H^T + R$. The statistics of r_k change according to the presence or absence of faults, as explained below.

In the absence of faults, the ζ_k is simply

$$\zeta_k = H\left(x_k - \hat{x}_{k|k-1}\right) + n_k. \tag{10}$$

Under these conditions, Kalman Filter theory assures that the innovations sequence $\{\zeta_k;\ k \in \mathbb{Z}\}$ is a gaussian, white noise sequence, with, $\zeta_k \sim \mathcal{N}(0, Z_k)$. Hence, the scalar residual is distributed as a central chi-squared variable with M degrees of freedom, $r_k \sim \chi^2_M$.

In the presence of a sensor fault, however, the measurement equation (2) changes to equation (5); hence, ζ_k becomes

$$\zeta_k = H\left(x_k - \hat{x}_{k|k-1}\right) + \mu_k + n_k\,, \tag{11}$$

so $E[\zeta_k] = \mu_k$, and

$$E\left[(\zeta_k - \mu_k)(\zeta_k - \mu_k)^T\right] = HP_{k|k-1}H^T + R = Z_k\,. \tag{12}$$

Therefore, in the presence of a sensor fault, $\zeta_k \sim \mathcal{N}(\mu_k, Z_k)$. Hence, the scalar residual is distributed as a noncentral chi-squared variable $r_k \sim \chi^2_M(\lambda)$ with M degrees of freedom and non-centrality parameter $\lambda = \mu_k^T Z_k^{-1} \mu_k$.

In the presence of a system fault, ζ_k is still given by equation (10), but $\hat{x}_{k|k-1}$ is corrected under no-fail hypothesis, although x_k is. Because of this, the state estimation error $x_k - \hat{x}_{k|k-1}$ is no longer a zero mean gaussian variable; say, $x_k - \hat{x}_{k|k-1} \sim \mathcal{N}\left(\phi_k, P_{k|k-1}\right)$. Under these conditions, $E[\zeta_k] = H\phi_k$, and

$$E\left[(\zeta_k - H\phi_k)(\zeta_k - H\phi_k)^T\right] = HP_{k|k-1}H^T + R\,. \tag{13}$$

Therefore, in the presence of a system fault, $\zeta_k \sim \mathcal{N}(\phi_k, Z_k)$. Hence, the scalar residual is distributed as a noncentral chi-squared variable $r_k \sim \chi^2_M(\lambda)$ with M degrees of freedom and non-centrality parameter $\lambda = \phi_k^T Z_k^{-1} \phi_k$.

From all these considerations, it is possible to infer that in the absence of faults, the scalar residual r_k is distributed as a chi-squared variable with M degrees of freedom, i.e., its statistics are well known *a priori*. In the presence of a sensor or system fault, on the other hand, the scalar residual r_k is distributed as a chi-squared variable with M degrees of freedom *and non-centrality parameter* $\lambda > 0$, since Z_k is non singular and positive-definite.

Considering all these assumptions, a composite hypothesis test is designed. For all cases, $r_k \sim \chi^2_M(\lambda)$, and the hypotheses are: $H_0 : \lambda = 0$ and $H_1 : \lambda > 0$. The corresponding (uniformly most powerful) test is to decide for H_1 if r_k is greater than a predetermined threshold r_{FAD}, and for H_0 otherwise: This threshold r_{FAD} is determined based on the statistics of the χ^2_M distribution and a chosen *detection false alarm probability* p_{FAD}. This calculation is straightforward, and specific details can be found in Van Trees (2001).

3.4 Isolation Algorithm

After the detection of a fault, the FDI system performs a test to decide if the deviation in the innovation is consistent with a sensor fault or not, and if so, it determines which sensor is most likely faulty. This is done to prevent a sensor fault from disturbing the state/unknown parameter estimates.

The Isolation Algorithm runs on the innovation ζ_k, and it is based on the assumption that although several sensors may fail during a test, two sensors cannot fail during a single controller time step (Bickmore, 1992). The controller time step considered for this simulation is 20ms for the simulations in this work. Therefore, the central rationale is: If the anomaly, *i.e.*, deviation from expected statistic, is consistent with the hypothesis of a single sensor having become faulty, then the referred sensor is most likely faulty and must have its validity verified. Else, then a system fault is most likely present, and the test must be stopped at once.

The mathematical formalization of this argument is now presented. As seen before, in absence of a fault, $\zeta_k \sim \mathcal{N}(0, Z_k)$. Then,

$$v = Z_k^{-1/2} \zeta_k = \zeta^0 \sim \mathcal{N}(0, I_M).$$

In the presence of a sensor fault, say, in the $j-$th sensor (referred as sensor j), $\zeta_k \sim \mathcal{N}(\mu_k, Z_k)$, with $\mu_k = f_k \bar{e}_j$, where $\bar{e}_j$ is the unit vector along the $j-$th coordinate. Then,

$$v = Z_k^{-1/2} \zeta_k = \zeta^0 + f_k Z_k^{-1/2} \bar{e}_j.$$

In the presence of a system fault, $\zeta_k \sim \mathcal{N}(\phi_k, Z_k)$, with $\phi_k \neq f_k \bar{e}_j$, $\forall j \in \{1, \ldots, M\}$, $\forall f_k \in \mathbb{R}$ because system faults provoke significant alterations in more than one measured state. Then,

$$v = Z_k^{-1/2} \zeta_k = \zeta^0 + Z_k^{-1/2} \phi_k.$$

Therefore, the isolation algorithm evaluates vector $v = X\zeta_k$, where $X = Z_k^{-1/2}$, matrix square root of the known, positive-definite matrix Z_k. Then, v is projected onto the columns $X\bar{e}_j$ of X, in order to assess the likelihood of each hypotheses $v \sim \zeta^0 + fX\bar{e}_j$: for each $j \in \{1, \ldots, M\}$, let

$$v_j = \frac{\langle X\bar{e}_j, v \rangle}{\langle X\bar{e}_j, X\bar{e}_j \rangle} \quad \text{and let } j^* = \arg\max_j |v_j|$$

be the component with the maximum projection of v. It makes no statistical sense to consider fault in another sensor than j^*; the fault is either in sensor j^* or in the engine itself. If $w = |v - v_{j^*} \bar{e}_{j^*}| \leq r_{\text{FAI}}$ for a predefined false alarm threshold r_{FAI}, then it is considered that the residual *is consistent* with a fault in sensor j^*. In this case, the sensor must have its consistency checked by the Sensor Recovery algorithm. Conversely, if the inequality above does not hold, then the residual *is inconsistent* with a fault in the j^* sensor. There are more components of spurious residual in other sensors. In this case, the isolation algorithm declares the presence of a system fault, and the test is interrupted for safety reasons and system checking.

3.5 Sensor Recovery Algorithm

The purpose of the Sensor Recovery Algorithm is to avoid unnecessary rejection of sensors, since after each detection, either a sensor or the system is claimed to be faulty. After a sensor fault is declared (say, on discrete time k_0), the isolated sensor's readings are analysed by the Sensor Recovery Algorithm for a predetermined amount of sample times (k_Q), referred to as "quarantine". While in quarantine, the referred sensor's readings are ignored for filtering purposes, but the

Kalman filter keeps processing the remaining measurements in order to keep obtaining optimal state and parameter estimates $\hat{x}_{k_0+m|k_0+m}$, $m \in \{1, \ldots, k_Q\}$. Meanwhile, the Sensor Recovery Algorithm computes the accumulated residual for the quarantined sensor (j):

$$s_m = s_{m-1} + \bar{e}_j^T (z_{k_0+m} - H\hat{x}_{k_0+m|k_0+m})$$

as well as the variance of s_m under no fault hypothesis:

$$\sigma_m^2 = \sigma_{m-1}^2 + \bar{e}_j^T \left(HP_{k_0+m|k_0+m}H^T + R \right) \bar{e}_j$$

At the end of the "quarantine", the accumulated residual s_{k_Q} is tested against expected statistics under the hypothesis of absence of faults. So, the Sensor Recovery Algorithm decides for reconsidering the quarantined sensor to filtering purposes if $s_{k_Q} \leq r_{\mathrm{FAR}} \sigma_{k_Q}$, where r_{FAR} is a predetermined threshold. Conversely, if the equation above does not hold, than the referred sensor is considered faulty, and is permanently disconsidered until the end of the test.

3.6 Main Algorithm

The main algorithm performs the management of all three algorithms mentioned above, and also declares a system fault in any of the following two cases: sensor fault during quarantine and excess of faulty sensors. It decrees the termination of the test when the Detection Algorithm determines the presence of a fault while a sensor is already in quarantine. This is because some system faults manifest themselves by deviating some sensor readings more than others, which might be interpreted by the Isolation Algorithm as many sensor faults happening sequentially. It also finishes the test when more than N_{Lim} (8, in this work) sensors are declared faulty consecutively. This is mainly because after disregarding so many sensors, the test is not meaningful anymore. Naturally, these two "cases" of test termination by detection of system fault increase the system fault isolation rate, but also inevitably raise the Isolation False Alarm probability, especially in the first case.

4. RESULTS

It is clear that the true detection rates for the hypotheses tests cannot be calculated analytically, only determined by simulation. For this purpose, many simulation experiments are performed, varying settings such as detection false alarm rate, isolation false alarm rate, fault magnitude and starting time, etc. Hence, all sucess rates (detection, sensor/system fault isolation, etc) are assessed by extensive Monte Carlo simulations, in a Design of Experiments framework: every combination of the factors being studied is run several times, to ensure enough realizations of measurement noise and uncertain parameters.

Generally speaking, the fault detection rate depends on many factors, such as fault type, magnitude, start time, transition mode, as well as the ammount of available sensors when the fault manifests itself and, naturally, all the settings of the FDI system. In order to narrow down the study, a single fault was selected for results shown in this paper, namely, a decrease in the equivalent passage area of the oxidizer injectors. The transition mode for the fault is chosen to be by step , for this is the simplest transition mode (in terms of fewer parameters to be set). It is worth mentioning that there is an uncertain parameter for the same variable, i.e., at the beggining of each simulation, a new random disturbance for the injector passage area is inserted, which does *not* count as a fault in the statistics of detections.

Figure 3 shows the statistics of detection rates for the mentioned fault. A total of 3600 simulations were made, varying detection false alarm rate p_{FAD}, the fault level, and fault start time. The circles mark the measured detection rate; the squares and the triangles, the lower and upper bounds of the confidence intervals, respectively. The selection of p_{FAD} must take into account both the false alarm probability and the true detection probabilities assessed in this study. As expected, the mean detection rate rises with both fault level and p_{FAD}.

For this same set of simulations, another variable was studied: fault start time. Figure 4 presents the same statistics obtained before, but organizing the results only by fault start time. The marker convention of last figure is maintained. The observed trend is clear: the detection rates for the start times of 5.11 and 8.33 have considerable overlaps in their confidence intervals, but the detection rate for the start time of 0.06 is significantly lower than the first two. This trend can be explained by the fact that the covariance of the estimation error of the uncertain parameters is still quite elevated at the first time steps, so most faults ocurring in these parameters and at the first time steps are misidentified as natural variations in the uncertain parameters, as expected. Nevertheless, the mean detection rates are still considered satisfactory.

5. CONCLUDING REMARKS AND FUTURE WORK

In this work, a novel Fault Detection and Isolation system for a LRE in a test bench is proposed, using Kalman filter residual-based hypothesis testing. The detection rates, assessed by Monte Carlo simulations, demonstrate that the system performance is adequate even for relatively small fault magnitudes, with only a small loss of performance if the faulty parameter is also being identified as the test runs. Nevertheless, the classic Detection Theory trade-off, where raising the

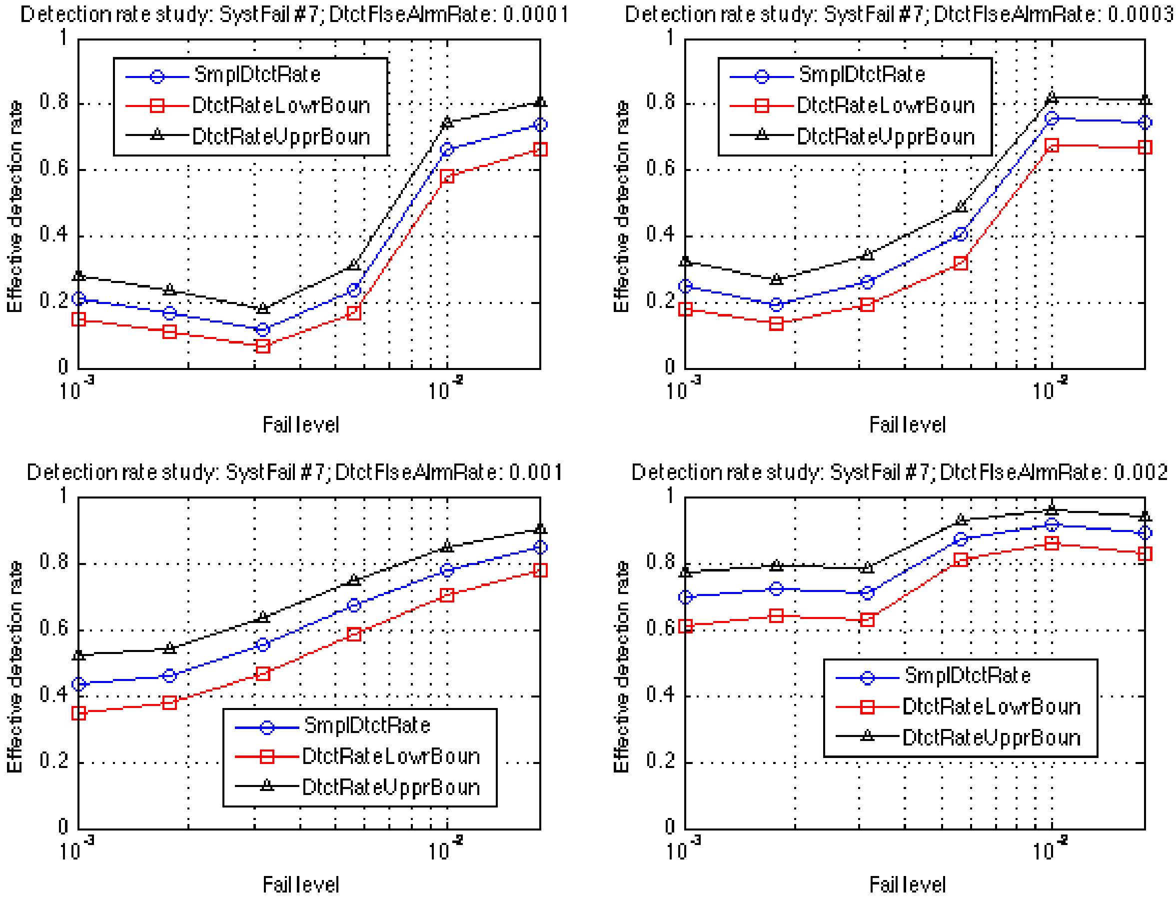

Figure 3. Mean system fault detection rate for several false alarm rates and fault levels.

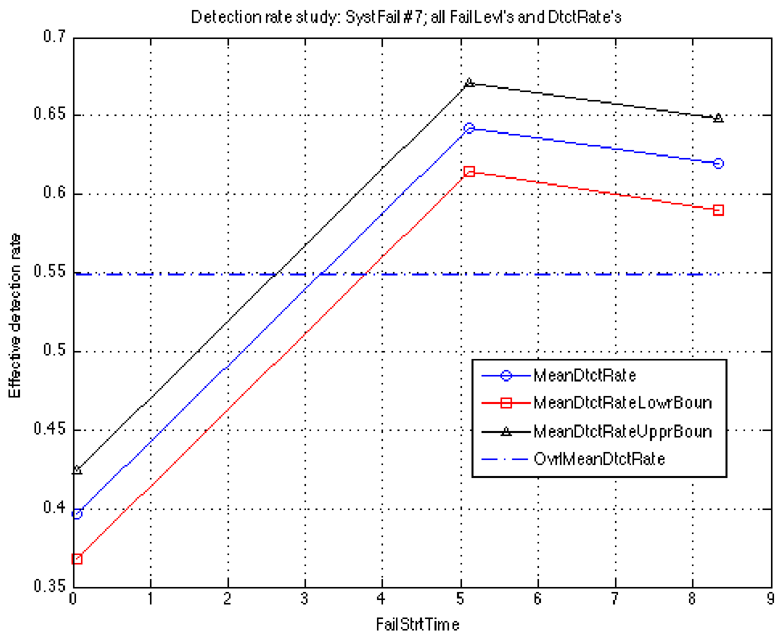

Figure 4. Mean system fault detection rate for different fault start times.

detection rate also raises the false alarm probability, is present as well. For future work, the true isolation rates must also be assessed, in order to provide data to allow proper selection of the FDI system parameters: the false alarm rates p_{FAD},

p_{FAI} and p_{FAR} as well as the quarantine duration k_Q.

6. ACKNOWLEDGEMENTS

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