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Built-in Test Design for Fault Detection and Isolation in an Aircraft Environmental Control System ⋆

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Abstract:
A novel built-in test (BIT) design method for fault detection and isolation (FDI) is presented, in which the test information extracted is maximized using parametric sensitivities derived by a system model. Two case studies are presented to demonstrate this approach. The first test focuses on fouling identification in an aircraft heat exchanger, in the presence of uncertain system inputs. The second example expands this method to a subsystem of an aircraft environmental control system (ECS) to calculate optimal conditions for component FDI.

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1. INTRODUCTION

Advances in technology of engineering systems have led to increase in complexity, which is often the reason for increased uncertainty and faults during operation. The accuracy and timeliness of the methods used for fault detection and isolation (FDI) significantly impact system reliability, cost, safety, quality, and environmental footprint. Research aimed at developing more sophisticated FDI methods has increased over the past couple of decades due to their application in a variety of industries like aerospace, automotive, chemical, defense, energy, electronics, and transportation (Isermann (1984); Isermann and Ballé (1997); Venkatasubramanian et al. (2003a,b,c); Isermann (2005); Hwang et al. (2010)). In aircraft systems, built-in tests (BIT) are implemented as a method of FDI to address the issues of faulty operation. As improvements are made to sensing equipment and signal processors, more sophisticated BITs can be developed.

BIT is a system test used to detect, display and isolate faults during operation. BIT is also capable of applying fault-based control to maintain system functionality in the presence of faults (AC-9 Aircraft Environmental Systems Committee (2011); Airlines Electronic Engineering Committee (1988)). During BIT, the state of a line replaceable unit (LRU) is verified using various BIT equipment (BITE) and ground support equipment (GSE) (AC-9 Aircraft Environmental Systems Committee (2011)). Complications occur when systems and subsystems with interconnecting components can produce similar system responses for different faults. Manually initiated BIT (also known as initiated/instantiated BIT or IBIT) usually operates during aircraft maintenance and can extend outside of the normal system operating conditions, within the bounds of component and system safety. IBIT is the intended application of the method presented in this paper, due to the relaxed operating bounds and the increased flexibility in system operating conditions during ground operation. One way to improve fault detection for built-in tests is to adjust the system conditions prior to testing, through *a priori* model-based analysis. If a system has exhibited faults, the goal is to obtain outputs that generate a unique response capable of providing reliable fault detection and isolation.

In this work, a methodology for IBIT has been structured based on Optimal Experimental Design (OED) techniques. Estimation of test conditions to maximize the information with respect to a fault or system uncertainty is best approached through a structured statistical analysis with origins in the work of Fedorov (2010). OED combines measurements of a system, its model and expected variances to reduce parameter uncertainty (Rodriguez-Fernandez et al. (2007); Bruwer and MacGregor (2006)). It is often used to improve the precision of experimentally estimated system parameters and states (Han et al. (2016a,b)), and has been applied in many fields of statistics (Franceschini and Macchietto (2008)). OED uses available information taken from a set of experiments to solve an optimization problem that minimizes the uncertainty of future tests. OED can be applied to a linear or nonlinear system.

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The problem of optimal experimental design for FDI seeks for a system state or state trajectory in which faults (expressed as model parameters) are locally identifiable. Identifiability is helpful in determining not only if faults are present, but to what extent they are unique. Many fault detection applications are prone to signaling false positives, instances where a fault is "detected" but not actually present in the system. False positives are a major concern in the aerospace industry and a goal for BIT design is to reduce their rate of occurrence (Koushanfar et al. (2003); Stelling et al. (1999)). False positives reduce the reliability of the BIT and increase effective cost and maintenance time. The effectiveness of a BIT can be substantially improved if the BIT design allows for verification of the method in that the faults are uniquely identifiable for all possible situations of system states, inputs, uncertainty and other faults. To accomplish the latter, the system model can be tested for Structural Global Identifiability (SGI) (Ljung and Glad (1994)). This posterior test solves another optimization problem to explore if the system can be deemed globally identifiable with respect to its parameters (Asprey and Macchietto (2000)). This analysis indicates whether false alarms are feasible or likely and if their rate of occurrence can be reduced. If the SGI test fails, then the inputs (and corresponding system state) chosen to identify and assess faults are not adequate given the expected system variance and uncertainty, and false positives are likely to occur. If the test is successful, the proposed BIT is ready for further experimental verification.

Two case studies were chosen to test the effectiveness of the proposed approach. The first study involved an air-cooled, plate-fin heat exchanger with particulate fouling and only thermocouple sensors at its exit channels. Analysis was conducted for this system for the purpose of fouling identification, to observe the effects of thermal outputs caused by fouling and other inputs with uncertainty. The second study expanded the method to a subsystem of an aircraft environmental control system (ECS) experiencing multiple faults. The BIT design in this case adjusted multiple inputs using measurements of the mass flow, pressure drop, temperature and inferred surge margin. For both case studies, the system inputs were optimized to maximize the sensitivities of the available measurements with respect to a fault parameter through a D-optimal design framework that reduces the joint confidence regions of these parameters (Pukelsheim (1993); Kitsos and Kolovos (2013)). Thereafter, the optimal designs were tested to ensure that models were structurally globally identifiable at the BIT design calculated and for the anticipated fault severity. It was assumed that the models used in these case studies were essentially "perfect," in that they effectively capture the process and fault-based behavior within acceptable accuracy and precision. Dealing with model error in active FDI will be the subject of future work.

2. METHOD

2.1 Optimal Design Formulation

The model or submodel used for optimal fault detection can be written as a set of differential algebraic equations (DAEs) as shown in (1):

$$\begin{aligned} \mathbf{f}(\dot{\mathbf{x}}(t), \mathbf{x}(t), \mathbf{u}(t), \hat{\theta}, t) &= 0, \\ \hat{\mathbf{y}}(t) &= \mathbf{h}(\mathbf{x}(t), \mathbf{u}(t), \hat{\theta}). \end{aligned} \tag{1}$$

Where $\mathbf{f}$ is the system of DAEs that describe the model (both clean and faulty aspects), $\mathbf{x}(t)$ is the vector of time-dependent state variables, $\mathbf{y}(t)$ is the vector of measured outputs, $\mathbf{u}(t)$ is the vector of manipulated inputs, $\hat{\theta}$ is the system parameters, and t is the time. The system parameters can be divided into two main categories, the design-related parameters $\hat{\theta}_p$ and the fault-related parameters $\hat{\theta}_f$, shown in (2),

$$\hat{\theta} = [\hat{\theta}_p; \hat{\theta}_f]. \tag{2}$$

The fault-related parameters affect the overall system performance, observed through the outputs $\mathbf{y}$. These parameters correlate to the various faults that can occur in the system. Any uncertain parameters $\hat{\theta}_p$ that can affect the estimation of these faults need to be considered for optimal experimental design as well. In this work, uncertainty is treated as a variance interval for each parameter or input that is estimated from the available measurements $\mathbf{y}$. The magnitude of these intervals depends on the acceptable error in the actuation system, variability of the operating boundaries and model error. Uncertainty in system inputs is considered when their values are unknown or within a predetermined range of accuracy. Therefore, the fault-related parameters and the unknown inputs can be expressed as a vector used as a basis for optimal design,

$$\hat{\xi} = \hat{\theta}_f \cup \hat{\mathbf{u}}. \tag{3}$$

After determination of the vector that the design needs to estimate, the next step is to compile together the controllable variables. The vector $\mathbf{u}(t)$ contains the admissible inputs with their sequence of adjustments during the test. The inputs are controlled in a number of discrete step changes, n_s, and their duration, $\mathbf{t}_s$. τ represents the overall duration of the test and it is typically assigned a value that ensures that the built-in test operates within an acceptable timeframe. The inputs, step changes, initial conditions, and overall timespan are compiled into the experimental design vector. Lower and upper bounds are assigned to the admissible inputs and the stepsize and number of control actions. The initial conditions $\mathbf{y}^0$ of the experiment can be optimized as well. The experimental design vector is arranged as:

$$\boldsymbol{\varphi} = [\mathbf{u}(t), \mathbf{t}_s, n_s, \mathbf{y}^0, \tau] \in \Phi. \tag{4}$$

The design space Φ contains the lower and upper variable bounds mentioned. The model outputs corresponding to system measurements are used to calculate parametric sensitivities through central finite differences. These sensitivities are compiled into $\mathbf{Q}_r$, a $N_{sp} \times N_\theta$ matrix describing the dynamic sensitivity of the r-th response variable with respect to the estimated parameters $\hat{\theta}_f$ and uncertain system inputs $\hat{\mathbf{u}}$. These matrices are compiled together into a covariance matrix that is calculated from the Fisher information matrix, $\mathbf{H}_\xi$, presented in (5):

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