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.

Keywords: Fault Detection and Isolation, Global Optimization, Identifiability, Optimal Experiment Design, and Uncertainty.

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)).

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):

$$ f(\dot{x}(t), x(t), u(t), \hat{\theta}, t) = 0, $$

$$ \dot{y}(t) = h(x(t), u(t), \hat{\theta}). $$

Where $f$ is the system of DAEs that describe the model (both clean and faulty aspects), $x(t)$ is the vector of time-dependent state variables, $y(t)$ is the vector of measured outputs, $u(t)$ 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 $\theta_p$ and the fault-related parameters $\theta_f$, shown in (2),

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

The fault-related parameters affect the overall system performance, observed through the outputs $y$. These parameters correlate to the various faults that can occur in the system. Any uncertain parameters $\theta_p$ 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 $y$. 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,

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

After determination of the vector that the design needs to estimate, the next step is to compile together the controllable variables. The vector $u(t)$ 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, $t_s$. $\tau$ 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 $y^0$ of the experiment can be optimized as well. The experimental design vector is arranged as:

$$ \varphi = [u(t), t_s, n_s, y^0, \tau] \in \Phi. $$

The design space $\Phi$ 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 $Q_x$, a $N_{sp} \times N_{sp}$ matrix describing the dynamic sensitivity of the $r$-th response variable with respect to the estimated parameters $\hat{\theta}_f$ and uncertain system inputs $\hat{u}$. These matrices are compiled together into a covariance matrix that is calculated from the Fisher information matrix, $H_x$, presented in (5):

\[ f(\dot{x}(t), x(t), u(t), \hat{\theta}, t) = 0, \]

\[ \dot{y}(t) = h(x(t), u(t), \hat{\theta}). \]
where \( \sigma_{rs} \) is the \( rs \)-th element of the inverse of the matrix of experimental error, and \( N_{resp} \) is the total number of available measurements. The measurement errors are assumed to be uncorrelated and have zero-mean normal distribution. The objective for optimizing the experimental design vector was chosen to be the D-optimal design criterion to minimize the correlation between the parameters estimated from the test information. This provides the best conditions for isolating and estimating what faults occurred in the system.

\[
\varphi_D = \arg \min_{\varphi \in \Phi} \det \left[ H_{\xi}^{-1}(\dot{\xi}, \varphi) \right] \quad \text{s.t.} \quad f(\ddot{x}(t), x(t), u(t), \dot{\theta}, t) = 0, \quad \dot{y}(t) = h(x(t), u(t), \dot{\theta}), \quad y^0 = \begin{cases} f(\ddot{x}(t_0), x(t_0), u(t_0), \dot{\theta}, t_0) = 0, \\ \dot{y}(t_0) = h(x(t_0), u(t_0), \dot{\theta}) \end{cases},
\]

\[
u^L \leq u(t) \leq u^U, \quad x^L \leq x(t) \leq x^U, \quad \forall t \in [0, \tau].
\]

The optimal test design vector, \( \varphi_D \), is the recommended input strategy to be applied as system IBIT.

### 2.2 Structural Identifiability Analysis

The method described in the previous section can be used to determine whether the system at the specified conditions is locally identifiable. However, to ensure that the identified faults are unique, a global identifiability test needs to be conducted. SGI, as described in detail by Asprey and Macchietto (2000), is used here to verify that the model is globally identifiable with respect to its faults and uncertainty at the stage trajectory determined by the BIT design of (6). Essentially, the SGI test strives to find the largest distance between parameter sets that create similar output trajectories. If dissimilar parameters can provide practically the same output trajectory then a false alarm is feasible in the BIT. Similar to the optimal design problem, this part of the method requires the model described in (1) and (2), and the input design (3) and (4). These equations are applied twice with two separate sets of values for the system variables \( \xi^1 \) and \( \xi^2 \). The integrated differences are calculated for the overall timespan \( \forall t \in [0, \tau] \). Each parametric set contains \( N\xi \) parameters. The parametric sets are bounded as \( \xi^1 \in \overline{\Xi} \), and \( \xi^2 \in \Xi \) and the second parameter vector is adjusted to find a maximum for \( \Phi_{SGI} \), shown in (7). SGI is achieved if \( \Phi_{SGI} \leq \epsilon_{SGI} \), the integrated expected variance of the normalized test measurements. Both parameter sets are kept within the same upper and lower bounds, the expected allowable fault threshold for the system.

\[
\Phi_{SGI} = \max_{\xi^1, \xi^2} \mathbf{E}(\xi^1 - \xi^2)^T W_{\xi}(\xi^1 - \xi^2)
\]

\[
s.t. \quad \int_0^\tau \left( \dot{y}(u(t), \dot{\theta}, t) - \dot{y}(u(t), \dot{\theta}, t) \right)^T W_y \left( \dot{y}(u(t), \dot{\theta}, t) - \dot{y}(u(t), \dot{\theta}, t) \right) dt < \epsilon_y,
\]

for \( i = 1, 2 \):

\[
f(x(t), x(t), u(t), \dot{\theta}, t) = 0,
\]

\[
y(t) = h(x(t), u(t), \dot{\theta}),
\]

\[
y^0 = \begin{cases} f(\ddot{x}(t_0), x(t_0), u(t_0), \dot{\theta}, t_0) = 0, \\ \dot{y}(t_0) = h(x(t_0), u(t_0), \dot{\theta}) \end{cases},
\]

\[
\xi^1_j \leq \xi^1_j(t) \leq \xi^2_j, \quad j = 1, ..., N\xi,
\]

\[
\forall t \in [0, \tau].
\]

\( \Phi_{SGI} \) is the largest feasible distance between the two parameter sets \( \xi^1 \) and \( \xi^2 \). If the built-in test can still identify between these two parameter sets through the output trajectories, meaning it is less than some small arbitrary value \( \epsilon_{SGI} \), then the faults for this system can be considered structurally globally identifiable. This method is able to quantifiably determine whether it is feasible to conduct fault detection with the expected variance and current understanding of the physical system.

### 2.3 Tool Chain

The equations listed above were applied in a series of case studies modeled with the object-oriented language Modelica (Modelica Association (2010)) used in the software implementation Dynola (Cellier (2015)). Each model was exported through the Functional Mockup Interface (FMI) (Modelisar (2010)), a multi-platform standard for describing dynamic models, as functional mockup units to MATLAB (The Mathworks Inc. (2013)) with the Modelon FMI-Toolbox (Modelon AB (2014)). The optimal design was solved using the Mesh Adaptive Direct Search algorithm, NOMAD (Le Digabel (2011)).

### 3. APPLICATION EXAMPLES

The effectiveness of this approach was tested in two separate case studies, both of which were subject to parameter estimation through least squares estimation (LSE) method before (that is, the nominal case) and after optimizing BIT designs. The nominal and optimal simulations were used to solve for the 95% confidence intervals for each parameter, to determine whether estimation precision for faults was improved.

#### 3.1 Case Study I: Fouling Quantification in a Plate Fin Heat Exchanger

Air-cooled heat exchangers are a primary component in aerospace environmental control systems, decreasing the temperature of high pressure air flow from compressors, turbines and other upstream components. Cold air used comes directly from outside the aircraft, containing varying levels of particulates that make contact with the heat...
exchanger surface and foul its passages. Particulate fouling is a common issue in aircraft heat exchangers (Pérez-Grande and Leo (2002)). Dust and other undesirables attach to heat exchanger walls, leading to loss of heat transfer effectiveness, and higher energy and fuel expenditure. In more extreme cases, the blockage caused by fouling may damage upstream equipment. Online detection methods are used to monitor sensors and predict fouling levels. At low fouling rates, it is difficult to discern deviations caused by faults or system uncertainty.

Aircraft ECS BIT was designed using a plate fin heat exchanger model. The model was validated against steady-state and dynamic literature data (Shah (2009)). Fouling was expressed in the model as a change in thermal fouling resistance. More details on the modeling aspects of this system were reported in Palmer et al. (2016). There are several uncertain conditions in aircraft ECS that can affect the heat exchanger outputs in similar ways; namely: humidity levels, cold air mass flow rate, and cold air inlet temperature. These inputs were compiled together with the thermal fouling resistance to create a vector of fault-relevant parameters and uncertain system variables $\xi$. The faulty system model was ascribed a thermal fouling resistance $6.2 \times 10^{-3}$ m$^2$K/W, describing severe particulate fouling at equilibrium. It was assumed that the air moisture would not condense along the heat exchanger, but instead would solely affect the specific heat capacity of the ram stream. The moisture in the air was set to 1.2 wt%, and the inlet ram channel flow and temperature were set to 1.0 kg/s and 15 °C, respectively. These values all serve as initial parameter estimates in the BIT design algorithm.

Table 1. Conditions for the heat exchanger fouling estimation case study

<table>
<thead>
<tr>
<th>Flow Condition</th>
<th>Nominal Setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{hi}$ (°C)</td>
<td>175</td>
</tr>
<tr>
<td>$T_{ci}$ (°C)</td>
<td>15</td>
</tr>
<tr>
<td>$m_{a}$ (kg/s)</td>
<td>0.30</td>
</tr>
<tr>
<td>$m_{c}$ (kg/s)</td>
<td>1.00</td>
</tr>
<tr>
<td>$p_{hi}$ (kPa)</td>
<td>250</td>
</tr>
<tr>
<td>$p_{ci}$ (kPa)</td>
<td>100</td>
</tr>
</tbody>
</table>

Fouling affects the measured outputs of the heat exchanger, which in this case are the exit bleed (hot) and ram (cold) fluid temperatures, $T_{bo}$ and $T_{co}$. The bleed air flow is controlled in the upstream bleed system. Therefore, the BIT design was simplified to adjusting solely the inlet bleed temperature $T_{hi}(t)$ for fouling detection. The inlet flow rates and conditions were assigned the nominal values shown in Table 1. The design variable, $T_{hi}(t)$, was bound between 100 to 250 °C, and was divided into a series of discrete steps, lasting 60 - 240 s. The overall timespan of the BIT was fixed to 300 s, the maximum allowable time for a single BIT in ground operation.

The proposed method for fouling detection was tested using the tool chain previously mentioned to calculate an optimal sequence of control actions for estimating thermal fouling resistance, along with the other unknown or uncertain inlet conditions. Each measured variable was given a zero-mean white measurement noise with a standard deviation of 0.5 °C. An optimal BIT design was calculated using (6) to adjust the inlet bleed temperature over the given time span. As shown in Figure 1, the optimal design started $T_{hi}$ at its lower bound (100 °C) for 60 s, and then imposed a step change to move it to its upper bound (250 °C) for the remainder of the test. This design was the best in minimizing the correlation between uncertain system parameters. The upper bound was the most useful in discerning thermal fouling resistance. At that point, heat transfer was at the allowable maximum, making it most sensitive to deviations in the heat transfer coefficient. The ram inlet temperature was better predicted when bleed and ram inlet temperatures were similar. At identical inlet temperatures there is no energy transfer, therefore the outlet temperatures would remain the same. Any change in the inlet temperature would then be more discernible, like the input step change from the lower bound, shown in Figure 1. Unknown moisture in the ram air inlet affected the ram stream heat capacity. The step change in the inlet temperature produced a strong dynamic response from the outlet temperature, which helped predicting moisture content and ram mass flow rate. This is further illustrated in Table 2 that presents the 95 % confidence region at nominal and optimal designs for each fault-related parameter and uncertain system variable.

Table 2. Estimated values and 95 % confidence intervals of uncertain heat exchanger inlets and fouling at nominal and optimal settings

<table>
<thead>
<tr>
<th>Uncertain Conditions</th>
<th>Nominal</th>
<th>Optimal</th>
<th>True</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_f$ (m$^2$K/W × 10$^4$)</td>
<td>5.44±13.15</td>
<td>5.44±0.98</td>
<td>6.20</td>
</tr>
<tr>
<td>$w_{H_2O}(\times 10^2)$</td>
<td>1.03±65.50</td>
<td>1.13±0.33</td>
<td>1.20</td>
</tr>
<tr>
<td>$T_{ci}$ (°C)</td>
<td>15.85±54.45</td>
<td>15.05±0.33</td>
<td>15.00</td>
</tr>
<tr>
<td>$m_{ci}$ (kg/s)</td>
<td>1.03±1.65</td>
<td>1.00±0.008</td>
<td>1.00</td>
</tr>
</tbody>
</table>
The faults were assumed to be constant throughout the simulation. Three faults, common to ECSs, were simultaneous to better handle system uncertainties, including those components, inputs and outputs is given in Hale et al. (2011). Given the criteria, a more structured approach to BIT design to ensure satisfaction of the FDI capability and improved controllability, increasing its overall operational cost, safety risk, and environmental impact. Due to system uncertainties, the FDI problem presented here is often challenging to solve for structural global identifiability. If the fault parameters can be uniquely identified with the measured system outputs obtained from the BIT, it is concluded that the optimal design for BIT is structurally identifiable, meaning that fouling is detectable regardless of the values of the other uncertain system conditions.

### 3.2 Case Study II: Environmental Control System

The objective of an aircraft ECS is to provide fresh air at appropriate conditions to the passengers and crew, while performing secondary heating and cooling tasks to various aircraft components (Pérez-Grande and Leo (2002)). To accomplish this objective, aircraft ECSs consist of primary components such as pipes, valves, ozone converters, turbines and compressors, in addition to heat exchangers, in order to condition the external air. During the ECS operation, these components are subject to faults like corrosion, degradation, blockage and fouling over time due to stress and the introduction of foreign objects. These faults can lead to losses in ECS efficiency, power generation, and lack of controllability, increasing its overall operational cost, safety risk, and environmental impact. Due to system uncertainties, the FDI problem presented here is often handled in the aerospace industry via a shotgun approach to BIT design to ensure satisfaction of the FDI capability criteria laid out by the SAE Aerospace Information Report 1266A AC-9 Aircraft Environmental Systems Committee (2011). Given the criteria, a more structured approach to BIT design can be developed, such as the methodology described here, to better handle system uncertainties, improve fault isolation and increase cost savings.

An in-depth description of the ECS subsystem and its components, inputs and outputs is given in Hale et al. (2016). Three faults, common to ECSs, were simultaneously injected to the model to observe their identifiability. The faults were assumed to be constant throughout the BIT and were modeled by altering component parameters from their nominal value. Table 3 describes the three faults studied and their respective altered “faulty” parameter values.

### Table 3. Faults in the ECS case study

<table>
<thead>
<tr>
<th>Faults</th>
<th>Description</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pipe</td>
<td>Alteration of pipe characteristics due to exposure to contaminating fluid.</td>
<td>$\Delta P_{\text{pipe}}$ (bar)</td>
</tr>
<tr>
<td>Corrosion</td>
<td>Degradation of compressor seals due to time resulting in increased leakage.</td>
<td>$\Delta m_{\text{compressor}}$ (kg/s)</td>
</tr>
<tr>
<td>Compressor</td>
<td>Degradation of valve seals over time resulting in decreased pressure drop and increased mass flow.</td>
<td>$\Delta P_{\text{valve}}$ (bar)</td>
</tr>
</tbody>
</table>

The model was assigned nominal values for its “fault” parameters, representing a clean design state. These nominal values served as initial parameter estimates used for the optimal BIT designed. For the ECS case, the optimal BIT configuration utilizes the following three admissible inputs: compressor speed, variable diffuser position and valve position. The pressure downstream the ECS was assumed constant due to the inability to control it when executing BIT around the cabin air compressor. The impact of faults on the ECS system were observed by the available measured system variables: inlet compressor pressure, outlet compressor pressure, temperature and surge margin, and outlet ECS subsystem mass flow rate. Table 4 shows the parameter values used for the nominal and faulty model.

### Table 4. Parameters for the ECS case study

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Nominal Value</th>
<th>Faulty Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta P_{\text{pipe}}$ (bar)</td>
<td>0.10</td>
<td>1.00</td>
</tr>
<tr>
<td>$\Delta m_{\text{pipe}}$ (kg/s)</td>
<td>1.00</td>
<td>0.75</td>
</tr>
<tr>
<td>$\Delta P_{\text{compressor}}$ (bar)</td>
<td>5.00</td>
<td>3.00</td>
</tr>
<tr>
<td>$\Delta m_{\text{compressor}}$ (kg/s)</td>
<td>0.1</td>
<td>5.00</td>
</tr>
<tr>
<td>$\Delta P_{\text{valve}}$ (bar)</td>
<td>2.50</td>
<td>1.50</td>
</tr>
</tbody>
</table>

The proposed method for fault detection was tested using the tool chain previously mentioned to calculate an optimal BIT design for estimating the parameters of the three fault cases. Each measurable outlet was given a zero mean white measurement noise with standard deviation of 0.5 °C, 50.0 Pa, and 0.015 kg/s for each respective sensor. An optimal BIT design was calculated by (6) at various steady states over a 200 s time span. The estimates of the ECS faults are presented in Table 5. It was seen that the optimal design vector provides a more accurate parameter estimation, with greater confidence than the nominal design vector. This is illustrated by the 95% confidence region at nominal and optimal conditions for each fault-related parameter.

### Table 5. Estimated values and 95% confidence intervals of uncertain ECS subsystem fault parameters at nominal and optimal settings

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Nominal</th>
<th>Optimal</th>
<th>True</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta P_{\text{pipe}}$ (bar)</td>
<td>0.59±0.52</td>
<td>0.97±0.61</td>
<td>1.00</td>
</tr>
<tr>
<td>$\Delta m_{\text{pipe}}$ (kg/s)</td>
<td>1.06±0.22</td>
<td>0.78±0.43</td>
<td>0.75</td>
</tr>
<tr>
<td>$\Delta P_{\text{compressor}}$ (bar)</td>
<td>4.23±4.23</td>
<td>3.02±4.22</td>
<td>3.00</td>
</tr>
<tr>
<td>$\Delta m_{\text{compressor}}$ (kg/s)</td>
<td>0.01±0.120</td>
<td>4.91±0.95</td>
<td>5.00</td>
</tr>
<tr>
<td>$\Delta P_{\text{valve}}$ (bar)</td>
<td>1.52±1.52</td>
<td>1.50±1.50</td>
<td>1.50</td>
</tr>
</tbody>
</table>
Similar to the BIT design for the plate fin heat exchanger, the next step in the BIT methodology is to solve for structural global identifiability in the ECS subsystem and conclude if the optimal design for BIT is globally identifiable. As noted before, one factor not considered here is sensor bias, which can have a considerable effect on FDI and will be explored in future work to determine its severity.

4. ACKNOWLEDGEMENTS

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