Fault Detection and Isolation for a Supermarket Refrigeration System - Part Two: Unknown-Input-Observer Method and Its Extension

Zhenyu Yang* Karsten B. Rasmussen** Anh T. Kieu** Roozbeh Izadi-Zamanabadi***

* Department of Energy Technology, Aalborg University, Esbjerg Campus, Niels Bohrs Vej 8, 6700 Esbjerg, Denmark (e-mail: yang@et.aau.dk)
** Former students of Intelligent Reliable Systems (IRS) Master Program at Aalborg University, Denmark
*** Department RA-DT, Danfoss A/S, Nordborgvej 81, 6430 Nordborg, Denmark (e-mail: Roozbeh@danfoss.com)

Abstract:
The Fault Detection and Isolation (FDI) using the Unknown Input Observer (UIO) for a supermarket refrigeration system is investigated. The original system’s state $T_{\text{goods}}$ (temp. of the goods) is regarded as a system unknown input in this study, so that the FDI decision is not disturbed by the system uncertainties relevant to this state dynamic and the original system disturbance $Q_{\text{airload}}$ (the thermal feature of the air). It has been observed that a single UIO has a very good detection capability for concerned sensor and parametric faults. However, only the parametric fault can be isolated by using a bank of UIOs. Thereby, a complete FDI approach is proposed by combining the Extended-Kalman-Filter (EKF) and UIO methods, after an extensive comparison of KF-, EKF- and UIO-based FDI methods is carried out. The simulation tests show that the complete FDI approach has a good and successful FDI capability regarding to concerned fault scenarios.

Keywords: Fault detection and isolation, unknown input observer, EKF, refrigeration system

1. INTRODUCTION

Fault Detection and Isolation (FDI) using observe-based methods has been extensively studied in recent decades, typical work can be found in Chen and Patton (1999), Frank and Ding (1997), Isermann (2006) and references therein. The Unknown Input Observer (UIO), as a type of robust estimation method, can be very interesting when the considered system is affected by some unknown input/disturbance and this effect can not be ignored in the state estimation. The crucial benefit of using UIO is that the effect from the unknown input to the state estimation can be completely decoupled by elegantly arranging the observer structure and coefficients. Since Chen et al. (1996) investigated the UIO for robust FDI design, the UIO method has been one of the popular robust design method in FDI research and applications.

Recently, a detailed model of a typical supermarket refrigeration system is introduced in (Larsen et al. (2007)). There is no doubt that any efficiency and reliability improvement of these type of systems can bring significant economic benefits and potential environmental protection. In our sister paper (Yang et al. (2011)), the potential fault scenarios within this considered system are introduced, and the Kalman Filter (KF), Extended Kalman Filter (EKF) based FDI methods are explored for this system afterwards. The proposed KF- and EKF-based FDI methods require the system dynamic of the state $T_{\text{goods}}$ (temp. of the goods) and the disturbance $Q_{\text{airload}}$ (the thermal feature of the air insider) to be known beforehand. However, this condition may not be true in many practical situations. Thereby, here we dedicate to investigate the UIO-based FDI method for this considered system. The basic idea is to regard $T_{\text{goods}}$ and $Q_{\text{airload}}$ as a system unknown input, so that their uncertainties wouldn’t disturb the FDI decision.

The rest of the paper is organized in the following: Section 2 gives a brief summary of the UIO technique; Section 3 introduces some model modifications so that it’s suitable to employ UIO design; Section 4 explores the UIO-based FDI and presents results; Some comparison of UIO-, KF, and EKF-based methods is carried out in Section 5; Following that, a complete FDI solution by combining EKF and UIO methods is proposed and tested in Section 6; Finally, we conclude the paper in Section 7.

2. UIO THEORY

Consider a LTI system formulated as
where system state $x(t)$, known input $u(t)$, unknown input $d(t)$ and output $y(t)$ are with proper dimensions. If there exists an observer whose state estimation corresponding to system (1), denoted as $\hat{x}(t)$, has the property that the state estimation error $x(t) - \hat{x}(t)$ approaches to zero asymptotically, regardless of the presence of the unknown input $d(t)$ in the system, then this observer is often called Unknown Input Observer (Chen et al. (1996)).

According to the UIO theory (Chen et al. (1996), Chen and Patton (1999)), if the following two conditions are satisfied by system (1), i.e.,

(1) $\text{rank}(CE) = \text{rank}(E)$
(2) $(A_1, C)$ must be a detectable pair,

where $A_1 = A - HCA$ and $H = E [(CE)^TCE]^{-1} (CE)^T$.

Then, there exists an UIO solution for the concerned system (1).

An UIO can be constructed as shown in Figure 1, where

$$\dot{z}(t) = Fz(t) + TBu(t) + Ky(t),$$

$$\dot{x}(t) = z(t) + H y(t).$$

Here $z(t)$ is the UIO state, while $\dot{x}(t)$ is the estimation of $x(t)$. Matrices $F$, $T$, and $K$ can be designed according to:

$$H = I - HC$$
$$T = A - HCA - K_1 C$$
$$F = K_1 + K_2$$
$$K_2 = FH$$

(3)

The state estimation error is $\dot{e}(t) = Fe(t)$. This means that if $F$ is stable, then $\dot{e}(t)$ will approach zero asymptotically. In the following, the UIO will be used for FDI design for a supermarket refrigeration system.

3. MODIFIED SYSTEM MODEL

The considered refrigeration system is proposed in Larsen et al. (2007). In general, the mathematical model of the system consists of four main parts, namely compressor, condenser, evaporator and expansion valve. The system variables/parameters which will be used in the following are listed in Table 1. In our sister paper (Yang et al. (2011)), the four-state nonlinear model is employed for KF- and EKF-based FDI investigation. Two sensor faults with four different fault scenarios, namely sensor drift, offset, freeze and hard-over, and one parametric fault are considered in Yang et al. (2011). In order to investigate these fault scenarios using some UIO-based FDI method, two modifications of the current model need to be done, i.e., the definition of unknown input $(s)$ and linearization.

The original system model consists of four states, $T_{\text{goods}}$, $T_{\text{air}}$, $T_{\text{wall}}$ and $M_{\text{refrig}}$. In the following, we define $\dot{T}_{\text{goods}}$ as the unknown input to the concerned system. The benefit of this definition lies in (i) the original disturbance $Q_{\text{airload}}$ can be implicitly included into $\dot{T}_{\text{goods}}$ effect; (ii) any change in type, amount and heat parameters for the goods will not affect the considered model’s structure and parameters; and (iii) it is no more necessary to know when the display cases are during their day- or night cycle or room temperature etc..

The modified state space model is described as

$\dot{T}_{\text{air}} = \frac{MA_{\text{goods-air}}T_{\text{goods}} - UA_{\text{air-wall}}T_{\text{air}}}{M_{\text{air}}C_{\text{air}}} + \frac{MA_{\text{air-wall}}T_{\text{wall}}}{M_{\text{air}}C_{\text{air}}}$

$T_{\text{wall}} = \frac{UA_{\text{air-wall}}T_{\text{air}}}{M_{\text{wall}}C_{\text{wall}}} + \frac{UA_{\text{wall}}M_{\text{refrig}}}{M_{\text{wall}}C_{\text{wall}}}$

$\dot{M}_{\text{refrig}} = V_p \left( \frac{M_{\text{refrig}_{\text{max}}} - M_{\text{refrig}}}{\tau_{\text{fill}}} \right) + (V_p - 1)$

(4)

where $\dot{M}_{\text{refrig}} = \dot{U}_{\text{air}}$ and $\dot{U}_{\text{air}} = U_{\text{air}} + \dot{U}_{\text{wall}}$.

(5)

This nonlinear system is linearized at some proper equilibrium point, which is found by experimentally running the original model. Define $x = [T_{\text{air}} T_{\text{wall}} M_{\text{refrig}}]^T$, $u = [V_p P_{\text{suc}}]^T$, $\alpha = [T_{\text{goods}}] y = [T_{\text{air}} T_{\text{wall}}]^T$, then a linear model, as formulated by (1), is obtained with (nominal) system parameters as

$A = \begin{bmatrix} -0.0139 & 0.0110 & 0 \\ -0.0090 & -0.6004 & 0 \\ 0 & 0 & -0.1049 \end{bmatrix}$, $B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & -0.0168 & 0.0576 \\ 0 & 0 & 0 \end{bmatrix}$

(6)

4. UIO-BASED FDI

4.1 Single UIO Construction

The two preconditions for UIO existence need to be checked firstly. Based on the data (6), it is concluded that $\text{rank}(E) = \text{rank}(CE)$, and $H$ and $A_1$ calculated as

$H = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$, $A_1 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$

(7)
are observable pair \((A_1,C)\). These results verify that an UIO exists for the considered system \((6)\).

According to the UIO theory, a stable \(F\) can be managed through selecting \(K_1\). The design of \(K_1\) can be formulated as an observer design based on the pair of \((A_1,C)\). The poles for \(A_1\) can be found as \(\text{eig}(A_1) = \{-0.0090 \ 0 \ -0.1049\}\). The system is marginally stable. Thereby, three new stable poles are selected according to the principle that they are relatively close to the ones of \(A_1\), i.e., \([-0.001 \ -0.01 \ -0.1]\). By pole placement method, matrix \(K_1\) can be figured out and consequently all other system parameters can be calculated according to \((3)\). For instance, one set of parameters are found as

\[
K_1 = \begin{bmatrix} 0.0025 & 0.0005 \\ 0.0511 & -0.0054 \\ 0.0034 & -0.0008 \end{bmatrix}, \quad K_2 = \begin{bmatrix} -0.0025 & 0 \\ -0.0401 & 0 \\ -0.0034 & 0 \end{bmatrix}, \quad T = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}.
\]

(8)

4.2 Detection of System Faults

A single UIO can be used for fault detection purpose. A fault indicator, denoted as \(r(k)\), can be calculated recursively by the following

\[
r(k) = e(k)^T e(k),
\]

where \(e(k) = x(k) - \hat{x}(k)\). The signal \((r(k))\) need to be compared with some upper bound (a threshold) for detection purpose, where this bound is determined empirically through a number of experiments by delicately operating system at different fault scenarios. The effect of the faults can be seen in Figure 2 and 3 for \(T_{\text{air}}\) and \(T_{\text{wall}}\) sensor faults, respectively, and Figure 4 for a parametric fault in \(U A_{\text{air} \rightarrow \text{wall}}\). All faults are introduced after 9000 samples, except for the parametric fault which is nominal up to time 6000sec where a downward slope is added until 16000sec where \(U A_{\text{air} \rightarrow \text{wall}}\) stabilizes at 250 value. As can be seen from Figures, all faults can be easily detected. The residual changes dramatically, so a suggested threshold of 10 is used in these analysis.

4.3 Isolation of Parametric Fault

The feasibility of use of a bank of UIOs for fault isolation is also investigated, as we did for KF-based methods in (Yang et al. (2011)). However, it is observed that there is no possibility to construct a bank of UIO filters using the method of splitting sensor measurements (Isermann (2006)) for sensor fault isolation. This is due to the UIO’s detectability problem. Instead, the isolation of parametric faults (ice-over and dirt buildup) is investigated in the following. Three new models are created with \(U A_{\text{air} \rightarrow \text{wall}}\) values of 450, 375 and 300. Correspondingly, three UIOs are constructed based on these values using the procedure mentioned in Section 4.1.

The isolation can be done by comparing these fault indicators at each sample and selecting the smallest value. With an isolation border of 50 which is empirically defined beforehand, it can be assumed that when at least one of the models have a fault indicator below 50, the fault is related to the \(U A_{\text{air} \rightarrow \text{wall}}\) parameter, and thereby this fault can be isolated from sensor faults. It has been noticed that values for \(U A_{\text{air} \rightarrow \text{wall}}\) below 250 should no longer be thought of as a parametric fault. Figure 5 illustrates a test, where \(U A_{\text{air} \rightarrow \text{wall}}\) is gradually taken down from 500 to 250 in steps of 50. The isolation border of 50 is used here. A parametric fault on \(U A_{\text{air} \rightarrow \text{wall}}\) is claimed when the minimum of these three fault indicators is below the defined threshold. If all the fault indicators go above the border, the fault is no longer assumed to be due to ice/dirt buildup, and it could be passed on to some other further isolation procedure.

In order to be sure that a sensor fault will not be claimed as a parametric fault, two tests have been made with the system under the identical operating conditions. The first is a drift fault on \(T_{\text{wall}}\) with a slope of 0.001, while the other is an offset fault on \(T_{\text{air}}\) of +2.5 degrees, both
beginning at 9000sec. These faults have been confirmed to trigger a detection alarm, and from Figure 6 it is clear that these faults can not be isolated as the parametric fault.

As the UIO-based method cannot isolate sensor faults, it is not possible to create a complete FDI solution using only UIOs. However, the UIO-based method provide a very fast and simply solution for fault detection. The systematic comparison of UIO-based method and KF- and EKF-based methods, being done in (Yang et al. (2011)), has been elaborated in the following, before we explore their combination.

5. COMPARISON OF UIO- AND KF-BASED METHODS

The main criteria for a good FDI method is the ability to detect and isolate faults correctly, quickly, efficiently and reliably. The investigation of which method can be used for what, and how long it takes to detect a fault etc. could help a lot for choosing the best method for further use or combining the strengths of different methods. In the following, the KF-, EKF- and UIO-based methods are compared from different FDI perspectives.

5.1 Detection Ability and Time

This study and (Yang et al. (2011)) have verified that both KF-based methods (incl. KF- and EKF-based) and UIO-based method can detect all considered fault scenarios. Table 2 illustrates the detection time for all methods and fault scenarios under identical operating conditions.

<table>
<thead>
<tr>
<th>Fault</th>
<th>Method</th>
<th>KF</th>
<th>EKF</th>
<th>UIO</th>
</tr>
</thead>
<tbody>
<tr>
<td>(T_{\text{air\ drift}})</td>
<td>2277</td>
<td>474</td>
<td>1408</td>
<td></td>
</tr>
<tr>
<td>(T_{\text{air\ offset}})</td>
<td>8</td>
<td>11</td>
<td>219</td>
<td></td>
</tr>
<tr>
<td>(T_{\text{air\ freeze}})</td>
<td>274</td>
<td>172</td>
<td>245</td>
<td></td>
</tr>
<tr>
<td>(T_{\text{wall\ hard-over}})</td>
<td>1</td>
<td>1</td>
<td>13</td>
<td></td>
</tr>
<tr>
<td>(T_{\text{wall\ drift}})</td>
<td>3050</td>
<td>1079</td>
<td>1414</td>
<td></td>
</tr>
<tr>
<td>(T_{\text{wall\ offset}})</td>
<td>101</td>
<td>10</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>(T_{\text{wall\ freeze}})</td>
<td>128</td>
<td>153</td>
<td>110</td>
<td></td>
</tr>
<tr>
<td>(U_{\text{air\ to\ wall\ drift}})</td>
<td>4474</td>
<td>569</td>
<td>567</td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Detection Time (in sec) Comparison

It is clear that the the KF-based method is far away as effective as the EKF-based and UIO-based methods. By including a CUSUM for the UIO-based method, there could be a chance to further reduce the detection delay. Of course, the selection of fault thresholds is also a key issue in improving the detection delay.

5.2 Isolation Ability

As shown in our studies, the critical issue in the fault isolation is to correctly distinguish the sensor and parametric faults. Table 3 gives some indication of which algorithm could be used for which type of fault isolation.

In Table 3, notation ”+” indicates that the fault can be isolated using the corresponding method, while ”-” indicates the opposite. The superscripts (1,2) refer to:

1. "A parametric fault might be identified as a sensor fault. Therefore, parametric faults must be ruled out before the method is used.
2. "A sensor fault might be identified as a parametric fault. Therefore, sensor faults must be ruled out before the method is used.

Generally, all the methods can detect and isolate a parametric fault. The the EKF-based method is the only one which is able to isolate sensor faults reliably. With this in mind, if a method combination needs to be developed, the EKF is necessary for isolation of sensor faults.

5.3 Different Load Conditions

From practical point of view, the FDI system can only be seen as successful if is can adapt itself to both night and day time operations. As almost all tests being done are based on day-time operating condition, a few different night-time scenarios have been tested for the developed FDI methods. Two scenarios listed here are:

1. *Simple night time test* - 5 hours (18000 samples) and known \(Q_{\text{airload}} = 1500\). Case A: Nominal operation without any faults; and Case B: \(T_{\text{wall\ sensor}}\) fault - Offset (+2.5 C) at 9000sec.
2. *Full day (24-hour) test with night and day time change*. The night operating condition is the same as in Scenario 1, but the day time operation has the following two cases. Case A: The store open time is kl.9.00 - kl.20.00, with known \(Q_{\text{airload}} = 3000\); and Case B: Same as Case A, but there is a faulty information to the FDI system indicating the store open during kl.10.00 - kl.21.00.

In Scenario 2B, the proper value of \(Q_{\text{airload}}\) is given to the FDI system with one hour delay. It emulates a type of communication fault/problem that the store opens at kl.9.00 (display is uncovered at that time), while the FDI system is told that the display is uncovered at kl.10.00. Table 4 shows the detection capabilities of proposed methods w.r.t. these scenarios. The ”+” indicates a success of detection, while ”-” indicates a failure. The UIO-based
method exhibits its advantage here, it regards $Q_{\text{airload}}$ as a unknown input, thereby there is no influence to the detection result subject to wrong information of $Q_{\text{airload}}$, while the other models require a correct estimate of $Q_{\text{airload}}$.

The superscripts regarding to UIO method in Table 4 represents: (1) New detection threshold required; (2) No difference in results. It has been observed that the UIO model does not fit well for night time operation, it could be due to the fact that some specific night operating conditions are ignored in the modeling. The magnitude of the fault indicator signal is notably larger for nominal operation during night-time. However, the ratio between a faulty signal and a non-faulty signal is still quite evident. Thereby some new (higher) detection threshold needs to be defined.

This analysis clearly show that the UIO-based method has a big advantage if there is no way to clearly know if the display case is covered up or not for a while. Furthermore, the UIO-based method could also provide a more robust decision in the case that the air-load changes more dynamically throughout the day. Nevertheless, if the system has access to precise knowledge of whether it is covered or not, and has reasonable estimation of $Q_{\text{airload}}$, the detection results for both KF- and EKF-based methods can be as good as for UIO-based method.

5.4 Computational Loads

All three fault detection algorithms have been tested with the same scenario. The Simulink models are stripped down to contain only the necessary elements and a single detection algorithm for each method. The execution time is measured with the ‘tic-toc’ function in MATLAB and the fastest time is set as index 1. Three tests are carried out for each scenario and the average time is calculated afterwards, as shown in Table 5.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>KF</th>
<th>EKF</th>
<th>UIO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test 1</td>
<td>1.13</td>
<td>1.47</td>
<td>1</td>
</tr>
<tr>
<td>Test 2</td>
<td>1.2</td>
<td>1.47</td>
<td>1</td>
</tr>
<tr>
<td>Test 3</td>
<td>1.2</td>
<td>1.47</td>
<td>1</td>
</tr>
<tr>
<td>Average</td>
<td>1.18</td>
<td>1.47</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 5. Execution Time with Dymola

These tests were made with the Dymola link active, where the original model is built using Dymola software (Larsen et al. (2007)). In order to distinguish the Dymola effect to the execution time, a test is arranged with both detection and isolation systems active, and the Dymola block is replaced with a block which reads logged data just from the workspace. The execution time is summarized in Table 6. It can be observed that the EKF-based method took far longer time than the other methods do. This is mainly due to the fact that EKF is nonlinear-system oriented and thereby requires much more computation power while the KF- and UIO-based methods are linear model based methods.

6. COMBINED-EKF-UIO METHOD FOR FDI

Based on the comparison analysis of these three proposed methods, a combination of EKF- and UIO-based methods is proposed as a complete FDI solution for the considered refrigeration system, we name it as Combined-EKF-UIO (CEU) Method in the following.

6.1 CEU System Structure

As shown in Figure 6, the CEU system consists of two blocks, namely UIO-Detection (UIOD) block and Fault Identifier (FI) block, at the top level. The CEU system interacts with the refrigeration plant modeled in Dymola through the data conversion block.

The UIOD block commits the fault detection task, and it consists of only one UIO. This detection block should all the way be active in a real-time manner. The functionality of this block should be robust against any disturbances while be sensitive to potential faults. Due to the purpose of saving computational power, the FI-Block will be standby unless it is triggered by UIOD block. The UIO-based method is picked for detection purpose here. Even though the EKF-based method is generally faster at detecting faults, as shown in Table 2. The main reason is that (i) the UIO-based method takes $T_{\text{goods}}$ and $Q_{\text{airload}}$ as system disturbances. Thereby, any Changes relevant to them would not trigger a fault alarm. It makes the fault detection more robust; (2) the ratio of the residuals between faulty and non-faulty systems is significantly large generated by the UIO-based method; and (3) UIO solution require much less computation power and time, which is already indicated in Table 6.

The structure of the FI-Block is illustrated in Figure 8. The purpose of having a “Hold Fault” block, which acts as an account of fault claims sent from UIOD block, is to keep the isolation system wait for some while before running into action. This can help smooth out some “noise” (incident over-threshold). The “Hold Fault” block
The Fault Isolation block takes the input and output from the monitored system. Inside this block is the fault isolation routine using a bank of UIOs constructed according to different $U_{air\rightarrow wall}$ values (predefined), and two EKF’s constructed according to the splitting output method (Yang et al. (2011)). As the EKFs also need $Q_{airload}$ as an input, which can be either fixed at some average value, or estimate based on some available logistic information. The logic inside this block is summarized as

1. Claim the parametric fault if UIO-bank can find a fitness;
2. If no parametric fault is claimed by UIO-bank, and only one EKF model claims to be faulty, claim a fault corresponding to that sensor;
3. If both EKFs claim to a fault, or none of them claim to a fault, while the UIO-bank can not find any fitness, then, an “unknown” fault should be claimed.

### 6.2 CEU System Tests

The proposed CEU framework is tested based on concerned fault scenarios. Furthermore, a few other (unexpected) faults have also been introduced in these tests to see how the system react on them. A number of results are listed in the following, where the integer numbers 0-4 have their counter-parts as: 0 - No fault; 1 - $U_{air\rightarrow wall}$ parametric fault; 2 - $T_{air}$ Sensor fault; 3 - $T_{wall}$ Sensor fault; and 4 - Unknown fault.

The results with all four types of $T_{air}$ and $T_{wall}$ sensor faults are shown in Figure 11 and Figure 11, respectively. Figure 12 shows four other scenarios, including the unexpected situation. The fourth sub-graph with a combination of sensor and parametric fault makes the isolation unreliable, but the detection is still very useful.

### 6.3 CEU System Tests

Compared with the KF- and EKF-based methods, the UIO-based method leads to equally good or even better capability for detecting faults. The residual ratio between faulty and non-faulty systems is quite significantly high. Another good thing using this method is that both $T_{goods}$ and $Q_{airload}$ are regarded as unknown disturbances, which effects are completely decoupled from the UIO residuals. This leads to many benefits in using this method in reality. The payoff of these benefits is that the UIO-based method can only used for isolating parametric fault. The current UIO-based development can not handle sensor fault isolation. This drawback is compensated by combining other method, i.e., the EKF-based method, as a complete FDI solution. This combined method is named as CEU method here. The proposed CEU system can handle all considered fault scenarios in a successful manner. The capability analysis and improvement of the current CEU system will be part of our future work.

### 7. CONCLUSION

REFERENCES


