DOI: 10.48011/asba.v2i1.1048

Robust Model-Based Fault Detection and Isolation of a Six Degree of Freedom Helicopter ⋆

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Abstract: Helicopters are high cost and safety systems with a strong control system designed to maintain the helicopter performance, stability, and flight qualities. However, there exist faults that negatively affect the helicopter desirable behaviour; therefore, fault detection and isolation must be done to early detect, isolate and eliminate these faults. Because of helicopters are strongly nonlinear systems, and are affected by uncertainties and by external disturbances as wind bursts, robust residuals generation is required to correctly detect and isolate faults in the helicopter actuators and sensors. This paper leads with the robust fault detection and isolation of a six-degree of freedom helicopter benchmark using the disturbance decoupling method and the unknown input observer robust residuals generator. A generalized observer scheme is employed for fault isolation purposes.

Keywords: fault detection and isolation, robust residual generation, disturbance decoupling, unknown input observer, eigenstructure assignment.

1. INTRODUCTION

In the last decades the Fault Detection and Isolation (FDI) methods have increased the interest of researchers in the academic and industry. This is due to the fact that more efficiency, safety, availability and autonomy are required in processes. Frequently, control systems cannot detect behaviours that could lead the process to malfunctions and failures (Isermann, 2006). FDI, as a part of the monitoring and supervision process, allows an early detection and isolation of faults. FDI also helps in the decision making and predictive maintenance (Isermann, 2011), representing an economical saving, and guaranteeing the safety of the process and the environment protection.

A fault is an unpermitted deviation in at least one characteristic, property or parameter of the system from the standard or normal behaviour, as shown in Isermann and Balle (1997). This condition could lead the system to a malfunction or failure. Therefore, faults should be detected, isolated, treated, and eventually eliminated to maintain the system in the normal state of performance. In general, three approaches have been adopted for FDI: Model-based FDI, Knowledge-Based FDI and Data-Driven FDI (Isermann, 2006; Venkatasubramanian et al., 2003c,b,a).

⋆ This research was sponsored by the Brazilian Federal Government Coordination for the Improvement of Higher Education Personnel (CAPES) and the Federal University of ABC (UFABC).

Model-based approach has been developed over the last years. The main issue in this approach is the need of a good model of the system. However, obtaining a good model of the system is not easy. Thus, system identification methods are often used to build an adequate model of the system (Ljung, 1999; Aguirre, 2015).

The major research problem in FDI is the robust residual generation. Residuals are affected by nonlinearities, uncertainty, modelling errors, noise, disturbances, etc. A lot of work in this research field is available. Freddi et al. (2009); Tahraoui et al. (2014); Negash et al. (2016); Chaves et al. (2018); Zhang et al. (2018) are examples of results on robust FDI.

Among the robust FDI methods, Unknown Input Observer (UIO) have been useful in the robust residual generation. There are evidence of UIO applications in many processes such as chemical processes, electrical systems, aircraft and helicopters (Chen and Patton, 1999; Termehchy et al., 2013; Zhang et al., 2016; MA et al., 2018).

Helicopters are aircrafts with a complex dynamics and behaviour. These aircrafts are considered very unstable and relevant research about its modelling and control may be found in Luo et al. (2003); Padfield (2008); Cook (2012); Ren et al. (2012). In order to achieve desirable flight qualities and system stability, helicopters are equipped with sensors and actuators from which a lot of information is obtained, processed and monitored. That information is useful in designing and applying FDI schemes. Fault detection and isolation of helicopter sensors and actuators have a tremendous impact in economy and safety. The faults occurrence in sensors and actuators can lead to a non-desirable and dangerous situation compromising the helicopter flight qualities and stability, and, in the worst case, a system break-down can arise.

This paper addresses the robust FDI of a six Degree of Freedom (DoF) helicopter using simple Unknown Inputs Observers as robust residuals generators. A Generalized Observer Scheme (GOS) is adopted to implement sensor and actuator faults isolation schemes based on UIOs. A linear model of the helicopter in the state of hover is employed for the FDI system design.

2. HELICOPTER MODEL

Helicopters are high order systems with a strong non-linear dynamics and complex behaviour. The helicopter dynamics in flight can be modelled as the combination of a large number of interacting subsystems. The equations governing this dynamical interaction are obtained from the application of physical laws to the individual components of the helicopter and generally have the form of nonlinear differential equations as (1).

$$\frac{d\mathbf{x}}{dt} = \mathbf{f}(x,u_c,t)) \tag{1}$$

where, $x(t)$ is the state vector, $u_c(t)$ is the control vector and, $f(x, u_c, t)$ is a nonlinear function of the aircraft motion (Padfield, 2008).

This research only considers the special case of a six DoF of the rigid body approximation. The six DoF are the three translational movements and the movements of pitching, yawing and rolling. This case is a suitable one and very employed in helicopter control systems. The state vector comprises the six DoF is:

$$\mathbf{x} = [u, w, q, \theta, v, p, \phi, r, \psi]^T \tag{2}$$

where, u, v and w are the translational velocity components, p, q, r the rotational velocity components and, ϕ, θ, ψ the Euler angles.

The nonlinear equations of motion are divided into force (3), moment (4), and attitude (5) equations (Padfield, 2008).

$$\begin{aligned}
\dot{u}(t) &= -(wq - vr) + \frac{X}{M_a} - g\sin\theta \\
\dot{v}(t) &= -(ur - wp) + \frac{Y}{M_a} - g\cos\theta\sin\psi \\
\dot{w}(t) &= -(vp - uq) + \frac{Z}{M_a} - g\cos\theta\sin\psi
\end{aligned} \tag{3}$$

$$\begin{aligned}
I_{xx}\dot{p}(t) &= (I_{yy} - I_{zz})qr + I_{xz}(\dot{r} + pq) + L \\
I_{yy}\dot{q}(t) &= (I_{zz} - I_{xx})qr + I_{xz}(r^2 - p^2) + M \\
I_{zz}\dot{r}(t) &= (I_{xx} - I_{yy})qr + I_{xz}(\dot{p} + qr) + N
\end{aligned} \tag{4}$$

$$\begin{aligned}
\dot{\phi}(t) &= p + (q\sin\phi + r\cos\phi)\tan\theta \\
\dot{\theta}(t) &= q\cos\phi - r\sin\phi \\
\dot{\psi}(t) &= \frac{q\sin\phi + r\cos\phi}{\cos\theta}
\end{aligned} \tag{5}$$

where, M_a is the mass of the fuselage, X, Y, Z are the external forces, L, M, N N are analytic functions of the disturbed motion variables and their derivatives, and I_{xx}, I_{yy}, I_{zz}, I_{xz}, are the fuselage moments of inertia about the reference axes,

A nonlinear model is hard to manipulate and difficult to employ in fault detection and diagnosis, since the state-space observer-based methods for robust FDI are generally based on linear models of the system; a linear model of the helicopter system in equations (3), (4), (5) is given. The helicopter here studied is the DRA research Westland Lynx Mk7 and the process of linearization is exposed in Padfield (2008) and Luo et al. (2003). This is a known benchmark aircraft and is widely used in research to calibrate agility standards of future helicopter types. Equation (6) presents the state-space representation of the helicopter linear model.

$$\begin{aligned}
\dot{x}(t) &= Ax(t) + Bu_c(t) \\
y(t) &= Cx(t)
\end{aligned} \tag{6}$$

where, $x = \begin{bmatrix} u & w & q & \theta & v & p & \phi & r \end{bmatrix}^T$ and $u_c = \begin{bmatrix} \theta_0 & \theta_{1s} & \theta_{1c} & \theta_{0T} \end{bmatrix}^T$, θ_0 is the main rotor collective pitch control, $(\theta_{1s}, \theta_{1c})$ are the cyclic collective pitch controls, and θ_{0T} is the tail rotor collective pitch control. The output vector is selected as $y(t) = \begin{bmatrix} q & \theta & \phi & r \end{bmatrix}^T$.

3. ROBUST MODEL-BASED FAULT DETECTION AND ISOLATION SYSTEM

Nonlinearities, modelling errors, signal noise, disturbances and uncertainty, negatively impact the performance and the reliability of a diagnosis system. Model-based FDI methods require a good mathematical model of the plant in order to make steady-state output error tends to zero. The accuracy of the model is compromised by disturbances and unknown inputs which decrease the sensitivity of residuals to faults and increase the number of false alarms and wrong classifications.

A system can be modelled in the state-space as in equation (7), where $x(t) \in R^n$, $u(t) \in R^r$ and $y(t) \in R^m$. The vector $d(t) \in R^q$ is an unknown input term which is an additive disturbance vector, matrix E is the disturbance distribution matrix.

$$\begin{aligned}
\dot{x}(t) &= Ax(t) + Bu_c(t) + Ed(t) \\
y(t) &= Cx(t)
\end{aligned} \tag{7}$$

Disturbance decoupling approach is widely used for robust residual generation (Chen and Patton, 1999; Patton et al., 2013; Simani et al., 2003). The objective of the disturbance decoupling methods is to decouple faults from disturbances and increase the sensitivity of the residuals to faults. In this research, a method from disturbance decoupling approach is employed to achieve robust fault detection and isolation.

3.1 Unknown Input Observers

Unknown input observers are a special kind of observers in which all disturbance signals are considered as unknown inputs to the model of the plant. A formal definition of UIO is shown below.

Definition 1. An unknown input observer is an observer in which the state estimation error vector *e(t)* approaches zero asymptotically, regardless of the presence of the unknown inputs or disturbances on the system (Chen and Patton, 1999).

A full order observer structure is shown in equation (8), where $z(t) \in R^n$ is the full order observer state vector and $\dot{x}(t) \in R^n$ is the estimated state vector. If matrices F, T, K and H are selected correctly, the full order observer in equation (8) is converted in an UIO and disturbance decoupling is achieved.

$$\begin{aligned} \dot{z}(t) &= Fz(t) + TBu_c(t) + Ky(t) \\ \hat{x}(t) &= z(t) + Hy(t) \end{aligned} \tag{8}$$

When the observer in equation (8) is applied to the system in equation (7), the state estimation error is governed by equation (9).

$$\begin{aligned} \dot{e}(t) = \dot{x}(t) - \dot{\hat{x}}(t) &= (A - HCA - K_1C)e(t) \\ &+[F - (A - HCA - K_1C)]z(t) \\ &+[K_2 - (A - HCA - K_1C)H]y(t) \\ &+[T - (I - HC)]Bu(t) + (HC - I)Ed(t) \end{aligned} \tag{9}$$

In order to make:

$$\dot{e}(t) = Fe(t) \tag{10}$$

the conditions in equation (11) must be reached.

$$\begin{aligned} (HC - I)E &= 0 \\ T &= I - HC \\ F &= A - HCA - K_1C \\ K_2 &= FH \\ K &= K_1 + K_2 \end{aligned} \tag{11}$$

Matrix F must be a stable matrix, i.e. the eigenvalues of F lie in the open left complex half-plane. Therefore, $e(t)$ will approach asymptotically to zero, so the full order observer in equation (8) is an unknown input observer of the system in equation (7). Now, the necessary and sufficient conditions for the existence of the unknown input observer is given by Theorem 1

Theorem 1. **Necessary and sufficient conditions for the existence of unknown input observer:**

(1) $rank(CE) = rank(E)$

(2) (C, A_1) is a detectable pair, where $A_1 = A - E[(CE)^TCE]^{-1}(CE)^TCA$

The proof of this theorem will be omitted but it is shown in Chen and Patton (1999). If the first condition of theorem 1 is achieved, then a solution for conditions in equation (11) is given in equation (12).

$$H = E[(CE)^TCE]^{-1}CE^T \tag{12}$$

3.2 Robust fault detection and isolation schemes based on UIOs

The fault isolation procedure is the determination of the sensor or the actuator in which a fault has occurred. The strategy here is to design a structured residual set which is sensitive to a group of faults and insensitive to others. The ideal situation is to make each residual sensitive to a particular fault. This ideal situation is hard to achieve; even when it is possible. Usually, the design freedom available will be exhausted and no other improvements will be performed including robustness. An accepted criterion is to design residuals to be sensitive to all faults except to faults in one sensor or actuator.

The system in equation (7) with faults in actuators and sensors could be modelled in state space as in equation (13). Vectors $f_a(t) \in R^r$ and $f_s(t) \in R^m$ are the actuator and sensor faults respectively and matrices $L_1 = B$ and $L_2 = I_m$ are the fault distribution matrices.

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu_c(t) + Ed(t) + L_1f_a(t) \\ y(t) &= Cx(t) + L_2f_s(t) \end{aligned} \tag{13}$$

If the UIO in equation (8) is applied to the system in equation (13) the estimation error ($\dot{e}(t) = Fe(t)$) and the residual will be:

$$\begin{aligned} \dot{e}(t) &= \dot{x}(t) - \dot{\hat{x}}(t) = (A_1 - K_1C)e(t) \\ &\quad +TBf_a(t) - K_1f_s(t) - H\dot{f}_s(t) \\ r(t) &= Ce(t) + f_s(t) \end{aligned} \tag{14}$$

From equation (14) a fault in the i_{th} actuator will affect the residual if and only if $Tb_{i_{th}} \neq 0$, $b_{i_{th}}$ is the i_{th} column of matrix B. In the same way, if a fault occurs in the i_{th} sensor, the residual must be sensitive to this fault to detect it. However, $f_s(t)$ has a direct effect on the residual and this condition is normally satisfied.

The fault isolation schemes based on UIOs generalized observer schemes are well explained in Chen and Patton (1999). The implementation is summarized below.

3.3 Robust actuator faults isolation scheme

For actuator fault isolation scheme it is assumed that there is no faults in sensors. Then system in equation (13) can be described as:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + B^iu_c^i(t) + B^if_a^i(t) + E^id^i(t) \\ y(t) &= Cx(t) \end{aligned} \tag{15}$$

where, $B^i \in R^{n\times(r-1)}$ is the matrix B by deleting the i_{th} column, $u^i \in R^{r-1}$ is the input vector by deleting the i_{th}

input, f_a^i is the fault vector by deleting the fault in the i_{th} actuator f_{ai}, $E^i = \left[\, E \;\, b_{i_{th}} \,\right]$ and $d^i(t) = \left[\begin{smallmatrix} d_i(t) \\ u_{c_i}(t)+f_{ai} \end{smallmatrix}\right]$, where $u_i(t)$ is the i_{th} system input, for $i = 1, 2, ..., r$

The r_{th} UIO residual generator is constructed as in equation (16). The residuals generated from the i_{th} UIO are sensitive to all faults except the i_{th} actuator fault.

$$\begin{aligned} \dot{z}^i(t) &= F^i z^i(t) + T^i B^i u_c^i(t) + K^i y(t) \\ r^i(t) &= (I - CH^i)y(t) - Cz^i(t), \\ i &= 1, 2, ..., r \end{aligned} \tag{16}$$

3.4 Robust sensor faults isolation scheme

In the case of sensor faults isolation scheme, it is assumed that no faults occur in actuators. The system in equation (13) is described as:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu_c(t) + Ed(t) \\ y^j(t) &= C^j x(t) + f_s^j(t) y_j(t) = c_j x(t) + f_{sj}(t), \\ j &= 1, 2, ...m \end{aligned} \tag{17}$$

where $c_j \in R^{(1\times n)}$ is the j_{th} row of matrix C, $C^j \in R^{(m-1\times n)}$ is obtained from the matrix C by deleting c_j, y_j is the j_{th} component of y ,and $y^j \in R^{(m-1)}$ is obtained from y by deleting y_j.

The m_{th} UIO residual generator are constructed as in equation (18). The residuals generated from the j_{th} UIO are sensitive to all faults except the j_{th} sensor fault.

$$\begin{aligned} \dot{z}^j(t) &= F^j z^j(t) + T^j B u_c(t) + K^j y^j(t) \\ r^j(t) &= (I - C^j H^j) y^j(t) - C^j z^j(t), \\ j &= 1, 2, ..., m \end{aligned} \tag{18}$$

4. RESULTS

The linear model of the helicopter presented in equation (6) is used in the design of a FDI system based on UIOs following the theoretical basis established in the last sections. The helicopter hover operating point is considered, i.e. flight at $0m/s$. Matrices A and B are obtained from the first-order partial derivatives of function $f(x, u, t)$ with respect to the state vector and the input vector respectively as shown in Padfield (2008). Matrices A, B, and C are presented in equations (19), (20), and (21) respectively.

$$A = \begin{bmatrix} -0.0199 & 0.0215 & 0.6674 & -9.7837 \\ 0.0237 & -0.3108 & 0.0134 & -0.7215 \\ 0.0468 & 0.0055 & -1.8954 & 0 \\ 0 & 0 & 0.9985 & 0 \\ 0.0207 & 0.0002 & -0.1609 & 0.0380 \\ 0.3397 & 0.0236 & -2.6449 & 0 \\ 0 & 0 & -0.0039 & 0 \\ 0.0609 & 0.0089 & -0.4766 & 0 \end{bmatrix} \tag{19}$$
$$\begin{bmatrix} -0.0205 & -0.1600 & 0 & 0 \\ -0.0028 & -0.0054 & 0.5208 & 0 \\ 0.0588 & 0.4562 & 0 & 0 \\ 0 & 0 & 0 & 0.0532 \\ -0.0351 & -0.6840 & 9.7697 & 0.0995 \\ -0.2715 & -10.9759 & 0 & -0.0203 \\ 0 & 1.0000 & 0 & 0.0737 \\ -0.0137 & -1.9367 & 0 & -0.274 \end{bmatrix}$$

$$B = \begin{bmatrix} 6.9417 & -9.2860 & 2.0164 & 0 \\ -93.9179 & -0.0020 & -0.0003 & 0 \\ 0.9554 & 26.4011 & -5.7326 & 0 \\ 0 & 0 & 0 & 0 \\ -0.3563 & -2.0164 & -9.2862 & 3.6770 \\ 7.0476 & -33.2120 & -152.9537 & -0.7358 \\ 0 & 0 & 0 & 0 \\ 17.3054 & -5.9909 & -27.5911 & -9.9111 \end{bmatrix} \tag{20}$$

$$C = \begin{bmatrix} 0&0&1&0&0&0&0&0 \\ 0&0&0&1&0&0&0&0 \\ 0&0&0&0&0&0&1&0 \\ 0&0&0&0&0&0&0&1 \end{bmatrix} \tag{21}$$

Uncertainty in helicopter hover operating point is simulated as a random input variable, representing the uncertainties in the flapping blades. It is considered a random variable with zero mean and a relatively high covariance of 5% to represent the aerodynamic and atmospheric parameters. The unknown input uncertainty signal is shown in figure 1.

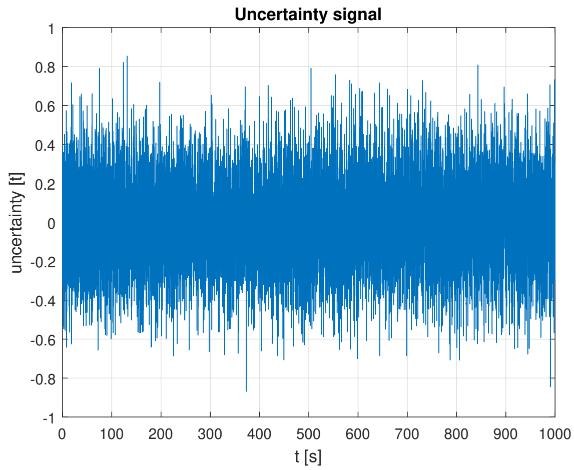

Figure 1. Helicopter hover state flapping blades uncertainty simulation.

Two Unknown Input Observers banks are designed. Each bank has four UIOs and consequently, four sets of robust residuals are available. One bank of observers is dedicated to detect and isolate faults in the helicopter actuators. The other bank is dedicated to detect and isolate faults in the helicopter sensors. It is assumed that two faults do not exist at the same time, that is a realistic assumption because the probability of the occurrence of two faults at the same instance of time is almost zero.

A fault in the main rotor collective pitch actuator is simulated as a step signal of magnitude 0.5. A simple Luenberger observer-based residual generator is designed. The residuals obtained are sensitive to both the fault and the uncertainty as shown in figure 2.

On the other hand, robust residuals are obtained by applying the proposed methodology. They are shown in figures 3, 4, 5, and 6. In this case, residuals are sensitive to the fault in the main rotor collective actuator and insensitive to the uncertainty. Due to the isolation scheme applied, it is possible to determine that the fault has occurred in this actuator by analyzing the residuals. The residuals generated by the UIO corresponding to the main rotor collective actuator, are insensitive to the fault as

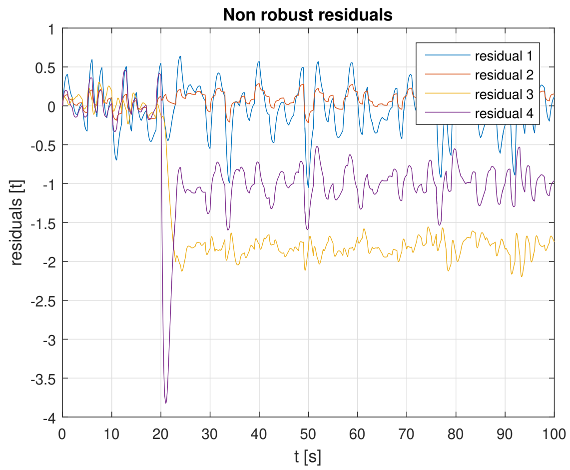

Figure 2. Non robust residuals for a fault in the main rotor collective pitch actuator.

shown in figure 3. Nevertheless, the other residuals are sensitive to the fault.

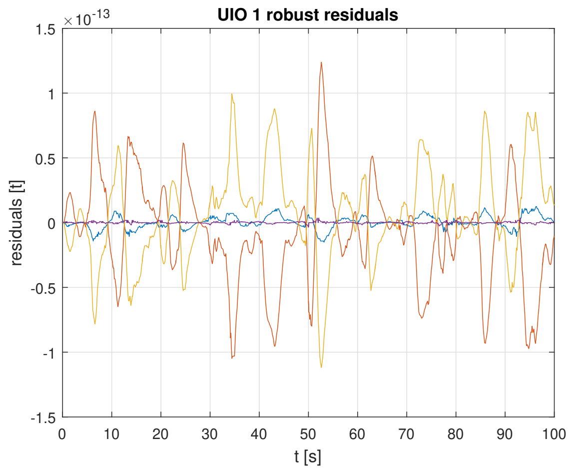

Figure 3. Robust residuals generated from the first UIO of the input bank of observers, which excludes the main rotor collective control input.

For the detection and isolation of faults in sensors, a fault in the rotational velocity respect to axis -z (r) sensor is simulated. The fault is considered a step signal of magnitude 2.0. Following the same methodology employed in the main rotor collective pitch fault situation, a simple Luenberger observer is designed and non-robust residuals are obtained see figure 7.

When a fault occurs in the rotational velocity sensor, the resultant residuals obtained from the second bank of observers are robust to the system uncertainty and sensitive to the sensor fault. Figures 8, 9, 10, and 11 present the robust residuals when this kind of fault occurs. As a result of the isolation scheme applied, the residuals generated by the UIO correspondent to the rotational velocity sensor, are insensitive to that fault, see figure 11. The other residuals are all sensitive. Then, it is possible to isolate the fault and determine in which sensor the fault has occurred.

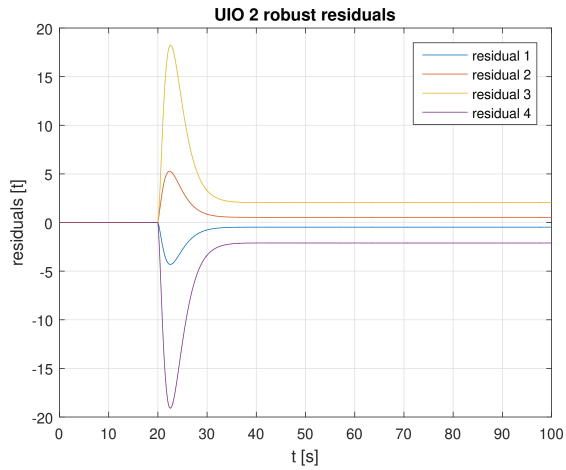

Figure 4. Robust residuals generated from the second UIO of the input bank of observers, which excludes the lateral cyclic control input.

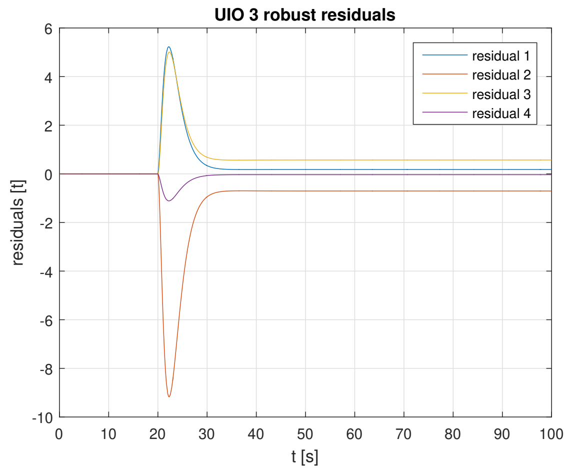

Figure 5. Robust residuals generated from the third UIO of the input bank of observers, which excludes the longitudinal cyclic control input

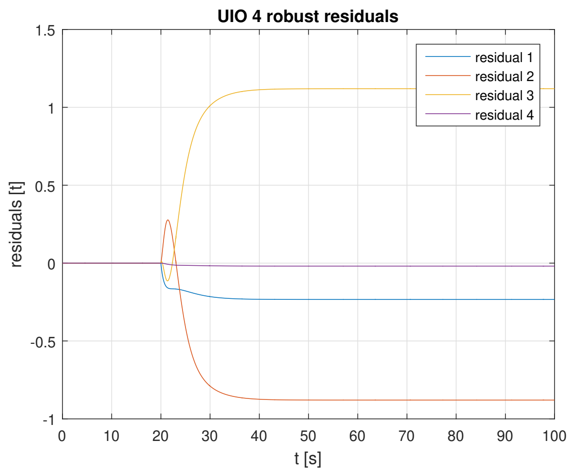

Figure 6. Robust residuals generated from the fourth UIO of the input bank of observers, which excludes the tail rotor collective control input

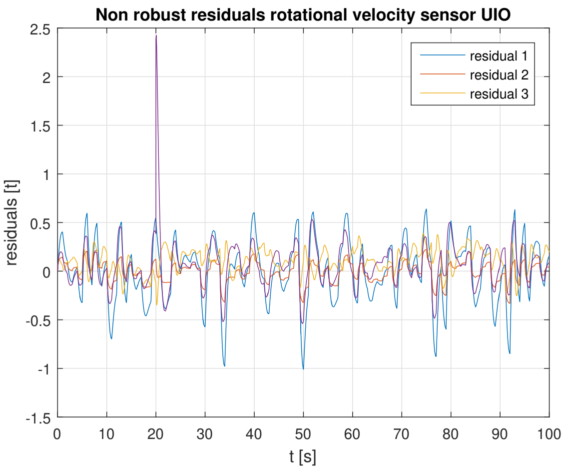

Figure 7. Non robust residuals for a fault in the rotational velocity sensor respect to axis -z.

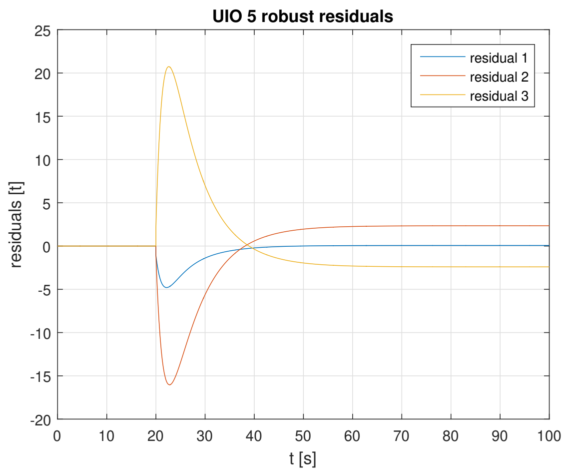

Figure 8. Robust residuals generated from the first UIO of the output bank of observers, which excludes the rotational velocity in axis -y sensor output.

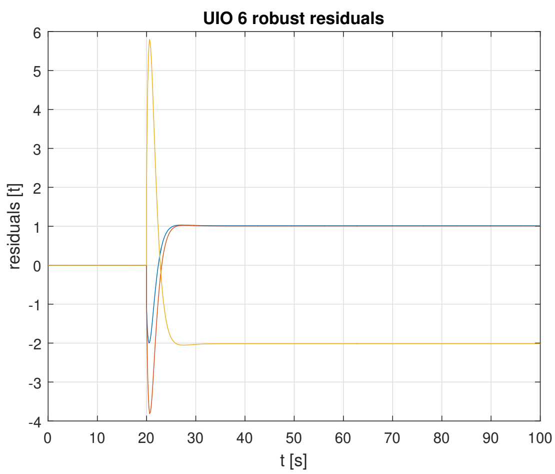

Figure 9. Robust residuals generated from the second UIO of the output bank of observers, which excludes the θ angle sensor output.

5. CONCLUSIONS

Unknown input observers method allows decoupling disturbances from fault residuals increasing the sensitivity of

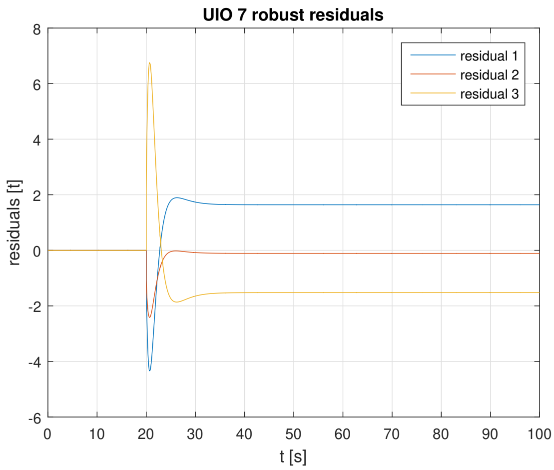

Figure 10. Robust residuals generated from the third UIO of the output bank of observers, which excludes the ϕ angle sensor output.

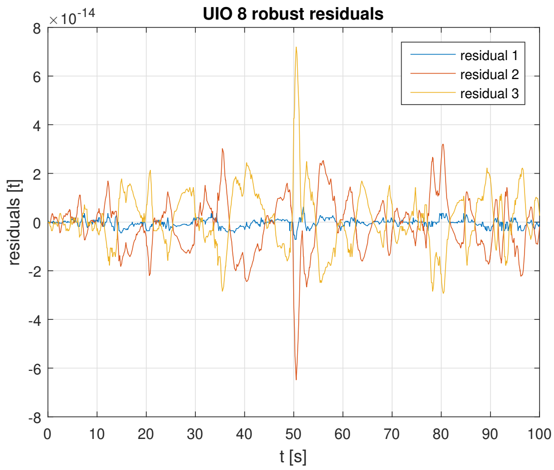

Figure 11. Robust residuals generated from the first UIO of the output bank of observers, which excludes the rotational velocity in axis -z sensor output.

the residuals to faults and reducing the effect of unknown inputs on them. This method could be employed to detect faults in actuators such as in sensors. Applying isolation schemes based on UIOs, faults can be isolated and located. This method could be applied to systems where a good mathematical model is provided.

Despite linearization error, uncertainty, noise and disturbances affecting the helicopter behaviour, the UIO method applied to the aircraft system decouples this unknown signals and robust residuals are generated. From this residuals, fault detection and isolation can be performed leading to condition maintenance and predictive maintenance which have a tremendous impact in economic saving, safety, quality, autonomy and availability.

Fault tolerant control system can be implemented by using this FDI system for online reconfiguration of the control law. Hence the helicopter flight qualities will be guaranteed and the helicopter performance will be maintained despite of the faults. The interaction between robust model-based FDI and Fault tolerant control is under research.

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