SENSOR FAULT DETECTION AND ANALYTICAL REDUNDANCY SATELLITE LAUNCHER FLIGHT CONTROL SYSTEM

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Abstract A study on the inclusion of analytical redundancy and of an instrument fault detection scheme (IFD) into a flight control system has been performed for a satellite launcher using the longitudinal model. The study was mainly focused in the fault diagnosis aspect, and it reports the conclusions obtained for this kind of control system. A fault diagnosis logic has been created based on nonlinear functions, its derivatives with respect to time, and on the control rate effort. Several simulations were run to assess the system performance, and a study about the robustness of the system with respect to system parameters uncertainties was also performed and both are reported here. It was found that the system is able to reconfigure the control law safely in almost all the situations and the false alarm rate presented was also very low. The system is simple as the same observers are used for the decision logic and for the alternative observer-based control laws. The main feature of the work is the inclusion of the derivatives of the nonlinear functions into the decision logic.

1 INTRODUCTION

In the case of unstable vehicles, as is the case of the satellite launchers and high performance aircrafts, the failure of one sensor can be catastrophic if the control system has not some degree of redundancy, physical or analytical. Due to this characteristic, it is very important to these vehicles to have a redundant flight control system with the ability to identify sensor failures as quickly as possible and then to reconfigure the control law from the failed control law to an alternative control law. Although many systems achieve fault tolerance by using hardware redundancy, there are several problems associated with hardware redundancy. Some of these problems are, extra cost, additional space and weight and extra software. Besides, it has been noticed that redundant sensor tend to have similar life expectancies, so, it is likely that when one of a set of sensors fails the other will be failing very soon too. In view of these problems it is much better to use the analytical redundancy approach to design a fault tolerant system.

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2 BACKGROUND WORK ON IFD

A list of good references about design methods for failure detection in dynamic systems can be found in Willsky (1976) and Frank (1986). Practical examples of IFD design with analytical redundancy are reported in several works as, Chow and Willsky (1984), Cunningham and Poyneer (1977) (where an application is designed for the A-7D aircraft). Decket(Deckert, 1978) (where an application is deigned for the F-8 digital flight by wire aircraft) and in Shapiro and Decarli, (1979)' (where an application is made using one observer of full order to drive an autopilot). The inclusion of random disturbances into the system can be found in Clark, and Setzer, (1979) (where one Kalman filter is driven by one system output signal). The robustness aspect is studied in Emani, (1986) (where an application is made for the F-100 aircraft using hypothesis testing,) and in Patton *et alii*, (1987) (where the parameter uncertainty is studied). A very good example of deterministic observers applied to an IFD system is showed in the work of Stuckenberg (1986) (where the application is for the HFB 320 aircraft, with one observer for each sensor). The approach given in these works was followed in this work with the inclusion of a robust observer into the system, and with the inclusion of derivatives of the decision functions as auxiliary decision functions.

3 MATHEMATICAL MODEL USED FOR THE LONGITUDINAL MOTION

The mathematical model used to describe the longitudinal motion of the satellite launcher is given by equation (1) and can be found in McLean (1990) for example, as in other flight dynamics references,and it describes the open loop dynamics of the longitudinal motion.

$$\dot{x} = Ax + Bu \qquad (1)$$

with the state vector given by

$$x^T = \begin{bmatrix} w & q & \theta \end{bmatrix} \qquad (2)$$

and

$$u = \beta_z \qquad (3)$$

The matrices A and B in equation (1) are given by

$$A = \begin{bmatrix} Z_w & Z_q + U_0 & -g \\ M_w & M_q & 0 \\ 0 & 1 & 0 \end{bmatrix} \qquad (4)$$

$$B^T = \begin{bmatrix} Z_{\beta z} & M_{\beta z} & 0 \end{bmatrix} \qquad (5)$$

The parameters Z_w, Z_q, M_w, M_q, $Z_{\beta z}$ and $M_{\beta z}$ contained in matrix A and in matrix B, are the aerodynamic derivatives of the satellite launcher vehicle, obtained from wind tunnel tests.

The parameter U_0 is the flight speed of the vehicle and the parameter g is the gravity acceleration.

The state variable w is the vehicle velocity along the z-body axis, called normal velocity, the state variable q is the vehicle pitch-rate, that is, its angular velocity around the y-body axis, and the state variable θ is the vehicle pitch-attitude with respect to y-body axis. Finally the control β_z is the pitch control deflection.

The control system was designed based on this model with the objective to track a reference pitch attitude (θ_{ref}) and the regulation of the remaining states. So the control system will require three sensors to work adequately, that is, sensors for w (normal velocity) , q (pitch-rate) and θ (pitch-attitude). Certainly, if one of these sensors fail, specially the sensors of q and θ, the vehicle will become unstable. If the sensor for (w) fail the vehicle will not be unstable, however it will work with a degraded performance with respect to the designed performance. In view of these facts it is very important the inclusion of analytical or physical redundancy into the system. Here the case of analytical redundancy will be discussed.

4 LONGITUDINAL CONTROL SYSTEM

The longitudinal control system was designed based on the following model :

$$\begin{bmatrix} \dot{w} \\ \dot{q} \\ \dot{\theta} \\ \dot{e}_\theta \end{bmatrix} = \begin{bmatrix} Z_w & Z_q + U_0 & -g & 0 \\ M_w & M_q & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & -1 & 0 \end{bmatrix} \begin{bmatrix} w \\ q \\ \theta \\ e_\theta \end{bmatrix} + \begin{bmatrix} Z_{\beta z} \\ M_{\beta z} \\ 0 \\ 0 \end{bmatrix} \beta_z + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \theta_{ref} \qquad (6)$$

where the state variable e_θ , that is, the pitch-attitude error integral, has been included to keep the steady state error near zero. The control system was designed by LQR method as described in Rynaski (1982) , and the control law is given by

$$\beta_z = -G_1 x - G_0 \theta_{ref} \qquad (7)$$

with the state vector given by

$$x^T = \begin{bmatrix} w & q & \theta & e_\theta \end{bmatrix} \qquad (8)$$

and the vector for the feedback gains is given by

$$G_1 = [\, G_w \;\; G_q \;\; G_\theta \;\; G_{e\theta} \,] \qquad (9)$$

and G_0 is the feedforward gain.

Figure 1 shows the vehicle with this control law.

5 OBSERVERS FOR THE CONTROL SYSTEM

To include analytical redundancy it is necessary to include observers into the control law, and in this way to include alternative control laws, that is, the observer based control laws. In this case three reduced order observers will be included.

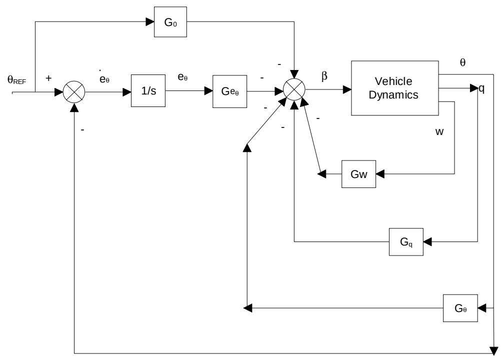

Figure 1 - block diagram of the vehicle with the basic control law.

The method used to design the observers can be found in Chen (1984). The observers dynamics are given by

$$\dot{z} = Fz + Gy + H\beta_z \qquad (10)$$

where F is a (2x2) matrix which defines de observer dynamics, G is a (2x1) vector, H a (2x1) vector and z a (2x1) vector too. The estimated states will be given by

$$\hat{x} = My + Nz \qquad (11)$$

where $\hat{x}$ is the vector of the estimated states, in this case a (2x1) vector.

The F matrix was chosen to have a Doyle-Stein observer (Doyle and Stein, 1989), that is, a robust observer. So the F matrix was taken as a diagonal matrix with his elements taken among the transmission zeros of the open loop transfer functions θ/β_z , w/β_z and q/β_z . As these transfer functions have only two finite transmission zeros, the use of a reduced order observer was more suitable than a full order observer to design the Doyle-Stein robust observer (Doyle and Stein, 1989). The vector G was taken to get the { F,G} controllable. So G was taken as

$$G^T = [\, 1 \;\; 1 \,] \qquad (12)$$

to simplify the design. Then it is necessary to solve the Lyapunov equation

$$TA - FT = GC \qquad (13)$$

where the matrix A is given by equation (4),to obtain the T matrix and to build the matrix P, given by

$$P^T = \begin{bmatrix} C & T \end{bmatrix} \qquad (14)$$

where C is the output matrix that, in the case of normal velocity (w) output, will be given by

$$C = C_w = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \qquad (15)$$

but, in the case of pitch-rate (q) output, C will be given by

$$C = C_q = \begin{bmatrix} 0 & 1 & 0 \end{bmatrix} \qquad (16)$$

Finally in the case of pitch-attitude (θ) output, C will be given by

$$C = C_\theta = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} \qquad (17)$$

then it is possible to obtain H given by

$$H = TB \qquad (18)$$

where the matrix B is given by equation (5). and so the estimated states will be given by

$$\hat{x} = P^{-1}\begin{bmatrix} y \\ z \end{bmatrix} = \begin{bmatrix} M & N \end{bmatrix}\begin{bmatrix} y \\ z \end{bmatrix} \qquad (19)$$

after this equation it is possible to get the M and N matrices of equation (12), and then the observer design is completed.

6 DECISION FUNCTIONS

It is now necessary to build decision functions that will allow the detection of a failed sensor and then to reconfigure the control law from the basic control law to an observer based control law. To build these decision functions the idea of Patton (1989) has been adopted here. Three reduced order observers were designed for the system, namely,

observer n.1, that was designed considering

$y_1 = \theta$

observer n.2, that was designed considering

$y_2 = q$

observer n.3, that was designed considering

$y_3 = w$

The inputs to observer n.1 will be y_1 and β_z and his outputs will be

$$\hat{x}_{11} = \hat{w} \qquad (20)$$

$$\hat{x}_{21} = \hat{q} \qquad (21)$$

It is then possible to build the following functions,

$$f_{11} = \left| y_2 - \hat{x}_{21} \right| \qquad (22)$$

$$f_{12} = \left| y_3 - \hat{x}_{11} \right| \qquad (23)$$

$$\eta_1 = f_{11} f_{12} \qquad (24)$$

The inputs to observer n.2 will be y_2 and β_z and his outputs will be

$$\hat{x}_{12} = \hat{w} \qquad (25)$$

$$\hat{x}_{32} = \hat{\theta} \qquad (26)$$

So it is then possile to build the functions

$$f_{21} = \left| y_1 - \hat{x}_{32} \right| \qquad (27)$$

$$f_{22} = \left| y_3 - \hat{x}_{12} \right| \qquad (28)$$

$$\eta_2 = f_{21} f_{22} \qquad (29)$$

The inputs to the observer n.3 will be y_3 and β_z , and the outputs will be

$$\hat{x}_{23} = \hat{q} \qquad (30)$$

$$\hat{x}_{33} = \hat{\theta} \qquad (31)$$

It is then possible to build the functions

$$f_{31} = \left| y_1 - \hat{x}_{33} \right| \qquad (32)$$

$$f_{32} = \left| y_2 - \hat{x}_{23} \right| \qquad (33)$$

$$\eta_3 = f_{31} f_{32} \qquad (34)$$

And the functions η_1 , η_2 and η_3 will be used as decision functions together with their derivatives with respect to time ($\dot{\eta}_1, \dot{\eta}_2$ and $\dot{\eta}_3$), and with the control rate effort , $\dot{\beta}_z$, allowing to prevent a high false alarm rate from the system.

7 DECISION LOGIC

Based on the nonlinear functions given by equations (24) , (29) and (34) it is possible to build a decision logic. If, for example the sensor of pitch-attitude (θ) fails , the functions f_{11} and f_{12} will grow very quickly and so η_1 will grow much faster than f_{11} and f_{12} . This fact allow to identify that the pitch-attitude sensor has failed. It is necessary to find an appropriate threshold for the function η_1, and it is also necessary to prevent the system to give a false alarm. To find an appropriate threshold for η_1 is not an easy task, since: the flight envelope for the vehicle is wide, the vehicle parameters can have some values not so close from those used in the observers design, there are several failure modes and the vehicle can perform several kinds of manoeuvres. To prevent false alarms it has been found that the inclusion of $\dot{\eta}_1$ in the decision logic is very useful as it is the inclusion of $\dot{\beta}_z$, that is, the control rate effort. So it is not only necessary to find an appropriate threshold for η_1 but also for $\dot{\eta}_1$ and $\dot{\beta}_z$. These thresholds can be adjusted by simulation. In a similar way it is also necessary to find appropriate thresholds for the functions η_2 , $\dot{\eta}_2, \eta_3$ and $\dot{\eta}_3$, what can be done by simulations. The procedure to find these thresholds is an iterative one, starting with simulations for the vehicle with the nominal parameters and for a step input in θ_{ref} , then going for the cases where there are some non nominal parameters. In Figure 2 the system is showed with the IFD included.

From the performed simulations it was noticed that the system working only with thresholds for η_1 , η_2 and η_3 does not show a very good performance. However, using also thresholds for $\dot{\eta}_1, \dot{\eta}_2$ and $\dot{\eta}_3$ it has been noticed an improvement in the system performance, due to the fact that some times the threshold for η has been reached but the threshold for its derivative has not been reached. This is the case, for example, when there are some uncertainty in the model parameters: in this case the threshold for η can be reached, however the threshold for $\dot{\eta}$ takes more time to be reached, and in this way a false alarm can be prevented. The contrary will happen for example in a failure situation, where both thresholds (η and $\dot{\eta}$) are reached much faster than in the case of uncertainty in the model parameters. The inclusion of the threshold for $\dot{\beta}_z$ is due to the fact that it is necessary to take into account if the vehicle is maneuvering or not. Certainly if the thresholds for η and $\dot{\eta}$ were reached and the threshold for $\dot{\beta}_z$ was not reached (the vehicle is not maneuvering) a failure occurred.

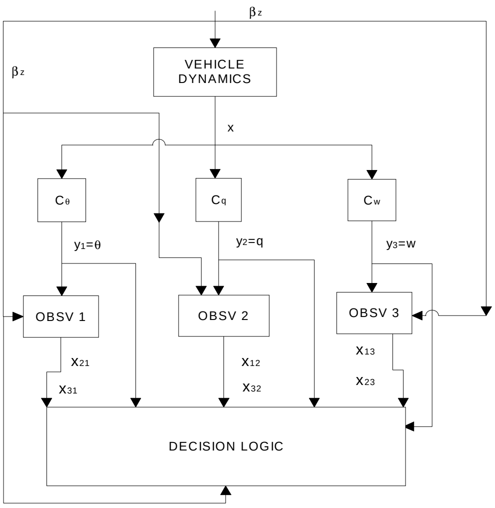

Figure 2 - IFD diagram to be implemented into the onboard computer.

The performed work used the following decision logic :

If $\eta_1 > \eta_{1lim}$ and $\dot{\beta}_z \langle \dot{\beta}_{z\lim}$ it was considered that the pitch-attitude (θ) sensor has failed.

If $\eta_2 > \eta_{2lim}$ and $\dot{\eta}_2 \rangle \dot{\eta}_{2\lim}$ and $\dot{\beta}_z \langle \dot{\beta}_{z\lim}$

it was considered that the pitch-rate (q) sensor has failed.

If $\eta_3 > \eta_{3lim}$ and $\dot{\beta}_z \langle \dot{\beta}_{z\lim}$ it was considered that the normal velocity (w) sensor has failed.

Where η_{1lim} , η_{2lim} and η_{3lim} are the thresholds for η_1 , η_2 and η_3 respectively, $\dot{\beta}_{z\lim}$ is the threshold for the control rate effort , $\dot{\beta}_z$, and $\dot{\eta}_{2\lim}$ is the threshold for the derivative of η_2.

8 CONTROL LAWS

The system in normal mode will be working with the basic control law, that is

$$\beta_z = -G_w y_3 - G_q y_2 - G_\theta y_1 - G_{e\theta} e_\theta - G_0 \theta_{ref} \qquad (35)$$

and after a sensor failure it will be possible to change for one of the three alternative control laws, that is, observer based control laws, depending on the failed sensor. These observer based control laws are given by ,

$$\beta_{z1} = -G_w \hat{x}_{11} - G_q \hat{x}_{21} - G_\theta y_1 - G_{e\theta} e_\theta - G_0 \theta_{ref} \qquad (36)$$

$$\beta_{z2} = -G_w \hat{x}_{12} - G_q y_2 - G_\theta \hat{x}_{32} - G_{e\theta} e_{\theta 2} - G_0 \theta_{ref} \qquad (37)$$

$$\beta_{z3} = -G_w y_3 - G_q \hat{x}_{23} - G_\theta \hat{x}_{33} - G_{e\theta} e_{\theta 3} - G_0 \theta_{ref} \qquad (38)$$

where $e_{\theta 2}$ and $e_{\theta 3}$ are obtained from the defined auxiliary states,

$$\dot{e}_{\theta 2} = \theta_{ref} - \hat{x}_{32} \qquad (39)$$

$$\dot{e}_{\theta 3} = \theta_{ref} - \hat{x}_{33} \qquad (40)$$

So, after the identification of the failed sensor, the system will commute to one of the three observer based control laws. If, for example, the sensor of pitch-attitude (θ) has failed, then the system can change to β_{z2} or β_{z3} ; however it is best to change to β_{z2} due to the fact that it uses pitch-rate as the input sensor to the observer resulting in a control law with better performance than a control law obtained with w as input sensor. If the pitch-rate sensor has failed, the system can change to β_{z1} or to β_{z3} ; again the option for β_{z1} is used for the same reason explained for the failure of pitch-attitude sensor. Finally if the sensor of normal velocity (w) suffers a failure, the system can change to β_{z1} or β_{z2} ; in this case both control laws offer the same performance. In Figure 3 the system is showed when working with the control law β_{z2} . In this case, a failure of pitch-attitude sensor occurred or a failure of normal velocity sensor occurred.

9 EXAMPLE CASE

An example case has been studied for a satellite launcher in order to assess the system. The data used for the vehicle are given in Table 1,

The observer poles were chosen among the transmission zeros of the open loop transfer functions, and then, the F matrix was taken as a diagonal matrix with poles -20 and -0.1224 .

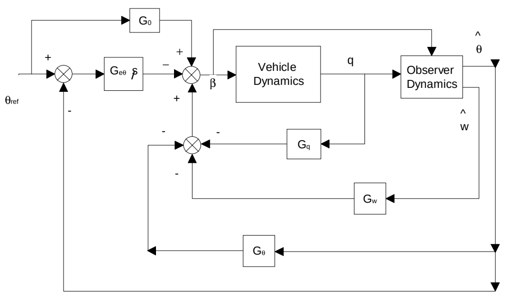

Figure 3 - Observer based control law β_{z2} for observer no.2 - This control law is used when pitch-attitude sensor or normal velocity sensor has failed.

Table 1 - Data used for the vehicle

g ($m\ s^{-2}$)	9.7886
$M_{\beta z}$ (s^{-2})	7.2769
$Z_{\beta z}$ ($m\ s^{-2}$)	19.3761
Z_w (s^{-1})	-0.0968
M_w ($m^{-1}\ s^{-1}$)	0.0096
Z_q ($m\ s^{-1}$)	0.1631
M_q (s^{-1})	0.0568
U_0 ($m\ s^{-1}$)	544.46

The gains used for the control law are reported in Table 2

Table 2 - Gains for the control law

G_w ($m^{-1}\ s$)	0.0013
G_q (s)	1.4551
G_θ (rad)	3.2581
$G_{e\theta}$ (rad)	-3.1623
G_0 (rad)	-3.257

10 OBTAINING THE THRESHOLDS FOR η_1 , η_2 AND η_3

To get the first approximation for the thresholds values for η_1 , η_2 and η_3 several simulations were performed for the vehicle with a step input in θ_{ref} and varying the vehicle parameters in 30% one by one, to allow for uncertainties in the parameters and to prevent a high false alarm rate for the system. Some simulations were also made for the vehicle suffering a failure in each sensor, when the sensor fails to zero 3 seconds after the input in θ_{ref} . After this first attempt, the threshold values for η_1 , η_2 and η_3 were taken as, 0.5 for η_1 , 2 for η_2 and 150 for η_3 .

For this first study a threshold value of 20 for $\dot{\eta}_2$ and a threshold value of 0.2 for $\dot{\beta}_z$ were used.

11 FAILURE CASES STUDIED

A sensor can fail in many different ways. In this work the most common used failures were used to assess the performance, as in Cook (1991). A fault monitor which is robust to fault types must include hypothesis generation and hypothesis testing, which is beyond the scope of this work; so, this system is not robust with respect to any failure kind.

Four failure cases were studied for the system, namely:

1 zero, when the sensor fails to zero, that is, the sensor suffers a step to zero.
2 maximum, when the sensor fails to its maximum value, that is, the sensor suffers a step to its maximum value.
3 stop, when the sensor fails to the last sensed value.
4 incipient, when the sensor fails slowly, that is, the sensed value is growing slowly or smoothly.

In the case of pitch-attitude sensor the used maximum was 20°, a value used for example for a satellite launcher vehicle. The maximum used for the pitch-rate sensor was 20°/sec, that it is a value very close to a pitch-rate sensor used in a satellite launcher vehicle. The maximum used for normal velocity sensor was the value correspondent to a maximum of 10° of angle of attack. For the incipient failures the used values are as follows:

for pitch-attitude sensor,

$\theta_{indic} = \theta_3 + 0.05$ (time - 3)

where θ_3 is the pitch-attitude at 3 seconds of simulation.

for the pitch-rate sensor,

$q_{indic} = q_3 + (1/57.3)$ (time - 3)

where q_3 is the pitch-rate at 3 seconds of simulation.

for the normal velocity sensor,

$w_{indic} = w_3 +$ (time - 3)

where w_3 is the normal velocity at 3 seconds of simulation.

The θ_{indic} , q_{indic} and w_{indic} are the indicated values by the respective failed sensors.

These cases have been chosen because they are the more referred in the relative literature, as for example, in Patton *et alii,* (1989) and in Cook (1991). The probability of occurrence of each kind of failure will be a function of the sensor being used in the vehicle, and can be obtained from the sensor manufacturer. So, when designing the IFD system for a specific vehicle these probabilities can be taken into account in the design.

Simulations for each case were run for the three sensors (θ , q , w) with uncertainty in one parameter at each time, and the time at which the system detected the failure was recorded. It is necessary to say that a failure in the sensors of pitch-attitude or pitch-rate can be very dangerous because the system will became unstable; on the other hand, a failure of normal velocity (w) sensor is not dangerous, since in this case the system will not became unstable. As an example, Table 3 shows the results obtained for failures in pitch-attitude sensor at 3 seconds, reporting the time at which the failure was detected by the system. The results have been obtained for a step manoeuvre at the beginning of the simulation, that is, time = 0 sec, in θ_{ref} .

Table 3 - Results for θ sensor failures

	zero	max	stp	incp
base	3.03	3.02	-	3.18
30% U_0	3.02	3.02	-	3.03
30% $Z_{\beta z}$	3.02	3.02	-	3.16
30% $M_{\beta z}$	3.03	3.02	-	3.18
30% Z_q	3.03	3.02	-	3.18
30% M_q	3.03	3.02	-	3.18
30% Z_w	3.02	3.03	-	3.11
30% M_w	3.02	3.02	-	3.16

From Table 3 it is possible to notice that the system can detect the failure in about 20 to 30 milliseconds, in the case of zero or maximum. In the case of incipient failure it takes more time due to the fact that the failure happens smoothly. In the case of stop, the system has not detected the failure due to the fact that at 3 seconds the θ response is in steady state, that is, the value at which the sensor has failed is practically the value of the state.

12 ROBUSTNESS STUDY FOR THE SYSTEM

In this work, as in Patton *et alii* (1989), only the deterministic IFD was considered, and so, sensor noise has not been modelled. However, as mentioned in Patton *et alii*, (1989), this kind of IFD works quite well when sensor noises are not excessive and are accurately modelled as Gaussian processes.

A robustness study for uncertainties in the system parameters was performed to assess the false alarm rate of the system, and so to find a new decision logic. The parameters that were considered in the study were:

Z_w, Z_q, M_w, M_q, $Z_{\beta z}$, $M_{\beta z}$ and U_0.

That is, several simulations were performed

without any failure, but with uncertainties in the parameters, and with the IFD system working. The study took uncertainties in each parameter one at each time; then combinations of two parameters with uncertainties at each time; then combinations of three parameters with uncertainties at each time; then four; and, at the end, five. As there was so many tables it is only possible to report the final results. So, for one parameter with uncertainty, the system has not reported any false alarm. With combinations of two parameters with uncertainty the system has reported a 9.5% rate false alarm, for q sensor and w sensor. With combination of three parameters with uncertainty, the system has reported a 17% false alarm rate, in this case for the three sensors. For the system with combination of four parameters with uncertainty the system has reported a 20% false alarm rate, again only for the sensors of q and w. For the system with combination of five parameters with uncertainty the system has reported a 19% false alarm rate. For the system with combination of six parameters with uncertainty the system has reported a 14% false alarm rate. Finally with uncertainty on the seven parameters the system has not reported any false alarm.

The false alarm has been reported only when there is uncertainty in the parameters U_0, M_w and $M_{\beta z}$, that is, the system has much more sensitivity to these three parameters. The false alarm rate reported can be reduced if thresholds for $\dot{\eta}_1$ and $\dot{\eta}_3$ are included in the decision logic for the sensors of w and q respectively.

It is necessary to say that the uncertainty used for the parameter U_0 (30 %) is very high indeed and was not representative of a real flight condition. So with a more realistic uncertainty for U_0, that can be around 5% , the system performance will be much better, and probably will not report false alarms, since the false alarms were reported only to the conditions where there was 30% uncertainty in U_0.

13 RESPONSE OF THE SYSTEM WITH AND WITHOUT THE IFD SYSTEM

To illustrate the effects of false alarm cases, in Figure 4 there is the pitch-attitude response of the vehicle without the IFD system and in Figure 5 with the IFD system, for the case of 30% uncertainty in U_0 and 30% uncertainty in M_w. In this case a false alarm was reported at 0.67 seconds of simulation without any failure. As can be noticed, the false alarm does not deteriorate too much the system response, except that the system looses the capability to detect a failure.

In Figure 6 there is the control effort time history corresponding to the case of Figure 4; and in Figure 7 it is showed the control effort time history corresponding to Figure 5. In Figure 7 it is possible to notice the moment of transition (0.67 sec) between the failed control law and the alternative observer based control law. It can also be noticed that the control effort is not very degraded. In Figure 8 there is the time history for the decision function η_2 for the case when the vehicle is working with the IFD and there is 30% uncertainty in U_0 and in M_w. It can be noticed that, around 0.55 seconds, the threshold is reached. In Figure 9 there is the time history for the decision function $\dot{\eta}_2$, where it is possible to notice that around 0.61 seconds the threshold is reached. In Figure 10 there is the time history for the control rate effort $\dot{\beta}_z$, where it can be noticed that only close to 0.65 seconds its value goes below the threshold (0.20), and so indicating a failure condition, with the system being reconfigured after this. In Figure 11 there is the control effort β_z time history for the transition phase, where it is possible to notice the transition between the basic control law and the observer based control law, around 0.67 seconds. In Figure 12 there is the η_1 decision function time history, where it can be noticed that the threshold (0.5) has not been reached. Finally, in Figure 13 there is the η_3 decision function time history, where it can be seen that the threshold (150) has also not been reached,

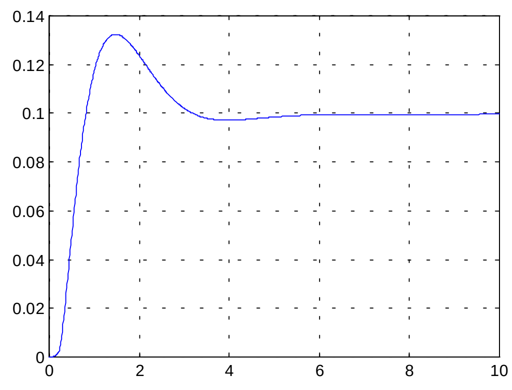

Figure 4 - Pitch-attitude time history for a 0.1 step in reference pitch-attitude (θ_{ref}) for the vehicle without the IFD system.

14 CONCLUSIONS AND COMMENTS

From the study performed it has been noticed that the system has detected almost all the simulated failures (four cases, zero ,maximum, stop and incipient). We remember that in the stop case the failure has not been reported because the sensor was showing the actual state.

However, it is necessary to study other failure kinds and to assess the system working with the nonlinear model of the vehicle, actuator and sensor models.

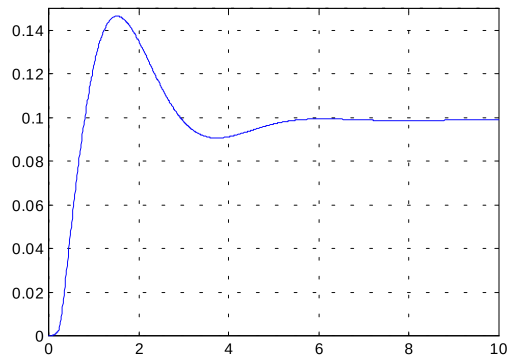

Figure 5 - Pitch-attitude time history for a 0.1 step in reference pitch-attitude (θ_{ref}) for the vehicle with the IFD system.

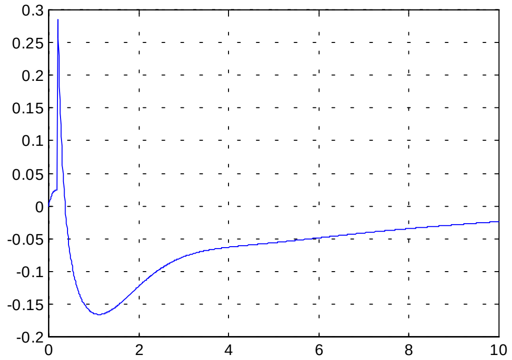

Figure 6 - Control effort (β) response for a 0.1 step in reference pitch-attitude (θ_{ref}) for the vehicle without the IFD system.

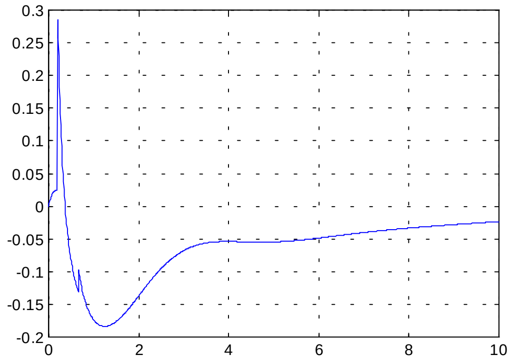

Figure 7 - Control effort (β) response for a 0.1 step in reference pitch-attitude ,(θ_{ref}) for the vehicle with the IFD system.

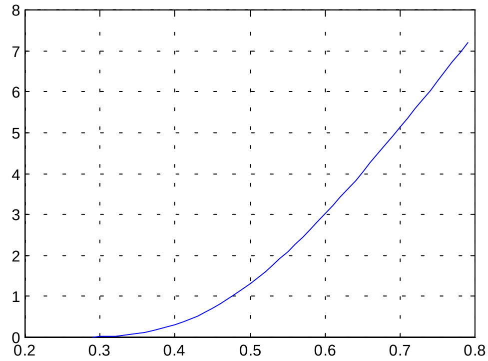

Figure 8 - Time history for the decision function η_2 for the vehicle with the IFD system, 30% uncertainty in U_0 and 30% in M_w

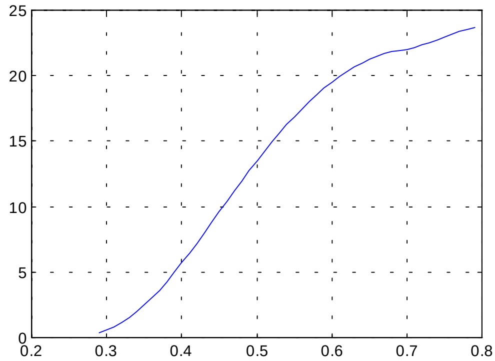

Figure 9 - Time history for the decision function $\dot{\eta}_2$ for the vehicle with the IFD system, 30% uncertainty in U_0 and 30% in M_w

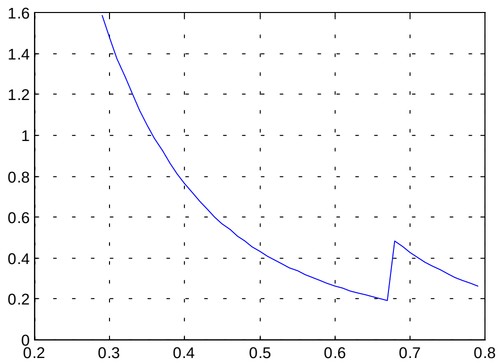

Figure 10 - Time history for the control rate effort $\dot{\beta}_z$ for the vehicle with the IFD system, 30% uncertainty in U_0 and 30% in M_w during the transition phase.

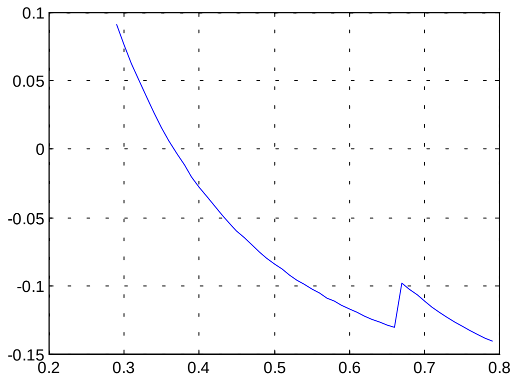

Figure 11 - Time history for the control effort β_z for the vehicle with the IFD system, 30% uncertainty in U_0 and 30% in M_w during the transition phase.

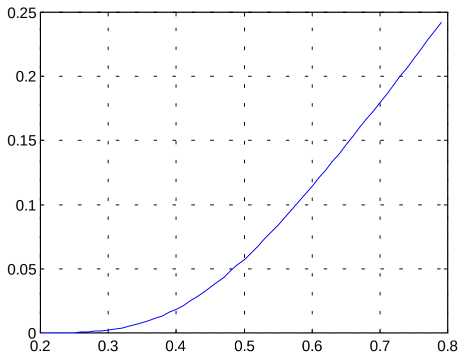

Figure 12 - Time history for the decision function η_1 for the vehicle with the IFD system , 30% uncertainty in U_0 and in M_w

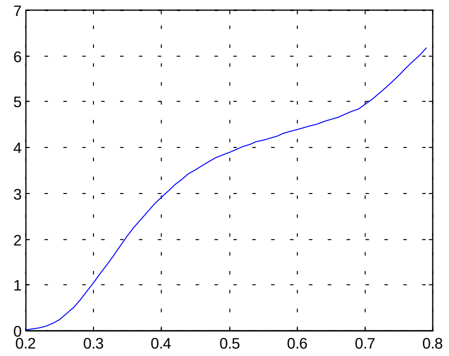

Figure 13 - Time history for the decision function η_3 for the vehicle with the IFD system , 30% uncertainty in U_0 and in M_w

As mentioned before the false alarm rate can be reduced with the inclusion of thresholds for the rates $\dot{\eta}_1$ and $\dot{\eta}_3$ into the detection logic and by trying to find more appropriate values for the thresholds of η_1 , η_2 and η_3 working together with these new logic ($\dot{\eta}_1$ and $\dot{\eta}_3$). As observed from the performed work, the system is detecting a failure between 20 to 70 milliseconds in the case of zero or maximum failure, a time sufficient enough to a safe reconfiguration of the flight control law. In the case of incipient failures it takes more time to detect the failure, however this does not degrade the system performance, since the failure is growing slowly, and so does not affect the vehicle safety.

The example system studied can only support a simple failure due to the fact that it uses only three sensed states. If the forward speed (U_0) had also been used as a sensed state variable, then it would be possible for the system to support a double failure. In this case, four observers could be designed and used.

As a problem for the studied system it can be mentioned that it is difficult for a satellite launcher to use angle of attack sensor, and so the practical implementation of the system described here is not so easy, however not impossible, since there are several high performance aircrafts that make use of angle of attack sensor . As it is well known, the angle of attack sensor can be replaced by an accelerometer, and so, the system can be implemented with sensors for normal acceleration, pitch-attitude and pitch-rate. In view of this, the implementation of this technique is more easy when there is an appropriate sensor, as is the case of the lateral-directional mode for a satellite launcher, when it is possible to use sensors for roll-rate (p), yaw-rate (r), roll-attitude (ϕ) and yaw-attitude (φ), and then the system will be able to support even a double failure, and still reconfigure the control law. It can also be mentioned that the present study did not take care of noise in the sensor outputs, a feature that can be included in future studies.

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