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Embedding FDI in launcher attitude controllers

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***Abstract*—It looks interesting the idea of obtaining more than a controller after designing a control system. In fact, given some conditions, it is possible to rearrange the controller states, revealing an observer structure, without changing the original system. Such proposition does not only means that the estimations of the plant states are available, but also that fault estimators can be built, providing an unexpected horizon of fault tolerance and even control reconfiguration. In order to illustrate that, a generalization aimed at obtaining observer-based forms from augmented, reduced or full order controllers will be applied to a launcher model, subject to sensor faults and external disturbance.**

I. Introduction

For aerospace applications, control system design is not only a matter of satisfying important requirements such as stability, performance, robustness to parameter variations and external disturbances, and so on, but there are also practical issues related to on-board implementation or even Fault Detection and Isolation (FDI), which draw the attention of the control engineer; it would not be surprising if complexity, flexibility, and memory storage could influence and even decide the choice between rivalling structures.

In such aspect, linear quadratic or PID controllers, which rely on single sets of scalar gains, would be preferable to H_∞ controllers, the latter ones typically possessing the same order than the plant model used for design (normally a simplified version of a even more complex validation model). By the other side, one may argue if and what additional features and benefits can be uncovered when using these larger realizations. Fortunately, it can be shown that almost any controller has an observer-based realization, as demonstrated by the deterministic separation principle [1]. By that principle, controller states can be made to correspond to the plant states, which can be conveniently arranged according to a suitable model realization so that they represent meaningful physical variables. In other words, the controller is redesigned as an observer and provides the estimates of the plant state vector, and maybe other desired estimates as external disturbances, biases, or faults, based on an augmented on-board model.

Starting from simple and practical techniques to compute the observer form [2], a generalization [3] was developed to augmented and reduced order controllers, where the Q-parametrization (YOULA form) and Luenberger formulation were exploited and produced explicitly separated structures, encompassing non-strictly proper models and the discrete domain as well. The generalization fits perfectly to robust control techniques such as H_∞ and μ syntheses, where the dynamics of the weightings (if any) can be accommodated in the YOULA parameter. Furthermore, the closed-loop poles partition of the resulting control system should be chosen with care, since the deterministic separation principle relies on reduced sets of state-feedback poles, state-estimator poles, and remaining YOULA parameter poles (or a static one), as it will briefly reviewed in this work.

Observer-based realizations can supply signals to be used in the detection and isolation of sensor or actuator faults and failures (bias), and to estimate external disturbances as well. Indeed, for a given controller, several observer-based realizations involving different on-board models (each of them taking into account a particular condition) can be devised; for each on-board model, one have to choose the best closed-loop eigenvalue distribution to satisfy given indexes on maximum estimation error and noise levels. One intends to cover the following subjects :

- The section II presents briefly the new techniques for determining the observer-based realization of any controller with arbitrary order.
- The section III presents the decoupled full pitch plane launcher model used in this study, the general H_∞ standard problem adopted for the attitude control and the design procedure combining H_∞ control and computational intelligence (CI).
- In the section IV, the CI-designed H_∞ controller and an on-board model are used to redesign the original controller as an observer, providing estimates not only of the plant states but also of the angle of attack and plant output bias, when noise and external disturbance are simultaneously acting on the system.
- In the section V, simulation results are supplied to validate the overall approach.
- The last section states the main conclusions and the next steps toward non-linear digital and hardware-in-the-loop simulations.

II. Observer-based structure with YOULA parameter

The general block diagram of the closed-loop system involving an observer-based controller is shown in the figure 1. In this section we recall (from [3]) the procedure to compute the observer-based realization (that is : the YOULA parameter $\mathbf{Q}(s)$, the state feedback gain $\mathbf{K_c}$ and the state estimator gain $\mathbf{K_f}$) of a given controller $\mathbf{K}(s)$ for a given on-board-model $\mathbf{G_0}(s)$ of the plant.

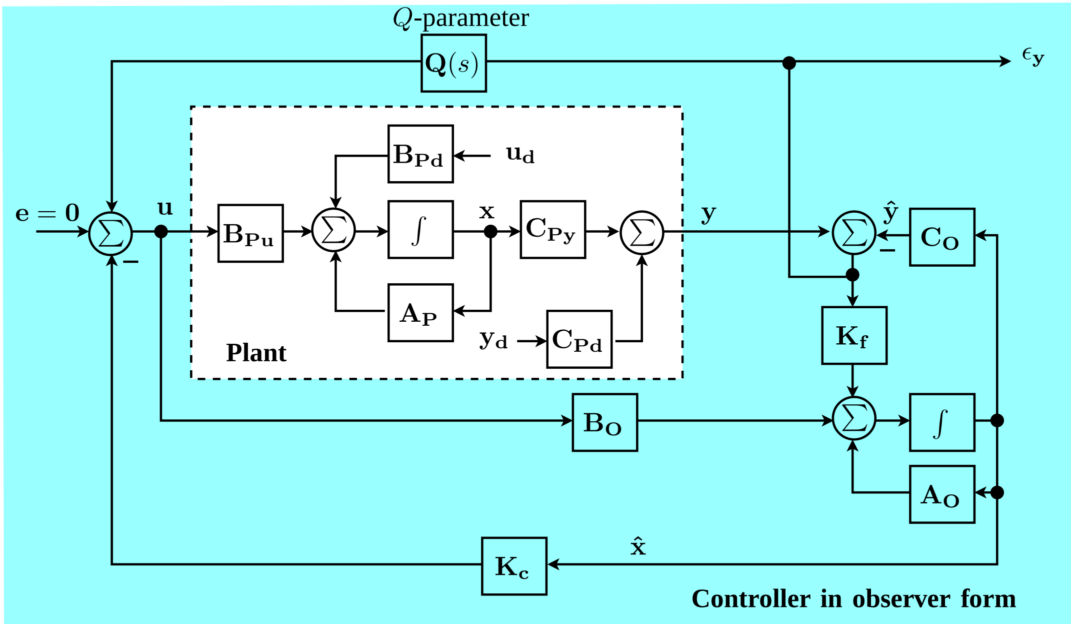

Figure 1. Observer-based structure using YOULA parameterization.

Consider the stabilizable and detectable n^{th} order on-board model $\mathbf{G_0}(s)$ (m inputs and p outputs) with state-space realization (1a) and the respective stabilizing n_K^{th} order controller $\mathbf{K}(s)$ with minimal state-space realization (1b) :

$$\begin{bmatrix} \dot{\mathbf{x}} \\ \mathbf{y} \end{bmatrix} = \begin{bmatrix} \mathbf{A_O} & \mathbf{B_O} \\ \mathbf{C_O} & \mathbf{0} \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{u} \end{bmatrix} \quad (1a)$$

$$\begin{bmatrix} \dot{\mathbf{x_K}} \\ \mathbf{u} \end{bmatrix} = \begin{bmatrix} \mathbf{A_K} & \mathbf{B_K} \\ \mathbf{C_K} & \mathbf{D_K} \end{bmatrix} \begin{bmatrix} \mathbf{x_K} \\ \mathbf{y} \end{bmatrix} . \quad (1b)$$

Remark : at first, input and output external disturbances (resp. $\mathbf{u_d}$ and $\mathbf{y_d}$ seen in the figure 1) are not considered, so that $\mathbf{A_O} = \mathbf{A_P}$, $\mathbf{B_O} = \mathbf{B_{Pu}}$ and $\mathbf{C_O} = \mathbf{C_{Py}}$.

The key idea is to express the controller as an LUENBERGER observer with a state vector $\mathbf{z} = \mathbf{Tx}$ and thus, we will denote $\mathbf{x_K} = \widehat{\mathbf{z}} = \widehat{\mathbf{Tx}} = \mathbf{T}\hat{\mathbf{x}}$. It can be shown [3] that $\mathbf{T}$ is the solution of a generalized non-symmetric RICCATI equation :

$$[-\mathbf{T}\ \mathbf{I}] \overbrace{\begin{bmatrix} \mathbf{A_O} + \mathbf{B_O D_K C_O} & \mathbf{B_O C_K} \\ \mathbf{B_K C_O} & \mathbf{A_K} \end{bmatrix}}^{\mathbf{A_{cl}}} \begin{bmatrix} \mathbf{I} \\ \mathbf{T} \end{bmatrix} = \mathbf{0}. \quad (2)$$

The characteristic matrix $\mathbf{A_{cl}}$ associated with the RICCATI equation (2) is nothing else than the closed-loop (c.-l.) dynamic matrix built on the state vector $[\mathbf{x}^T\ \mathbf{x_K}^T]^T$. Such a RICCATI equation can then be solved in $\mathbf{T} \in \mathbb{R}^{n_k \times n}$ by standard subspace decomposition techniques, that is :

- compute an invariant subspace associated with the set of n eigenvalues spec($\mathbf{\Gamma_n}$), chosen among $n + n_K$ eigenvalues in spec($\mathbf{A_{cl}}$), that is, $\mathbf{A_{cl}} \left[\mathbf{U_1}^T\ \mathbf{U_2}^T\right]^T = \left[\mathbf{U_1}^T\ \mathbf{U_2}^T\right]^T \mathbf{\Gamma_n}$, where $\mathbf{U_1} \in \mathbb{R}^{n \times n}$ and $\mathbf{U_2} \in \mathbb{R}^{n_K \times n}$. Such subspaces are easily computed using SCHUR decompositions of $\mathbf{A_{cl}}$.
- compute the solution

$$\mathbf{T} = \mathbf{U_2}\ \mathbf{U_1}^{-1} . \quad (3)$$

Then, 3 cases can be encountered :

- Full-order controller ($n_K = n$) : one can compute a state feedback gain $\mathbf{K_c} = -\mathbf{C_K}\ \mathbf{T} - \mathbf{D_K}\ \mathbf{C_O}$, a state estimation gain $\mathbf{K_f} = \mathbf{T}^{-1}\mathbf{B_K} - \mathbf{B_O}\ \mathbf{D_K}$ and a static YOULA parameter $\mathbf{Q}(\mathbf{s}) = \mathbf{D_K}$ such that the observer-based structure fitted with the YOULA parameter (depicted in the figure 1) is equivalent to the initial controller form according its input-output behaviour.
- Augmented-order controller ($n_K > n$) : the YOULA parameter becomes a dynamic transfer of order $n - n_K$.
- Reduced-order controller ($n_K < n$) : in this case, the observer-based structure shown in the figure 1 is no longer valid. However, if $n_K \geq n - p$ (p stands for the number of plant measurements), one can built a reduced-order estimator with a static YOULA parameter, involving an estimate $\hat{\mathbf{x}} = \mathbf{H_1}\hat{\mathbf{z}} + \mathbf{H_2}\ \mathbf{y}$ by a linear function of the controller state $\hat{\mathbf{z}}$ and the plant output $\mathbf{y}$, with the constraint $\mathbf{H_1}\ \mathbf{T} + \mathbf{H_2}\ \mathbf{C_O} = \mathbf{I_n}$. Otherwise, if $n_K < n - p$, a model reduction is required to built a (partial) state-observer realization.

Note that there is a combinatoric set of solutions according to the choice of n auto-conjugate eigenvalues among $n + n_K$ c.-l. eigenvalues. The range of solutions can be reduced according to the following considerations :

- a set of auto-conjugated eigenvalues must be chosen in order to find a real parametrization,
- an uncontrollable (resp. unobservable) eigenvalue in the system must be selected in the state-feedback dynamics (resp. state-estimation dynamics),
- lastly, the state-estimation dynamics (spec($\mathbf{A_O} - \mathbf{K_f C_O}$)) is usually chosen faster than the state-feedback dynamics (spec($\mathbf{A_O} - \mathbf{B_O K_c}$)).

Remark : Note that an observer-based realization cannot be computed if the model of the system exhibits an unobservable and uncontrollable (stable or unstable) eigenvalue. Indeed this eigenvalue is also a closed loop eigenvalue and it is not possible to affect it to state-feedback dynamics and state-estimator dynamics at the same time. (This remark will be considered in section IV to set-up the on-board model taking into account a model of the disturbance.)

The separation principle of the observer based realization allows to state that :

- the c.-l. eigenvalues can be separated into n c.-l. state-feedback poles (spec($\mathbf{A_O} - \mathbf{B_O K_c}$)), n c.-l. state-estimator poles (spec($\mathbf{A_O} - \mathbf{K_f C_O}$)) and the YOULA parameter poles (spec($\mathbf{A_Q}$)),
- the c.-l. state-estimator poles and the YOULA parameter poles are uncontrollable by $\mathbf{e}$,
- the c.-l. state-feedback poles and the YOULA parameter poles are unobservable from $\varepsilon_{\mathbf{y}}$. The transfer function from $\mathbf{e}$ to $\varepsilon_{\mathbf{y}}$ always vanishes.

Finally, as long as the order condition ($n_K \geq n - p$) is met, it is possible to augment the state of the on-board model $\mathbf{G_O}$ to take into account a model of external disturbances or faults (u_d and y_d in Figure 1). Therefore it will be possible to have on-line estimates of these disturbances for monitoring or FDI purposes. This property will be used in section IV. For instance it is possible to take into account a bias term b associated with a single output. Then the correspondent on-board model could be given by equation 4.

$$\left[\begin{array}{c}\dot{\mathbf{x}}\\ \dot{b}\\ \hline y\end{array}\right] = \overbrace{\left[\begin{array}{cc|c}\mathbf{A_P} & \mathbf{0} & \mathbf{B_P}\\ \mathbf{0} & 0 & \mathbf{0}\\ \hline \mathbf{C_P} & 1 & \mathbf{0}\end{array}\right]}^{\left[\begin{array}{c|c}\mathbf{A_O} & \mathbf{B_O}\\ \hline \mathbf{C_O} & \mathbf{0}\end{array}\right]} \left[\begin{array}{c}\mathbf{x}\\ b\\ \hline \mathbf{u}\end{array}\right] \qquad (4)$$

III. LAUNCHER MODELS AND DESIGN PROCEDURE

The full pitch plane decoupled model $\mathbf{G_L}$ of the Brazilian launcher VLS ([4], [5]) will be chosen to illustrate the design method. The generalized model used for the H_∞ technique is depicted in the figure 2.

The following transfer functions will be considered :

1) $\mathbf{G}_{\theta\beta}$ and $\mathbf{G}_{\theta\mathbf{d}}$ are the transfer functions of the linear rigid body decoupled model from control inputs β_z and w_v to the output $\theta = \theta_L$ (see the equation 5, where $\bar{Z}_\alpha$, $\bar{M}_\alpha$, $\bar{M}_q$, $\bar{Z}_{\beta z}$ and $\bar{M}_{\beta z}$ are aerodynamic coefficients, $\bar{U}$ is the velocity component in the vehicle body axis X_b, w is the linear velocity component according to the vehicle body axis Z_b, q is the angular velocity component according to the vehicle body axis Y_b, θ is the pitch angle, $\bar{x}_e$ is the length of the gases exhaustion arm ($\approx$ length of the pitch control arm), $\bar{g}$ is the gravity acceleration and $\bar{m}$ and $\bar{\dot{m}}$ are the launcher mass and its derivative).

$$\begin{bmatrix}\dot{w}\\ \dot{q}\\ \dot{\theta}\end{bmatrix} = \begin{bmatrix} -\dfrac{\bar{Z}_\alpha}{\bar{U}} & \dfrac{2\ \bar{\dot{m}}\ \bar{x}_e}{\bar{m}} + \bar{U} & -\bar{g}\cos(\bar{\theta})\\ \dfrac{\bar{M}_\alpha}{\bar{U}} & -\bar{M}_q & 0\\ 0 & 1 & 0\end{bmatrix}\begin{bmatrix} w\\ q\\ \theta\end{bmatrix} + \begin{bmatrix}\bar{Z}_{\beta z}\\ -\bar{M}_{\beta z}\\ 0\end{bmatrix}\beta_z + \begin{bmatrix}\dfrac{\bar{Z}_\alpha}{\bar{U}}\\ -\dfrac{\bar{M}_\alpha}{\bar{U}}\\ 0\end{bmatrix} w_v \qquad (5)$$

2) G_{B1} and G_{B2} are the transfer functions of the 1^{st} and 2^{nd} bending modes, given by the expression :

$$G_{Bi}(s) = \frac{\bar{K}_{Bi}}{s^2 + 2\ \zeta_M\ \bar{\omega}_{B,i}\ s + \bar{\omega}_{B,i}^2},\ i = 1,2 \qquad (6)$$

where $\bar{K}_{B,i}$, $\bar{\omega}_{B,i}$ and $\zeta_{B,i}$ are respectively the gain, the frequency and the damping factor of the i^{th} bending mode. Note that the complete model $\mathbf{G_L}$ comprises the models G_{Bi}, $G_{\theta\beta}$ and $G_{\theta d}$, and is associated to the state vector $[w\ q\ \theta\ \theta_{B11}\ \theta_{B12}\ \theta_{B21}\ \theta_{B22}\ ]^T$, where the latter four variables describe the bending dynamics.

3) $G_{e\theta}$ is the transfer function representing the (approximated) integral of the error signal $k_{w\theta}\, w_\theta - \theta$:

$$G_{e\theta}(s) = \frac{1}{s + \epsilon_{e\theta}} \qquad (7)$$

This transfer function is required to reduce the steady-state error to a step function at input w_θ (or otherwise reference input θ_{ref}). The parameter $\epsilon_{e\theta}$ is necessary to comply with the properties of the generalized model required by the H_∞ technique.

4) W_u is the weight on the control signal u :

$$W_u(s) = \left(\frac{s}{a_{u2}} + 1\right)^{-1}\left(\frac{s}{a_{u1}} + 1\right) \text{ with: } a_{u2} > a_{u1} \qquad (8)$$

The design procedure is based on computational intelligence and is illustrated by the figure 3, where the genetic algorithm (GA) is the sole responsible by the generation, combination, mutation and selection of the candidates[1] used in the controller design, according to the engineering requirements stored in a fuzzy system. Some of the main characteristics of the GA employed in the CI-based design mechanism are :

- Each gene is a binary number in the form 2^n, where n is the number of bits.
- Each weight $k_{\bullet\bullet}$ used in the H_∞ standard problem depicted in the figure 2 is composed of two genes in the form g_1/g_2 producing a numeric interval from $1/2^n$ to $2^n/1$. An entire set of weightings is called an individual.
- The roulette wheel is used for the reproduction of the individuals.

[1] Due to the text limitations, the reader is asked to refer to the existing literature (e.g., [6]) on the definition of each term used in this section.

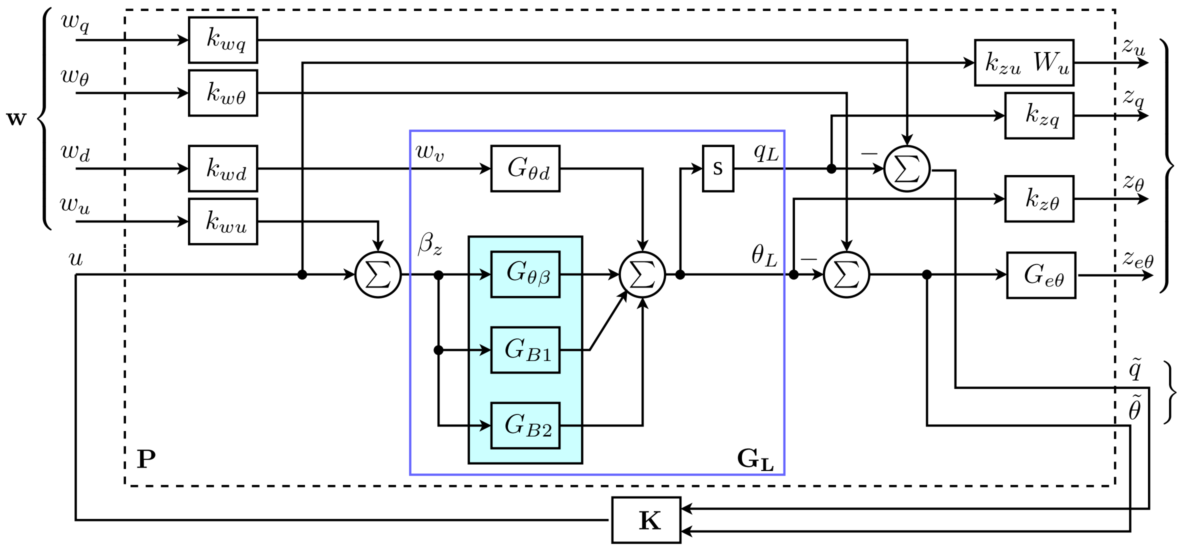

Figure 2. Generalized standard control problem for the VLS launcher.

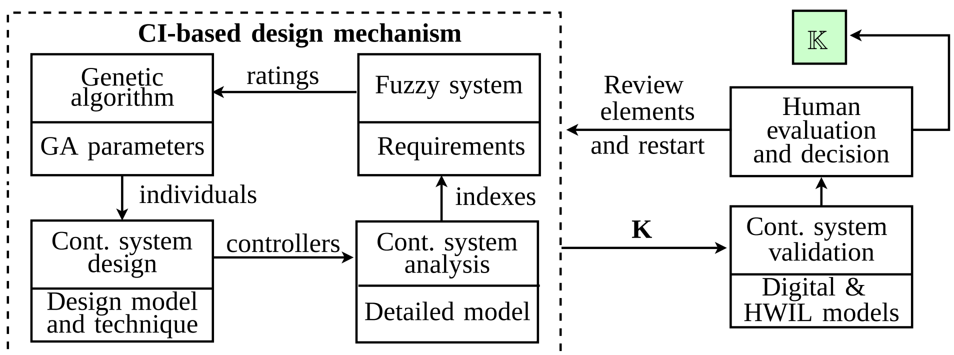

Figure 3. Block diagram of the CI-based design mechanism.

- Each run is finished by a stop criterion, based on the standard deviation of the last n ratings.
- A record of every individual is kept in order to avoid wasted time in repeated evaluations.
- The fitness function is a fuzzy system.

The fuzzy system is composed of linguistic variables, fuzzy sentences and fuzzy rules. The fuzzy sentences adopted in this work are Mamdani ones, based on mathematical expressions such as Gaussian or polynomial functions, with engineering specifications as linguistic input variables (rise time - t_r, settling time - t_s, overshoot - M_p, maximum amplitude of the control signal - u_{max}, gain margin - m_g, phase margin - m_p and dynamics of the closed-loop poles - p_{cl}, see the section IV). The linguistic output variable is "Rating" (the global rating). Each linguistic variable comprises the respective fuzzy sentences and an universe of discourse. An hypothetical example according to the specification "gain margin" would be :

- The linguistic variable m_g is associated with the control system gain margin, where its universe of discourse is [0, 20] [dB]. The fuzzy sentence $\{$*Unsatisfactory* $m_g\}$ is defined by a z-polynomial function (equation 9) and the pair $\langle a, b\rangle$, with $a = 0$ and $b = 6$.

$$f(x) = \begin{cases} 1, x \leq a \\ 1 - 2\left[(x-a)/(b-a)\right]^2, a < x \leq (a+b)/2 \\ 2\left[b - x/(b-a)\right]^2, (a+b)/2 < x \leq b \\ 0, x > b \end{cases} \tag{9}$$

The fuzzy system rules are given by the equation (10).

$$\begin{aligned} E \triangleq\ & (\text{“}t_r \text{ is Satisfactory”}) \text{ and } (\text{“}t_s \text{ is not Large”}) \\ & \text{and } (\text{“}u_{max} \text{ is Satisfactory”}) \\ & \text{and } (\text{“}m_g \text{ is not Unsatisfactory”}) \\ & \text{and } (\text{“}m_p \text{ is not Unsatisfactory”}) \\ & \text{and } (\text{“}p_{cl} \text{ is Slow”}) \\ R_1 :\ & \text{If } E \text{ and } (\text{“}M_p \text{ is Satisfactory”}) \\ & \text{then } (\text{“Rating is Good”}) \\ R_2 :\ & \text{if } E \text{ and } (\text{“}M_p \text{ is not Satisfactory”}) \\ & \text{then } (\text{“Rating is Regular”}) \\ R_3 :\ & \text{If not } E \text{ then } (\text{“Rating is Bad”}) \end{aligned} \tag{10}$$

Remark : a further implicit specification is represented by the initial upper bound on the cost γ used in the H_∞ design, associated with system robustness.

IV. OBSERVER-BASED REALIZATION

Remark : To prevent numerical problems when solving in $\mathbf{T}$ the RICCATI equation (2) required to compute the observer-based realization, it is recommended to adopt balanced realizations of both the on-board model $\mathbf{G_O}$ and the initial controller $\mathbf{K}$. Particularly for the former, such balancing will most probably produce state variables without physical meaning. However, it is possible to keep the original state-space matrices and states by recalculating the state feedback and the state estimator gains such that $\mathbf{K_c} = \bar{\mathbf{K}}_\mathbf{c}\ \mathbf{M}$ and $\mathbf{K_f} = \mathbf{M}^{-1}\ \bar{\mathbf{K}}_\mathbf{f}$, where $\mathbf{M}$ is the transformation matrix from the original meaningful state vector $\mathbf{x}$ to the new one $\bar{\mathbf{x}}$ (i.e. $\bar{\mathbf{x}} = \mathbf{M}\ \mathbf{x}$). A second approach (which is used in this work) is to keep the original controller $\mathbf{K}$, and to recover the estimates of the original states by means of the equivalent transformation $\hat{\mathbf{x}}_\mathbf{i} = \mathbf{T_i}^{-1}\mathbf{x_K}$, where $\mathbf{T_i}^{-1}$ is the i^{th} row of the inverse of $\mathbf{T}$, a compound matrix built upon the balanced realization and the observer-based redesign transformation matrices.

Observer-based redesign. In few words, the closed-loop control system composed by the on-board model $\mathbf{G_O}$ and the original controller $\mathbf{K}$ is used to compute the equivalent observer-based controller $\mathbf{K_{OBC}}$. In this work, the on-board model $\mathbf{G_O}$ (equation 11b) is built from the balanced realization $\mathbf{G_L}$ (figure 2) added to the estimates $\hat{b}_q$ (output bias on q_L) and $\hat{w}_v$ (formerly disturbance input w_v). It follows that $\mathbf{G_O}$ has one state more than $\mathbf{K}$, the condition "reduced-order controller ($n_K > n - p$)" stated at the section II is applied, and two matrices $\mathbf{H_1}$ and $\mathbf{H_2}$ must be calculated (see [3]).

$$\begin{bmatrix} \dot{\mathbf{x}}_\mathbf{L} \\ \hline \tilde{q} \\ \tilde{\theta} \end{bmatrix} = \left[\begin{array}{c|cc} \mathbf{A_P} & \mathbf{B_{Pd}} & \mathbf{B_{Pu}} \\ \hline \mathbf{C_{Pq}} & D_{Pdq} & D_{Puq} \\ \mathbf{C_{P\theta}} & D_{Pd\theta} & D_{Pu\theta} \end{array}\right] \begin{bmatrix} x \\ \hline w_v \\ \beta_z \end{bmatrix} \tag{11a}$$

$$\begin{bmatrix} \dot{\mathbf{x}}_\mathbf{L} \\ \dot{\hat{w}}_v \\ \dot{\hat{b}}_q \\ \hline \tilde{q} \\ \tilde{\theta} \end{bmatrix} = \left[\begin{array}{ccc|c} \mathbf{A_P} & \mathbf{B_{Pd}} & \mathbf{0} & \mathbf{B_{Pu}} \\ \mathbf{0} & \lambda_\alpha & 0 & 0 \\ \mathbf{0} & 0 & \lambda_q & 0 \\ \hline \mathbf{C_{Pq}} & D_{Pdq} & 1 & D_{Puq} \\ \mathbf{C_{P\theta}} & D_{Pd\theta} & 0 & D_{Pu\theta} \end{array}\right] \begin{bmatrix} \hat{x_L} \\ \hat{w_v} \\ \hat{b}_q \\ \hline \beta_z \end{bmatrix} \tag{11b}$$

Comment on the choice of the estimation dynamics. The steady state of the variable w_v cannot be observed, according to the transfer function $G_{\theta d}$ (there is a zero at $s = 0$). By the other side, if one replaces the state variable w in the equation 5 by the expression $\bar{U}\alpha + w_v$ (where α is the angle of attack), then one realises that the steady state of w_v has no effect on α, θ and q (equation 12), only its time derivative.

$$\begin{bmatrix} \dot{\alpha} \\ \dot{q} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} -\frac{\bar{Z}_\alpha}{\bar{U}} & \frac{A_{12}}{\bar{U}} & \frac{A_{13}}{\bar{U}} \\ M_\alpha & -M_q & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \alpha \\ q \\ \theta \end{bmatrix} + \begin{bmatrix} \frac{\bar{Z}_{\beta z}}{\bar{U}} \\ -M_{\beta z} \\ 0 \end{bmatrix} \beta_z + \begin{bmatrix} -\frac{1}{\bar{U}} \\ 0 \\ 0 \end{bmatrix} \dot{w}_v \tag{12}$$

Therefore, these variables can be observed even if the steady state of the disturbance is not observable (clearly, the lateral velocity w cannot be observed at this level of the attitude control loop but could be observed at the level of the guidance loop taking into account other measurements). For that reason, one considers also the estimation of the attack angle $\hat{\alpha}$ as given by the expression $(\hat{w} - \hat{w}_v)\ \bar{U}^{-1}$. Assigning $\lambda_\alpha = 0$ means to follow a constant steady state of the variable w_v, which is not only unobservable, as noted before, but is also uncontrollable. Therefore, this choice is prohibited as the resulting on-board model would have an unobservable and uncontrollable eigenvalue and it would not possible to affect it to state-feedback dynamics and state-estimator dynamics at the same time, according to the remark stated at the end of section II; as $\lambda_\alpha \neq 0$, one chooses $\lambda_\alpha = -1$. By the other side, the variable b_q is observable, and one assigns $\lambda_q = 0$, a common choice for unknown input estimation; hence, the model of the bias $\hat{b}_q$ is a pure integrator with an unknown initial condition and, as the initial controller is a stabilizing controller, the state $\hat{b}_q$ will converge to this unknown initial condition (i.e. bias steady state) with the state-estimation dynamics $(\mathbf{A_O} - \mathbf{K_f C_O})$.

Choice of the closed-loop poles. As stated in the section II, once that $\mathbf{K}$ is a reduced-order controller, the YOULA parameter is static, and no pole is assigned to it. Therefore, only the controller and the observer share the poles, and the two uncontrollable ones (n. 16 and 17 in the table I) are allocated to the state-feedback dynamics, and also the 7 slowest poles of the remaining set, forming the option "A" in the table I; option "B" results from the exchange of one of the slowest poles (no. 15) with a faster one (pole n. 11). The reason for defining these two options will be clarified later (see section V). Furthermore, it should be told that the choices above were defined manually according to the noise levels and estimation errors, but an automatic procedure could also be adopted.

A further point related to the closed-loop poles is associated with their natural frequencies : sets with faster poles most probably imply noisier estimates; that was the reason to add the design specification p_{cl} to the fuzzy system (see the section III), which gives better ratings to candidates with more compressed sets of poles near the origin of the complex plane.

V. EVALUATION OF THE COMPLETE DESIGN

The validation model used in the simulations includes the actuator dynamics, a realistic wind profile, noise sources and a bias profile applied to one of the plant outputs. The estimates were produced with the expressions $\hat{\alpha} = \mathbf{H_{\alpha 1}}\ \hat{z} + \mathbf{H_{\alpha 2}}\ y$ and $\hat{b}_q = \mathbf{H_{q1}}\ \hat{z} + \mathbf{H_{q2}}\ y$. There is a reason for using independent matrices $\mathbf{H_{\alpha i}}$ and $\mathbf{H_{qi}}$: during the simulations, it was noted that the option "A" is beneficial to the estimate $\hat{b}_q$ but not to $\hat{\alpha}$ regarding noise levels. By the other side, the effect of option "B" is opposite. However, on doing the redesign for each option and then composing the matrices $\mathbf{H_1}$ and $\mathbf{H_2}$ respectively for each estimate, it was possible to profit better noise levels as shown in the figures 4 and 5, where a disturbance signal (wind gust profile) and a bias level on the q_L output (combined with noise sources added to both outputs)

Table I
CLOSED-LOOP DISTRIBUTION, OPTIONS "A" AND "B".

Closed-loop poles no.	Value	Option "A"	Option "B"
1,2	$-1.3887 \pm 80.4553\ i$	$\mathbf{K_c}$	$\mathbf{K_c}$
3,4	$-3.2979 \pm 80.5979\ i$	K_f	K_f
5,6	$-2.3452 \pm 29.6751\ i$	$\mathbf{K_c}$	$\mathbf{K_c}$
7,8	$-4.1625 \pm 29.6290\ i$	K_f	K_f
9,10	$-5.3201 \pm 4.3009\ i$	K_f	K_f
11	-4.6420	K_f	$\mathbf{K_c}$
12	-3.4123	K_f	K_f
13	-0.0062	$\mathbf{K_c}$	$\mathbf{K_c}$
14	-0.0919	$\mathbf{K_c}$	$\mathbf{K_c}$
15	-0.8594	$\mathbf{K_c}$	K_f
16 (UC)	-1.0000	$\mathbf{K_c}$	$\mathbf{K_c}$
17 (UC)	0.0000	$\mathbf{K_c}$	$\mathbf{K_c}$

UC = uncontrollable.

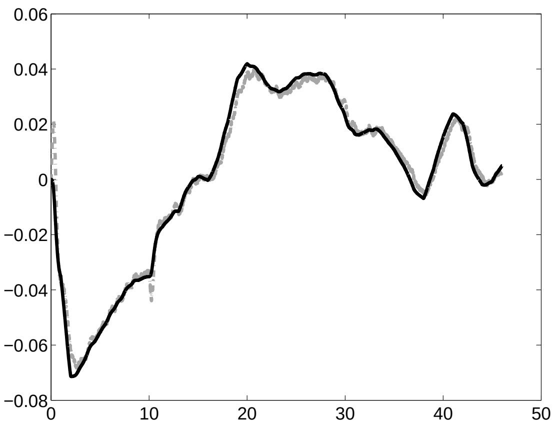

Figure 4. Estimation of the attack angle $\hat{\alpha}$ (grey line) with simultaneous occurrence of q_L output bias (abrupt variation at 10 seconds) and external disturbance (wind gust profile); noise sources added to both plant outputs. Black line: real attack angle.

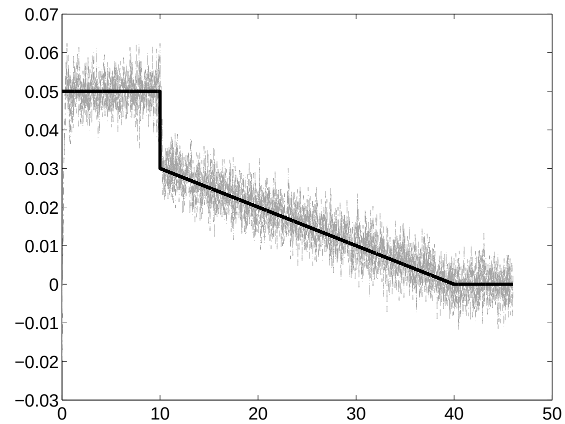

Figure 5. Estimation of the bias $\hat{b}_q$ at the q_L output (grey line) with simultaneous occurrence of external disturbance (wind gust profile); noise sources added to both plant outputs. Black line: real bias.

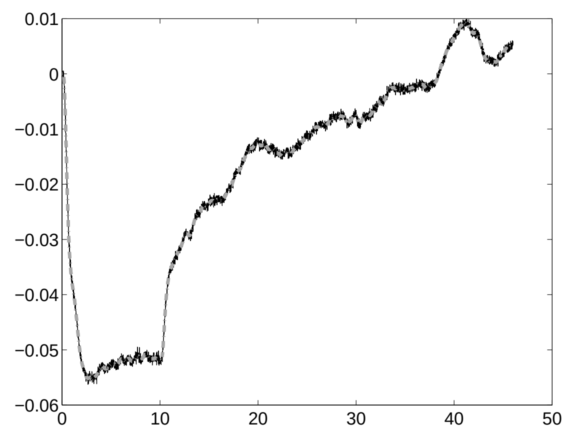

Figure 6. Estimation of the output $\hat{\theta}$ (grey line) with simultaneous occurrence of q_L output bias (abrupt variation at 10 seconds) and external disturbance (wind gust profile); noise sources added to both plant outputs. Black line: real attitude angle θ.

were applied simultaneously into the system. The estimate $\hat{b}_q$ could be used in fault detection and isolation (bias fault). The abrupt variation of the bias b_q at 10 seconds yields a small and temporary deterioration of the estimate $\hat{\alpha}$. Finally, the estimate $\hat{\theta}$ is not only insensitive to that variation, but is also very close to the real attitude angle θ.

VI. CONCLUSION

As it was shown in this work the controller structure can be employed not only in the control action but also to provide estimates of the plant state variables and other relevant signals, as faults acting on the system. The procedure demonstrated here relies on a CI-based mechanism combined with an H_∞ design technique with further observer-based redesign, and one intends to expand that mechanism to find the best combinatoric of the c.l.-poles as well. Non-linear and hardware-in-the-loop simulations are also previewed in the future work, and the same strategy [7] that provided linear-quadratic gain scheduled controllers will be employed, that is, to include a specification in the fuzzy system taking into account the smoothing of a particular characteristic of the controller (for instance: gains $\mathbf{K_c}$ and $\mathbf{K_f}$).

REFERENCES

[1] J. Schumacher, "Compensator synthesis using (c,a,b)-pairs," *Automatic Control, IEEE Transactions on*, vol. 25, no. 6, pp. 1133–1138, Dec 1980.
[2] D. J. Bender and R. A. Fowell, "Computing the estimator-controller form of a compensator," *International Journal of Control*, vol. 41, no. 6, pp. 1565–1575, 1985.
[3] D. Alazard and P. Apkarian, "Exact observer-based structures for arbitrary compensators," *International Journal of Robust and Non-linear control*, no. 9, pp. 101–118, 1999.
[4] W. C. L. Filho and D. S. Carrijo, "Control system of Brazilian launcher," in *Proc.* 4^{th} *ESA International Conference on Spacecraft Guidance, Navigation and Control Systems*, 1999.
[5] P. Oliva and W. C. L. Filho, "Rocket tracking and decoupling eigenstructure control law," *Journal of the Brazilian Society of Mechanical Sciences*, vol. 22, no. 2, 2000.
[6] P. J. Fleming and R. C. Purshouse, "Evolutionary algorithms in control systems engineering: a survey." *Control Engineering Practice*, vol. 10, pp. 1223–1241, 2002.
[7] F. O. Ramos and W. C. L. Filho, "Design upgrade and validation of a launcher vehicle attitude controller combining genetic and linear quadratic optimization," in *Proc.* 19^{th} *International Congress of Mechanical Engineering*, 2007.