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COMPUTATIONAL INTELLIGENT SATELLITE ATTITUDE CONTROL DESIGN

Fausto Ramos
Instituto de Aeronáutica e Espaço (IAE/CTA), São José dos Campos, Brazil
fausto@iae.cta.br
Luiz Carlos Gadelha De Souza
Instituto Nacional de Pesquisas Espaciais (INPE), São José dos Campos, Brazil
gadelha@dem.inpe.br
Ernesto Araujo
Instituto Nacional de Pesquisas Espaciais (INPE), São José dos Campos, Brazil
ernesto.araujo@lit.inpe.br
Universidade Federal de São Paulo (UNIFESP), São Paulo, Brazil
ernesto.araujo@unifesp.br

ABSTRACT

A Computational Intelligent (CI) mechanism for control system design employing robust and random search techniques applied to a satellite model and using a reaction wheel is presented in this paper. The embedding of computational intelligence mechanisms in control system design can be attractive for on-board re-design purposes, according to the FireSat satellite model considered here. Moreover, it is demonstrated that effective search and scoring procedures can replace human-performed trial-and-improvement actions for gain computation, and produce performance indexes and torque levels compatible with real world specifications. The Computational Intelligence mechanisms employed in this paper intertwine genetic algorithm, which generates, combines, and selects candidate controllers, with fuzzy system, for scoring performance indexes and torque levels of the controller candidates which, in turn, are subsequently used by the genetic algorithm. A combination of this design approach, recently proposed by the authors in a previous paper, demonstrated its usefulness according four different techniques, while in this paper an H_2 truncated controller is adopted in order to consider the disadvantage of robust techniques that usually supply high-order controllers.

INTRODUCTION

Several control system design techniques are available nowadays as alternatives to improve control performance. Only to mention few, these techniques encompasses Optimal, Robust and Adaptive Control techniques. Additionally, approaches that merge control techniques, such as Multiobjective Control which combines H_2, H_∞ and L_1 norms from Robust Control [1], emerged due to the increasing demands of new problems and requirements.

Despite the success of classical mathematical techniques behind these theories, which guarantee stability and performance bounds, Computational Intelligence (CI) approach has been presented as an important alternative for control design. Furthermore, due to its features and applications it has also demonstrated its value in modern control systems. In the control engineering area, CI provides the use of

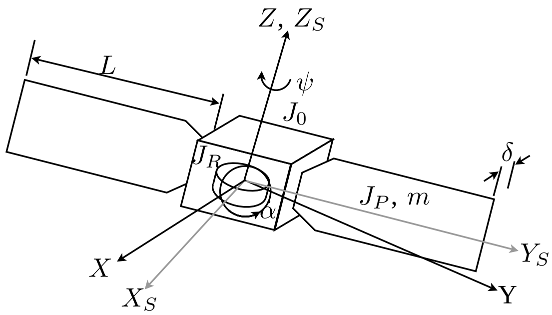

Fig. 1. Satellite description.

classical and modern techniques [2] for system identification and modeling as well as design, and optimization. Computational intelligence allowed the recent appearance of many works dealing with the automated design of automatic control systems (sometimes multidisciplinary [3]), mostly off-line (but also on-line ones [4]) and based on genetic algorithms (GAs) [5]. For instance, tuning procedure of weighting functions of an H_∞ controller is presented in [6]; genetic-Taguchi algorithm to design robust and optimal controllers for a F-16 fighter is described in [7]; multi-objective physical programming methodology associated to GAs is introduced in [8] and employed it to the ACC robust control benchmark in [9], resulting in the improvement of all previous solutions; linear-quadratic design of a launch vehicle attitude controller is extended to work with GAs in [10].

Concerning the aerospace area, in turn, fuzzy systems are applied to attitude control system design of launchers ([11], [12], [13]), including the Space Shuttle [14], [15], and also aircrafts, missiles and satellites ([16], [17], [18]). Stability may be achieved by combining the linear-quadratic approach with fuzzy controllers ([19], [20]) or by Lyapunov Stability Theory ([21],[22]). Fuzzy Systems are frequently combined with Neural Networks ([22],[23]) with integrated benefits of learning, computational efficiency and knowledge representation.

This work addresses an automated on-board re-design for the FireSat satellite model by using some elements of CI, namely genetic algorithms and fuzzy systems. The on-board re-design is (*i*) desired, once variations of the satellite parameters may degrade its performance, and (*ii*) possible, because the design time is compatible with the manoeuvring time of the satellite.

SATELLITE MODEL

Consider a satellite as depicted in Fig 1. The linear model with appendages and reaction wheel [24] is represented by eq. 1, such that L is the appendage length; m is the appendage mass; J_0 is the inertia moment of the rigid body related to its mass centre; J_R is the inertia moment of the reaction wheel related to its mass centre; J_P is the inertia moment of the appendage related to its mass centre; $J = J_0 + J_R + J_P$; K is the elastic constant

$$\begin{aligned}
\ddot{\psi}(t) &= \beta^{-1}\left[2LK_d\dot{\delta}(t) + 2LK\delta(t) - \tau(t)\right] \quad \text{where } \beta = \left(J - J_R - 2L^2 m\right) \\
\ddot{\delta}(t) &= \beta^{-1}\left[L\tau(t) - K_d m^{-1}\left(J - J_R\right)\dot{\delta}(t) - K m^{-1}\left(J - J_R\right)\delta(t)\right] \\
\ddot{\alpha}(t) &= \beta^{-1}\left[\left(J - 2L^2 m\right)J_R^{-1}\tau(t) - 2LK_d\dot{\delta}(t) - 2LK\delta(t)\right]
\end{aligned} \tag{1}$$

$$\begin{gathered}
\dot{\mathbf{x}}(\mathbf{t}) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\tau(t),\ \mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) + \mathbf{D}\tau(t),\ \mathbf{x}(t) = \left[\psi(t)\ \delta(t)\ \dot{\psi}(t)\ \dot{\delta}(t)\right]^T \\
\mathbf{A} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 2LK\beta^{-1} & 0 & 2LK_d\beta^{-1} \\ 0 & -K\eta & 0 & -K_d\eta \end{bmatrix}, \mathbf{B} = \begin{bmatrix} 0 \\ 0 \\ -\beta^{-1} \\ L\beta^{-1} \end{bmatrix}, \quad \begin{matrix} \mathbf{C}, \mathbf{D}, \\ \eta = \left(J - J_R\right)m^{-1}\beta^{-1} \end{matrix}
\end{gathered} \tag{2}$$

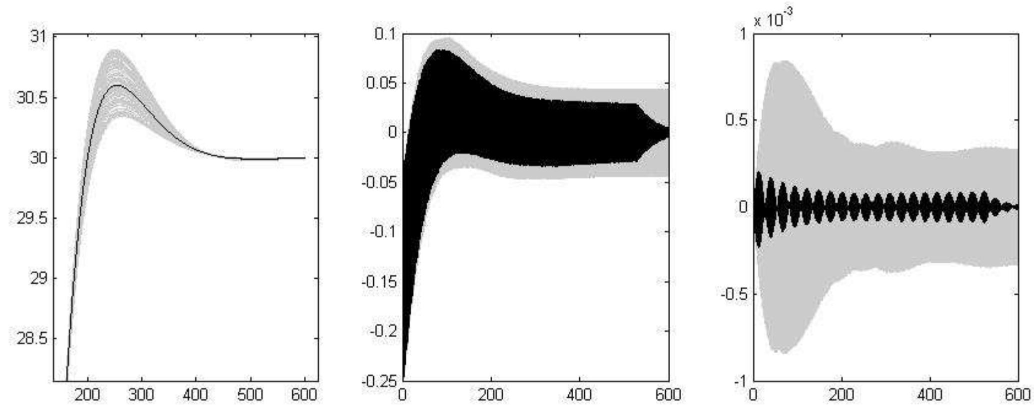

Fig. 2. Degradation of the performance indexes (grey lines). From the left to the right: overshoot, actuation signal and elastic displacement for a set of random combinations of K and m (10% maximum uncertainty), based on a satellite control system designed with the nominal model (black lines).

of the appendages; K_d is the mechanic dissipation constant of the appendages; $[X, Y, Z]$ e $[X_S, Y_S, Z_S]$ are, respectively, the main and satellite reference axes; $\delta(t)$ is the elastic displacement of the appendages related to the Y_S axis; $\psi(t)$ is the satellite yaw angle; $\dot{\alpha}(t)$ is the rotation velocity of the reaction wheel related to the Y_S axis; $\tau(t)$ is the torque applied to the reaction wheel. The disturbance input in the original set of equations, without loss of generality, is not considered.

Due to the fact that eq. (1) is a linearly dependent set; only the first two sub-equations ($\ddot{\psi}$ and $\ddot{\delta}$) are considered in the design. The last equation is useful to obtain the α output. The state-space description of the satellite model is represented by eq. (2).

Parametric uncertainty

The influence due to the parametric uncertainty of the satellite model in the control system design is presented in Fig.2, where a random combination of uncertainties only for the mass m and the elastic constant K is considered. Deterioration of the overshoot according to the step response, a higher demand of the actuator, and a considerable impact on the elastic displacement of the panels is observed. Such deterioration can not be reverted, unless the control system can be tuned on-board. This problem is the motivation for the re-design mechanism proposed in this work.

The FireSat satellite

The FireSat satellite model [25] is employed to devise the requirements associated to a satellite with appendages. Its mission is Earth-looking, except for one optional manoeuvre per month to a chosen target, in which it must rotate up to 30^o in less than 10 minutes. The actuation element is a reaction wheel; its choice is dependent of the maximum amplitude on the actuation signal required by the designed controller. Commercial models are available with torque output ranges of 0.01-1.0 [Nm], influencing weight (2-20 [kg]) and power consumption (10-110 [W]); therefore, the smaller the actuation torque, the most attractive the controller.

CONTROL SYSTEM

The control system of the satellite model is depicted in Fig.3. The sizes and contents of the measurement vector γ (reflecting the matrices $\mathbf{C}$ and $\mathbf{D}$ of eq. (2)), the reference input γ_{ref} and the controller input $\mathbf{u}_c$ depend on the controllers. The output y is renamed to γ to avoid misinterpretation of the variable y_{ref}.

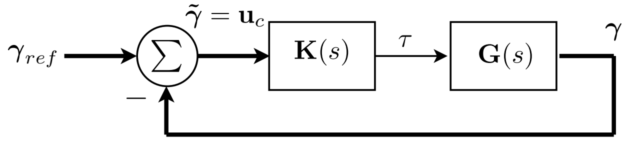

Fig. 3. Attitude control system of the satellite.

DISO controller
A double-input-single-output (DISO) controller with first order transfer functions $a/(s+b)$ and $c/(s+b)$ from inputs to output is defined as:

$$\begin{aligned} \boldsymbol{\gamma}(t) &= \left[\psi(t) \;\; \dot{\psi}(t)\right]^T \\ \boldsymbol{\gamma}_{ref}(t) &= [\psi_{ref}(t) \;\; 0]^T \\ \dot{x}_c(t) &= -b\, x_c(t) + [a \;\; c]\, \mathbf{u}_c(t) \\ \tau(t) &= x_c(t) + \mathbf{0}\; \mathbf{u}_c(t) \end{aligned} \tag{3}$$

Robust controller
The gain, $K(s)$, may also be assigned, for instance, as an H_2 robust control technique by using eq. (4).

$$\begin{aligned} \boldsymbol{\gamma}(t) &= \left[\psi(t) \;\; \dot{\psi}(t)\right]^T \\ \boldsymbol{\gamma}_{ref}(t) &= [\psi_{ref}(t) \;\; 0]^T \\ \dot{\mathbf{x}}_c(t) &= \mathbf{A}_c\, \mathbf{x}_c(t) + \mathbf{B}_c\, \mathbf{u}_c(t) \\ \tau(t) &= \mathbf{C}_c\, \mathbf{x}_c(t) + \mathbf{D}_c \mathbf{u}_c(t) \end{aligned} \tag{4}$$

The controller is built according to the generalized feedback model of the satellite control system as shown in Fig. 4. The augmented plant $\mathbf{P}$ contains the external disturbances w_τ and $\mathbf{w}_y$, respectively, at the input and the output of the plant. Moreover, it incorporates the weighting values $\mathbf{k_y} = \text{diag}(k_\psi,\ k_r)$ (amplitude of the output vector $\mathbf{y}$), k_τ (amplitude of the actuation signal τ) and k_w (amount of the disturbance at the plant input). In the transfer function matrix, $\mathbf{G}$, of the satellite model given in eq. (2) the matrices $\mathbf{C}$ and $\mathbf{D}$ are chosen so that $\mathbf{y} = \left[\psi\ \dot{\psi}\right]^T$, such that $r \triangleq \dot{\psi}$.

Applying the H_2 control technique requires a state-space description of the generalized model, that is given by eq.(5).

COMPUTATIONAL INTELIGENT CONTROL APPROACH

The CI-based control approach proposed here is represented in Fig. 5. First, a GA generates, reproduces and mutates the candidates, reinserting the best fitted one (the elite) of the last generation in the current candidate. Afterward, these candidates are employed in the design of candidate controllers. Performance indexes, such as rise time, settling time, and overshoot, as well as the amplitude of the actuation signal, $\tau(t)$, are obtained from the step response of the resulting control systems (Fig. 3). They are evaluated with a cost function implemented with a fuzzy system. According to the results, the GA chooses a new elite and the process keeps on until a stop criterion is satisfied.

GA characteristics
The main characteristics of the GA are: 10 binary bits per gene of each individual (the H_2 controller is composed of four gains $k_i = a_i/b_i$

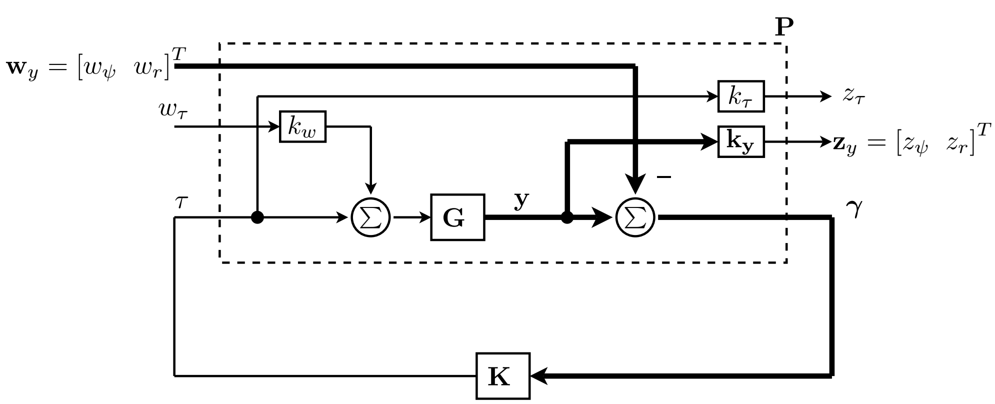

Fig. 4. Satellite generalized feedback control system.

$$
\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \\ \dot{x}_3(t) \\ \dot{x}_4(t) \\ z_\psi(t) \\ z_r(t) \\ z_\tau(t) \\ \gamma_\psi(t) \\ \gamma_r(t) \end{bmatrix} = \left[\begin{array}{cccc|ccc|c} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & k_1 & k_2 & 0 & 0 & k_w & 1 \\ \hline -k_\psi K & -k_\psi K_d & -k_\psi m & 0 & 0 & 0 & 0 & 0 \\ 0 & -k_r K & -k_r K_d & -k_r m & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & k_\tau \\ \hline K & K_d & m & 0 & 1 & 0 & 0 & 0 \\ 0 & K & K_d & m & 0 & 1 & 0 & 0 \end{array} \right] \begin{bmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \\ x_4(t) \\ w_\psi(t) \\ w_r(t) \\ w_\tau(t) \\ \tau(t) \end{bmatrix} \tag{5}
$$

$k_1 = -K_d m^{-1} \beta^{-1} (J - J_R), \;\; k_2 = -K m^{-1} \beta^{-1} (J - J_R)$

and a multiplier, or 9 genes, so 90 binary bits are required for each individual); 10 individuals per generation; mutation rate of 10%. Each run has a minimum of 5 and a maximum of 20 generations. In order to assure high population diversity, for each new run and depending on the rating, part of the population is recreated randomly. Each run is finished by a stop criterion supplied by the ratings of the generations and is followed by a new run. This batch running process also finishes if the coletive rating meets that same criterion. The stop criterion is based on the standard deviation of the last n ratings (< 0.1%). The roulette wheel is used for reproduction based on the logarithmic function in the form $log_{10}(rating - min.rating + 1)$. Only the first bit (most significative) of each gene is not used for mutation operations. The fitness function is a fuzzy system.

Fuzzy system characteristics

The fuzzy system is Mamdani-type. The linguistic input variables are related to the performance indexes, as detailed next. The linguistic output variable is "Rating". The membership functions for the fuzzy sets follows three types: (*i*) Gaussian membership function given by the pair $\langle a, b \rangle$ denoting the shape and the position of the membership function in eq. (6); (*ii*) z-polynomial membership function given by the pair $\langle a, b \rangle$ in eq. (7); (*iii*) triangular membership function given by the triple $\langle a, b, c \rangle$ in eq. (8).

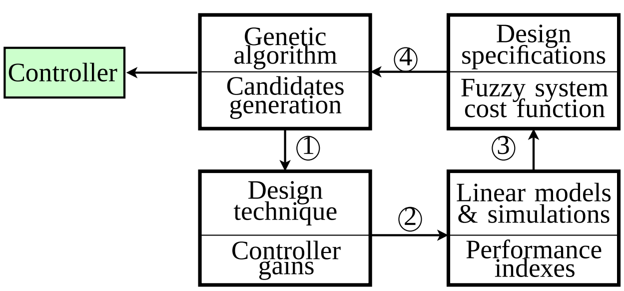

Fig. 5. The CI-based control approach.

$$f(x; a, b) = 1/(1 + exp(-a(x - b))) \tag{6}$$

$$
f(x; a, b) = \begin{cases} 1, x \leq a \\ 1 - 2\left[(x-a)/(b-a)\right]^2, \\ \quad a < x \leq (a+b)/2 \\ 2\left[b - x/(b-a)\right]^2, \\ \quad (a+b)/2 < x \leq b \\ 0, x > b \end{cases} \tag{7}
$$

$$
f(x; a, b, c) = \begin{cases} 0, x \leq a \\ (x-a)/(b-a), a \leq x \leq b \\ (c-x)/(c-b), b \leq x \leq c \\ 0, x \geq c \end{cases} \tag{8}
$$

The fuzzy sets and their respective universes of discourse are defined as follows:

- The linguistic variable t_r is associated to the rise time of the control system step response. The universe of discourse is [0, 600] [s]. The Gaussian fuzzy set is defined as *small* = $\langle 0, \;\; 200 \rangle$.
- The linguistic variable t_s is associated to the settling time of the control system step response. The universe of discourse is [0, 600] [s]. The Gaussian fuzzy set is defined as *large* = $\langle 600, \;\; 200 \rangle$.

- The linguistic variable M_p is associated to overshoot size of the control system step response. The universe of discourse is [0, 100] [%]. The z-polynomial fuzzy set is defined as *satisfactory* = $\langle 20,\ 50\rangle$.
- The linguistic variable Ac is associated to the maximum actuation signal of the control system step response. The universe of discourse is [0, 2] [Nm]. The Gaussian fuzzy set is defined as *small* = $\langle 0,\ 0.5\rangle$.
- The linguistic variable $Rating$ is associated to the total score. The universe of discourse is [-100, 100]. The triangular fuzzy set $\{$*bad, regular, good*$\}$ are defined as *bad* = $\langle -100,\ -100,\ 20\rangle$, *regular* = $\langle -40,\ 0,\ 40\rangle$ and *good* = $\langle -20,\ 100,\ 100\rangle$.

The fuzzy system rules are given as:

R_1: If ("t_s is Large") or ("Ac is not small")
then ("Rating is Bad")
R_2: If ("t_r is not Small") and ("t_s is not Large") and ("M_p is not Satisfactory") and ("Ac is small")
then ("Rating is Regular")
R_3: If ("t_r is Small") and ("t_s is not Large") and ("M_p is Satisfactory") and ("Ac is small")
then ("Rating is Good")
(9)

Regarding the controller candidates, when the resulting control system is unstable the candidate is immediately assigned the worst rating, thus avoiding time wasting to calculate the step response and fuzzy system cost.

THE DESIGN PROCESS

In a previous work [26], it was demonstrated how different classical control techniques – proportional-derivative (PD); Double-Input-Single-Output (DISO); linear-quadratic (LQ); H_2 – could be combined with computational intelligence approach to produce suitable controllers for the FireSat satellite specifications. In particular, two controllers (PD and DISO) were directly found by the CI. The other two (LQ and H_2) had their weighting functions chosen by the CI. Nevertheless, the design was accomplished in a separate step. The second approach is attractive, once it is mathematically assured that optimality or robustness, i.e., key features associated to each technique are guaranteed. Further, H_2 controller would be preferred to DISO, however, the latter achieved the best rating. In the other hand, robust techniques in general produce high order controllers. In particular, the H_2 controller yielded a 4^{th} order; DISO, 1^{st} order. Due to that, some care must be taken when comparing both controllers according their ratings.

H_2 controller order reduction

One way to directly compare them is by reducing (or truncating) the order of the H_2 controller to became the same of the DISO one. The side effects of this action may be undesirable. For example, reduction to order less than 3^{rd} for the system in Fig. 2 leads to instability.

Truncating the order of the controller is problematic if carried out after a final CI-based controller is found. An alternative is each candidate be truncated during the automated process and, then, the specifications checked with a fuzzy system.

Techniques Trade-off

The embedded truncation is performed here with the H_2 design in [26]. Computed controllers and results are available in Table 1. These results are obtained after five designs for each technique, and the best ratings are chosen and by using the parameter set for the satellite model: $J_0 = 720[kg\,m^2], J_P = 40[kg\,m^2], K = 320[kg\,rad^2/s^2], K_d = 0.48[kg\,rad^2/s], L = \sqrt{2}[m]$, and $m = 20[kg]$. According to the Table 1, (*i*) the rating of the truncated H_2 controller is now very close to DISO, suggesting a relationship with controller degree and performance; (*ii*) there is a remarkable reduction of the design time; (*iii*) the position of the poles is defined differently for each technique, but the gain at low frequencies is almost the same for both controllers.

TABLE 1
RESULTS FOR DISO AND H_2 TECHNIQUES [26], H_2 TRUNCATED AND H_∞ TRUNCATED.

Tech.	**Genes**	**Design Time** [s]	**Controller**	$\mathbf{t_r}$ [s]	$\mathbf{t_s}$ [s]	$\mathbf{M_p}$ [%]	**Ac** [Nm] (max.)	**Rating**
DISO	$\{a, b, c\}$	143	$-\begin{bmatrix} \frac{0.1675}{s+0.4185} \\ \frac{11.3856}{s+0.4185} \end{bmatrix}^T$	108.5	143.9	2	0.177	48.6
H_2	$\{k_\psi, k_r, k_w, k_\tau\}$ $\{m\}$ = multiplier	181	$\begin{bmatrix} \frac{\sum_{i=0}^{3} a_i s^i}{\sum_{i=0}^{4} b_i s^i} & \frac{\sum_{i=0}^{3} c_i s^i}{\sum_{i=0}^{4} b_i s^i} \end{bmatrix}$	126.5	191.5	2	0.238	41.2
H_2 truncated	$\{k_\psi, k_r, k_w, k_\tau\}$ $\{m\}$ = multiplier	84	$-\begin{bmatrix} \frac{9.461}{s+23.73} \\ \frac{653.6}{s+23.73} \end{bmatrix}^T$	106.2	160.9	2	0.207	46.5
H_∞ truncated	$\{k_\psi, k_r, k_w, k_\tau\}$ $\{m\}$ = multiplier	221	$-\begin{bmatrix} \frac{8.524\,\mathrm{x}10^4}{s+2.065\,\mathrm{x}10^5} \\ \frac{5.832\,\mathrm{x}10^6}{s+2.065\,\mathrm{x}10^5} \end{bmatrix}^T$	105.4	160.2	2	0.216	46.6

CI truncated design and H_∞ norm

Another robust technique is based on the H_∞ norm, which shares the same satellite feedback control of the H_2 technique given in Fig. 4. Truncating H_∞ controller is also possible and the results are shown in Table 1. Despite the very high value of the controller pole, the performance achieved rivals that one of DISO.

Reducing the design time

Aside the good results of the CI design shown in the Table 1 for a set of 5 runs, a larger set of 100 runs is accomplished for random combinations of 10% maximum uncertainty of all model parameters (J_0, J_P, J_R, K, K_d, L and m) and the H_2 truncated controller. A small group with high design times ($\approx 400[s]$) is unvealed in Fig.6. The respective settling times may lead the total time near to the maximum allowed manoeuvring time of the FireSat satellite model.

One solution to this problem is to consider an initial elite set (inserted in the first run) composed of elites from the original set of 100 combinations, exhibiting the highest design times. A new set of 100 random combinations of the parameters is, then, evaluated, with an initial elite of 10 elements. The maximum design time is reduced almost an half and the mean value of the rating increased, demonstrating the effectiveness of the proposed approach (Fig. 7).

Additional features.

The CI design example presented in this work is simple and purposely didactic, but could be improved by:

- The fuzzy system cost function could incorporate additional indexes (*e.g.*, those ones associated to stability [10]).
- For nonlinear systems where gain scheduling is adopted, the fuzzy system cost function could also incorporate a gain smoothing index [27], in order to avoid large discontinuities of the gain vector and possible degradation of the stability.
- Strategies of combined design could be employed, such as updating the control system with a re-designed preliminary controller (*e.g.*, a linear-quadratic one, presenting a good rating and very small design time [26]), while a secondary controller

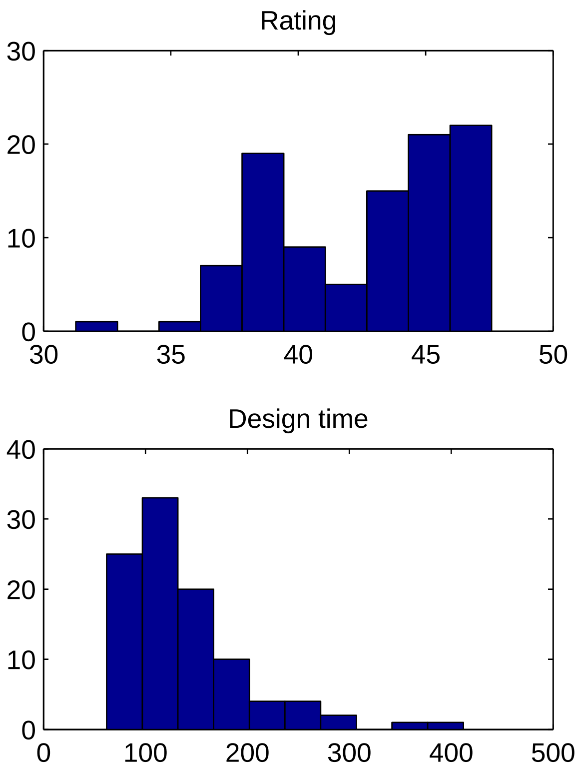

Fig. 6. Histogram for a set of 100 random combinations with 10% maximum uncertainty of model parameters J_0, J_P, J_R, K, K_d, L and m, and the H_2 truncated controller seen in the Table 1. The first elite is the nominal controller.

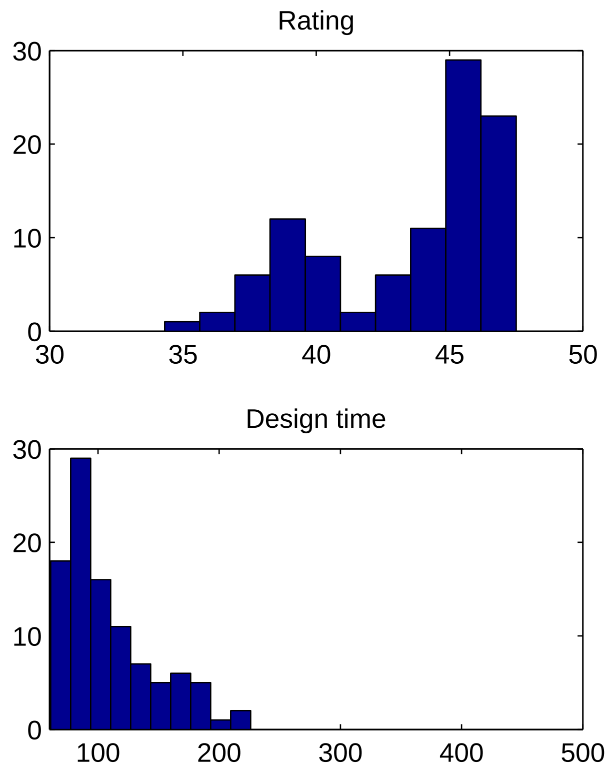

Fig. 7. Histogram for a set of 100 random combinations with 10% maximum uncertainty of model parameters J_0, J_P, J_R, K, K_d, L and m, and the H_2 truncated controller seen in the Table 1. The first elite is composed of 10 elites with the highest design times of a previous set.

– with much better rating – is designed and posteriorly replaces the preliminary one; the same gain smoothing index given earlier could also be employed here.

PRACTICAL CONSIDERATIONS

From the FireSat satellite model and its on-board CI-based control system design to a real-world implementation, certain conditions and possibilities should be taken into account:

- **Parameter identification.** An on-board identification algorithm is necessary, estimating the model parameters in an affordable time interval. The time interval does not necessarily represent a disadvantage, once the parameter identification could be carried outside the CI controller design.
- **Compiled versions instead of interpreted ones.** The results presented in this work are based in a interpreted software rather than a compiled one. More speed and, thus, less design time is possible by creating stand-alone executable files. Future work will incorporate this item.
- **Processor speed and power dissipation.** An on-board processing unit for aerospace applications usually is operated in environments which poses severe restrictions; *e.g.*, temperature rise directly proportional to the clock speed but accentuated by depressurisation. Therefore, despite the reduction of the design time, an increase is expected due

to the migration from the commercial PC to the rugged one with a lower clock speed.

- **Combination with FDIR mechanisms.** The CI re-design given in this work could also be combined with a Fault Detection, Isolation and Reconfiguration mechanism. In so doing, after the occurrence of a fault or failure (actuator or sensor), the reconfigured control system may recover from the degraded condition to an acceptable operation. Thus, the controller gains could be re-designed, but the whole structure of the control system, as well. The structure re-design can also employ an initial elite set, computed off-line, as shown in this work for controller re-design.

CONCLUDING REMARKS

Despite the majority of off-line applications, CI design has potential for being employed online. The FireSat example given in this work is particularly interesting once the satellite manoeuvring time is suitable for the controller re-design process, where re-design is required due to the performance degradation resulting from parameter uncertainty. Composed of a genetic algorithm for generating and combining candidates intertwined with a fuzzy system to score candidates according to the system specifications, the CI-based control approach produced controllers with low demands of control signal – suitable to the satellite FireSat – and satisfactory performance indexes, within a time interval where a human designer most probably would not.

Complementing and extending a previous work, it is shown that robust techniques (H_2 and H_∞) can be employed and even supply low-order controllers simply by adopting controller order truncation (reduction) for each candidate found during the re-design process. These truncated robust controllers presented ratings closer to the free-search controllers found. This is very attractive, once that the mathematical reasoning of the formers is preserved.

An important aspect of the re-design process analysis is the design time for a large set of random combinations of the model parameters, which presented an disadvantage of increased design time. That problem is, however, tackled and successfully solved by inserting an initial elite set composed of the off-line computed solutions with the highest design times. A positive side effect is the increasing of the mean rating of the entire set.

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