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Flight Control Laws Clearance Based on Coverage-granted Multi-strategy Global Optimization

OUJJA GHANAM Nidal[1]
Airbus Defence and Space, Getafe, Madrid, 28906, Spain, nidal.oujja@airbus.com

VELASCO BARCENILLA Gregorio[2]
Airbus Defence and Space, Getafe, Madrid, 28906, Spain, gregorio.velasco-barcenilla@airbus.com

RODRÍGUEZ ROBLES Rodney[3]
Airbus UpNext, Getafe, Madrid, 28906, Spain, rodney.rodriguez@airbus.com

ANTÓN DIEZ Antonio[4]
Airbus Defence and Space, Getafe, Madrid, 28906, Spain, antonio.anton@airbus.com

ASENSIO NIETO Francisco[5]
Airbus Defence and Space, Getafe, Madrid, 28906, Spain, francisco.asensio@airbus.com

Abstract
This paper describes the main functionalities of the Multi-strategy Adaptive Global Optimization algorithm with inter-clearance-criteria information eXchange (MAGO-X) with respect to the previous version of MAGO, emphasising on those features that improve the balance between exploration (coverage) and exploitation (worst cases) of the optimization space. In addition a coverage methodology is described to verify that the new algorithm MAGO-X is able to find all the violations of a provided cost function ensuring that there are no unexplored regions, which is of paramount importance for certification and airworthiness regulations. Coverage evidences of a linear stability of a fighter flight control laws Clearance are presented.

1. Introduction

The method used to assess the adequacy of the Flight Control Laws (FCL) for safe operation is the flight dynamics Clearance, which is part of the validation and verification process that encompasses a set of Flight Mechanics and Handling Qualities analyses to ensure the controller's robustness to model uncertainties and system measurement errors. This assessment usually results in hundreds of millions of cases to analyse, as it comprises all the system configurations and scenarios that the aircraft might face during its service life, ensuring there are no potential unsafe conditions left unexplored.

One of the issues that characterises typical grid-based clearances is the inability to find needle-sized problems resulting from specific parameter combinations out of the grid breakpoints, a field in which the application of global optimization techniques has proven to be very effective, increasing the probability of finding them. Nevertheless, considering the nature of global optimization techniques, a proper balance between exploitation and exploration is of paramount importance to ensure the adequate coverage of the optimization domain, while still being able to find local

[1] Flight Control Laws Engineer, Dept. of Flight Dynamics and Control Laws, Military Aircraft Division
[2] Flight Control Laws Engineer, Dept. of Flight Dynamics and Control Laws, Military Aircraft Division
[3] Lead Flight Physics Engineer, Autonomy Demonstrator Program
[4] Technical Manager General A/C Design NGFD, Chief Engineering Office, Military Aircraft Division
[5] Flight Dynamics Senior Expert, Dept. of Flight Dynamics and Control Laws, Military Aircraft Division

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cliff-edge problems in the Flight Control Laws Clearance. Many studies are dedicated to explain how the algorithms find this hidden problems, but only few tackle the topic of the optimization space coverage, ensuring that there are no unexplored regions, which is crucial for certification and airworthiness regulations.

This work presents an optimization space coverage analysis of the MAGO-X algorithm in a particular linear stability flight control laws clearance. Optimization space coverage strategy is based on two steps:

- Definition of a metric based on flight control laws Clearance experience to determine the coverage criteria of the optimization space.
- In case of a low-coverage metric values in isolated areas of the optimization space, an alternative approach will be followed, applying a grid-based approach to provide evidence that the algorithm has not explored that area because there are not critical cases in that area.

In this paper, the new features of a Multi-strategy Adaptive Global Optimization algorithm with inter-clearance-criteria information eXchange (MAGO-X) developed from [1] will be introduced, comparing convergence and worst solutions between both. The functionalities of the algorithm which provide an excellent balance between exploration (coverage) and exploitation (worst cases) of the optimization space will be listed. Coverage methodology and evidences of a fighter Flight Control Laws Linear Stability Clearance assessment will be presented as well. Finally, conclusions and future lines of work will be enumerated.

2. Multi-strategy Adaptive Global Optimization Algorithm with Information eXchange (MAGO-X)

The Multi-strategy Adaptive Global Optimization algorithm consists in an optimizer fitted for flight control laws linear and non-linear clearance purposes to assess the different aircraft capabilities and features that lie within a clearance scope. The new development of the MAGO algorithm (MAGO-X) presents a new innovative feature which enhances the exploration and exploitation capabilities of the algorithm, the cross-information exchange. This new version of the algorithm has been improved from its previous version, MAGO (see [1] for more information).

MAGO-X allows the user to launch several parallel optimizations and assess different cost function outputs that may be correlated. Therefore, the sharing of information between optimizations has proved to be helpful in terms of exploitation and exploration, as critical regions of the domain that may hold potential worst cases are located more efficiently. Figure 1 depicts conceptually the new MAGO-X algorithm feature, exemplifying the cross-information exchange between the cost function outputs Δ_{11} and Δ_{21} and its main advantage in convergence speed towards a global optimum.

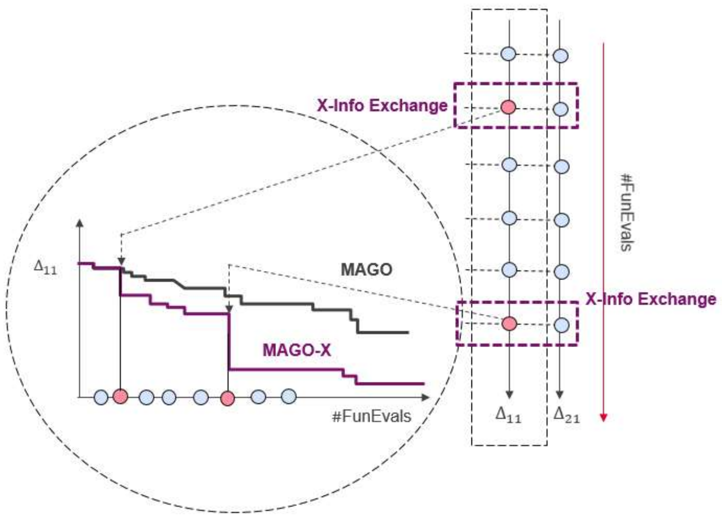

Figure 1: MAGO-X cross information process

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Different cross-information strategies are available in MAGO-X for the end-user to choose from, which are *p-best*, *best*, *mixed* and *random*. They differ from each other in the criterion for selecting the individuals to use in the information exchange, which varies from total randomness to the worst-value individuals found so far in a buffer of previous cost function evaluations.

As previously stated, the information exchange is set to happen between specific assessments as there exists a connection between the phenomena involved. The normalisation of the existing links is embodied in the concept of an adjacency matrix, which determines the connectivity and which aircraft features' assessment prove to be information-sharing worthy. Figure 2 shows an example of the adjacency matrix and its basic features, which are null trace and symmetry. As it can be seen, not all outputs are linked as no profit would result from their information exchange.

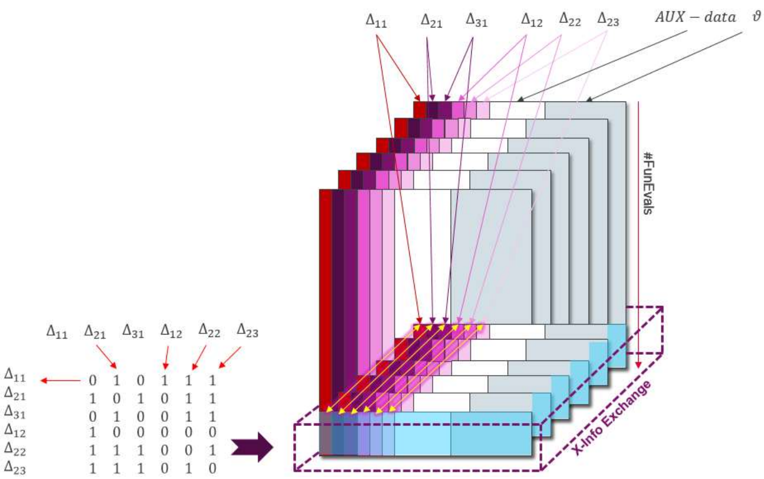
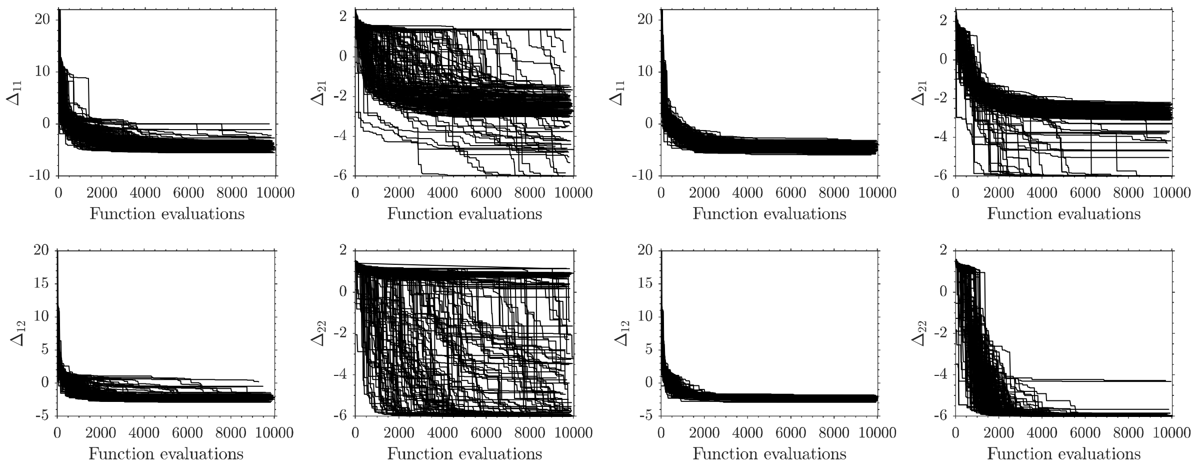


Figure 2: Cross-information process through the adjacency matrix

A comparison between the new MAGO-X and the previous MAGO version in terms of performance and convergence speed towards the global optimum is depicted in Figure 3. Similar to the conceptual description of Figure 1, the optimizer's convergence to the worst case value is enhanced, and less evaluations are required for each of the batch optimization runs to reach it. Moreover, more batch runs are capable of finding the global optimum and end the optimization process with more individuals acquiring lower cost values. This is portrayed in Figure 4, where the density of individuals is higher for the worst values in the MAGO-X optimizations than in those of the MAGO optimizations, proving anti-stall capabilities thanks to the exploration boost in the subfigure corresponding to the variable Δ_{22} as well.



(a) (b)

Figure 3: Optimization results for each variables with 200 runs and 10,000 function evaluations for MAGO without crossing information (a) and MAGO-X crossing information (b)

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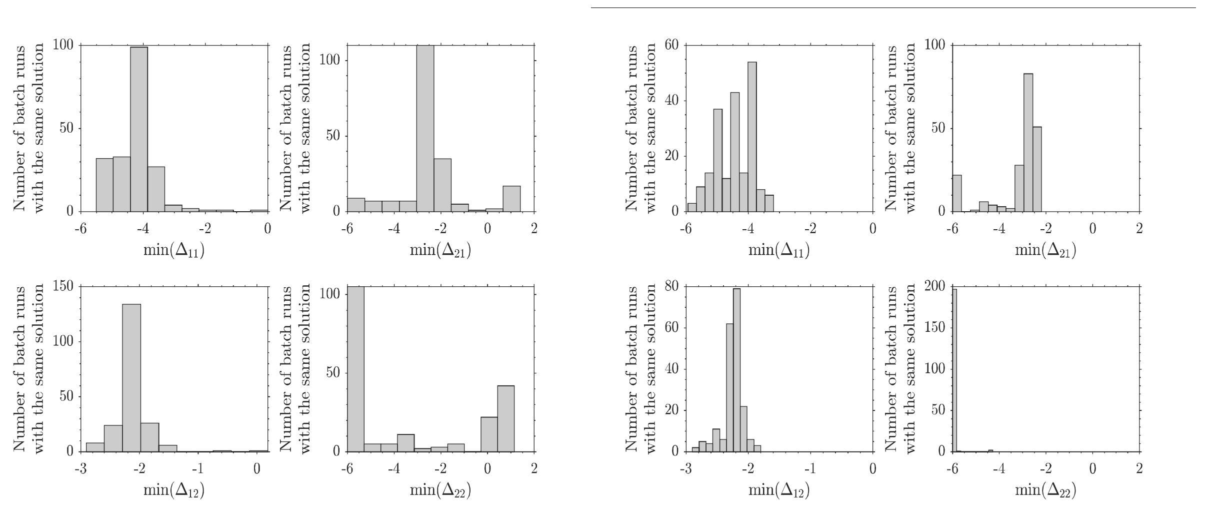

(a) (b)

Figure 4: Number of batch runs with the same worst solution found with 200 runs and 10,000 function evaluations for MAGO without crossing information (a) and MAGO-X crossing information (b)

Regarding the nature of the algorithm and its features, one of the main concerns of its performance arises when considering the coverage of the optimization space. As coverage cannot be theoretically granted by the optimization algorithm itself, modifications to the optimization schemes and additional functionalities are necessary to ensure a proper exploration of the optimization domain for FCL Clearance purposes. Detailed information on the matter at hand can be found in [1] and a brief explanation of its coverage capabilities is given below.

First of all, the MAGO-X algorithm makes use of two main optimization strategies: the Covariance Matrix Adaptation Evolution Strategy (CMA-ES), and the Differential Evolution (DE) algorithm. Despite the fact that the second of both optimization strategies resembles Genetic Algorithms in many aspects of its optimization scheme, it differs from them in the mutation of individuals. In this case, the differences between the population individuals is key to the generation of new candidates, and the most usual mutation operators are:

$$\begin{aligned}
&\textbf{DE rand-1} && \boldsymbol{v}_i^g = \boldsymbol{x}_{r1}^g + F \cdot (\boldsymbol{x}_{r2}^g - \boldsymbol{x}_{r3}^g) \\
&\textbf{DE best-1} && \boldsymbol{v}_i^g = \boldsymbol{x}_{best}^g + F \cdot (\boldsymbol{x}_{r1}^g - \boldsymbol{x}_{r2}^g) \\
&\textbf{DE current to best-1} && \boldsymbol{v}_i^g = \boldsymbol{x}_i^g + F \cdot \left(\boldsymbol{x}_{best}^g - \boldsymbol{x}_i^g\right) + F \cdot (\boldsymbol{x}_{r1}^g - \boldsymbol{x}_{r2}^g) \\
&\textbf{DE best-2} && \boldsymbol{v}_i^g = \boldsymbol{x}_{best}^g + F \cdot \left(\boldsymbol{x}_{r1}^g - \boldsymbol{x}_{r2}^g\right) + F \cdot (\boldsymbol{x}_{r3}^g - \boldsymbol{x}_{r4}^g) \\
&\textbf{DE rand-2} && \boldsymbol{v}_i^g = \boldsymbol{x}_{r1}^g + F \cdot \left(\boldsymbol{x}_{r2}^g - \boldsymbol{x}_{r3}^g\right) + F \cdot \left(\boldsymbol{x}_{r4}^g - \boldsymbol{x}_{r5}^g\right)
\end{aligned} \tag{1}$$

where r_k are random and mutually different integers generated within the range $[1,N]$ and different from index i, with $k = 1, \dots, 5$, N is the population size, g is the optimization generation, F is the mutation factor, $\boldsymbol{x}_i^g$ $i = 1, \dots, N$ is the *ith* population individual, and $\boldsymbol{x}_{best}^g$ is the fittest population individual.

Regarding the vector along which the mutated individual can vary as a parameter, the mutation factor F becomes the mutation variable. In that sense, the mutation can be conceived as a one-dimensional operation where its mutation schemes are originally intended to be confined within a vector. By the addition of different vectors and parameters in addition to the mutation factor, the exploration capabilities are increased to a multi-dimensional search space, like the following ones:

$$\begin{aligned}
&\textbf{DE best-2*} && \boldsymbol{v}_i^g = \boldsymbol{x}_{best}^g + F \cdot \left[K \cdot \left(\boldsymbol{x}_{r1}^g - \boldsymbol{x}_{r2}^g\right) + (1-K) \cdot \left(\boldsymbol{x}_{r3}^g - \boldsymbol{x}_{r4}^g\right)\right] \\
&\textbf{DE rand-2*} && \boldsymbol{v}_i^g = \boldsymbol{x}_{r1}^g + F \cdot \left[K \cdot \left(\boldsymbol{x}_{r2}^g - \boldsymbol{x}_{r3}^g\right) + (1-K) \cdot \left(\boldsymbol{x}_{r4}^g - \boldsymbol{x}_{r5}^g\right)\right] \\
&\textbf{DE rand-3*} && \boldsymbol{v}_i^g = \boldsymbol{x}_{r1}^g + F \cdot \Big[K_1 \cdot \left(\boldsymbol{x}_{r2}^g - \boldsymbol{x}_{r3}^g\right) + (1-K_1) \\
& && \qquad \cdot \Big(K_2 \cdot \left(\boldsymbol{x}_{r4}^g - \boldsymbol{x}_{r5}^g\right) + (1-K_2) \cdot \left(\boldsymbol{x}_{r6}^g - \boldsymbol{x}_{r7}^g\right)\Big)\Big]
\end{aligned} \tag{2}$$

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where $K_i \equiv U(0,1)$.

When addressing the initial population generation, the dimensionality of the domain plays an important role in the selection of the method to make use of for it. As most of the problems for which the algorithm has been designed comprise a high number of dimensions, these methods must behave properly when sampling the initial population, and one of the most fitted sequences for this kind of problems is the Stratified Sampling Without Replacement (SSWR). It is a sequence which solves the degradation of the low-discrepancy in mathematical systems with a high number of dimensions. Its working principle lies in the permutation of a vector that contains a low-discrepancy sequence and its algorithm for the generation of N n-dimensional vectors is the following one:

1. A reference vector of N quasi-random numbers as the basic vector for the first dimension is generated.
2. For each dimension $k, k = 2, \dots, n$ the sample vector of length N is generated with independent random permutations for the elements of the reference vector.

The Van der Corput sequence is the one used for the first quasi-random numbers, where the *j*th number of the sequence, in base p (p must be a prime number) follows these rules:

1. The integer j is written in base p as:

$$j = \sum_{i=0}^{I} a_i \cdot p^i \tag{3}$$

   where I is the lowest integer that makes $a_i = 0$ for $i > I$ and it is equal to the integer part of $\frac{\ln(j)}{\ln(p)}$

2. Then, the j^{th} number of the sequence is written as:

$$x_j = \sum_{i=0}^{I} \frac{a_{I-i}}{p^{i+1}} \tag{4}$$

Another feature introduced in order to provide better coverage by increasing the diversity of individuals during the optimization is the explorer concept. An exploration initiator is an individual chosen randomly from the population which is the basis of a new set of individuals that display a different behaviour from that of the main population. These individuals are originated by defining a random hypercube within which they are held in each step of the optimization process. As equation 5 shows, one of the corners is located on the exploration initiator and the opposite one on a random individual from the initial population:

$$\boldsymbol{H}_{\boldsymbol{D}_i} = \boldsymbol{x}_{r1}^{g} - \boldsymbol{e}_i^{g};\ \ \boldsymbol{e}_i^{g} = \boldsymbol{v}_i^{g} \tag{5}$$

where $\boldsymbol{x}_{r1}^{g}$ is an individual randomly selected from the population, $\boldsymbol{e}_i^{g}$ is the exploration initiator and r_1 is a random integer between 1 and N (population size) different from i. Within the hypercube a new population is created using the SSWR sequence as shown in equation 6 and evaluated in terms of the cost function. Once the optimization step is finished, the new exploration initiator will be the individual with the best fitting of the sub-population, including the exploration initiator of the optimization step.

$$\boldsymbol{v}_i^{g+1} = \boldsymbol{e}_i^{g} + \boldsymbol{SSWR}(0,1) \cdot \boldsymbol{H}_{\boldsymbol{D}_i} \tag{6}$$

One of the key aspects of hybrid optimization algorithms is migration, the concept through which a fraction of the population is spread again all over the domain at each optimization step or every number of optimization steps. It allows to overcome the consistent search for local minima and enforce the optimizer to evaluate other regions of the optimization space. The algorithm provides the user with the possibility of declaring the fraction of the population to migrate, so that the user can choose the balance between exploration and exploitation of every optimization. As for the algorithm, its migration feature is characterized for its randomness at the time of migrating the fraction of the population within the domain.

3. FCL Linear Stability Case of Study for Optimization Space Coverage Analysis

Having defined the new functionalities of MAGO-X respect to its previous version (MAGO), and the common features that balance the trade-off between exploration and exploitation, it is now of upmost importance to analyse if

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the new algorithm fulfils a fundamental property of a flight control laws clearance: the clearance domain must be appropriately covered to ascertain that no potential problems have been left unexplored.

This clearance coverage assessment will be performed for MAGO-X in a fighter linear simulator environment in which the linear stability requirements are transformed into a Multi-Input Multi-Output (MIMO) black box cost function that provides a compliance metric of the different linear stability Clearance requirements.

The minimum stability margins definition is based on MIL-DTL-9490E requirements, which ensure that the level of the augmented system stabilization does not lead to unsafe situations, covering system modelling errors, flight measurements, etc. The flight control laws stability margins for an unstable unaugmented aircraft are defined by the Upper Gain Margin (UGM), defined as the upper stability limit when increasing gain values, the Lower Gain Margin (LGM), defined as the lower stability limit when decreasing gain values, and the Phase Margin (PHM), defined as the system delay margin with respect to the instability point and based on Nyquist criterion.

The linear parametric cost function $\Delta = f(x, \vartheta)$ provides a multi-dimensional cost Δ (stability margins) as a function of the optimization space coordinates x and the parameter vector ϑ. The global optimization algorithm (MAGO-X) optimizes Δ, providing the x independent variables where Δ is minimum.

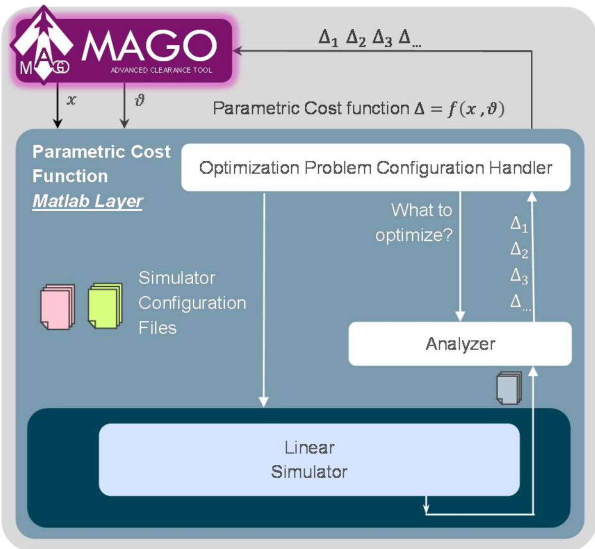

Figure 5: Linear stability optimization process with MAGO

The inputs involved in a typical flight control laws linear stability Clearance are divided into flight envelope inputs, aircraft store configurations and modelling uncertainties, which include aerodynamics, sensors, mass and inertia:

- Flight Envelope: The dimensionless region of the flight considered as part of the domain is defined by the function $\mathcal{g}$: $\mathcal{J}_M \in [0,1] \times \mathcal{J}_H \in [0,1] \times \mathcal{J}_\alpha \in [0,1] \times \vartheta \rightarrow$ {Mach, Altitude, Angle of Attack} where $\mathcal{J}_M$, $\mathcal{J}_H$ and $\mathcal{J}_\alpha$ are the inputs components of the cost function corresponding to the Mach, altitude and angle of attack variables respectively. All information about the lower bounds of M_{lb}, CAS_{lb}, H_{lb} and α_{lb} and the upper bounds M_{ub}, CAS_{ub}, H_{ub} and α_{ub} to non-dimensionalize the flight envelope is held in the parameter vector ϑ. Therefore, the optimization space relative to the flight envelope comprises three non-dimensional variables that, through the use of the cost function, recover their dimensions thanks to the information provided by ϑ, consequently fulfilling the nonlinear constraints.

- Aircraft store configuration: All possible aircraft store configurations are held in a single continuous optimization variable representative of the external stores distribution, which are strongly related to possible changes in the aerodynamic model and mass-inertia-CG values.

- Aerodynamic tolerances: to test the control laws robustness against uncertainties in the aerodynamic model, the implementation of tolerances affecting different aero-derivative coefficients is required. The relevance of each aero-derivative coefficient on the assessment depends on the nature of the clearance task at hand, therefore only those coefficients that truly affect longitudinal characteristics are considered when assessing the longitudinal loop and ditto for the lateral-directional loop.

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- Air Data System (ADS) errors: aircraft sensors might be subjected to measurement errors, therefore their corresponding error model must take them into consideration and the existent relations between them. In this case, airspeed errors are influenced by temperature and static pressure errors, corresponding to Mach value computation.
- Mass and Inertial errors: the basis of gain scheduling in highly manoeuvrable aircraft lies in the estimation of several mass and inertia properties. For instance, the aircraft's centre of gravity, whose variation is ruled by the fuel sloshing while manoeuvring or in fuel system failure scenarios, plays a crucial role in the gain selection as it affects many aero-derivative coefficients. For flight control laws clearance purposes, the extreme mass states of the aircraft are transformed into a discrete optimization variable.

The uncertainties are measured in probabilistic terms, where the higher errors in the models are, the lower probability of occurrence is associated. Aerodynamic, mass and sensor tolerances are combined to cover the required level of probability.

For the stability analysis case, in order to find the worst cases violations in the stability optimization problem using MAGO-X algorithm, the following strategies are considered based on the nature of the problems. On the one hand, low-frequency violations (associated with under-gearing problem in which the gain is not sufficient to stabilise the unstable unaugmented aircraft), which include LGM and PHM violations, cross information between them and, on the other hand, high frequency violations, UGM (associated with over-gearing problems in which the gain is excessive). The optimizer's parameter setting is adjusted considering the number of batch runs and evaluations, as both are representatives of the exploration and exploitation magnitudes respectively.

Although MAGO-X algorithm has demonstrated to be a very effective technique to find needle-sized hidden problems, the question that arises is whether if only the worst case scenarios have been found, or all possible violations as well, without leaving any regions of the flight envelope unexplored. Here is where the exploration vs exploitation concept (e^2 problem) becomes an essential metric for optimization problems regarding flight control laws Clearance assessment, and therefore an optimization space coverage analysis is required.

3. Coverage Methodology

In the FCL Clearance, given the high number of degrees of freedom and their combination (including the uncertainties), it is crucial to verify that all critical combinations have been computed, with the certainty that nothing that might be a potential risk has been undiscovered.

It is necessary to set a coverage metric that allows to quantify the exploration of the optimization space. The coverage analysis aims to identify those areas of the optimization space where no violations have been found, since in case of encountering a problem during the optimization, it is assumed that the optimizer is primed in that area.

The configuration of a case with which to test the coverage capabilities of MAGO-X within a typical fighter stability clearance scope involves the definition of a Mach-Altitude-Angle of Attack (AoA) grid and the different types of tolerances to which the aircraft is subjected in a grid-based approach (i.e. different standard mass, aerodynamic and ADS tolerance combinations, etc.). The rule by which the tolerance combinations are set obeys a minimum value rule, therefore stating the feasible tolerance combinations. Nevertheless, although these tolerance combinations are bound to happen regardless of the aircraft configuration or flight condition, their features provide them with more critical effects depending on the assessment and aircraft configuration.

Experience has allowed engineers to differentiate the tolerance combinations at each flight condition whose violations' severity is higher than those of whose relevance is low. This information, which is specific of each aircraft, helps setting a coverage criteria so as to validate the features and capacities of the MAGO-X tool. First, continuous Mach-Altitude-AoA points of the MAGO analysis are collapsed into their corresponding Mach-Altitude-AoA grid points. In terms of over-gearing coverage, each Mach-Altitude-AoA grid point is covered if, at least, all aircraft configurations with a forward centre of gravity are subjected to a control power excess aerodynamic tolerance and two specific sensor measurement tolerances are present. In terms of under-gearing coverage, each Mach-Altitude-AoA grid point is covered if, at least, all aircraft configurations with aft centre of gravity are subjected to basic aerodynamic stability deficiencies and control power reduction aerodynamic tolerances and two specific sensor measurement error tolerances. Those flight envelope regions where no problem has been detected are the object of

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this coverage assessment as there is no certainty about the reason behind the MAGO-X algorithm does not found stability non compliances in the area.

Reflecting on the uncertainties of the use of MAGO-X, those optimizations with low coverage values (that are those zones that there are no violations), depending on the task at hand, are subjected to a simplified grid based analysis in the flight envelope region where stability non compliances has not been found. This simplified grid based analysis consists in evaluating in the previously mentioned areas the most critical tolerance combinations and aircraft configurations to check that there are not hidden stability problem areas. For the upper gain margin, the most forward CG configuration with mass over-read, an aerodynamic tolerance increasing the control power of corresponding surface and two sensor measurement errors are evaluated, whereas for the low frequency margins, the most aft CG configurations with mass under-read, two aerodynamic tolerances decreasing the aircraft's static stability and control power and two sensor measurement errors are evaluated.

In case that no violation is located in the areas specified above the assessment is finished and MAGO-X has found all stability problems without spending many evaluations on non-problematic, consequently reducing the overall computing needs. Nevertheless, if there is any violation, a full grid based assessment is performed in the problematic areas where new violations arose after the MAGO-X's assessment.

This coverage methodology, where a stability analysis based on optimization that finds those areas with the worst stability margins violations is combined with a reduced grid-based analysis in the areas where MAGO-X does not found stability non compliances, allows to achieve higher coverage values without performing a full grid based analysis which would increase significantly the number of calculations.

4. Results

The coverage evidences will be presented for a stability margin optimization. For this case of study, the variable Δ_{31} is a dimension stability margin. In Figure 6 MAGO-X optimization results for Δ_{31} stability margin (upper gain margin) are presented as a function of flight envelope variables ($\mathcal{J}_M$, , $\mathcal{J}_H$ and $\mathcal{J}_\alpha$). Only values lower than 4.5dB are shown and indicate that there are stability margin violations that might need additional assessment to determine if it is a potential problem because there is not enough stability margin to the instability point in case of higher uncertainties in the models.

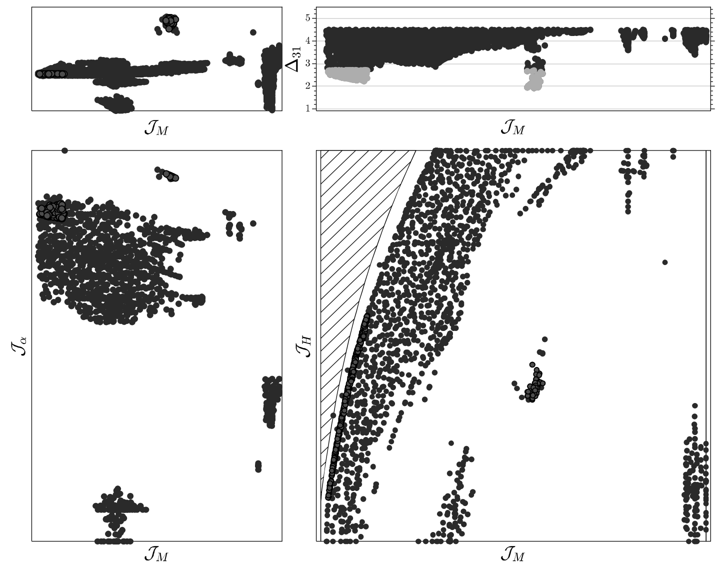

Figure 6: Stability margin MAGO-X optimization results for Δ_{31}

According to the coverage methodology exposed, from the previous results, continuous Mach-H-AoA points are collapsed into a Mach-H-AoA grid. Each point of the grid will be covered if the optimizer has analysed at least one mass configuration with forward centre of gravity, one aerodynamic tolerance that increases the control power of the surface and two ADS tolerances.

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The coverage results for the $\boldsymbol{\Delta_{31}}$ based on the criteria for each aircraft configuration is shown in Table 1. There are 6505 M-H-AOA grid-based points, and for aircraft configuration 1, only the 48% are covered, while for configuration 2 and 3, the 37% and 43% of the points are covered respectively.

Table 1: Coverage results for $\boldsymbol{\Delta_{31}}$ for each aircraft configuration

A/C CONFIGURATION	GRID M-H-AOA POINTS	MAGO GRID POINTS	COVERAGE
CONF1	6505	3578	48%
CONF2	6505	2405	36.97%
CONF3	6505	2780	42.74%

Figure 7 shows the coverage results at $\mathcal{J}_M = 0.6$, $\mathcal{J}_H = 0.45$, with $\mathcal{J}_\alpha \in [0,1]$, for each aircraft configuration (configuration 1, configuration 2 and configuration 3) and ADS tolerance (AeroTol, ADS 1 ADS 2, ADS 3 or ADS 4). The colorbar represents the value of the coverage metric in percentage. Given an aircraft configuration, ADS value and Angle of Attack ($\mathcal{J}_\alpha$), this coverage metric is computed as the ratio of evaluated mass configurations and aerodynamic tolerances to the total possible.

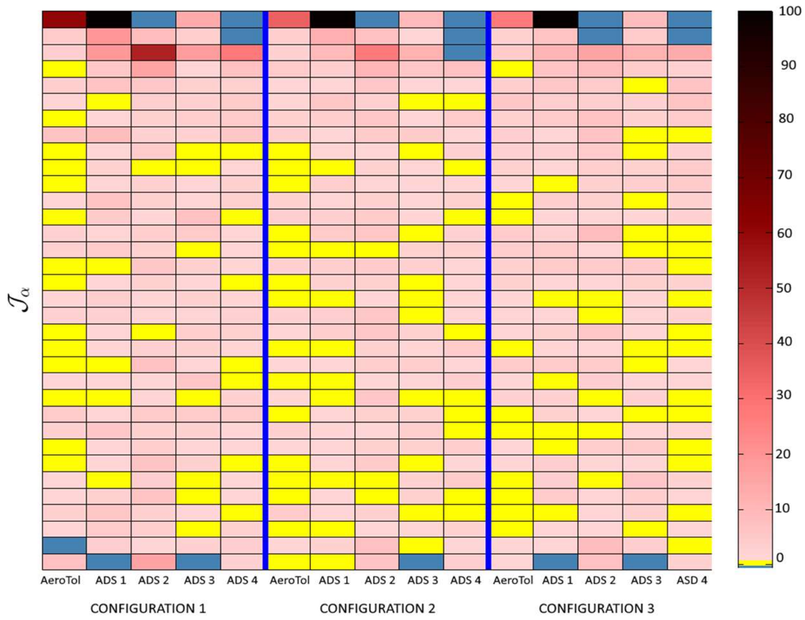

Figure 7: Coverage results for $\mathcal{J}_M = 0.6$, $\mathcal{J}_H = 0.46$ for each aircraft configuration and combination of aerodynamic and ADS tolerances

To increase the coverage metric and ensure that all stability non-compliances have been found without performing a full grid-based analysis, a reduced grid-based assessment is performed to check that the optimizer has not left anything in those areas where stability non-compliances have not been found with the combination of critical parameters that usually result in upper gain margin violations.

Figure 8 depicts simplified coverage grid-based results of Δ_{31} stability margin. In the right upper subplot shows the Δ_{31} values, where none of the values from this assessment are lower than the values of Δ_{31} showed in Figure 6. This confirms the hypothesis that MAGO-X has been able to find all parameter combinations that lead to stability margin violations, leaving less explored those areas where stability non-compliance exist.

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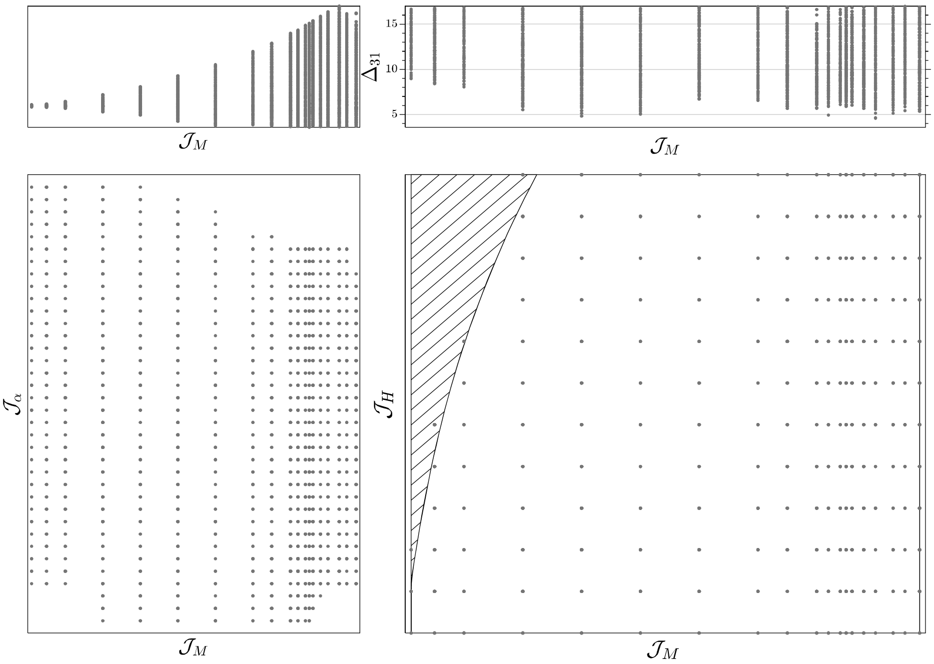

Figure 8: Simplified coverage grid-based assessment for Δ_{31}

With this methodology, the coverage of the optimization space is increased without encountering any additional problems, increasing the confidence in the optimization space coverage of MAGO-X. It is important to notice that with values around 50% of coverage, the optimizer finds all the problems associated to the upper gain margin. Furthermore, the convergence towards the worst cases is much faster with MAGO-X compared to the initial version of MAGO, as well as the number of individuals reaching the worst conditions is higher.

5. Conclusions

A coverage analysis of the optimization space with MAGO-X has been addressed in this work. MAGO-X results indicate that this hybrid optimization with cross-information exchange between optimization variables enhances the exploration of the domain as well as increases convergence speed to find the worst case values in comparison with the initial version of MAGO. A methodology has been established to ensure that there are no unexplored zones with violations, applying it in stability FCL clearance of a fighter.

The exploitation vs. exploration problem (e^2) has been introduced and analysed. It has been demonstrated that although there is no certainty about the coverage of the optimization space using optimization techniques, MAGO-X algorithm has an excellent balance between exploitation and exploration of the optimization space. It has been verified through the proposed methodology that no areas that could encounter requirement violations in the case of study have been left unexplored, ensuring that MAGO-X has found all critical parameter combinations.

6. Future Work

Future work includes the continuous development of the MAGO-X optimization algorithm, such as the implementation new differential evolution (DE) mutation strategy, empowering the trade-off between exploration and exploitation, a key aspect for the flight control laws clearance.

Abbreviations

AoA	Angle of Attack
CMA-ES	Covariance Matrix Adaptation Evolution Strategy
DE	Differential Evolution
FCL	Flight Control Laws

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MAGO-X Multi-strategy Adaptive Global Optimization algorithm with inter-clearance-criteria information eXchange

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