MULTIDISCIPLINARY DESIGN OPTIMIZATION FOR MISSIONISATION OF RE-ENTRY VEHICLES: PRELIMINARY MISSION DESIGN AND MISSION CAPABILITIES EVALUATION OF WINGED RE-ENTRY VEHICLES CASE STUDY

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ABSTRACT

The main goal of this paper is to present two complementary Multidisciplinary Design Optimization (MDO) approaches in the context of the Mission Analysis and GNC missionisation for Winged Re-entry Vehicles (WRV). Within this research, missionisation has the aim at evaluating the mission capabilities of a re-entry vehicle with respect to several design parameters, to provide robust solutions for multiple missions. In this context, missionisation is a complex process that concerns several multidisciplinary aspects of the system and mission design. Thus, MDO is proposed to handle the broad set of system and mission constraints while optimizing multiple objectives. This technique allows for the evaluation of different design options to perform trade-off studies and analyse optimal designs. In this paper, two MDO approaches have been considered and compared: the first one exploits metamodeling techniques to approximate the original problem to reduce the computational effort, while the second method uses a Multi-Objective Particle Swarm Optimization (MOPSO) algorithm. The results show that a metamodeling MDO approach can efficiently provide a set of solutions for the test case analysed, assessing preliminary mission capabilities of a WRV.

1 INTRODUCTION

The work presented in this paper is part of the European H2020 ASCenSIon program. In this context, the overall purpose of this research is the definition and development of a Mission Analysis (MA) and GNC missionisation tool for autonomous re-entry vehicles.

In recent years, space agencies and private firms are investing in reusable spacecraft and launch vehicles to make space access and in-orbit operations more sustainable and economical. The re-flight capability, requested by a reusable space system, motivates the need for a dedicated missionisation tool. The objective of missionisation is the minimization of the tailoring effort during the mission design phase of each flight. One approach, which can address this goal, is to provide solutions for re-entry vehicles that are qualified for multiple missions. For this reason, a crucial step for missionisation is the computation of the set of missions that a vehicle can perform concerning its design parameters. The focus of this paper is on the preliminary mission design and the evaluation of the mission capabilities of a Winged Re-entry Vehicle (WRV) by means of a Multidisciplinary Design Optimization (MDO) approach available within the proposed MA and GNC missionisation tool [1].

One of the key challenges in missionizing a re-entry vehicle is the need to balance the trade-offs between a broad set of system and mission requirements and constraints to obtain robust trajectories. Missionisation is a complex and challenging task that requires a thorough understanding of the multidisciplinary aspects of the system and mission design. For this reason, the paper reports the Multidisciplinary Design Analysis (MDA) framework with an overview of the set of disciplines embedded in the tool. The disciplines numerically quantify the related performance and assess the feasible space domain containing the design variables. Then, the MDA problem is exploited by the optimization routine to optimize the design variables while maximizing prescribed performance.
The MDO is a crucial feature because it allows the simultaneous optimization of multiple design parameters and objectives to achieve the performance targets and mission feasibility of the re-entry vehicle [2] [3]. By using this technique, the goal is to evaluate different design options to perform trade-off studies and identify the optimal designs, especially when a multi-objectives approach is considered and nondominated optimal Pareto solutions are obtained. Within the MDO process, indeed, the solution space domain is explored through the variation of the design parameters.
In this research, metamodeling techniques have been adopted to reduce the computational cost. One of the main challenges faced by MDO concerns the efficiency in solving the optimization problem due to the relatively expensive evaluations of the MDA [3] [4] [5]. In particular, in this work, the MDA has been integrated with the DEIMOS Space proprietary tool EDL/GNC Sizing and Analysis Tool (ESAT), which employs Radial Basis Functions (RBFs) to create a surrogate model of the original problem [2] [5]. To validate the optimization process, the results obtained for the test scenario are compared with the outcomes achieved by solving the original problem with a Multi-Objective Particle Swarm Optimization (MOPSO) algorithm [6]. The solutions are analysed both in terms of accuracy and computational time.
This study is performed to determine the best design solutions within the scope of the WRV category, in a nominal mission which maximise prescribed performances, without violating a set of system and mission constraints. The considered mission performances assess the flying capability, the controllability and the static longitudinal stability of the vehicle along the nominal trajectory.
The structure of this paper is organized as follows: Section 2 gives an overview of the MDA architecture of the tool, and reports an insight of the MDO approaches exploited in this research. In Section 3, the analysed scenario is presented, by focusing on the considered performance indices. Section 4 presents the results, while Section 5 highlights the conclusion and the future work.

2 MISSIONISATION TOOL OVERVIEW

This section describes the multidisciplinary architecture of the tool by focusing on the disciplines involved in the analysis considered in this paper. Moreover, Section 2.2 details the MDO approaches embedded in the tool.

2.1 Multidisciplinary architecture of the tool

As specified within Section 1, the missionisation of an autonomous re-entry vehicle is a complex multidisciplinary problem. Therefore, a minimum set of disciplines has been considered in order to assess several system and mission performance [1]. For the case analysed within this paper, the disciplines involved are five:

- **Geometry and mass estimation (GEOM)**: this discipline estimates the reference surface and the mass of the vehicle from a set of geometric parameters and aero-mechanical loads by exploiting semi-empirical relations. The geometric parameters are the length of the vehicle, the fuselage diameter, the wing span and the mean aerodynamic chord.

- **Aerodynamic database estimation (AEDB)**: this model builds a representative aerodynamic database (drag, lift and pitching moment coefficients) of the re-entry vehicle by interpolating datasets from the knowledge of the slenderness ratio (length divided by the diameter) and the wing aspect ratio of the vehicle (the wing span divided by the mean aerodynamic chord) [7].
- **Flying Quality Analysis (FQA):** this discipline evaluates the trim and the static longitudinal stability of the vehicle [8]. The FQA provides the stability domain, so-called Angle-of-Attack corridor and assess the thickness of this corridor. It also selects the Angle-of-Attack trim line within the stability domain.
- **Entry Corridor (EC):** this tool estimates the domain within which the vehicle can fly without violating the aerothermal-mechanical constraints. The method consists of the solving of a set of nonlinear equations to find the drag profile associated to each load in function of the specific energy [9].
- **Footprint Evaluation (FE):** this discipline exploits the bounds of the EC to estimates the reachable area of the vehicle from a given Entry Interface Point (EIP), that is the point where the vehicle enters the atmosphere. The tool is based on the Evolved Acceleration Guidance Logic for Entry (EAGLE) algorithm, that schedules the bank manoeuvres from a prescribed drag profile [10].

For a deeper understanding and for the explanation of the engineering modelling of the disciplines, the reader is referred to [1]. These disciplines constitute the core of the MDA and are strictly interconnected, especially in term of input/output relation. The inputs parameters of a discipline are the outputs of a previous one. When two disciplines share both inputs and outputs, an internal loop exists and convergence is needed to obtain coherent results.
Figure 1 shows the Design Structure Matrix (DSM) of the disciplines involved for the study reported in this paper [11]. Table 1 reports the design variables, the coupling variables, the parameters and the outputs of each discipline illustrated in Figure 1.

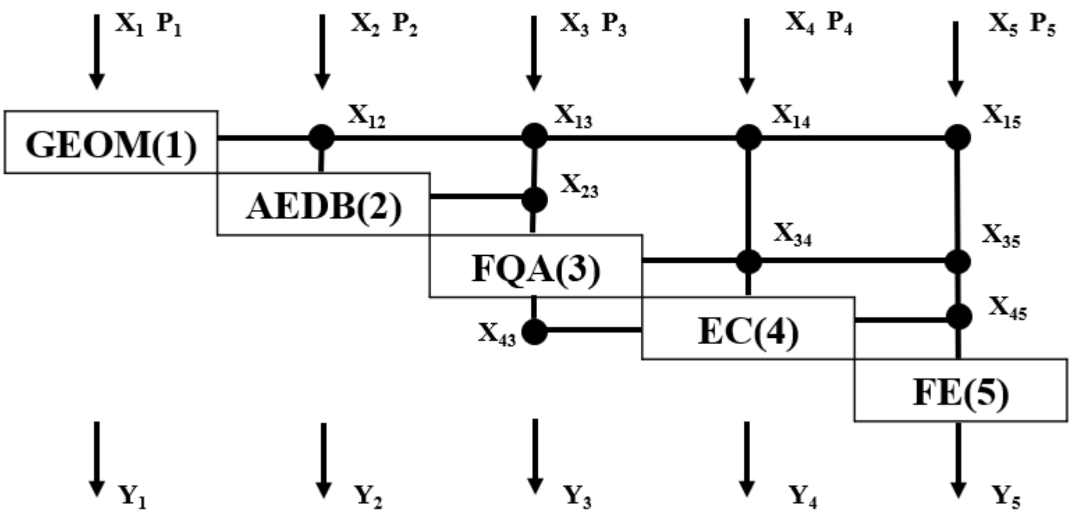


Figure 1. Qualitative Design Structure Matrix of the involved disciplines for the mission capabilities evaluation.

Table 1: Qualitative definition of the parameters for the DSM in Figure **1** for the test case in the paper. Xi are the design variables for discipline *i*, Xij are the coupling variables among disciplines *i* and *j*. Pi are the parameters for discipline *i*, while Yi are the outputs generated by discipline *i*.

ID	Parameters	ID	Parameters
$\mathbf{P_1}$	Vehicle class, aero-mechanical loads, Payload mass	$\mathbf{X_{14}}$	Reference surface, Mass
$\mathbf{P_2}$	Vehicle class	$\mathbf{X_{15}}$	Reference surface, Mass
$\mathbf{P_3}$	Max and Min flap deflection, Nominal CoG position	$\mathbf{X_{23}}$	Untrimmed AEDB
$\mathbf{P_4}$	Aerothermal-mechanical loads, environment parameters, Boundary conditions	$\mathbf{X_{34}}$	Trimmed AEDB, Angle-of-Attack line, Flap deflection margin
$\mathbf{P_5}$	Environment parameters, Boundary conditions, Uncertainty ellipse at final point	$\mathbf{X_{35}}$	Trimmed AEDB, Angle-of-Attack line
$\mathbf{X_1}$	Length, Diameter, Wing Span	$\mathbf{X_{43}}$	Angle-of-Attack line, Flap deflection margin
$\mathbf{X_2}$		$\mathbf{X_{45}}$	Entry Corridor bounds
$\mathbf{X_3}$	Shifted CoG position	$\mathbf{Y_1}$	Reference surface, Mass, Slenderness ratio, Wing aspect ratio, Reference length for Cm
$\mathbf{X_4}$		$\mathbf{Y_2}$	Untrimmed AEDB
$\mathbf{X_5}$		$\mathbf{Y_3}$	Trimmed AEDB, Angle-of-Attack line, Angle-of-Attack Corridor thickness, Flap deflection margin
$\mathbf{X_{12}}$	Slenderness ratio, Wing aspect ratio	$\mathbf{Y_4}$	Entry Corridor bounds
$\mathbf{X_{13}}$	Reference length for Cm	$\mathbf{Y_5}$	Range Capability, Distance between final point and footprint edge

2.2 Multidisciplinary Design Optimization approaches

The preliminary mission design and mission capability evaluation is performed by an MDO process, that optimizes desired mission performance while satisfying a set of mission and system constraints by evaluating the MDA core in several design points. Within the MA and GNC Missionisation tool, the user can choose among two MDO approaches: the first employs a DEIMOS Space proprietary tool called EDLS/GNC Sizing and Analysis (ESAT) [12], which exploits a metamodeling technique to approximate the original problem and to support trade-off process. The second approach uses a MOPSO algorithm [6].

ESAT is a metamodeling tool that builds performance maps by evaluating a given external module seen as a black box (in this case, the MDA reported in Section 2.1). ESAT calls such external module in a given set of sample points, and it interpolates the obtained responses with Radial Basis Functions (RBFs), in order to get predictions of the performances in any point of the search space domain. ESAT can exploit the metamodel to solve single or multi-objective problems. The advantage of this approach is that the evaluation time of the metamodel (the performance maps) is much lower than the run time of the external module. Nevertheless, the accuracy of the metamodel must be verified, especially when the problem requires a high number of design variables.

MOPSO is a population-based stochastic algorithm that applies the coordinated movement of a swarm of particles. Moreover, the algorithm uses the concept of Pareto dominance to find solutions for multi-objective problems. MOPSO is very efficient and effective in solving multi-objective problems [6]. One of the drawbacks, in this case, is that each evaluation along the optimization process is performed by calling the full computation of the MDA module. The number of calls needed to converge is typically higher than the one necessary to build the metamodel. So, the computational time required is longer than a metamodeling approach [5]. Since the accuracy of the MOPSO solution has been extensively verified in literature, the results obtained with this method are used as the benchmark.

It is worth mentioning that in both cases, the optimization problem has been formulated with the Multidisciplinary Feasible (MDF) architecture, where the optimizer handles only the “real” design variables and ensures the multidisciplinary feasibility at each evaluation along the optimization process [3].

3 TEST CASE: WINGED RE-ENTRY VEHICLES MISSION CAPABILTIES EVALUATION

The proposed MDO approaches included in the MA and GNC Missionisation tool have been used to evaluate the mission capabilities of a WRV depending on prescribed design variables and to analyse possible best solutions which maximise a set of performance. The two MDO methods are compared both in term of obtained solution and computational performance.

3.1 Analysed Scenario: Problem Parameters

The scenario presented in this paper is a nominal descent mission from the Entry Interface Point (EIP, here assumed at 90 km of altitude) to the Terminal Area Energy Management (TAEM, here assumed at Mach ~2, and at 27 km of altitude) interface point of an unpowered winged re-entry vehicle. The chosen entry conditions are set at 30º S, 80º W latitude and longitude, and initial heading angle of 38.4º (from the local North). The final point is at 5.2º N and 52.7º W latitude and longitude, characterized by an uncertainty ellipse of 400x200 km. The scenario simulates a descent mission from a LEO orbit with an inclination of 51.6º with a scheduled landing at the Guiana Space Center. The entry vehicle is assumed to carry a payload mass of 1000 kg.

During the descent, the re-entry vehicle can withstand a set of maximum aerothermal-mechanical loads. These loads are defined from typical mission and system requirements [9] [13]: dynamic pressure of 10 kPa, heat flux at the stagnation point of 530 kW/m^2, and total acceleration load of 4 g. The maximum deflection of the aerodynamics surface used to trim and control the vehicle have an excursion within -30º and +30º.

The analysis considers the "US76" atmospheric model for the estimation of the atmospheric pressure, density and Mach number [14]. The gravity assumes a spherical Earth with a standard gravitational parameter μ = 3.986 x 10^{14} m^3/s^2 and a radius of 6371 km. Table 2 reports the problem parameters.

For this test case, the design variables are five and consist on the length of vehicle *L*, the fuselage diameter *Diam*, the wing span *b*, and the delta position of the Centre of Gravity (X_{cog} and Z_{cog}) with respect to the nominal condition. The CoG nominal position is an output of the GEOM discipline. The mean aerodynamic chord is considered linked to the *Diam* in order to avoid unfeasible geometries. The research space of the design variables is bounded with the ranges defined in Table 3.

Table 2: Problem parameters: boundary conditions, aerothermal-mechanical loads, flaps deflection constraints, environmental parameters.

Parameter	Value	Parameter	Value
EIP altitude, *h*, km	90	TAEM altitude, *h*, km	27
EIP velocity, *v*, km/s	7.5	TAEM velocity, *v*, km/s	0.6
EIP latitude, λ, º	-30	TAEM latitude, λ, º	5.2
EIP longitude, θ, º	-80	EIP longitude, θ, º	-52.7
EIP Flight path angle, γ, º	-1	TAEM Flight path angle, γ, º	n.s.
EIP Heading angle, ψ, º	38.4º	TAEM Heading angle, ψ, º	n.s.
Max dynamic pressure, q_{dyn}, kPa	10	Max heat flux at stagnation point, q_{heat}, kW/m^2	530
Max acceleration load, n_{load}, g	4	Payload mass, m_p, kg	1000
Max flap deflection, δ_{max}, º	30º	Max flap deflection, δ_{min}, º	-30
Earth radius, r_p, km	6371	Standard gravitational parameter, μ, m3/s2	3.986e^{14}
Uncertainty Ellipse dimension, [*a b*], km	[400,200]		

Table 3: Design variables upper and lower bounds.

Variable	Ranges	Variable	Ranges
Length, *L*, m	[24, 35]	Longitudinal CoG shift, X_{cog}, m	[-1.5, 1.5]
Fuselage diameter, *Diam*, m	[5, 6]	Vertical CoG shift, Z_{cog}, m	[-0.5, 0.5]
Wing span, *b*, m	[18, 35]		

3.2 Performance Indices

The exploration of the solution space domain, the trade-off analysis and the evaluation of the best design solutions have been performed by considering three performance indices:

- Edge distance (D_{min}): defined as the minimum distance between a prescribed uncertainty ellipse at the final point (in this case TAEM interface point) and the edge of the footprint. It provides a representation of the flying capability of the vehicle in nominal conditions.
- Deflection margin (Δ_{δ}): it is the difference among the aerodynamic surface deflection to get the trim and the maximum deflection attainable. It is defined by Eq. 1:

$$\begin{aligned} \Delta_{\delta} &= \delta_{max} - \delta_{trim} \text{ if } \delta_{trim} \geq 0 \\ \Delta_{\delta} &= |\delta_{min} - \delta_{trim}| \text{ if } \delta_{trim} < 0 \end{aligned} \tag{1}$$

  The minimum value along the trajectory is considered for the evaluation of the performance index. This parameter represents the control authority available to the GNC to compensate disturbances along the trajectory.
- Angle-of-Attack corridor thickness (Δ_{AoA}): this parameter evaluates the minimum width of the stable region of the Angle-of-Attack corridor; thus, it can be considered as a proxy stability performance index of the vehicle in nominal conditions.

These three performance indices have been maximized along the optimization process in order to obtain robust solution options from the mission analysis view point. Figure 2 reports an example of the three performance indices considered in this context. The dummy solution is X = [25m 5m 20m 0m 0m], and the performance indices are 674.76 km for D_{min}, 4.43º for Δ_{δ}, and 10º for Δ_{AoA}.

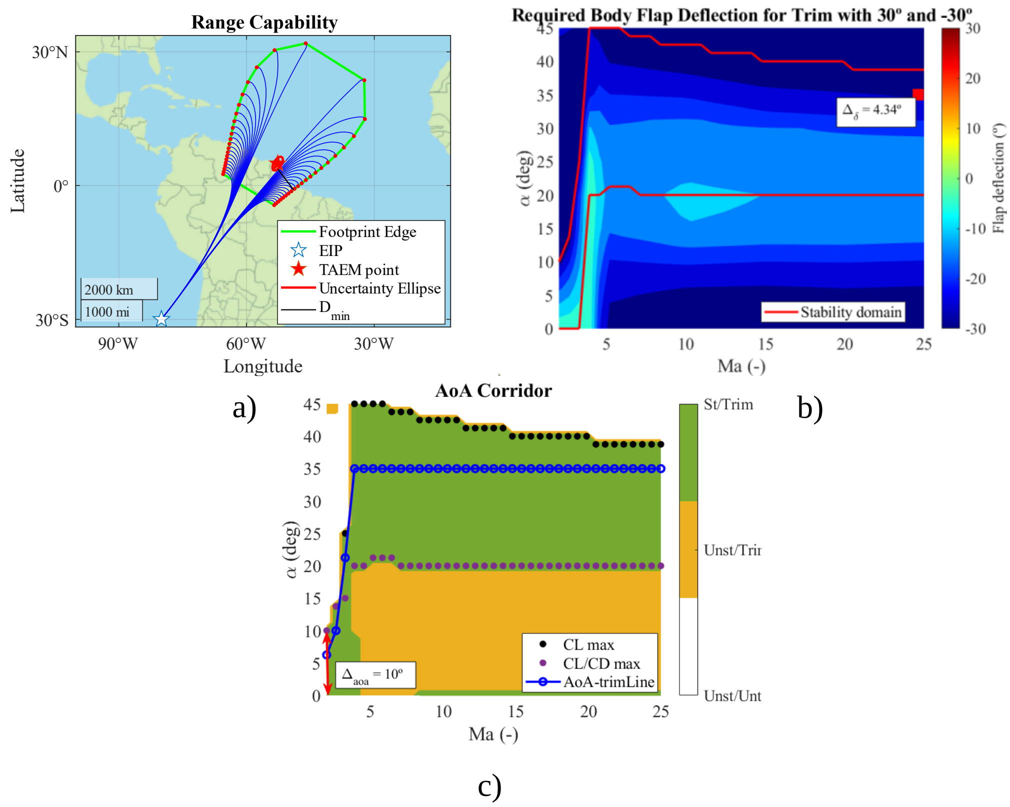


Figure 2: a) Minimum edge distance example (black line), **b)** minimum deflection margin example (red point), and **c)** minimum Angle-of-Attack corridor thickness (red arrow).

4 RESULTS

This section reports the results of the test case introduced in Section 3. Firstly, the solution obtained with both ESAT and MOPSO are compared. Then, the optimum solution space domain is explored and the preliminary system and mission design solutions are analysed.

4.1 Comparison of ESAT and MOPSO solutions

Concerning the optimization process performed with ESAT, the RBFs metamodel has been created by calling the MDA in 532 points (500 plus 32 hypervertices) generated with Latin Hypercube Sampling (LHS) within the research space domain. The optimal Pareto-Front is given by evaluating the metamodel in 70000 query points. The whole process takes about 45 minutes on Intel® Core™ i7-8750H processor, by using five cores in parallel. With these parameters, the metamodel describes the output of the MDA for the analysed case, with the errors shown in Figure 3. The error of the predictions is, in fact, < 80 km for the D_{min}, and < 10° for Δ_{δ}, and <15° for Δ_{AoA}, which is deemed acceptable for this test case. Regarding the MOPSO, the analysis considers a population of 50 particles with a maximum of 100 generations, thus a total of 5000 evaluations of the MDA. The MOPSO routine takes approximately 5 hours and a half to complete the process, on the same computer. In future research the drawback and benefit of using less generations will be studied.
Figure 4 shows the input distribution of the Pareto solutions obtained with ESAT (Figure 4a) and MOPSO (Figure 4b). The comparison of the plots shows similar patterns in the optimal solutions found by the two methods. The position of the Pareto solutions within the research space domain predicted by ESAT is visually similar to the results obtained with the MOPSO. This aspect is also visible in Figure 5, which illustrates the two Pareto-Fronts.
Comparison highlights that the metamodel approach may not capture the entire range of optimum solutions for the analysed test case. This behaviour is due to the approximation introduced by the metamodel itself, whose accuracy depends on the number of sampling points used for its construction. In contrast, MOPSO directly explores the search space and generates solutions based on the objectives without approximations. The accuracy of the metamodel method may be improved by both using more sample points and exploiting more advanced techniques for the generation of the surrogate [5]. However, the lack of accuracy is balanced by the higher computation efficiency of the metamodel approach (in this case, about 87% of run time reduction). Table 4 reports the parameters and the performance used for this test case. The results show that the metamodeling MDO is a valuable approach for the preliminary mission capability evaluation for the analysed scenario, so ESAT outcomes have been used for the solution analysis in the next section.

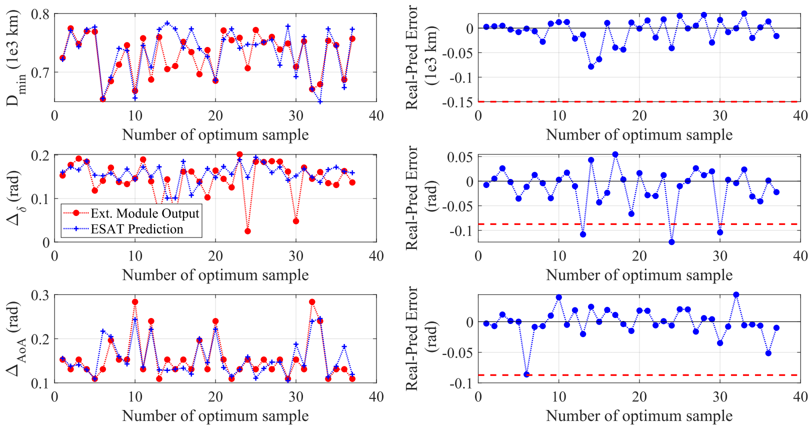
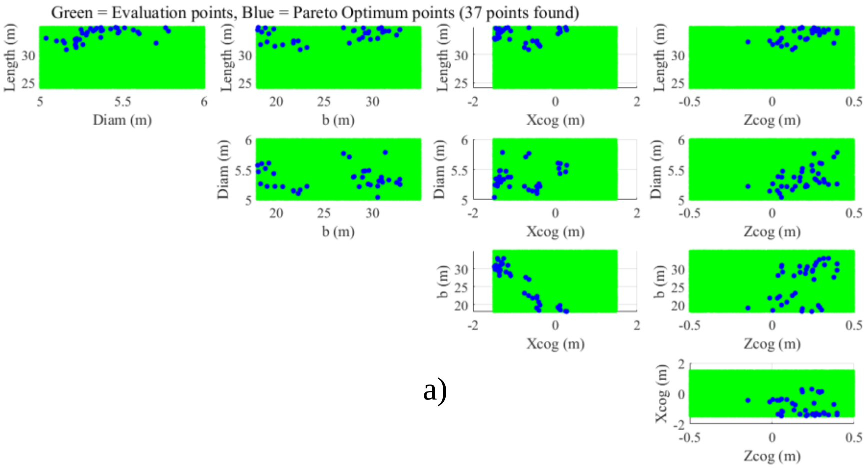
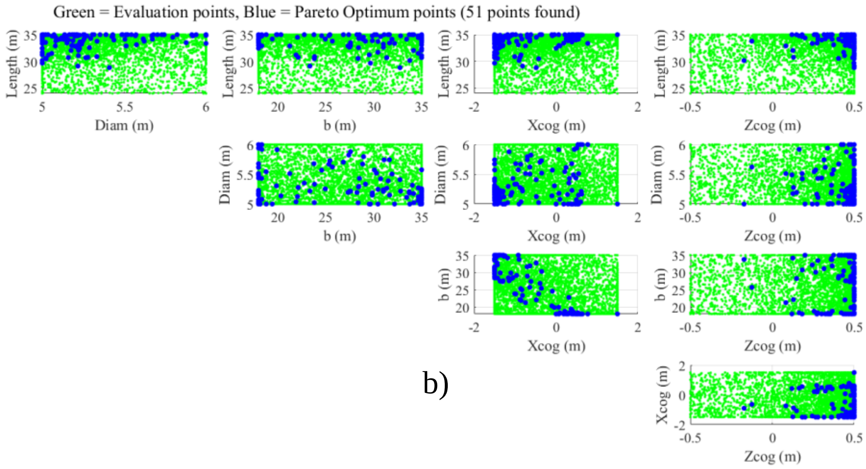


Figure 3: ESAT prediction of the optimum solution and validation with the MDA. On the left the figure shows the ESAT predictions (blue) are compared with the exact MDA evaluations (red), while on the right the correspondent errors are reported.



a)



b)

Figure 4: Comparison of the inputs distribution of the Pareto solutions computed with ESAT (a) and the MOPSO (b). Blue points are the optimal solutions, while the green ones are all evaluations.

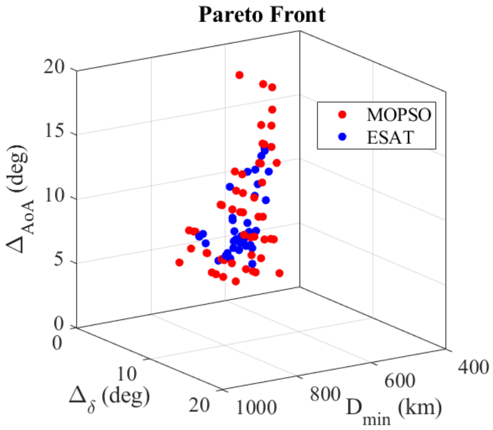


Figure 5: Comparison of the Pareto-Front obtained with ESAT and the MOPSO (right plot).

Table 4: Comparison between ESAT and MOPSO.

	MOPSO	**ESAT**
MDA Evaluation	5000	532
Metamodel Evaluation		70000
Pareto-Front points	51	37
Computational time, min	~340	~45

4.2 Solution Analysis: Preliminary System and Mission Design

Multidisciplinary design can benefit from optimization tools, leading to significant enhancements in the design process by exploiting cross disciplinary synergies [4]. However, the engineers must remain involved in the design process, ensuring control over the outputs and the results through their experience.

The solution space domain exploration is an interesting analysis that can be performed to trade-off the optimal solutions obtained in the previous subsection. This operation is supported by analysing the correlation between the input and the output, and the sensitivity analysis of the performance indices concerning the inputs. The objectives are to better understand the whole problem and to identify promising regions where more detailed analysis can be performed along the iterative design process. The research space exploration analysis is improved by exploiting the computational efficiency of the metamodel.

An example of this analysis applied to the test case is reported in this section. Figure 6 shows the correlation among the inputs-outputs. For the test case, the correlation between the length L, the wing span b, and the X_{cog} is evident, when the minimum edge distance (D_{min}) and the minimum deflection margin (Δ_{δ}) are taken into account. On the other hand, *Diam* and, Z_{cog} have a relatively small correlation regarding all the outputs. Moreover, Figure 4a shows that the optimal solutions are located mostly in a region where the length of the vehicle is in a neighbourhood of 35 m. The same discussion can also be done for the diameter and the z-position of the CoG. For these reasons, in the in-depth analysis that follows, these three parameters have been set to 35 m for L, 5.4 m for the *Diam*, and 0.25 m for Z_{cog}.

By reducing the problem from five to two variables, it is possible to visualize how b and X_{cog} influence the performance indices. Figure 7 reports the dependency of the outputs with respect to the two variable inputs. The white areas identify non-feasible regions, while the dots are the subset of the Pareto solutions characterized by length, diameter and Z_{cog} equal to the fixed values. These performance maps are crucial inputs for the engineers during the design process, in order to identify promising research space areas where local optimization can be carried out.

Out of 10 Pareto points found of the reduced problem, three of them are chosen as representative candidates. The first one is taken from the right part of the domain (blue dot, Figure 7). The second solution is the one in the middle of the research space (red dot, Figure 7), while the third one is in the left part of the map (green dot, Figure 7). These three points cover the denser area of the domain and the middle point. Table 5 lists the values of the design variables and the associated performances. Figure 8 shows the variation of the geometries of the three design solutions and the associated mission analysis performance. The plots illustrate the aerodynamic surfaces deflection required to trim the vehicle, the associated Angle-of-Attack corridor, and the estimated range capabilities.

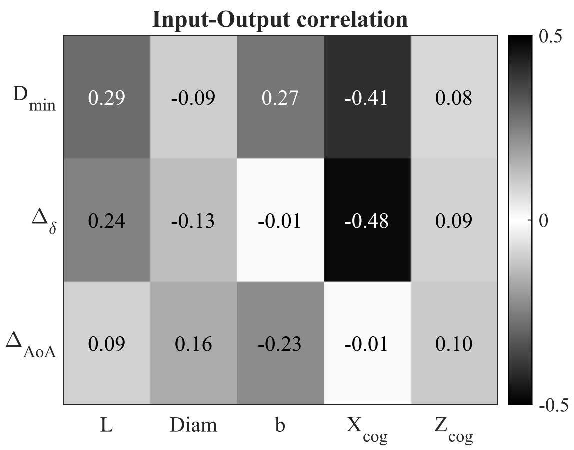


Figure 6: Inputs-Outputs correlation for WRV mission capability test case.

These examples show how different design options can provide similar mission capability performances. Solutions 1 and 2 perform well especially for the edge distance, and they have good performance for Δ_δ and Δ_{aoa}. Solution 3, on the other hand, has the best value of Δ_{aoa} between the three. The selection of the best one is not a trivial task, because several objectives must be considered and other drivers and requirements must to be taken into account. For instance, a larger wing span (candidate 1 and 2) implies a larger mass of the system, and so higher launch performance and costs. Moreover, such concepts can be more difficult to build from a technological and structural view point. Additional constraints, in fact, can be set by the customer, the launcher provider and more detailed analysis carried out along the design process, also considering other phases of the descent mission.

Table 5: 3 examples of optimal solutions. The table reports both ESAT predictions and MDA evaluations.

	Variables		**Performance Indices ESAT**			**Performance Indices MDA**		
	b, m	X_{cog}, m	D_{min}, km	Δ_δ, deg	Δ_{AoA}, deg	D_{min}, km	Δ_δ, deg	Δ_{AoA}, deg
Solution 1	30.70	-1.36	772.75	10.67	7.43	769.82	10.56	7.50
Solution 2	27.01	-0.64	773.91	5.80	7.51	710.38	3.33	7.50
Solution 3	18.15	0.26	708.50	8.47	12.70	685.22	9.41	13.75

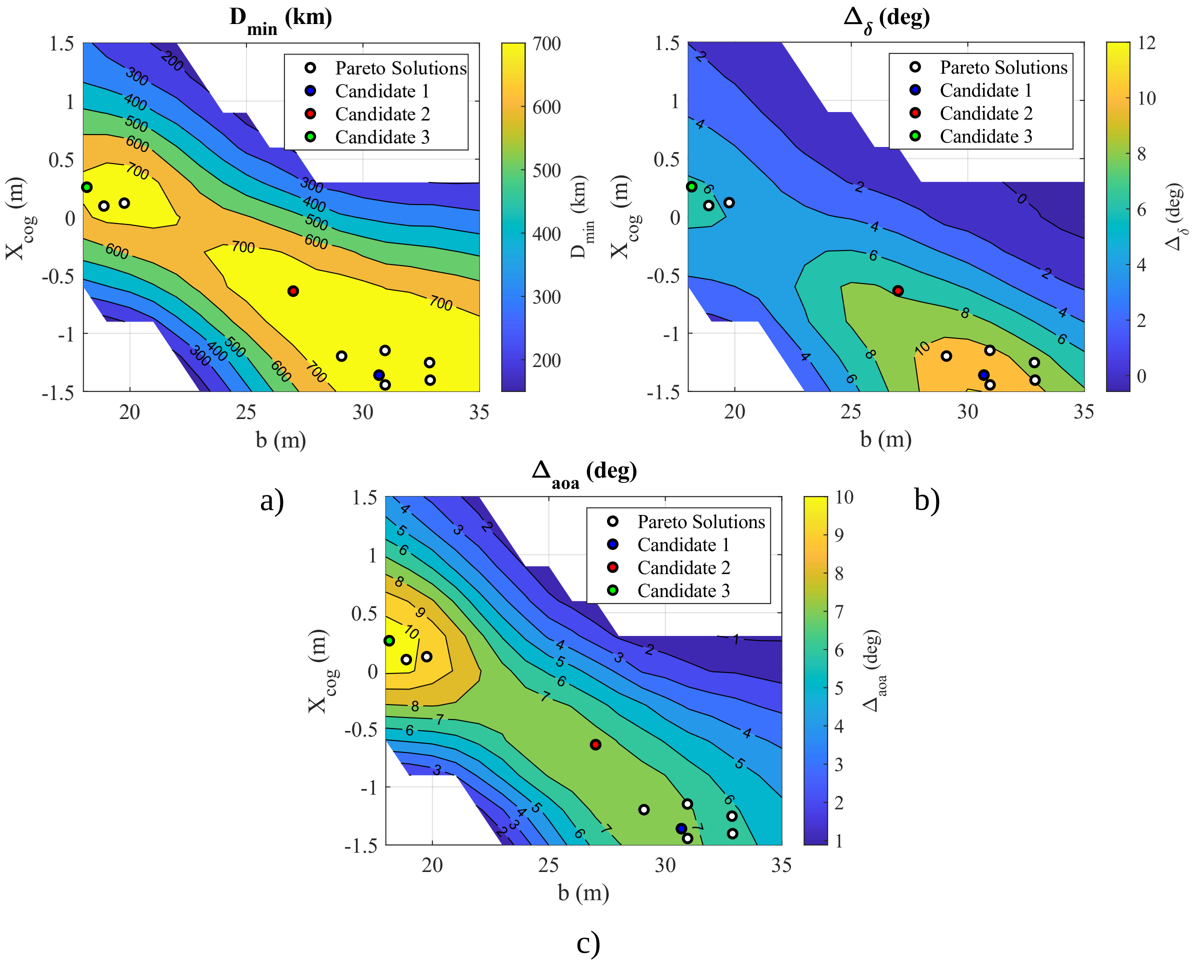


Figure 7: Minimum edge distance with respect to the X_{cog} and b (a); minimum deflection margin with respect to X_{cog} and b (b); minimum AoA corridor thickness with respect to X_{cog} and b (c). The dots show a subset of the Pareto solutions. For these plots, L, $Diam$ and Z_{cog} are kept fixed with values 35 m, 5.4 m and 0.25 m respectively. The white areas are the non-feasible regions.

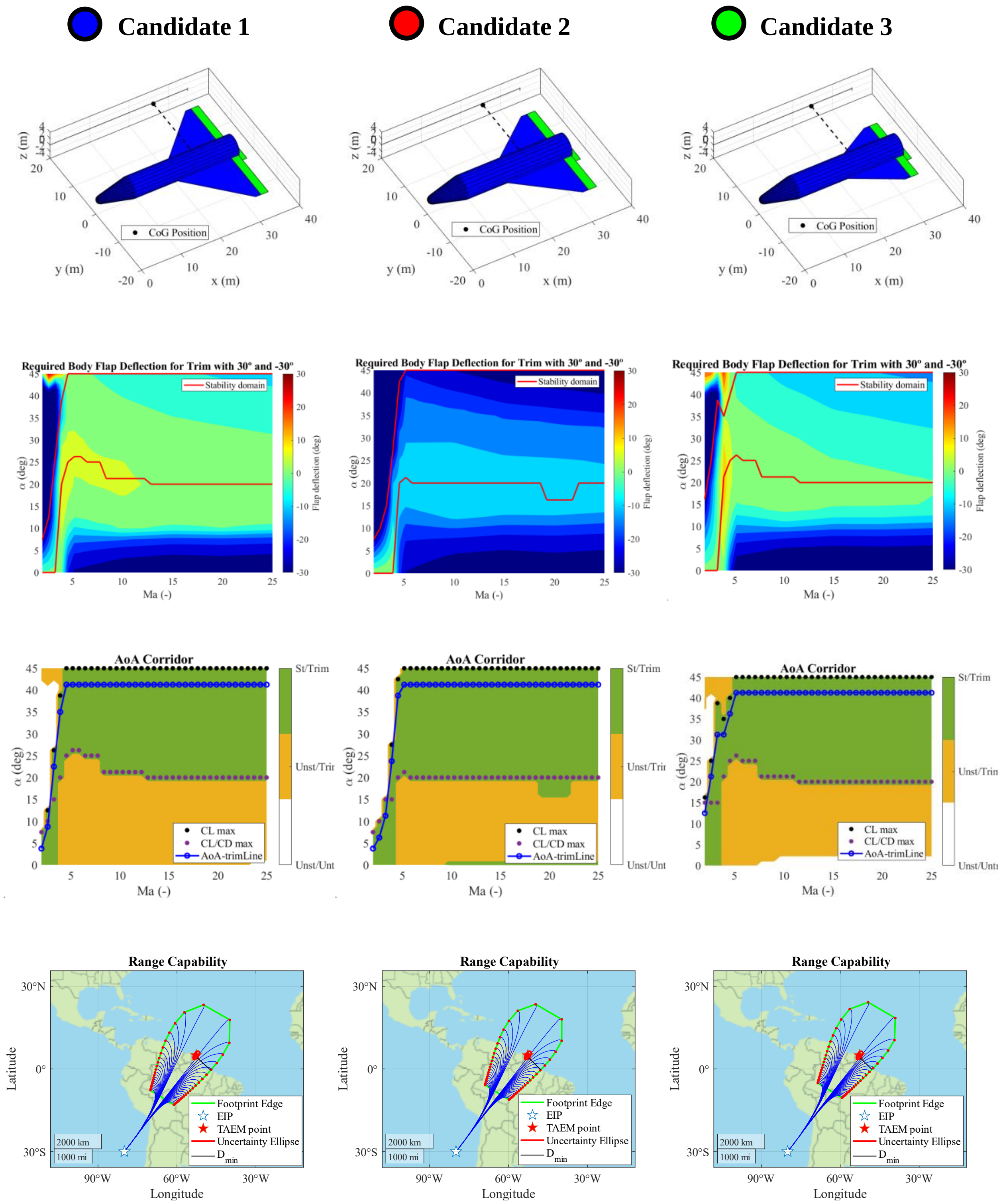


Figure 8: Geometries and mission analyses performance associated to the three selected candidates. The left plots refer to the candidate 1 (blue dot, Figure 7). The plots in the middle show the results for the candidate 2 (red dot, Figure 7). The right plots are relative to the candidate 3 (green dot, Figure 7).

5 CONCLUSION

The MA and GNC missionisation for autonomous re-entry vehicles is a problem characterised by multiple cross-disciplinary interactions. The paper presents two MDO approaches to handle the evaluation of the mission performance of WRVs with respect to a set of design parameters. The MDO can manage simultaneously several design variables and multi-objective performance indices, while satisfying a broad set of mission and system requirements. In particular, the study demonstrates that a metamodeling MDO approach can achieve complementary results of the MOPSO algorithm for the optimization routine in terms of accuracy, for the considered test case. In this paper, the metamodel has been constructed through Radial Basis Functions interpolation. Since the accuracy of the metamodel depends on the methods used, different functions can be tested in future work.

The higher computational efficiency of the metamodel MDO activity can be exploited for the rapid generation and exploration of the solution space domain. The surrogate can be probed practically in real time on consumer hardware. This process helps the engineers during the design process to identify and assess interesting regions, where more accurate optimization and more detailed analysis may be performed. The solutions obtained with the metamodel, in fact, can be used within an iterative design process as warm start guess solutions for local optimization.

This paper reports an example of search space exploration in order to trade-off different Pareto optimal solutions. The analysis shows how different solutions can be valuable candidates to fulfil the objectives. The selection of the best design solution is not a trivial work, especially in the first phase of the design where preliminary analyses are performed, and additional constraints may be added along the process. However, an MDO approach coupled with a critical inspection of the solution space domain can drive the engineers towards good designs solutions even in the early phases of the design.

In the context of missionisation, the metamodel MDO approach studied in this paper is a promising method to evaluate the mission capabilities of a winged re-entry vehicle and to provide robust solutions options in terms of mission analysis in the preliminary phase of the design process.

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