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Global and Local Multidisciplinary Design Optimization of Expendable Launch Vehicles

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The paper presents engineering models, optimization algorithms and design results from a Multidisciplinary Design Optimization (MDO) research in the framework of ESA's PRESTIGE PhD program. The application focuses on the conceptual design of classical unmanned Expendable Launch Vehicles, and results are presented from sensitivity studies and validation tests on European launchers (Ariane-5 ECA and VEGA). Relatively simple models and a mixed global/local optimization approach allow obtaining reasonable results with limited computational effort. A critical analysis of the results also leads to the identification of the most critical modeling aspects to be improved to allow for early preliminary design applications.

Nomenclature

α	=	engine mixture ratio
ε	=	nozzle expansion ratio
θ	=	pitch angle
ψ	=	yaw angle
μ	=	mean value
σ	=	standard deviation
A_e	=	nozzle exhaust area
AoA	=	total angle of attack
a	=	orbit semiaxis
C_L	=	lift coefficient
C_D	=	drag coefficient
C_m	=	pitching moment coefficient
CCB	=	common core boosters configuration
CpL	=	cost per launch
e	=	orbit eccentricity
GTOW	=	gross take-off weight
i	=	orbit inclination
I_{sp}	=	specific impulse, nominal conditions (i.e. nozzle optimal expansion)

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$I_{sp,vac}$ = specific impulse in vacuum
$I_{sp,sea}$ = specific impulse at sea level
L/D = length over diameter ratio
LSP = launch success probability
MR = Engine mixture ratio
M = Mach number
M_{prop} = Propellant mass (usable propellant only)
M_{dry} = Dry mass = inert mass + unused propellants mass
N_s = number of stages
N_{bs} = number of booster sets
$N_{b,j}$ = number of boosters for j-th boosters set
n_{ax} = axial acceleration
p_{cc} = chamber pressure
PL = payload
PLSF = payload scaling factor
q_{dyn} = dynamic pressure
q_{heat} = heat flux
SET = single engine type configuration (i.e. same engine type for all stages)
T_{nom} = total thrust, nominal conditions (i.e. nozzle optimal expansion)
$T_{,vac}$ = total thrust in vacuum
T_{sea} = total thrust at sea level

I. Introduction

The European Space Agency (ESA) proposed in 2009 to co-fund together with the Aerospace Engineering Department of Politecnico di Milano and the Center for Industrial Mathematics of Universität Bremen a joint research in the field of Multidisciplinary Design Optimization (MDO). This work is aimed at developing and comparing different optimization algorithms, MDO architectures and engineering methods to identify the most suitable for Expendable Launch Vehicles (ELV) design, up to the early preliminary level of detail and considering extensions to more complex applications such as manned and reusable systems.

A research in this field stems from the consideration that, when looking at the future of space exploration, the area with the higher potential for the development of new vehicles is surely that involving space transportation and space launch systems, both for manned and unmanned scenarios. In Europe, the Future Launchers Preparatory Program (FLPP)[1] is aimed at paving the way for a Next Generation Launcher (NGL), both in terms of technology developments and system studies. In this context, the availability of a reliable MDO environment supporting the designers up to an early preliminary level has the potential to drastically reduce the manpower, and therefore time and cost, necessary for the early design phases. Through the MDO approach in fact, the design space can be more rapidly explored, analyzing a high number of possible solutions and obtaining Pareto optimal fronts under different aspects, such as mass, cost, reliability, or mission flexibility. Designers can then select the most promising solutions to be used as good starting points for concepts refinements with more traditional design methodologies.

The first steps in the development of multi-disciplinary models were undertaken in the 1990s by Olds, Braun and others[2-5], but the lack of computational power restrained the application to the study of specific launcher configurations and prevented from the introduction in the optimization cycle of complex disciplinary models; besides, the Global Optimization (GO) approach that appears necessary when dealing with large multi-modal and mixed continuous-discrete search spaces and with multiple contrasting objectives, was never used due to its limited maturity. More recently, some industrial[6,7] and academic[8] researches in this area have considered automatic trade-offs among different configurations with Genetic Algorithms (GA), leading to interesting results. However, these solutions are limited to a conceptual level, employing rather simple disciplinary models and lacking of efficient distributed architectures as well as of multi-objective and Local Optimization (LO) refinement capability. On the other hand, a purely local approach has been followed in an industrial environment[9,10] allowing to achieve optimized design at a conceptual level starting from an initial guess in the desired region of the global search space.

Elaborating on the background presented above, the present research combines the advantages of GO and LO, with the aim of introducing engineering models suitable up to an early preliminary design phase of space launch vehicles. This approach, synergically developed by the two involved research centers, is being implemented by means of a modular object oriented (C++) software tool. The end customer is the European Space Agency who will use it in the context of concurrent design and industrial design evaluation. In this frame, a few key aspects of the research can be highlighted:

- *Hybrid global and local optimization*: whereas a global algorithm is required in order to tackle with architectural and technological discrete trade-offs, as well as with design from scratches in a large search space, local optimization should be exploited for efficient subproblem optimizations and solutions refinement.
- *Multi-objective optimization*, with the purpose of extending the classical "Design-To-Performance" approach to compromises with "Design-To-Cost", "Design-To-Reliability", etc.
- *User interactivity*, with the purpose of complementing the tool with the user's experience: it is not intended to replace but to support designers, by providing full control of the optimization process. This is realized by letting the user continuously vary - throughout successive global and local refinements - the design variables and their boundaries, the set of constraints and the optimization objectives and/or their weights, effectively guiding the optimization process towards the desired regions of the search space.
- *Computational efficiency* for both engineering models and optimization algorithms, to be coupled with *parallel computing* capabilities, of key importance in a computationally demanding area as MDO.
- *Modularity* of the MDO framework and *flexibility of the data storage structure*, aimed at improving the maintainability and expandability of the design environment, with the final goal of obtaining a generic MDO tool that can be easily extended to other classes of vehicles.

Even though these key aspects ensure a flexible and efficient MDO environment, the main obstacle to the successful application of the MDO approach still lays in the difficult task of finding a compromise between models simplicity and accuracy. To tackle this issue, the engineering models have been developed in two successive levels of detail, from conceptual to early-preliminary design. Previous papers[11-13] describe in detail models and algorithms introduced for the conceptual level step, and show disciplinary methods and optimization algorithms validation results. The present work draws on this experience, and focuses on a critical analysis of the system design results, with a twofold objective: to assess their accuracy, and to identify the most critical modeling aspects to be improved for the successive early-preliminary design step.

The paper is therefore divided in the following sections:

- Section II: brief overview of engineering models and Multidisciplinary Design Analysis (MDA) cycle for the conceptual design of ELV.
- Section III: high level description of the developed global and local optimization architecture.
- Section IV: critical analysis of the results in three areas: global and local trajectory optimization problem, sensitivity of system level figures to disciplinary errors, and MDA/MDO processes on existing European launch vehicles (Ariane 5 ECA and VEGA).
- Section V: concluding remarks with focus on the main modeling aspects being targeted for upgrade in the early preliminary design application.

II. ELV conceptual design models

The engineering modeling of launch systems is a particularly complex task, even restricting the targeted vehicles to classical (i.e. simple cylindrical stages and boosters with no wings), expendable, unmanned launchers. To simplify the implementation and employ a basic "black-box" optimization architecture without parallel computing, the models for conceptual design have been kept simple enough to allow for execution of a full MDA on a single processor[*] in a computational time in the order of one second. Due to this requirement and the need to integrate only freely available external tools, the choice of the engineering models has converged towards common software already selected by other MDO researchers[6,7,9], such as NASA's Chemical Equilibrium with Applications (CEA)[14] and USAF's Missile DATCOM[15]. These well-known tools are complemented by ad hoc developed models in the disciplines of propulsion, geometry, aerodynamics, weights, trajectory, guidance and control, costs estimation and reliability assessment.

Figure 1 presents the Design Structure Matrix (DSM) representing the design cycle closure for ELV conceptual MDA. All optimization variables, constraints and objectives, fixed user parameters and cross-disciplinary variables shown in the DSM are qualitatively reported in Table 1. Although more detailed description as well as validation results are given in Ref. 13, a brief overview of the implemented disciplinary models is given here:

[*] All computational times in the paper are referred to a 2.10 GHz single processor, 4 GB DDR2 RAM

- ***Propulsion***: the analysis is performed by either picking up an Off-The-Shelf (OTS) Liquid Propulsion (LP) or Solid Propulsion (SP) engine in a database collected mainly from Ref. 16 and the web*, or by designing a new SP or LP system. For new designs, the chamber pressure is determined on the basis of the feed system or solid grain parameters and CEA is used to determine theoretical performance. Additional empirical, historical and analytical models are implemented for I_{sp} losses, minimum operational altitude, inert masses, and dimensions.
- ***Geometry:*** only the vehicle's external geometry is defined, using the Langley Wireframe Geometry Standard[17] (LaWGS) and tools from the Public Domain Aeronautical Software (PDAS)† for 2D and 3D visualization.
- ***Aerodynamics***: Missile DATCOM is run to determine C_L, C_D and C_m databases. Interference coefficients are used to synthesize the full launcher aerodynamics from core and boosters for non-inline configurations.
- ***Weights***: historical Weight Estimation Relationships (WER), mainly taken or adapted from the comprehensive collection in Ref. 18, are implemented for all structural and and non structural component, allowing to assess the Gross Take-Off Weight (GTOW) of the launch vehicle.
- ***Trajectory***: 3-DoF dynamics (zero-order gravity, US 76 atmosphere, no wind) is integrated with a variable stepsize Runge-Kutta-Fehlberg 45 algorithm. Standard guidance laws define a reference flight profile, which is then optimized with few pitch and yaw parameters. Discretized thrust throttling, coast phases durations and circularization burn ignition time complete the set of control parameters. Additionally, a Payload Scaling Factor (PLSF) can also be optimized to evaluate the sensitivity of the launcher dimensions to the payload performance. Finally, models are included to account for propulsion performance with altitude, boosters or core in-flight ignition, and path constraints evaluation (q_{heat}, q_{dyn}, n_{ax},, static controllability, geographic heading).
- ***Costs and reliability***: The total Cost per Launch (CpL) is estimated through mass-based Cost Estimation Relationships (CERs), adapted to fully reflect all propulsion and vehicle technological trade-offs. Main sources are the TRANSCOST model[19] and internal ESA databases. The Launch Success Probability (LSP) is instead assessed through a time-dependant analysis of the failure chains in the different mission phases, with ESA provided components failures rates.

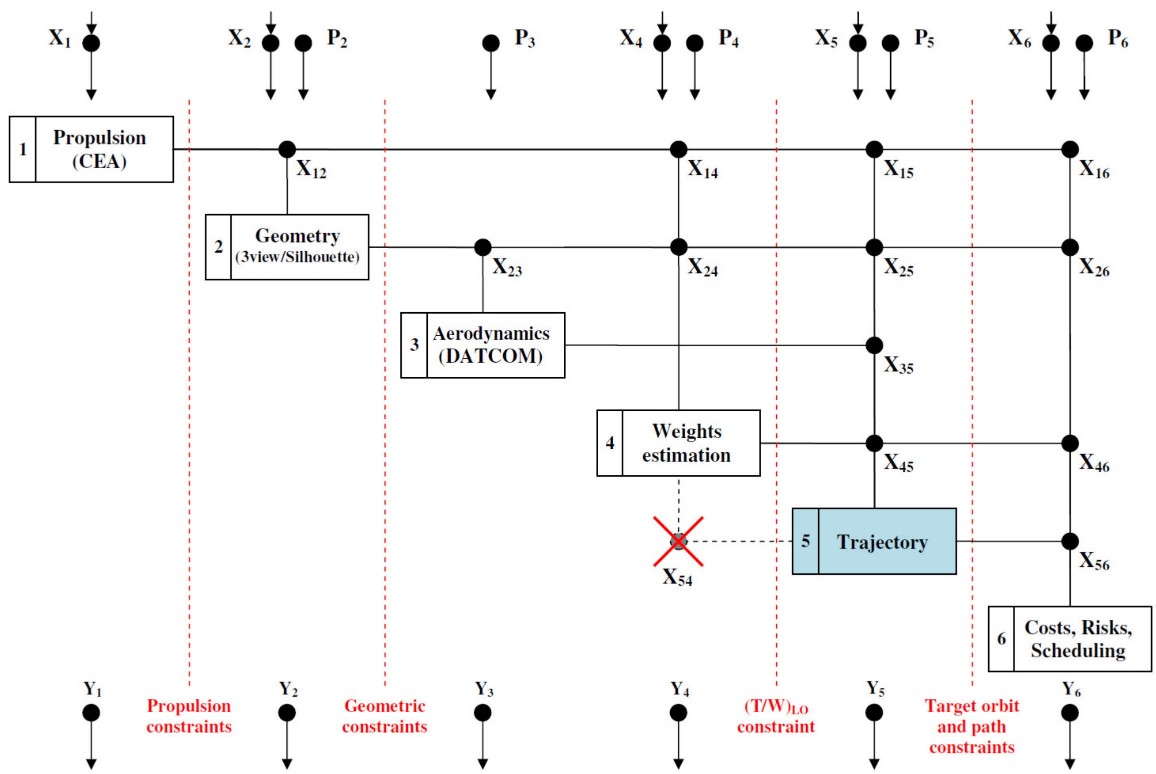


Figure 1: DSM for classical ELV conceptual design. P_j, X_j, and Y_j: fixed user parameters, optimization variables, and constraints/objectives outputs for discipline j, X_{ji}: variables from discipline j to discipline i (feed-forward/back information are above/below the diagonal).

* Most widely used sources are www.astronautix.com and engine manufacturers websites

† PDAS is available at www.pdas.com

Table 1: Qualitative description of the sets of variables reported in the DSM of Figure 1 (see Nomenclature section for the definition of all symbols)

P_2	Payload (PL) length and diameter	**X_{12}**	Prop. system lengths and diameters	**X_{46}**	All non propulsion masses
P_3	Aerodyn. database discretization settings	**X_{14}**	Prop. system masses and CoG positions	**X_{56}**	Flight phases durations
P_4	PL max q_{heat} and n_{ax}	**X_{15}**	I_{sp}, min. operative altitude, exhaust area	**X_{54}**	Max q_{dyn}, q_{heat} and n_{ax} loads. NOTE: this feedback is eliminated by using q_{dyn}, q_{heat} and n_{ax} as both optimization variables, input to weights, and path constraints for the trajectory
P_5	PL mass and target orbit (a, e, i)	**X_{16}**	Prop. system masses		
P_6	Program and cost factors	**X_{23}**	Complete launch vehicle geometry	**Y_1**	Propulsion constraints and specifications
X_1	Architecture (N_s, N_{bs}, $N_{b,j}$,CCB,SET), propulsion type (OTS or new, prop, feed) and design (p_{cc}, α, ε, T_{nom},…)	**X_{24}**	Lengths for all stages and boosters	**Y_2**	Geometric constraints, complete LaWGS geometry and PDAS visualizations
X_2	Architecture	**X_{25}**	Aerodynamic reference area	**Y_3**	Complete vehicle aerodynamic database
X_4	Architecture, structural trade-offs, max. q_{heat}, q_{dyn} and n_{ax}	**X_{26}**	Fairing length and volume	**Y_4**	Detailed weights breakdown structure, GTOW, take-off T/W constraint
X_5	Architecture, propulsion type and design, trajectory control parameters	**X_{35}**	Complete vehicle aerodynamic database C_L, C_D, C_m (M, AoA)	**Y_5**	All ascent trajectory data, final orbit, path constraints, PLSF if optimizable
X_6	Architecture, all technological trade-offs, cost & reliability oriented variables	**X_{45}**	All non propulsion masses and CoG longitudinal positions	**Y_6**	Detailed cost breakdown structure, mission success probability vs. mission time, CpL, LSP

Given a reference mission (payload mass and target orbit), the above disciplinary analyses therefore allow to close the design cycle, so that the ELV design can be optimized in single or multi-objective optimization mode with respect to four main aspects: 1) minimum GTOW, 2) minimum CpL, 3) maximum LSP and 4) maximum PLSF, subject to a variety of geometric, propulsive, controllability, loads and target orbit constraints.

III. Global and local optimization algorithms

The problem of efficiently integrating several disciplines in a single optimization problem leads to the design of the MDO architecture, the formulation of the overall optimization problem and the selection of a suitable optimization strategy.

The most straightforward Black-Box Optimization (BBO) approach is preferred due to the simple and fast analysis process. This can be classified as a No Decomposition (ND), Multi Disciplinary Feasible (MDF) problem formulation with System Level Optimization (SLO) architecture.

In Black-Box Optimization, the MDA is not divided in blocks but it forms a single block. It takes as inputs from the top level optimizer the design and trajectory optimization variables and it returns as outputs back to the optimizer the current values of the design objectives and constraints. The optimizer then recursively calls the model evaluation procedure moving toward feasibility and optimality.

The MDF formulation of the problem, as opposed to other methodologies such as Individual Discipline Feasible or All-At-Once architectures[20], is suitable for small and dense problems, or when no iterative loops are necessary to obtain multidisciplinary feasibility. The optimization algorithm controls only the optimization variables of the problem (that can either be at system-level or related to a single or more disciplines), limiting their number to the minimum possible. The full multidisciplinary feasibility is ensured at each optimization iteration, so that all outputs of each discipline exactly match the inputs of the others through the interdisciplinary mappings, and vice versa. It is a straightforward formulation suitable for the kind of problem we want to solve.

Another investigated approach to the MDO architecture is to include a Nested Optimization Loop (NOL) in the trajectory design. The trajectory optimization variables are in fact not shared with other subsystems, so that the variables defining the design of the launcher can be frozen at system level and a nested trajectory optimization loop can be performed within the MDA. Full multidisciplinary feasibility is maintained in both the outer and the inner loops. This approach can be identified as MDF - Hierarchic Decomposition (HD) since information to the guidance module are coming from the top level. It has two main advantages: a sustantial decrease of the number of optimization variables in the outer cycle. Moreover the possibility to employ more efficient local strategies in the solution of the trajectory optimization sub-problem since all variables are continuous and a good first guess solution is available through the guidance strategies. However, an optimization problem has to be solved for each MDA, even far from the optimum leading to a more complex computational problem.

The overall optimization problem has been classified as Mixed Integer Non Linear Programmin problem (MINLP). It presents a large number of mixed discrete and continuous optimization variables and nonlinear inequality constraints. The selected global optimization strategies are the following:

- Global Stochastic approach based on Evolutionary Algorithms, with the collaborative hybridization of three different algorithms: Non-Dominated Sorting Genetic Algorithm (NSGA-II)[21], Double Grid Multi Objective Particle Swarm Optimization (DGMOPSO)[11], and Multi Objective Ant Colony Optimization for continuous domains (MOACOr)[22]. The idea is to steer the algorithm toward the strategy that achieved the best results, in terms of contribution to the current Pareto Front, in the previous iteration. For single-objective optimization problems, the original Particle Swarm Optimization (PSO)[23] algorithm has been chosen, since it has been shown to be generally more efficient than the more traditional single-objective genetic algorithms.
- Deterministic derivative free optimization technique that employs direct search methods, the Mesh Adaptive Direct Search (MADS)[24,25]. The MADS algorithm is implemented in an open source library called Nonsmooth Optimization by Mesh Adaptive Direct Search (NOMAD)[*]. This method generates iterates on a tower of underlying meshes, starting from a set of trial points given by the user, on the design variable space domain, adapting the fineness of the mesh approaching local optima.
- Nested Optimization Loops that integrate local optimization techniques (Sequential Quadratic Programming and Interior Point methods) and heuristic techniques (Tabu Search method) in two nested loops. The heuristic strategy handles the discrete variables in an outer loop solving a pure Integer Programming Problem generating a feasible set of integer solutions for the inner Non Linear Programming (NLP) problem.

The final achieved design solutions can be refined with single-objective local optimization runs, freezing the discrete variables at the value found by the former global optimization strategy.

The NLP solver selected for the refinement of the solutions, for the nested trajectory optimization loop and for the nested heuristic/local optimization startegy is We Optimize Really Huge Problems (WORHP)[26,†]. WORHP is a combined SQP (Sequential quadratic programming) and primal-dual IP (Interior-Point) method, that was designed to solve sparse large-scale NLP problems with more than hundreds of millions of variables and constraints. It has been developed by the joint work of the teams from the University of Bremen and the team from the University of W¨urzburg. Its robustness was proved by the CUTEr test set, consisting of 920 sparse large-scale and small dense problems, of which WORHP is able to solve 915. Moreover WORHP successfully solved several space application problems, e.g. reentry, ascent and low thrust trajectory optimization problems.

IV. Conceptual level ELV design results

This section presents a critical analysis of design results obtained with the engineering methods and optimization algorithms described in Sections II and III, focusing on the accuracy of the models in terms of global performance indexes and on the identification of the modeling aspects being the larger cause of errors. Although other vehicles have been analyzed, the two European launchers Ariane 5 ECA and VEGA are used throughout this section as test cases.

First, global and local trajectory optimization capabilities are presented. This allows to understand the level of confidence in the payload mass assessment that can be achieved with the developed trajectory models. Building on this, a Montecarlo analysis is shown that aims at estimating the expectable (1σ) errors in payload mass, starting from the errors on the design parameters determined in the disciplinary-level validation phase. Finally, MDA and MDO results are discussed, with focus on three aspects: the performance assessment accuracy of the overall multidisciplinary design cycle, the improvements in the launcher's design obtained through optimization, both in terms of variables space and constraints/objectives space, and the capability to represent trade-offs with respect to multiple objectives, in particular mass, cost and payload mass excess.

A. Global and local trajectory optimization

Test cases for the trajectory optimization as well as for all MDA/MDO problems are the European Ariane 5 and VEGA, with the following mission specifications:

[*] The NOMAD software library is available at http://www.gerad.ca/nomad

[†] The WORHP software library is available at http://www.worhp.de

- Ariane-5 ECA: standard Geostationary Transfer Orbit (GTO) (250x35943 km, 6 deg) from Kourou, nominal payload of 10050 kg, fairing jettison triggered at 1035 W/m^2, max axial acceleration 4.55 g, max dynamic pressure 57000 kPa.
- VEGA: circular polar Low Earth Orbit (LEO) at 700 km from Kourou, nominal payload of 1500 kg, fairing jettison triggered at 1035 w/m^2, max axial acceleration 7.5 g, max dynamic pressure 57000 kPa.

Using the actual launcher design parameters, trajectories for Ariane 5 and VEGA have been optimized with both the global PSO, performing 3 runs of 300 iterations and 250 particles for stochastic effects, and the local WORHP. The ascent trajectory model defines a phase structure that includes standard guidance laws for the generation of first guess pitch and yaw profiles, as well as of thrust throttle and coast phases duration. This way local optimization processes are started with a reasonable first guess (i.e. a "flying" trajectory rather than one ending in a crash on the planet), allowing for fast convergence to the final optimum. Moreover, particular attention has been paid so that the trajectory modeling results in a smooth optimization problem. For example, automatic stopping of the integration when the target orbital energy is reached is useful to reduce computational times in case of global optimization, but causes a huge number of small discontinuities and oscillations in the final orbit constraints due to the integration discretization. This constitutes a large hindrance to the local algorithms, which get trapped in different feasibility regions when slightly varying the first guess or any of the launcher design or algorithm's parameters, drastically affecting the robustness of the process. Particularly good results have been achieved when this and other smoothness issues have been solved, allowing to obtain comparable or better solutions with respect to PSO in much shorter computational times.

The optimization problems for Ariane 5 ECA and VEGA slightly differ in terms of variables and flight phases. In particular, for the Ariane5 ECA to GTO, the trajectory model is divided in 4 phases, the throttle of the liquid engines is constant at 100% and the solid boosters have a simplified two-level thrust profile. Hence, only trajectory optimization variables related to payload mass and pitch and yaw profiles are used, for a total of 10 continuous variables. Instead, VEGA's ascent to a polar LEO is divided in 9 phases, including a coast phase between Z23 and Z9 flights and the upper stage coast and circularization burn. As in the previous case the trajectory optimization variables are related to payload mass, pitch and yaw profiles, with the addition of the coast times, for a total of 12 variables. In both cases constraints are imposed on the final orbital parameters as well as on Q_{dyn}, Q_{heat}, N_{ax}, atmospheric AoA and static controllability.

Results from the trajectory optimizations are presented in Table 2, showing comparable values for PSO and WORHP. Note that the stochastic effects do not lead to excessive standard deviations in the payload mass among the different PSO runs, but this is obtained through a large number of model evaluations (75000) and therefore long computational times, in the order of 1.5-2.0 hours per each run. This is approximately halved when a multiprocessor OpenMP implementation for shared memory machines is used on a standard dual-core pc, but global algorithms still result much less efficient than the local WORHP, which is able to find the optimal solutions in 5 to 20 minutes.

From the models accuracy point of view, it is clear that the trajectory models tend to overestimate the payload mass, specifically by 13% for Ariane and 8% for VEGA. Although this may in part be due to inaccuracies in the launcher parameters data, two modeling aspects also contribute to an optimistic evaluation of the payload mass: steering losses throughout the ascent are fully neglected and the specific impulse is assumed constant. Introduction of a steering ΔV in the propellant budget as well as of an empirical evalution of the effect of throat erosion, particularly relevant in case of SP motors, may therefore allow to improve the payload assessment accuracy.

Table 2: Trajectory optimization results for Ariane 5 ECA and VEGA test cases, payload mass values obtained with PSO and WORHP for launcher parameters frozen to the actual design values

	Reference	PSO best	PSO stdev	WORHP
Ariane 5 ECA to GTO	10050 kg	11440.3 kg (+13.4%)	69.4 kg	11453.1 kg (+14.0%)
VEGA to polar LEO	1500 kg	1616.9 kg (+7.8%)	20.6 kg	1624.7 kg (+8.0%)

B. Sensitivity analyses

Payload mass performance sensitivity analyses start from the modeling errors identified within a disciplinary level validation phase, presented in Ref. 13 and summarized in Table 3, where maximum absolute value, average and standard deviation of the errors on several design parameters are reported. Errors are evaluated on a database of European, US, Russian and Japanese ELVs, collected from Ref. 15 and web sources.

Sensitivity analyses are then executed by varying one or more of the actual design parameters of Ariane 5 or VEGA, and optimizing the trajectory to the evaluate the payload performance variation with respect to the reference cases reported in the previous subsection. Two different types of sensitivity analysis have been performed:

- ***One-variable-at-a-time:*** by perturbing only one of the parameters in Table 3 by the quantities μ+σ and μ-σ, the impact of the 1σ worst case error on this parameter can be evaluated, taking into account both the modeling fidelity and relevance of all disciplinary outputs. This analysis, repeated for all variables and for all stages/boosters of Ariane and VEGA, shows how the most critical discipline is the weights analysis, with up to 15% error on the payload. In particular, the large payload sensitivity to the upper stage mass $\left(\partial M_{PL} / \partial M_{dry,us} = -1\right)$ suggests to increase the effort in the modeling of the upper stage mass components. On the contrary, the vacuum specific impulse of the different stages and boosters, although having a large influence on the PL performance, is modeled with much higher accuracy and therefore results less critical. Finally, the exhaust area (determining the I_{sp} altitude variation) and the aerodynamic coefficients both seem to have a small impact on the PL mass (<2%).
- ***Montecarlo analyses***: by randomly varying all parameters at the same time according to Gaussian distributions of the errors (μ and σ from Table 3), the launcher payload performance distribution can be derived, again in terms of Gaussian μ and σ. These respectively define the bias towards payload mass over or underestimation and the expectable variability in the launcher's performance due to modeling errors. This latter parameter is extremely important in a MDO context, allowing to achieve confidence that a given optimized design solution is actually better with respect to the discarded options, if the difference is larger than σ.

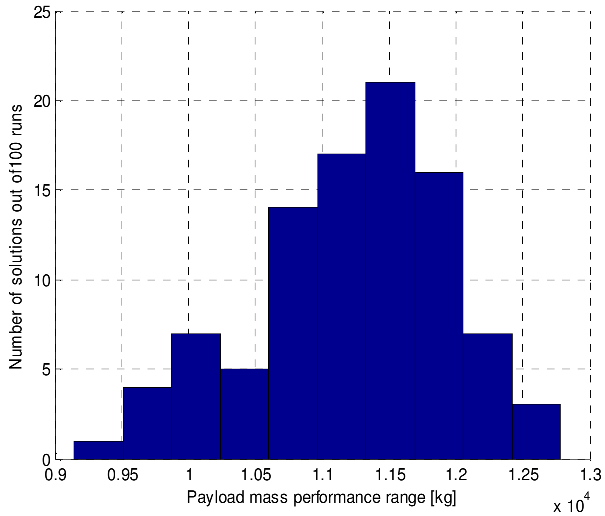
Table 3: Disciplinary models validation summary: max, mean and std of errors on the output parameters

Discipline	Parameter	Max abs error [%]	Mean error μ [%]	Error stdev σ [%]
Propulsion	$I_{sp,vac}$ [s]	3.09	-0.59	1.27
Propulsion	A_e [m^2]	31.19	-0.85	15.03
Propulsion	M_{engine} [kg]	28.74	-0.00	11.15
Aerodynamics	C_D	81.80	+4.28	9.27
Aerodynamics	C_L	98.47	+9.10	14.27
Weights	$M_{fairing}$ [kg]	33.62	-8.68	16.40
Weights	$M_{dry,SPboosters}$ [kg]	21.09	-0.04	13.50
Weights	$M_{dry,SPstages}$ [kg]	36.06	+8.31	16.07
Weights	$M_{dry,LPupperstage}$ [kg]	21.24	-5.30	14.18
Weights	$M_{dry,LPlowerstage}$ [kg]	37.60	+5.63	13.47

Results of the Montecarlo analyses are presented in Figure 2 and Figure 3, and summarized in Table 4. The mean values of the performance distributions show a bias towards respectively over and underestimation of the payload mass for Ariane 5 and VEGA, with 11217.0 kg and 1487.6 kg. This different behaviour can be again traced back mainly to the weight models, and in particular to the different mean errors for the dry masses of stages and boosters: Ariane 5 cryogenic upper stage shows in fact a negative mean error, therefore resulting in higher mean payload mass, whereas all VEGA solid stages masses have a positive mean error, that more than offsets the lower mass of the small storable upper stage. As regards to the standard deviation of the performance distributions, σ=16% for Ariane 5 and σ=8% for VEGA have been obtained. These are reasonable figures for expected 1σ launcher performance error in a conceptual-level design environment employing simplified engineering models.

Table 4: Montecarlo analysis results, payload performance Gaussian distribution

	Ariane 5 ECA	VEGA
Payload mass distribution mean value μ	11217.0 kg (+11.6%)	1487.6 kg (-0.2%)
Payload mass distribution stdev σ	761.8 kg (+15.9%)	239.1 kg (+7.6%)



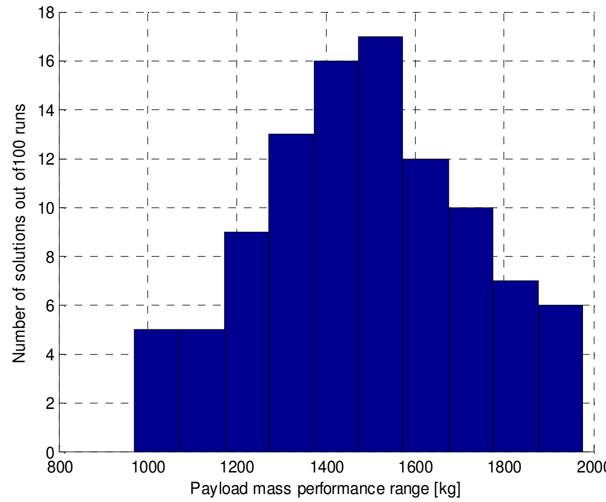


Figure 2: Montecarlo sensitivity analysis results for Ariane 5 ECA payload performance distribution

Figure 3: Montecarlo sensitivity analysis results for VEGA payload performance distribution

C. MDA for Ariane 5 ECA and VEGA

Before introducing the full MDO capabilities, results are presented for stand-alone MDAs of Ariane 5 and VEGA, with the purpose of providing additional figures of payload performance accuracy in confirmation of the Montecarlo analyses. For MDAs, all input design variables (i.e. X_j in Figure 1) are frozen to the actual values, and the complete design cycle is executed, including a nested trajectory optimization to determine the payload performance for the launcher primary mission.

Since propulsion parameters computed within the MDA closely match the available data, only mass and geometry properties are reported in Table 5 and Table 6, whereas Figure 4 and Figure 5 present the drag coefficient for different AoA. Overall system level figures such as take-off mass, payload mass, cost per launch and reliability are instead summarized in Table 7. All data are presented in comparison with the actual values taken from manual or internal ESA data. Although the total wet masses at launch match very well the actual values for both launchers, the mass breakdowns show significant differences. In particular, Ariane upper stage dry mass is underestimated by 2.7 tons with respect to the ESC-A stage plus Vehicle Equipment Bay, due to insufficient modeling of the different structural and non structural components located in an upper stage. For VEGA, P80 and Z23 motors dry masses are sensibly overestimated (25% and 19%), probably because VEGA nozzles employ new technologies and materials which are not captured with historical SP motors weight models. In light of these design errors, the nested trajectory optimization results confirm what observed in the Montecarlo analyses, with a +24.1% payload mass with respect to the reference value for Ariane 5 and -8.0% for VEGA.

Although it has been possible to quantitatively assess the accuracy of the developed models with respect to performance indexes, only a qualitative understanding of the fidelity of the cost and reliability models is possible, since detailed cost breakdown structures or failure data are not available for comparison. However, launch costs appear to be in general overestimated with respect to the available prices for Ariane 5 ECA and VEGA. The calculated CpL includes however the development costs spreaded over 120 launches (under the assumption of 6 launches per year, 20 years of operations), which mat noy be fully considered in the advertised launch price. The LSP=0.975 obtained for VEGA matches very well the target 98% reliability, whereas a pessimistic LSP=0.927 for Ariane 5 ECA (97% success rate with 1 failure out of 29 launches) suggests that liquid propellants reliability is underestimated with the developed models. As a final remark, a wider validation effort for the cost and reliability disciplines has been performed considering non European launchers (Sojuz, Atlas, Delta and Falcon families), showing that the correct ranking among the different launchers in terms of CpL and LSP is reproduced. Although full confidence cannot be placed on the absolute values of CpL and LSP, this supports the use of the models for the representation of performance vs. cost vs. reliability trade-offs.

Parameter	MDA	Actual
Mass properties		
Payload fairing mass [kg]	2718	2675
Upper stage inert mass [kg]	3261	6000
Lower stage inert mass [kg]	17413	14700
Boosters inert mass [kg] (each)	31446	30955
Total launch mass [kg]	**764835**	**763695**
Geometry		
Payload fairing length [m]	17.0	17.0
Upper stage length [m]	5.22	4.71
VEB length [m]	1.55	1.40
Lower stage length [m]	25.42	30.52
Boosters length [m]	32.76	34.61
Total launcher length [m]	**49.19**	**52.53**
Reference aerodynamic area [m^2]	**37.51**	**37.51**

Table 5: Mass and geometry, comparison of MDA results and actual values for Ariane 5 ECA

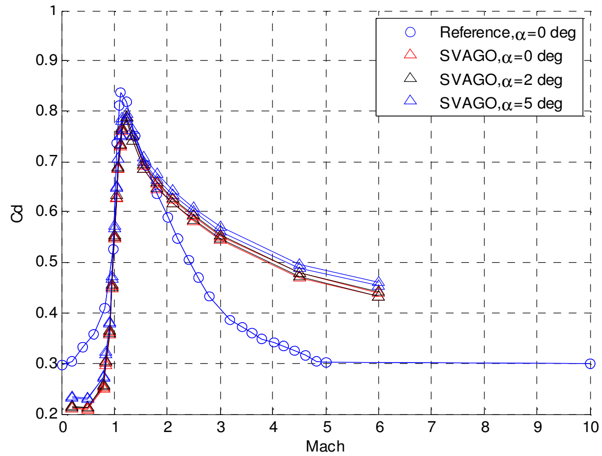


Figure 4: Aerodynamic drag coefficient, comparison of MDA results and actual profile for Ariane 5 ECA

Parameter	MDA	Actual
Mass properties		
Payload fairing mass [kg]	650.8	529
1st stage inert mass [kg]	9297	8497
2nd stage inert mass [kg]	3091	2725
3rd stage inert mass [kg]	1317	1416
Upper stage inert mass [kg]	781	687
Total launch mass [kg]	**139391**	**138089**
Geometry		
Payload fairing length [m]	7.88	7.88
1st stage length [m]	12.32	11.20
2nd stage length [m]	8.74	8.39
3rd stage length [m]	5.21	4.12
Upper stage length [m]	2.48	2.04
Total launcher length [m]	**36.63**	**33.63**
Reference aerodynamic area [m^2]	**7.21**	**7.21**

Table 6: Mass and geometry, comparison of MDA results and actual values for VEGA

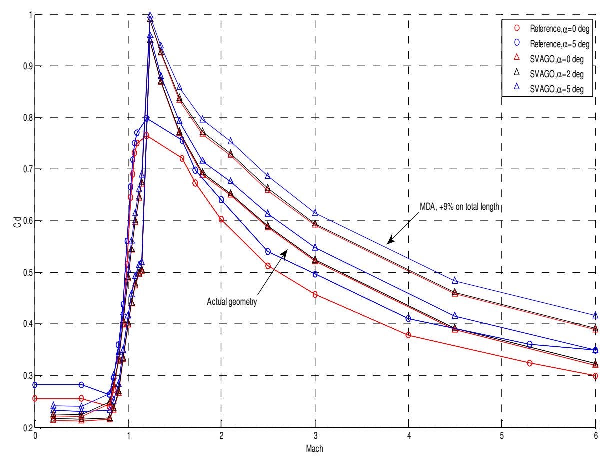


Figure 5: Aerodynamic drag coefficient, comparison of MDA results and actual profile for VEGA

Table 7: summary of system level MDA results for Ariane 5 and VEGA, in comparison with actual values

	Ariane 5 ECA actual	Ariane 5 ECA MDA	VEGA actual	VEGA MDA
Payload mass	10050.0 kg	12476.3 kg	1500 kg	1380.0 kg
Total launch mass	763.395 tons	764.835 tons	138.089 tons	139.391 tons
Total launcher length	52.53 m	49.19	33.63 m	36.63 m
Total cost per launch	150 M€	171 M€	30 M€	37 M€
Development costs	-	37 M€	-	7 M€
Production costs	-	99 M€	-	19 M€
Operations costs	-	36 M€	-	12 M€
Launch success probab.	0.966 (historical)	0.927	0.980 (estimated)	0.975

D. Single-objective MDO for Ariane 5 ECA and VEGA

With the twofold purpose of evaluating how the optimization process steers the design in both the variables and objectives space and of verifying the representation of trade-offs with respect to multiple objectives, different MDO runs have been executed, freezing all discrete optimization variables and allowing for rather small variability of the continuous design parameters. First, the single objective PSO algorithm has been used to minimize the total launch mass with fixed payload, then DG-MOPSO has been applied to a min launch mass vs. min launch cost and to a min launch mass vs. max payload mass multi-objective optimization problems. Reliability has not been included among the objectives since it largely depends on the discrete variables, in particular number of staging and re-ignition events, propulsion technologies (solid against liquid, feed system type, throttle level) and redundancy approach (engine out capability, avionics and power system outline).

Three PSO runs have been executed, allowing for long computation times in order to verify the convergence properties and determine the extent to which the stochastic nature of the global algorithms affects the final solution. Local refinement processes have followed, using the global solutions as starting points. Global and local optimization results for Ariane 5 and VEGA are shown in Figure 6 and Figure 7. For Ariane, the MDO problem consists of 14 continuous design optimization variables and 12 trajectory optimization variables. A good convergence is reached in 1000 iterations (100000 MDA evaluations, single processor CPU time of ~13 hours), with ~2% consistency of final objective value among the different runs. Similar convergence histories are obtained for VEGA, for a larger problem consisting of 25 continuous design variables and 15 trajectory variables, with a ~3% variability in the final objective value and increased CPU times (~16 hours) due to a longer ascent trajectory.

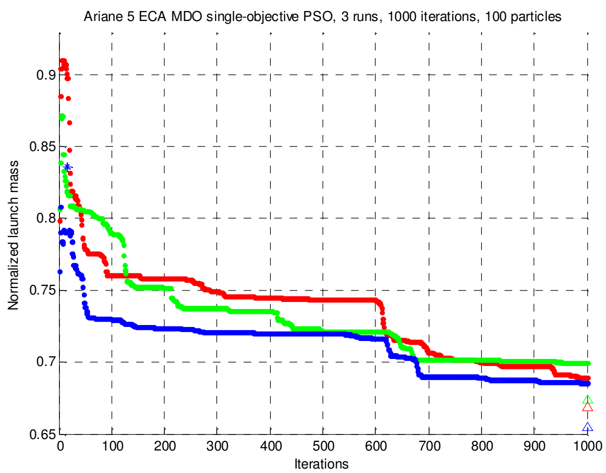


Figure 6: Ariane 5 ECA min GTOW MDO process, PSO convergence and WORHP refined solutions (triangles) for 3 runs with different random seeds

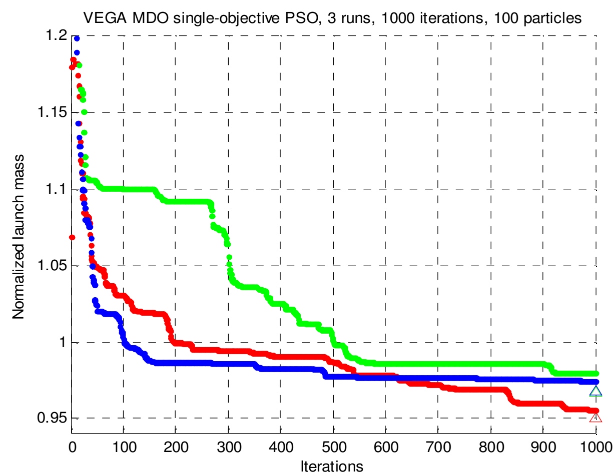


Figure 7: VEGA min GTOW MDO process, PSO convergence and WORHP refined solutions (triangles) for 3 runs with different random seeds

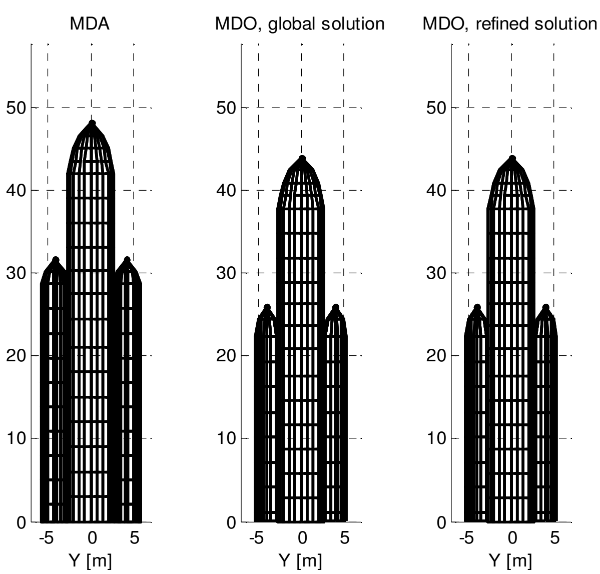


Figure 8: Ariane 5 ECA min GTOW MDO results, comparison of external geometries

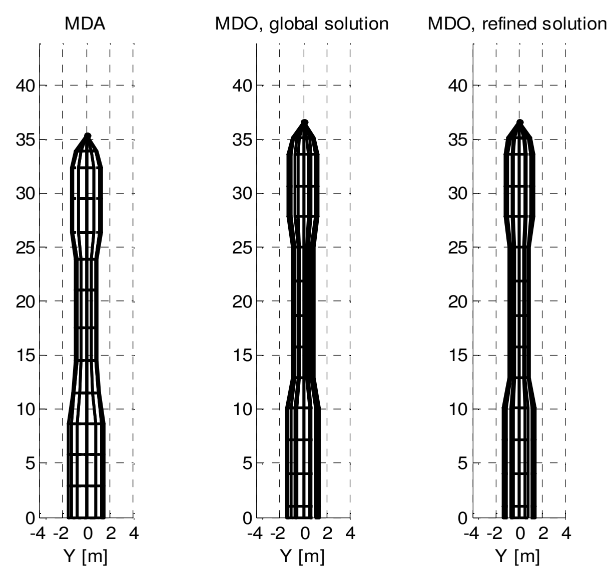


Figure 9: VEGA min GTOW MDO results, comparison of external geometries

The local optimization process in general improves the design obtained by PSO, but the refinement of the final solutions from three different runs leads to different local minima. Although the difference is not large (<2%), this suggests that improvements on the smoothness of the model may allow to shorten the global optimization in favour of the local refinement, improving the efficiency of the overall process.

As regards to the design solutions obtained with the min GTOW global and local MDO processes, results are shown in Figure 8 and Figure 9, reporting the geometries of the best global and local solutions found in comparison with the reference MDA geometry, and in Table 8 and Table 9 summarizing some of the most relevant design variables.

For Ariane 5, a minimum launch mass of 504 tons is obtained with PSO, further reduced to 498 tons by WORHP refinement, corresponding to a 34% reduction with respect to the launcher's GTOW from the MDA. This result confirms the performance overestimation reported in subsection IV.C, showing that an additional performance increase can be obtained with the MDO process. Since the design parameters of Vulcain-2 and HM-7B liquid engines have not been allowed to change, the optimization mainly acts on the propellant loading of core, upper stage and boosters, as well as on the boosters thrust and length-over-diameter ratio. Table 8 shows a drastic reduction in the size of SP boosters (M_{prop} and T_{nom}), justified by the lower I_{sp} with respect to LP engines. Propellant mass of the core is also reduced, in front of an increase in the upper stage loading. This suggests a non mass-optimal allocation of propellant in the actual design of Ariane 5, although the structural ratio of the upper stage is largely underestimated by the weight models, hence favoring an higher load. Among the other design optimization variables, the maximum allowed trajectory loads Q_{dyn}, Q_{heat} and N_{ax} are decreased in the optimization process, since this allows reducing the structural mass while still meeting the path constraints. The dynamic pressure is the only active path constraint, and the optimal solutions present a steeper trajectory with respect to the MDA ascent, to allow flying the lower max Q_{dyn} profile.

Table 8: Ariane 5 ECA min GTOW MDO results: main design variables for MDA, global and local solutions

Parameter	MDA (actual design)	PSO best optimal	WORHP optimal
$M_{prop,core}$ [tons]	173.3	137.5	138.7
$M_{prop,upperStage}$ [tons]	14.4	17.0	17.0
$M_{prop,boosters}$ [tons] (each)	240.1	143.0	139.4
$T_{nom,boosters}$ [MN] (each)	5.796	3.979	4.088
$L/D_{boosters}$	7.61	7.24	6.83
GTOW [tons]	764.8	504.4	498.1
CpL [M€]	170.9	139.9	139.1

Table 9: VEGA min GTOW MDO results: main design variables for MDA, global and local solutions

Parameter	MDA (actual design)	PSO best optimal	WORHP optimal
$M_{prop,P80}$ [tons]	87.7	76.9	76.6
$M_{prop,Z23}$ [tons]	23.8	25.0	25.4
$M_{prop,Z9}$ [tons]	10.6	10.7	9.6
$M_{prop,avum}$ [kg]	550	770	770
L/D_{P80}	2.84	3.40	3.40
L/D_{Z23}	1.39	1.63	1.62
GTOW [tons]	139.4	127.9	126.9
CpL [M€]	36.9	34.8	34.7

For VEGA, minimum launch masses of 128 tons with PSO and 127 tons after WORHP refinement are achieved, corresponding to an 8% reduction with respect to the MDA design. Although the performance of VEGA has been shown to be underestimated, the design optimization allows reducing the total mass. Propellant mass distribution and length-over-diameter ratios are the design variables most affected by the MDO, and are reported in Table 9. Again, the better performance of LP engines favors an increase in the propellant load of the AVUM upper stage, which is pushed to the upper bound, whereas the P80 first stage is reduced in size and Z23 and Z9 remain close to the actual design. The mass optimized launcher is longer with respect to the MDA design (see Figure 9), although its mass is smaller, due to an increase in the L/Φ ratios, both pushed to the upper bound for aerodynamic reasons. Note that the static controllability path constraint only considers the torque requested during the pitch-over phase to counteract the non-null AoA, whereas a perfect gravity turn is assumed for the rest of the atmospheric flight. Introduction in the modeling of wind or other non nominal flight conditions would lead to a more conservative controllability evaluation. This as well as simplified methods to evaluate the launcher's flexibility would contrast the aerodynamic push towards thinner configurations, resulting in more realistic configuration trade-offs. As regards to the SP motors, nominal thrusts are not sensibly varied, except for a ~5% reduction for the first stage. However, an almost 20% decrease in the chamber pressure of both P80 and Z23 indicates that a reduction in the motor's dry mass outweights the loss of I_{sp} performance, confirming the inadequate modeling of the VEGA SP engines inert masses. Finally, as for Ariane, Q_{dyn}, Q_{heat} and N_{ax} are sensibly decreased in the optimization, with the axial acceleration being the active constraint in the case of VEGA.

E. Multi-objective MDO for Ariane 5 ECA and VEGA

MDO for min GTOW and min CpL have been executed with DG-MOPSO algorithm with the same input data (discrete variables settings, continuous variables bounds) as for the single-objective runs. However, for Ariane 5 a single optimal solution similar to the minimum mass PSO design has been obtained, instead of a well spread Pareto front. Contrary to what could be expected, propellant loading is not shifted from the liquid core to the solid boosters to obtain minimum cost solutions. This indicates that the reduction in cost due to the different technology is more than offset by the larger overall mass of the system. The development and production CERs for the large solid boosters give in fact rather high cost estimates, and due to lack of detailed cost breakdown structures for existing launchers, a better the correlation of the CERs has not been possible. It has however been verified that by arbitrarily varying the SP CERs slopes, it is possible to obtain mass vs. cost Pareto fronts showing larger SP boosters for minimum cost solutions. Due to lack of data to support this reduction, the original CERs have however been maintained in the model.

The mass-based nature of the CERs is mostly confirmed by the multi-objective MDO runs on VEGA test case. Nevertheless, a cost vs. mass trade-off has been identified in the allocation of propellant mass among the three solid motors, as shown in Figure 10. Due to a discontinuity in the slope of SP stages CERs, occurring at an interface between small and large SP motors (assumed at M_{prop}=40 tons), small motors such as Z23 and Z9 tend to be favoured with respect to the larger P80 in terms of cost. Hence minimum cost/mass solutions are obtained respectively with a lower/higher propellant mass for P80, balanced by an increase/decrease of propellant in the second and third stages to match the payload performance.

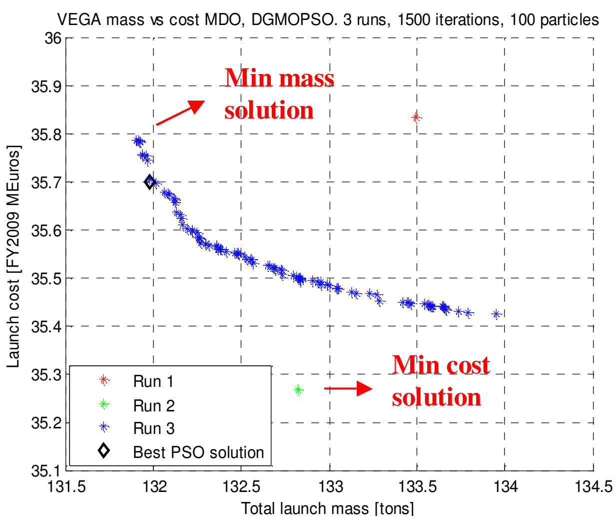


Figure 10: VEGA min GTOW vs. min CpL MDO results, Pareto fronts

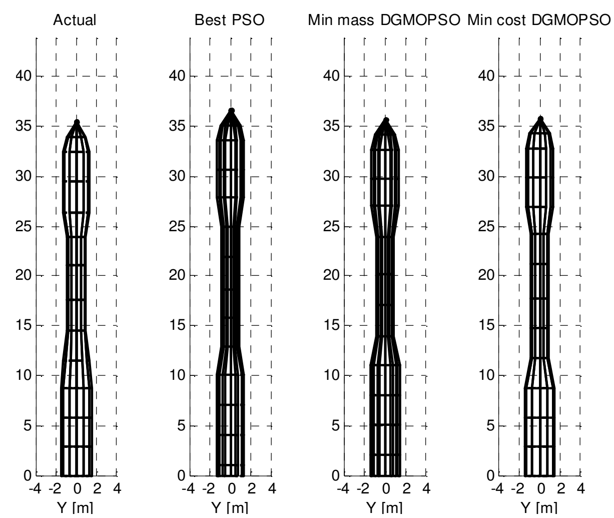


Figure 11: VEGA min GTOW vs. min CpL MDO results, external geometry

From the multi-objective results presented above, it is clear that realistic min cost vs. min mass design trade-offs can be obtained with the present version of the developed models only when the discrete optimization variables are not frozen to a given reference architecture. Moreover, Pareto-optimal solutions are strongly affected by the parameters in both the WERs and CERs, highlighting an issue which is intrinsic to the nature of historical based mass and cost estimation. This again stresses the need for component level mass estimation methods, based on the physics rather than on historical databases. Although there are no feasible alternatives to mass-based cost estimation for preliminary design, a better correlation of the CERs parameters against actual cost breakdown structures would also be desirable.

Maximum payload mass vs minimum launch mass multi-objective optimization, defining a purely performance-based trade-off, allows on the other hand to obtain a well spread range of design solutions for different payload masses delivered to the target orbit. Figure 12 shows the Pareto front obtained when allowing the PLSF to vary in a [70, 100]% range with respect to the reference 10.05 tons of payload, with the geometries of the min mass and max payload solutions represented in Figure 13. It has to be noted that the design parameters are very similar for all solutions in the front, except for the scaling of the propellant masses in the stages and boosters to match the target performance. The successful application of multi-objective min GTOW vs max PLSF optimizations increases the flexilibility of the MDO environment, ensuring the capability to contemporarily study a family of design solutions with flexible payload values for later program level decisions.

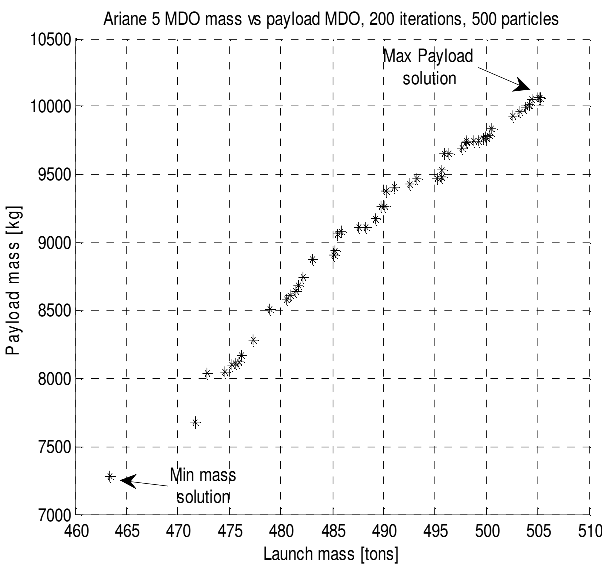


Figure 12: Ariane 5 ECA min GTOW vs. max PLSF MDO results, Pareto front

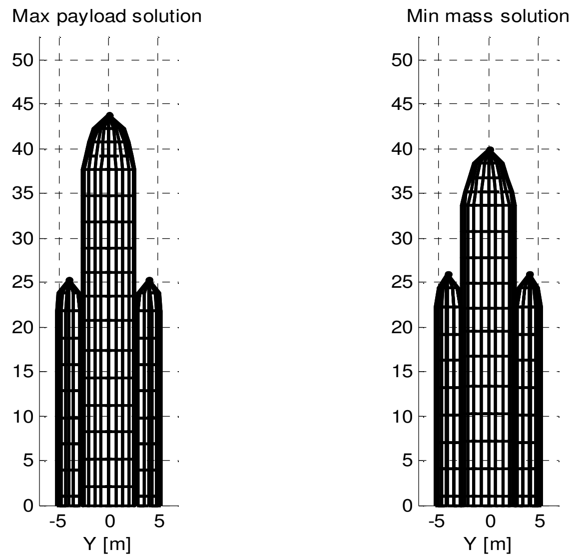


Figure 13: Ariane 5 ECA min GTOW vs. max PLSF MDO results, external geometry

V. MDO of ELVs, lessons learned and perspectives

The paper has focused on the critical analysis of the design results obtained with a conceptual-level MDO environment for ELVs, with the main goal of quantitatively assessing the suitability of simplified engineering methods for the early phases of launchers design. Ariane 5 ECA and VEGA test cases have shown reasonable accuracies with respect to global performance figures in the 10-25 % range, with very limited computational effort. However, for the successful application of the MDO approach to industrial design, an improvement of this accuracy and a better representation of physical phenomena as well as of cost and reliability related trade-offs appear necessary. With this purpose in mind, the analysis of the results from trajectory optimimizations, sensitivity analyses, MDAs, single and multi-objective MDO processes has led to the identification of several critical modeling aspects, that constitute the basis of an effort currently under way to improve the fidelity of the developed design environment. In particular, several lessons learned from these analyses are summarized here:

- Trajectory models lead to a generic overestimation of launchers performance in the order of 8-13%, mainly due to the lack of steering losses and, especially for SP motors, of I_{sp} degradation with time. Although optimizer trade-offs are only partially affected by the error, which is rather similar for all launcher configurations, the introduction of these modeling features would improve the performance assessment accuracy, increasing the overall fidelity of the MDO model.
- Smoothness of the trajectory model is particularly critical for the robust and efficient local optimization of ascent trajectories, as testified by considerable improvements in the results following the identification of few significant discontinuity issues.
- As for the trajectory, problem smoothness is of substantial importance for MDO local refinements. Improvements with respect to this aspect are still being investigated to allow for faster local convergence.
- Weights estimation has been identified as the most critical discipline from several types of analysis (one-variable-at-a-time sensitivity analysis, MDAs and MDOs). In particular, upper stages and advanced SP motors

nozzles masses are not well represented by the adopted models. In general, the introduction of a more refined evaluation of the trajectory loads followed by structural sizing of the different components is a priority deemed necessary for the extension of the design environment to early preliminary design. Another important feature in this area is the flexibility assessment, that together with a better static controllability evaluation considering off-nominal flight conditions such as wind, should improve the fidelity of launcher configuration trade-offs.

- MDO runs for European test cases have allowed verifying the capability to steer the main optimization variables to improve the design in terms of performance. Min launch mass vs max payload mass multi-objective optimization is also successful in identifying Pareto-optimal solutions for wide payload ranges. However, the mass-based nature of the CERs does not allow to obtain well-spread min cost vs min mass Pareto fronts with the current set of WERs and CERs parameters, which sensibly affect the design results. This also supports the need for higher fidelity evaluation of the structural and non-structural masses.

In addition to the model enhancements suggested in the above key points, several other features are deemed necessary for better applicability in an industrial context. Of particularly interest is the introduction of safety analyses, such as boosters and lower stages impact point determination or the upper stage de-orbiting/passivation evaluation. Moreover, concurrent optimization of several launcher configurations for different payloads and/or target orbits is fundamental for the current European strategy, and would largely increase the flexibility of the MDO environment.

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