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Optimization and Model Order Reduction on Launch Vehicle Aerodynamic Design

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Abstract
This paper presents the methodology used to assess aerodynamic calculations of a launch vehicle and optimize aerostructures. This methodology, developed internally at CT Paris, has been applied in the frame of different projects. This methodology relies on the use of an internal CFD tool, CPS_C™, which has been modify to allow its use in an optimization environment.
Aerodynamics has a major impact on launch vehicle performances and a global aerodynamic characterization is required for structural sizing through general loads evaluation. During early stage of a project, at system trade-off and preliminary design level, semi-empirical models are often applied. This approach is used to allow fast design and account for possible evolution but it is limited in terms of geometry complexity and precision of results. So, in order to increase the relevance of preliminary system design, it is necessary to perform more detailed and reliable analysis based on computational fluid dynamics calculations. Usually, this modeling tool is not considered in design phase because it's highly demanding in resources and time for models preparation and updating as well as computation. In order to profit from CFD precision without impacting resources and time consumption, CT Paris' strategy is to foster automation by coupling aerodynamics, geometry and mesh model generation in order to run a parametric study case allowing to elaborate specific surrogate models. The work flow integrates an automatic mesh procedure, pre-treatment calculations, CFD calculation and post-processing, all integrated in HADES optimization environment based on modeFRONTIER, as shown on Figure 2. In that framework, this process has multiple objectives:

- define the aerodynamics database thanks to Design of Experiments Algorithms,
- optimize structural mass and geometry of the launch vehicle (including aerodynamics appendices)
- and elaborate surrogate models for aerodynamic coefficients evaluation.

This process has several uses, from aerodynamic coefficients calculations to the optimization of aerodynamic elements. One aim was to widen and enhance its reduced model building capacities, by implementing state-of-the-art methods on an industrial case; innovative techniques which appears adapted to CFD models, such as POD, PGD are assessed. The paper will present this process, the applications carried out and the gain obtained compared to classical methodology. It will also highlight the last results performed in aerodynamics analysis context on the building and use of surrogate models.

Nomenclature

CFD	Computational Fluids Dynamics
HADES	Help on Advanced launcher DESign
POD	Proper Orthogonal Decomposition
PGD	Proper Generalised Decomposition
SLV	Space Launch Vehicle
Ca, Cn	Aerodynamic coefficients of drag and lift respectively, in engine axial/normal axes frame
MDO	Multidisciplinary Design Optimization
ROM	Reduced Order Model
RBF	Radial Basis Functions
RANS	Reynolds-Averaged Navier-Stokes

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1. Introduction

A Space Launch Vehicle (SLV) is a complex system which demands a large number of closely interdependent disciplines. Some of these are, for example, propulsion, structure, aerodynamics, flight mechanics, thermal control, etc. [1]. As a result of this interaction, final SLV design and performance optimization is a complicated problem to solve.
Historically, in order to satisfy mission requirements, launch system designers used to apply an analytic approach to initiate an iterative design process [2] where the only objective of the procedure was to maximize the performance. In general, using this kind of approach, results are improved after several iteration loops from the initial assumptions. Moreover, often solutions achieved following this approach may be not globally optimal [3]. Today, the space sector demands assessments having both high performance and cost-effectiveness. Furthermore, in the last decade, the number of space missions based on relatively low-cost small satellites has grown. In the same way, the request of new small launch vehicles built around lightweight and cheap payload has increased since they provide affordable orbital access to this class of satellites.
While a direct cost criterion needs a first concept to start the design process, therefore adding complexity, a Multidisciplinary Design Optimization (MDO) approach allows the handling of relevant technical disciplines and economic drivers and in the meantime reducing human intervention. In this way, the optimal solution can be identified through a rapid exploration of several design concepts ensuring a final design with optimized performances together with significant costs saving and risks mitigation. Technical and economics limitations, such as unphysical solutions, are account for by adding constraints to the system loop. A schematic representation of the classical method using iteration loops and the MDO approach is presented in Figure 1.

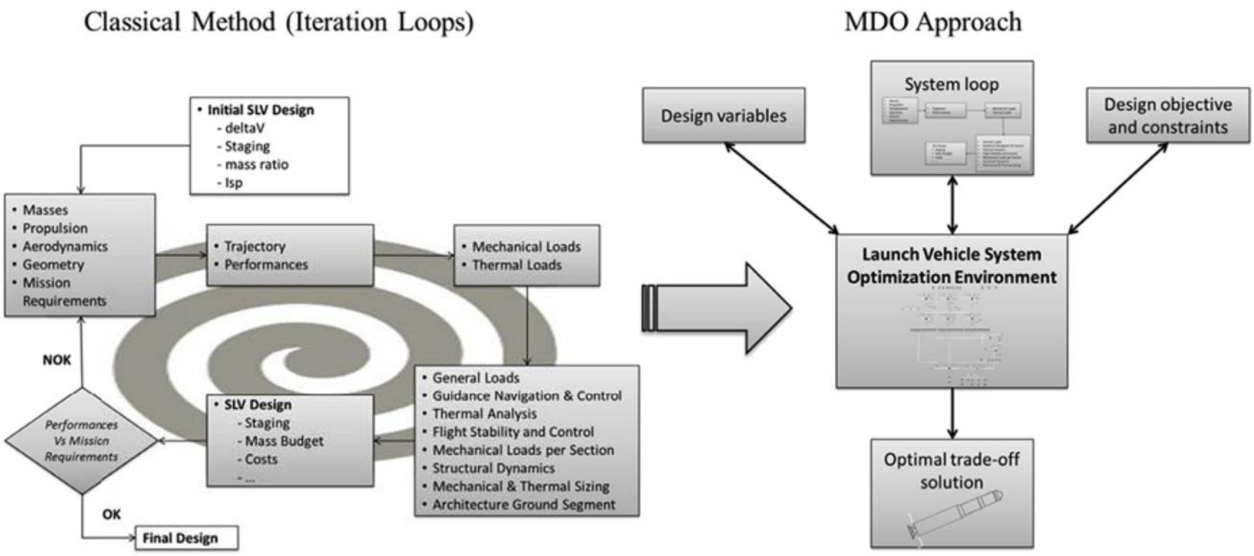

Figure 1: Schematic representation of the classical method with iteration loops and the MDO approach

Whatever optimization algorithm is applied in the engineering design process, many evaluations of the functional relationship are needed in order to get a satisfying result. Thus a model reduction approach can be used to provide an estimate of the input-output relationship with a considerable reduction of the computational cost, compared to the use of a CFD tool. In this context, a model reduction method, named POD with interpolation (PODI) [4], is considered in this work. Several initial CFD simulations are required, corresponding to a design of experiments related to parameters to be involved in the future optimization, to create the parametric dataset on which CFD model will be reduced, or condensed. As an example, PODI is employed in aerodynamic shape optimization in [5], where the flow passing a few selected geometries is used to generate the snapshots. Then, the reduced order model (ROM) can be used to describe flow fields around varying body shapes.

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2. Methodology and techniques

2.1 Launch Vehicle MDO and Aerodynamic Analysis

The works presented in this paper are based on the methodology adopted to optimize the size and the number of the fins presented for the project in [6]. The method uses the multidisciplinary design analysis and optimization approach (MDA/MDO) combined with the aerodynamic analysis of the air launch vehicle performed using the Multiphysics tool CPS_C™.

CPS_C™ is CT Paris' multi-physics modeling & simulation platform developed and constantly enhanced since its first operational version in 1986. Among other usage-oriented features, CPS_C™ includes:

- a wide variety of physical models: turbulence, combustion, diphasic, condensation & evaporation, cavitation & collapse, real gas law state laws, non-equilibrium thermodynamics, radiation, conduction, thermal constraints, viscoelasticity
- many options for boundary conditions and source terms to address the diverse array of issues faced in industry

CPS_C™ is now handling a very wide range of situations, for example behavior laws going from uncompressible up to hypersonic flows (Mach 30).

On SLV design side, CT Paris gathers different tools and subsystems data into a global loop, in order to assess various architectures and configurations and to optimize the multi-disciplinary tradeoff from a system point of view. The workflow of the MDO procedure starts from a design of experiment on input variables, then includes automatic mesh generation, pre-treatment of the input data, CFD calculations and post-processing of the output parameters. All these steps are integrated into HADES optimization environment based on modeFRONTIER. The simplified MDO process used for the launcher optimization is presented in Figure 2. See [6] for further details.

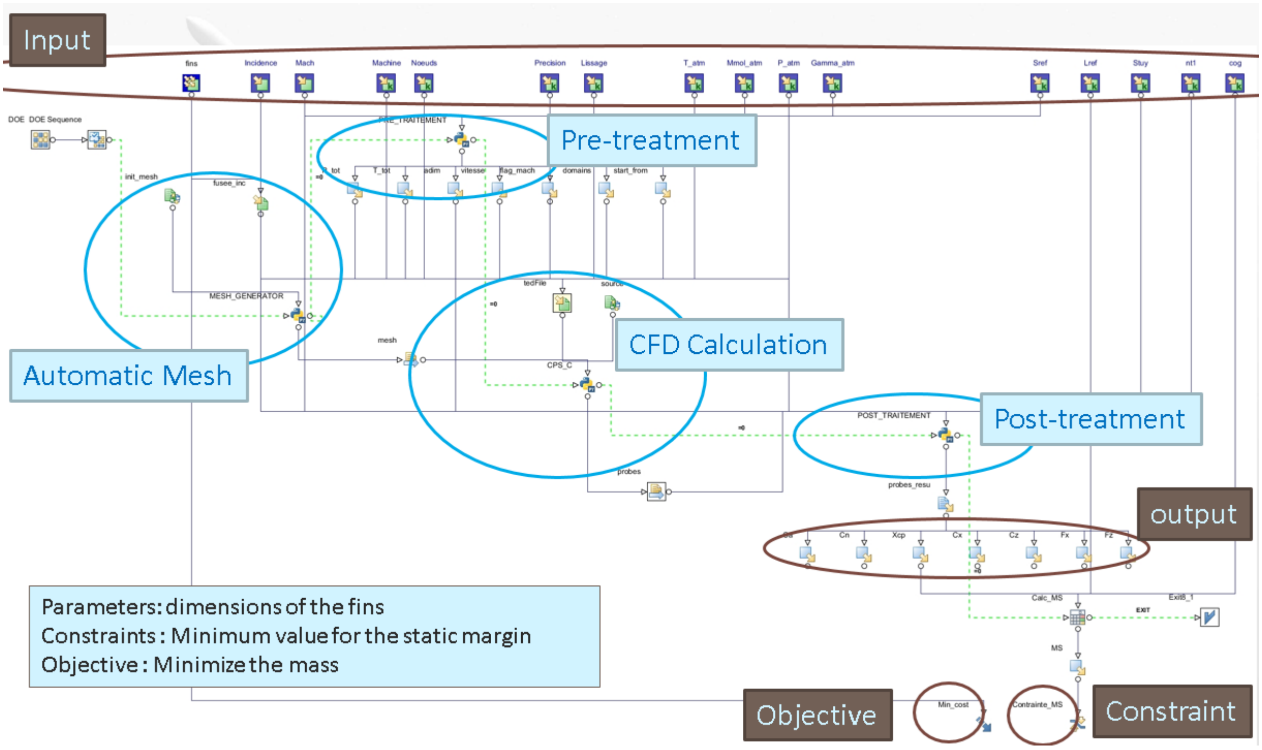

Figure 2: MDO process for launcher design. Example of optimization of the size and the number of the fins

The meshes are built through automatic generation, using scripts in which the characteristic cells size parameters are defined. The geometrical input data are the number of stages, the diameter and length of the stages, the inter-stage length, the number of engines, the nozzle diameter, the fairing profile and the size and the number of fins (zero, four or five). An example of two meshes generated varying the number of fins is shown in Figure 3.

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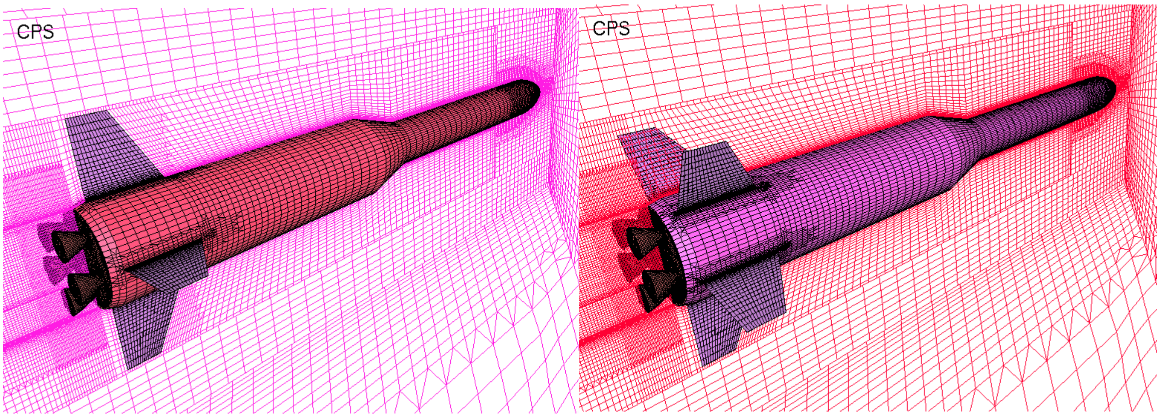

Figure 3: some meshes generated using the automatic procedure

The physical input data used in the process are:

- the inlet Mach number (from 0.5 to 10),
- the incidence (from 0° to 30°),
- the external pressure (12 111 Pa) and temperature (216 K) corresponding to the condition at an altitude of 15 km.

The outputs retrieved from the computations are the drag and lift coefficients (Ca and Cn, see Figure 4) and the position of the centre of pressure (Xcp, relative to the fairing nose).

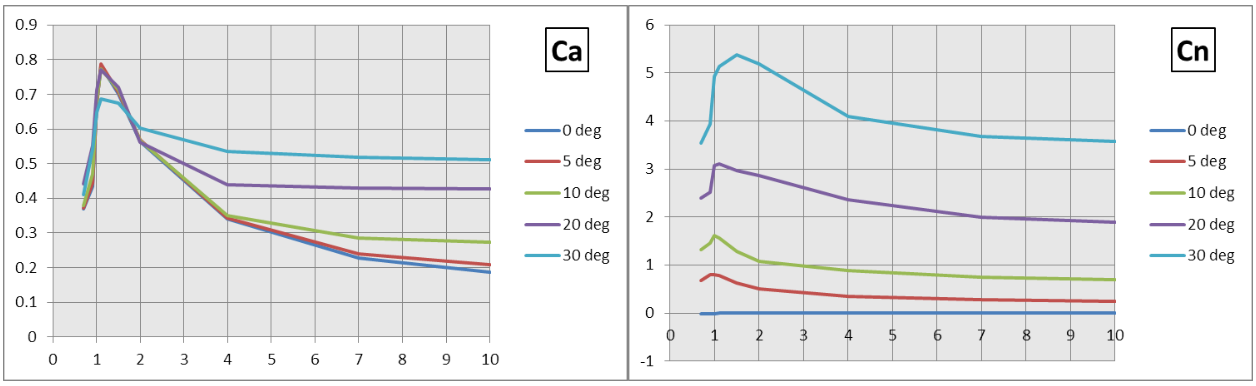

Figure 4: CPS_C™ computed drag coefficient Ca (left) and lift coefficient Cn (right)
as a function of the Mach number for different incidences

For this particular model, the average computation time is on the order of magnitude of 1 hour on 24 cores of a dedicated cluster, or 6.5 hours on a desktop PC (bi-processor quadri-core, i.e. 8 cores).

2.2 Model Order Reduction

Last decade has seen the rise of both:

- digital models: variety of models, fast-evolving hardware, high fidelity together with resources demand
- simulation scenarios: multiple queries (such as statistics and parametric studies, optimisation and inverse problems, stochastic models), (quasi) real-time (in process control, user interface), light resources platform (web apps, mobile devices, industrial controllers)

This first axis tends towards models taking more and more physics, parameters and details into account, in other words increasing model order; while the second axis claims lighter use of models, whether in terms of resources or response time. Model Order Reduction aims at bridging the gap between those two axes in a smart way versus a brute force.

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Within Model Order Reduction (MOR) context, “order” refers to the degrees of freedom of the model, which includes either space dimensions or time dimension as well as parameters’ dimensions. This “order” notion might have different meanings depending on the type of model, the objective of reduction, the quantity of interest for main examples.
In this case, the idea is to exploit aerodynamics properties of the SLV in every design process step involving aerodynamics discipline; since CFD modelling allows to get accurate values of these properties for different conditions, this accuracy should benefit all other computations during the whole design phase. The basis of MOR is to reduce response time while keeping most of the model behaviour.
In addition, our own requirements for MOR, at least in the frame of this study, is that the initial heavy model, aka full order model (CFD model here) is treated as a black box: no assumption neither modification should be done on it. This implies so-called non-intrusive reduction methods or *a posteriori*.
In this framework, the Proper Orthogonal Decomposition (POD) [7] is applied in a multidimensional parameter space retrieved by the modelling of complex flows using CFD and RANS. In general, the numerical or experimental dataset u_j is represented as a combination of POD modes φ_l

$$u_j = \sum_{l=1}^{m} (\alpha_{lj}\varphi_l)$$

for j = 1, …, m.
The POD expansion coefficients

$$\alpha_{lj} = < \varphi_l, u_j >$$

retrieved from the projection of the bases φ_l on the dataset u_j are discrete functions in the parameter space with values defined at the points corresponding to the individual snapshots of the dataset. Then, to derive the ROM using the PODI approach mentioned above [4, 5], these POD coefficients are continuously extended in the parameter space by the response surface method (RSM) [5] using different techniques, such as least-square regression, radial basis functions (RBF) [8], cubic splines, neural networks, etc. In this way, starting from a database of experiments (blue dots), new design points (orange dots) can be predicted using a ROM (Figure 5) with a response time that is faster than using CFD. The corresponding workflow is represented in the schematic of Figure 6 using similar colors (database of experiments in blue, new input/results in orange).

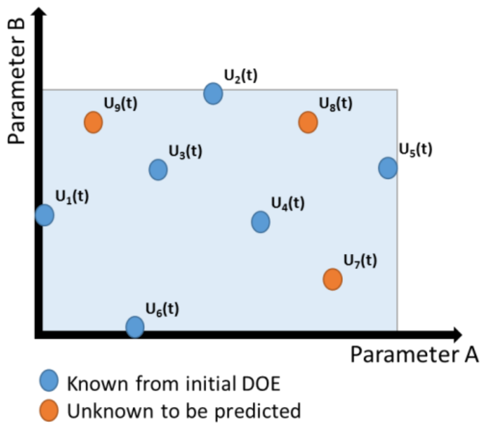

Figure 5: Example of initial dataset (blue dots) and new parameters set (orange dots) in design space (light blue domain)

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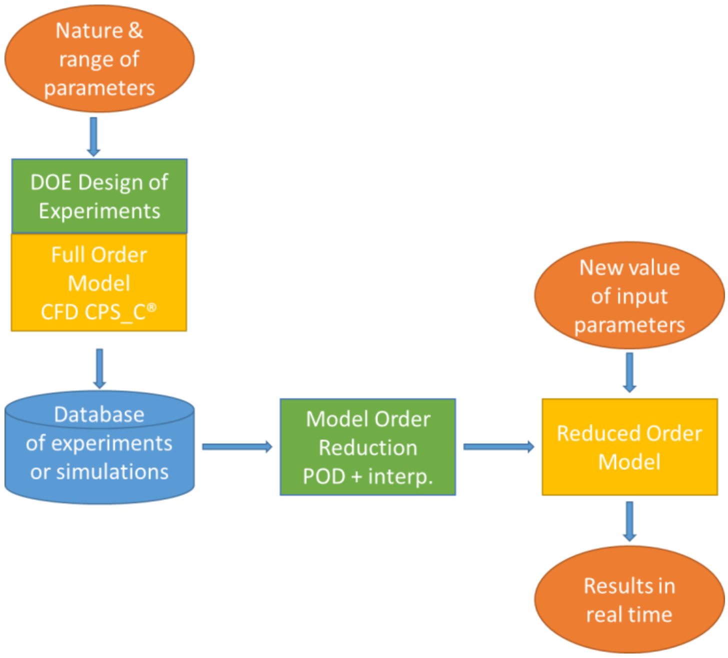

Figure 6: Schematic of the Model Order Reduction procedure used

Among the several techniques available to perform the reconstruction step of the coefficients, adaptive RBF or the Kriging method [9] may be used. In the Kriging method, the function to interpolate is composed by a constant regression model plus localized deviations to match the sample values. The RBF method has the property of being grid free and may use an adaptive algorithm which allows the methods to maintain an overall high order of accuracy. To estimate the accuracy, cross validation algorithms split the data into two sets. The first part (the training set) is used to build the surrogate model and the second part (the test set) is used to validate the model. In the leave-one-out method, the size of the test set is simply equal to 1 and it requires training and validating the model N times, where N is the number of observations (or snapshots). The error analysis achieved eventually provides indications on how to refine the dataset thanks to the detection of regions with large errors. Snapshots can therefore be added to enrich the POD basis.

3. First results

3.1 Use case

In a first step, the ROM procedure has been tested considering the following fixed parameters (see Figure 3)

- five engines
- fixed length of few meters
- launcher with two fixed diameters (i.e. two stages)
- four fins
- cone profile assigned

Furthermore, only one altitude is used in this initial study, assuming that its influence on the aerodynamic coefficients is weak compared to other input parameters.

The input parameter varied in this study are the Mach number (between 0.7 and 10) and the incidence (from 0° to 30°). As seen in §2.2, ROM requires some full order model results; these computations are heavy, therefore their number should ideally be as low as possible with regards to ROM quality. Although in our case, we chose to start from existing computations campaign, which had previously been set and run on an expert basis, knowing the shape of resulting curve. This way value is added to available simulation database instead of running an initial simulation campaign dedicated to MOR.

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3.2 Leave-one-out

A leave-one-out strategy has been set: among the 45 cases available (5 values of incidence x 9 values of Mach):

- 44 are used as learning sample : to build the reduced order model
- 1 is used as validation sample : to compare the outputs of
  - Full Order Model (FOM = CPS_C™)
  - Reduced Order Model (ROM) ;

Two MOR methods have been tested: POD + Adaptive Radial Basis Function and POD + Kriging
This learning/validation procedure has been looped on each one of the 45 cases in turn, in order to see the importance of each case on the built ROM.
Bigger relative errors that we can see on the first graph of Figure 7 are for Cn prediction on points at null incidence and Mach values of 10, 7 et 4; since Cn theoretically equals zero at null incidence, it explains why relative errors (error divided by theoretical value) is huge for these cases. The second graph of Figure 7 shows all other error values, which are mainly lower than 0.5%, under 1.5% anyway.

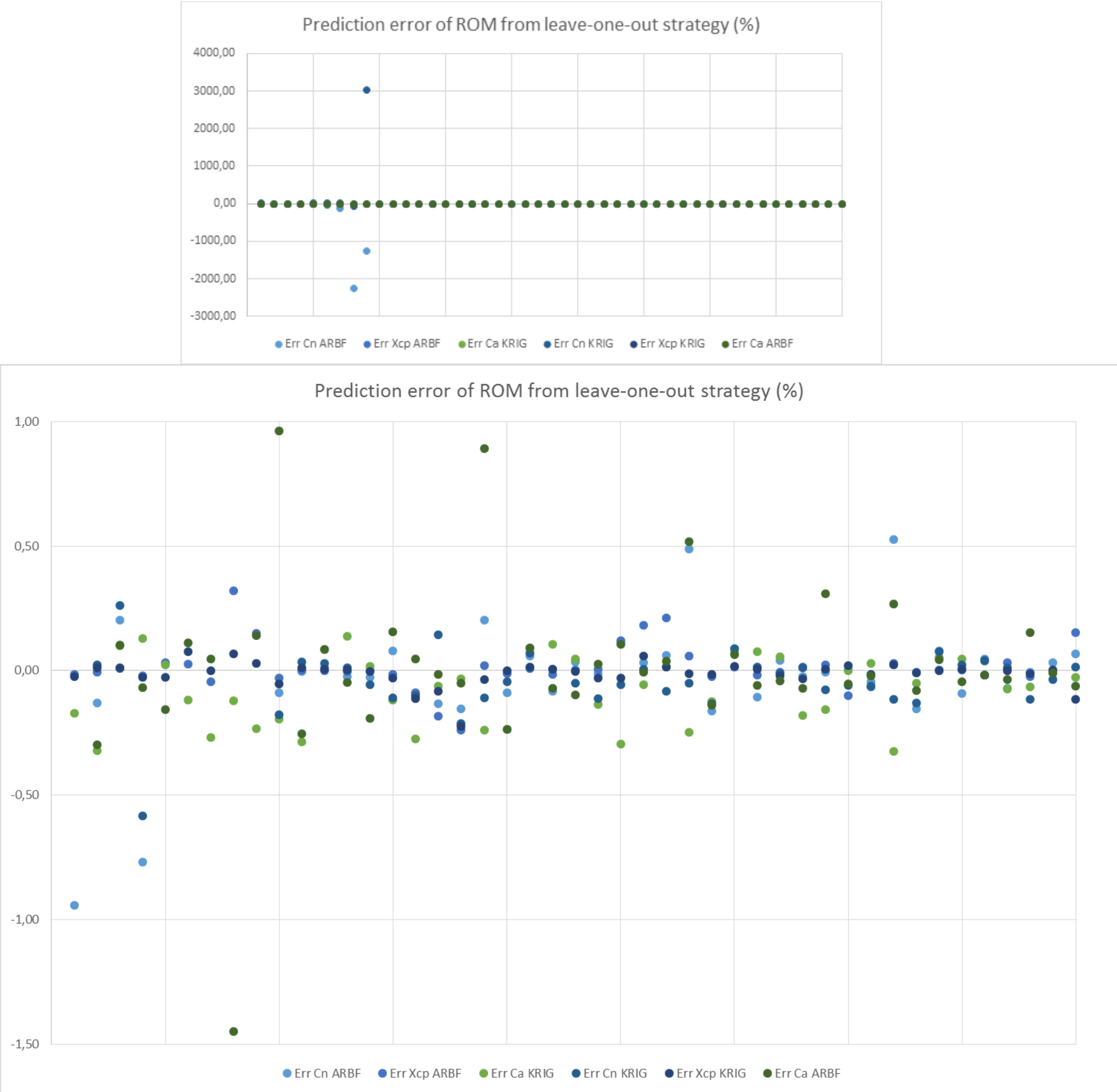

Figure 7: Relative prediction error from leave-one-out strategy

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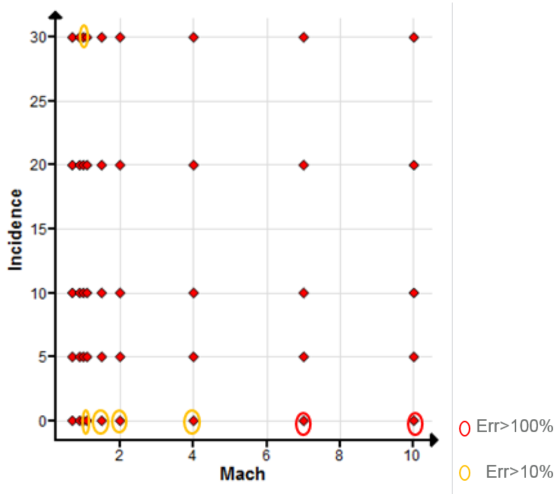

Figure 8: Identification of high relative prediction error points in the parameters space

3.3 ROM assessment

Another test has been made: taking advantage of ROM fast computation, ROM curves of Ca, Cn have been plotted as a function of Mach number (by step of 0.1 from 0.5 to 2 then by step of 0.5 from 2 to 12) for intermediate incidence values (2, 8, 15 and 25°); ROM built by POD+ARBF and POD+KRIG techniques have been compared, on the learning sample of 45 available cases previously shown on Figure 8.

On these configurations, Figure 9 for Ca and Figure 10 for Cn show that ROM does not reach FOM model's level on sonic peak, especially when built with Kriging technique which smoothes the curves. Anyway, ROM results respect the shape and hierarchy of Cn curves, especially with ARBF technique of interpolation, except for incidence of 15°. There is hope that a dedicated DOE and minor adaptation should lead to better results, therefore satisfying ROM could be reached for Ca as well as it already is for Cn coefficient on Figure 10. Above all, since FOM initial step Ca curves do not precisely reveal an expected physical behaviour, thus reduction depending on it could hardly do better.

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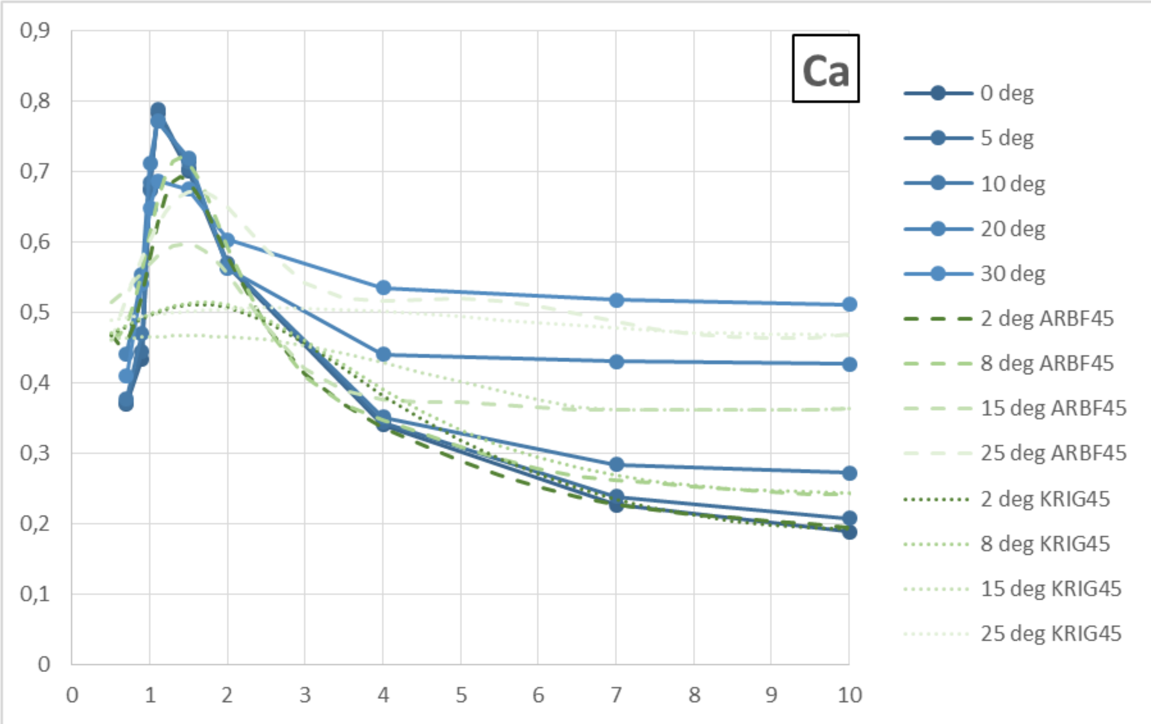

Figure 9: Ca coefficient curves from FOM reference (solid lines),
ROM based on 45 cases learning sample by POD+ARBF (dashed lines) and ROM by POD+Kriging (dotted lines)

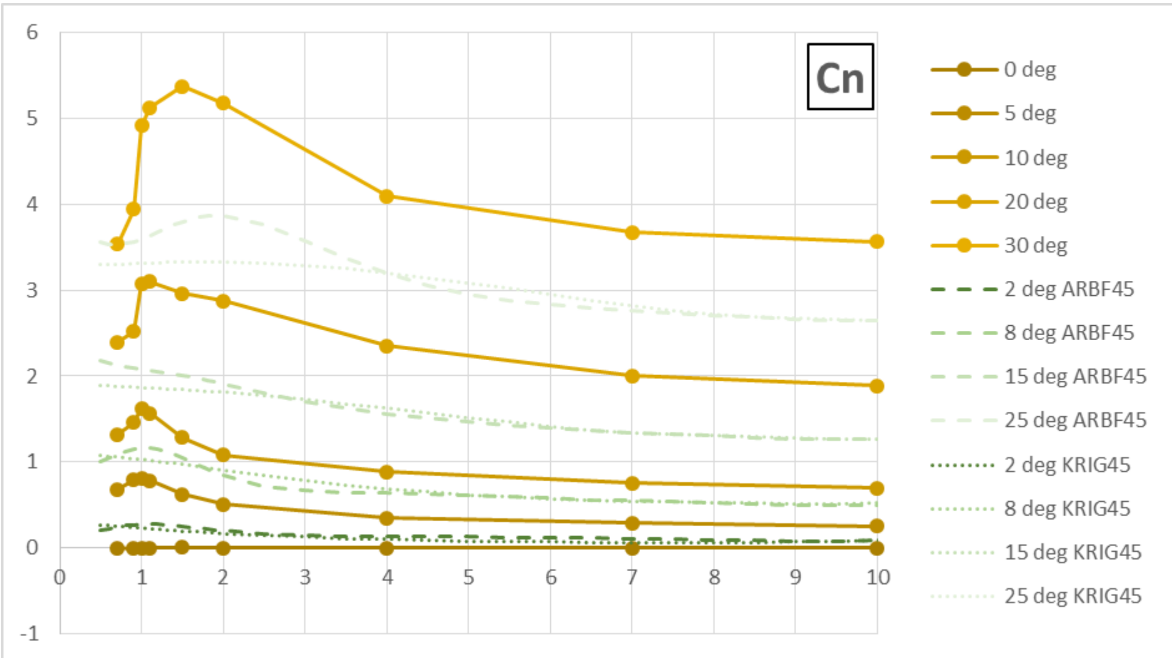

Figure 10: Cn coefficient curves from FOM reference (solid lines),
ROM based on 45 cases learning sample by POD+ARBF (dashed lines) and ROM by POD+Kriging (dotted lines)

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4. Perspectives

First results are encouraging: there is a ***big gain in computation time***, from hours to milliseconds, together with ***weak prediction error*** (lower than 0,5% most part of the time) provided that new case stay inside variation range or ROM is adaptively enriched with extended FOM simulations.
In the future work, a more general case will be studied in which additional parameters are added, such as:

- diameter of the stage(s), linked by inter stages whenever it is relevant
- the number and the shape of the fins,
- varying nose cone profile
- a range of altitudes.

Ultimately, the aim would be to replace aerodynamic coefficient tables with reduced aerodynamic models in all relevant steps of the SLV design process, such as general loads computations, trajectory optimization and thermal loads prediction. Furthermore, it seems particularly interesting to integrate this reduced model within a 6 DOF simulator. In the same idea, many models used in SLV detailed design would benefit from ROM, especially when it comes to heavy computations due to multiscale aspects (propulsion for instance). CT Paris also uses these techniques in other sectors, with similar issues.

Acknowledgements

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References

[1] B.N. Suresh, K. Sivan, Integrated Design for Space Transportation System, Springer, India, 2015.
[2] C. Dupont, L. Guadagni, P. Baiocco, Development of an MDO procedure for the preliminary design of space launch systems, Second International Conference on Multidisciplinary, Design Optimization and Applications, 2008.
[3] A.A. James, A. Martin, Optimum stage weight distribution of multistage rockets, AIAA J., 11 (2), 255-256, 1973.
[4] Walton S., Hassan O., Morgan K., Reduced order modelling for unsteady fluid flow using proper orthogonal decomposition and radial basis functions, College of Engineering, Swansea University, 2013.
[5] Dolci V., and Arina R., Proper Orthogonal Decomposition as Surrogate Model for Aerodynamic Optimization, DIMEAS, Politecnico di Torino, 2016.
[6] C. Dupont, A. Tromba, S. Missonnier, New strategy to preliminary design space launch vehicle based on a dedicated MDO platform, Acta Astronautica, 2018.
[7] Cordier, L., Bergmann, M., Réduction de dynamique par Décomposition Orthogonale aux Valeurs Propres (POD), LEMTA, UMR 7563 (CNRS – INPL – UHP), 2006.
[8] R. H. Myers, D. C. Montgomery, and C. M. Anderson-Cook, Response Surface Methodology, John Wiley & Sons, Hoboken, NJ, USA, 3rd edition, 2009.
[9] T. Braconnier, M. Ferrier, J.-C. Jouhaud, M. Montagnac, P. Sagaut, Towards an adaptive POD/SVD surrogate model for aeronautic design, Computers & Fluids, (40), 195-209, 2011.

