Surrogate-Based Conception for Aerodynamic/Stealth Compromise

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ABSTRACT

Specifications related to radar signature reduction are nowadays taken into account from the preliminary conception stage in the design of military aircrafts (missile, UCAV, manned fighters). The performance level required in terms of Radar Cross Section (RCS) reductions constrains the design and competes with traditional disciplines such as aerodynamics. The present work aims at optimizing the planform of an UCAV (Unmanned Combat Aerial Vehicle). The idea is to search the best compromise solutions for the multi-objective optimization problem in presence of antagonist criteria. The RCS is evaluated by means of asymptotic and exact computation methods by varying the bearing angle of the incident wave. Several frequencies between 100 MHz and 3 GHz were chosen and the polarization is fixed. On the aerodynamic side, the lift to drag ratio (L/D) has been chosen as a merit function. Moreover, the computation of the pitching moment allows identifying instable configurations. A first optimization exercise aiming at identifying the Pareto front in the space defined by the objective functions has been first led with only two parameters (the fuselage and wing sweep angles). A novel algorithm based on a coupling between a genetic algorithm (NSGA-II) and Multi-objective Efficient Global Optimization approach is proved to successfully to improve the description of the Pareto Front by means of a parsimonious iterative enrichment of the meta-models in relevant zones of the parameter space.

1.0 INTRODUCTION

Specifications related to radar signature reduction are nowadays taken into account from the preliminary conception stage in the design of aircrafts (missile, UCAV, manned fighters). The performance level required in terms of Radar Cross Section (RCS) reductions constrains the design and competes with traditional disciplines such as aerodynamics. It results in a compromise between these traditional disciplines and radar signature reduction which can be difficult to establish. The paper by Tianyuan & Xiongqing (2009) has addressed this issue focusing on the optimization of an UCAV planform. The authors have considered two objective functions, namely the drag coefficient and the structural weight, RCS being treated as constraint. A surrogate model is built for each discipline. The kriging approach has been retained and a multi-objective genetic algorithm (NSGA2) has been implemented to advance the optimisation process. For the same type of application, Pan *et al.* (2017) have proposed a two-step strategy which relies on a genetic algorithm and a local optimization to refine the parameter choice. The objective function is the drag coefficient, lift coefficient and RCS being considered as constraints. In a recent work, Çakin (2018) has proposed a multidisciplinary optimization of an UCAV planform. The objective functions are the range and the RCS. Statistical weight equations are used to provide an estimate of the total fuel mass which determinates the range. The shape is dependent of 12 parameters. The aerodynamic evaluation is similar to the one of the present work but the RCS evaluation is simplified, a unique frequency computed with physical optics method being considered. The meta-modelling is based on the MARS approach (Multivariate Adaptive Regression Splines).

In the same way as in the previous references, the ONERA internal project AERODIS aims at proposing a coupling methodology between aerodynamics and electromagnetism. The optimization of an UCAV planform is also retained as a goal for this exercise. The idea is to search the best compromise solutions for the multi-objective optimization problem in presence of antagonist criteria. A challenge of this study is to share the tools between disciplines in order to conduct efficiently a multidisciplinary optimization. This first attempt is limited to aerodynamics and electromagnetism but the present optimization strategy is built to support the addition of new disciplines (structure, materials). To this end, an approach based on meta-models which are intended to be enriched in the most parsimonious way to find a good compromise between exploration of the design space and exploitation of the best existing solution has been developed. A significant part of our efforts was devoted to address the issue of limited calls to the disciplinary solvers which is of major importance when the problem dimension increases.

The paper is organized as follows. In Section 2, the parametrisation of the problem is exposed. The section 3 is devoted to the presentation of the tools used to evaluate the aerodynamics figure of merit. In section 4, the specificities of the tools employed to evaluate the RCS are exposed and examples of RCS results are highlighted. The optimization process is detailed in section 5 underlining the specificities of the Kriging EGO based surrogate modelling approach and demonstrating the capacity of the method to propose a parsimonious enrichment of the database converging toward a good compromise between good aerodynamic performance and low RCS.

2.0 SHAPE PARAMETRIZATION

The choice of the planform is performed first in initial design phases of an UCAV. It is more influential on the global architecture and the global performances in terms of aerodynamics and RCS than the airfoil profile shape for example. The latter includes in particular the specification of the leading edge radius which will be treated in a forthcoming work. The shape parametrization retained for this study is presented in Figure 1. Four main parameters have been selected, namely, the two sweep angles, the wingspan (L) and the wing chord (c). The fuselage length is essentially the sum of the engine, intake and nozzle lengths. The two latter being in practice a slowly varying function of the engine diameter, the fuselage length is very constrained and cannot vary significantly. One reasonable assumption is then that the fuselage length is constant (and chosen equal to 10 m in this study). In the same way, landing gear, weapon bay, and fuel tank impose that the fuselage volume has to be sufficient. For this reason, the fuselage width has been chosen equal to 1/3 of the length. Using this parametrization it is possible to represent most of existing UCAV typical shapes at the exception of wing tip sweep angle for which an additional parameter would be necessary. The fuselage volume contours have been strongly inspired from the ones of the X47B. The airfoil profile is a NACA 64-212. In this paper, the case with only two parameters (the fuselage and the wing sweep angles) is considered. The half wingspan is taken equal to 3.5 m and the chord is set to 2.5 m. The case for 4 parameters is the subject of an ongoing work.

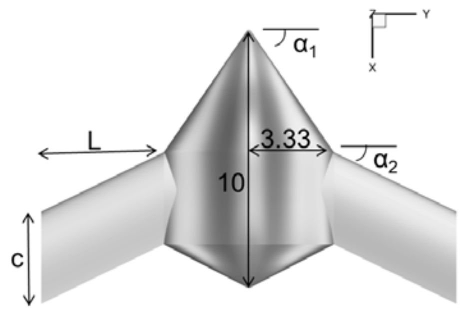


Figure 1: Parametrization of the UCAV.

The sweep angles are both allowed to vary between 30 and 60 degrees. A LHS algorithm (Swiler *et al*, 2006) has permitted to generated 20 shapes homogeneously distributed in the two-parameter space. The diversity of the generated shapes is illustrated by the Figure 2.

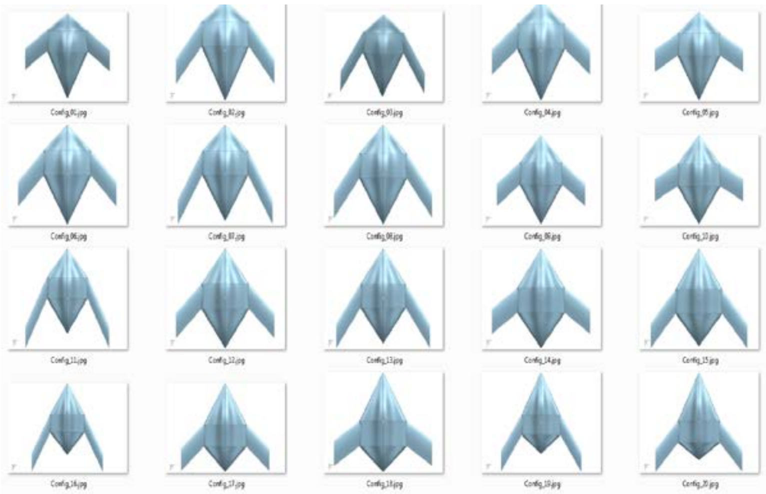


Figure 2: The 20 UCAV initial geometries generated by the LHS algorithm.

3.0 AERODYNAMIC FIGURE OF MERIT EVALUATION

The CANOE suite which is based on the non-structured Euler solver SU2 has been employed. The friction is estimated by considering that it is equal to the one of a flat plate of same surface as the UCAV. Classical flat plate friction correlations are then used. The Figure 3 shows the comparison of the pressure distribution on the suction side of generic UCAV called SWIFT whose shape has been retained in the RTO group AVT 298 for a Navier-Stokes solver (elsA) and for CANOE. The agreement is more than reasonable even if the recompression at the trailing edge is underestimated by CANOE. The latter has been eventually selected for this study.

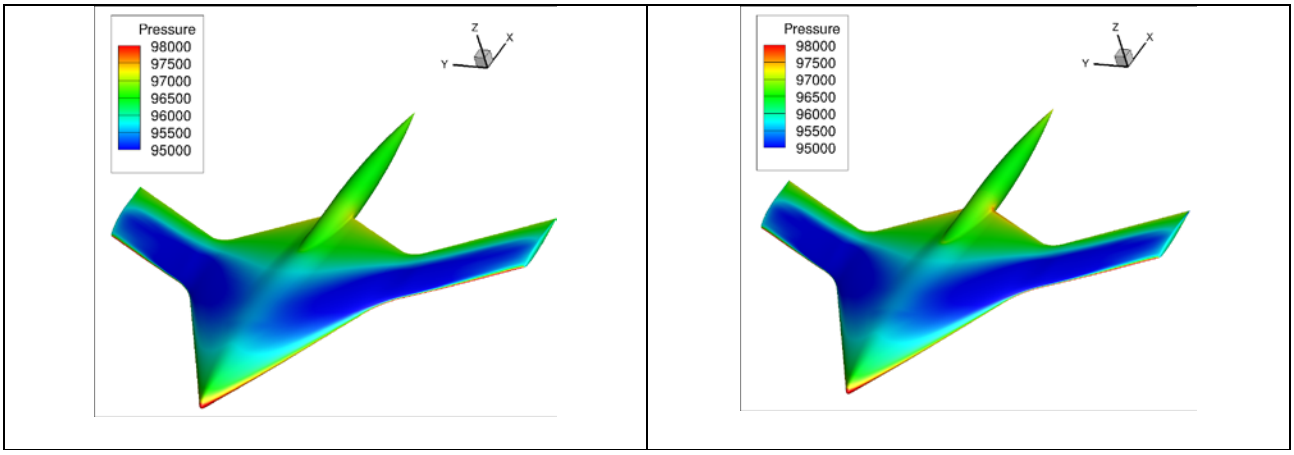


Figure 3: Pressure distribution on the SWIFT model. Left: CANOE (Euler) computation. Right: elsA (Navier-Stokes) computation.

Figure 4 illustrates the pressure field for two individuals of the present study. The rightmost one has a better L/D but is statically unstable whereas the leftmost one is stable at the price of an inferior L/D. This clearly highlights the necessity of considering the stability which introduces a frontier in the parameter space discarding the best individuals in terms of L/D. The stability has been computed considering that the mass distribution in the UCAV is homogenous. It is a strong assumption which is wrong in practice but useful to avoid devoting too much time to the development of a structure module. Nevertheless, future work will include such a module. The UCAV mass is fixed (13.3 tons). Even if the projected surface is the same for every individual, the lift coefficient is configuration-dependent and an inner loop insures that the incidence is adapted to balance weight for each individual assuming the linearity of the lift coefficient between 2 and 4 degrees of angle of attack. Considering a Mach number equal to 0.75 and an altitude of 8 km, typical value of the lift coefficient is 0.16. The computation of the pitch moment allows determining the static margin. Considering the fact that an active control can accommodate for some static instability, a negative margin equal to 35% of the cord has been considered as acceptable. This figure is highly debatable but does change the rationale of the optimization process. Aerodynamic results in terms of L/D will be presented in the section 5.

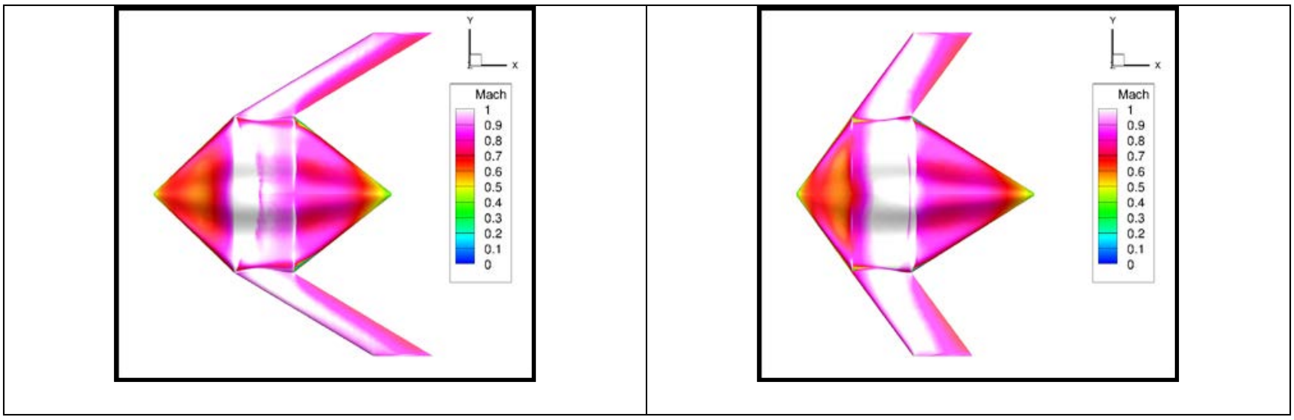


Figure 4: Mach number distribution on the suction side. Left: individual number 11 (stable). Right: individual number 4 (unstable).

4.0 RADAR CROSS SECTION FIGURE OF MERIT EVALUATION

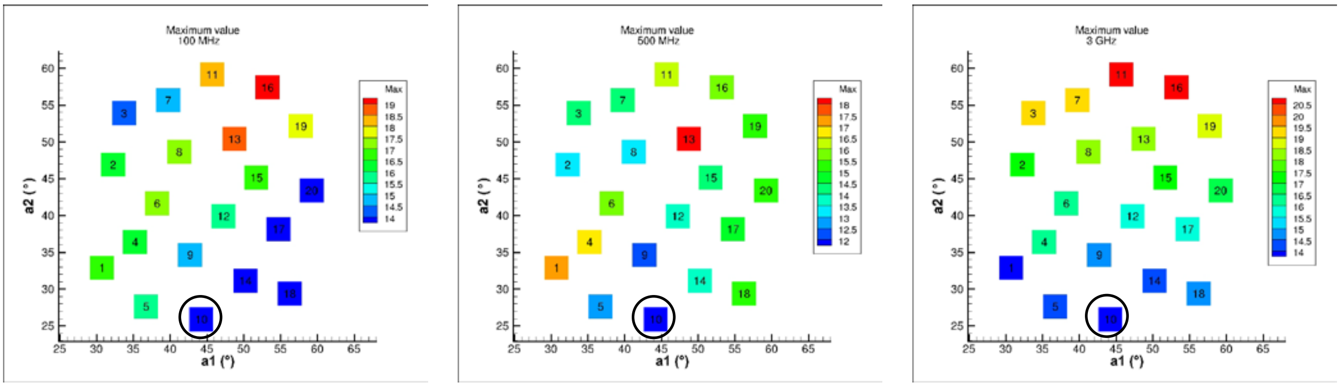
Two software have been used to compute RCS. The first one named Maxwell3D is an "exact" solver developed at ONERA resolving the Maxwell equations. It is based on a direct solver or an iterative one. The formulation of the problem can rely on Electric Field Integral Equations, Magnetic Field Integral Equations or a combination of the two former termed Combined Field Integral Equations. The choice of formulation depends on the size, complexity and expected precision of the considered case.

The second software is SE-RAY-EM (also called FERMAT) developed by the company OKTAL-SE based on active scientific participation of Onera. This solver is based on an asymptotic model and on ray tracing. The ray tracing allows a geometrical exploration with incident beam permitting a fast discretization of the target. The main electromagnetic interactions taken into account are the geometrical optics, physical optics and edge diffraction for metal objects.

Three different frequencies, corresponding to different class of threats for the UCAV, have been considered in this study: 100 MHz, 500 MHz and 3 GHz. The RCS of the UCAV illuminated by a beam at a frequency of 3 GHz is computed with FERMAT whereas the RCS corresponding to the two other frequencies are computed with Maxwell3D. The choice of the tool is a compromise between precision, limiting method and computation time: the condition of large target with respect to the wavelength is not well verified for the 2 lowest frequencies.

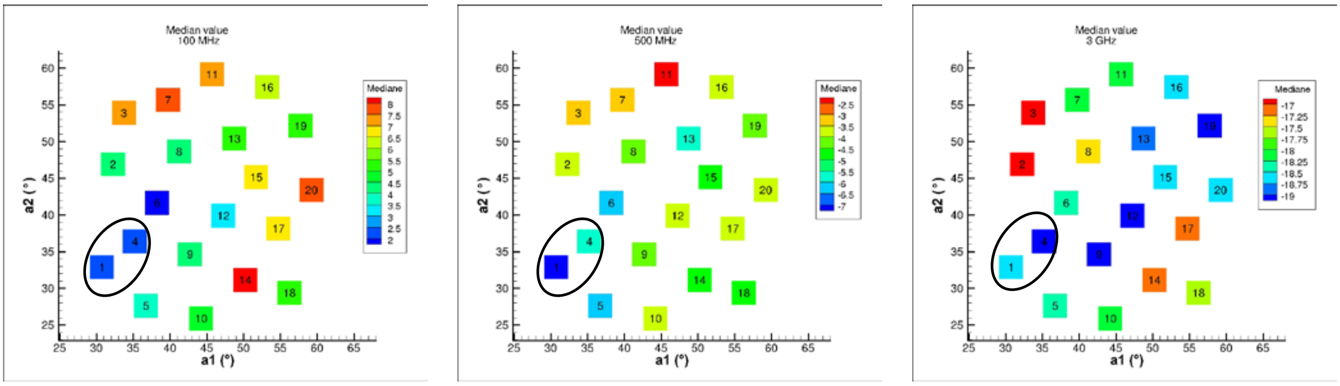
For the 3 calculated frequencies, the bearing angle is varied from 0 to 70 degrees (from 180 to 250 degrees in the convention of the solver). The sole elevation angle is fixed to -5 degrees. A polarization HH is considered. The discretization step in bearing angle is equal to 0.2 degree for the 3 GHz frequency and 1 degree for 500 MHz and 100 MHz. These angular steps are consistent with the Shannon criterion for the dimension of the target studied.The maximum and median values of the RCS are gathered for each frequency and individuals in Figure 5.

Maximum value :



100 MHz 500 MHz 3 GHz

Median value :



100 MHz 500 MHz 3 GHz

Figure 5: Top: numbering of the individuals. Middle: maximum value of the RCS for each frequency. Bottom: median value of the RCS for each frequency.

It can be observed that considering the maximum value, the individual number 10 is the best for every frequency. Considering the median value, individuals 1 and 4 are the best ones. The individual number 1 has to be preferred for the two lowest frequencies whereas individual number 4 should be chosen for the highest one. Nevertheless, a peak value or a median value is not necessary meaningful to characterize the radar survivability. In this work, it has been proposed to retain as an objective function for RCS the sum over the 3 frequencies of the number of points which exceed a certain detection threshold (which is frequency dependent). The results with this objective function will be presented in the next section.

5.0 OPTIMIZATION5.1Surrogate-Based Optimization

Design of complex engineering systems is a time consuming process due to the cost of high-fidelity simulations and the large number of simulations required. To be able to provide optimal designs in a reasonable period of time, high-fidelity simulations are substituted in the process by cheap-to-evaluate surrogate models, also known as metamodels or response surface models (Forrester *et al.*, 2008).

Surrogate-Based Optimization (SBO) is a black-box optimization algorithm based on the evaluation of both objective and constraints functions by mean of surrogate models (cf. Figure 6 for the general framework of the optimization process). To mitigate the low accuracy of these models which limits the convergence of the optimization process, models are enriched by the addition of new sample points prior to their reconstruction (online framework).

Surrogate models are analytical expressions characterized by their negligible evaluation time, resulting from statistical learning and a design of experiments (DOE) (Wang et al, 2007). Most well-known models are artificial neural networks (Dreyfus, 2005), Radial Basis Functions (RBF) networks (Regis et al., 2005), Kriging, Support Vector Regression (SVR), etc. (Liu et al, 2018).

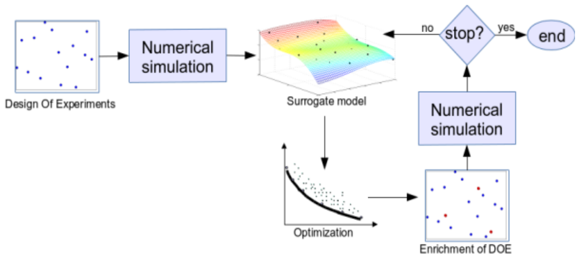


Figure 6: Online Surrogate-Based Optimization framework

5.2 Bayesian Optimization

Kriging (Kleijnen, 2009) is a probabilistic surrogate model: it considers that the output is a realization of a Gaussian process, conditioned by the design of experiments. Thanks to this characteristic, Kriging models consist in not only offering a prediction of the objective function at every location of the design space but also an estimate of the related uncertainty. To build such models it is required to choose a prior distribution and then to compute a posterior distribution using the likelihood of the samples. Then Bayesian optimization (Rasmussen, 2003) is a three-step process: it creates a kriging model using a regression method, maximises an acquisition function to decide where to sample and finally updates the posterior distribution. Two last steps are repeated until convergence. In this process, the acquisition function is the key point to simultaneously reduce the model uncertainty along the exploration phase and improve the prediction near the optimum along the exploitation phase. The technique of Efficient Global Optimization (Jones *et al.*, 1998) based on the Expected Improvement function (EI) estimates the expectation of improving the knowledge of the minimum of the function in comparison with the best individual of DOE. Its formulation combines both high predicted variance and promising minima to improve global exploration and local optimality. The efficiency of this optimization strategy comes from the parsimonious enrichment, essential since high fidelity simulations are usually very expensive. The principle of the kriging which relies on the knowledge of the error associated to the model. As illustrated by Figure 7, the exploitation of this error and of the modelled values of the function are combined to define the enrichment zone associated to a high expected improvement.

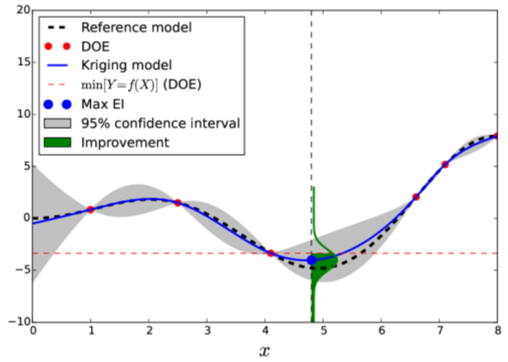


Figure 7: Bayesian Optimization with Expected Improvement

5.3 Multi-objective Bayesian Optimization with MOEGO NSGA-II

The EI acquisition function has been generalized in the multi-objective framework (MOEI) to determine the added point the most susceptible to improve the Pareto Front (PF). In this context, the acquisition function replaces in its formula the best individual of DOE with the Pareto front individuals. Unfortunately, the maximization of EI for multiobjective optimization has two drawbacks. Firstly, it is by definition optimal only for one-step-ahead methods so the use of this acquisition function is not suited to distributed computations. Secondly, the exploration of the design space can be insufficient for high dimensional design spaces. To overcome those restrictions, a combined strategy sequentially enriches the DOE with distributed computations is newly proposed in the MOEGO NSGA-II algorithm (Guerra, 2016). Firstly the genetic algorithm NSGA-II (Deb *et al.*, 2002) is used to search initialization points for the maximization of the EI criterion. To achieve this goal, kriging predictions of the fitness functions are firstly minimized using the genetic algorithm until obtention of an optimal population. Secondly, the objective space is decomposed in subdomains to force the optimizer to improve the PF simultaneously in different areas. Then, for each of these subdomains several local maximizations of EI initialized by the NSGA-II optimal population are carried out. The spatial decomposition which allows distributing the search of optimal solutions by MOEI among the individuals of the PF indentified by the NSGA-II is illustrated by Figure 8. Finally, only the most interesting individuals resulting from these multiple constrained maximizations of the multi-objective EI are selected and then evaluated with high fidelity models. The overall enrichment procedure described above is illustrated by Figure 9. In presence of constraints, kriging predictions of the fitness functions are multiplied by the probability of feasibility. Usually, the number of subdomains is linked to the number of available computational cores. This strategy aims to parsimoniously decrease the uncertainty of the surrogate model and thus to improve the accuracy of the Pareto Front (Emmerich *et al.*, 2002).

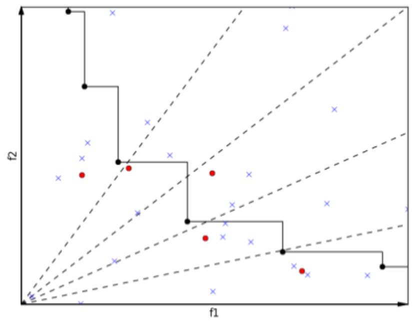


Figure 8: Maximization of EI for multi-objective optimization through objective space partition with crosses for NSGAII solutions and circles for results of EI maximization

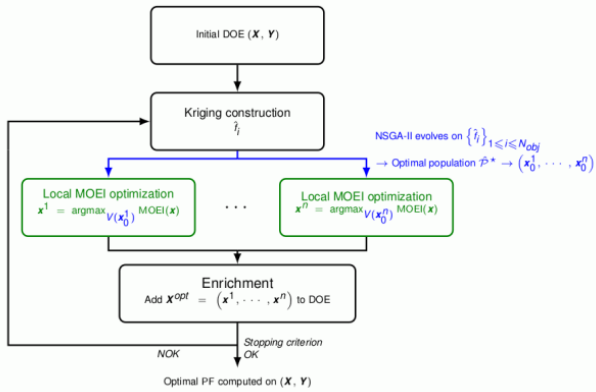


Figure 9: Distributed enrichment with MOEGO NSGAII

5.4 Application to aerodynamic-stealth optimization

Although this optimization problem is multidisciplinary, aerodynamic and electromagnetic computations are uncoupled and though can be led without multi-disciplinary optimization methods. Hence, each discipline is linked to an optimization criterion and the overall optimization problem is solved by means of multi-objective methods. The general optimization process which takes advantage of the uncoupling between the two disciplines is described in Figure 10. Those criteria are the lift-to-drag ratio and the percentage of bright points above a given threshold, computed for three observation frequencies. Moreover aircraft stability is ensured by adding a pitching stability constraint to the optimization problem.

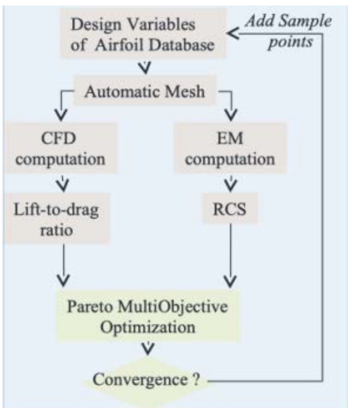


Figure 10: Aerodynamic-stealth optimization

Surrogate-Based Optimization process starts from a 20 samples design of experiments, updated by three additional samples chosen by MOEGO NSGAII. Kriging models for the aerodynamic and stealth objective functions are plotted in Figure 11 and Figure 12 for 20 and 23 samples respectively. On the latter one, filled circles identify the 3 added points. The dark line indicates the boundary of the stability constraint and the feasibility domain extends at its right. In our problem, lift-to-drag ratio must be maximized while stealth is minimized. Due to the constraint, one can observe that objective functions are antagonistic: when one is maximal the other is far from being optimum. As often, better solutions are located along the domain boundary of feasible designs and the comparison between the two aforementioned figures evidences the fact that the addition of new points improves the constraint boundary knowledge and thus allows finding best compromised solutions.

The functioning of the process is evidenced by Figure 13 which illustrates the optimization results in the design and objective spaces with samples plotted with blue circles or green squares according to their feasibility. Besides, black crosses identify the 3 added samples. The solutions obtained by maximization of MOEGO (plotted as triangles) are issued from local optimization starting from NSGAII solutions (plotted as orange dots). MOEGO and NSGAII solutions do not differ indicating a very small kriging uncertainty. The Pareto Front solution defines compromised solutions between lift-to-drag ratio and stealth. Because of the constraint, they are surrounded by unfeasible samples. One can notice that Pareto front solutions are very close to each other in the design space and then their shapes are similar. In order to minimize detectability, the best solution could be to choose the leftmost design. But a better compromise is the individual surrounded by the pink ellipse which, for a modest loss in terms of detectability, improves the L/D from 11.8 to 12.5. More generally, the PF allows the designer quantifying at which rate the gain of one objective function translates into a loss on the other one.

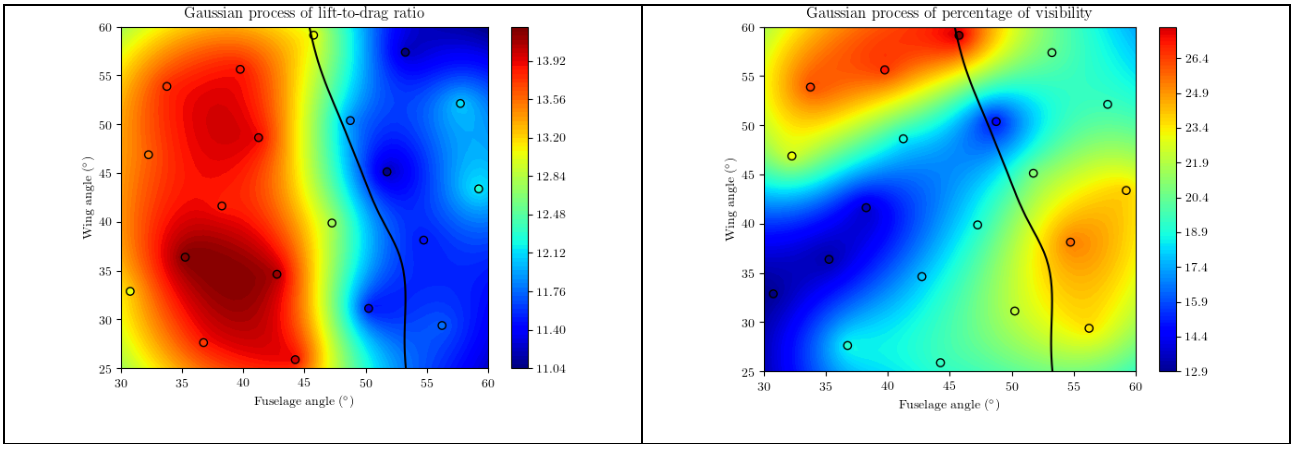


Figure 11: Kriging models of aerodynamic (left) and stealth (right) objective functions for 20 samples

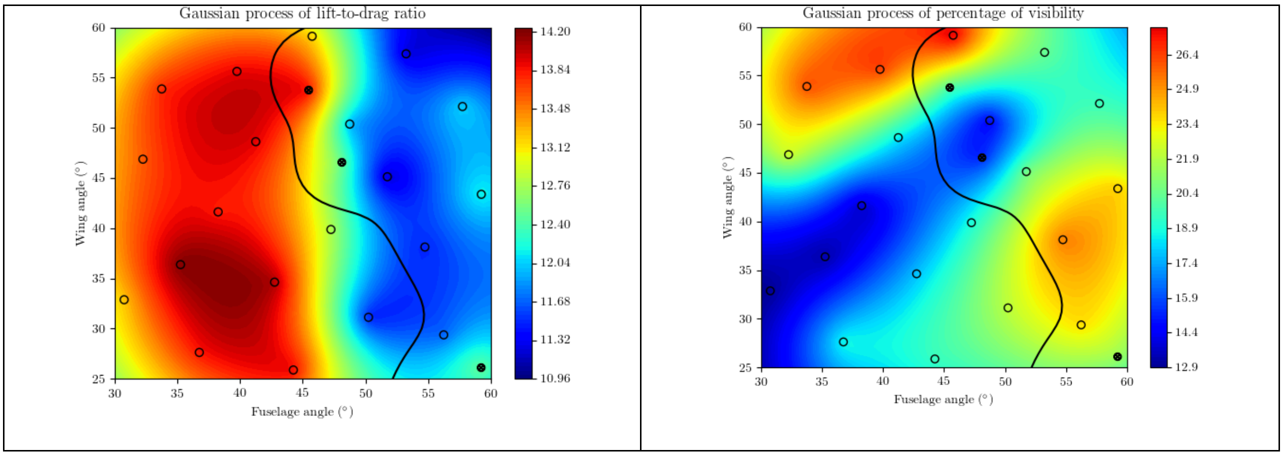


Figure 12: Kriging models of aerodynamic (left) and stealth (right) objective functions for 23 samples

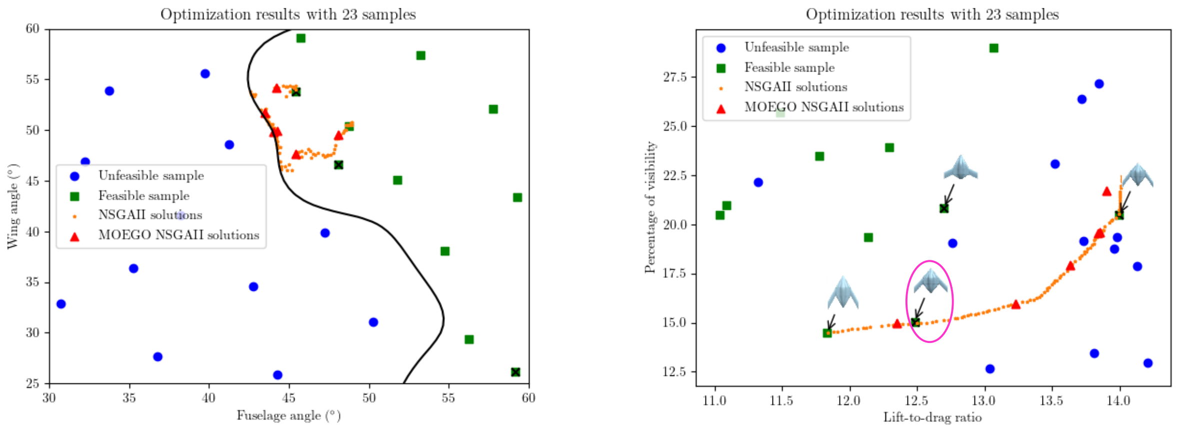


Figure 13: Optimization results in the design space (left) and objective space (right)

6.0 CONCLUSION

The planform of an UCAV has been optimized both taking into account aerodynamics and electromagnetism. The optimization strategy relies upon a meta-model based approach, one meta-model being built for each discipline. A first optimization exercise aiming at identifying the Pareto front in the space defined by the objective functions has been first led with only two parameters (the fuselage and wing sweep angles). A longitudinal stability margin constrain imposes that only stable or reasonably unstable design are considered. Due to the constraint, a good aerodynamic performance (high L/D) is antagonist of a weak detectability. A novel algorithm based on a coupling between a genetic algorithm (NSGA-II) and Multi-objective Efficient Global Optimization approach is proved to successfully to improve the description of the Pareto Front by means of a parsimonious iterative enrichment of the meta-models in relevant zones of the parameter space. The case with 4 parameters is the topic of an ongoing work.

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