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SURROGATE-BASED GLOBAL OPTIMIZATION OF A CYLINDER BY THE USE OF EVOLUTIONARY ALGORITHMS, SUPPORT VECTOR MACHINES AND NON UNIFORM B-SPLINES

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Abstract. *Nowadays, one of the priorities of the European Commission is to reduce the environmental impact of aviation through the advanced design of novel aircraft configurations. This implies that new methods and tools for aerodynamic shape optimization will have to be developed, allowing aircraft configurations that cannot be obtained with traditional strategies. Evolutionary optimization algorithms have the potential to find a global optimal candidate but on the other hand, they involve a vast number of evaluations, which are CFD runs in aerodynamic analysis. The use of surrogate modeling has been proposed in the literature [1, 2] as a suitable method to speed up the global optimization process. This work presents an application of a surrogate-based global optimization method (SBGO) to the aerodynamic shape optimization of a 2D infinite circular cylinder in laminar flow conditions. The geometry of this test case is parameterized by a Non-Rational B-Splines (NURBS) control box with 10 design variables. An approach based on Support Vector Machines (SVMs) in combination with Evolutionary Algorithms (EA) is applied.*

1 INTRODUCTION

Currently there is a strong need of computational tools for the design of the type of aircraft that will be demanded by the European industry, according to the guidelines stated at the ACARE 2020 [3] and 2050 [4] flight paths. The aeronautical industry agrees that these objectives make necessary the design of an innovative aircraft shape rather than further local improvements in the traditional wing-body-tail configuration. Efficient and accurate shape design optimization tools, able to consider novel concepts through the use of flexible geometry parameterization, are becoming a must for the aeronautical industry. Considering this, aerodynamic shape design and optimization problems based on evolutionary algorithms and surrogate models (also called surrogate-based optimization or SBO) have recently found widespread use in aeronautics, due to the potential to reach optimal configurations that are far away from their baseline geometries, and therefore their ability to enable non-conventional aircraft configurations. In addition, their increasing applicability in aerodynamic shape optimization problems is also due to the promising potential of these methods to speed-up the whole design process by the use of a "low cost" objective function evaluation to reduce the required number of expensive computational fluid dynamics (CFD) simulations.

However, the application of these SBO methods for industrial configurations still requires facing several challenges. The most crucial challenges nowadays are the so-called "curse of dimensionality", the ability of surrogates when handling a high number of design parameters, efficient constraints handling, adequate exploration and exploitation of the design space, and last but not least, how to deal with grid deformations in case of large displacements, which is always the case when trying to achieve novel configurations from the traditional ones.

This work focuses on the application of enhanced methods in aerodynamic shape design optimization to enable novel aircraft configurations. In particular, it aims to demonstrate the feasibility of a combined approach, based on Evolutionary algorithms and Support Vector Machines, to reach optimal configurations that are far away from its baseline geometry. In order to validate this, the optimization approach is applied to the selected baseline geometry, a landing gear master cylinder, resulting on optimal configurations for each of the defined flow conditions. This very simple test case (clean cylinder) has been selected for several reasons: it will allow to validate the potential of the proposed approach to reach non-conventional configurations (those which are far from the initial one), and in addition, it is of interest for an European aircraft manufacturing industry, which is looking for flow optimization in this region. However, in order to further exploit the results in industry, more complex geometries and constraints, including also structural aspects should have to be taken into consideration.

2 PREVIOUS WORK

A physics-based surrogate model was recently applied in [5] to the drag minimization of a NACA0012 airfoil in inviscid transonic flow and RAE2822 airfoil in viscous transonic flow, both using PARSEC parameterization with up to ten design parameters. The drag minimization problem was also addressed by SBO in [6] for the NFL0416 airfoil, parameterized with ten design parameters.

Moreover, a combination of a generic algorithm (GA) and an artificial neural network (ANN) was applied in [7] to the shape optimization of an airfoil, parameterized by a modified PARSEC parameterization involving ten design variables. In [8] a surrogate based on Proper Orthogonal Decomposition (POD) was applied to the aerodynamic shape optimization of an airfoil geometry parameterized by sixteen design variables defined with Class Shape Transformation method (CST). In summary, the ability of SBO methods to manage a high number of design parameters still remains an open challenge and have been studied by several authors in the last few years, as well as the strategies for efficient infill sampling criteria with constraint handling. [8, 9].

3 PROPOSED APPROACH

A surrogate-based global optimization method with an adaptive sampling strategy is used, called 'The intelligent Estimation Search with Sequential Learning (IES-SL)'. Support Vector Machines for regression (SVMr) are combined with Evolutionary Algorithms (EA) in order to perform an efficient adaptive sampling guiding the optimization algorithm towards the most promising regions of the design space. The geometry is parameterized with volumetric Non-Uniform Rational B-Splines which vertical movements are the design variables for this study.

As can be observed, it comprises two steps: First, the algorithm generates an initial database by evaluating a small number of random designs (four in this application study). The initial surrogate model is then generated using this reduced database. Then, the algorithm searches for the position of the optimum value with the surrogate model to use it as an estimation for the real optimum position [1]. The estimated optimum is evaluated using the CFD solver, obtaining a new pair [design, cost] that will enrich the database. After that, the surrogate is updated by adjusting it to the complete database and the cycle is finished, starting again the search for the new sample. When the maximum number of iterations is reached, the optimum design is obtained as the best parameters on the database. In this way, it is ensured that the design obtained is optimum with respect to the simulator system (CFD solver) and not only to the surrogate model. For more information about the SVMr, EAs and IES-SL readers can consult [6, 7, 10, 11].

4 DEFINITION OF THE OPTIMIZATION PROBLEM

4.1 Geometry parameterization

The cylinder grid is deformed through a volumetric b-spline, as shown in Figure 1. The design variables are the control points located on the upper and lower side, which can freely move in any direction, while the control points located in the middle are kept fixed during optimization. In this method, the original geometry is deformed by the movement of control points in a similar way than the Free Form Deformation technique (FFD) [12], but in contrast to FFD, deformations of the upper-side and lower-side are considered independently one of each other, which provides more flexibility.

The computational surface grid vertices are mapped into the NURBS (Non-Uniform Rational B-Splines) space through the parametric coordinates, which are previously calculated using an appropriate inversion point algorithm [12, 13]). These parametric coordinates are invariant throughout the optimization, allowing to recalculate the spatial coordinates at any time of the process. A second mapping is performed on the cylinder geometry, by means of a discrete uniform rasterization, in order to accurately calculate the volume throughout the optimization.

This geometry mapping is done in parallel, independently of the computational grid and it is used for handling the volume constraints within the optimization process.

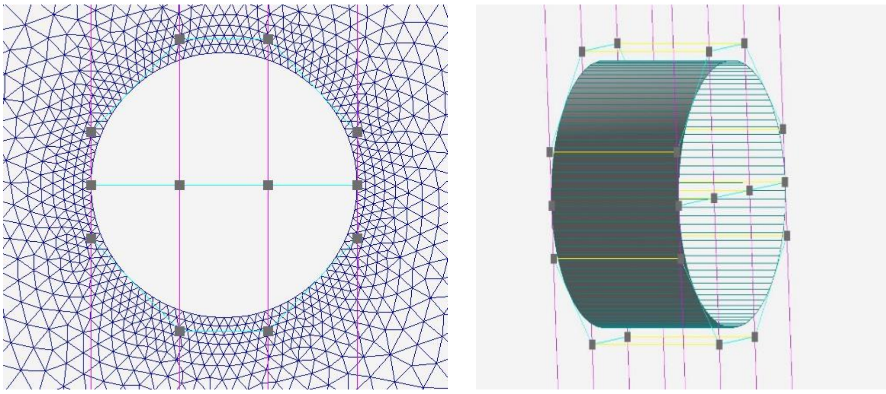

Figure 1. Parameterization of the cylinder. 2D (left) and 3D (right) views.

4.2 Test cases definition

The approach is applied to the aerodynamic shape optimization of a cylinder parameterized as shown in section 4.1, with the problem formulation defined on Table 1. The location of the design parameters on the surface of the test case was previously displayed in Figure 1. A symmetric movement of the upper and lower face control points was imposed. The objective function was to minimize drag while preserving, at least, the 80% of the baseline volume, which was considered the minimum valid volume due to structural requirements. This volume preservation was implemented as a strong penalization of the objective function, which allows exploring the whole design space even if several geometries will finally be discarded by the optimization algorithm. Furthermore, DV's are allowed to move ± 60% of their initial value in both directions, horizontal and vertical.

M	**Re**
0,05	1214
0,1	2490
0,15	3735
0,2	4980
0,25	6226
0,3	7471
0,35	8716
0,4	9961

Table 1. Problem formulation (the Re reference length considered is the cylinder diameter)

The optimization study was performed for a range of Mach numbers from 0.05 and 0.4, meaning a Reynolds below 10^5 (Table 1), ensuring laminar boundary layer separation conditions, as can be observed in Figure 2 [15]. This problem formulation allows using laminar flow conditions, therefore reducing the required computational cost (compared with turbulence RANS modeling).

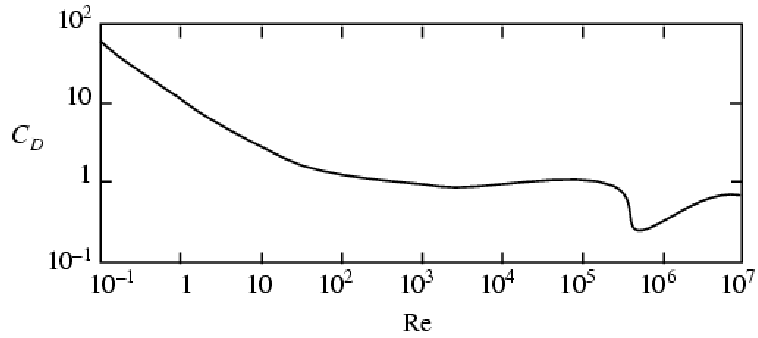

Figure 2. Drag coefficient versus Reynolds number for an infinite circular cylinder [15].

4.3 Drag minimization of a 3D cylinder for different flow conditions

In this section, the approach is applied to the drag minimization and results are displayed in Table 2 & Table 3. In particular, Table 2 shows the optimization results regarding the whole objective function (which includes both drag and volume values considerations), where it can be seen that the total reduction of the objective function was between 73-77% of its original value. Table 3 shows the drag coefficient values of the original and optimized geometries. It can be observed that the drag was minimized between 92-94% of its original value in the base-line geometry (depending on the Mach number considered), while at the same time fulfilling the constraints imposed in the volume.

M	0.05	0,1	0,15	0,2	0,25	0,3	0,35	0,4
$OF_{baseline}$	0,39248	0,30123	0,26356	0,24341	0,23173	0,22510	0,22124	0,21910
OF_{optim}	0,08918	0,07525	0,06751	0,06385	0,06031	0,05784	0,05740	0,05817
%Improvement	77,28%	75,02%	74,39%	73,77%	73,97%	74,31%	74,05%	73,45%

Table 2. Optimization results (OF means objective function)

M	0,05	0,1	0,15	0,2	0,25	0,3	0,35	0,4
C-$drag_{baseline}$	0,95672	0,84988	0,80707	0,78708	0,77838	0,77638	0,77909	0,78578
C-$drag_{optim}$	0,06924	0,05842	0,05241	0,04957	0,04682	0,04490	0,04472	0,04570
C-$drag_{optim\_p}$	0,05391	0,04875	0,04507	0,04353	0,04162	0,04033	0,04057	0,04189
C-$drag_{optim\_v}$	0,01532	0,00967	0,00733	0,00604	0,00520	0,00457	0,00415	0,00381
%Improve-ment	92,76%	93,13%	93,51%	93,70%	93,98%	94,22%	94,26%	94,18%

Table 3. Optimization results (C-drag minimization)

From the mentioned tables, it can be also observed that the gain in the objective function tends to decrease with the Mach number while, on the other hand, the improvement in the drag coefficient tends to increase. This behavior is explained because the optimizer proposes thinner shapes as the Mach number increases, producing a geometry with less drag, but also less volume, which is penalized in its global objective function.

The optimized shapes returned by the optimizer are displayed in Figure 3. For clearness, only the baseline geometry and the optimized geometries for Mach numbers 0.10, 0.20, 0.30

and 0.40 are shown. It can be observed that all the optimized shapes are similar except the one returned for Mach=0.40, where the optimizer returns a geometry with a wider area near the trailing edge, in order to ensure the volume constraint, even when it will affect the drag value.

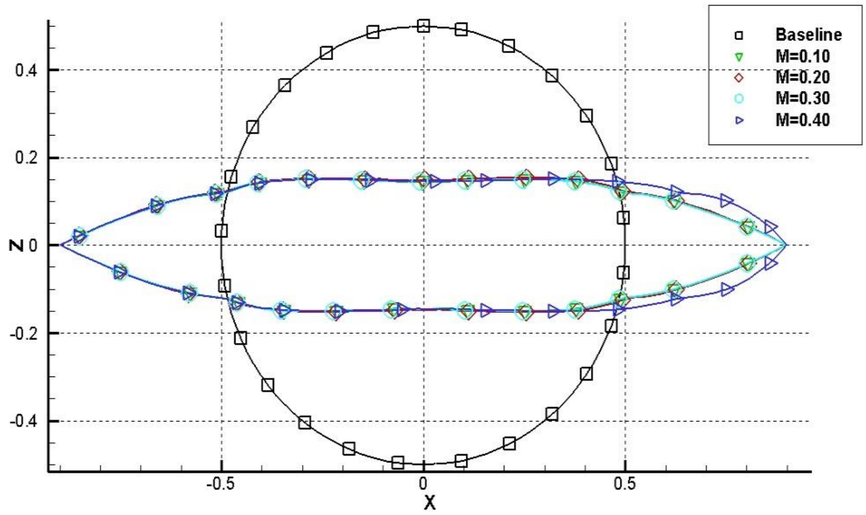

Figure 3. Comparison of baseline and optimal shapes for Mach numbers 0.10, 0.20, 0.30 and 0.40

Finally, **¡Error! No se encuentra el origen de la referencia.** shows the Mach number contours of the original (left) and optimized (right) geometries for each of the Mach numbers considered in the range [0.05, 0.4]. As expected, a pair of vortices (bigger with the Mach number) appear downstream of the baseline geometry. In the optimized shapes, the cross-sectional area has been reduced as much as the geometric and volume constraints allows. This explains the vortices disappearance and the drag reduction, as expected from the aerodynamic point of view, since the objective function was to reduce drag while maintaining the volume. Some asymmetric effects can be seen in the Mach contours of the optimized geometries, which are due to asymmetric volume grid deformation since the geometric surface deformation is propagated to the volume.

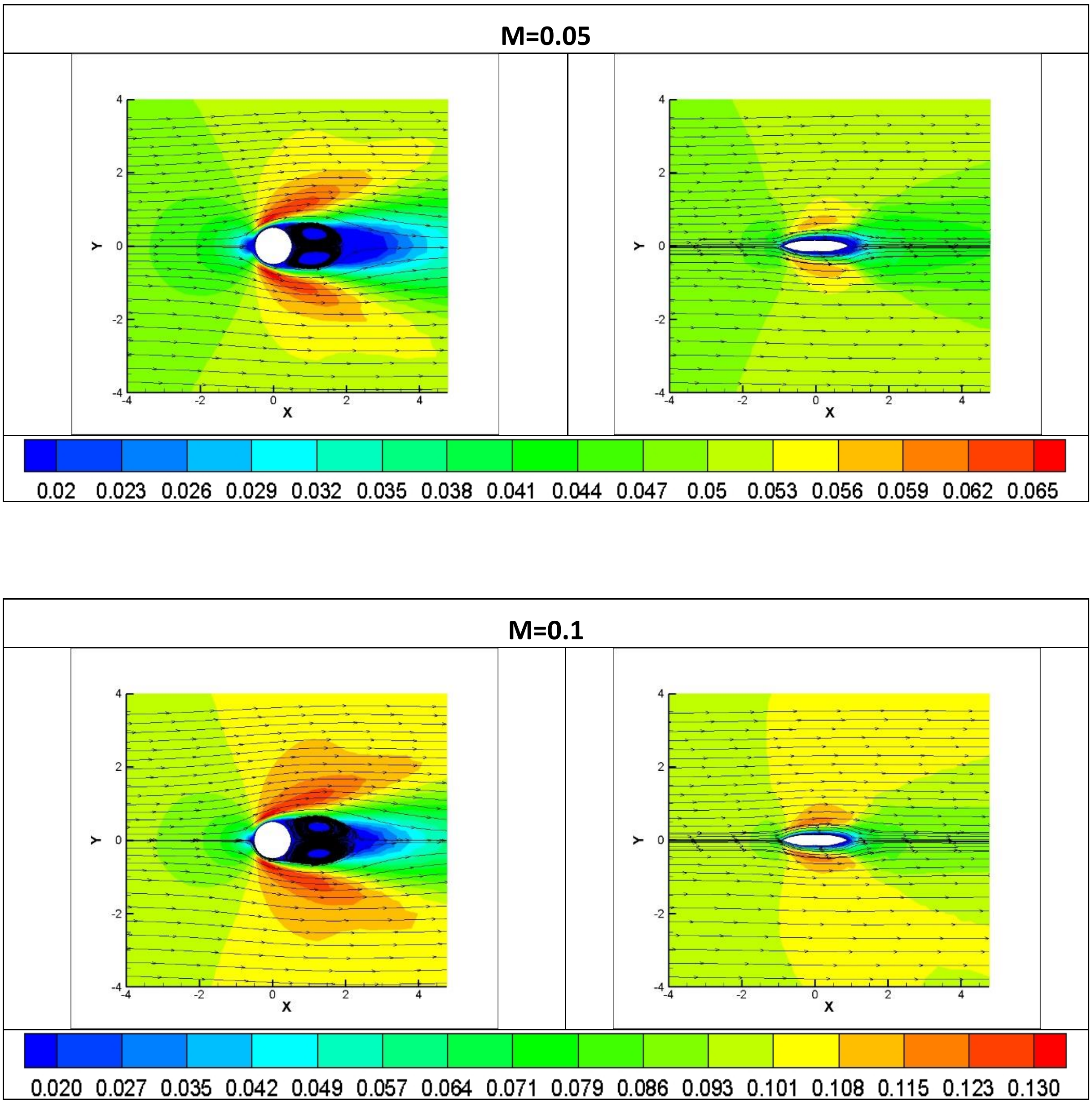

Figure 4. Mach contours and velocity streamlines of the baseline and optimized geometries for Mach numbers 0.05 and 0.1

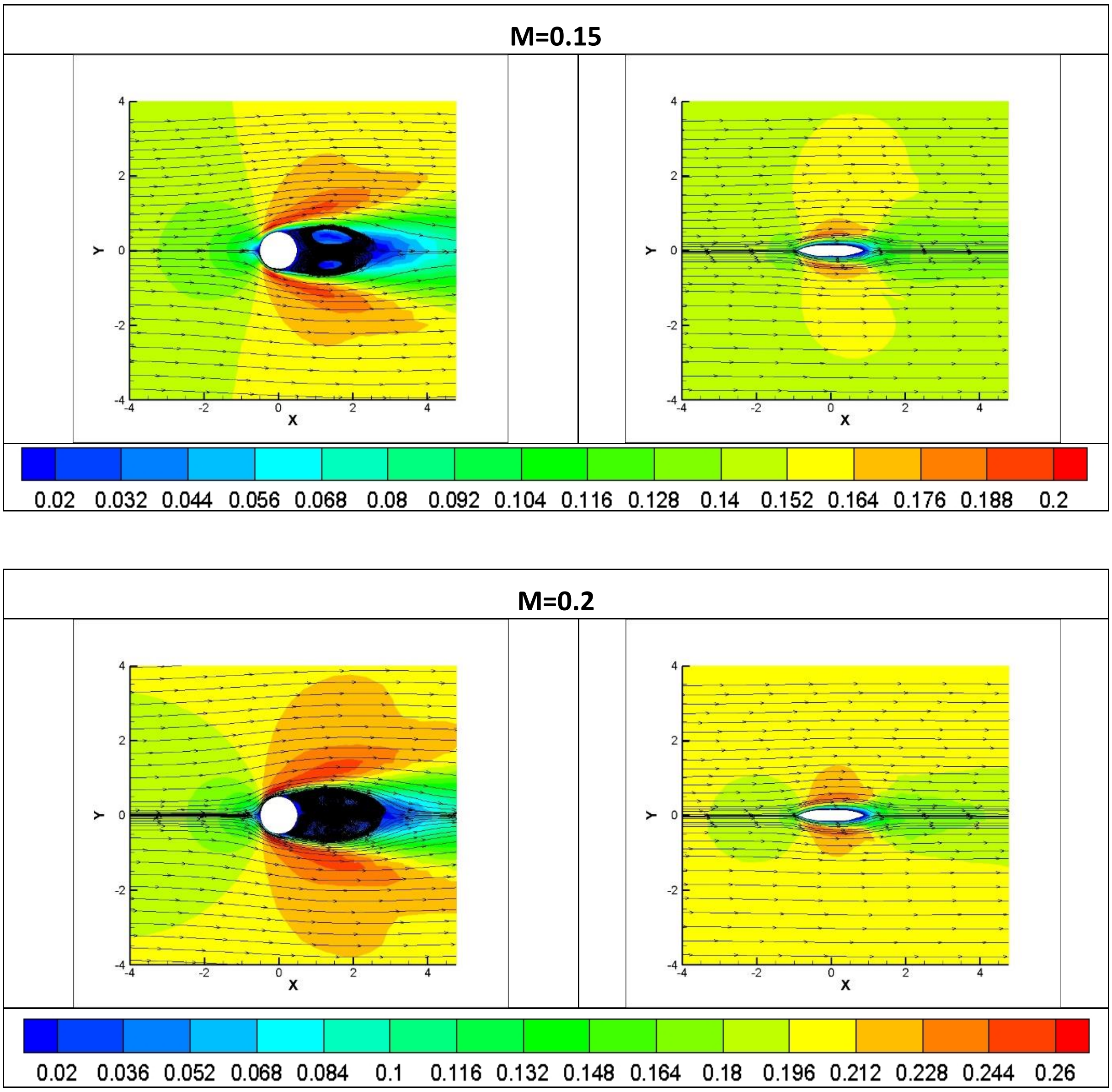

Figure 5. Mach contours and velocity streamlines of the baseline and optimized geometries for Mach numbers 0.15 and 0.2

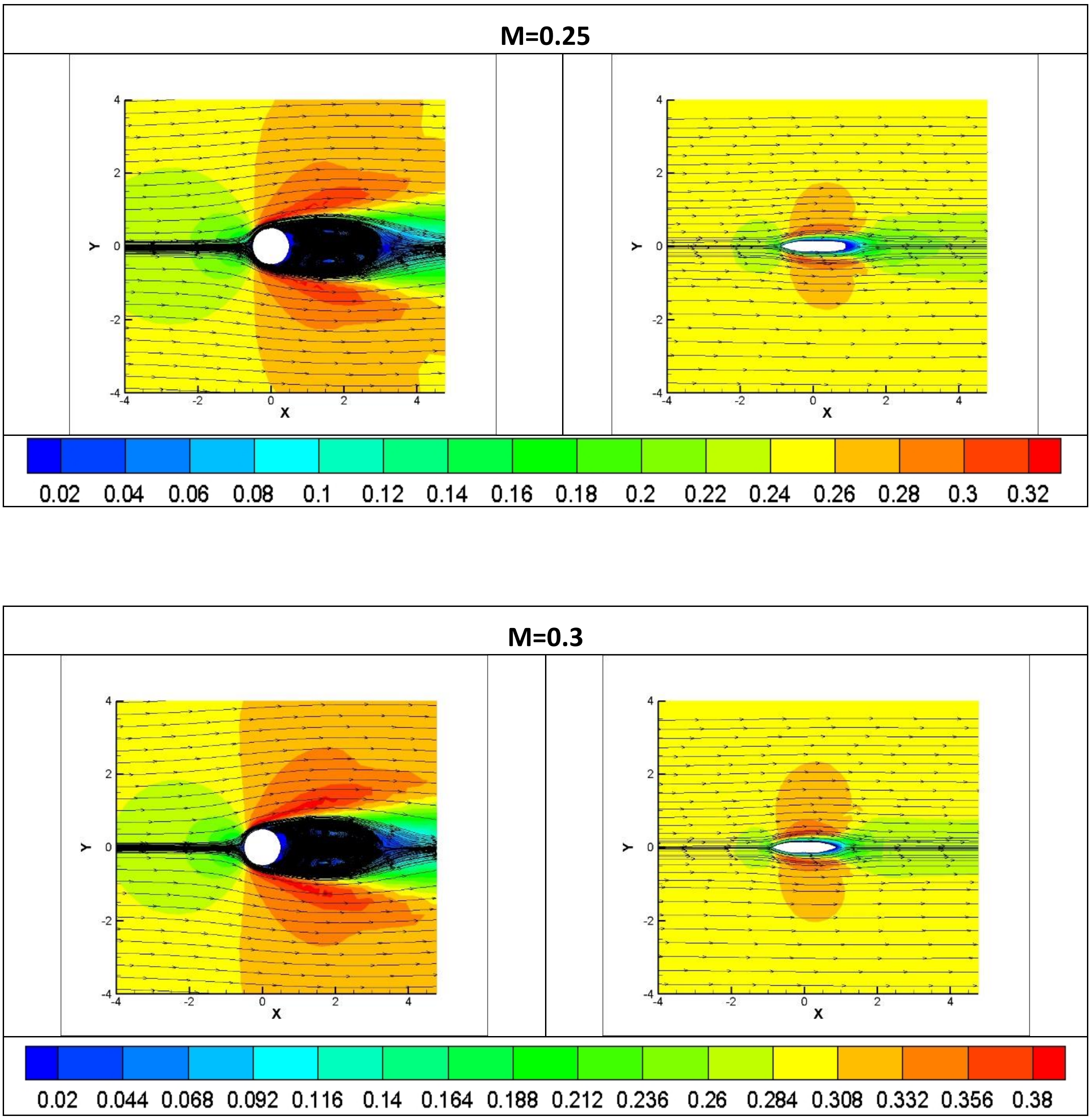

Figure 6. Mach contours and velocity streamlines of the baseline and optimized geometries for Mach numbers 0.25 and 0.3

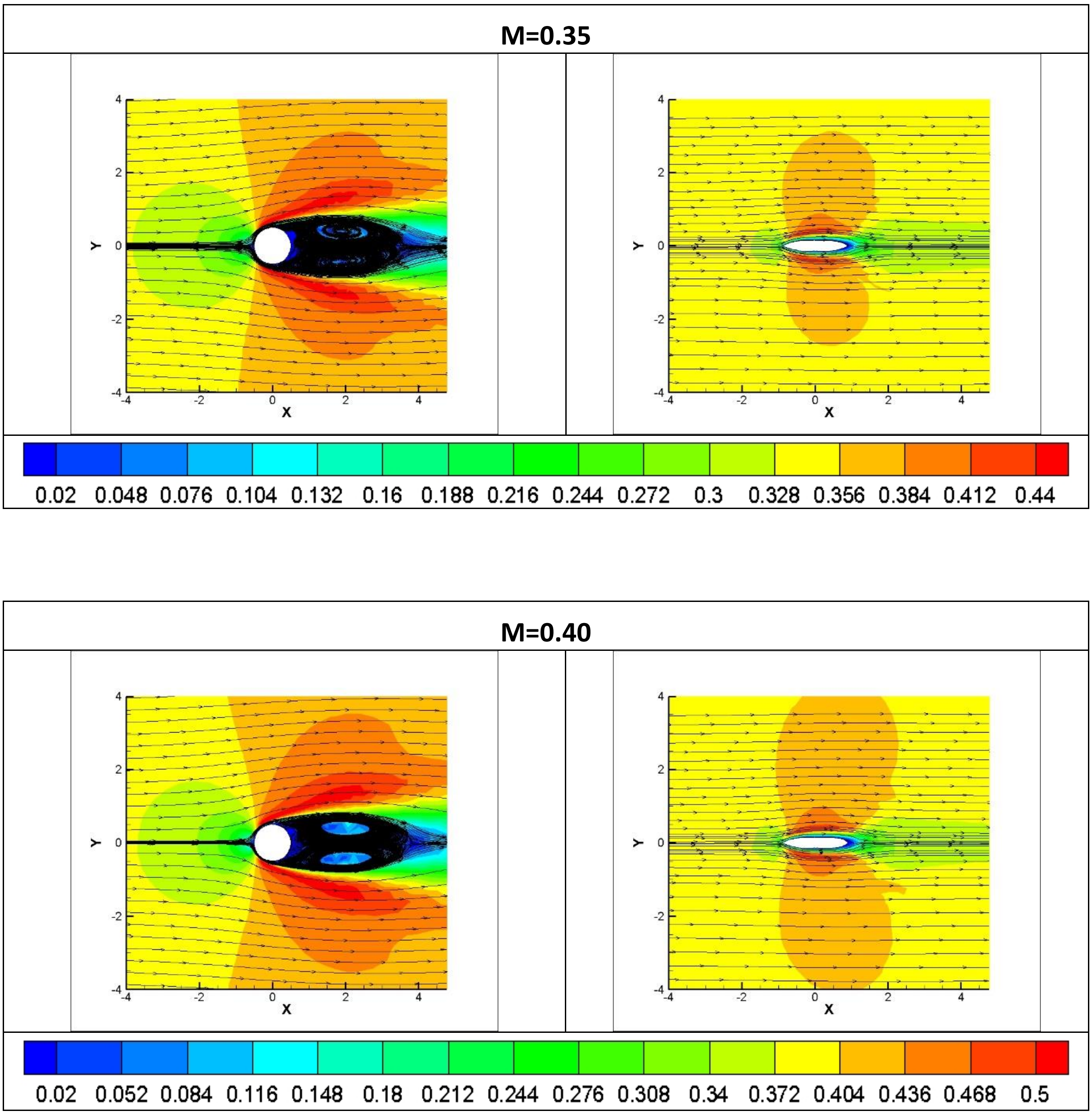

Figure 7. Mach contours and velocity streamlines of the baseline and optimized geometries for Mach numbers 0.35 and 0.4

5 CONCLUSION

This article presented the application of a global optimization strategy using the Intelligent Estimation Search with Sequential Learning (IES-SL) and the hybridization of EA and SVMr to the aerodynamic shape optimization of a clean cylinder representing a simple model of the landing gear master cylinder. The objective of this work was to demonstrate the feasibility of the proposed strategy to reach optimal configurations that are far from the baseline geometry.

This approach allows extensively exploring the design space, without any dependence on an initial solution and expensive CFD computations, since it uses a metamodel (based on SVMr) to estimate the aerodynamic coefficients. At the same time, accuracy is ensured, because in each iteration the result is validated with the CFD tool.

REFERENCES

[1] E. Andrés, S. Salcedo-Sanz, F. Mongue y A. Pérez-Bellido, «Efficent aerdoynamic design through evolutionary programming and support vector regression algorithms,» *Expert Systems with Applications,* vol. 39, pp. 10700-10708, 2012.

[2] A. I. Forrester y A. J. Keane, «Recent advances in surrogate-based optimization,» *Progress in Aerospace Sciences,* vol. 45, nº 1-3, p. 5079, 2009.

[3] ACARE, «Aeronautics and Air Transport: Beyond vision 2020 (towards 2050),» Advisory Council or Aeronautics Research in Europe, 2010.

[4] P. Argüelles y M. Bischoff, «European Aeronautics: A vision for 2020. ACARE».

[5] L. Leifsson, S. Koziel y Y. Tesfahungen, «Aerodynamic Design Optimization: Physics-based Surrogate Approaches for Airfoil and Wing Design,» de *AIAA SciTech*, 2014.

[6] S. Koziel y L. Leifsson, «Multi-Level Surrogate-Based Airfoil Shape Optimization,» de *51st AIAA Aerospace Sciences Meeting including the New Horizons Forum and Aerospace Exposition*, Grapevine (Dallas/Ft. Worth Region), Texas, 2013.

[7] A. Jahangirian y A. Shahrokhi, «Aerodynamic shape optimization using efficent evolutionary algorithms and unstructured CFD solver,» *Computers & FLuids,* vol. 46, pp. 270-276, 2011.

[8] E. Iuliano y D. Quagliarella, «Aerodynamic Shape Optimization via non-intrusive POD-based Surrogate Modeing,» de *IEEE Congress on Evolutionary Computation*, Cancún, Mexico, 2013.

[9] J. Parr, C. Holden, A. Forrester y A. Keane, «Review of Efficent Surrogate Infill Sampling Criteria with Constraint Handling,» de *2nd International Conference on Engineering Optimization*, Lisbon, Portugal, 2010.

[10] Y. Jin, «Multi-Level Surrogate-Based Airfoil Shape Optimization,» de *51st AIAA Aerospace Sciences Meeting including the New Horizons Forum and Aerospace Exposition*, Grapevine (Dallas/Ft. Worth Region), Texas AIAA2013-0778., 2013.

[11] E. Ortiz-García, S. S. Sanz, Á. M. Pérez-Bellido y J. A. Portilla-Figueras, «Improving the training time of support vector regression algorithms through novel hyper-parameters search space reductions,» *Neurocomputing,* 2009.

[12] D. Chauhan, C. Praveen y R. Duvigneau, «Wing Shape Optimization Using FFD and Twist Parametrization,» *Aerospace Sciences and Technologies,* pp. 225-230, 2010.

[13] M. Martin, E. Andrés, M. Widhalm, P. Bitrian y C. Lozano, «Non-Uniform Rational B-Splines based aerodynamic shape optimization with DLR TAU code,» *Proceedings of the Institution of Mechanical Engineers, part G, Journal of Aerospace Engineering*, vol. 226, nº 10, pp. 10-13, 2012.

[14] M. Martin, E. Andrés, E. Valero y C. Lozano, «Volumetric B-splines shape parametrization for aerodynamic shape,» *Aerospace Science and technology*, vol. 37, pp. 26-36, 2014.

[15] D. Tritton, Physical FLuid Dynamics 2nd Ed, Oxford University Press, 1998.

[16] B. Epstein, A. Jameson, S. Peigin, D. Roman, N. Harrison y J. Vassberg, «Comparative Study of 3D Wing Drag Minimization by Different Optimization Techniques.,» de *46th AIAA Aerospace Sciences Meeting and Exhibit. AIAA paper 2*, Reno, Nevada, 2008.

[17] E. Andrés, D. González, M. J. Burgos y L. Carro, «Constrained Single-Point Aerodynamic Shape Optimization of the DPW-W1 wing through Evolutionary Programming and Support Vector Machines,» de *International Conference on Evolutionary and Deterministic Methods for Design, Optimization and Control (EUROGEN 2015)*, Glasgow, 2015.

[18] «Garteur AD/AG52 members 2013. Partial report on Surrogate-based Global Optimization Methos in Aerodynamic Design. http://ag52.blogspot.com.es/».

[19] D. González, E. Andrés, M. Burgos, L. Carro y S. Salcedo, «Influence of geometry parameterization in aerodynamic shape design of aeronautical configurations by evolutionary algorithms,» de *6th European Conference for Aeronautics and Space Sciences (EUCASS)*, Krakow, Poland, 2015.

[20] «AIAA 3rd Drag Prediction Workshop. URL: http://aaac.larc.nasa.gov/tsab/cfdlarc/aiaa-dpw/Workshop3/workshop3.html,» [En línea].

[21] M. Martin, E. Andrés, E. Valero y C. Lozano, «Gradients Calcultion for Arbitrary Parameteizations via Volumetric NURBS: The Control Box Approach,» de *EUCASS*, 2013.