ECCOMAS Congress 2016
VII European Congress on Computational Methods in Applied Sciences and Engineering
M. Papadrakakis, V. Papadopoulos, G. Stefanou, V. Plevris (eds.)
Crete Island, Greece, 5–10 June 2016

CONSTRAINED MULTI-POINT AERODYNAMIC SHAPE OPTIMIZATION OF THE VISCOUS DPW WING THROUGH EVOLUTIONARY PROGRAMMING AND SUPPORT VECTOR MACHINES

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Keywords: Aerodynamic shape design, Surrogate-based global optimization, Evolutionary programming, Computational Fluid Dynamics.

Abstract. *This work presents an application of Surrogate-Based Optimization (SBO) to the multipoint constrained design of the 3D DPW wing [1]in viscous transonic flow conditions. The geometry is parameterized by a control box with 36 design variables. An adaptive sampling technique focused on the optimization problem, the Intelligent Estimation Search with Sequential Learning (IES-LS), is applied. The selected SBO approach is based on the use of Support Vector Machines (SVMs) as the surrogate model for estimating the objective function, in combination with an evolutionary algorithm (EA) to enable the discovery of global optima. The aim of this work is to complement a previous one [2] by adding a study of the capability of this method to obtain an improvement for this multipoint constrained three-dimensional test case.*

1 INTRODUCTION

In the last few years, there has been an increasing interest in the topic of Surrogate-based Optimization (SBO) methods for aerodynamic shape design. This is due to the promising potential of these methods to speed-up the 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 industrial applications of these SBO methods has still to face several challenges, as for instance, the ability of surrogates when handling a high number of design parameters, efficient constraints handling, adequate exploration of the design space, etc.

The aim of this work is to complement a previous one [2] by adding a study of the capability of this method to obtain an improvement for a constrained multipoint three-dimensional viscous test case.

This work is under the scope of the GARTEUR Action Group (AD/AG52) [3], with the objective of providing a comprehensive survey about different surrogate methods for surrogate-based aerodynamic shape optimization, started at the beginning of 2013. Within this AG, research activities are planned over four-year period, with the objective of performing a fair comparison between different surrogate modeling methods applied to the aerodynamic optimization of baseline geometries, sharing the parameterization (volumetric NURBS) and mesh deformation algorithms..

2 PREVIOUS WORK

A physics-based surrogate model was recently applied in [4] 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 [5] 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 [6] to the shape optimization of an airfoil, parameterized by a modified PARSEC parameterization involving ten design variables. In [7] 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. [7, 8].

Finally, the authors also presented recent works on this topic [2, 9]. This paper is an extension of previous research, here considering the constrained multi-point aerodynamic optimization of the DPW-W1 wing for viscous transonic flow.

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 [10]. 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 [5, 6, 11, 12]

4 DEFINITION OF THE OPTIMIZATION PROBLEM

4.1 Baseline geometry: DPW-W1 wing

The public domain transonic DPW-W1 wing (a test case of the Third AIAA Drag Prediction Workshop) was used [1, 10]. Reference quantities for this wing are displayed in the following table:

Sref (wing ref. area)	290322 mm^2
Cref (wing ref. chord)	197.55 mm
Xref*	154.24 mm
b/2 (semi span)	762 mm
AR (aspect ratio, AR=b2/Sref)	8.0

*(relative to the wing root leading edge)

Table 1. DPW reference quantities

The initial geometry (in IGES format) was downloaded from [10]. A set of grids are also available in the website of the 3rd AIAA Workshop on Drag Prediction.

4.2 Parameterization

The DPW geometry is parameterized by a 3D control box (displayed in Figure 1) with 5 control points in direction u, 10 in direction v and 5 in direction w. The parametric u direction corresponds to the y axis, the v direction to the x axis, and the w direction to the z axis.

The design variables are the vertical displacement of those control points set up on the aerodynamic surface. The wing is split in three profile sections and the transition between sections is linear. Each section has 6 active control points for the upper side and other 6 for the lower side, which are independent (the movement of a control point at the upper side does not modify the lower side and vice versa), with a total of 36 design parameters for the whole wing. Authors have previously applied this parameterization technique to other local and global optimization problems [11]. During the optimization performed in this paper, the wing platform will be kept fixed, as well the angle of attack and the torsion.

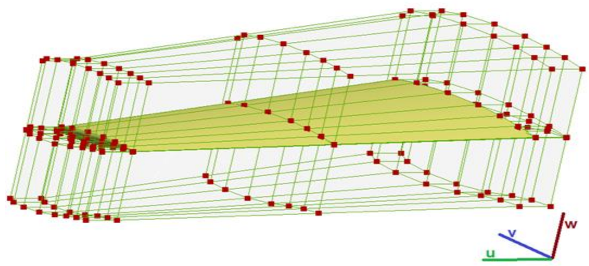

Figure 1. DPW wing parameterization

4.3 Aerodynamic constraints

The following aerodynamic constraints are considered:

1. Prescribed constant lift coefficient (C_L=C_L^0)
2. Minimum pitching moment: C_M>=C_M^0
3. Drag penalty: If constraint in minimum pitching moment is not satisfied, the penalty will be 1 drag count per 0.01 increment in C_M.

4.4 Geometric constraints

Each design variable will be constrained by its minimum and maximum values that will be chosen as the + or – 20% of their original value. Apart from this, other constraints have been defined, according to [1]:

1) Airfoils' maximum thickness constraints:

$$(t/c)_{\sec tion} \geq (t/c)^0_{\sec tion}$$

where the right term is the maximum thickness for the original wing sections, root, mid-span and tip, which has the value of 13.5%.

2) Beam constraints:

First, two locations (x/c) are fixed to represent the beam constraints:

$$(x/c)_{root,1} = (x/c)_{mid-span,1} = (x/c)_{tip,1} = 0.20$$
$$(x/c)_{root,2} = (x/c)_{mid-span,2} = (x/c)_{tip,2} = 0.75$$

The constraint here is that the thickness value of the optimized wing sections at these locations should be greater or equal than the thickness of the original ones. It is defined with the expressions:

$$(t/c)_{root,1} \geq 12\%, (t/c)_{mid-span,1} \geq 12\%, (t/c)_{tip,1} \geq 12\%$$
$$(t/c)_{root,2} \geq 5.9\%, (t/c)_{mid-span,2} \geq 5.9\%, (t/c)_{tip,2} \geq 5.9$$

4.5 Test cases definition & objective function

The proposed approach is applied to the multipoint aerodynamic shape optimization of a DPW-W1 wing in viscous transonic flow. The specific flow conditions are exposed in Table 2 for both Design Points (DP)

	DP1	**DP2**
M	0.76	0.78
Re	5×10^6	5×10^6
AoA	0	0
Turbulence	SA	SA

Table 2. Test cases definition

The design goal is to achieve a geometry with the minimum drag, while maintaining the specified aerodynamic constraints. Aerodynamic constraints are implemented as penalties in the objective function. The pseudo-code implementations is:

```
lift_penalty=1-(Cl/Cl0);
if (lift_penalty<0) lift_penalty=0;
cm_penalty = (Cm0-Cm)*0.0001/0.01;
if (cm_penalty < 0) cm_penalty = 0;
objective_function=(((Cd+cm_penalty)/Cd0 ) )+5*lift_penalty;
```

4.6 Computational grid

The DPW RANS grid was directly downloaded from [10]. The features of the unstructured grid are:

#points	#surface points	#elements	#surface elements
3770k	152k	9335k	310k

Table 3. Computational grid features

5 NUMERICAL ASSESSMENT

5.1 DPW-W1 optimization results

This section shows the results of the optimization approach exposed in previous sections. Table 4 summarizes the DPW the results of the optimization process. Results exhibit a reduction of 3 & 6 drag counts respectively for each DP which are in the same order that the results obtained in [1]

	DP1			DP2			fobj
	C_L	C_D	C_M	C_L	C_D	C_M	
DPW-W1	0.3632	0.0205	-0.0674	0.3718	0.0222	-0.0692	
Optimized	0.3637	0.0202	-0.0677	0.3712	0.0216	-0.0695	0.9746
Δ	0.0005	-0.0003	-0.0003	0.0006	-0.0006	-0.0003	

Table 4.DPW-W1 optimization results

Figure 2 depicts the baseline and optimized airfoils along wing span.

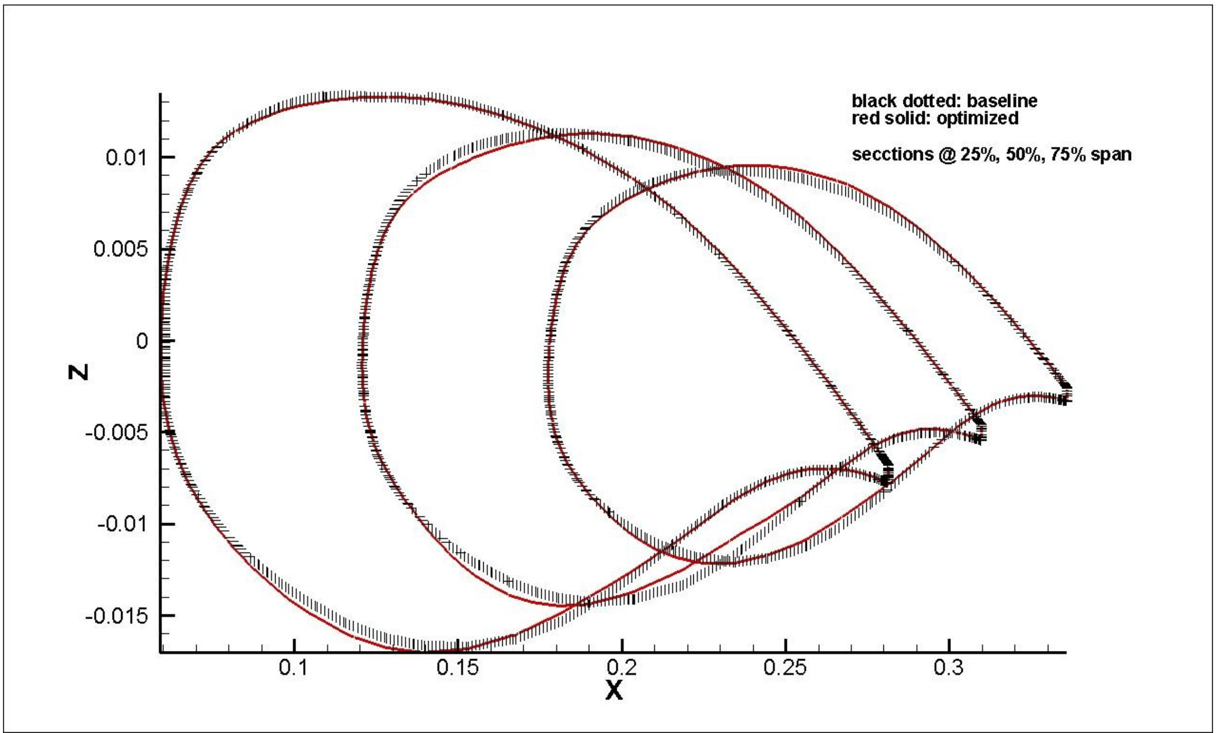

Figure 2. Baseline vs. optimized geometry

Figure 3 andFigure 4 show the C_p distribution @ 25% 50% and 75% of wing span while Figure 5 andFigure 6 contains the C_p contours for both baseline and optimized geometries at each flow conditions.

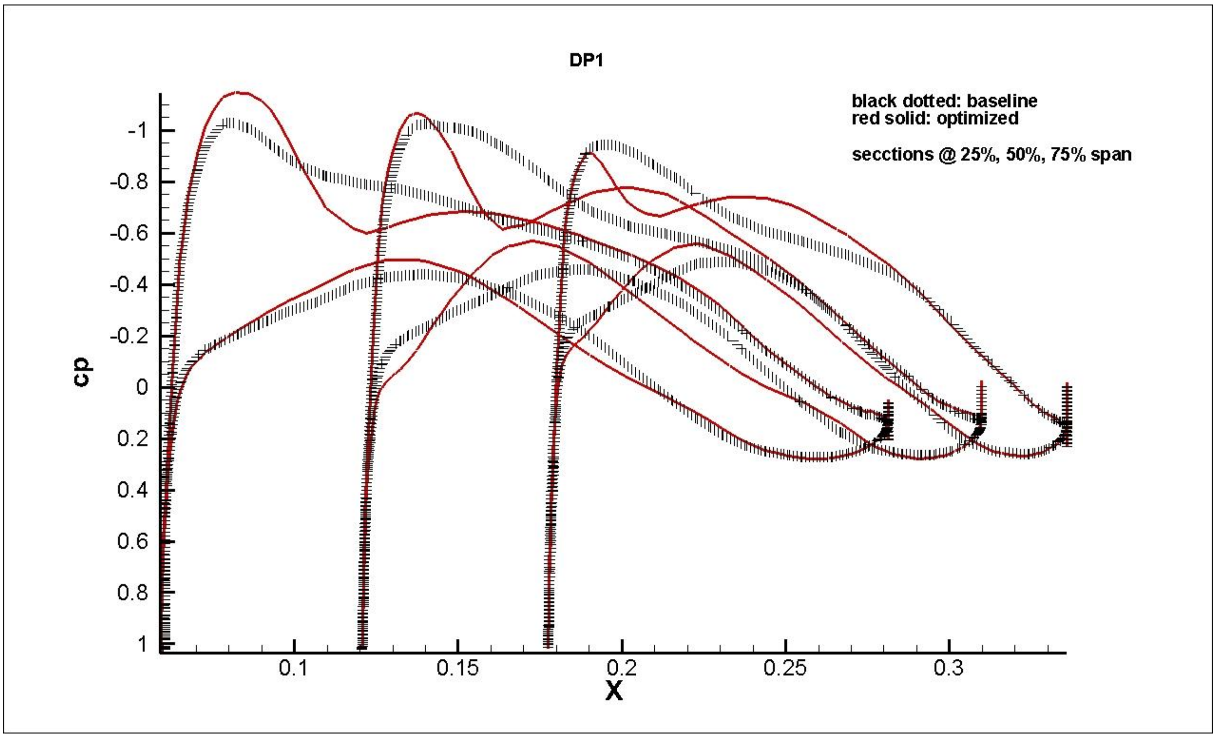

Figure 3. Cp distribution for DP1 along wing span

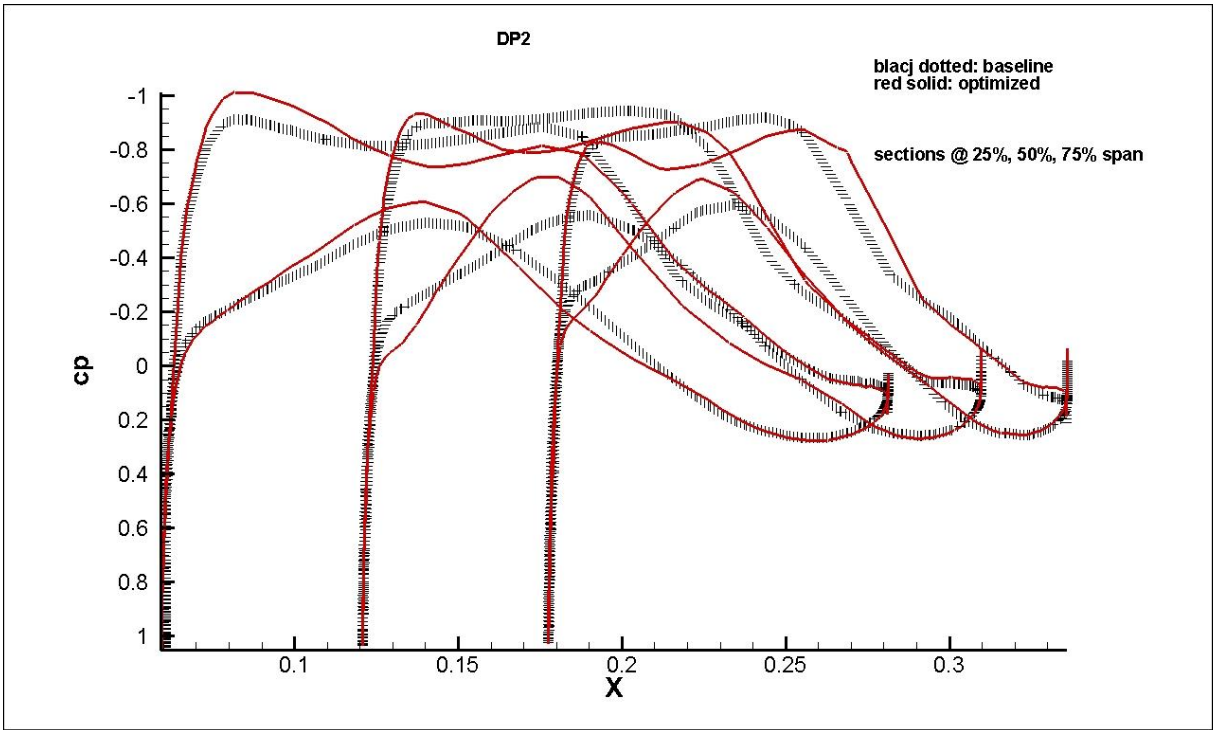

Figure 4. Cp distribution for DP2 along wing span

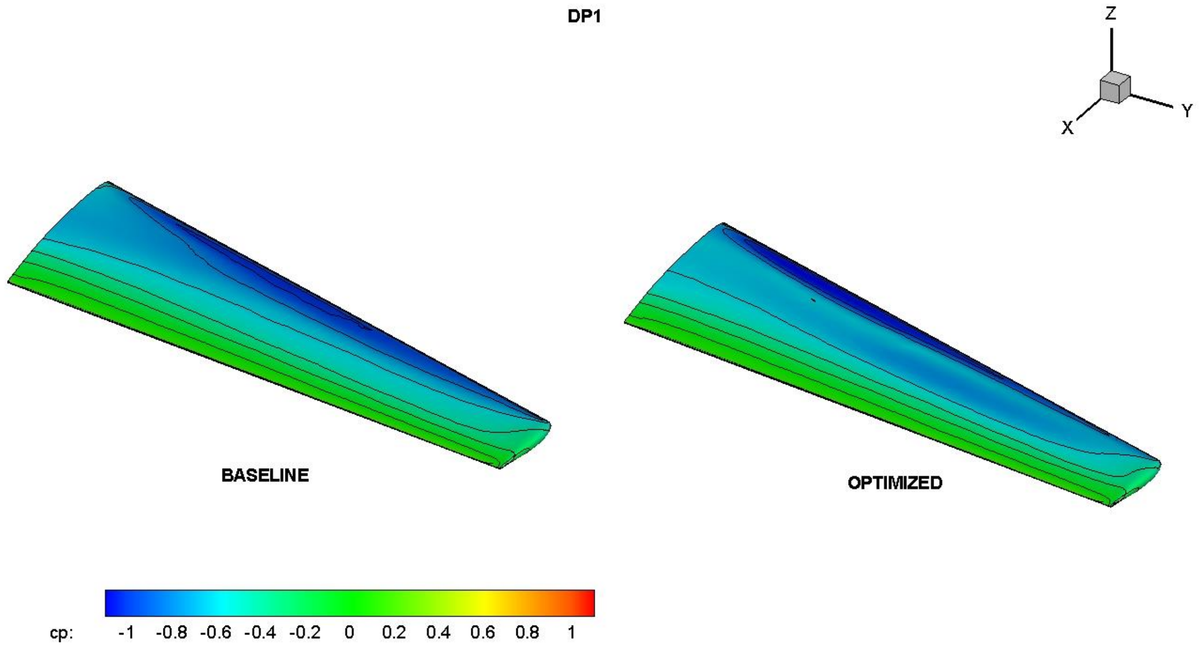

Figure 5. Cp contours for baseline and optimized geometries @ DP1 flow conditions

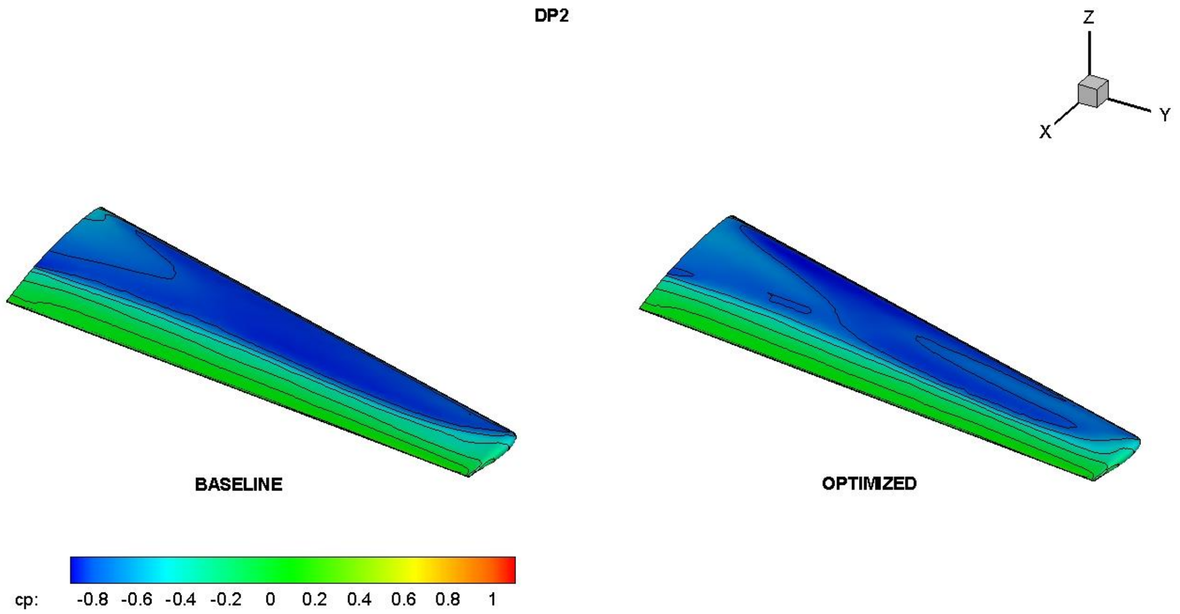

Figure 6. Cp contours for baseline and optimized geometries @ DP2 flow conditions

6 CONCLUSION

This paper 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 multi-point constrained optimization of a three dimensional DPW wing in viscous transonic flow conditions, showing first promising results. Future work will focus on the combination of this approach with traditional gradient-based methods to perform a deep comparison and also an enrichment of the search space in the evolutionary optimization algorithm.

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