Validating Surrogate models and incorporating Uncertainty Quantification in Aerospace Engineering Design Optimization

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Outline

• Multi element wings
• Test case
• Aims and objectives
• Methodology
• Grid generation failure analysis
• Results
• Surrogate model validation and performance metrics
• Further improvements
Multi element wings

A crucial need in aircraft take-off and landing

- ICAO regulates runway length and velocity for take-off and landing operations
- As a consequence, stall velocity must be properly regulated

\[ V_{stall} = \sqrt{\frac{2W}{S\rho C_{L,\text{max}}}} \]

- For a fixed \( C_{L,\text{max}} \), \( \downarrow V_{stall} \) and \( \uparrow \frac{W}{S} \) are conflicting

Fig.1: Increase of \( C_{L,\text{max}} \) due to the presence of a slat

Fig.2: Increase of \( C_{L,\text{max}} \) due to the presence of a flap
Test case

Airbus A310 Multi-element wing

- Many experimental studies performed between 1990 and 2000 by GARTEUR, available in public literature, such as AG(AD08)
- Payload dramatically increase for a 1% increase of aerodynamic efficiency in take-off conditions

Objective:

- Search the deployed configuration of the wing, for which $\max(C_L/C_D)$ and $\min(C_D)$
- Perform the optimization problem by means of surrogate models, predictive mathematical models of the output of CFD simulation
Aims and objectives

Step B
Quantification of sources of uncertainty

Step A
Model(s) of the system
Assessment criteria

Step C
Uncertainty propagation

Random variables
Computational model
Distribution
Mean, std. deviation
Probability of failure

Step C'
Sensitivity analysis
Methodology

- Airfoil stowed profile can not be modified, since it represents the best condition for the design point at cruise
- The chosen parameters will be the design variables of the optimization problem

![Diagram of Methodology Process]

<table>
<thead>
<tr>
<th>δx_s</th>
<th>δz_s</th>
<th>θ_s</th>
<th>δx_f</th>
<th>δz_f</th>
<th>θ_f</th>
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<td>[-0.05;0.09]</td>
<td>[-10°;10°]</td>
<td>[-0.09;0.17]</td>
<td>[0;0.06]</td>
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<td>Datum</td>
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<td>0.0558</td>
<td>0</td>
<td>0.0511</td>
<td>0.0354</td>
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</table>


Fig.5: Slat and flap cartesian parametrization – Source: Giuseppe Trapani EngD Thesis, Cranfield, 2014
Methodology

- Latin Hypercube Sampling (LHS) generates a uniform distribution of samples across the design space.
- Uniform distribution is fundamental to reduce the influence of systematic error produced by CFD and its propagation to the optimization process.
- LHS block available as pre-packaged code in pSeven.
- Sample size 20-30 times the number of design variables → 174 used in the optimization process.
Methodology

- Automatically generated hybrid quad dominant grids, with full cartesian boundary layer based on an advancing front ortho algorithm
- Regeneration mesh technique, implemented by means of Python
- C-grid topology for the farfield, extends for 20xchord
- Nearfield refinement length 10 x chordMax
- $Y^+$ max 1

Fig. 6: Multi element wing detail

Fig. 7: Structured boundary layer to quad dominant grid transition
• $k - \omega$ SST turbulence model
• Flowfield conditions simulating take-off condition of the A310: $M_\infty = 0.22$ for AoA= 12.21°
• Grid refinement studies performed over three grids with different refining
• $\frac{C_L}{C_D}$ and $C_D$ collected for every iteration, are the objective functions values to be examined by the Surrogate model
• Python paramiko module performs the simulation on the HPC DELTA Cranfield cluster
• Calculation performed over one cluster node of 16 CPUs
Methodology

- pSeven can automatically generate a wide range of Surrogate models. The following have been tested:
  - GP
  - HDAGP
  - HDA
- The computational time of the optimization process is drastically reduced: run time of a single step is estimated in the order of seconds, a single case can take more than 10 minutes
Methodology

- A uniform and a gaussian distribution of the design variables around their mean deterministic value are used
- The propagation of the uncertainties in the design variables is observed in the objective function by means of the surrogate model
- A new optimum is searched, accounting for a confidence interval

Fig.6: pSeven workflow
Grid generation failure analysis

• The combination of translation and rotation can generate intersections between the geometries, which are not allowed and not feasible.

• Developing an automatic error handler, to avoid intersections and reduce run time of the mesh generator software.

Fig.8: Mesh feasibility pie chart

41.67% Feasible
58.33% Unfeasible
**Results**

**Grid refinement study**

<table>
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<th></th>
<th>Coarse</th>
<th>Medium</th>
<th>Fine</th>
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</thead>
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<tr>
<td>Computational time [min]</td>
<td>12</td>
<td>28</td>
<td>32</td>
</tr>
<tr>
<td>CPUs</td>
<td>16</td>
<td>32</td>
<td>32</td>
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</table>

<table>
<thead>
<tr>
<th>Relative error</th>
<th>Coarse – Fine</th>
<th>Medium – Fine</th>
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<tbody>
<tr>
<td>CL</td>
<td>2.25%</td>
<td>0.83%</td>
</tr>
<tr>
<td>CD</td>
<td>6.64%</td>
<td>2.45%</td>
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</table>

**Fig.9:** Static pressure distribution in the x-direction; 
\[ C_{L, \text{exp}} = 2.958, C_{L, \text{CFD fine}} = 2.821 \]

**Fig.10:** Contours of static pressure on finest grid

**Fig.11:** Contours of Mach number on finest grid
Surrogate model validation

Fig.12: Scatter plot for $\frac{L}{D}$ and $C_D$ for GP, HDA, HDAGP
### Surrogate model evaluation – Performance metrics

<table>
<thead>
<tr>
<th>Surrogate model</th>
<th>$Q^2$</th>
<th>MAE</th>
<th>RMSE</th>
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</thead>
<tbody>
<tr>
<td>GP</td>
<td>0.52 , 0.62</td>
<td>1.28E-02, 7.668E-5</td>
<td>6.34, 0.017</td>
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<tr>
<td>HDA</td>
<td>0.55, 0.70</td>
<td>1.179E-1, 1.044E-4</td>
<td>5.84, 0.013</td>
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<tr>
<td>HDAGP</td>
<td>0.60, 0.75</td>
<td>5.997E-3, 1.437E-5</td>
<td>3.567, 0.007</td>
</tr>
</tbody>
</table>

**Tab.1: Performance metrics analysis**

**Fig.13: HDAGP based optimization Pareto front**
Further improvements

• Perform Surrogate Based Optimization of the test case, recalling the CFD code to improve the surrogate model itself, for deterministic inputs
• Quantify the variation in the output obtained for uncertain inputs
• Perform Surrogate Based Optimization of the test case, recalling the CFD code to improve the surrogate model itself, for uncertain inputs

[2] “Recent advances in surrogate-based optimization” A. I. J. Forrester, A. J. Keaney

[3] “Robust optimization and Sensitivity analysis with multi-objective genetic algorithms: single and multidisciplinary applications” Mian Li


Thank you for your attention!