Proper Orthogonal Decomposition based robust Surrogate Model for wing

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1. Introduction

In the case of Computational Fluid Dynamics (CFD) for simulating a real system, a large amount of computation is required to solve the nonlinear Partial Differential Equation (PDE). In addition, many simulations are required to carry out the optimization design.

The surrogate model is a way to reduce the amount of computation. The surrogate model is based on the data obtained from the higher-order function and approximated by a lower-order function. There are several methods such as Response Surface Methodology (RSM), Kriging and Radial Basis Function (RBF) [1].

Another method to construct the surrogate model is Proper Orthogonal Decomposition (POD). POD is a method of decomposing higher order equations into POD modes using ensembles of snapshots, which is a bundle of data. POD modes are combined in a linear combination, and each mode is characterized by orthogonal [2].

Aircraft simulation is one of the areas that CFD is widely used. Lift and drag are important parameters in aircraft performance evaluation. If the lift is too low, the aircraft will not be able to maintain altitude, and drag is related to fuel economy, a fatal issue these days.

In this paper, the surrogate model predicts the lift coefficient and the drag coefficient according to the change of Angle of Attack (AOA) and Mach number will be constructed. The accuracy of each surrogate model will be measured by comparing the predicted value through the surrogate model with the value obtained through CFD.

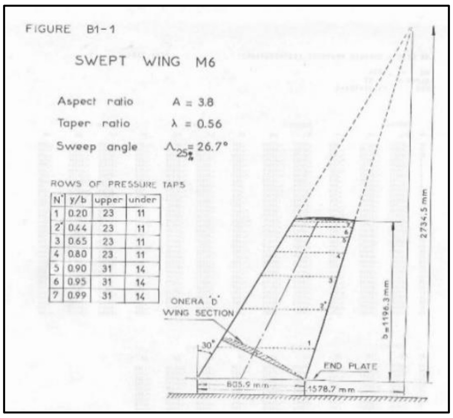


Fig.1 ONERA M6 Wing [3]

2. Numerical Analysis

The simulation to get the snapshots will be done through ANSYS 18.2 Fluent. The samples for the Design of Experiments were obtained through the Latin Hypercube Sampler (LHS) and are shown in Table 1.

The Mesh was generated using ANSYS 18.2 MESH and the mesh around the wing was arranged more densely than the outer mesh. The total number of meshes is 1,253,882. Fig.2 shows the generated mesh

The Spalart-Allmaras model will be used as the viscous model and the density of air will be assumed to be an ideal gas model.

Figure 3 shows the comparison of pressure coefficients between experimental data and CFD results. The condition of the test is shown in table 2. By comparing CFD data with experimental data, CFD results through the generated mesh can be determined to be reliable.

Table 1 Parameters of Samples

Model	Angle of Attack	Mach Number	Reynolds Number
Case1	2.685	0.6092	1.210.E+07
Case2	2.440	0.8871	9.673.E+06
Case3	1.094	0.6999	7.653.E+06
Case4	2.865	0.8236	1.077.E+07
Case5	0.632	0.7833	5.635.E+06
Case6	1.910	0.7548	8.729.E+06
Case7	2.197	0.6619	8.958.E+06
Case8	0.984	0.8714	7.222.E+06
Case9	3.241	0.7331	1.368.E+07
Case10	1.490	0.8423	1.285.E+07
Case11	1.719	0.7117	5.866.E+06
Case12	3.333	0.6265	1.144.E+07

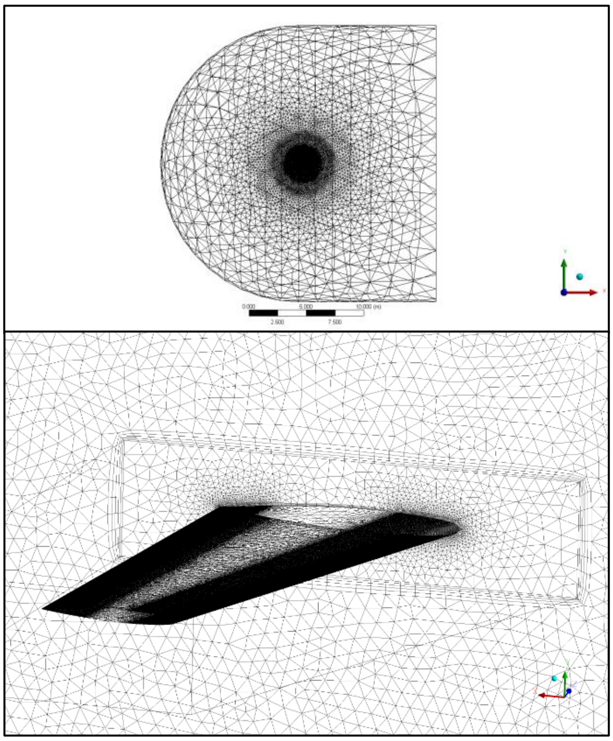
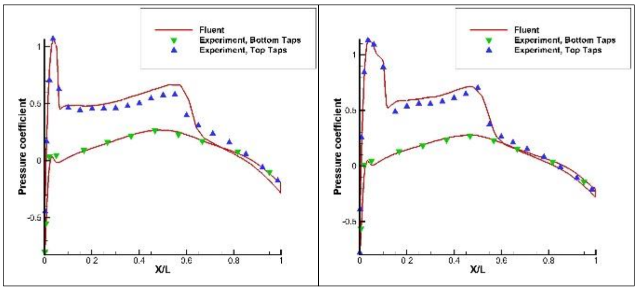
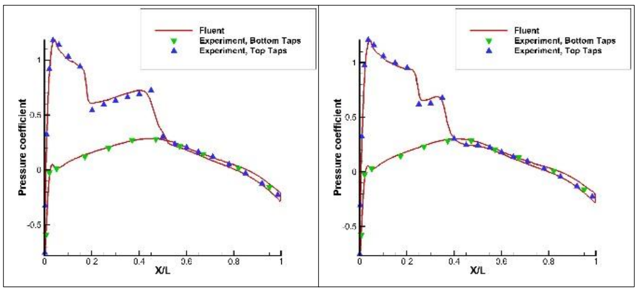


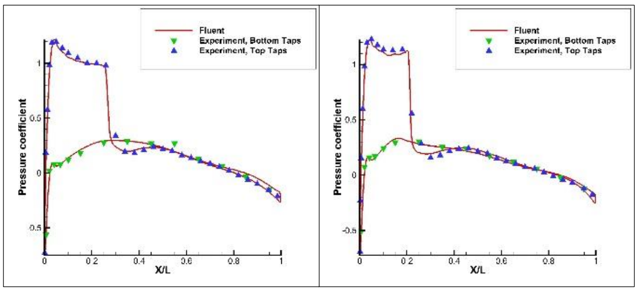
Fig.2 Shape of the generated mesh



y/b=0.20 y/b=0.44



y/b=0.65 y/b=0.80



y/b=0.90 y/b=0.95

Fig.3 Plots of the pressure coefficients on the wing surface at each section [3]

Table2 Freestream conditions for test [3]

Mach Number	0.8395
Reynolds Number	11.72E+06
Angle of Attack(deg)	3.06
Temperature(R)	460.0
Pressure(psia)	45.82899

3. Surrogate Model

The surrogate model will be constructed from the lift coefficients and drag coefficients calculated in the sample state shown in Table 1.

POD extracts POD modes from snapshots (In this case, we will have 12 snapshots) and then constructs a surrogate model with a linear combination of high energetic modes. As a result, a combination of high energetic modes can predict the value at a specific point.

Kriging predicts the value at a specific point by a combination of known values. Known values have a greater impact if they are placed close to the specific point in the sample data space.

References

[1] Tanmoy Chatterjee, A Critical Review of Surrogate Assisted Robust Design Optimization, Archives of Computational Methods in Engineering, (2019), 245-274

[2] Emiliano Iuliano, Proper Orthogonal Decomposition Surrogate modeling and evolutionary optimization in aerodynamic design, *Computers & Fluids*, (2013), 327-350

[3] Schmitt, V. and F. Charpin, Pressure Distribution on the ONERA-M6-Wing at Transonic Mach Numbers, Experimental Data Base for Computer Program Assessment. Report of the Fluid Dynamics panel Working Group 4, (1979)