Applying surrogate modelling for dynamic stall simulation

Vadim Surpin, Institute for Information Transmission Problems RAS, Moscow, Russia, vadim@iitp.ru
Alexander Bernstein, International Research Institute for Advanced Systems, Moscow, Russia, a.bernstein@irias.ru
Yuri Sviridenko, Central Aerohydrodynamic Institute, Moscow, Russia, ysviridenko@yandex.ru

I. Introduction

Presently, numerical techniques based on Navier-Stokes equation to investigate a dynamic stall event are widely used [1, 2]. Applying numerical methods to solve these equations allows defining the pressure distribution as well as forces and moments affecting the aerodynamic airfoil in dynamic stall mode. Despite the significant progress in computing and numerical techniques in Computational Fluid Dynamics (CFD) software, application of CFD codes for calculation viscous unsteady flow of aerodynamic units requires extensive calculating resources. It does not allow using CFD effectively in designing tasks and dynamic real-time simulation of objects (e.g. flight test-rigs).

The Predictive Simulation Technology [3] based on Data Handling developed in IRIAS&IITP RAS is used in the research for constructing the fast surrogate models (or metamodels) for predicting the integral and distributed aerodynamic time characteristics of the airfoils under the unsteady flow condition with dynamic stall for a given airfoil geometry, unperturbed flow parameters and parameters describing time fluctuation of airfoil's Angle of Attack in time.

The constructed surrogate model is based on the data – the results of the computational experiments performed by the in-house CFD-solver FlowVision intended for modeling 3D laminar and turbulent steady and unsteady gas and liquid flows in complex geometries.

II. Problem Statement

The problem of predicting the integral and distributed aerodynamic time characteristics of airfoils under the unsteady flow condition with dynamic stall is likely to arise in the industrial test cases. Thus it became the subject of an initial study for the construction of a Fast Data-based Reduced Order Model on the basis of the results of the computational experiments with chosen CFD solver considered as Full Order Model.

The dynamic stall event should be essentially considered under various industrial tasks and following conditions: passenger aircraft penetration in high turbulence zones, light aircraft maneuvers, helicopter rotor blade flow under various regimes and so on. For instance, one of the rotor blade aerodynamic characteristic features is that rotor blade cross-sections work under the unsteady flow at almost all helicopter flight regimes [4].

Dynamic stall simulation is a complicated problem and the main investigation method employed to date is carrying out extremely expensive experiments in wind tunnels [5]. Moreover, airfoil characteristics, which are traditionally used, were obtained from wind tunnels during steady blowing to calculate forces and moments of helicopter rotors [5]. For new helicopter airfoils such experimental data are not available. Due to the above difficulties, mathematical simulation under dynamic conditions is getting to be the main tool for the study of airfoil unsteady aerodynamic characteristics [6]. However, despite the significant progress in computing and numerical techniques, detailed CFD codes being applied to calculate detached viscous unsteady flow requires extensive computational resources, which limits its usefulness in real-time design and simulating object dynamics (e.g. flight test-rigs). For the above reasons, generation of fast Reduced Order Model for the time-consuming CFD-code, which describes loading of aircraft wing cross-sections or helicopter rotor blade under dynamic stall, was selected as a test case for the research.

Meanwhile the surrogate model should correctly indicate influence of the main factors: Mach and Reynolds numbers of incoming flow, the law of variation of angle of attack, cross-section geometry on unsteady forces and moments affecting the airfoil as well as on pressure distribution along the wing airfoil or blade section.

III. Experiment Setup

To model of dynamic stall under unsteady flow the following experiment proposed. The airfoil performs a pitching motion is expressed as

$$\alpha = \alpha(t) = \alpha_0 - \alpha_m \times \left(\cos\left(\frac{Sh \times V}{b} \times t\right) - 1\right), \qquad (1)$$

where: $\alpha(t)$ – represents the instantaneous angle of attack, α_0 – initial angle of attack, α_m – amplitude of airfoil's oscillation, Sh – Strouhal number, V – flow velocity, b – length of airfoil's chord.

A. Input data

The input data required for a detailed unsteady CFD analysis consists of:

- Description of airfoil geometry;
- Unperturbed flow parameters: Mach number (M) and Reynolds number (Re) of the incoming flow;

The research leading to these results has received funding from the European Community's Seventh Framework Programme (FP7 / 2007-2013) under a grant agreement number 233665. FFAST (Future Fast Aeroelastic Simulation Technologies) is a collaborative research project aimed at developing, implementing and assessing a range of numerical simulation technologies to accelerate future aircraft design. Advances in critical load identification and reduced order modelling methods will potentially provide a step change in the efficiency and accuracy of the dynamic aeroelastic loads process. The partners in FFAST are: University of Bristol, INRIA, CSIR, TU Delft, DLR, IRIAS, University of Liverpool, Politecnico di Milano, NUMECA, Optimad Engineering, Airbus, EADS-MS, IITP and UCT.

- Parameters (α_0, α_m, Sh) describing a fluctuation of airfoil's Angle of Attack α in time t - the current angle of attack $\alpha = \alpha(t)$.

B. Output Data

The output data consist of two functions of time t:

- The forces and moments affecting the airfoil;
- Pressure distribution along the airfoil.

C. CFD-solver

For solving the discussed problem, the CFD code FlowVision has been chosen as Full Order Model – a source of the experimental data for constructing the surrogate models. FlowVision is a general purpose CFD software for modeling 3D laminar and turbulent steady and unsteady gas and liquid flows in complex geometries.

D. Settings

To get results that can be used for surrogate model training the number of time steps n of the full order CFD experiment was set to a constant value so that every experiment produced exactly two periods $2T$ of airfoil oscillations and every period contained fixed number of data points $n/2$. Every data point contains lift coefficient value for the full airfoil and pressure distribution over both sides of the airfoil.

The data acquired for the first period is transient, i.e. the first period is the time required for the CFD code to set up and it isn't used to surrogate model training. Data of the second and further periods considered to be valid.

IV. Experiment Results

An overview of the physical processes of dynamic stall is shown on Fig. 2. It is a velocity vector field which shows a complex structure of air flows near the airfoil in presence of dynamic stall effect. The dynamic stall effect

For the purposes of building surrogate model there were produced about 300 full order computational experiments. A large part of them is fast experiments on a rough grid. A smaller part of experiments is higher accuracy experiments. Their results are used as a reference to ensure the lower accuracy results reflect the physics of the dynamic stall effect.

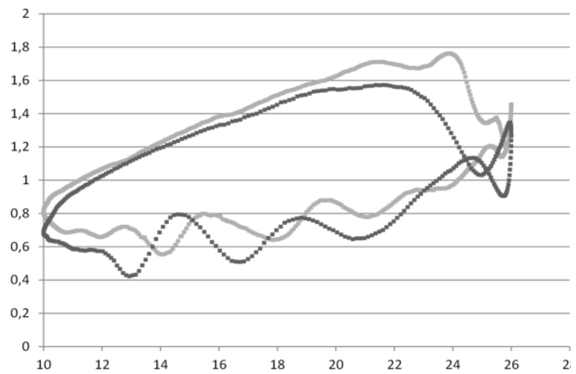

Figure 1. High accuracy (light line) and fast (dark line) lift coefficient CFD computation results for input parameters $Sh = 0.2$, $\alpha_0 = 10°$ and $\alpha_m = 8°$

Lower accuracy model reflects the general behavior of the flow but direct comparison to the high accuracy model using standard techniques such as root mean square error gives large values for residuals due to phase effects.

Despite this fact further research will be based on rough models as the reflect the basic physical effects and fast enough to produced required set of training data.

V. Surrogate Modelling Technology

The Predictive Simulation Technology based on Data Handling developed in IRIAS&IITP RAS is used for constructing the surrogate models (or metamodels) in this research. This technology was specifically dedicated to EADS Business Units (AIRBUS, EUROCOPTER, ASTRIUM, etc.), with a first successful phase called MACROS (Multidisciplinary Aeronautic Capability Research On Simulation) and completed in 2009. The technology [3] is based on advanced mathematical core and allows integrating the domain-specific knowledge, models and data into Surrogate models.

MACROS technology is implemented in MACROS Technological Tool for predictive modeling and simulation based on data handling. The MACROS Technological Tool allows reducing the dimension of the input vectors, constructing the data-based dependencies and evaluating its accuracy and doing the other data-processing procedures in automatic mode for designing the surrogate models.

The main points of the technology:

(1) The considered problem is to predict the values of the characteristic Y of some chosen object for the specified input vector X that includes the object's digital description and describes also its environment and control parameters.

(2) Let M be some chosen initial model (or method) considered as Full Order Model (FOM) that allows obtaining the value Y (response, output) for the specified input vector X. The model M determines the response function

$$Y = F_M(X), X \in \boldsymbol{X} \subset R^{\boldsymbol{p}}, Y \in R^q. \qquad (2)$$

where R^p and R^q are p-dimensional and q-dimensional Euclidean spaces respectively.

(3) Usually FOM M is either a full-scale experiment or a computational experiment based on a solution of the differential equations and hence may be expensive and time-consuming. The problem is to construct the new Reduced Order Model (ROM) that is "close" to the FOM (it has the same accuracy) but essentially increases the calculation speed.

(4) The results of the experiments with the initial model M are available. These results form the Data Set

$$D_N = \{(X_i, Y_i = F_M(X_i)),\, i = 1, 2, \dots, N\}. \quad (3)$$

(5) The Learning Data Set D_N is used for constructing the Data-based dependency

$$Y = F_{SM}(X) = F_{SM}(X|DN) \quad (4)$$

providing an approximate equality

$$F_{SM}(X) \approx F_M(X) \quad (5)$$

that has to hold for all $X \in \boldsymbol{X}$ and not only $X \in X_N = \{X_i, i = 1, 2, \dots, N\}$.

The High Dimension Approximator Generic Tool (a part of the MACROS Technological tool) is used for constructing the Data-based dependency.

(6) Thus the new Data-based model S_M described by the constructed dependency $Y = F_{SM}(X)$ can replace the initial model M and may be regarded as a Reduced Order Model, or a surrogate model, or a metamodel (model over model).

VI. APPLICATION OF THE TECHNOLOGY TO THE DYNAMIC STALL APPROXIMATION

To build a dynamic stall surrogate model based on the MACROS high dimension approximation tool we used several approaches:

- Direct MACROS approximator exploitation;
- MACROS Approximator coupled with dimension reduction;
- Approach based on time-series analysis.

First experiments using direct approximator exploitation approach were carried out using a training set of 50 data vectors. Each data vector $\bar{x}_i = \{x_i^1, \dots, x_i^N\}$, $N = 360$, consists of N data points where N is a number of CFD solver steps per one period.

Approximator build using $i = 50$ showed ability to catch the tendency but the error value was large. Increasing the number of experiments i to 100 gave better results and further growth of i leaded to error value decrease.

Along with extensive way of increasing number of data vectors used as a training base for the approximator, several alternative approaches where taken to increase accuracy.

The first alternative is a Dimension Reduction approach. It is based on the idea that our data vector is quite large – it has at least three hundred sixty points used as a training data. There should be interdependency between points which Dimension Reduction should eliminate. The approach give approximately the same error value as direct approximator exploitation.

The second alternative approach is based on the fact that we know that interdependency exists. The data is a time-series data and we can use the fact explicit. To employ the fact we used a time-series analysis methods.

The first attempt was to transform a data vector to a difference vector where each successive point $y_i = x_i - x_{i-1}$ is a difference of original point value and previous point value. Index i stands for number of time step or index of i-th component of initial data vector X. The approach gave the same results as the basic one.

Another attempt was to employ autoregressive methods to set up an explicit dependency between points of our time series. In general, the approach states that each successive point is a function of N previous points. The traditional approach is to use linear function or apply some kernel function. Our approach is to use MACROS as a function approximator:

$$x_i = f(x_{i-1}, \dots, x_{i-n}) + \varepsilon, \quad (6)$$

where f – non-linear function and ε – random error. In our case f was produced by the MACROS approximator and represented as executable computer code.

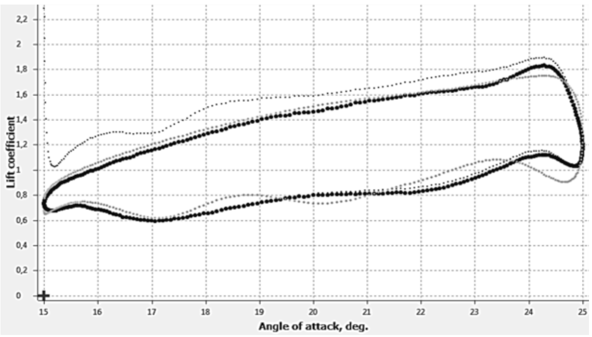

Figure 2. Full order (light line) and surrogate (dark line) lift coefficient computation results for input parameters $Sh = 0.4$, $\alpha_0 = 15°$ and $\alpha_m = 5°$

The approach demonstrated root mean square error in the range of 5-10 percent and calculation time less than one second. Fig. 4 shows a typical approximation result. The vertical axis is a lift coefficient and the horizontal axis is angle of attack. The dark line is the approximation result while the light one is full order CFD result. Its relative standard deviation is nearly 6 percent which is typical for the approach.

VII. CONCLUSION

Proposed approach using time-series analysis methods for data preprocessing and MACROS approximator as surrogate model production tool showed ability to approximate lift coefficient data in presence of dynamic stall effect with standard deviation in range 5-10% and calculation time less than 1 second.

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