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Global Surrogate Modelling of Gas Turbine Aerodynamic Performance

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Abstract

The prediction of compressor and turbine aerodynamic performance in gas turbine engines relies heavily on computational fluid dynamics (CFD) simulations. Prior to CFD, performance predictions were largely completed using simplified one- and two-dimensional methods coupled with empirical loss models. Although CFD has a number of advantages over the classical techniques, it does also have a number of drawbacks. Numerical stability, approximations required to model multiple blade rows, the cumbersome and manual meshing process, simulation time, the requirement for geometric and operational data to construct the models are some of the issues that need to be dealt with. The aim of this research is to overcome these drawbacks by combining the advantages of the current state-of-the-art in CFD and the speed, efficiency and fundamental understanding of legacy one- and two-dimensional methods in predicting compressor and turbine aerodynamic performance. This in turn will greatly enhance the efficiency and speed with which performance predictions are made.

Introduction

This paper presents results of a study in which CFD is used to conduct a large number of numerical experiments on single stator and rotor blade rows. Global surrogate models using different techniques of blade performance parameters are then constructed.

A global surrogate modelling study using numerical experimentation requires four main steps. Defining a parametric model of the geometry is the first step. The application of an appropriate design and analysis of computer experiment (DACE) technique to minimise the number of simulations is the second step. Model construction, meshing and CFD simulation is then followed by processing of the data and construction of the surrogate model.

The paper presents a novel approach in which the blade is parametrically described using non-uniform rational B-splines (NURBS) curves and surfaces based on key blade profile features such as chord length (c), blade inlet and outlet anlges (β), stagger angle (γ), leading and trailing edge radii (r) and wedge angles ($\Delta\beta$). These features are parametrically defined so that the blade geometry space is contained within a unit hypercube and that all parameter combinations yield valid blade geometries.

A stator blade geometry is modelled at a given operational condition using 28 independent parameters. Rotor blade geometry on the other hand is modelled using two additional parameters, namely tip clearance and rotational speed. Each blade is defined using a tip and a hub section profile. Stacking is done either at the trailing edge (stator) or at the centre of gravity (rotor). Blade lean and sweep features are accounted for using a total of four parameters. Sample population is generated using either the Latin hyper-cube or the Sobol DACE techniques. Geometry, meshing, CFD simulation and some aspects of post-processing is then completed using the commercial code Numeca and its FINE/Turbo suite of tools.

The creation of a large set of blade performance data using CFD requires a highly automated system in which blade parameter selection, geometry and mesh construction, CFD solution and post-processing are performed with minimal human intervention.

Surrogate models of total pressure loss, flow deviation angle, mass flow rate etc. are constructed using a number of different surrogate modelling techniques. These techniques include artificial neural networks (ANN), radial basis functions (RBF), support vector regression (SVR), multivariate regression splines (MARS) and Gaussian process regression or Kriging. Details of the construction process and results comparing the different techniques are presented.

Blade Parametric Modelling

The first step involved in designing an automated DACE system for gas turbine rotating components requires a robust blade parametric modelling system. The parametric blade modelling system needs to meet the following criteria:

- Capable of modelling all possible and realistic blade geometries. The modelling space should be flexible enough to generate a wide range of geometries that encapsulate both existing and expected future blade geometry features.
- Blade modelling should be flexible and allow for future refinement and/or enhancements. That is, the addition of new blade features (elliptic leading and trailing edge profiles, spanwise blade section resolution, blade cross section form complexity etc.) should not require a complete re-definition of blade parametric modelling system.
- The blade modelling system should not produce inconsistent geometric features. Blade section overlapping and unrealistic geometries should not be feasible.
- Blade parametric model should be based on blade physical features such as chord length, stagger angle, leading and trailing edge radii and wedge angle etc. Coordinate based parameters (x, y or r, θ) should be avoided.
- Blade parametric model should allow for further parameterisation within a unit hypercube space. That is, although not a strict requirement, defining the blade geometry space within a hypercube will greatly simplify the application of space filling computer experimentation algorithms and enhance the DACE process by eliminating uncertainties.
- Be numerically stable and compatible with the mesh generation system that will be used to construct and mesh geometry.

A number of different blade parametric systems have been published over the years. These can be loosely grouped into three categories, the first being feature-based-polynomials where geometric feature is captured using a summation of polynomials as demonstrated in [1], blade geometric design parameter based representation [3, 4] and the Bezier or more generally NURBS based geometry representation [2].

Blade Section Modelling

The current blade modelling system uses an enhancement of the last two techniques, namely, the design feature and NURBS based systems. The blade modelling system used in this study has a limited number of blade section parameters. This is done in order to minimise the total number of parameters over which the computer based experimentation is required. Using NURBS to represent the blade sections allows the system to be flexible for future enhancement where additional parameters may be introduced. Figure 1 shows the blade section parametric modelling technique.

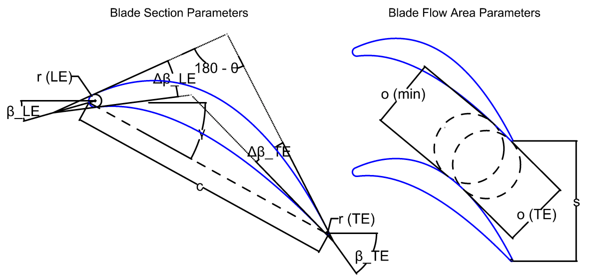

Figure 1. Blade section parameters.

Although the blade section modelling system is able to produce accurate and realistic turbine blade geometries (while maintaining continuity between different components of the blade section), it does not satisfy two of the constraints outlined above. That is, the blade section needs to be further refined and represented using scaled parameters to conform with the unit hypercube requirement and parameters need to be constrained so that overlapping and unrealistic geometries are not generated.

Table 1 shows a list of blade section parameters, parametric equivalent and constraints imposed to eliminate geometry overlap and achieve realistic turbine blades.

	Min	Max
h/c	0.8	1.2
γ	0	60
β^*_{LE} & β^*_{TE}	0	60
$\Delta\beta_{LE}$ & $\Delta\beta_{TE}$	4	30
r_{LE}	1	4
r_{TE}	0.2	1
$0 \leq \theta \leq 90$		
$\beta_{LE} + \frac{\Delta\beta_{LE}}{2} \leq 70 \quad \beta_{TE} + \frac{\Delta\beta_{TE}}{2} \leq 70$		
$\beta_{LE} - \frac{\Delta\beta_{LE}}{2} \leq 5 \quad \beta_{TE} - \frac{\Delta\beta_{TE}}{2} \leq 5$		

* β_{LE} and β_{TE} when blade rotated so that stagger angle is 0.

Table 1. Blade section parameters and constraints.

Span-wise Stacking

The three-dimensional blade is constructed using two blade sections defined in the (r, θ) plane. The sections are located at the hub and tip. When constructing the mesh geometry five blade sections are defined at 0, 25, 50, 75 and 100 percent span. The blade section parameters at 25, 50 and 75 percent are obtained by linear interpolation between hub (0%) and tip (100%) blade sections.

The blade mean-line reference radius is set at 250mm. The end wall geometry is defined using two parameters to define a conical end-wall geometry. The first is the mid-span angle (with the turbine centre-line) and the second is the ± deviation in the hub and tip end-walls.

The stacking axis for each blade section is dependent on the type of blade that is simulated. Trailing edge centre is used for stator blades and centre of gravity for rotor blades. Two parameters are used to represent blade lean and sweep each. Figure 2 shows the parameters used to define blade lean and sweep.

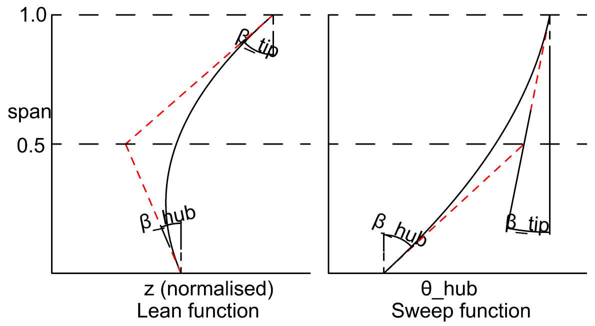

Figure 2. Blade lean and sweep functions.

The number of blades is constrained such that:

$$10 \leq NB \leq \frac{0.63}{o_{min}} \tag{1}$$

Note that the maximum number of blades is dependent on the blade section geometry, hence coupled.

The total number of geometric parameters required to represent a stator and rotor blade is 24 and 25 respectively.

Automated Geometry, Mesh and CFD Simulations

The geometry is constructed using OpenNURBS and SISL c/c++ libraries. The geometry is then ported to FINE/Turbo suit of software from Numeca. Autoblade is used to represent the geometry in FINE/Turbo format and AutoGrid5 is used to automatically mesh the blade using 04H grid topology. Mesh optimisation is conducted based on blade geometric features. Automated mesh quality checking is completed in all cases and adjustments made to satisfy mesh quality criteria if necessary. FINE/Turbo flow solver is then used to complete the CFD calculations. An automated turbo text output file which summarises key performance parameters along with CFView is then used to automatically generate performance tables for the simulated geometry.

The main objective of the CFD simulations is the calculation of steady state performance parameters such as relative pressure loss across the blade, flow exit turning angle deviation, flow and loading coefficients amongst others. Hence all simulation were conducted using the steady state solver. Each blade geometry was meshed using approximately 800k grid points. The cell distance at the wall and CFD related reference flow conditions were calculated using an ideal mean line solution flow conditions and the Blasius equation. The inlet and outlet boundaries of the mesh were extended by 1/4 distance of maximum axial chord length at both inlet and outlet. The main constraint in extending the inlet and outlet flow domains is the adverse effect caused by area change at inlet and outlet in a tapered configuration where blade height (h) and flow area is changing. Figure 3 demonstrates the turbine blade parametric modelling system.

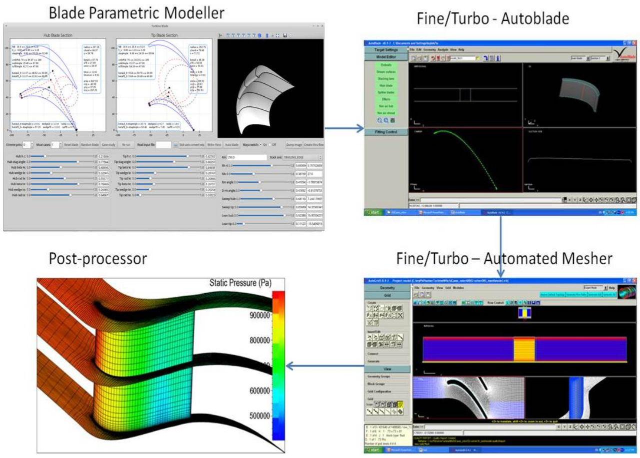

Figure 3. Blade geometry and mesh modelling system.

In all cases, to achieve flow similarity the inlet total pressure is set to 10 bar and inlet total temperature to 1000K. Standard compressible air used to represent the working fluid. The Spalart-Allmaras turbulence model is used for all experiments along with the extended wall function to simulate the boundary layer.

Manufacturing related properties included in the parameter space includes blade and endwall surface roughess (ε) for both stator and rotor and tip clearanance (δ) for the rotor.

Operational conditions require the definition of 3 additional parameters for the stator and 4 for the rotor giving a total of 28 and 30 parameters respectively. Static pressure (P_2) at the outlet, hub and tip absolute flow angles (α) are the three common operational parameters. Rotor blades require the addition of a rotational speed parameter (rpm). The constraints imposed on these parameters can be seen in Table 2.

Param.	Stator		Rotor	
	Min	Max	Min	Max
ε	1.00E-07	6.00E-06	1.00E-07	6.00E-06
δ / h	NA		0.001	0.1
P_{t1}/P_2	0.5	0.8	Ideal solution dependent	
α_{hub}	β_{LE} - 20	β_{LE} + 20	20	75
α_{tip}	β_{LE} - 20	β_{LE} + 20	20	75
rpm	NA		1000	50000

Table 2. Blade operational and manufacturing related parameters.

DACE

A number of different techniques are available for the construction of space-filling experimental designs. The main focus on space-filling designs is the spread of experimental points such that maximum information is extracted with minimum number of experiments. Popular space-filling techniques include the Monte Carlo, Latin hypercube and variants (LHS), orthogonal array (OA) and Sobol sequence to name a few. Although LHS and OA algorithms yield better space-filling properties, Sobol was chosen as the DACE method used in this investigation. The main reason for this is that Sobol does not require the number of experiments to be pre-determined. Sobol does provide good space-filling properties while allowing the consecutive addition of experiment points. This is particularly important in the initial phases of the experimentation when surrogate model prediction quality and CFD simulation time and resource requirements are unknown. The Sobol implementation in [6] was used in this study.

Surrogate Model Construction and Validation

The increased focus on data mining and machine learning algorithms over the last two decades has seen considerable research being conducted into surrogate modelling algorithms. RBF, ANN, SVR, Kriging (also known as Gaussian Regression) are some of the most widely used algorithms to construct models for large data sets. The main tool used in generating the global surrogate models was the Python based open source machine learning library scikit-learn [5] and code written specific for this study.

One of the objectives of the research program is to evaluate competing surrogate modelling algorithms to determine how well they predict gas turbine aerodynamic performance and what their advantages and disadvantages are compared to one another.

Each surrogate modelling technique contains a number of meta-parameters associated with it. Hence, an optimisation process needs to be undertaken to obtain parameters that yield the best fit to the data set. Meta-parameter optimisation and validation is accomplished by initially splitting the data set into a validation set (25%) and a training (75%) data set. Surrogate model construction is completed on the training set using a 5-fold cross validation method. In this method the training set is split into 5 equal sizes. For a given meta-parameter set the surrogate model is constructed 5 times, each iteration leaving one of the 5 sets out and then testing against the unused set. The coefficient of determination (R^2) is used as a measure of goodness of fit metric. Since meta-parameters include a mixture of continuous and discrete parameters, a grid search method has been used to reach optimum surrogate model.

Final validation of the surrogate model and comparison between competing surrogate modelling techniques is then completed using the validation set.

Computational Results

Turbine Stator

A total of 6600 computer based turbine stator experiments were conducted for different geometric and operational conditions as determine by the Sobol space-filling algorithm. Approximately 5000 of the randomly selected cases were used in constructing and optimising the surrogate models with the remainder used for validation. Figure 4 shows the change in the goodness of fit metric (1-R^2) with the number of experiments for total pressure ratio across the stator. This trend is also observed for surrogate models of mass flow rate, swirl and relative mach number at blade exit.

From Figure 4 it can be seen that the goodness of fit reaches a minimum value around 3500 experiments for all surrogate model cases. Further addition of experimental cases does not increase the goodness of fitness. Since 28 parameters are used to describe the geometry and operational conditions for the turbine stator, the ratio of number of experiments to input parameters is approximately 125.

A comparison of the different surrogate models show that goodness of fit using Kriging or Gaussian process consistently yields the best output. All other techniques yield approximately the same level of goodness of fit whereas Kriging results, depend-

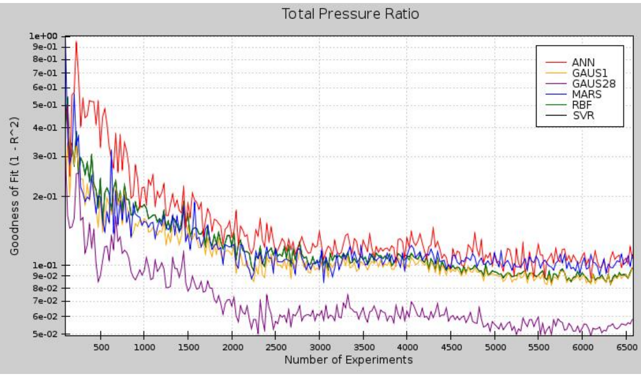

Figure 4. Goodness of fit plot for stator total pressure ratio vs number of experiments.

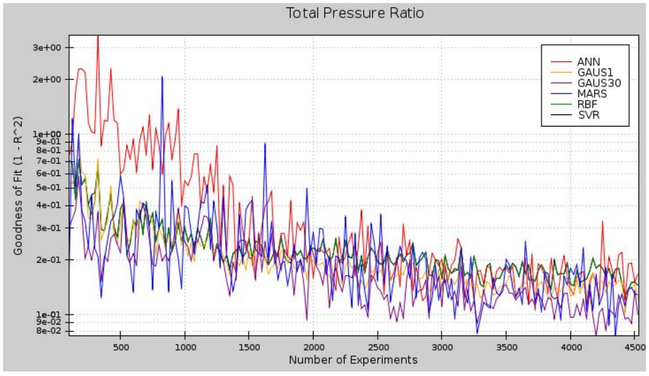

Figure 5. Goodness of fit plot for rotor total pressure ratio vs number of experiments.

ing on output parameter being simulated yields 40% - 60% better results. Considering that Kriging not only provides better estimates but also yield confidence intervals for the prediction make this technique more attractive. The ability to generate a confidence interval at any given point has further applications in that it can be used to replace and/or enhance the space-filling algorithm to reduce maximum error band using minimum number of experiments. This aspect will be the subject of research in the future.

One disadvantage of using the Kriging surrogate modelling technique is the computational resources required to find the best linear unbiased prediction (BLUP). Each iteration in the optimisation cycle requires a n $\times$ n matrix inversion (where n is the number of data points). The function to be optimised for BLUP is not convex. Although not essential, this would require the use of a global optimisation technique which in almost all cases results in a greater number of function calls (hence matrix inversions) than a local optimisation algorithm.

The second disadvantage with Kriging is the storage of the Cholesky decomposition of the correlation matrix. The Cholesky decomposition matrix can be very large and may prove difficult to process.

Turbine Rotor

A total of 18000 turbine rotor experiments were conducted which produced 4500 valid experiment cases. It was assumed that very little or no information was available about turbine rotor aerodynamic performance and the outlet boundary static pressure and rotational speed was allowed to vary such that $0.5 \leq P_{t1}/P_2 \leq 0.95$ and $1000 \leq rpm \leq 5000$. This results in a significantly large portion of experiments producing invalid simulations.

Constructing surrogate models of the valid turbine rotor experiments total pressure ratio results in the goodness of fit plot in Figure 5. This same trend is also found in surrogate models of mass flow rate, swirl and relative mach number at blade exit for the rotor case.

As it can be seen from Figure 5 the number of experiments to reach an optimum goodness of fit is approximately 3500. Comparing the goodness of fit values with the stator case shows that the level of fit in absolute terms is not as good as that seen in the stator case. This is expected as the flow field for a rotating component with tip clearance is always going to be much harder to predict.

Although Kriging still provides a better fit to the rotor experiment data set, the contrast is not that great when compared to the stator case.

Conclusions

A new blade parametric modelling strategy has been devised and successfully tested. This blade modelling system is not only able to construct a wide range of blade shapes and configurations, it is numerically and geometrically robust and can be represented using a hypercube sampling space.

An automated CFD based experimentation tool has been developed which allows alternative space filling techniques to be utilised and experiments conducted without any intervention. Different techniques have been reviewed and the most suitable one for the given problem was selected.

More than 24000 simulations were completed in order to construct a viable performance prediction database. A number of different surrogate modelling techniques were tested. It was found that the Kriging surrogate modelling technique provided the best approximation which was also able to yield confidence estimates to the predictions.

Acknowledgements

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