Applications of UQ and Robust Design in Turbomachinery Industry

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Uncertainty Quantification (UQ)

• UQ is not just about an error bar

• It is a rapidly developing field encompassing
  • CFD prediction
  • Meshing and geometry generation and processing
  • Algorithms for efficient sensitivity analysis
  • Computationally tractable frameworks for robust design
  • Statistical analysis on sparse data

• Must be factored when designing with models for engine
  • Uncertainties (variability) exist in both models & engine

• Goal of UQ research in CFD methods is to
  • Increase engine efficiency given variability
  • Maintain engine efficiency given variability
How do the uncertainties manifest?

Aleatory UQ vs. Epistemic UQ

The uncertainties sources are not all the same

Aleatory
- **Boundary conditions**: free stream state, wall temperatures, etc.
- **Material properties**: inhomogeneity, reaction rates, etc.
- **Geometry**: manufacturing tolerances, contamination, etc.

Epistemic (characterizes lack-of-knowledge, is often prevalent in engineering applications)
- **Physical modeling assumptions?**

(a) Aleatory uncertainty that causes the dispersion due to inherent variability. (b) Epistemic uncertainty that causes a systematic error in the prediction
Epistemic vs Aleatory – An Example

The plain annulus model suffers from epistemic uncertainty that can be addressed by improving the model set-up.
Example of operational variation…
Example of Uncertainty in Design

- The mighty *Vasa* ship capsized and sank in *Stockholm* 1628.
Engine Aleatory Uncertainties

- Uncertain inlet boundary conditions
- Unsteady aero uncertainties
- Combustion Exit flowfield (temperature traverse)
  - Using GOM data to characterize surface uncertainties
  - Squealer tip thermal deterioration uncertainty
- HP-NGV manufacturing variations on capacity
- Combustion UQ
- Aero-acoustics UQ in fans – Structure of the Honeycomb Short-Intake- Fan interactions
- Inlet lip manufacturing uncertainties
- Ice accretion uncertainty in compressors
- Fan rear seal leakage flows
- Tip clearance variations in HP compressors

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Engine Epistemic Uncertainties

- Surface roughness models in RANS
- Transition modeling
- Bayesian hybrid modeling for experimental data – CFD validation
- Mesh independence during optimization
- Hybrid RANS-LES approaches
- Structured / unstructured meshing techniques
- RANS turbulence modeling uncertainties
- Conjugate heat transfer modeling uncertainties
Propagation of the Uncertainty Methods

Steps in Monte Carlo analysis

1) Input Range Definition and Distribution Selection
2) Random or Latin Hypercube
3) Model Execution
4) Uncertainty Analysis
5) Sensitivity Analysis

Too Expensive for long running Simulation tools

Alternative methods:
- Moment methods
- Polynomial Chaos
- ....

But can also use Surrogate Model
- Polynomial
- RBF, ANN
- Kriging
- ....

...... HPC time is needed (not just Big Simulation, but also Big Robust Optimisation)

<= # design parameters ~20
(MAM ~50-100)

......
Design Methodology with Uncertainty

Rolls-Royce CFD Methods
3D Designs (SOPHY)

Optimization: SOFT
Uncertainty Quantification: SOFT+UQ
Grid & Geometry Generation: PADRAM
CFD Solution: HYDRA

R&D for UQ & Optimisation Methods

STATE OF THE ART METHODS USED & APPLICATIONS (Pranay Seshadri PhD at Cambridge on PC Methods Development & Applications)

- Sparse Pseudospectral Approximation Methods
- Stochastic Collocation
- Robust design optimization
- Active-subspace methods
R&D for UQ & Optimisation Methods

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- Sparse Pseudospectral Approximation Methods
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- Active-subspace methods

Investigated effect of uncertain leakage flow for rotor to address CFD-experiment discrepancy.

In Collaboration with J. Adamczyk

Case used: NASA Rotor 37


UMIRIDA: Uncertainty Management for Robust Industrial Design in Aeronautics
20th - 22nd September – Brussels - Belgium
R&D for UQ & Optimisation Methods

STATE OF THE ART METHODS USED & APPLICATIONS

Sparse Pseudospectral Approximation Methods

Stochastic Collocation

Robust design optimization

Active-subspace methods

Investigated effects of surface roughness, clearances and inlet pressure profiles on performance using stochastic collocation

Case used: NASA Rotor 37


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Sparse Pseudospectral Approximation Methods

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Robust design optimization

Active-subspace methods

Re-designed a rotor blade to be-desensitized to operational tip clearance variations

Case used: NASA Rotor 37

*Seshadri, P., Shahpar, S., Parks, G., “Robust Compressor for Desensitizing Operational Tip Clearance Variations”, ASME Turbo Expo 2014, Dusseldorf, Germany

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R&D for UQ & Optimisation Methods

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Robust design optimization

Active-subspace methods

Complex multivariate problems can be recast as problems on a low-dimensional subspace – the *active subspace*. This method can be thought of as a least-squares based dimension reduction technique for use in either optimization or UQ.

Cases used: NACA0012, NASA Rotor 37


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A simple experiment
Finding an active subspace

Define the following matrix and vector

\[
\hat{X} = \begin{bmatrix}
1 & \hat{x}_1 \\
\vdots & \vdots \\
1 & \hat{x}_{150}
\end{bmatrix},
\mathbf{f} = \begin{bmatrix}
f_1 \\
\vdots \\
f_{150}
\end{bmatrix}
\]
A simple experiment
Finding an active subspace

Define the following matrix and vector

\[ \hat{\mathbf{X}} = \begin{bmatrix} 1 & \hat{x}_1 \\ \vdots & \vdots \\ 1 & \hat{x}_{150} \end{bmatrix}, \quad \mathbf{f} = \begin{bmatrix} f_1 \\ \vdots \\ f_{150} \end{bmatrix} \]

where

\[ \hat{x}_1 = \begin{bmatrix} x_1, \ldots, x_{25} \end{bmatrix} \]

\( f_1 \) is the output from hydra

are the normalized PADRAM design vectors
A simple experiment
Finding an active subspace

Define the following matrix and vector

\[
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1 & \hat{x}_1 \\
\vdots & \vdots \\
1 & \hat{x}_{150}
\end{bmatrix}, \quad f = \begin{bmatrix}
f_1 \\
\vdots \\
f_{150}
\end{bmatrix}
\]

where

\[
\begin{align*}
\hat{x}_1 &= \begin{bmatrix} x_1, \ldots, x_{25} \end{bmatrix}^T \\
f_1 & \text{is the output from hydra}
\end{align*}
\]

are the normalized PADRAM design vectors

Now solve the least squares problem for the linear coefficients, \( u \)

\[
\hat{X}u = f
\]
A simple experiment
Finding an active subspace

Once we have the coefficients of the least squares fit

\[ \mathbf{u} = \begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_m \end{bmatrix} \]
A simple experiment

Finding an active subspace

Once we have the coefficients of the least squares fit

$$u = \begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_m \end{bmatrix}$$

We can compute the active subspace, defined by

$$w = u' / \|u'\|_2$$

where

$$u' = \begin{bmatrix} u_1 \\ \vdots \\ u_m \end{bmatrix}$$
A simple experiment
Finding an active subspace

Design efficiency values

Design $\eta$ - Manufactured $\eta$

Original

$\mathbf{f}_j$

Active variable

$\mathbf{w}^T \mathbf{\hat{x}}_j$
A Novel Application
Finding an active subspace

Design efficiency values

Original

Design $\eta$ - Manufactured $\eta$

Active variable

Normalized magnitude

Design variable

$w^T$
Recent R&D for UQ & Optimisation Methods

METHODS DEVELOPED – AGGRESSIVE DESIGN

In light of high cost for multi-objective robust design optimization – new methodology has been developed based on PDF matching. It’s single-objective and gradient enhanced!

Objective function

$$\min_{s} \delta (s) = (t - K_\text{Se})^T W (t - K_\text{Se})$$

Gradients

$$\nabla_s \delta (s) = 2 (t - K_s e)^T W K_S F'$$

*Target is selected by the designer

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Recent R&D for UQ & Optimization Methods

METHODS DEVELOPED – AGGRESSIVE DESIGN

Extensive studies carried out on a NACA0012 design problem with a Mach number uncertainty. Comparisons with robust design optimization also undertaken.


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Recent R&D for UQ & Rare Events

METHODS DEVELOPED – Stochastic Variations of Metal Temperatures

- Black Swans are generated by the tail of the PDF:
  - Rare: the events have a low Probability
  - Possible: the probability is not zero

- Not all the systems are affected by BS
  usually complex systems are affected

F. Montomoli, D. Amirante, N. Hills, S. Shahpar and M. Massini, “Uncertainty Quantification, Rare Events and Mission Optimization, Stochastic Variation of Metal Temperature During A Transient”, GT 2014-25398, Dusseldorf, Germany. Also accepted to Journal of Power & Propulsion
Summary

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Deterministic Engineering ...

- ... answers a question with a single number, assumed to occur with certitude, while probabilistic methods provide a range of likely answers, plus a statement on the probability of a given result.

Statistical Engineering ...

- ... makes predictions about uncertain future events based on less than ideal observations of the past.
- It quantifies factors often left to intuition, like uncertainty, incomplete information and complicated interdependencies.

And finally – Some decisions are binary

Wimbledon men's singles final in July 2007:

Roger Federer Vs Rafael Nadal: Nadal contested his own shot and Hawkeye show that the ball was IN by 1mm.

However, Hawkeye has an “accuracy” of 3.6mm. Tolerance required 5mm. How can a machine with an uncertainty of 3.6mm be able to ascertain that the ball was in by 1mm?

The response from the scientists:

"Hawk-Eye attempts to take the element of uncertainty out of umpiring decisions, and the truth is that this cannot and should not be done. There will always be errors," he says. Hawk-Eye presents its decisions as if it were 100 percent certain, but in reality that just isn't possible, he says. The public, says Collins, would be better served by a system that gave its result with error bars so that people could make up their own minds.

The response from Hawk-eye’s makers:

“you couldn’t have a trophy that said, 'We are 99.76 percent certain that Roger Federer won.'”

Thank you for your Attention & Questions?

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https://www.researchgate.net/profile/Sharrokh_Shahpar/info
Thank you for your Attentions & Questions?

Back-Up Sides
Verification and Validation

**Verification** (are we solving the equations correctly?):
- estimates the magnitude of the error in the computational implementation of the mathematical model.
- compares the numerical methods used in the code to exact analytical results.
- tests for computer programming errors.

**Validation** (are we solving the correct equations?):
- estimates the magnitude of the difference between the results of the computational simulation and physical reality.
- compares the computed results with experimental results.

Thematic Network supported by the European Commission in the area of Quality and Trust in Industrial CFD:
"Unlike linear finite element stress analysis, CFD still requires expertly trained users for good results. In situations where non-experienced users have to be used, some restriction on their freedom to adjust critical parameters might be advisable, and they should be limited to simulations of routine types."
Taxonomy & Classification of Errors & Uncertainties in CFD

Sandia National Laboratories:

- **V&V**
- Physical Modelling Errors
- Discretization Errors (grid refinement?)
- Programming Errors
- Computer Round-Off Errors
- **User error**
  - Poor practice,
  - Lack of standards
  - Inadequate training
- **Iterative Convergence error**
  - Code cannot achieve a satisfactory level of convergence due to numerics
  - Code cannot achieve a satisfactory level of convergence due to Physics
  - User stops the simulation due to time

  - using a steady solver to simulate unsteady flow
  - using RANS (Reynolds-averaged Navier-Stokes) instead of DNS (Direct Numerical Simulation)
  - using wall functions instead of a fine mesh near the walls
  - placing far-field boundaries a finite distance from the region of interest modelling a compressible flow as incompressible
  - modelling a viscous flow as inviscid
  - modelling temperature dependent properties as constant
  - using the Boussinesq approximation for natural convection
  - modelling a mixture of gas species as a single gas, e.g. modelling engine exhaust gas as air
  - using a simple radiation model