2016 Product Development Symposium – Robust Design Day

Simulation and Uncertainty Quantification as a Part of the Product Verification and Validation Process

An outline of the typical processes and mathematical techniques used to analyse real-world data, together with an outline of the equivalent processes involved in synthesising data based on the results of simulation or mathematical models within a stochastic framework.

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About Rolls-Royce

- Rolls-Royce Group is a pre-eminent engineering company, focused on winning and retaining customers by developing and delivering products that provide more capability and offer better through-life value than those of our competitors
- Our businesses include: Aerospace (both Civil and Defence), Power Systems, Marine and Nuclear sectors, collectively employing over 50,000 people in 46 countries world-wide
- Our current order book is £76.4bn with underlying revenue of £13.4bn and underlying profit of £1.4bn
- We spend £1.2bn on R&D annually and fund 31 University Technology Centres and 7 Advanced Manufacturing Centres world-wide

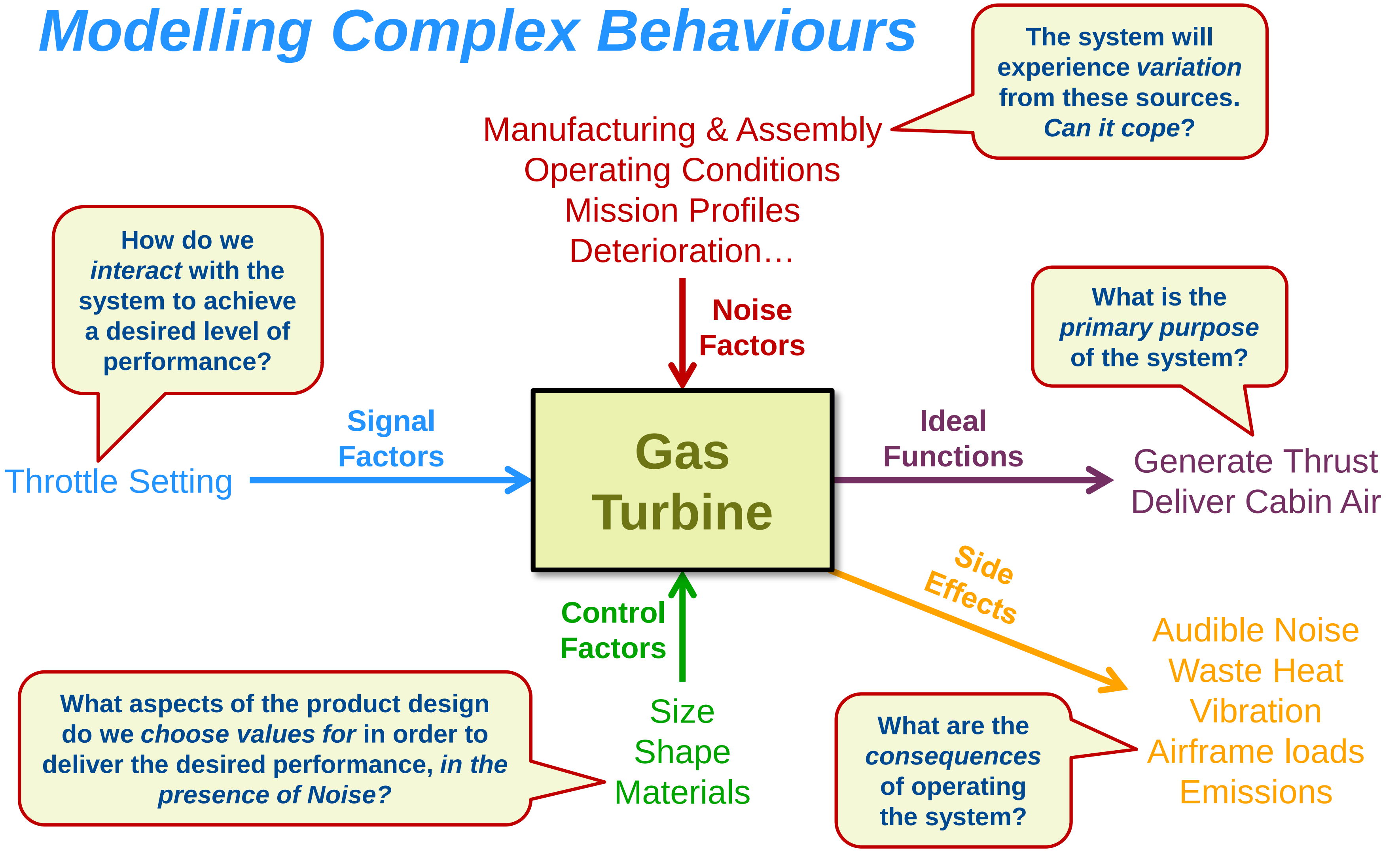
A Definition of Verification and Validation*

- Validation is the process of answering the question:
  "*Are you building the right thing?*"
- In contrast, Verification is the process of answering the question:
  "Are you building it right?"
- Answering the *first* question checks whether or not we have properly expressed the Customers' requirements in the *specification*, whereas answering the *second* question checks that the specifications are *correctly implemented* by the system
- In the context of mathematical modelling and simulation techniques, their *use* in the context of Product Design is clearly part of (Product) Verification, but their *development* has in fact a V&V cycle of its own:
  - Validation becomes *are we developing the right model?*
  - Verification becomes *is the model we've developed right?*

* Barry Boehm, Software Engineering Economics, 1981

The Gas Turbine Challenge

Modelling Complex Behaviours

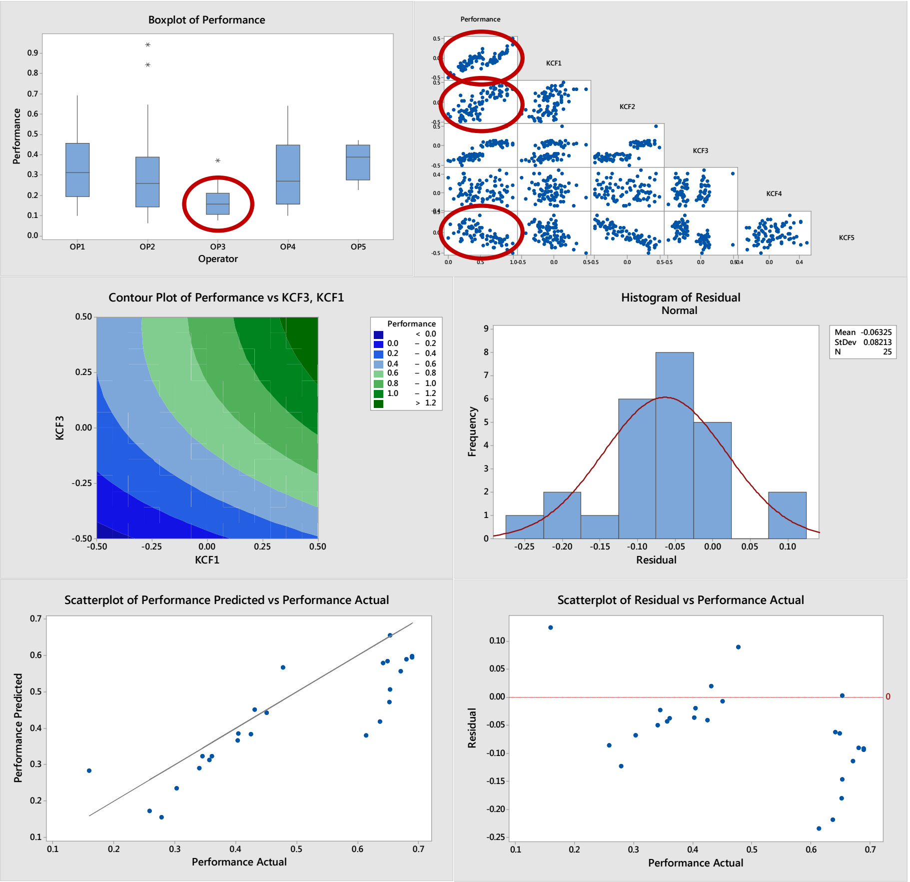


The Gas Turbine Challenge
Modelling Complex Behaviours

- Modern Gas Turbines are highly complex systems involving many thousands of mechanical and electronic components that combine together to provide thrust, auxiliary power (and cabin air!) for an aircraft
- In order to assess all the behaviours exhibited by a gas turbine a wide variety of different physics must be modelled, including: thermal, aerodynamic, noise, electro-magnetic, materials, mechanical and structural analyses
- All of this will contribute to aid in the design of a gas turbine, and will provide much of the supporting evidence for proof of compliance to the certifying authorities
  - In key areas of safety however, physical tests are also required to demonstrate compliance – for extreme events such as bird strike and containment, for example
- While much of the mathematical modelling techniques used are "physics based" simulation techniques (such as FEA and CFD), the time and effort required to fully explore issues arising and decisions required in support of an engine development programme can be prohibitive, and so such simulations are often supplemented by the use of "abstract" mathematical models

"Reverse Engineering"
Data Analysis to Explain What's Happened

1. Collate available Build and Performance Data
   - Classify into likely "special causes" such as Production Facility, Operator, Engine Standard, etc.
2. Analyse Performance Data to test for differences in the mean and variance *across* classifications
   - Is there a *statistically significant* difference between the mean and variance of each classification of special cause? *Is there an explanation as to what might be causing the observed differences?*
3. Analyse Build Data to test for correlations with Performance Data *within* each classification
   - Are there any factors that might singly (or in combination) define a *causal relationship* with the Performance Data?
4. Develop mathematical models that relate the correlated Build Data to Performance Data
   - Validation of these models will require that we can test their ability to predict *accurately and precisely* the performance of engines that were *not* involved in the analysis or in the development of the models



"Reverse Engineering"
Data Analysis to Explain What's Happened

- The "Reverse Engineering" approach is direct, and can effectively *allow useful inferences to be drawn from real-world observations*, however the approach inevitably suffers from:
  - Lag – we can only make inferences *(long) after the fact* – which may very much turn out to be too late!
  - Limited applicability – it is difficult to know if the data used is *fully representative* i.e. that it effectively covers a wide range of possibilities, and in particular, if it includes all potential extreme outcomes (which may severely limit its accuracy for predictive purposes
  - Aliasing – we can only include factors in the model that have been *measured and recorded*, but it is possible that in fact other factors are the true cause of the observed behaviours and are correlated with the included factors

"Forwards Engineering"
Developing Models for Prediction

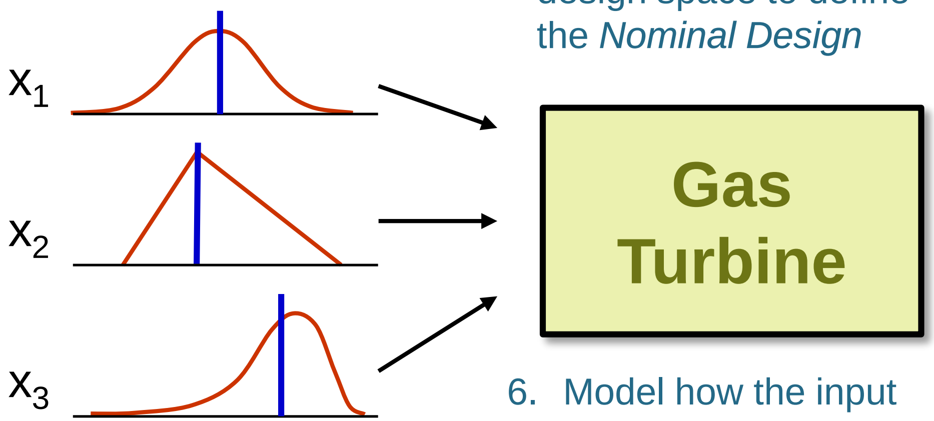
- A direct "one to one" comparison of the results of any computer-based simulation or mathematical model to real-world measurements is not in fact possible, due to the inherent variability present in real-world systems that makes the outcome a single real-world observation uncertain
- To make a comparison possible, we need to combine the computer-based simulations or mathematical models with a stochastic framework that will represent the effects of real-world variation on the modelled behaviours
- We can then compare the characterised population behaviours of the synthesised data generated from the computer-based simulations or mathematical models to those observed in the real-world

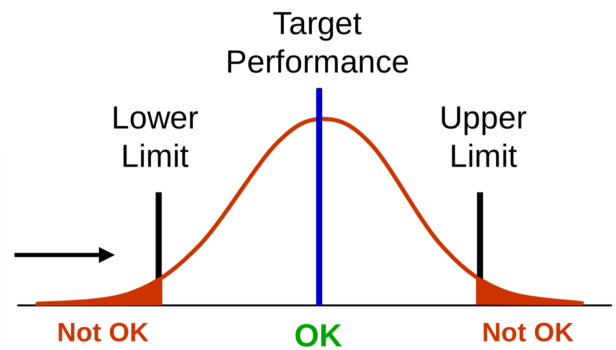
"Forwards Engineering"
Using Models for Prediction

1. Capture the *critical customer requirements*

2. Identify the *critical design parameters* that influence performance

3. Use a *structured experimental approach* to explore the available design space to define the *Nominal Design*





4. Understand *why the design parameters might vary* around their nominal values:
   - Manufacturing variation?
   - Environmental variation?
   - Customer usage?

5. *Model* the expected variation

6. Model how the input variation is transmitted through the design…

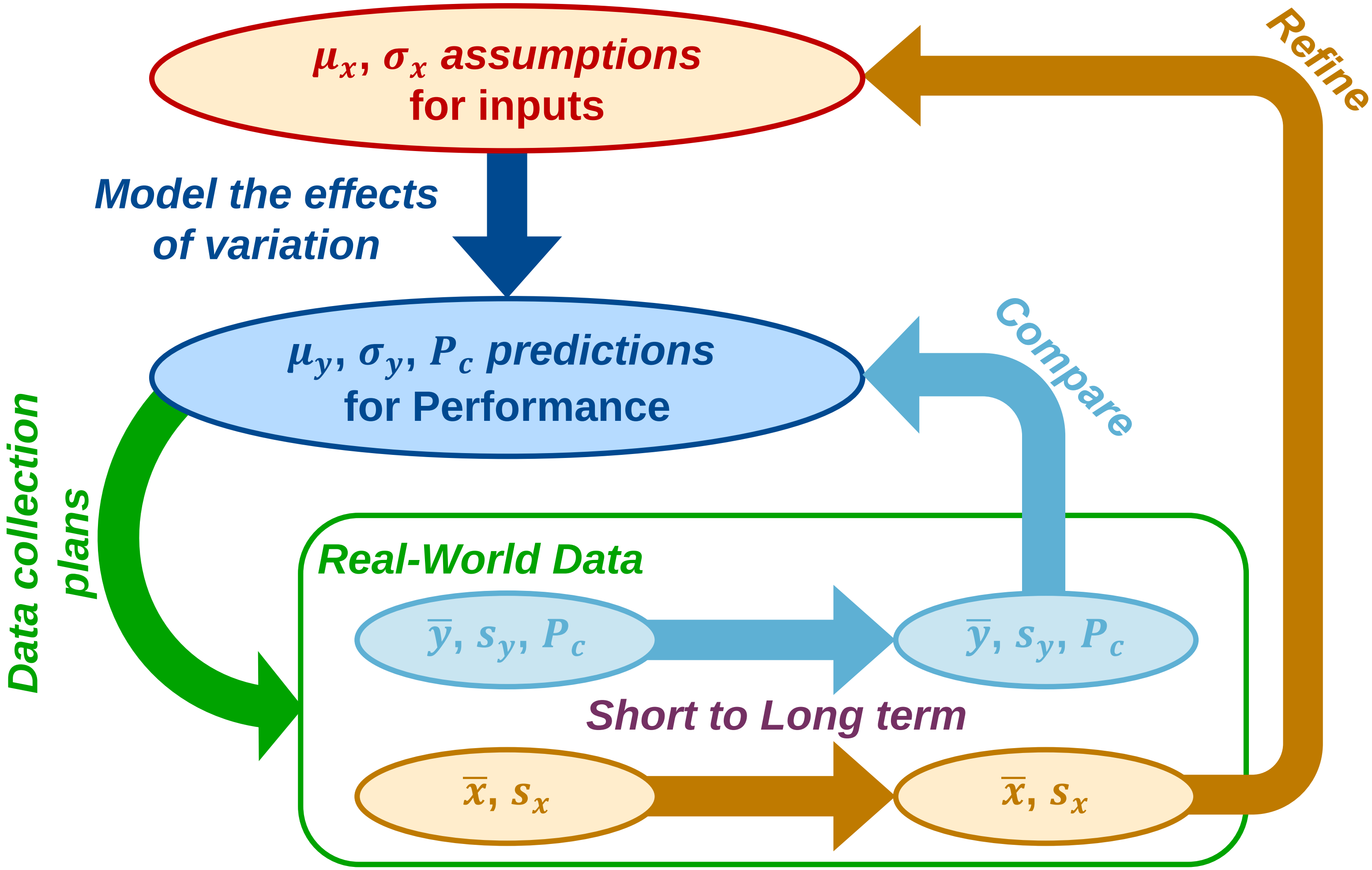
7. …to identify what variation in performance we can expect, so that we can predict with *quantified probability* how consistently the design will meet the customer requirements

"Forwards Engineering"
Using Models for Prediction

- Key Assumptions that must be stated – and confirmed:
  - That the model used for predicting performance is a precise and accurate predictor of individual response values
  - That the included uncertainty in the inputs is a precise and accurate representation of the true uncertainty
  - That the methodology used for propagating uncertainty is a precise and accurate quantification of the effects of uncertainty
  - That all the factors whose uncertainty is not included in the model do not affect the outcome

"Forwards Engineering"
Using Models for Prediction

Key:	
μ_x, μ_y	*population* means
σ_x, σ_y	*population* standard deviations
$\bar{x}, \bar{y}$	*sample* means
s_x, s_y	*sample* standard deviations
P_c	probability of conformance



Thank You Very Much!

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