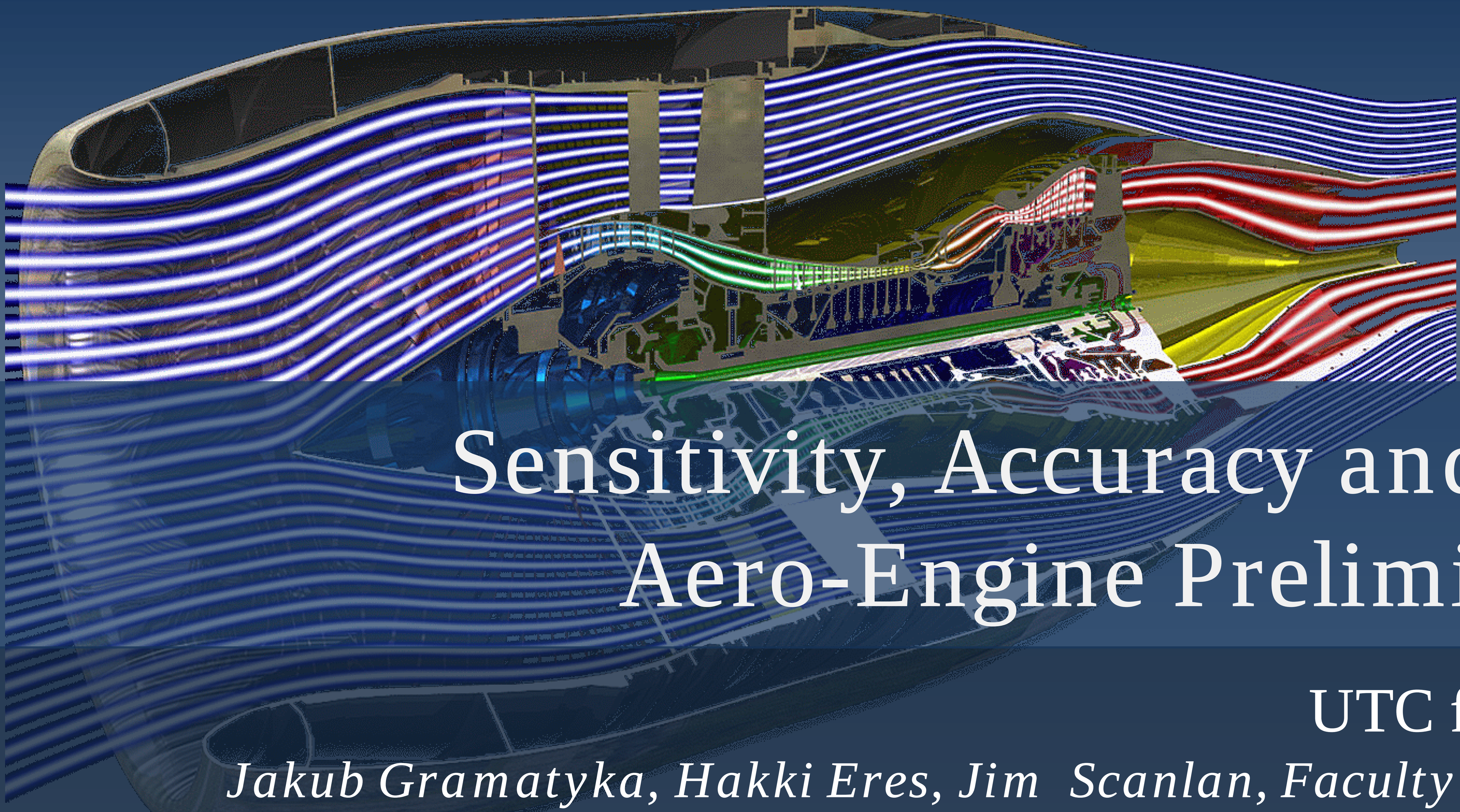

UNIVERSITY OF Southampton

Engineering and the Environment

Aeronautics, Astronautics and Computational Engineering

Sensitivity, Accuracy and Risk Assessment of Aero-Engine Preliminary Design Process

UTC for Computational Engineering

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The impact of design choices on the engine life-cycle cost and its final performance is not uniformly distributed over the whole design cycle. Instead, a significant proportion of the most critical design decisions is made at the very early design stages, which directly results in a large fraction of the engine attributes being frozen by the end of the preliminary design phase (See Figure 1). This combined with the fact that at the same stage in the design cycle, design knowledge is very limited, means that the most important design decisions must be made in the presence of uncertainty.

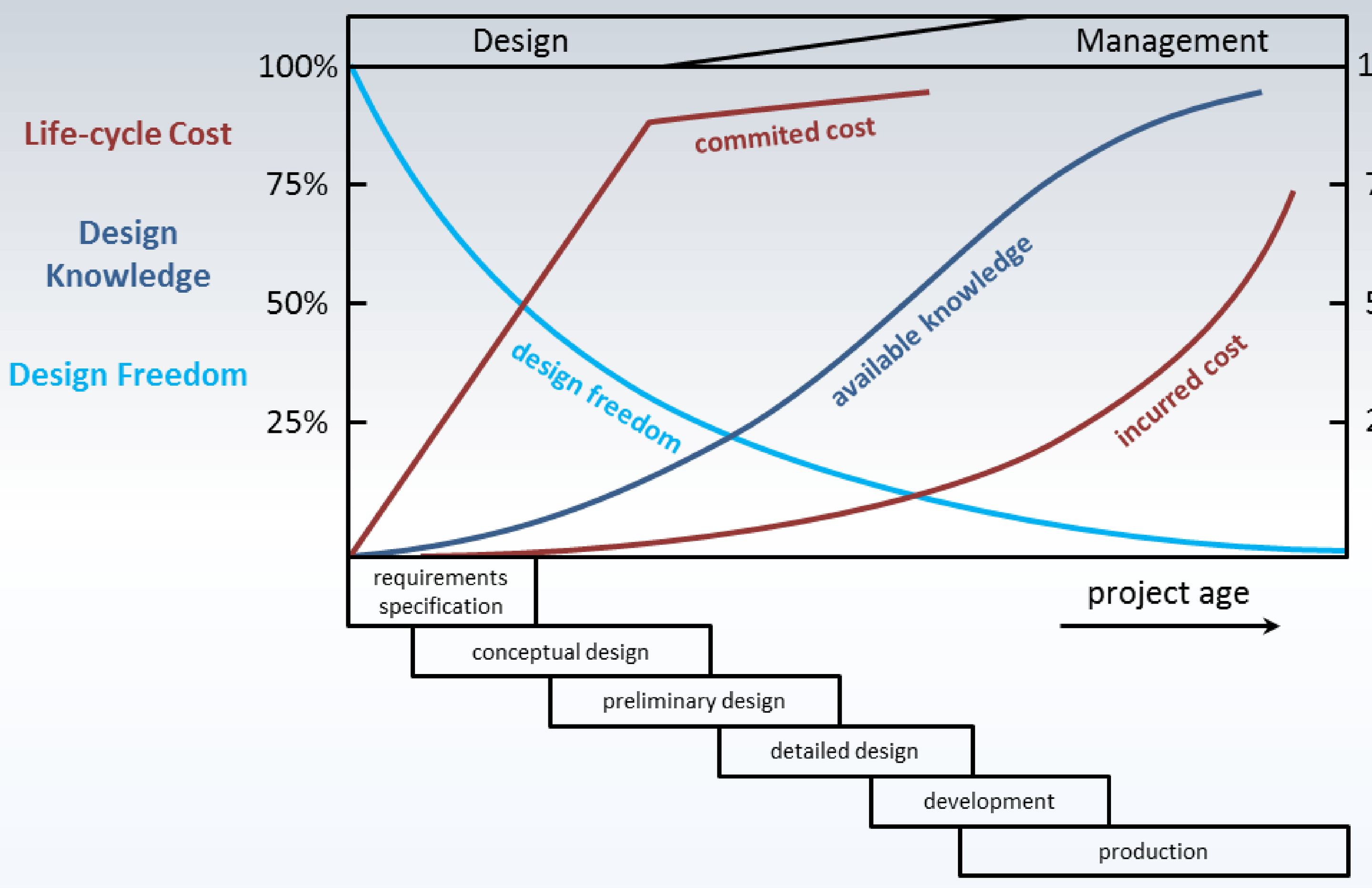


Figure 1: The variation of product life-cycle cost, design knowledge and design freedom with project age [1]

In the aero-engine development programmes, a wide range of methods and data is used to support architectural decisions made at the preliminary design stage. In order to ensure that the best decisions are made, the modelling uncertainty associated with the tools used to support them need to be properly identified, captured and eliminated if possible.

In the preliminary work on the project, a variety of uncertainty quantification frameworks were researched and applied to a relatively straightforward spreadsheet-based engine sizing model, developed specifically for the aforementioned trials.

In the first Monte-Carlo based framework [2], epistemic uncertainty (uncertainty due to lack of knowledge) was represented with simple intervals, whereas aleatory uncertainty (uncertainty due to randomness) was represented with probability density functions. Both types of model parameter uncertainties were propagated through the model, giving uncertainty in the model output, which was represented with probability boxes. Results of the uncertainty assessment were then used to update the engine design space (See Figure 2). This allowed choosing an engine design point, which position was based on well-founded analysis rather than heuristics.

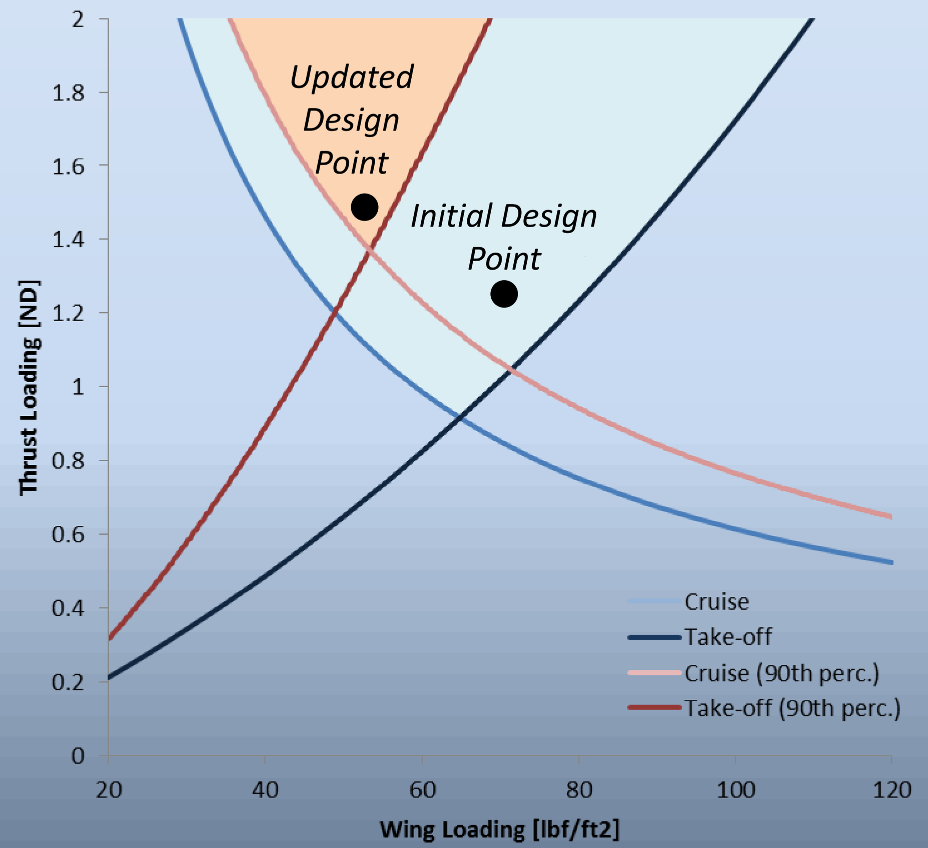
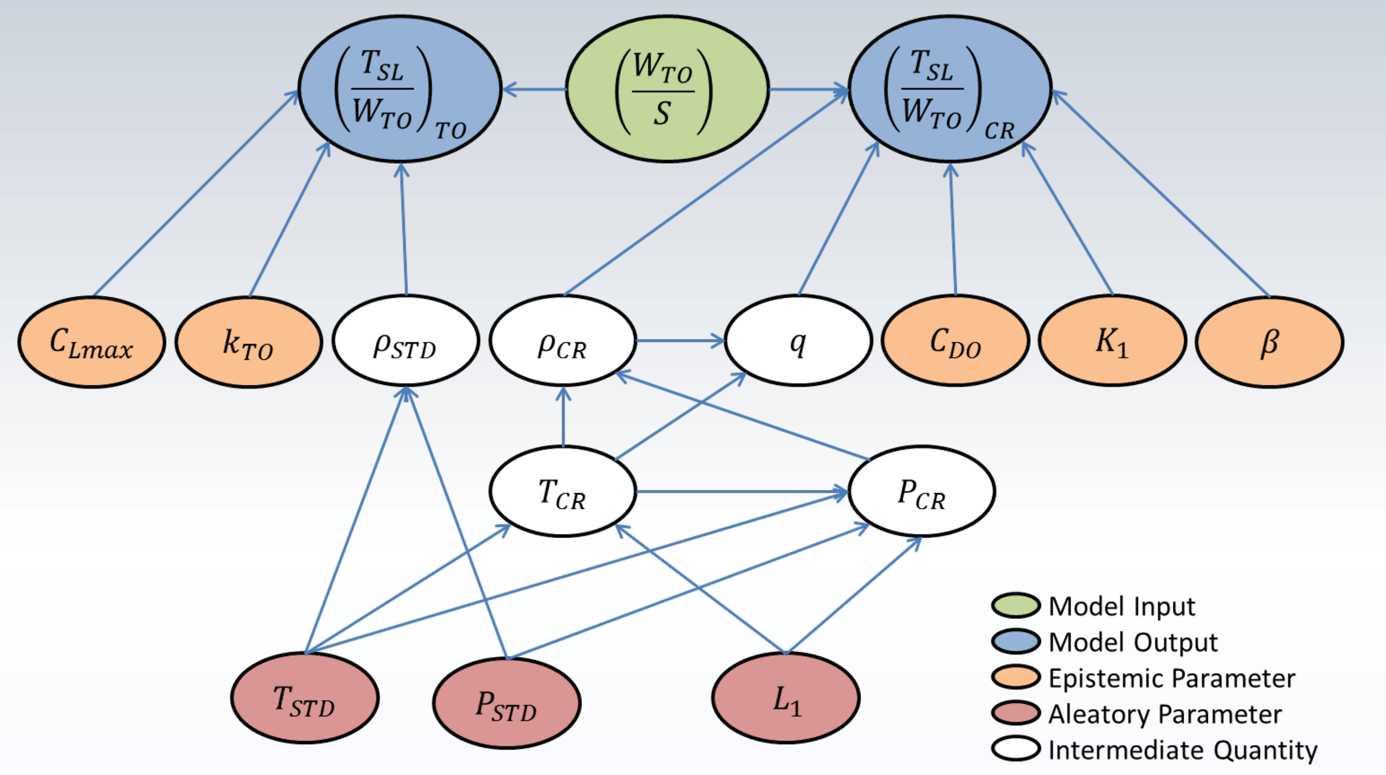


Figure 2: Diagram showing updated design space and updated design point position

In the second, Bayesian based approach, relationships between uncertain quantities were represented with a Bayesian Network (See Figure 3). It was demonstrated that increasing the amount of experimental data used for uncertainty assessment allows improving the accuracy of model predictions (See Figure 4 and 5). It was therefore shown that due to their ability to incorporate all-level experimental data into the analysis, Bayesian Networks could form a solid basis for uncertainty quantification framework development.



T_{STD} – air temperature (reference altitude)

P_{STD} – air pressure (reference altitude)

ρ_{STD} – air density(reference altitude)

T_{CR} – air temperature (cruise altitude)

P_{CR} – air pressure (cruise altitude)

ρ_{CR} – air density(cruise altitude)

$\left(\frac{W_{TO}}{S}\right)$ – wing loading

$\left(\frac{T_{SL}}{W_{TO}}\right)_{CR}$ – minimum thrust to weight ratio at cruise condition (TWCR)

$\left(\frac{T_{SL}}{W_{TO}}\right)_{TO}$ – minimum thrust to weight ratio at take-off condition (TWTO)

C_{Lmax} – maximum lift coefficient

k_{TO} – take-off speed to stall speed ratio

C_{DO} – coefficient of drag at zero lift

K_1 – lift-drag polar equation coefficient

β – instantaneous weight fraction

q – dynamic pressure at cruise conditions

L_1 – temperature lapse rate

Figure 3: Bayesian Network representing engine sizing model.

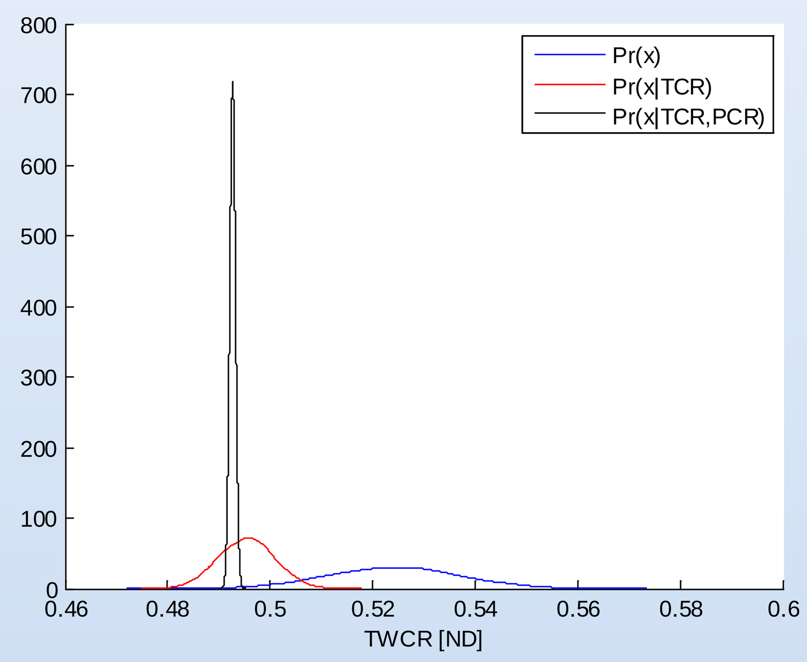


Figure 4: Kernel Density Plots showing change in TWCR prediction accuracy

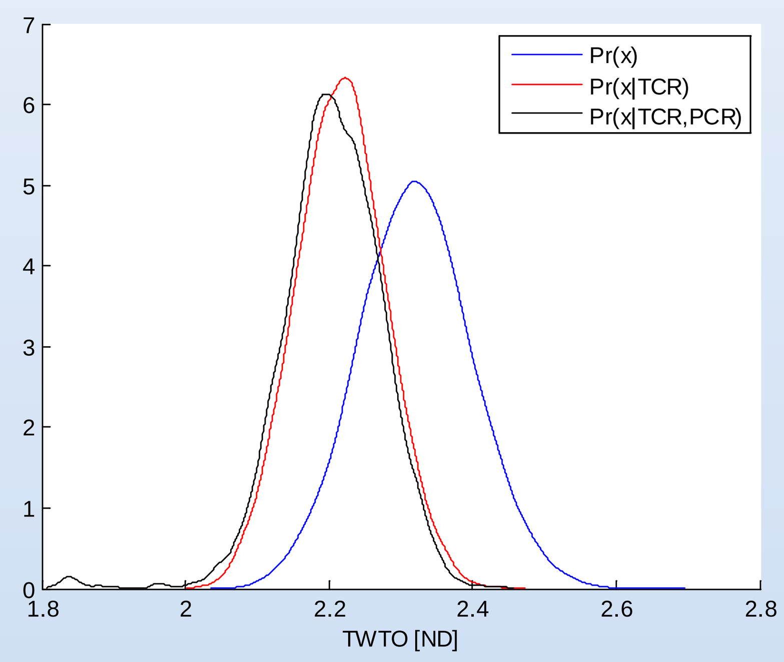


Figure 5: Kernel Density Plots showing change in TWTO prediction accuracy

Future work on the project will involve translating customer requirements into the real capabilities of the prospective design decision support tools. This will be followed by design and development of such tools and research into the most efficient strategies for their use.

Acknowledgement

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[2] Roy, C. J., & Oberkampf, W. L. (2011). A comprehensive framework for verification, validation, and uncertainty quantification in scientific computing. *Computer Methods in Applied Mechanics and Engineering, 200*(25-28), 2131-2144. doi: 10.1016/j.cma.2011.03.016

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