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The Implementation of Probabilistic Methods for Uncertainty Analysis in Computational Fluid Dynamics Simulations of Fluid Flow and Heat Transfer in a Gas Turbine Engine

John Faragher

Air Vehicles Division
Defence Science and Technology Organisation

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ABSTRACT

Probabilistic methods have been implemented with a computational fluid dynamics simulation of fluid flow and heat transfer in a gas turbine engine. The simulation models the temperatures in the T-56 series III 1-2 spacer. Three input quantities are treated as random variables. A random sampling method is used to generate the input values from a probability density function. The implemented Monte Carlo method uses a large number of samples of the input variables to calculate results repeatedly for the output variables (i.e. the predicted temperatures). Statistics of the predicted temperatures, such as the mean and variance, are then calculated. The variation in the predicted temperature at one point in the turbine of the T56 engine is seen to be more sensitive to variability in some parameters than in others.

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Executive Summary

DSTO has developed a risk and reliability management capability for mechanical components in propulsion systems. This includes an assessment of relative airworthiness risks resulting from modifications to life limits as a consequence of operational, logistic and repair requirements. It will expand the understanding of the fundamental mechanisms and processes responsible for the statistical distribution of lives in aircraft dynamic components. The overall purpose of this capability is to provide technical airworthiness advice to the RAAF on those critical factors that underpin the promulgation of operational lives of propulsion system components, and on the risks associated with varying these life limits.

The life of engine components is determined by a combination of the material properties and the applied stresses and temperatures. As a consequence of variability in these parameters, the component life is not fixed (deterministic) but stochastic (random) and may be characterised by a probability density function (PDF). In order to reduce the cost of ownership of ADF aircraft these PDFs need to be determined as accurately as possible. Probabilistic techniques offer significant potential for accurate and realistic estimates of component lives by quantifying stochastic elements of an analysis rather than introducing excessive conservatism to allow for them. The objective is to devise a methodology that brings together probabilistic and deterministic approaches in a manner that best supports improved component life estimates. This will reduce under-utilisation and cost of spare parts, and increase safety.

This report describes the implementation of probabilistic methods with a computational fluid dynamics simulation of fluid flow and heat transfer in a gas turbine engine. The simulation models the temperatures in the T-56 series III 1-2 spacer. Three input quantities are treated as random variables. A random sampling method is used to generate the input values from a probability density function. The implemented Monte Carlo method uses a large number of samples of the input variables to calculate results repeatedly for the output variables (i.e. the predicted temperatures). Statistics of the predicted temperatures, such as the mean and variance, are then calculated. The variation in the predicted temperature at one point in the turbine of the T56 engine is seen to be more sensitive to variability in some parameters than in others.

Author

John Faragher Air Vehicles Division



John Faragher obtained a B.E.(Hons) from the University of Melbourne in 1987. He commenced work in the Propulsion Research Area at the Aeronautical and Maritime Research Laboratory in 1988. He worked in the areas of Engine Performance and Engine Mechanical Integrity including research into engine component lifing. He was awarded a cadetship to study full-time at the University of Melbourne from 1992 to 1995 and was awarded a Ph.D. (Engineering). Since 1995 he has continued to work in the Propulsion Research Area at the Aeronautical and Maritime Research Laboratory (now called Platform Sciences Laboratory). In addition to the work described in this report, he has been developing computer models for research into gas turbine engine temperature modelling and heat transfer problems.

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1. Introduction

A probabilistic CFD analysis estimates the magnitude of uncertainty in the output data caused by uncertainty and variability in the input data. Until very recently CFD analysis methods have been entirely deterministic, which means that single values of the input variables and physical constants are used to calculate single-point estimates of the fluid flow and heat transfer behaviour. In reality the input data are not known exactly because they contain uncertainties.

As explained in a previous report (Faragher 2004) uncertainty in the input data needed for the analysis is sometimes called "parameter uncertainty", "parametric uncertainty" or "parameter variability". This class of uncertainty in the input data has two components "aleatory uncertainty" and "epistemic uncertainty":

- Aleatory uncertainty is also called "variability", "stochastic uncertainty", "inherent uncertainty" or "irreducible uncertainty". It is the physical variation present in the system being analysed or its environment. It is not due to a lack of knowledge and cannot be reduced.
- Epistemic uncertainty is also called "reducible uncertainty" or simply "uncertainty". This is what the American Institute of Aeronautics and Astronautics (AIAA) "Guide for the Verification and Validation of CFD Simulations" (AIAA 1998) defines as "uncertainty", i.e. "a potential deficiency that is due to a lack of knowledge". Epistemic uncertainty can be reduced by an increase in knowledge about the system being analysed. The other kind of uncertainty (aleatory) is not mentioned in the AIAA Guidelines.

The combined effect of these two sources of uncertainty in each of the input data variables can be quantified by a mean value and a probability distribution function. Probabilistic CFD analysis methods then propagate this uncertainty through the mathematical model to the output. Each of the output variables, such as flow velocity, pressure or temperature, is then described by a mean value and a probability distribution around that mean value.

It is important to remember that while a probabilistic analysis appears to define the uncertainty in the output data it only takes into account one part of the uncertainty. That is, it estimates the magnitude of the uncertainty in the output caused by parameter uncertainty and variability. It does not take into account the uncertainty about how well the mathematical model represents the true behaviour of the real physical system. This type of uncertainty is called "model form uncertainty", "structural uncertainty", "nonparametric uncertainty" or "unmodelled dynamics". It is very difficult to characterise model form uncertainty in terms of probability density functions. In CFD, the model with the greatest amount of this type of uncertainty is the turbulence model because the phenomenon of turbulence is not fully understood.

To estimate the magnitude of the model form uncertainty it is necessary to "validate" the model by comparing the computed results with experimental results. The process of

validation can be thought of as answering the question, "are we solving the correct mathematical equations?"

This leads us to another important definition. "Prediction" is defined as using a CFD model to foretell the state of a physical system under conditions for which the CFD model has **not** been validated. Calculating results for conditions for which the CFD code has been validated is not "prediction" but "interpolation" within the experimental data (AIAA 1998). A complete estimation of the uncertainty in a CFD simulation must therefore include an estimate of how far the prediction state is from the validation state, and how much uncertainty this introduces to the results.

The computational fluid dynamics (CFD) discipline is less mature than the linear finite element stress analysis discipline because CFD requires much greater computer power to solve problems of practical engineering interest. For this reason probabilistic methods have been too computationally expensive to be adopted widely in CFD. In contrast, probabilistic methods have been used with finite element stress analysis in aircraft engine component structural design and fatigue life prediction for decades (Yang & Chen 1985, Fox 1994, Kappas 2002). Now, computer power has increased to the point where probabilistic CFD is "coming of age" (Walters and Huyse 2002).

2. Implementation of Probabilistic CFD

2.1 CFD Test Case

The standard Monte Carlo simulation method has been implemented with a CFD simulation of fluid flow and heat transfer in a gas turbine engine. The simulation predicts the temperatures in the turbine section of the T-56 series III engine. The output variable chosen for statistical analysis is the temperature at the neck of the spacer between the first and second turbine disks, known as the 1-2 spacer.

2.1.1 T56 Series III Turbine Cooling Air Flow

The front and rear faces of the 1st, 2nd and 3rd stage turbine disks are cooled to prevent them from overheating. The T56 series III turbine cooling air flow is shown in Figure 1. Cooling air, which is bled off from the fourteenth stage of the compressor, enters at the bore of the first stage disk and flows axially along to the cavities between the disks. It flows outwards between the disks, passing through holes in the curvic splines which connect the disks to each other. Most of the flow is entrained in the boundary layer along the surface of the disks and spacers. The cooling air rejoins the hot mainstream gas at the rim of the disks.

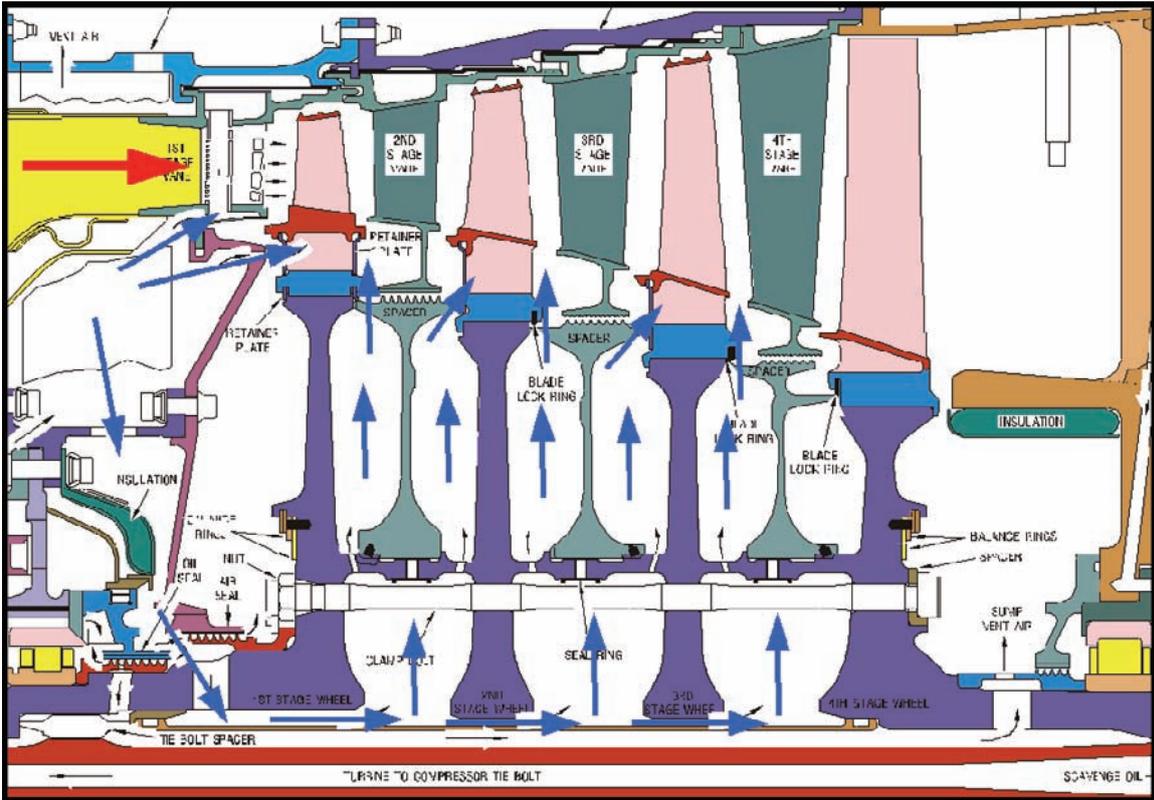


Figure 1: T56 Series III Turbine Cooling Air Flow

2.1.2 Computational Fluid Dynamics

The internal flow and heat transfer for the entire T56 turbine assembly is modelled with the commercial Fluent CFD software using a two-dimensional, axisymmetric solver with swirl. The conjugate heat transfer capability is used to model both the convection heat transfer between the gas and the solid components, and also the conduction heat transfer within the disks and spacers. The gas is assumed to be incompressible (constant density) and the standard $k-\epsilon$ turbulence model with wall functions is employed. The engine rotational speed is 13,789 rpm.

2.1.3 Boundary Conditions

Cooling air mass flows were based on design data. Turbine cooling air inlet temperature was based on compressor outlet temperature. Temperatures at the rim of each disk and spacer were fixed at values equal to measured data from Rolls-Royce Allison engine tests for take-off power.

2.1.4 Thermal Analysis Results

The predicted streamlines of cooling air flow inside the T56 turbine assembly are shown in Figure 2. It shows how most of the flow is entrained in the boundary layer along the surface of the disks and spacers.

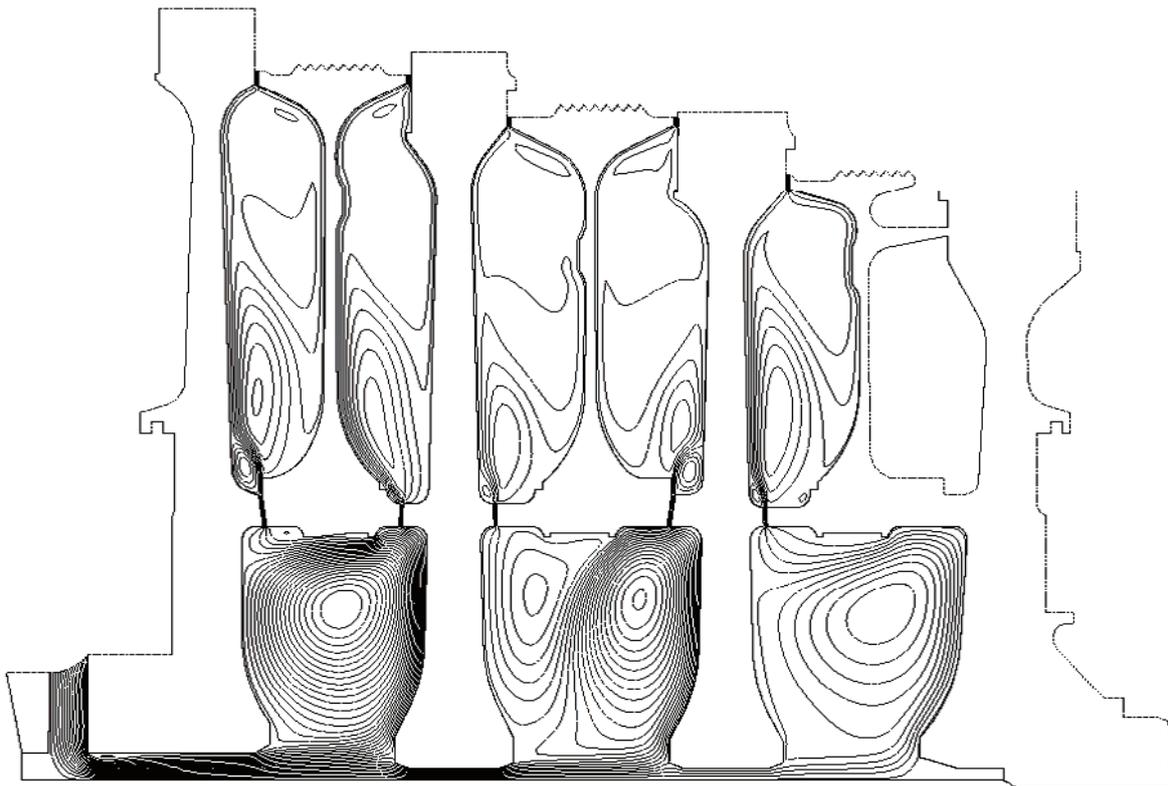


Figure 2: Predicted Streamlines of Cooling Air Flow Inside the T56 Turbine Assembly

Figure 3 shows the contours of static temperature (K) for both the metal components and the cooling air. It indicates that there are fairly steep temperature gradients near the rim of the disks and spacers. The heat from the mainstream hot gas does not diffuse very far radially inwards towards the bore of the spacer. This is not surprising because the material from which the spacer is made (Incolloy 901) has relatively poor thermal conductivity. There is almost no temperature gradient in the bore region of the disks and spacers. The bore temperature is almost equal to the temperature of the cooling air from the compressor (i.e. $670\text{K} \approx 400^\circ\text{C} \approx 750^\circ\text{F}$).

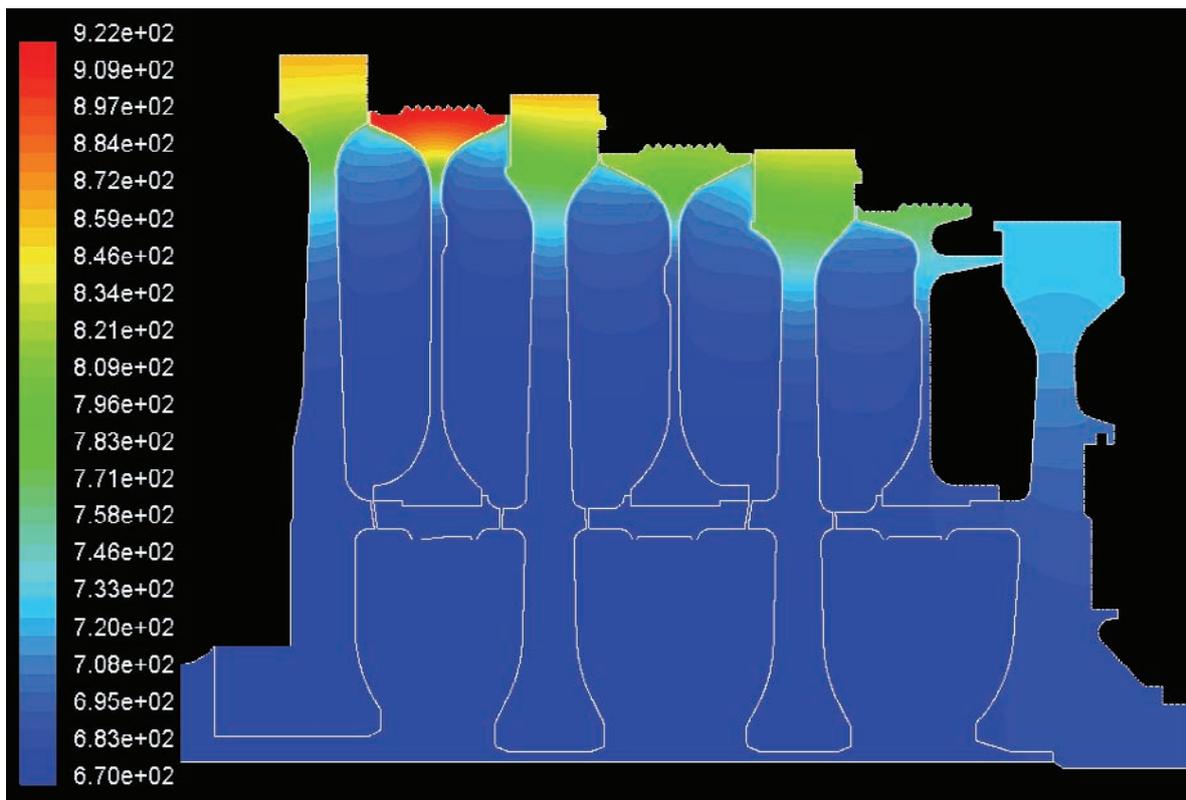


Figure 3: contours of static temperature (K) for both the metal components and the cooling air.

2.2 Implementation Method

The method chosen for this implementation of probabilistic CFD analysis is the standard Monte Carlo simulation method. This method is also known as the "basic" or "crude" Monte Carlo method to distinguish it from the various modified Monte Carlo methods which have been developed to reduce the computational expense. These efficiency improvements are known as "variance reduction techniques". Two of the modified Monte Carlo methods are called "Importance Sampling" and "Latin Hypercube Sampling".

2.3 Standard Monte Carlo Simulation

Monte Carlo methods, which are also called "statistical simulation methods", can be loosely defined to include any method that utilizes sequences of random numbers to perform the simulation. The procedure for the standard Monte Carlo method involves three steps:

1. for each input variable, generate a set of values by randomly sampling the known or assumed probability density function;
2. for each set of random input data execute a deterministic mathematical model and then aggregate the output data from all of the calculations;
3. use the statistics of the output data set (mean, variance, skewness, kurtosis, etc.) to define its probability density function.

2.3.1 Generation of Values For Each Input Variable

In this implementation of the probabilistic CFD method three input quantities (cooling air mass flow, cooling air temperature, and spacer rim temperature) are treated as random variables. A random sampling method is used to generate the input values from a probability density function. For each input variable the probability density function is assumed to be the normal distribution with the mean equal to the nominal value of the variable. The standard deviation, σ , is set so that 3σ is equal to 10% of the mean value. This value is arbitrary because the aim of this exercise is only to demonstrate the feasibility of implementing a probabilistic CFD method on current generation computers. Probability distributions other than normal can also be used as required.

The MATLAB software was used, with the specified mean and standard deviation for each input variable, to generate a set of 100 values for each of the three stochastic input variables.

2.3.2 Execute A Deterministic Mathematical Model

The three sets of 100 input values generated with MATLAB are read by a specially written Fortran program which produces a large journal file, incorporating these values, in the correct format to be read by the Fluent CFD software as a set of commands. For each group of three input values the journal file instructs the Fluent software to:

1. set the boundary conditions of the model;
2. iterate the solver from the previous solution until a new converged solution is obtained;
3. write the calculated temperatures for the 1-2 spacer to a file.

It is important to note that while the Monte Carlo method converges to the exact stochastic solution as the number of samples goes to infinity, the convergence of the mean error estimate is slow. This is because the standard deviation of the mean is inversely proportional to the square root of the number of samples. Hence thousands or millions of data samples may be required to get the required accuracy, and for each sample the deterministic mathematical model, in this case the CFD simulation, must be executed. Fortunately, the CFD simulation does not have to be started from the beginning each time. After one converged solution has been obtained, subsequent simulations with slightly different boundary conditions are started from the previous converged solution. The new solution is usually not very far away from the previous solution so the solver converges very quickly. Typically, starting without a previous solution, it takes 500 - 1000 iterations to converge to a solution. Then, obtaining another solution after a small change in the boundary conditions only requires 5 - 10 iterations to converge.

2.3.3 Calculation of the Statistics of the Output Variable

Another Fortran program reads the temperature data from the files which have been created for the solutions corresponding to each different set of input variables. This program extracts the value of the temperature at the specified location at the neck of the 1-2 spacer for each case

and writes all the values to a single file. Statistics, such as the mean and variance, of the predicted temperatures are then calculated.

3. Results of Probabilistic CFD

The mean value (μ_{out}) and the standard deviation (σ_{out}) of the temperature at the neck of the 1-2 spacer have been calculated for four different cases as shown in Table 1. In the first three cases two of the input variables are held constant (the standard deviation σ_{in} set to zero); and the third one was treated as a random variable. The first input variable (μ_{in1}, σ_{in1}) is the spacer1-2 rim wall temperature; the second input variable (μ_{in2}, σ_{in2}) is the cooling air mass flow; the third input variable (μ_{in3}, σ_{in3}) is the cooling air temperature. In the fourth case all three input variables (cooling air mass flow, cooling air temperature, and spacer rim temperature) are treated as random variables. As mentioned above, the standard deviation of the input variables, σ_{in} , is set so that 3σ is equal to 10% of the mean value.

Table 1: Results of CFD with stochastic inputs.

	μ_{in_1}	σ_{in_1}	μ_{in_2}	σ_{in_2}	μ_{in_3}	σ_{in_3}	μ_{out}	σ_{out}	$3 \times \sigma_{out}$	$(3 \times \sigma_{out}) / \mu_{out}$
	K	K	kg/s	kg/s	K	K	K	K	K	%
Nominal	922	0.0	0.15	0.0	671	0.0	807.8	0.0	0.0	0.0
Case 1	922	30.7	0.15	0.0	671	0.0	808.0	16.5	49.5	6.1
Case 2	922	0.0	0.15	0.0045	671	0.0	807.9	0.9	2.6	0.3
Case 3	922	0.0	0.15	0.0	671	22.4	807.4	9.3	27.9	3.5
Case 4	922	30.7	0.15	0.0045	671	22.4	807.6	20.9	62.7	7.8

The results for case 2 show that the value of the predicted temperature at the neck of the spacer is fairly insensitive to small changes in the mass flow rate of the cooling air, with 3σ being only 0.3% of the mean value of the temperature at the neck of the spacer. The predicted temperature at the neck of the spacer is mildly sensitive to changes in the temperature of the cooling air with $3\sigma = 3.5\%$ of the mean value in case 3. Case 1 shows that the predicted temperature is most sensitive to variation in the wall temperature boundary condition specified at the rim of the spacer with $3\sigma = 6.1\%$ of the mean value. This indicates that the conduction of heat from the rim of the spacer to the neck has a greater influence on the temperature at the neck than the convection heat transfer involving the cooling air on the side of the spacer. This is true in spite of the relatively poor thermal conductivity of the spacer material. In the fourth case, when all three boundary conditions are treated as stochastic, the total variation in the predicted temperature at the neck of the spacer increases a little more so that $3\sigma = 7.8\%$ of the mean value.

4. Conclusions

A probabilistic computational fluid dynamics (CFD) analysis has been performed using the standard Monte Carlo simulation method. This work demonstrates the feasibility of implementing probabilistic CFD techniques. It shows that results can be obtained in an acceptable amount time without an excessive amount of computational expense using current generation computers. The variation in the predicted temperature at one point in the turbine of the T56 engine is seen to be more sensitive to variability in some parameters than in others.

In the future, the probabilistic CFD analysis method could be accelerated by implementing Importance Sampling or Latin Hypercube Sampling method.

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John Faragher

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