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The Burnett Honors College

I hereby recommend that the thesis prepared under my supervision by
Sameer A. Khan
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Be accepted as partial fulfillment of the requirements for Honors in the Major

---

Dr. Ali P. Gordon — Date
Thesis Committee Chair
Department of Mechanical Engineering

Recommendation Concurred:

Dr. Jayanta Kapat — Date
Department of Mechanical Engineering

Dr. Christopher Geiger — Date
Department of Industrial Engineering

Dr. Ranganathan Kumar — Date
Department Chair
Department of Mechanical Engineering

Dr. Alvin Y. Wang — Date
Dean
The Burnett Honors College

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PROBABILISTIC STRESS RUPTURE LIFE ANALYSIS OF TURBINE BLADES

by

SAMEER A. KHAN

A thesis submitted in partial fulfillment of the requirements for the Honors in the Major Program in Mechanical Engineering in the College of Engineering and Computer Science and in The Burnett Honors College at the University of Central Florida Orlando, Florida

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Thesis Chair: Dr. Ali P. Gordon

Abstract

The on-going effort to improve the efficiency of gas-powered turbines has facilitated incremental increases in the temperature and stress imposed on turbine components, such as blades, vanes, etc. The incipient failure of blades subjected to mechanical loads of 60 MPa to 950 MPa and temperatures up to 600ºC or higher lead to failure manifesting in irreparable damage to the entire engine system. One of the primary failure modes of turbine blades is creep, which is facilitated by the high temperature at the turbine inlet coupled with the centrifugal stresses.

This thesis will employ a probabilistic design approach to better assess the probability of failure due to creep rupture rather than accepting an unknown level of risk associated with the creep stress rupture criteria used for the deterministic analysis. NESSUS will be used to perform probabilistic analysis in order to predict the life and probability of failure of internally-cooled turbine blades due to creep rupture. Probabilistic analysis of the simulation results from this thesis will provide a probability distribution of the creep rupture lives and their sensitivity to the input variables for manufacturing, operational, thermal load and material property variations. It will predict the distribution of blade creep lives for a population of engines as well as determine the most sensitive input variables. This study will also be significant in determining and evaluating the effects of parameters that control component life and finally assist in improving performance, reducing cost, extending life of the component, and making the design robust.

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Table of Contents

List of Figures

List of Symbols/Abbreviations

σ_{sa}	Critical stress (MPa)
B-B	Blade to blade variation
BPull	Blade moment weight (kg)
CDF	Cumulative Distribution Function
CFlow	Coolant flow (kg/s)
CTemp	Coolant supply temperature (˚C)
E-E	Engine to engine variation
Eq	Equation
F_{matl}	Material stress rupture scatter factor
HGTemp	Hot gas temperature (˚C)
MCS	Monte Carlo Simulation
N_{sr}	Creep stress rupture life (hrs)
NESSUS	Numerical Evaluation of Stochastic Structures Under Stress
P_f	Probability of failure
PDA	Probabilistic Design Approach
PDF	Probability Density Function
PDM	Probabilistic Design Method
T_{sa}	Blade section average temperature (˚C)
TBCcon	TBC thermal conductivity (W/m/K)
TBCth	TBC thickness (mm)
VBA	Visual Basic of Applications

1. Introduction

Historically, gas turbine technology has steadily advanced since its creation and is used to power aircrafts, marine vehicles, land-based applications, and so on. The term “gas turbine” is most often used as an abbreviation for gas-turbine engine. The gas turbine engine is a heat engine that extracts energy from the flow of a combustion gas and thus generates power. This engine system consists of the following sub-systems: a compressor that compresses the incoming gas to a higher pressure; a combustor that burns the fuel and raises the temperature of the compressed gas; and a turbine that extracts energy from the high pressure, high velocity gas and drives the output shaft to produce work.

Over the years, there have been on-going efforts focused on developing more efficient turbines. These studies have facilitated continual increases in the temperature and stress that must be sustained by the turbine components. For example, when blades are exposed to very high mechanical and thermal stresses, they exhibit irreparable damage leading to failure of the entire engine system. Generally, these stresses may range from 60 MPa to 950 MPa and the temperature from 600ºC to 1000ºC. The typical failure modes of turbine blades are creep, low-cycle fatigue (LCF), high-cycle fatigue (HCF), and corrosion. Creep, in particular, is considered to be the primary failure mode of turbine blades due to the high temperature at the turbine inlet combined with the centrifugal forces that facilitate tensile stresses. Currently, creep rupture is predicted in these engine systems using traditional engineering design approach. This approach is considered to be inefficient because it lacks the ability to determine the probability of failure. The motivation of this investigation is the lack of an effective computational approach to assess the probability of turbine blade failure due to creep rupture.

2. Creep and Creep Rupture

Creep is time-dependent deformation of a material that is exposed to tensile stress at a very high temperature (Kraus, 1980). It can be divided into three regions: primary, secondary, and tertiary, as shown in Fig. 1. In the primary region, the strain rate decreases with time and occurs only over a short period. The secondary region tends to have a constant strain rate and is also known as steady state region. The minimum strain rate occurs in this region. Finally, in the tertiary region, the strain rate increases rapidly and rupture occurs due to creep. In application, a turbine blade can experience each form of creep deformation. A blade that was subjected primarily to creep conditions is shown in Fig. 2.

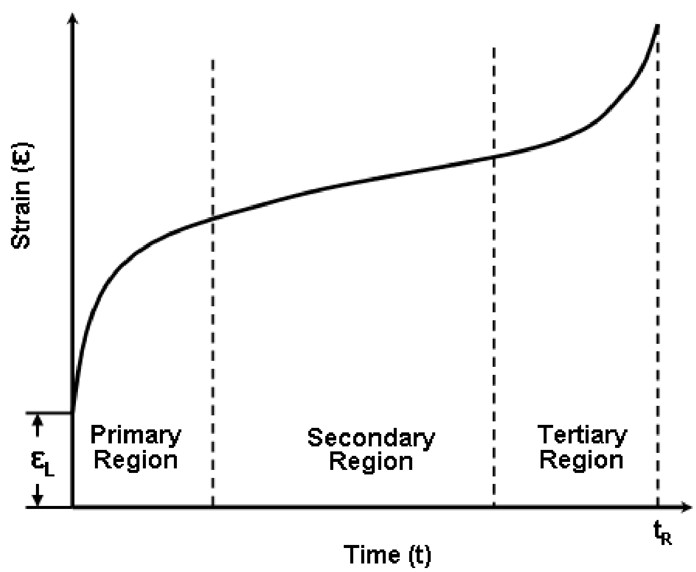


Figure 1. Stages of creep deformation (Kraus, 1980).

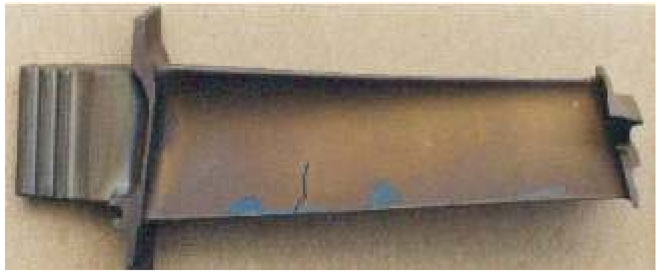


Figure 2. Damaged turbine blade (Rhodes *et al.*, 2003).

Creep deformation and rupture in parts can take years to accumulate. The consequent losses in operation time due to repair and replacement costs millions and billions of dollars (Air Force Research Laboratory [ARFL], 2001). Additionally, creep deformation and rupture experiments that simulate the exact service conditions of turbine blades are highly impractical to carryout. In order to overcome these limitations, computational methods are used to approximate creep behavior facilitated by service conditions.

3. Existing Computational Analysis Approaches for Product Design

3.1 Deterministic Design Approach

The most classical approach used by gas turbine designers to predict creep rupture is known as the deterministic approach. This approach employs safety factors to design parameters in order to allow for uncertainties. These safety margins are incorporated in the design to consider the worst case such as using maximum load, maximum allowable temperature, minimum material properties, etc. Depending on the complexity of the design, these safety factors can compound to cause costly over-design of thousands and millions of dollars. Even though this technique has the advantage of being straightforward and computationally inexpensive, its main drawback is that the reliability of the component or system under consideration is not explicitly quantified. Moreover, this approach is limited in that it does not determine the probability of failure of typical components.

3.2 Probabilistic Design Approach (PDA)

As an alternative, probabilistic design approach (PDA) employs statistics-based engineering design for enhancing product design. More specifically, PDA uses the probability distributions of the input design parameters rather than using nominal or mean values. This allows PDA to consider uncertainty in product design. Several probability distributions are explained in detail by Ang and Tang (1975). As a result, the probability of failure, structural sensitivity of the stochastic variables, and reliability functions can be more accurately estimated.

Probabilistic design approach considers input uncertainties applied to a physical model to establish a reliability function, as shown in Fig. 3. It allows for design with a specific reliability, performance, or specification conformance. The result is the improvement of safety, quality, performance and cost-reduction of the component or system. One of the primary reasons to employ probabilistic design approach in conducting this study is because there are many blades and many engines across the world. Each of these engines is subjected to its own set of conditions. This approach allows the gas turbine designers to apply the conditions that are relevant to a specific engine model.

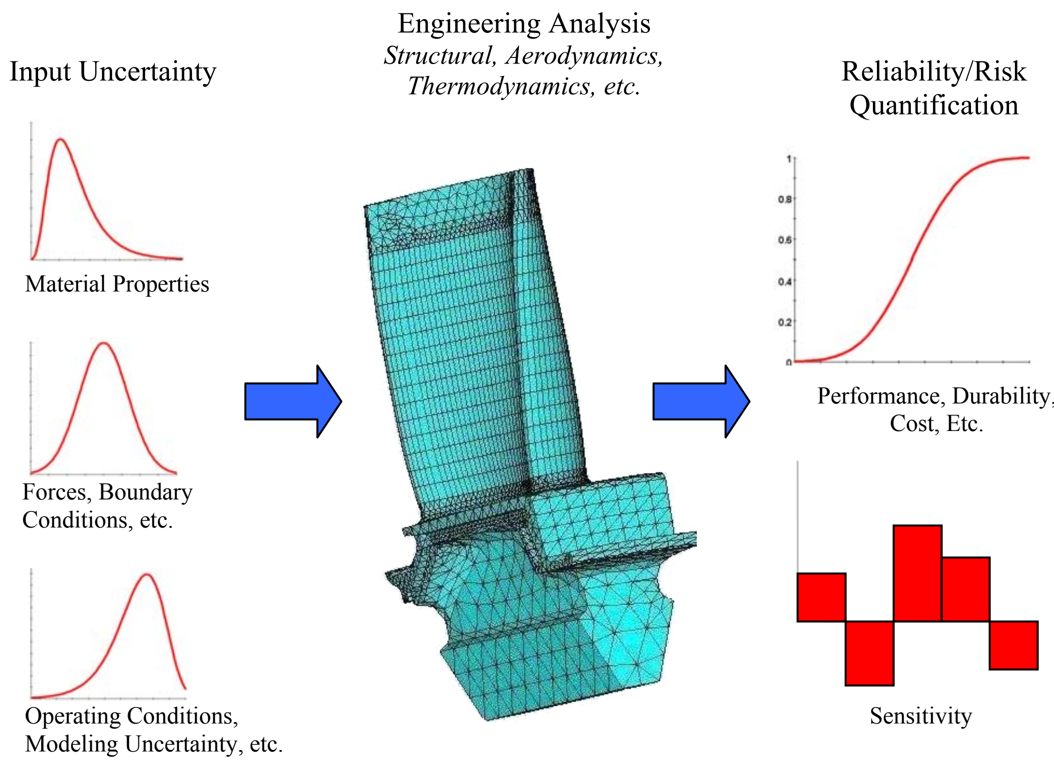


Figure 3. Probabilistic design schematic.

A primary advantage of PDA is that it provides the capability to determine the risk of failure and survival. It evaluates the sensitivity to variation and is very effective in making the design robust. Performing PDA is useful in optimization of specification limits for manufacturing, operation and service. It is helpful in establishing and optimizing management plans (*e.g.*, for inspections, maintenance, repair) as well as operational cost models. It is also very beneficial in maintaining or improving performance. It exploits probabilistic design methods to quantify reliability and risk in order to make strategic decisions based on replacement cycle, warranty, cost and safety. There are a wide range of engineering problems where probabilistic design approach has been considered to be very useful in predicting the probability of failure and sensitivity of input parameters (Mücke, 2000; Chamis and Abumeri, 2003).

4. Probabilistic Design Methods (PDMs)

Probabilistic design approach employs probabilistic design methods (PDMs) to provide consideration for randomly distributed input variables instead of steady (deterministic) values such as mean, minimum or maximum values to perform probabilistic analysis.

Above all, the main advantage of these methods is that they eliminate the need for safety factors. The uncertainties in the design parameters lead to uncertainties in the output variables and consequently lead to over-designed or under-designed parts, which have a reliability that is difficult to predict. Probabilistic methods are useful in representing and incorporating the input design parameters into the engineering algorithms and models as probability functions. Applying randomly distributed design parameters allows conscious consideration of variability, eliminates uncertainties and the necessity for conservative safety factors. These methods have significantly enhanced the ability to predict and simulate real life behavior.

A key limitation of PDMs is that they require significantly more computational resources as compared to deterministic analysis. Some applications require thousands of simulations to calculate low probabilities of failure. The number of simulations can be reduced by using advanced reliability methods for cost/time efficient probabilistic analysis. Additionally, PDMs are not considered to be very beneficial in the situations where the risk of failure or variability in influencing parameters is low. Under these circumstances, traditional deterministic methods are considered to be sufficient. Other drawbacks of PDMs are related to accuracy as it is very difficult to attain for complex engineering problems (Ryan and Townsend, 1993).

Probabilistic design methods (PDMs) are applicable to many major engineering applications. For example, risk assessment and prediction is used to quantify the risk of fracture associated with metallurgical/manufacturing defects in aircraft gas turbine engine components (Enright *et al.*, 2004). Life assessment and prediction, which is used to determine the number of cycles to crack initiation or until critical crack length is reached (Voigt *et al.*, 2003). Component design is applied to minimize the variation of tolerances to improve and control quality, cost, and cycle time of a product (Feng and Kusiak, 2000). Performance prediction is utilized to predict the performance based on varying input random variables such as material properties, loading, operational conditions etc. (Kong and Fangopol, 2005). Voigt and colleagues (2004) summarize many other applications where PDMs are applied to perform probabilistic analysis of structural/mechanical components and systems.

5. Existing Probabilistic Analysis Computational Software Tool

There are several software tools available that employ probabilistic methods to perform computational analyses. Among these, NESSUS (Numerical Evaluation of Stochastic Structures Under Stress) is considered to have one of the most powerful feature (Southwest Research Institute [SwRI], 2005). This feature includes its capability to efficiently compute probabilistic solutions to complex engineering problems.

The NESSUS software program performs probabilistic structural, reliability, and sensitivity analyses. This software program was developed by Southwest Research Institute (SwRI) for

National Aeronautics and Space Administration (NASA) under the research program of Probabilistic Structural Analysis Methods (PSAM) for Select Space Propulsion System Components (SwRI, 1995). It is a general-purpose structural analysis tool, which integrates various probabilistic and general purpose optimization algorithms to perform probabilistic structural analysis of engineered components and systems. It has been used in broad range of engineering problems to predict the probabilistic response and sensitivity of stochastic variables to improve reliability and robustness (Bast *et al.*, 2001; Riha *et al.*, 1999; Shah *et al.*, 1990).

The architecture of NESSUS is composed of three basic major modules: NESSUS/PRE, NESUSS/FEM, and NESSUS/FPI that form its core. The preprocessor, NESSUS/PRE allows input of statistical data such as mean, standard deviation and distribution type in order to perform probabilistic finite element analysis. The finite element code, NESSUS/FEM, is used to conduct structural analysis and evaluate the sensitivity of the primitive parameters. The NESSUS/FPI uses the database generated by NESSUS/FEM and extracts the data to develop a response or performance function. These modules are described further by Shiao *et al*. (1988) and Shiao and Chamis (1989). Finally, the response is described by a cumulative distribution function (CDF) or probability density function (PDF), which is acquired by running fast probability integrator (FPI) or conducting a Monte Carlo simulation study.

6. Approach to Probabilistic Analysis of Turbine Blades Creep Life

In order to conduct the probabilistic analysis of turbine blades, NESSUS and Excel were used to evaluate the distribution of parts and engine life with post processing of statistical results done using Minitab.

The construction of the probabilistic design study of the turbine blades stress rupture life analysis consisted of two loops -- an outer loop for generating random variables applicable to the engine and an inner loop for generating variables applicable to the blades. Although there are many parameters that affect the blades life, the ones considered for this study were material properties variations, metal temperature variations due to cooling and gas path conditions and stress variations due to manufacturing tolerances. For the engine loop, NESSUS was used to generate random variables such as hot gas temperature, coolant supply temperature (engine to engine), and coolant flow. For the blade loop, those random variables applicable to a blade were generated using Excel such as blade moment weight, coolant supply temperature (blade to blade), blade coolant flow, TBC conductivity, TBC thickness, and blade material properties.

6.1 Conversion of Probabilistic Model to NESSUS/Excel

The primary step in this project was to convert the probabilistic model to NESSUS code. This was done by inputting probabilistic creep life into NESSUS as a function of outer loop parameters and pressing “Apply” as shown in Fig. 4. This caused NESSUS to parse the problem and move all the dependent and independent variables in the declared random variables table.

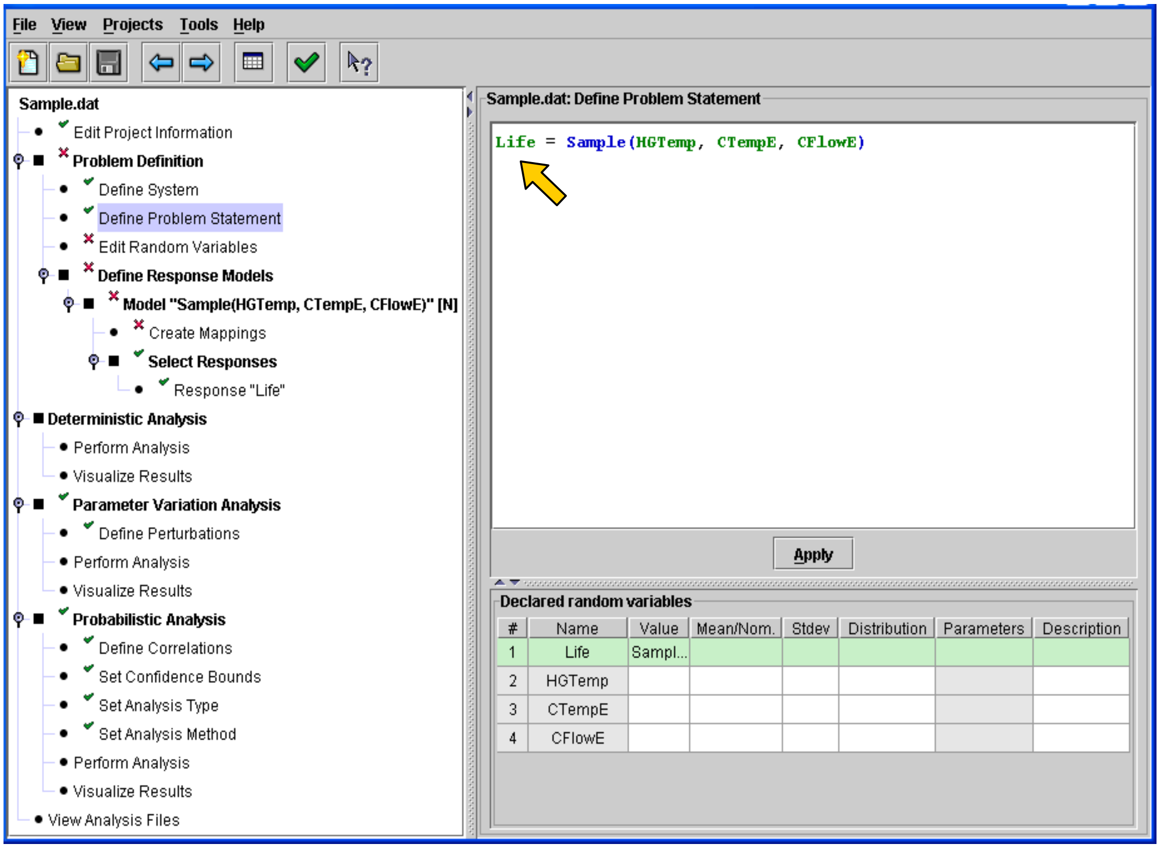


Figure 4. Defining problem statement in NESSUS.

6.2 Input of Statistical Data for Outer Loop Parameters

After defining the probabilistic creep life model in NESSUS, the statistical data such as mean, standard deviation, and distribution for each of the engine loop parameters were entered in NESSUS as shown in Fig. 5. Once the problem statement was defined and the statistical data was input for the stochastic variables, the next screen was to “Edit Random Variables”. In this screen, the different statistical distributions can be viewed and edited using the drop-down menu, as shown in Fig. 6. The different distributions available in NESSUS are Weibull, Normal, Lognormal, Chi Square (1-dof), etc.

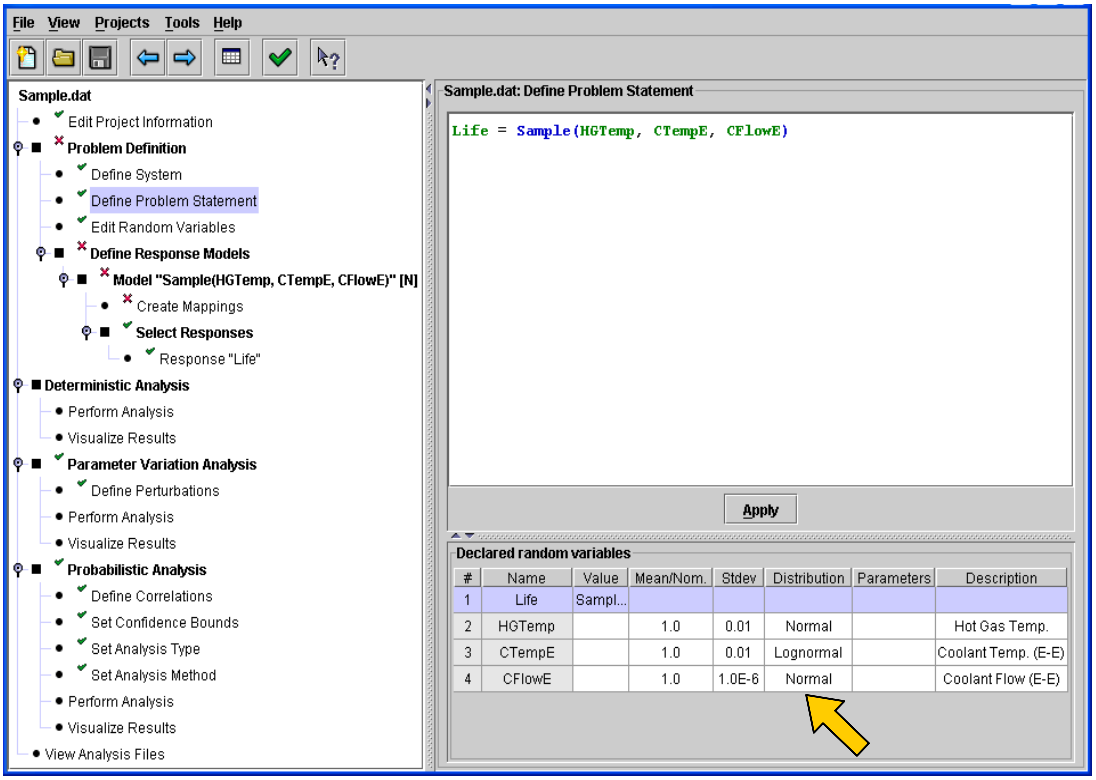


Figure 5. Input of statistical data in NESSUS.

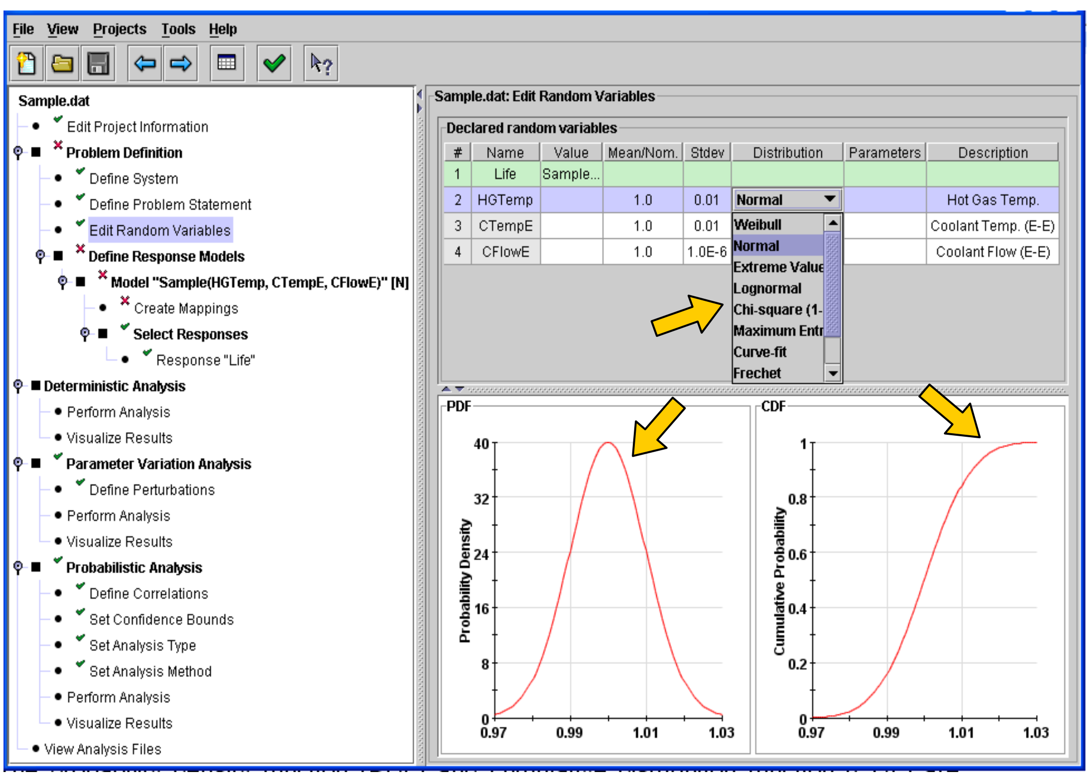


Figure 6. Editing statistical data in NESSUS.

The probability density function (PDF) and cumulative distribution function (CDF) are also shown for the selected random variables. Next, the batch mode was selected for the execution settings and each of the random variables were mapped using an input text file, refer to Fig. 7.

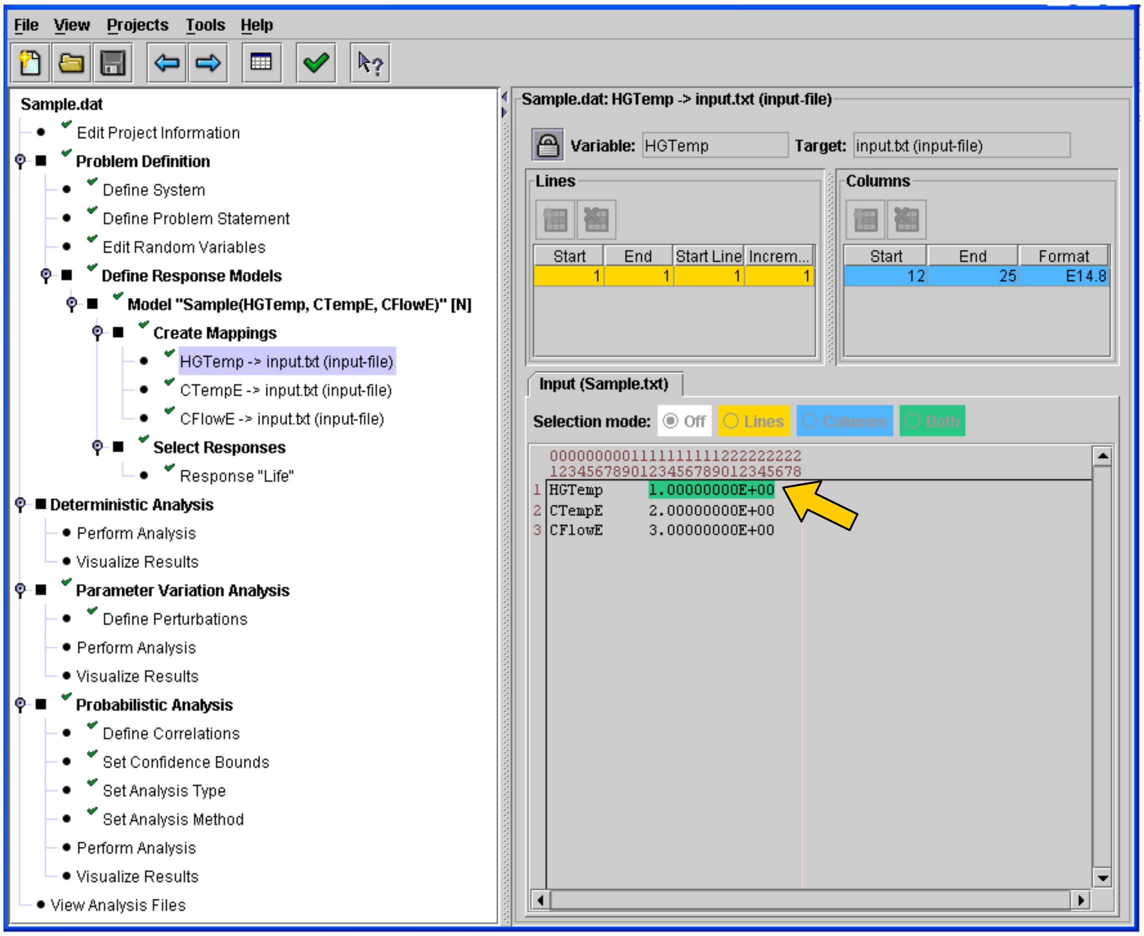


Figure 7. Creating mappings for random variables.

6.3 Generation of Outer Loop Parameters

After the mappings were created, Monte Carlo Simulation (MCS) was selected in the Set Analysis Method screen as shown in Fig. 8. The number of samples required for the probabilistic analysis was calculated using Eq. (1):

$$N_s = \frac{10}{P_f} \tag{1}$$

where N_s is the number of samples and P_f is the probability of failure. In order to evaluate the probability of failure of 1/1000 engines, the number of Monte Carlo samples required was 10,000.

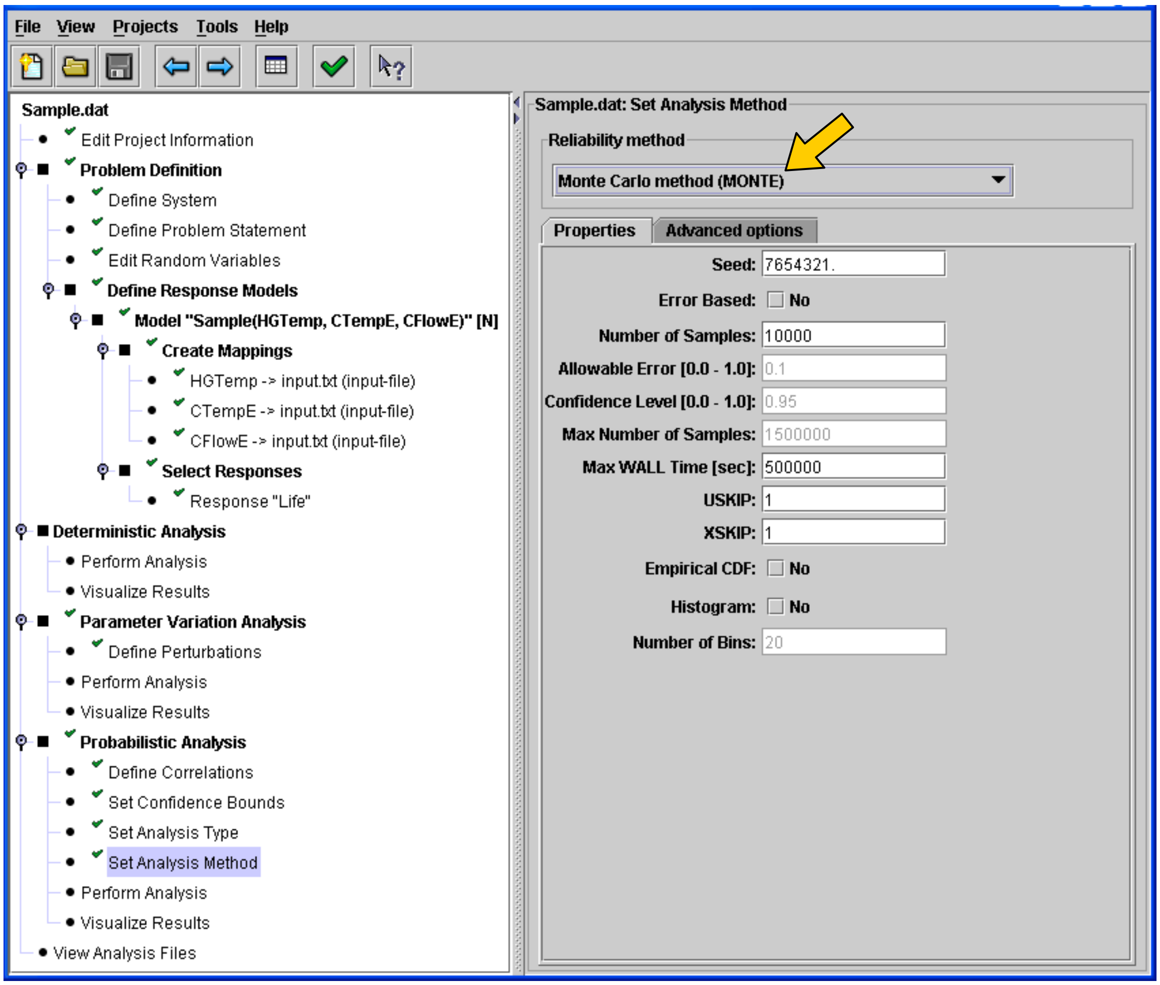


Figure 8. Selection of probabilistic analysis method.

Then, the Perform Analysis outline node under Probabilistic Analysis was selected. This displayed the NESSUS problem definition in a scrollable window, refer to Fig. 9. Finally, the samples of outer loop parameters (Hot Gas Temperature, Coolant Supply Temperature (engine to engine), and Coolant Flow (engine to engine)) were generated by pressing the "Run" button. These generated samples were automatically placed in a folder by NESSUS.

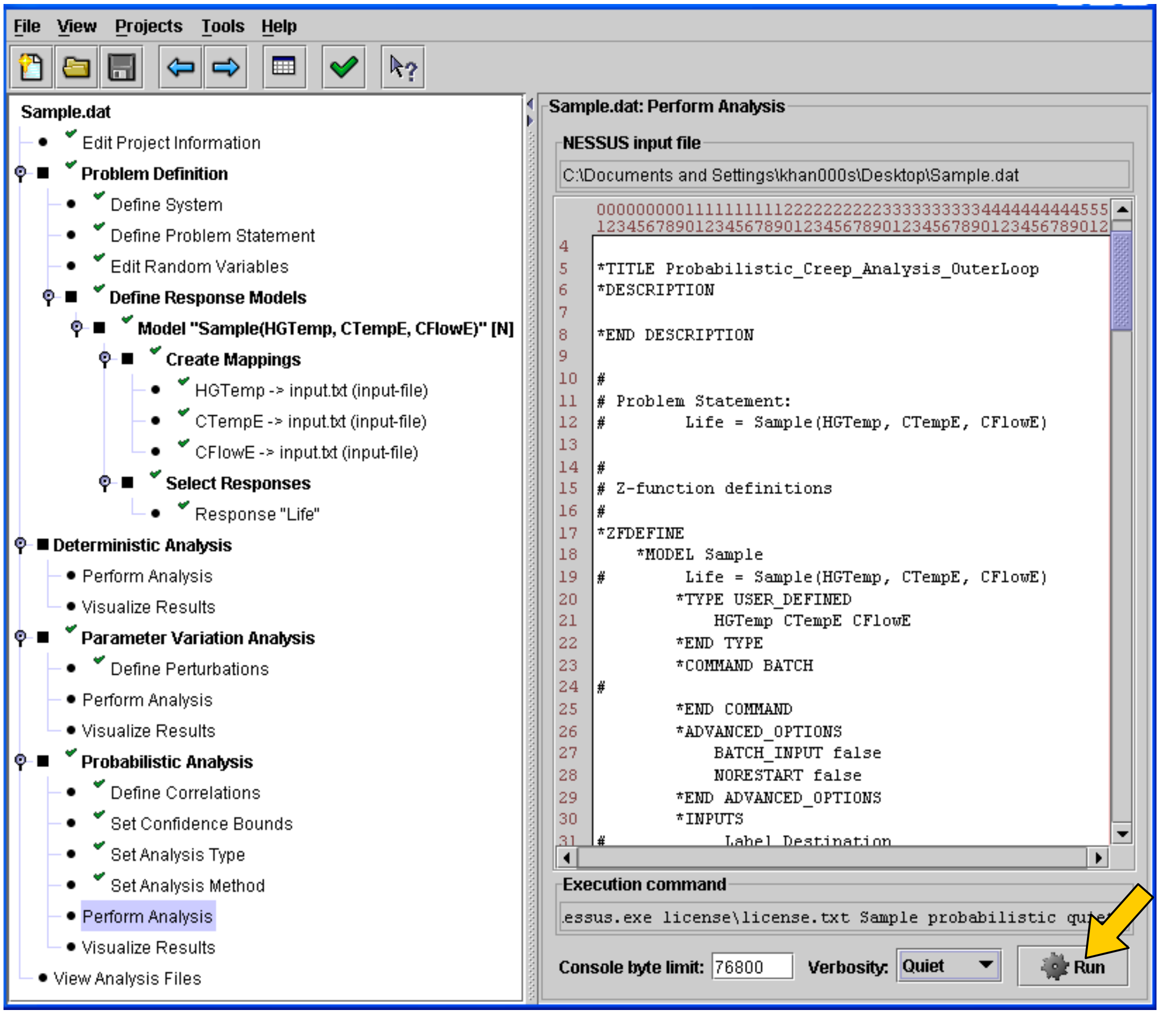


Figure 9. Running the analysis to generate outer loop samples.

6.4 Import Outer Loop Parameters to M.S. Excel

After all the outer loop samples were generated, a VBA (Visual Basic for Applications) code written in Excel was used to import these samples into an Excel sheet. This VBA code was executed by pressing the "Read Samples" button, see Fig. 10. Once the VBA code was executed, the samples of outer loop parameters generated by NESSUS were imported into Excel as shown in Fig. 11.

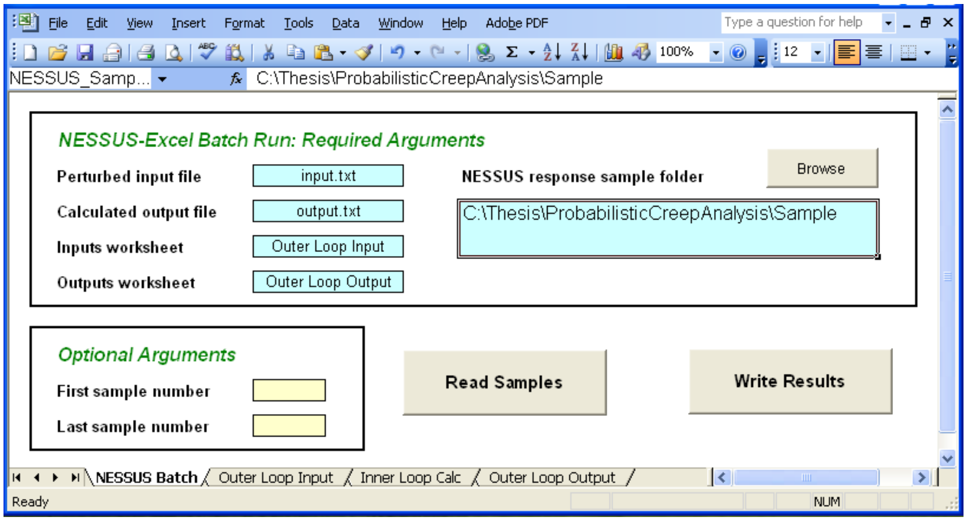
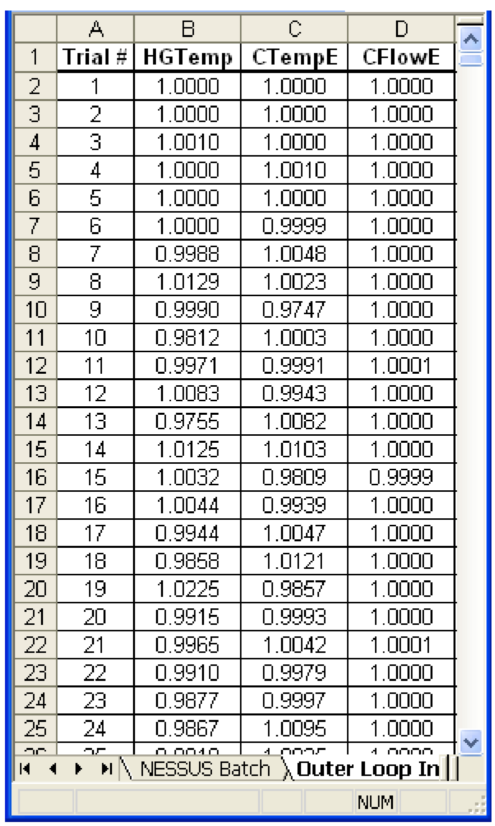


Figure 10. Snapshot of excel worksheet.

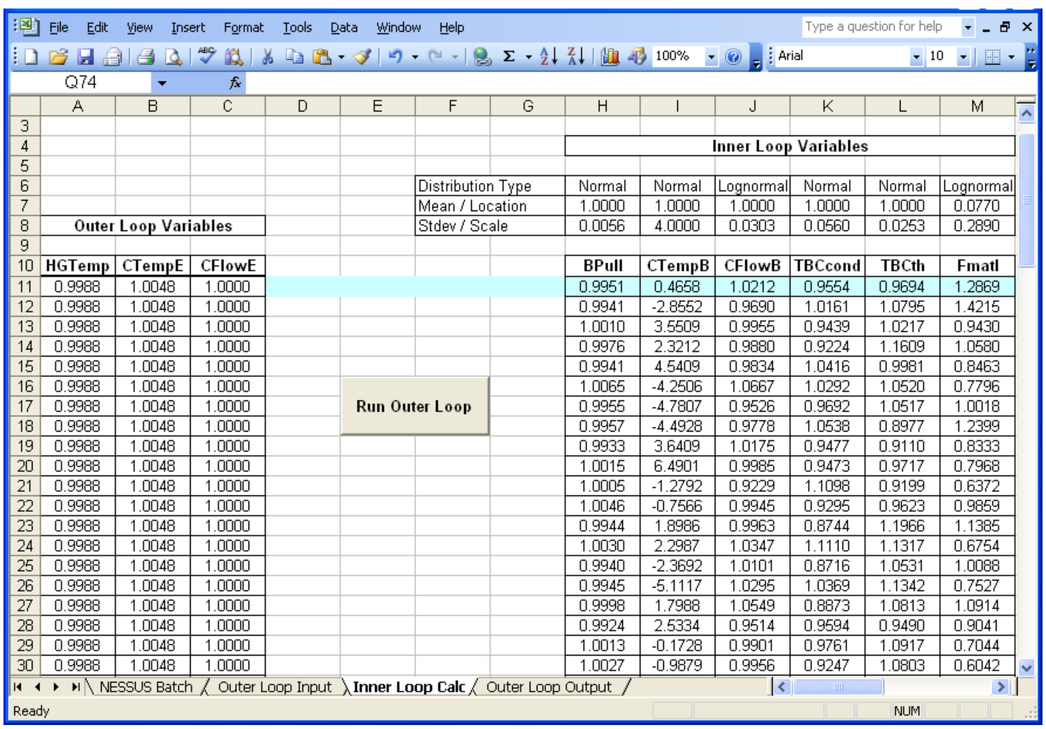


	A	B	C	D
1	Trial #	HGTemp	CTempE	CFlowE
2	1	1.0000	1.0000	1.0000
3	2	1.0000	1.0000	1.0000
4	3	1.0010	1.0000	1.0000
5	4	1.0000	1.0010	1.0000
6	5	1.0000	1.0000	1.0000
7	6	1.0000	0.9999	1.0000
8	7	0.9988	1.0048	1.0000
9	8	1.0129	1.0023	1.0000
10	9	0.9990	0.9747	1.0000
11	10	0.9812	1.0003	1.0000
12	11	0.9971	0.9991	1.0001
13	12	1.0083	0.9943	1.0000
14	13	0.9755	1.0082	1.0000
15	14	1.0125	1.0103	1.0000
16	15	1.0032	0.9809	0.9999
17	16	1.0044	0.9939	1.0000
18	17	0.9944	1.0047	1.0000
19	18	0.9858	1.0121	1.0000
20	19	1.0225	0.9857	1.0000
21	20	0.9915	0.9993	1.0000
22	21	0.9965	1.0042	1.0001
23	22	0.9910	0.9979	1.0000
24	23	0.9877	0.9997	1.0000
25	24	0.9867	1.0095	1.0000

Figure 11. Import outer loop samples in M.S. Excel.

6.5 Generation of Inner Loop Parameters

Then, the statistical data such as distribution type, mean/location, and standard deviation/scale for inner loop parameters were entered into M.S. Excel. All the inner loop parameters either had a Normal or Lognormal distribution; therefore, their samples were generated using the “NORMINV” or “LOGINV” formulas. The number of inner loop trials for each outer loop trial was set to be 101, which is equivalent to the number of blades present in the particular row of each engine being analyzed. The number of inner loop trials can be manually changed in Excel depending on the number of blades present in a row of an engine. In the setup of inner and outer loop parameters for each Monte Carlo Simulation, the outer loop parameters were held constant while the inner loop parameters vary, as shown in Fig. 12.



	A	B	C	D	E	F	G	H	I	J	K	L	M
3													
4								Inner Loop Variables					
5													
6						Distribution Type		Normal	Normal	Lognormal	Normal	Normal	Lognormal
7						Mean / Location		1.0000	1.0000	1.0000	1.0000	1.0000	0.0770
8	Outer Loop Variables					Stdev / Scale		0.0056	4.0000	0.0303	0.0560	0.0253	0.2890
9													
10	HGTemp	CTempE	CFlowE					BPull	CTempB	CFlowB	TBCcond	TBCth	Fmatl
11	0.9988	1.0048	1.0000					0.9951	0.4658	1.0212	0.9554	0.9694	1.2869
12	0.9988	1.0048	1.0000					0.9941	-2.8552	0.9690	1.0161	1.0795	1.4215
13	0.9988	1.0048	1.0000					1.0010	3.5509	0.9955	0.9439	1.0217	0.9430
14	0.9988	1.0048	1.0000					0.9976	2.3212	0.9880	0.9224	1.1609	1.0580
15	0.9988	1.0048	1.0000					0.9941	4.5409	0.9834	1.0416	0.9981	0.8463
16	0.9988	1.0048	1.0000					1.0065	-4.2506	1.0667	1.0292	1.0520	0.7796
17	0.9988	1.0048	1.0000		Run Outer Loop			0.9955	-4.7807	0.9526	0.9692	1.0517	1.0018
18	0.9988	1.0048	1.0000					0.9957	-4.4928	0.9778	1.0538	0.8977	1.2399
19	0.9988	1.0048	1.0000					0.9933	3.6409	1.0175	0.9477	0.9110	0.8333
20	0.9988	1.0048	1.0000					1.0015	6.4901	0.9985	0.9473	0.9717	0.7968
21	0.9988	1.0048	1.0000					1.0005	-1.2792	0.9229	1.1098	0.9199	0.6372
22	0.9988	1.0048	1.0000					1.0046	-0.7566	0.9945	0.9295	0.9623	0.9859
23	0.9988	1.0048	1.0000					0.9944	1.8986	0.9963	0.8744	1.1966	1.1385
24	0.9988	1.0048	1.0000					1.0030	2.2987	1.0347	1.1110	1.1317	0.6754
25	0.9988	1.0048	1.0000					0.9940	-2.3692	1.0101	0.8716	1.0531	1.0088
26	0.9988	1.0048	1.0000					0.9945	-5.1117	1.0295	1.0369	1.1342	0.7527
27	0.9988	1.0048	1.0000					0.9998	1.7988	1.0549	0.8873	1.0813	1.0914
28	0.9988	1.0048	1.0000					0.9924	2.5334	0.9514	0.9594	0.9490	0.9041
29	0.9988	1.0048	1.0000					1.0013	-0.1728	0.9901	0.9761	1.0917	0.7044
30	0.9988	1.0048	1.0000					1.0027	-0.9879	0.9956	0.9247	1.0803	0.6042

Figure 12. Setup of inner and outer loop samples in M.S. Excel.

7. Prediction of Blades Probabilistic Creep Life

For a full Monte Carlo simulation of each engine, the critical stress (σ_{sa}) and section average temperature (T_{sa}) were calculated. The critical stress was calculated as a function of rotor speed and blade moment weight. Blade section average temperature (T_{sa}) was calculated from the regression model as a function of hot gas temperature (HGTemp), coolant supply temperature (CTemp), coolant flow (CFlow), TBC conductivity (TBCcon), and TBC thickness (TBCth).

$$T_{sa} = f(HGTemp, CTemp, CFlow, TBCcon, TBCth) \tag{2}$$

The creep rupture life was then calculated from the critical stress and critical section average temperature using the combination of the Larson-Miller Parameter (LMP) and a sigmoidal function. The LMP is given as shown in Eq. (3):

$$LMP = (T) * (\log(t_r) + C) \tag{3}$$

where T is the test temperature measure in Kelvin, t_r is the time to rupture in hours, and C is the optimized constant. Generally, C is approximately 20 for Ni-base supperalloys. The sigmoidal function for stress was applied, e.g.,

$$\sigma(t) = \frac{1}{1 + e^{-t_r}} \tag{4}$$

It should be noted that Eq. (4) expresses a general type of sigmoidal function. The sigmoidal function employed for this study cannot be displayed due to confidential reasons. This function was then rearranged to solve for the creep rupture time, which is dependant on critical stress and critical section average temperature dependant coefficients. Finally, creep rupture life was multiplied by the material scatter factor to get the blade life. This was repeated for each blade in the disk. The minimum blade life for each engine was determined and this process was repeated for 10,000 engines. The entire process of performing the probabilistic analysis to predict stress rupture life of turbine blades is presented as a flowchart as shown in Fig. 13. The minimum blade life for each engine is used because the engine failure is assumed at the first blade failure. A distribution of minimums was generated and the major drivers in determining stress rupture life were evaluated.

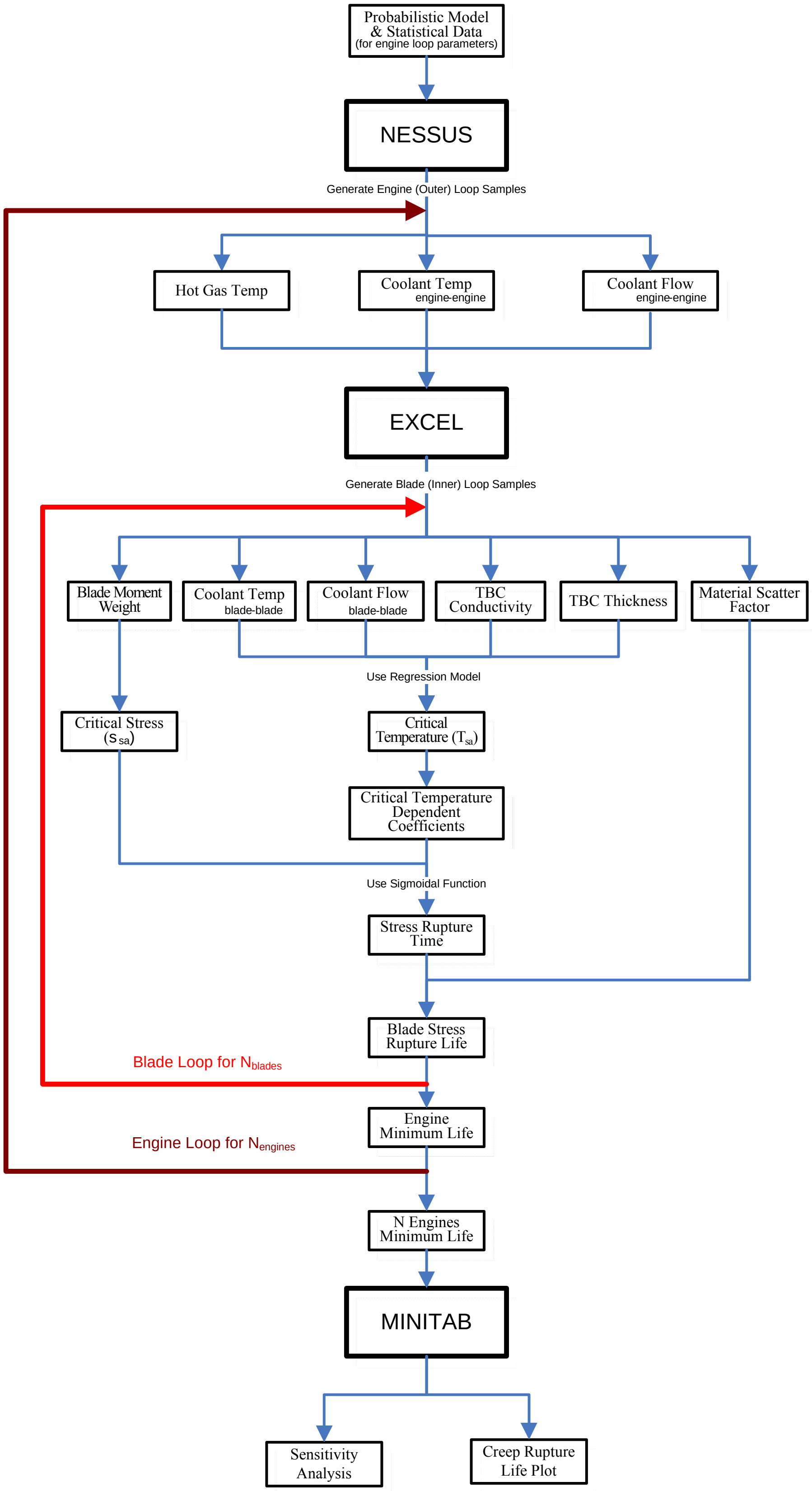
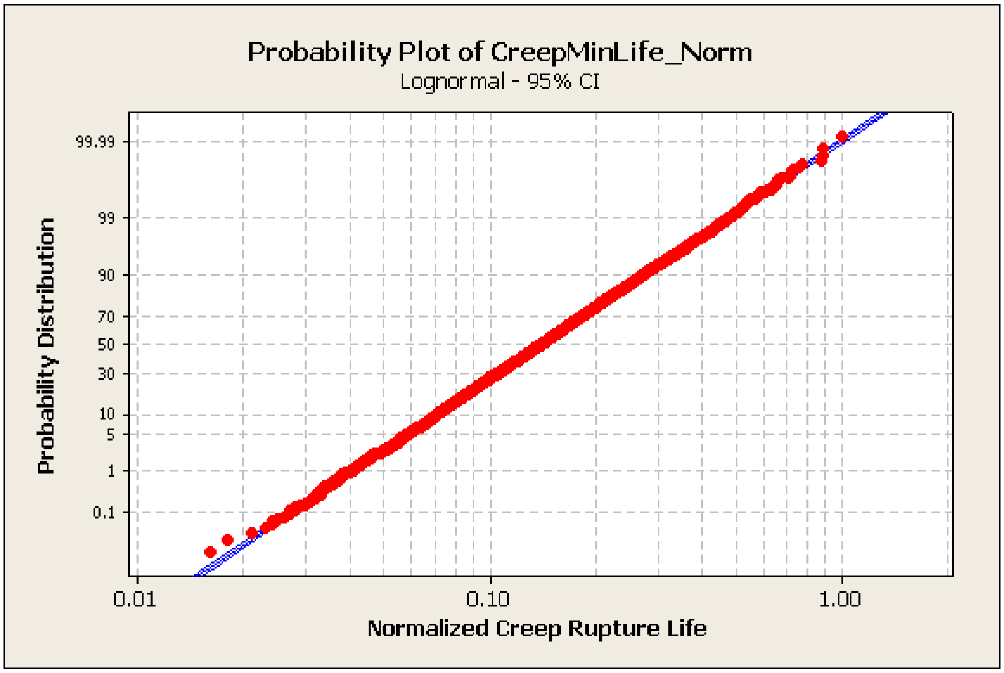


Figure 13. Probabilistic stress rupture life analysis flowchart.

8. Results

The probabilistic analysis of turbine blades stress rupture life has been completed. The normalized minimum of blades creep rupture life for 10,000 engines is shown in Fig. 14. This figure represents a single predicted blade failure in a fleet of 10,000 engines due to creep rupture. After calculating the minimum blade creep life, the sensitivity of input parameters to the blade creep rupture life was evaluated as shown in Fig. 15. This figure depicts that hot gas temperature has 2.5 times the effect as compared to TBC conductivity. In order to properly evaluate and compare the sensitivity of the input parameters, the standard deviation of each of the input parameters was doubled one at a time and the blade creep rupture lives were calculated. After carefully analyzing the effect of each of the input parameters, it was determined that hot gas temperature and material stress rupture scatter factor were the most sensitive parameters to the blade creep rupture life, on the other hand; blade moment weight, coolant temperature, and coolant flow were evaluated to be the least sensitive parameters. Combining the most sensitive parameters (hot gas temperature and material stress rupture scatter factor) has an effect of 63% on the blade creep life whereas the combined effect of all the least sensitive parameters (blade moment weight, coolant temperature, and coolant flow) has an effect of only 15%.



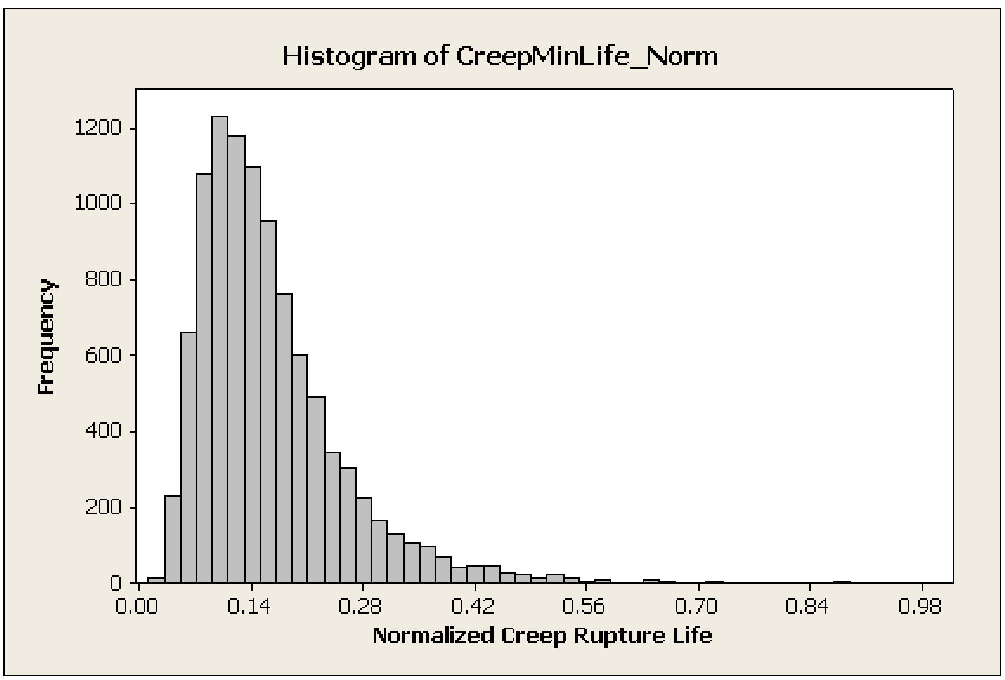


Figure 14. Distribution of the normalized minimum of blade creep rupture life.

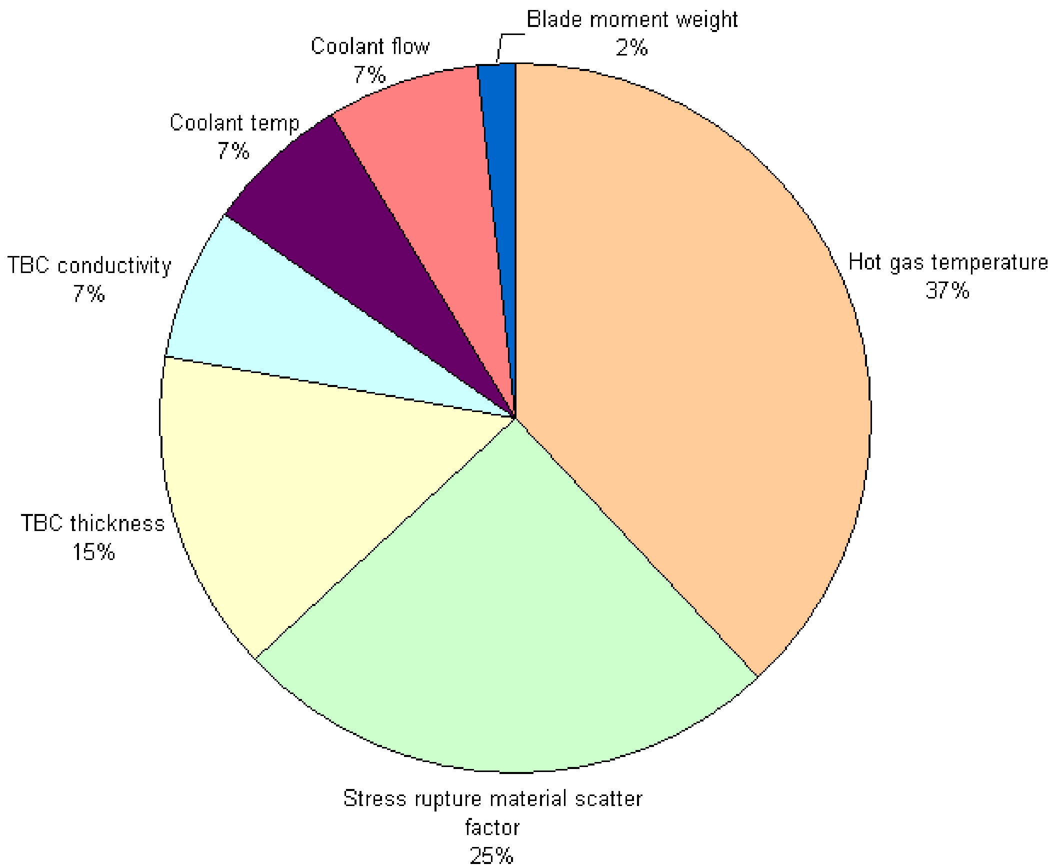


Figure 15. Sensitivities of stochastic variables with respect to creep rupture life.

9. Conclusions

Although performing probabilistic analysis using probabilistic design methods requires additional numerical effort, the probabilistic study has been determined to be very significant and valuable. After completing the probabilistic design study, the most sensitive parameters were determined and evaluated. The tolerances of these parameters can be restricted during manufacturing, to reduce their influence on the design. This can extend the life of the turbine blades and save millions of dollars that is spent each year in service and redesigning of these blades and turbine engines.

10. Future Work

Even though this study includes the most important parameters that affect the blade creep life, other parameters should also be considered for sensitivity analyses, such as: ambient temperature, percent load, etc. In order to perform a thorough sensitivity analysis the interaction between all the parameters should be considered. This analysis should be performed by varying multiple parameters simultaneously while evaluating the blade creep life. Also future studies can be performed to reassess the probability of failure of turbine blades using fast probabilistic design methods to reduce the computing time. The efficiency and accuracy of these methods can be evaluated by comparing the results obtained from these methods to the results obtained using Monte Carlo simulation. Finally, a cost/benefit analysis should be performed to evaluate the financial exposure to a blade failure relative to the cost of a blade redesign.

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