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NESSUS/EXPERT AND NESSUS/FPI IN THE PROBABILISTIC STRUCTURAL ANALYSIS METHODS (PSAM) PROGRAM

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NESSUS (Numerical Evaluation of Stochastic Structures under Stress) is the primary computer code being developed in the NASA PSAM project. It consists of four modules NESSUS/EXPERT, NESSUS/FPI, NESSUS/PRE and NESSUS/FEM. This presentation concentrates on EXPERT and FPI, while PRE and FEM are discussed in another presentation.

One challenge of the PSAM effort is the effective integration of advanced finite element and probabilistic methods. A code with linear static and dynamic capabilities has been provided to NASA. However, it is clear that, in the final version, the user must be provided with an interface program to effectively use features such as nonlinear analysis and confidence band estimation. Such an interface program will also expedite the process of conducting the analyses necessary for NESSUS verification.

To provide an effective interface between NESSUS and the user, an expert system module called NESSUS/EXPERT is being developed. That system uses the CLIPS artificial intelligence code developed at NASA-JSC. The code is compatible with FORTRAN, the standard language for codes in PSAM. The user interacts with the CLIPS inference engine, which is linked to the knowledge database as shown in Figure 1.

The essential features of EXPERT are its automated user input and automated results. The EXPERT module will provide the user with features such as interactive HELP, data set consistency checking, and defaults for the statistical models of random variables. EXPERT will also assist the analyst in managing the large database produced in perturbing the random variables. Such variables may include material properties, geometry, boundary conditions and loading. Because of the potentially large number of random variables, this process must be automated to free the analyst from basically a bookkeeping task. For analysis of certain critical SSME components, EXPERT will choose component specific perturbations. For example, in the case of a turbine blade shown in Figure 2, perturbations may be applied directly to parameters defining the blades geometry such as the twist and tilt angles and blade thickness.

The perturbation database generated by NESSUS/FEM and managed in EXPERT is used to develop the so-called response or performance model in the random variables. Figure 3 illustrates such a model in which natural frequency is a random function of material modulus. It is from this performance model that the probabilistic response is computed. Two independent probabilistic methods are available in PSAM for the computation of the probabilistic structural response. These are the Fast Probability Integration (FPI) method and Monte Carlo simulation. FPI is classified as an advanced reliability method and has been developed over the past ten years by researchers addressing the reliability of civil engineering structures. Monte Carlo is a well-established technique for computing probabilities by conducting a number of deterministic analyses with specified input distributional information.

For structural systems, the probability of failure is generally low. In such situations, Monte Carlo is inefficient since a large number of simulations are required to confidently predict low probability levels. The efficiency of FPI, on the other hand, is not tied to the probability level and can accurately predict the tails of the response distribution. However, Monte Carlo is still useful in PSAM to check the accuracy and robustness of the FPI algorithms. For a given performance function, FPI can compute point probability estimates or obtain full distributional information in terms of the cumulative probability distribution. In general, the performance function may be nonlinear in the random variables and contain mixed probability distribution types. Figure 4 qualitatively compares typical FPI and Monte Carlo results and illustrates the increasing inaccuracy in Monte Carlo at the low probability levels.

The process used by FPI to make the probability estimates may be considered a problem of constrained minimization. This is illustrated in Figure 5. Let us assume that material density and modulus of elasticity are random variables in an eigen-frequency analysis. The response function at a particular frequency is shown, with the lines of constant probability given by the circles. The design or most probable point is defined as the point with the highest joint distribution at a given value of the response function. The design point is geometrically located at the minimum distance β, called the safety index. In a first-order reliability analysis, β is related to the probability of exceeding the specified frequency.

The FPI algorithm uses an efficient iteration technique to converge to the most probable point. The first estimate of the design points uses the NESSUS-generated database at the mean state. From this initial guess, the automated algorithms in FPI use successive NESSUS perturbations at other points to converge to the design point as illustrated in Figure 6. Convergence is usually obtained in several (three to five) iterations. This procedure gives the probability of exceedence at a particular value of the response function. This is called a point probability estimate. Cumulative distributional information can be obtained by running FPI at several values of the response variables as shown on Figure 4.

In summary, the NESSUS/EXPERT and NESSUS/FPI modules provide the designer/analyst with computational methodologies and software for effectively and efficiently evaluating design sensitivities and uncertainties and quantifying the structural performance of SSME components.

EXPERT KNOWLEDGE WILL GOVERN USER INTERFACE

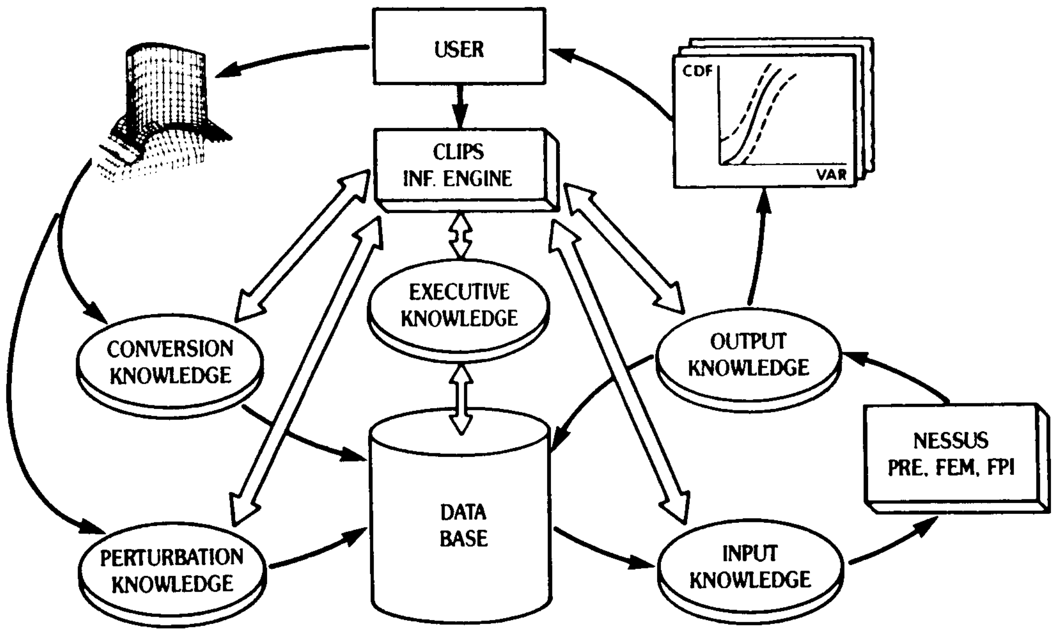
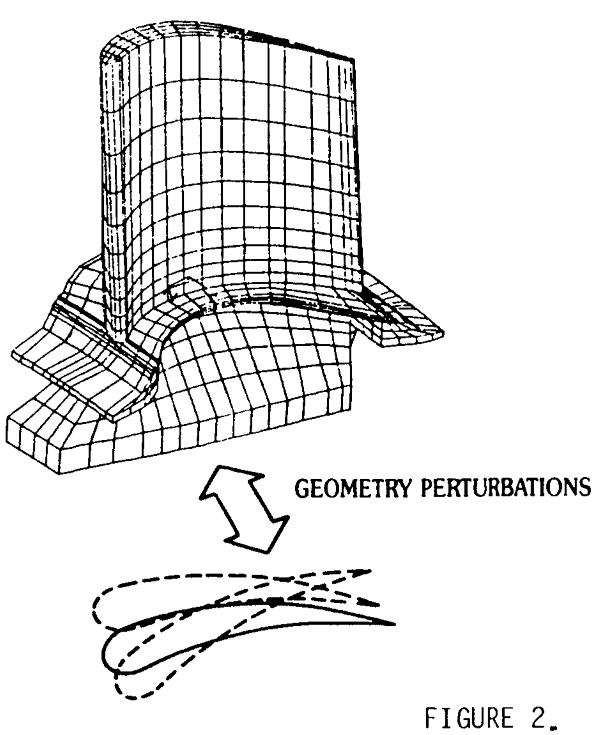


FIGURE 1.

NESSUS PERTURBATIONS TO BE AUTOMATED



MATERIAL PROPERTIES

- ANISOTROPIC CONSTANTS
- ANISOTROPIC ORIENTATIONS
- STRESS-STRAIN CURVES

GEOMETRY

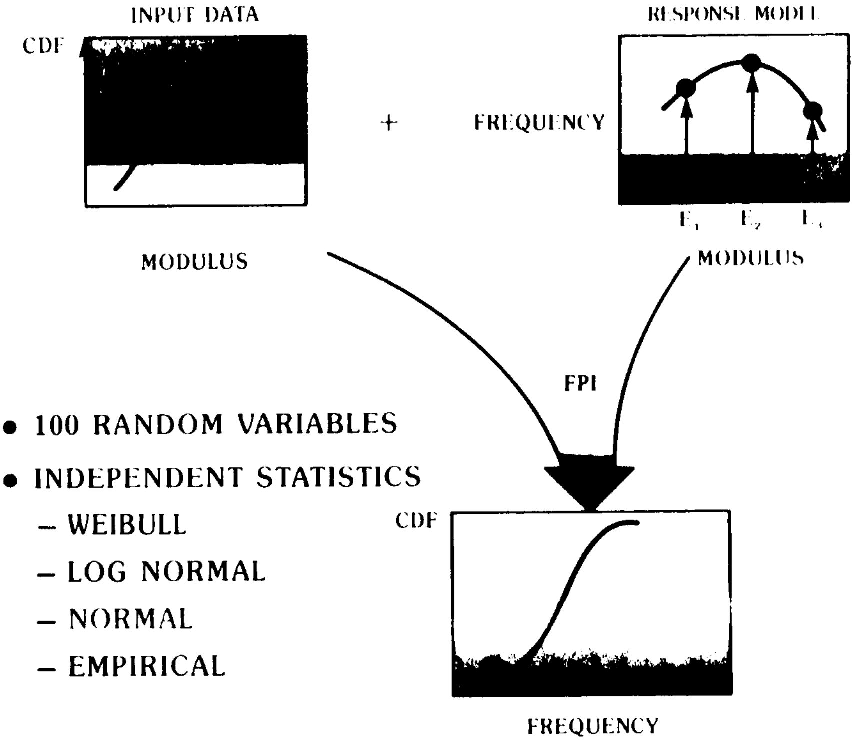
- TWIST
- TILT
- THICKNESS
- ETC.

BOUNDARY CONDITIONS

- LOADS
- CONSTRAINTS

FIGURE 2.

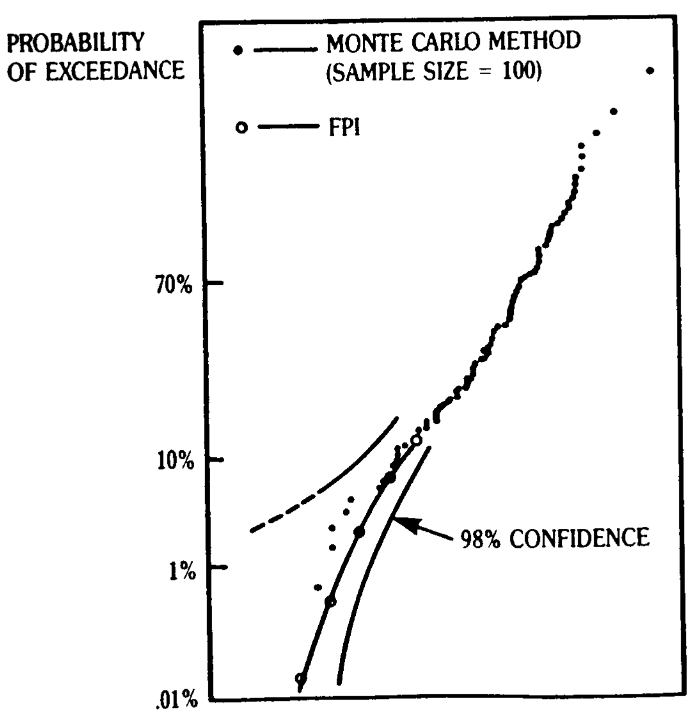
FPI CODE RELIES ON RESPONSE MODEL



- 100 RANDOM VARIABLES
- INDEPENDENT STATISTICS
  - WEIBULL
  - LOG NORMAL
  - NORMAL
  - EMPIRICAL

FIGURE 3.

FPI CODE VALIDATED BY MONTE CARLO

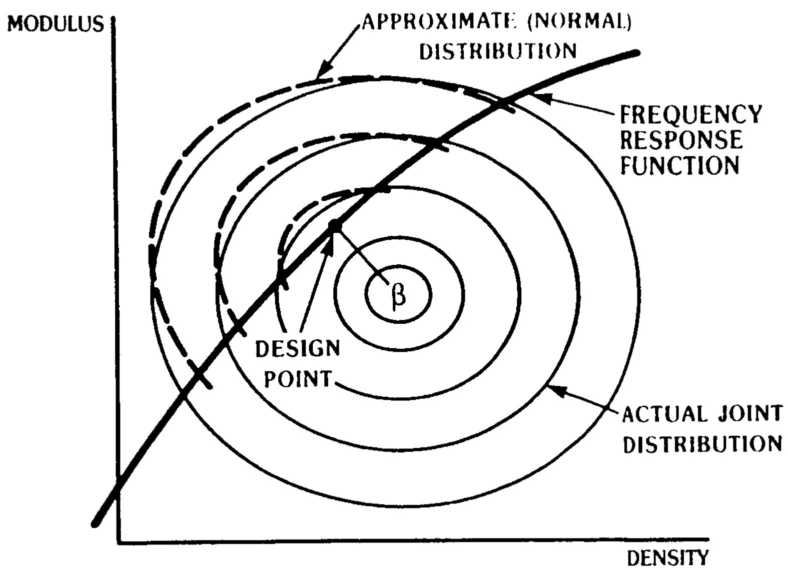


FPI ATTRIBUTES

- UP TO 100 TIMES FASTER THAN MC
- EFFICIENCY INDEPENDENT OF PROBABILITY LEVEL
- CAN USE LINEAR/QUADRATIC DESIGN SENSITIVITY DATA
- CAN BE COUPLED TO FEM
- USES ANY INPUT STATISTICS
- COMPUTES RISK LEVEL
- ESTIMATES CONFIDENCE BANDS

FIGURE 4.

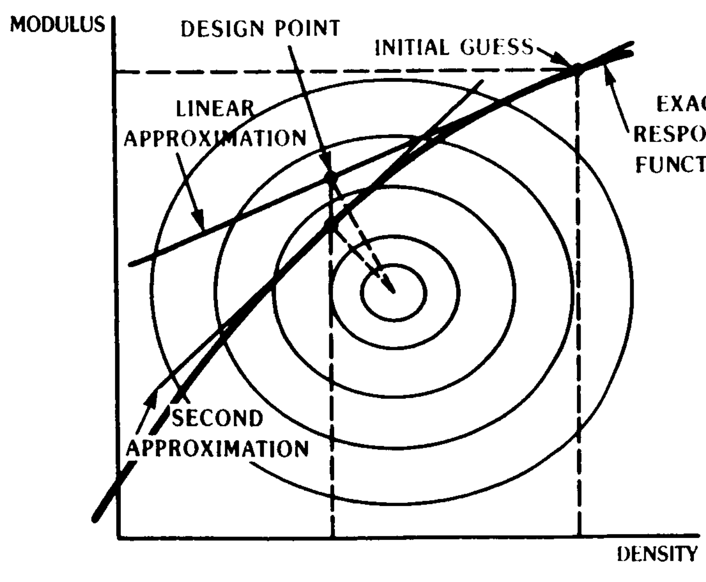
FPI ALGORITHM APPROXIMATES NONNORMAL VARIABLES



- APPROXIMATIONS BASED ON EQUAL CDF NEAR DESIGN POINT
- AREA OF EXCEEDANCE CALCULATED FOR EQUIVALENT NORMAL DISTRIBUTIONS
- ERRORS GREATEST AWAY FROM DESIGN POINT
- ERROR PROBABILITIES ARE SMALL
- PROBABILITY GIVEN FROM β DISTANCE

FIGURE 5.

FPI ALGORITHM ITERATES TO MAXIMUM LIKELIHOOD POINT



- ESTIMATE LINEAR RESPONSE FUNCTION
- CALCULATE MOST LIKELY DESIGN POINT
- SHIFT RESPONSE FUNCTION SURFACE
- RECOMPUTE DESIGN POINT

FIGURE 6.