DESIGN OF SMART COMPOSITE STRUCTURES IN THE PRESENCE OF UNCERTAINTIES

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ABSTRACT

A composite wing with spars, bulkheads and built-in control devices is evaluate and designed using a proposed methodology for smart composite structures. The proposed design methodology is probabilistic and accounts for all naturally-occurring uncertainties including those in constituent (fiber/matrix) material properties, fabrication variables, structure geometry and control related parameters. Probabilistic sensitivity factors are computed to identify those parameters that have the great influence on a specific structural reliability. Two performance criteria are used to demonstrate the design methodology. The first criterion requires that the actuated angle at the wing tip be bounded by upper and lower limits at a specified reliability. The second criterion requires that the probability of ply damage due to random impact load be smaller than an assigned value. The correlation between the sensitivity factors and reliability improvement is assessed. The results show that a reduction in the scatter of the random primitive variable with the highest sensitivity factor (absolute value) provides the lowest failure probability and vice versa. An increase in the mean of the primitive variable with the highest sensitivity factor provides the lowest failure probability and vice versa. Therefore, the design can be improved by controlling and adjusting parameters associated with random variables. This can be implemented during the manufacturing process to obtain the "maximum" benefit with minimum alterations.

Key Words: probability, hybrids, wing, sensitivities.

I. INTRODUCTION

Aerospace structures are complex assemblages of structural components that operate under severe and often "uncertain" service environments. These types of structures require durability, high reliability, light weight, high performance, and affordable cost. In order to meet these requirements, composite materials are attractive potential candidates. Composite materials possess outstanding mechanical properties with excellent fatigue strength and corrosion resistance. Their mechanical properties are derived from a wide variety of variables such as the constituent material properties and laminate characteristics (fiber and void volume ratios, ply orientation, and ply thickness). Those parameters are known to be statistical in nature (have a large scatter range).

In order to further enhance the structural performances for new challenges, other advanced concepts have been proposed. Recent developments in smart structure concepts by the use of actuation materials such as piezoelectric ceramics, show great potential to enhance the structural performances as well as durability/reliability (Wada, 1989) and (Song *et al.*, 1992). Fig. 1 depicts a conceptual diagram of a smart composite wing system. The essential parts of a smart composite structure include (1) a composite structure, (2) strategically located sensors, (3) signal processors which process the signals generated by the sensors, (4) dedicated computers with suitable hardware and software which continuously check the structural response magnitudes and compare them to predetermined acceptable "red line" values and provide desired corrections to the controller, (5) controller which signals the actuators to implement the desired corrections and (6) actuators.

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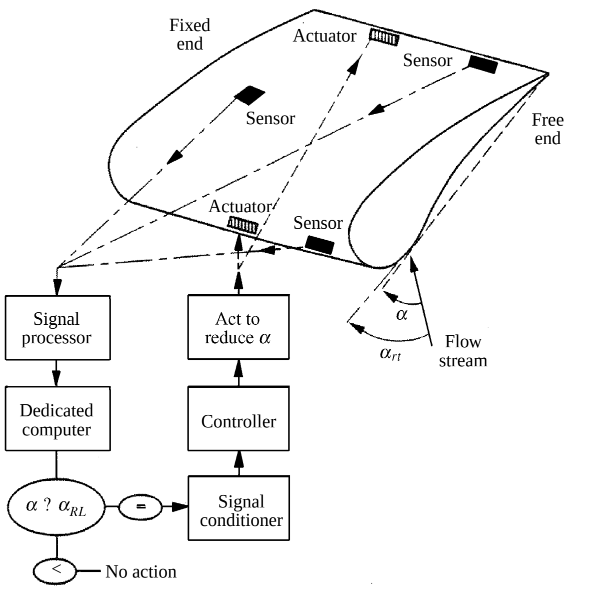

Fig. 1 Conceptual diagram of smart composite aircraft wing system

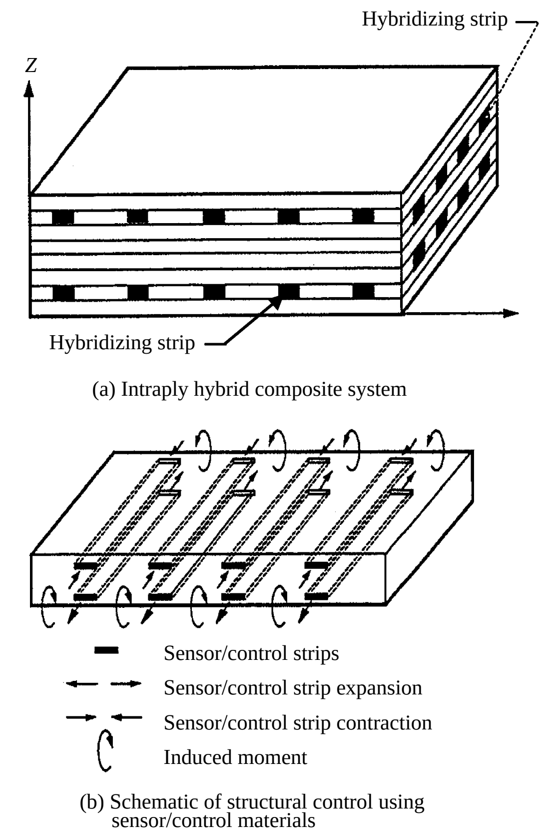

Fig. 2 Adaptation of intraply hybrid to smart composite system

The control devices in smart structures consist of: (1) a polarized material, (2) an electric field parallel to the direction of polarization, and (3) the expansion/contraction effects of the polarized material. When a control voltage is applied, the actuation material expands or contracts so that the structural behavior is altered by a desired amount and its reliability is enhanced. Present piezoelectric technology has been successfully applied to small-scale and low-stress structures. However, there are inevitable difficulties when current technology is applied to large-scale and high-stress composite structures. Those adversities can be alleviated if the special fibers such as piezoelectric fibers with fast actuation capability and the regular high-strength, high-modulus fiber are used together to form the smart intraply hybrid composites (Chamis and Sinclair, 1983). This concept can be readily integrated into a smart composite structure by using combinations of intraply and interply hybrid composites to ascertain that smart composite structures will operate in the design-specified range.

The adaptation of the intraply hybrid composite concept (Chamis and Sinclair, 1983) and (Murthy and Chamis, 1986) to smart composite structures is depicted schematically in Fig. 2. In Fig. 2(a), the intraply hybrid configuration is shown while in Fig. 2(b), its adaptation to smart composite structures is shown. It is observed in Fig. 2 that the smart composite consists of (1) regular plies which are made of traditional composite materials and (2) control plies which are made of regular strips of traditional composite materials and strips of mixed traditional and actuation materials. Actuators, made of actuation materials such as piezoelectric ceramics or piezoelectric fibers, are used to control the behavior of the composite structure by expanding or contracting the actuation strips to achieve the requisite design and operational goals. Because of the similarity between the thermal strain and the strain induced in the actuation materials, the actuation strains are simulated using thermal strains computed from a temperature field (representing the electric field strength) and thermal expansion coefficients (representing the actuation strain coefficients) (Shiao and Chamis, 1993). However, the strains induced by the actuator are affected by uncertainties in several factors that can only be quantified probabilistically. These include: (1) inaccurate measurements made by the sensors, (2) deviation from intended electric field, (3) uncertain actuation strain-electric field strength relationship, (4) uncertain material properties for the actuation materials, (5) uncertain electric field strength, and (6) improper location of the sensor/control materials. Because of these factors, the use of control devices increases the uncertainty in an already uncertain composite structural behavior.

In order to account for the various uncertainties and to satisfy the design requirements, knockdown (safety) factors are used extensively. These knockdown factors significantly reduce the design load of

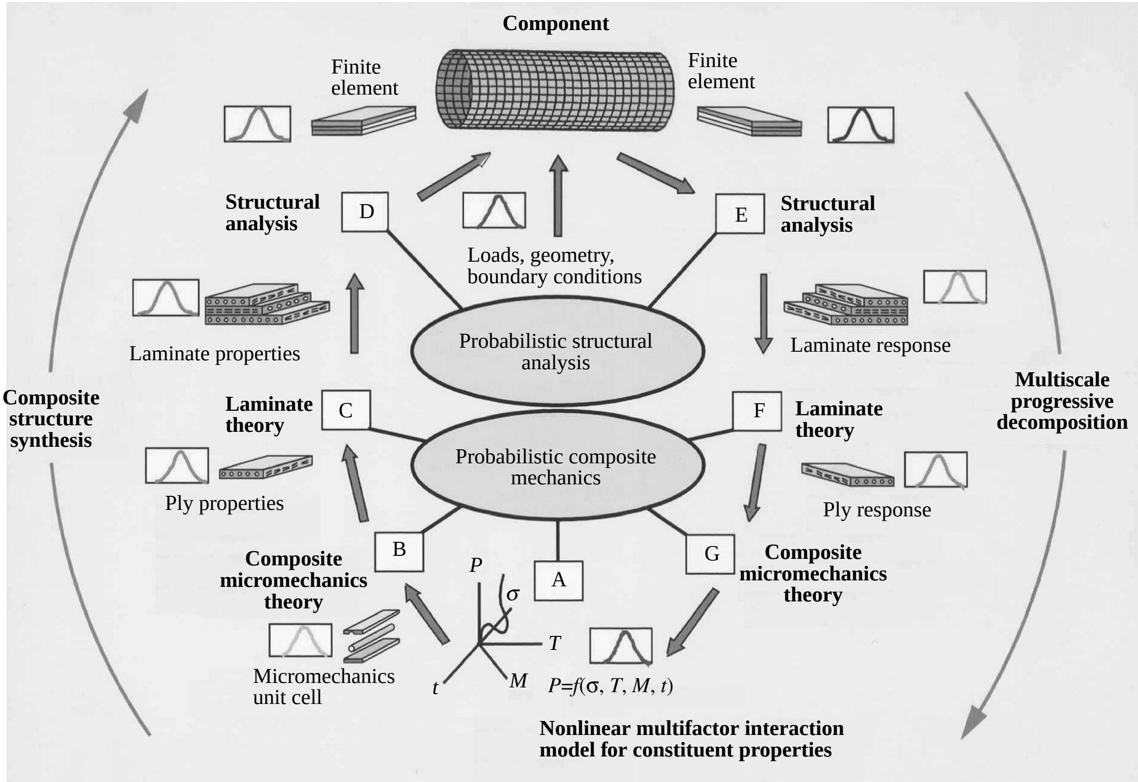

Fig. 3 Concept of probabilistic assessment of composite structures

composite structures which result in substantial weight increase, but without a quantifiable measure of their reliability. In this paper, an alternative approach based on probabilistic methods is described for a comprehensive probabilistic design assessment of smart composite structures. Note that primitive and random variables are used interchangeably herein.

II. PROBABILISTIC DESIGN USING IPACS COMPUTER CODE

The IPACS Computer Code (Chamis and Shiao, 1992) has evolved from extensive research activities at NASA Glenn to develop probabilistic structural analysis methods (Chamis, 1986) and computational composite mechanics (Chamis and Sinclair, 1983). The composite micromechanics, macromechanics and laminate theory (including interply and intraply hybrids) are embodied in ICAN (Chamis and Sinclair, 1983). IPACS consists of two stand-alone computer modules: PICAN and NESSUS. PICAN is used to simulate probabilistic composite mechanics (Mase, *et al*., 1991). NESSUS uses the information from PICAN to simulate probabilistic structural responses (Anonymous, 1991, Southwest Research Institute). A block diagram of IPACS is shown in Fig. 3. Direct coupling of these two modules makes it possible to simulate the uncertainties in all inherent scales of the composite - from constituent materials to the composite structure including its boundary and loading conditions, as well as environmental effects. It is worth to note here that special algorithms (Wu *et al*., 1985) are used instead of the conventional Monte Carlo simulation, to achieve substantial computational efficiencies which are acceptable for practical applications. Therefore, a probabilistic composite structural analysis becomes feasible which can not be done traditionally, especially for composite structures which have a large number of uncertain variables.

The first step for the probabilistic assessment of smart composite structures is to identify the uncertain primitive variables at all composite levels, as well as, control-related random variables. These variables are then selectively perturbed several times to create a database for the determination of the relationship between the desired structural response (or the desired material property) and the primitive variables. For every given perturbed primitive variable, micromechanics is applied to determine to corresponding perturbed mechanical properties at the ply and laminate level. Laminate theory is then used to determine the perturbed resultant force/moment-strain/curvature relationships. With this relationship at the laminate level, a finite element perturbation analysis is performed to determine the perturbed structural responses corresponding to the selectively perturbed primitive variables. This process is repeated until enough data is generated to enable the appropriate relationship between structural responses and primitive variables to be determined through a computational procedure.

Knowing probabilistic distributions of the primitive variables and a computationally determined relationship between the structural response and the primitive variables, Fast Probability Integration (FPI) (Wu *et al*., 1985) is applied. The output information from FPI for a given structural response includes the parameters for a special type of probability distribution function, reliability for a design criterion, and the probabilistic sensitivity factors of the primitive variables to the structural response and structural reliability (Singhal *et al*., 1994).

The commonly used sensitivity in a deterministic analysis is the performance sensitivity, $\partial Z/\partial x_i$, which measures the change in the performance Z due to the change in a design parameter x_j. This concept is extended to the probabilistic analysis to define the probabilistic sensitivity which measures the change in the reliability relative to the change in each random variable. The failure probability for a given performance is defined in Eq. (1) (Madsen *et al*., 1986).

$$P_f = \Phi(-\beta) \tag{1}$$

where β is the reliability index; ϕ is the cumulative distribution function of a normally distributed random variable. Probabilistic sensitivity factor (SF_j) for i^{th} random variable is defined in Eq. (2).

$$SF_i = \frac{\partial \beta}{\partial x_i} = \frac{U_j^*}{\beta} \tag{2}$$

where U^* is the most probable failure point of a limit state function in a unit normal probability space. These factors provide quantifiable information on which "design parameters" the reliability is most sensitive to. Subsequently, these design parameters can be manufacturing controlled and adjusted to obtain the "best" benefit with minimum alteration.

The next step is to extract useful information from the output of the simulation and to check against probabilistic design criteria. If target reliability is not satisfied, redesign is guided by adjusting or controlling parameters associated with the primitive variables which significantly influence the design reliability. For example, the change in β due to a change in the mean of random variable x_j (δm_j) can be represented by Eq. (3) (Madsen *et al*., 1986).

$$\delta_\beta = \frac{SF_j}{\sigma_i}\delta_{mi} \tag{3}$$

Similarly, the change in β due to a change in the standard deviation of i^{th} random variable x_j ($\delta\sigma$) can be computed from Eq. (4).

$$\delta_\beta = \frac{SF_j U_j^*}{\sigma_i} \tag{4}$$

With this information, alterations can be made to improve the structural reliability as to be demonstrated later (Shiao *et al*., 1995).

III. DEMONSTRATION FOR A SMART COMPOSITE WING

The probabilistic design assessment of a smart composite structure is demonstrated by evaluating a smart composite wing. The optimum exact deformed shape of a wing is a function of the particular flight condition. With smart structure concepts, proper deformation change can be obtained from flight condition to flight condition. To achieve these desirable geometries at required accuracy, the changes have to be inducible within an acceptable range. The feasibility of the desired magnitude of the change and the degree of their expected probabilistic inaccuracies have been studied here with simplification from what a practical system would have to be. The geometry of the composite wing internal structure is shown in Fig. 4(a). The wing is loaded with nonuniform pressure which varies from root to tip and from leading edge to trailing edge as shown in Fig. 4(b). The pressure is assumed to be deterministic in this study while it was assumed to be a random variable in (Shiao and Murthy, 1992).

The composite configurations for the skin, spars and bulkheads are $[\pm45/0/90_2/0/\pm45]_8$, $[0_8]$ and $[0_8]$ respectively. The 45° plies are selected to be control plies. In each control ply, both control (hybridizing actuation) and traditional strips exist. However, in this paper, control strip is assigned through out the control ply for computational simplicity. In each control ply, the secondary composite system volume ratio is used to define the percentage of volume for the control device. The percentage of the actuation materials in a secondary composite system is denoted by an actuation fiber (control) volume ratio. The constituent materials properties for traditional plies, their assumed probabilistic distribution and coefficient of variations (representing range of the scatter) are summarized in Table 1. The corresponding fabrication variables used to make the smart composite wing are summarized in Table 2. Since actuation materials are more expensive than traditional

Table 1 The ststistics of fiber and matrix properties for graphite-epoxy composite

Property symbols	unit	Distribution type	Mean	Coefficient of variation
E_{f11}	Msi	Normal	31.0	0.05
E_{f22}	Msi	Normal	2.0	0.05
G_{f12}	Msi	Normal	2.0	0.05
G_{f23}	Msi	Normal	1.0	0.05
v_{f12}	-----	Normal	0.2	0.05
v_{f23}	-----	Normal	0.25	0.05
E_m	Msi	Normal	0.5	0.05
G_m	Msi	Normal	0.185	0.05
v_m	-----	Normal	0.35	0.05
S_{fT}	Ksi	Lognormal	400.0	0.05
S_{fC}	Ksi	Lognormal	400.0	0.05
S_{mT}	Ksi	Lognormal	15.0	0.05
S_{mC}	Ksi	Lognormal	35.0	0.05
S_{mS}	Ksi	Lognormal	15.0	0.05

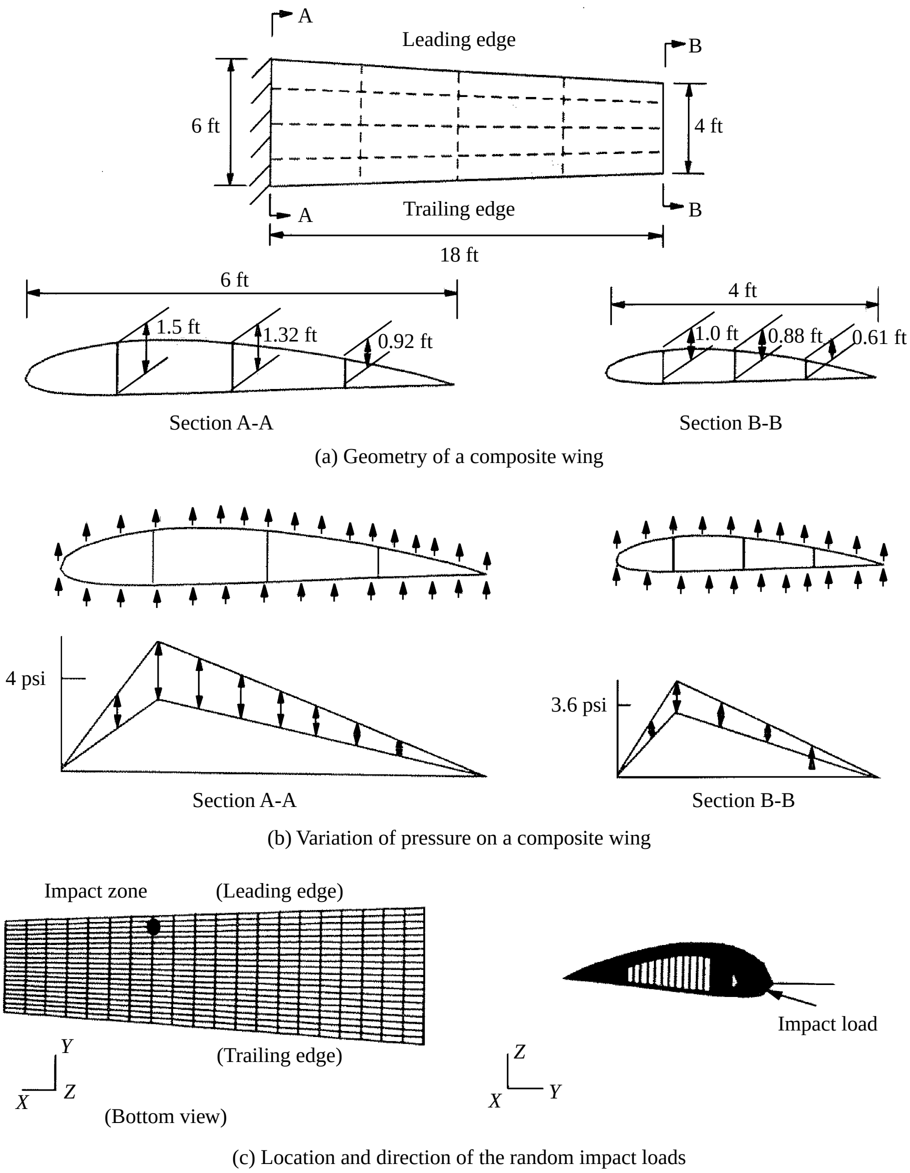

Fig. 4 Geometry and loads for composite wing

Table 2 The statistics of fabrication variables

Property symbols	unit	Distribution type	Mean	Coefficient of variation
Fiber volume ratio	-----	Normal	31.0	0.05
Void volume ratio	-----	Normal	2.0	0.05
Ply misalignment angle	deg.	Normal	0.0	1*
Ply thickness (regular skin)	in	Normal	0.015	0.05
Ply thickness (stringer/frame)	in	Normal	0.090	0.02
Ply thickness (control ply)	in	Normal	0.060	0.025

*standard deviation

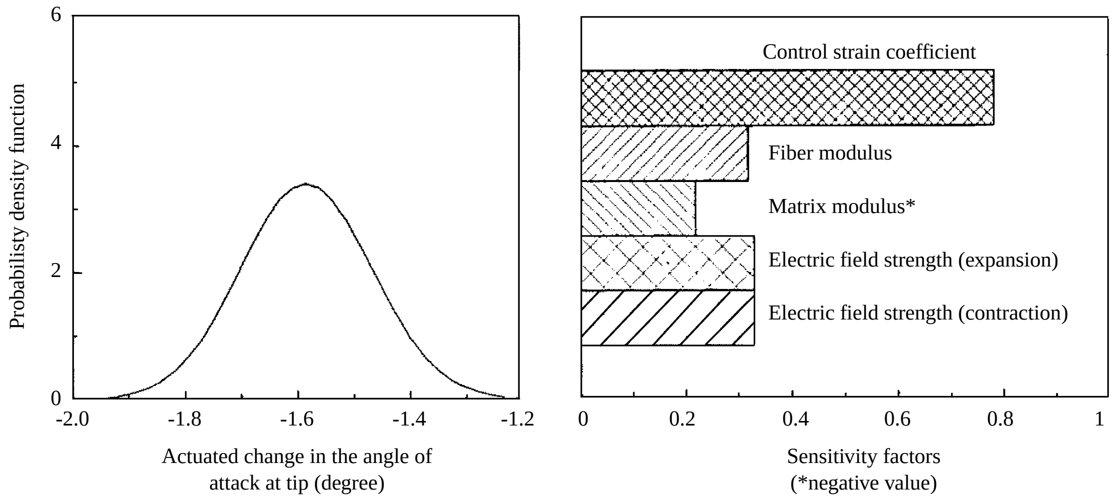

Fig. 5 Probability density function of actuated change in the angle of attack and sensitivity factors at 0.999 probability

materials, control volume ratio should be determined such that total cost for a smart composite structure be minimized and subjected to multi-design constraints. Constraints include (1) those typical for traditional composite structural designs, and (2) those for actuation materials due to their particular material characteristics such as strain, stress, applied voltage requirements, etc. Optimization is not considered herein. The emphasis is on the demonstration of the probabilistic design assessment of smart composite structures using intraply hybrid composites with actuation materials (Chamis, 1996).

In the following, the change in the angle of attack due to control and the ply damage due to random impact loads are probabilistic evaluated. Sensitivity factors which indicate the relative contribution of the uncertain variables to failure probability are determined. The correlation between the sensitivity factors and reliability improvement is investigated. A design is performed by varying the parameters associated with random variable distributions (such as the mean and the standard deviation) and is guided by the sensitivity information as discussed later (Shiao, *et al*., 1995).

1. Change in the Angle of Attack Due to Control

The uncertainty in the change of the angle of attack due to control using actuation materials is evaluated as the scatter from a reference position. The probability density function for the actuated change in the angle of attack at wing tip is shown in Fig. 5. Also shown in Fig. 5 are the sensitivity factors at 0.999 probability. In the following, failure probability for two performance criteria is computed. The first criterion requires the change in the angle of attack due to control at wing tip be less than -1.3 degree (upper bound). The second one requires the

Table 3 The statistics of control related variables

Property symbols	Unit	Distribution type	Mean	Coefficient of variation
Control strain coefficient	in/Volt	Normal	10^{-8}	0.05
Electric field strength	Volt/in	Normal	10^{5}	0.05

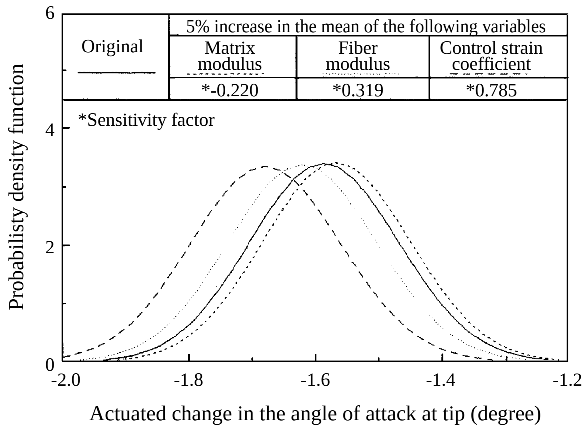

Fig. 6 Probability density function of actuated change in the angle of attack with 5% increase in the mean of one random variable

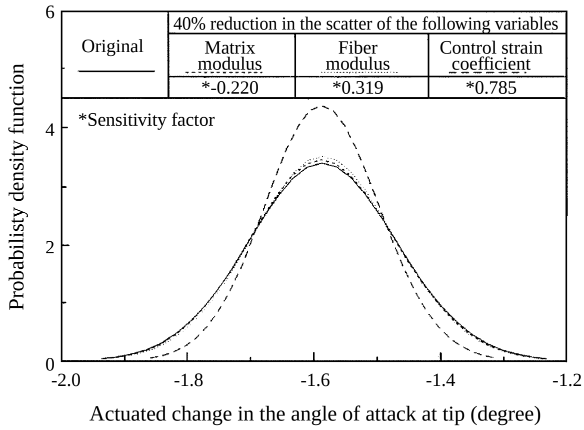

Fig. 7 Probability density function of actuated change in the angle of attack with 40% reduction in the scatter of one random variable

change in the angle of attack be greater than -1.8 degree (lower bound). The probability density function of the actuated angle due to a change in the parameter (mean or standard deviation) of a given random variable is computed.

The results are discussed as follows: The probability density function of the actuated angle for an increase in the mean of a given random variable is shown in Fig. 6. The mean value of the actuated angle due to a 5% increase in the mean value of a random variable with a positive (or negative) sensitivity factor shifts to the left (or right) while scatter remains the same. It indicates that the reliability for upper bound criterion can be improved by increasing the mean of the random variable with a positive sensitivity factor. However, the reliability for lower bound criterion is decreasing with the same arrangement. The probability density function of the actuated angle for a 40% reduction in the scatter of a given random variable is shown in Fig. 7. The mean response (change in the angle of attack) remains the same. The scatter of the response is reduced most with a 40% reduction in the scatter of the random variable with largest sensitivity factor. Also, a reduction in the scatter of any random variable always improves the reliability for both bounds. In the following, the mean values of control strain coefficient, fiber and matrix modules of control ply are increased by 5% for reliability improvement. Another study is conducted by reducing 40% of the standard deviation of the same random variables.

(i) Upper Bound for the Change in the Angle of Attack Due to Control

The failure probability for this performance requirement is 0.0075 (reliability index β=2.430). For a 5% increase in the mean or a 40% reduction in the scatter for each random variable, the change in the reliability index β estimated using sensitivity information is shown in Table 4. As indicated in the table, control strain coefficient has highest sensitivity factor (0.785), followed by fiber modulus and matrix modulus of the control ply (0.319, -0.220 respectively). Note that the sensitivity factor for matrix modulus is negative. It means that an increase in the mean of matrix modulus will decrease the reliability (due to a reduction in β). The reliability index for each case is also calculated via IPACS as shown in Table 5. It is found that estimated and calculated β agrees very well. The results show that a reduction in the scatter of a random variable always increases the reliability index (a reduction in failure probability). However, an increase in the mean of a random variable may result in a reduction in the reliability if the sensitivity factor is negative. Based on the information in Table 4, a designer can easily set up a strategy to improve the reliability without

Table 4 Estimated β for the upper bound criterion of the change in the angle of attack and sensitivity factors with manufacturing controlled random variables

Random variables being controlled (actuation material)	Sensitivity factor	5% increase in the mean		40% Decrease in the scatter	
		$\Delta\beta$	β	$\Delta\beta$	β
Matrix modulus	-0.220	-0.220	2.210	0.047	2.477
Fiber modulus	0.319	0.319	2.749	0.099	2.529
Control strain coefficient	0.785	0.785	3.215	0.599	3.029

$P_f = \Phi(-\beta)$

Table 5 Calculated β for the upper bound criterion of the change in the angle of attack and sensitivity factors with manufacturing controlled random variables

Random variables being controlled (actuation material)	Sensitivity factor	5% increase in the mean		40% Decrease in the scatter	
		β	P_f	β	P_f
Matrix modulus	-0.220	2.343	0.0095	2.469	0.0068
Fiber modulus	0.319	2.782	0.0027	2.513	0.0060
Control strain coefficient	0.785	3.230	0.0006	3.125	0.0009
Original		2.430	0.0075	2.430	0.0075

$P_f = \Phi(-\beta)$

Table 6 Estimated β for the lower bound criterion of the change in the angle of attack and sensitivity factors with manufacturing controlled random variables

Random variables being controlled (actuation material)	Sensitivity factor	5% increase in the mean		40% Decrease in the scatter	
		$\Delta\beta$	β	$\Delta\beta$	β
Matrix modulus	0.220	0.220	2.920	0.054	2.754
Fiber modulus	-0.319	-0.319	2.381	0.110	2.810
Control strain coefficient	-0.785	-0.785	1.915	0.667	3.367

$P_f = \Phi(-\beta)$

extensive analyses. In this particular example, one should increase the mean of the control strain coefficient by 5%, followed by a reduction in the scatter of the same variable by 40%, etc. This procedure is continued until the target reliability is met with minimum alterations in the design.

(ii) Lower Bound for the Change in the Angle of Attack Due to Control

The failure probability for this performance requirements 0.0034 (reliability index β=2.70). As indicated in the table, control strain coefficient has highest (absolute value) sensitivity factor (-0.785), followed by fiber modulus and matrix modulus of control ply (-0.319, 0.220 respectively). Notice that the sign of sensitivities is opposite to those for upper bound. Therefore, an increase in the mean of matrix modulus will increase the reliability. For a 5% increase in the mean or a 40% reduction in the scatter for each random variable, the change in the reliability index β estimated using sensitivity information is shown in Table 6. The reliability index for each case is also calculated via IPACS as shown in Table 7. Again, the estimated and calculated β agrees very well. As shown before, a reduction in the scatter of a random variable always increases the reliability index. However, an increase in the mean of random variables such as fiber volume ratio or control strain coefficient which have negative sensitivity factors will result in a reduction in the reliability. To improve the reliability for this case, one should reduce 40% of the scatter of control strain coefficient, and then increase the mean of the matrix modulus by 5%, followed by a reduction in the scatter of the same variable by 40%. Selection among possible arrangements

Table 7 Calculated β for the lower bound criterion of the change in the angle of attack and failure probability with manufacturing controlled random variables

Random variables being controlled (actuation material)	Sensitivity factor	5% increase in the mean		40% Decrease in the scatter	
		β	P_f	β	P_f
Matrix modulus	0.220	2.808	0.0025	2.744	0.0030
Fiber modulus	-0.319	2.315	0.0103	2.791	0.0026
Control strain coefficient	-0.785	1.820	0.0344	3.472	0.0003
Original		2.700	0.0034	2.700	0.0034

$P_f = \Phi(-\beta)$

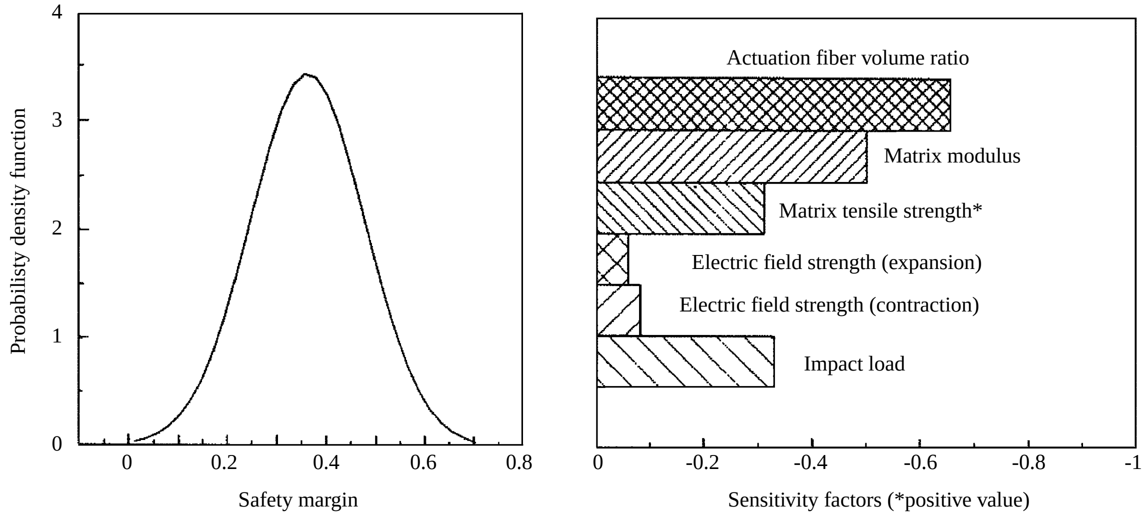

Fig. 8 Probability density function of safety margin and sensitivity factors at safety margin equal to zero

for reliability improvement may also depend on other considerations such as the cost of changing the mean value and cost of quality improvement which can be readily incorporated in the assessment.

2. Ply Damage Due to Random Impact Load

The wing is assumed to be struck by a foreign object. The direction and location of the impact loads are shown in Fig. 4(c). The procedure is used to assess ply damage in the vicinity of the impact (Minnetyan *et al*., 2000). The modified distortion energy is used for combined stress failure criterion (Murthy and Chamis, 1986). The probability density function of the safety margin (Murthy and Chamis, 1986) and the sensitivity factors at failure are shown in Fig. 8. Actuation fiber volume ratio has the largest (absolute) sensitivity factor (-0.645) followed by matrix tensile strength (0.5), impact load (-0.33), matrix modulus (-0.311). The sensitivity factors for both expansion and contraction electric field strengths are small (-0.060 and -0.083 respectively). To fully understand and utilize the sensitivity information in a redesign process, a parametric study is conducted. A 5% increase in the mean or a 40% reduction in the scatter for actuation fiber volume ratio, matrix modulus and matrix tensile strength are first considered for their large sensitivity values. For random variable with a small sensitivity factor, it can be seen from Eq. (4) that even with a 100% reduction in the scatter ($\delta\sigma=\sigma$), $\delta\beta$ is still negligible. However, if one can increase the ratio between δm and σ in Eq. (3), $\delta\beta$ will be sizable. Therefore, another assessment is performed for a 25% reduction in the mean of one of the electric field strengths. The ratio between δm and σ is equal to 5 which is much larger than the ratios in other cases. The estimated β and β calculated via IPACS are shown in Tables 8 and 9. It shows that estimated β correlate very well with calculated β. The reliability is improved by a reduction in the mean of the random variable with a negative sensitivity factor and vise versa. Moreover, efficient and economic redesign can be achieved by enhancing the quality of the random variable with large (absolute) sensitivity

Table 8 Estimated β using sensitivity factors for ply damage due to impact loads with manufacturing controlled random variables

Random variables being controlled (actuation material)	Sensitivity factor	5% increase in the mean		40% Decrease in the scatter	
		$\Delta\beta$	β	$\Delta\beta$	β
Actuation fiber (control) volume ratio	-0.645	-0.645	2.273	0.486	3.404
Matrix modulus	-0.334	-0.334	2.584	0.130	3.048
Matrix tensile strength	0.500	0.500	3.418	0.301	3.219
Electric field strength (Expansion)	-0.060	++ 0.300	++ 3.218		
Electric field strength (contraction)	-0.083	++ 0.415	++ 3.333		

$P_f = \Phi(-\beta)$
++ 25% Reduction in the Mean

Table 9 Calculated β of ply damage assessment due to random impact loads and failure probability with manufacturing controlled random bariables

Random variables being controlled (actuation material)	Sensitivity factor	5% increase in the mean		40% Decrease in the scatter	
		β	P_f	β	P_f
Actuation fiber (control) volume ratio	-0.645	2.106	0.018	3.375	0.0004
Matrix modulus	-0.334	2.435	0.0074	3.025	0.0012
Matrix tensile strength	0.500	3.616	0.0001	3.173	0.0007
Electric field strength (Expansion)	-0.060	++ 3.395	++ 0.0003		
Electric field strength (contraction)	-0.083	++ 3.666	++ 0.0001		
Original		2.918	0.0018	2.918	0.0018

$P_f = \Phi(-\beta)$
++ 25% Reduction in the Mean

factor. When the sensitivity factor of a random variable is small, quality of the random variable is not crucial for reliability improvement. However, the change in the mean of this random variable may have significant effect on the reliability (Chamis and Minnetyan, 2001) and (Minnetyan and Chamis, 2002).

IV. CONCLUSIONS

A formal methodology is described to probabilistically design smart composite structures using the IPACS (Integrated Probabilistic Assessment of Composite Structures) computer code. This methodology integrates micro- and macro-composite mechanics, laminate theory, structural mechanics (finite element methods), smart structures concept, and probability algorithms to perform a probabilistic assessment of composite structural design accounting for uncertainties in all requisite variables at all composite scales. Probabilistic sensitivity factors are key results from the probabilistic assessment of composite structures using the computer code IPACS. These factors provide quantifiable information on the relative sensitivity of design parameters on the structural responses. It is found from this study that the reduction in the scatter of the random variable with the highest sensitivity factor (absolute value) provides the lowest failure probability and vice versa. An increase in the mean of the random variables may result in reliability reduction if the sensitivity factor is negative. When the sensitivity factor of a random variable is small, quality of the random variable is not crucial for reliability improvement. However, the change in the mean of this random variable may have significant effect on the reliability. With this information, a smart composite structure can be redesigned efficiently by controlling and/or adjusting the parameters associated with random variables during manufacturing to obtain the “maximum” benefit with “minimum alterations.

NOMENCLATURE

E_ℓ	the ply normal modulus - numerical subscripts denote direction
f, ℓ, m	denote fiber, ply and matrix properties
G_ℓ	the ply shear modulus - numerical subscripts denote direction
i, j	denote dummy indices
P_f	the probabilistic performance function
S	denotes strength, subscripts denote type and direction
SF	are sensitivity factors
U^*	the most probable failure point
x_j	random variable or primitive variable
Z	the deterministic performance function
β	the reliability
δ	represents a small change or a small change in the function
σ	standard deviation of a random variable
υ_ℓ	the ply Poisson’s ratio - numerical subscripts denote direction
Φ	the cumulative distribution function
∂	denotes partial derivative of the function following it

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