유전자 알고리즘을 이용한 복합재료 곡면날개의 플러터 최적화
Flutter Optimization of Composite Curved Wing Using Genetic Algorithms

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Key Words : 곡면날개(Curved Wing), 유전자알고리즘(Genetic Algorithm), 플러터 최적화(Flutter Optimization), 복합재료(Composite Material), 공력탄성학(Aeroelasticity)

ABSTRACT

Flutter characteristics of composite curved wing were investigated in this study. The efficient and robust system for the flutter optimization of general composite curved wing models has been developed using the coupled computational method based on both the standard genetic algorithm and the micro genetic algorithms. Micro genetic algorithm is used as an alternative method to overcome the relatively poor exploitation characteristics of the standard genetic algorithm. The present results show that the micro genetic algorithm is more efficient in order to find optimized lay-ups for a composite curved wing model. It is found that the flutter stability of curved wing model can be significantly increased using composite materials with proper optimum lamination design when compared to the case of isotropic wing model under the same weight condition.

1. Introduction

In the development of new weapon systems such as bomb, projectile, guided or unguided missile, primary emphasis should be placed on the simplicity and reliability. A weapon will have far greater reliability if it can be sealed in a container of minimum volume and geometry. The solution for this problem can be efficient solved by using a wrap around fin or simply called spanwise curved wing concept. The curved wing offers a solution for many geometric constraints and at the same time can be sized to provide aerodynamic stabilizing characteristics equal to flat wing stabilizers. Because of its unique aerodynamic characteristics and geometry shape, it is also interesting for aerospace research engineers to investigate the flutter characteristics of the curved wing model.

This paper has focus on the flutter optimization by designing the proper lamination lay-up of the composite curved wing. The composite materials since its invention have been used widely in engineering especially for aircraft structures because of its advantage compared to the conventional engineering materials. Composite materials have many characteristics that are different from the conventional engineering materials such as high specific strength and directional stiffness. Use of all the characteristics advantage allows the tailoring of composite materials to meet a particular structural requirement. It is well-known that the optimum design of wing can be achieved by aeroelastic tailoring of composite wing structures [1-6].

The classical P-k flutter analysis technique and finite element method for structural dynamic analysis are simultaneously applied in this current study to effectively solve the aeroelastic governing equations in the frequency domain. For the optimization algorithm, the genetic algorithm is chosen because of its well-known performance as the robust global search algorithm [7-9]. Since introduce by Holland [10], genetic algorithm has been used by many researchers as a useful tool for search and optimization. However genetic algorithm is less efficient compared with the deterministic methods such as non-linear conjugate gradient and quasi-Newton methods in finding the optimized lay-up solution. This because genetic algorithm is made based on the stochastic methods. The deterministic methods are attractive because they are natural extensions of linear methods. That's why, in certain application they can be made to run extremely fast. The benefit of deterministic methods is that they are extremely efficient at locating the bottom of the valley, provided they start the search somewhere inside the valley. This is a great shortcoming since in many problems locating the valley that contains the global optima may be a problem as difficult as locating the global optima itself. We could say that deterministic methods are poor at 'exploration' (locating the best valley) but are very good at 'exploitation' (given the valley, locating its floor). The stochastic methods, on the other hand, perform a much more exhaustive search of the model space but are not as good at exploiting the

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early results of the search. We could say that stochastic methods such as genetic algorithms are very good at 'exploration' but are very poor at 'exploitation'. An interesting alternative to overcome this poor exploitation problem is to use the so-called micro genetic algorithm [11]. The micro genetic algorithm can improve the relatively poor exploitation characteristics of the standard genetic algorithm in finding the optimized lay-up solution without affecting their strong exploration capabilities. Finally the general analysis system for dynamic-flutter optimization has been developed using coupled computational technique of finite element method, efficient flutter analysis method and genetic algorithms. The optimum results for composite curved wing are also compared with the composite flat wing model as well as the isotropic model with the same weight.

2. Theoretical Backgrounds

2.1 Aeroelastic Analysis

The aeroelastic equations of motion for an elastic wing may be formulated in terms of generalized displacement response vector $\{q(t)\}$ which is a solution of the following equation:

$$[M_g]\{\ddot{q}(t)\}+[C_g]\{\dot{q}(t)\}+[K_g]\{q(t)\}=\{Q(t,q,\dot{q})\} \tag{1}$$

where t is the physical time, $[M_g]$ is the generalized mass matrix, $[C_g]$ is the generalized damping matrix which is practically assumed as proportional damping, $[K_g]$ is the generalized stiffness matrix, and $[Q]$ is the vector of generalized aerodynamic forces.

Assuming the harmonic oscillation for small wing as

$$\{q\}=\{\bar{q}\}e^{pt} \tag{2}$$

Eg. (1) can be converted into eigenvalue problem in the frequency domain. The eigenvalue problem for classical flutter equation can be written as follows:

$$[[M_g]p^2+[C_g]p+[K_g]-\frac{1}{2}\rho U^2[A(M,k_b)]]\{\bar{q}\}=0 \tag{3}$$

where p is the eigenvalue defined by $p=\omega(\gamma\pm i)$, ω is circular frequency, γ is transient decay rate coefficient (TDRC), and $[A]$ is the generalized aerodynamic influence coefficient (GAIC) matrix of complex form as a function of Mach number M and reduced frequency k_b. The GAIC matrix was calculated using doublet-lattice method.

The computed aerodynamic forces will be interpolated into the finite element node points using the surface spline method that is based on the infinite plate theory.

2.2 Optimization Method

Genetic algorithm is an optimization technique based on concepts of natural evolution and revolves around genetic reproduction processes and survival of the fittest strategies with some randomization or mutation [12-13]. During the evolution, individuals with higher fitness will have a higher probability to survive and gradually dominate the population as the individuals with lower fitness die off. The optimization model used in GA can be represented by

$$\text{Maximize } F(x)$$

$$\text{subject to} \quad \begin{aligned} &x\in\{A|(\theta_1,\theta_2,...,\theta_i)\}, \\ &\theta_i\in[0,\pm30,\pm45,\pm60,90] \end{aligned} \tag{4}$$

where F(x) is the objective function and is the flutter dynamic pressure defined by $q=\frac{1}{2}\rho V_f^2$, where V_f is the flutter speed. The ply orientation angles were used as the variables (x) in the algorithm to find the maximum flutter dynamic pressure for probable ply orientation angles.

In this paper the optimization of flutter dynamic pressure of the composite curved wing structures was did using two methods of genetic algorithms. First is standard genetic algorithm (SGA) and second is micro genetic algorithm (mGA). The standard genetic algorithm process begins with initial population of design variables created at random and represented as a binary number. The initial population with ply angle sets is then used in the flutter analysis to calculate the flutter dynamic pressure and frequency. The population is then newly evaluated using fitness evaluation, tournament reproduction, uniform crossover and jump mutation to create a better population. The tournament selection for reproduction has been used because this technique has the advantage of applying significant selection pressure while avoiding the pitfalls of fitness ranking [14]. The examples of uniform crossover and jump mutation used in the algorithm are shown in Table 1. In order to increase the reliability and search speed of standard genetic algorithm, the elitism selection and creep mutation option have been added into the program algorithm. By using elitism selection, the finest individual will always reproduce in new generation and makes the convergence faster. On the other side, the creep mutation that acts on the decoded individual will work together with jump mutation which acts on the coded individual to prohibit converging to local optima. Figure 1 illustrates the road map of the present coupling technique between standard genetic algorithm, finite element method and aeroelastic analysis technique used in this paper.

Table 1 Example of Uniform Crossover and Jump Mutation

Uniform crossover	10001111 00110000	→	10000000 00111111
Jump mutation	01011100	→	01011110

The micro genetic algorithm was employed as an alternative to overcome the time consuming algorithm which is a main problem of the standard genetic algorithm. In using micro genetic algorithm, a small population (commonly use 5 individuals) is used to find the global optima. Obviously, the small populations are unable to maintain diversity for many generations. In order to avoid this problem, the algorithm will be restarted whenever the diversity is lost, keeping only the very best fit individuals. In principle the micro genetic algorithm are similar to the standard genetic algorithm, however because the population always restarted if the diversity is lost, there is no need for jump and creep mutation.

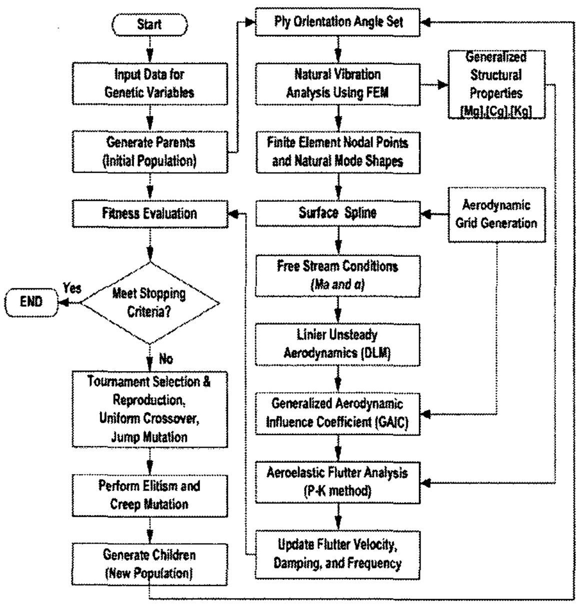


Fig. 1 Road map of the standard genetic algorithm with elitism and creep mutation

3. Results and Discussion

The geometric configurations of a curved wing and a flat wing model considered here are presented in Fig. 2. The curved wing model has the exactly same weight. The only different between them is just the geometrical shape. Figure 3 shows the corresponding finite element models for both the flat wing and the curved wing configurations.

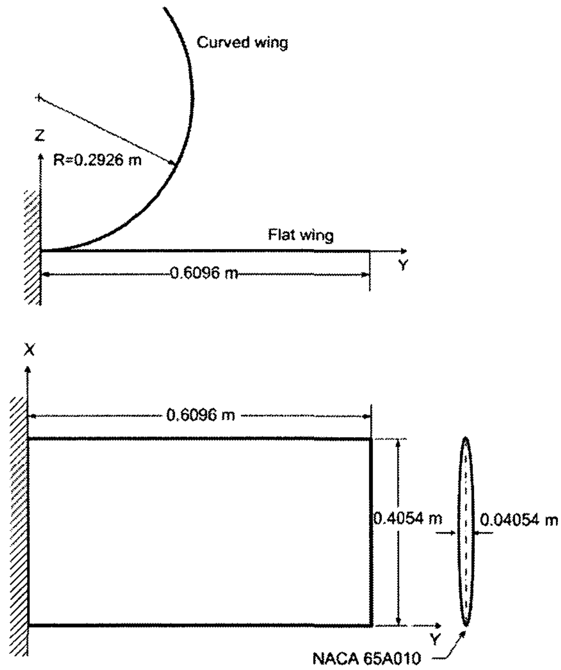


Fig. 2 Configuration of flat and curved wing

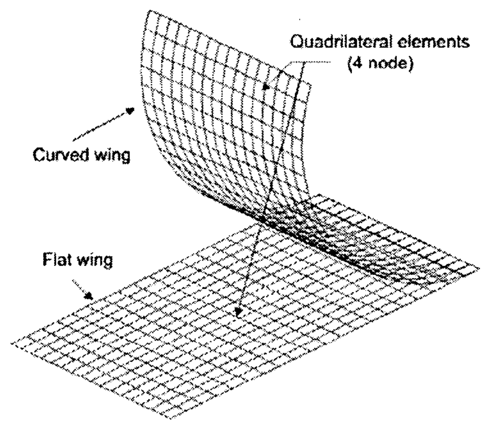


Fig. 3 Finite element models of flat and curved wing structures

The wing is simply assumed as platelike structures for the purpose of academic research. The root chord of the wing is fixed in order to impose structural boundary conditions. Material properties used in the model are presented in Table 2. In order to achieve strong potential for the practical application to realistic wing structures, the numerical algorithm and computational analysis system is practically designed and can be integrated with commercial finite element codes with general purposes. In this study, structural dynamic analysis of laminated composite curved and flat wing models have been conducted using MSC/NASTRAN which is a well-known and verified commercial finite element program.

The wing structure model is modeled using quadrilateral (CQUAD4) plate element with PCOMP entry to impose the composite material properties. The total number of plies is assumed as 32 and among them 24 inner plies can be changed according to the computational iteration coupled with the genetic algorithm. The lamination sequence is practically assumed as a symmetric lamination of [0/90/45/-45/...θ_{12}...]s. The variable angles of sets are practically selected based on the combination of 0^0, 30^0, 45^0, 60^0, and 90^0 ply orientations. Symmetric flow boundary condition on the x-z plane is assumed for the unsteady aerodynamic analysis. The flight condition is set-up at sea-level with the freestream Mach number of 0.7.

Table 2 Material properties of flat and curved wing

Al 6061-T6			
$E = 70\ GPa$	$\mu = 0.33$	$\rho = 2700\ kg/m^3$	$t = 2.286mm$
T300/5208 Graphite/Epoxy			
$E_1 = 138\ GPa$	$\mu = 0.28$	$\rho = 1543\ kg/m^3$	$t_{ply} = 0.125\ mm$
$E_2 = 9.7\ GPa$	$G_{12} = 5.5\ GPa$		

In this paper, four different optimization cases have been practically considered; two cases using standard genetic algorithm and the other two cases using micro genetic algorithm: Curved No Optimization (CNO) and Flat No Optimization (FNO) are the cases without conducting optimization (both flat and curved wing using initial lamination). Curved Optimization (CO-SGA) and Flat Optimization (FO-SGA) are the cases with optimization based on standard genetic algorithm. Curved Optimization (CO-mGA) and Flat Optimization (FO-mGA) are the cases based on micro genetic algorithm. In the application of genetic algorithms, the variable ply angles considered is expressed in binary number such as: [0]=000, [30]=001, [-30]=010, [45]=011, [-45]=100, [60]=101, [-60]=110, and [90]=111. The parameters used in the standard genetic algorithm and micro genetic algorithm are presented in Table 3. Numerical computations have been conducted using a server computer: Intel Pentium-4 3.0 GHz, 2 GB DDR2 RAM and 240 GB HDD. The total run-time of the converged solution for each case using the standard genetic algorithm is about 33 hours for 20,000 iterations but the total run-time using the micro genetic algorithm is just about 1.67 hours for 1,000 iterations.

Table 3 Parameters used in the standard genetic algorithm and micro genetic algorithm

Standard Genetic Algorithm			
Population size	200	Uniform crossover	0.5
Jump mutation rate	0.005	Elitism	Yes
Creep mutation rate	0.01	Number of children	1
Micro Genetic Algorithm			
Population size	5	Uniform crossover	0.5
Number of children	1	Elitism	Yes

The convergence history of standard genetic algorithm and micro genetic algorithm for each case are presented in Figs. 4 and 5. For the present models the standard genetic algorithm requires at least 40 generations in oder to obtain nearly converged maximum solution and micro genetic algorithm requires at least 50 generations. Micro genetic algorithm generally requires more generation number to obtain the convergence result than standard genetic algorithm, but faster in the total running time. The result practically shows that the same level of maximum flutter dynamic pressure for little different lamination lay-ups can be achieved using the micro genetic algorithm. In other word, micro genetic algorithm is more efficient to obtain the convergence solution and can overcome the time consuming problem of standard genetic algorithm.

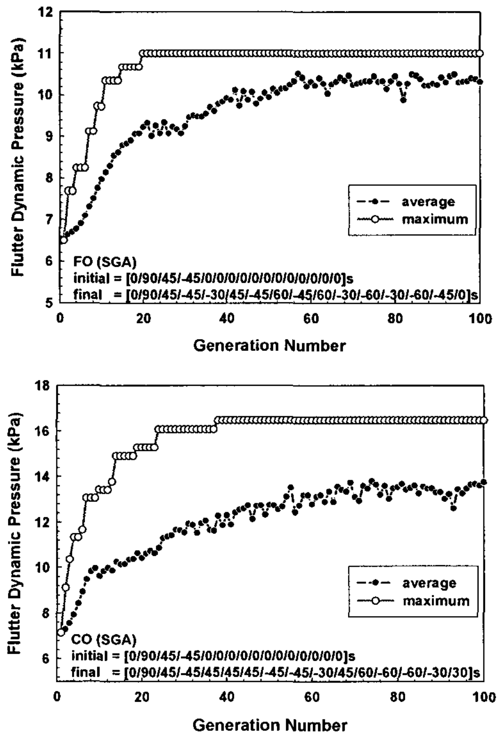


Fig. 4 Convergence history for flutter optimization using Standard Genetic Algorithm

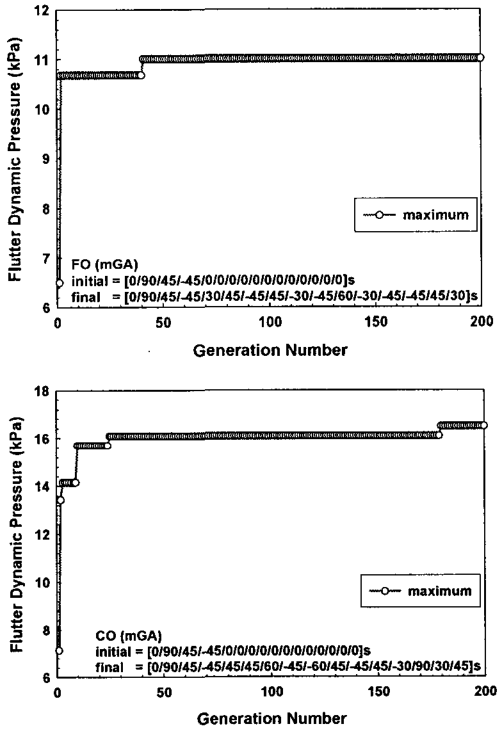


Fig. 5 Convergence history for flutter optimization using micro Genetic Algorithm

The results for optimum flutter design computations are summarized in Table 4. It is shown that the optimized flutter dynamic pressures are extremely higher than the case of the isotropic model under the condition of the same structural weight and aerodynamic shape. Flutter dynamic pressure of the isotropic material case for flat wing configuration is just 2.35 kPa and for curved wing is 2.58 kPa. The flutter dynamic pressure of the initial composite wing models (flat and curved configuration) are higher than isotropic material models for the same weight and shape condition. This result indicates the benefits of composite material properties and characteristics compared to the isotropic materials. The flutter dynamic pressure of FO cases (SGA and mGA) is 4.68 times greater than that of the isotropic material model. The flutter dynamic pressure of CO cases (SGA and mGA) is 6.37 times greater than its isotropic material model. This value is 49.8% higher than that of the FO cases for the given flight condition. The results presented in Table 4 also show that the flutter dynamic pressure for curved wing model is slightly greater than that of the flat wing configuration for isotropic material and moderately greater for composite material. Even for the optimization case, the flutter dynamic pressure of curved wing model is about 1.5 times than that of the flat wing configuration. The reasonable explanation about this phenomenon is that the curved wing model has different aerodynamic and natural vibration characteristics. Thus, the flutter stability of composite curved wing model can be largely improved.

Table 4 Comparison of flutter dynamic pressures and flutter frequencies

Model Case	Stacking Sequence	Max Q_f (kPa)	Flutter Freq (Hz)
Isotropic Flat wing	**N/A**	**2.35**	**9.54**
Isotropic Curved wing	**N/A**	**2.58**	**9.72**
Composite FNO (initial lamination)	**[0/90/45/-45/...θ...]s θ = 0/0/0/0/0/0/0/0/0/0/0/0**	**6.5**	**15.93**
Composite CNO (initial lamination)	**[0/90/45/-45/...θ...]s θ = 0/0/0/0/0/0/0/0/0/0/0/0**	**7.15**	**15.92**
Composite FO (SGA)	**[0/90/45/-45/...θ...]s θ =-30/45/-45/60/-45/60/ -30/-60/-30/-60/-45/0**	**11**	**20.07**
Composite CO (SGA)	**[0/90/45/-45/...θ...]s θ =45/45/45/-45/-45/-30/ 45/60/-60/-60/-30/30**	**16.48**	**20.43**
Composite FO (mGA)	**[0/90/45/-45/...θ...]s θ =-30/45/-45/45/-30/-45/ 60/-30/-45/-45/45/30**	**11**	**19.81**
Composite CO (mGA)	**[0/90/45/-45/...θ...]s θ =45/45/60/-45/-60/45/ -45/45/-30/90/30/45**	**16.48**	**20.62**

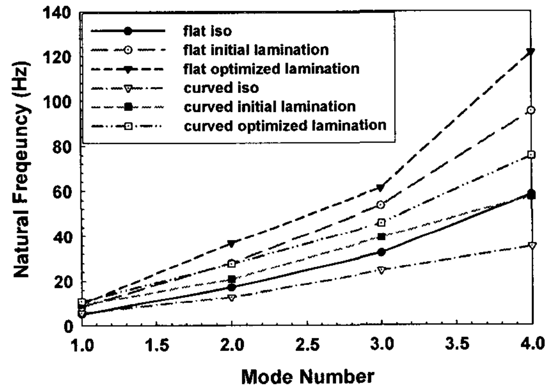
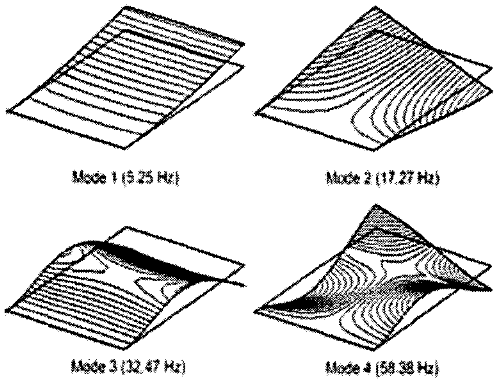
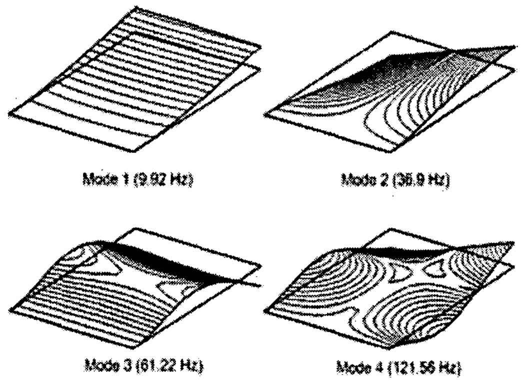


Fig. 6 Comparison of natural frequencies between isotropic and optimized composite models

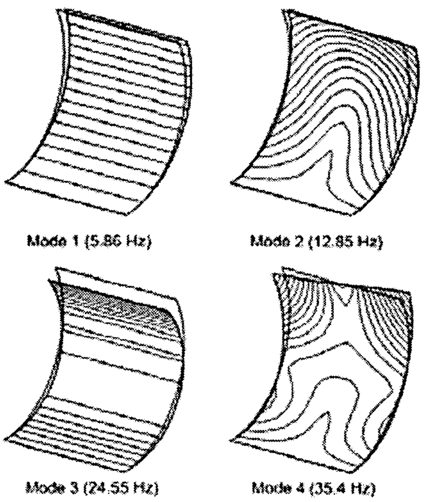
Figure 6 represents the comparison of natural frequencies between isotropic and optimized composite model for both the flat and the curved wing configurations. The natural frequencies of flat wing model are averagely higher than that of the composite wing model.



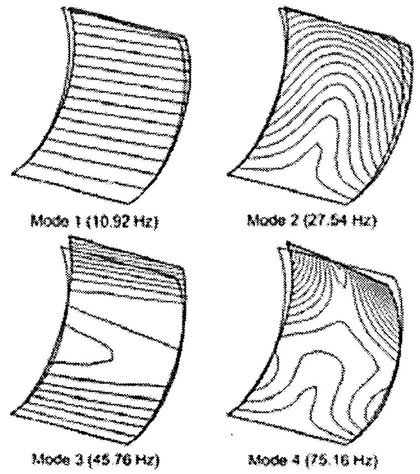
(a) Flat wing isotropic model



(b) Flat wing composite model



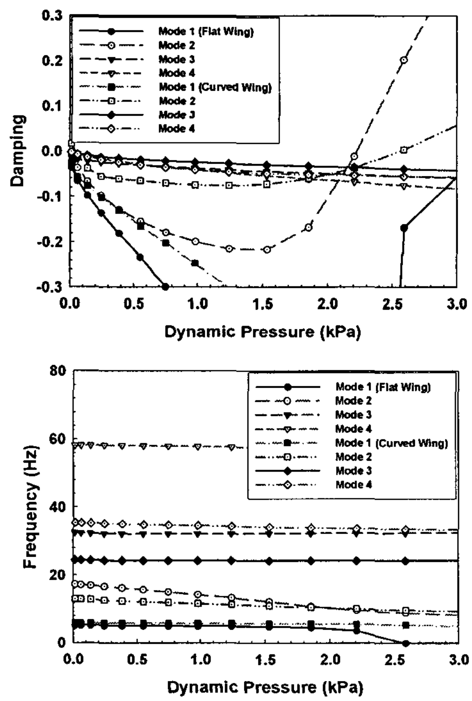
(c) Curved wing isotropic model



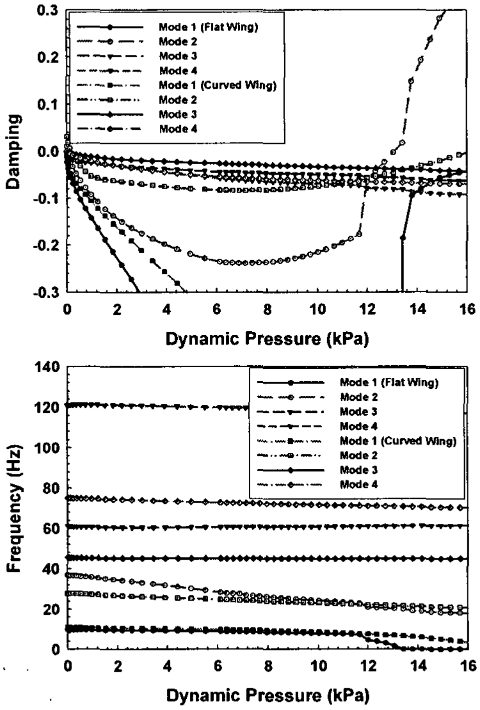
(d) Curved wing optimized composite model

Fig. 7 Natural mode shapes for isotropic and composite models

Figure 7 shows the natural vibration modes for curved wing and flat wing configuration. The natural mode shapes between isotropic material and composite material for flat wing model are similar although the natural frequencies are different. We can also see the same result on the curved wing model. The wings (flat and curved) tend to have bending motion in the first mode shape and torsion motion in the second mode shape.



(a) Flat wing and curved wing isotropic model



(b) Flat wing and curved wing optimized composite model using SGA

Fig. 8 Comparison of Q-g and Q-f plots for isotropic and optimized composite models

Figure 8 shows the comparison of Q-g and Q-f diagrams between curved wing model and flat wing configuration. For all models, it can be observed that the second mode is the dominant flutter model for the present curved wing and flat wing.

4. Concluding Remarks

The design studies of aeroelastic tailoring were conducted on the curved and the flat wing configurations. An efficient and robust analysis system for flutter optimization of laminated composite structures in frequency domain has been successfully developed using efficient computational method based on the genetic algorithms. Standard genetic algorithm and micro genetic algorithm are successfully employed in order to optimize the flutter dynamic pressure. The present results show that micro genetic algorithm is more efficient to obtain the maximum flutter dynamic pressure but gives slightly different optimized lamination lay-ups for the curved and the flat wing configurations. The flutter stability of the optimized curved wing configuration, because of its aerodynamic and structure modes characteristics, is much higher than the case of the flat wing configuration. The present results also indicate that flutter stability of both the curved and the flat wing structures can be significantly increased using optimized composite materials under the same weight condition.

Acknowledgements

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