Composite Structures 99 (2013) 181–192

Contents lists available at SciVerse ScienceDirect

Composite Structures

journal homepage: www.elsevier.com/locate/compstruct

Robust design optimisation of advance hybrid (fiber–metal) composite structures ☆

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ARTICLE INFO

Article history:
Available online 20 December 2012

Keywords:
Stacking sequence
Hybrid (fiber–metal) composite structures
Multi-Objective Optimisation
robust design optimisation
Finite Element Analysis

ABSTRACT

Hybrid Composite Structures (HCSs) are consisting of alternating layers of Fiber-Reinforced Polymer and metal sheets. Mechanical properties and responses for off-design conditions of HCSs can be improved using an innovative methodology coupling Multi-Objective Genetic Algorithm and robust design method. The concept of robust design approach ensures that a structure will be tolerant to unexpected loading and operating conditions. In this paper, two applications are considered; the first is to maximise the stiffness of the HCS while minimising its total weight through a Multi-Objective Design Optimisation. The second application considers a Robust Multi-Objective Design Optimisation (RMDO) to minimise total weight of HCS and to minimise both, the normalised mean displacement and the standard deviations of displacement, considering critical load cases. For the optimisation process, a distributed/parallel Multi-Objective Genetic Algorithm in robust multi-objective optimisation platform is used and it is coupled to a Finite Element Analysis based composite structure analysis tool to find the optimal combination of laminates sequences for HCSs. Numerical results show the advantages in mechanical properties of HCS over the metal structures, and also the use of RMDO methodology to obtain higher characteristics of HCS in terms of mechanical properties and its stability at the variability of load cases.

1. Introduction

The development of hybrid composites has been motivated from aerospace and marine industries to improve mechanical properties and lower operating cost [1]. The definition of Hybrid Composite Structures (HCSs) is consisted of several thin metal alloy sheets and plies of continuous Fiber-Reinforced Polymer (FRP) materials. HCSs have both the advantages of metallic and composite materials, including good plasticity, impact resistance, processability, low weight and excellent fatigue properties. They were originally developed at Delft University of Technology at the beginning of 1980 [2]. Recently, some new hybrid materials have been developed like the newest metal laminates consisting of thin titanium plies sandwiched by layers of polymer matrix composites. Boeing Airplane Company refers to this class of materials as Ti–Gr (titanium–graphite), while others have referred to them as Hybrid Titanium Composite Laminates (HTCLs) [3]. In HCS, the metal protects the FRP core from environmental effects such as thermal degradation and moisture ingress while potentially providing higher impact resistance and bearing properties. The FRP core has higher stiffness-to-weight ratios than monolithic metal that is less sensitive to fatigue effects. In addition, the composite can potentially outperform either of two constituent materials in elevated temperature structural applications [4].

From HCS literature reviews, it can be seen that most of researchers focused on experimental test of mechanical properties [3–12], and few studies deal with the optimisation of these hybrid composites; Nam et al. [13] consider a single-objective optimisation of HCS using GA to maximise the composite strength by altering the ply orientation of the composite. Peng et al. [14] consider

Abbreviations: Al-A, Aluminium 2024-T3; CAD, Computer Aided Design; CDF, Cumulative Distribution Function; CFD, Computation Fluid Dynamic; FEA, Finite Element Analysis; FEM, Finite Element Method; FRP, Fiber-Reinforced Polymer; GA, Genetic Algorithm; HCSs, Hybrid Composite Structures; HTCL, Hybrid Titanium Composite Laminate; Mo, Metal Orientation; MODO, Multi-Objective Design Optimisation; MOGA, Multi-Objective Genetic Algorithm; MS, metal structure; MS Al-A, reference Aluminium 2024-T3 metal structure; MS Ni-A, reference Nickel Aluminium Bronze UNS C63000 metal structure; MS Ti-A, reference Titanium Grade 12 Annealed metal structure; Mt, Metal thickness; Ni-A, Nickel Aluminium Bronze UNS C63000; NMD, normalised mean displacement; PDF, Probability Density Function; PM, Pareto member; PSO, Particle Swarm Optimisation; RDO, robust design optimisation; RMDO, Robust Multi-Objective Design Optimisation; RMOGA, Robust Multi-Objective Genetic Algorithm; RMOP, Robust Multi-objective Optimisation Platform; SDD, Standard Deviations of the Displacement; Ti-A, Titanium Grade 12 Annealed; Ti–Gr, Titanium–Graphite.

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http://dx.doi.org/10.1016/j.compstruct.2012.11.033

optimal strength design for FRP and HCS using Particle Swarm Optimisation (PSO) to minimise the failure by optimising fiber orientation angles. However, in practical situations, it is desirable to find a structural design that optimises various performances simultaneously at off-design conditions. Although the need for considering the multiple structural behaviours simultaneously as a set of objective functions is thus apparent, these previous studies are limited to the case of a single objective function.

Robust design optimisation (RDO) proposed by Taguchi [15] can be an emerging design method in composite structures where principal objective is to improve product quality by controlling the uncertainty effect. In engineering, the RDO cannot be ignored since the variations of manufacturing process parameters, environmental aspect and loads life conditions can affect the solution quality in terms of mean performance and its sensitivity [16,17]. Some researchers have considered such variances or tolerances applying uncertain design conditions in fiber laminated composites. Walter and Hamilton [18] described a procedure to design laminated plates for a maximisation of bucking load with manufacturing uncertainty in the ply orientation angle. Adali et al. [19] present an optimal design of composite laminates subjected to biaxial compressive loads belonging to a given uncertainty domain under the worst possible case of biaxial compressive loading. Liao and Chiou [20] proposed a method based on anti-optimisation technique by adding extra sensitivity terms in design constraints that is used for the robust optimum design of fiber reinforced composites with manufacturing uncertainties. Antonio and Hoffbauer [21] develop a mixed formulation of reliability-based design optimisation and robust design optimisation for reinforced composites, considering the ply angle, load factor, the elastic and strength materials properties as design variables. Lee et al. [22] set the differences between the damage tolerant design and robust design analysing composite panels. They studied the effect of laminate stacking sequence on the robustness and present a methodology to quantify it using Finite Element Analysis. Literature reviews considering the concept of robust design optimisation in composite structures show that only manufacturing uncertainties have been considered whereas uncertainties in loading conditions have not.

In this paper, a robust multi-objective optimisation methodology is developed for a hybrid (fiber–metal) composite structure (HCS) design considering a set of uncertain critical load cases (bending, shear and torsion) and also treating manufacturing process parameters as design variables. The paper investigates the robust multi-objective stacking sequence design optimisation for HCSs using a distributed/parallel Genetic Algorithm (GA) in Robust Multi-objective Optimisation Platform (RMOP) developed at CIMNE coupled with a Finite Element Analysis (FEA) based composite structure analysis tool named Compack [23–25]. Two HCS applications are addressed; the first application in a multi-objective manner is to improve mechanical properties (both weight and stiffness) of HCS, which is modelled as a simply (two opposite sides) supported quadrangular plate. The second application considers a robust design optimisation of HCS that is formulated to minimise its total weight while maximising HCS stiffness quality in terms of mean and standard deviation of displacement. In the second application, the boundary condition is set as one side rigid rectangular hybrid composite plate. For HCS manufacturing design variables, 32 design parameters are considered in total: six types of fiber (aramid, glass, boron, and carbon fibers), eleven fiber thicknesses, twelve fiber orientation angles, and also three different high performed metals allows (Aluminium 2024-T3 (Al-A), Titanium Grade 12 Annealed (Ti-A) and Nickel Aluminium Bronze UNS C63000 (Ni-A)).

The rest of this paper is organised as follows; Section 2 describes a methodology for HCS design optimisation. Section 3 presents a composite structure analysis tool. Section 4 considers two real-world HCS design optimisations. Section 5 concludes overall numerical results and present future research avenues.

2. Methodology

2.1. Multi-Objective Design Optimisation

Often, engineering design problems require a simultaneous optimisation of conflicting objectives and an associated number of constraints. Unlike single objective optimisation problems, the solution is a set of points known as Pareto optimal set. Solutions are compared to other solutions using the concept of Pareto dominance. A multi-criteria optimisation problem can be formulated as

Maximise/minimise the functions:

$$f_i(x)_i \quad i = 1, \ldots, N \tag{1}$$

Subject to constraints:

$$\begin{aligned} g_j(x) = 0 \quad j = 1, \ldots, M \\ h_k(x) \le 0 \quad k = 1, \ldots, M \end{aligned} \tag{2}$$

where f_i, g_j, h_k are, respectively, the objective functions, the equality and the inequality constraints. N is the number of objective functions and x is an n – dimensional vector where its arguments are the decision variables. For a minimisation problem, a vector x_1 is said partially less than vector x_2 if:

$$\forall_i f_i(x_1) \le f_i(x_2) \quad \text{and} \quad \exists_i f_i(x_1) < f_i(x_2) \tag{3}$$

In this case the solution x_1 dominates the solution x_2.

As Genetic Algorithms (GAs) evaluate multiple populations of points, they are capable of finding a number of solutions in a Pareto set. Pareto selection ranks the population and selects the non-dominated individuals for the Pareto fronts. A Genetic Algorithm that has capabilities for multi-objective optimisation is termed Multi-Objective Genetic Algorithms (MOGAs). Theory and applications of MOGAs can be found in Refs. [26–28].

2.2. Robust design optimisation

A robust design method, also called the Taguchi Method (uncertainty), pioneered by Taguchi [15], improves the quality of engineering productivity. An optimisation problem can be define as

Maximization/minimization:

$$f = f(y_1, \ldots, y_n, y_{n+1}, \ldots, Y_m) \tag{4}$$

where $y_1, \ldots, y_n$ represent design parameters and $y_{n+1}, \ldots, y_m$ represent uncertainty parameters. The range of uncertainty design parameters can be defined by using two statistical functions; mean (μx) and variance ($\delta x = (\sigma x)^2$) as part of the Probability Density Function (PDF). The Taguchi optimization method minimises the variability of the performance under uncertain operating conditions. Therefore in order to perform an optimisation with uncertainties, the fitness function(s) should be associated with two statistical formulas: the mean value μf and its variance δf or standard deviation $\sigma f = \sqrt{\delta f}$.

$$\mu f = \frac{1}{K} \sum_{i=1}^{k} f_i \tag{5}$$

$$\delta f = \frac{1}{K-1} \left(\sum_{i=1}^{K} (f_i - \mu f)^2 \right) \tag{6}$$

where K denotes the number of subintervals of variation conditions.

The values obtained by the mean (μf) and the variance (δf) or standard deviation (σf) represent the reliability of model in terms of the magnitude of performance and stability/sensitivity at a set of uncertain design conditions.