Reliability-based Design Optimization of Classical Wing Aeroelasticity

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Abstract
Flutter speed of aircraft is very important and needs to be firstly specified before a certification applied for a new aircraft by airworthiness regulator to make sure that the aircraft is free from flutter in its flight envelope. By assuming geometrical and physical parameters known, the speed is usually estimated from deterministic analyses in a design stage. In practice, some parameters are finitely measured by observing, especially for the geometrical parameters, material properties and so on due to the random in nature, which causes uncertainty of information often called uncertainties. The purpose of this paper is to combine reliability analysis and optimum design of aeroelastic aircraft wing. The classical two-dimensional wing with a typical airfoil section is used as an example in this study. To quantify uncertainty in the design of flutter speed, the discrete-time aero-elastic model and worst-case scenario are applied. Furthermore, the comparison between optimum design with/without reliability is provided in this study. The results show the proposed technique leads to the flutter speed being more conservative and realizable compared with the traditional technique.

Keywords: Distributed combustion, Thermal efficiency, Experiment

1. Introduction
According to FAA and EASA regulations for airworthiness, a new aircraft can be allowed for flight if a company can define its actual aero-elastic characteristics. The technique of simulation is selected to study the aero-elastic characteristics in a design process to ensure that an aircraft developed passes the regulation in the final stage. The aero-elastic phenomena can be separated into two groups as static and dynamic aeroelasticity. The most important static aeroelastic phenomena are divergence speed, control reversal and lift effectiveness, while the dynamic aeroelastic characteristics include flutter speed. The flutter and divergence speeds are called critical speed when considering the lowest of them as a design criterion. The flutter analysis programs for low-speed air-vehicles were studied by Nantasenee et al. [1]. The aero-elastic phenomena have been considered in aircraft and adaptive or morphing aircraft wing design [2-6]. A new reduced-order model for aeroelastic analysis was studied in Sleesongsom and
Bureerat [7] and Sleesongsom [8]. The aeroelastic phenomena have been studied for a long time, but they are random in nature. Material properties are evaluated by performing a finite number of experiments and by observing. We use the properties to design in engineering with developing the innovation to improve our human life. Obviously, changes in the material properties may cause damage to the engineering equipment and may be dangerous to human. In engineering design, the safety factor is used for increasing design reliability, but the high value of the safety factor causes a high price. The exactly unknown material property is called uncertainty. If we can define it, we can increase the reliability of a designed object. Moreover, it is known that dealing with uncertainty by using safety factors or worst-case scenarios in design causes inefficient design and overly conservative. The theory of uncertainty is important to increase the structural reliability analysis in designing aeroelastic optimization to offer the correct aeroelastic evaluation for designing purposes.

The techniques for handling uncertainty have been studied by many researchers especially in aircraft design, in the last decades. The most well-known and straightforward technique to deal with uncertainties is called a Monte Carlo simulation (MCS) [9]. This technique is in the group of probability analysis that has been used in studying the configuration variation of a Goland wing [10]. The model of aeroelastic analysis for finding flutter speed is analysed based on linear aerodynamics. A further technique in this group is polynomial chaos expansion (PCE), which is a well-known technique to decompose a random process in terms of deterministic functions of space and time, and orthogonal functions of random variables. This technique has been used to quantify the uncertainty of flutter speed due to composite plate wings layup with uncertain ply orientations [11]. Later, this technique has been extended to reduce the number of random variables [12]. In recent years, this technique has been extended to study the uncertainty qualification of a generic UAV wing by the same author [13].

Composites material is considerably popular for use in various structural applications due to its high mechanical strength-to-weight ratio, stiffness, resistance to corrosion, thermal insulation properties and the low volume-to-weight ratio [14]. Furthermore, combining structural reliability analysis with aeroelastic simulation in a simple form that has been studied and given a correct flutter speed evaluation to design results. Two types of commonly used material modelling are isotropic and composite materials. All of them have been employed with MCS, a first-order reliability method (FORM), a second-order reliability method (SORM), and including a response surface model coupled with FORM and MCS [15]. However, the anisotropic material behaviour of laminated composite structures leads to complicated analysis and design approaches. It implies that high fidelity computational simulation using Finite Element Analysis (FEA) can be more time-consuming. The MCS in combination with FEA is a direct approach for quantifying uncertainty, but a million of finite element runs is required. To reduce such a time consuming and impossible-to-do task, the use of surrogate models is needed as showed by the work [11, 12].

Another technique to quantify the uncertainty into a model excepts as mentioned above, it handles the uncertainties as an objective or constraint functions is called Reliability-Based Design Optimization (RBDO). This method aims to ensure that the constraints are acceptable by enforcing the threshold according to the probability failure [14].

Reliability has been used to increase the realization of structural topology, in which the uncertainty factors are varied and make the optimum design results impractical or unrealizable [16]. To address the problem, two strategies are robust topology optimization (RTO) [17] and reliability-based topology optimization (RBTO) [18] have been used to collect uncertainties into a topology optimization problem. The first technique is performed optimization design at the same time with considered variability of the system with respect to uncertainties, while the last method is performed optimization design with failure probability constraints to achieve the reliable design. Both methods can be based on probabilistic [19] or non-probabilistic [20-21] models. The first model is the most popular one due to its progress, but this technique requires a very good knowledge of uncertainties distribution. The knowledge of uncertainties distribution requires a large amount of objective data, which needs a huge computation time. The second model is non-probabilistic where the well-known techniques are a convex model [20] and a fuzzy set method [22]. The convex model required only bounds of uncertainties from a small number of samples.
to reduce time-consuming tasks, whereas the solution is too conservative. The fuzzy set model is an alternative technique to collect the uncertainties into RBTO by using a level set to softly separate between the members and non-members of the set. It makes the model to get an acceptable solution better than the convex method [16]. Another well-known technique in the group of non-probability approach is the worst-case reliability, which needs the interval of uncertainties without accurate probability distributions. This technique is called anti-optimization, which has been proposed by Elishakoff [23].

One strategy is to quantify the uncertainties in the group of probability techniques, although very time consuming, it uses approximation techniques to the model of real behaviours. In this strategy, a surrogate model is used to approximate the finite element model leading to significantly faster computing compared to actual function evaluations. The various surrogate models have been used for structural reliability. The advanced Kriging model (AKM) proposed by Zhang et al. (Date) is applied to approximate the mechanical model of a structure [24]. Examples of the Kriging models have been used with the surrogated model-based uncertainty are as Ordinary Kriging, Blind Kriging, and Co-Kriging [25]. Later, several Kriging-based strategies have been proposed for structural reliability analysis [26-27] including an adaptive sampling method to construct a surrogate model [28-29].

This work aims to study the reliability effect in an optimization problem of aeroelastic behaviour of classical aircraft wing model without statistical information of model-parameters and mechanical properties. The aircraft wing modelled as a two-dimensional classical wing model is used for demonstration. The computation cost is low for this model, so the model can combine with non-probabilistic and optimization technique without using an approximation approach.

2. Aeroelastic Model and Numerical Validate

Nowadays, reduced-order modelling (ROM) is used to study the design of aeroelastic structures. The traditional ROM is the ROM with a static correction technique. It has been used in analyzing unsteady incompressible aerodynamic flows with using only few unsteady flow eigenmodes to constructed the reduced-order unsteady flow model. Later this technique is adjusted to alternative ROMs, which is expected to increase its performance. They are constructed only based on the wake or body vortices without using a static correction technique [7, 8]. Aeroelastic analysis in this research applied ROM based on a vortex lattice method (VLM) in which the eigenvalue problem is defined only based on unknown wake vortices for flutter analysis of a two-dimensional airfoil for studying reliability design optimization.

2.2.1 Aeroelastic validation

In this section, we propose the flutter analysis validation of a classical aeroelastic model, which is used in reliability design optimization in this research. The model is considered as the aircraft wing, which has a typical airfoil section as shown in Fig.1. The model has two degrees of freedom, which are plunged and pitched [8]. The linear and torsion springs are attached at the elastic axis to restrain motions in plunge and twist. The validation model parameters include mass ratio $\mu$ is 20, the static imbalance $x_0=0.2$, the radius of gyration $r_0$ is 0.5, and the location of elastic axis stay after the mid chord at-0.1. The frequency ratio $R$ of uncoupled modes is 0.3. The chord is modelled with 10 vortex elements, while the wake is modelled using 100 vortex elements. The length of wake vortices is 10 times of the chord length. The result is shown in Fig. 2 where the reduced flutter speed is 1.95, which is in good agreement with the previous result [8]. This model used ROM based on wake vortex, where the numbers of body and wake vortices are 10 and 100, respectively. Furthermore, ROM exploits only the first 10 aerodynamic modes. Our aeroelastic result is in agreement with the previous result [8].
3. Design example

In this section, the reliability design optimization of aeroelasticity and design demonstration refers to a maximization of reduced flutter speed ($v_f(x)$) and maximizing the worst-case scenario ($\max(g(a))$), when considering the non-dimensional lift. The reduced flutter speed and non-dimensional lift are not over than the prescribed value. Design variables $x$ are the static imbalance ($x_\theta$), the ratio of natural frequency ($R$) and the location of the elastic axis after the mid chord ($s$). Uncertain parameters ($a$) are the radius of gyration $r_{\theta} \in (0.45, 0.5)$, and the mass density of air $\rho_{\text{air}} \in (1.15, 1.2)$. The anti-optimization problem is formulated as
\[
\begin{align*}
\min \left\{ v_f(x), \max(g_i(x, a)) \right\} \\
\text{Subject to} \\
g_i(x, a) - \bar{g}_i \leq 0, \quad i = 1, 2, ..., N \\
x_i \leq x_i \leq x_u, \quad i = 1, 2, ..., n \\
a_i \leq a_i \leq a_u, \quad i = 1, 2, ..., m
\end{align*}
\]  
(1)

where the number of constraints, design variables and uncertainties are \(N=2\), \(n=3\), and \(m=2\), respectively. \(\bar{g}_i\) is the allowable value of flutter speed and non-dimensional lift. The limit of the reduced flutter speed is 11 and the non-dimensional lift is 1.0. For the non-dimensional lift for the two-dimensional airfoil, it should not exceed 1.0. The objectives are two conflicting criteria in nature since it is impossible to increase both the flutter and the worst-case scenario. The optimizer is an adaptive multi-objective real-code population-based incremental learning and differential evolution (aRPBIL-DE), which has been presented in our very recent work [30]. The number of population size for aRPBIL-DE is 50 performs in 100 iterations with the external Pareto archive size is 100. Other parameters are initially assigned similar to [30].

4. Design results
From the design example, having solved the optimization problem, the obtained result is shown in Fig. 3. The technique used for clustering selection is from our previous work [31]. The selected solutions are obtained from the front, which is shown in Fig. 4. The minimum reduced flutter speed obtained is 7.740, while the maximum worst-case scenario is 1.704 at the parameter bound. The maximum reduced flutter speed obtained is 11, while the maximum worst-case scenario is 2.0 at the parameter bound. The lowest value for reduced flutter speed is 7.740, while the highest is 11. The highest reduced flutter represents the deterministic optimum solution, which gives the highest worst case too. Fig. 5 shows some selected solution and the corresponding flutter speed. The designer can choose the conservative solution which compromises between the flutter speed and uncertainty from the Pareto front. The box-plot in Fig. 6 shows distributions of the design variables of all solutions in the Pareto front in which \(R\) and \(x_\theta\) are more variation dimensions.

5. Conclusions
This paper focused on a combination of reliability analysis and optimum aeroelastic design of an aircraft wing to find a correct flutter speed. The classical two-dimensional aeroelastic wing model is used as an example in this study. The discrete-time aeroelastic model and worst-case scenario are applied to quantify an uncertainty into the design of flutter speed of a classical wing and provide a comparison between solutions with and without reliability analysis. The results show the proposed technique leads the flutter speed of classical typical section of an aircraft wing in design optimization to be more conservative, and realizable when compared with the deterministic design optimization technique. The designer can add the experience to select a more conservative solution from the solution set.

The extension of the proposed technique is to design a real aircraft wing, which is expected to make it more efficient and realizable.
Figure 3. Approximate Pareto front

Figure 4. Pareto front and selected solutions
Figure 5. Reduced flutter speeds from selected solutions in figure 4

Figure 6. Distribution of design variables

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