Qualitative and quantitative airfoil design optimisation using interactive genetic algorithms

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Abstract

This paper introduces the necessity of qualitative views on the evolutionary optimisation of airfoil shape design and applies multi-objective and parallel interactive genetic algorithms to combine qualitative evaluation with quantitative shape optimisation. The interactive evaluation enables user to embed domain specific knowledge which is frequently hard to describe. A comparison of the multi-objective and parallel IGA results is made using the fitness convergence, diversity and user preference performance metrics. Although the multi-objective IGA provides more diverse results the parallel IGA obtains significantly better fitness convergence and user preference. It is reported that the ability to vary population sizes and number of generations on separate population islands in parallel IGA is an ideal method to combine user guidance with computationally intensive search.

Keywords: Interactive Genetic Algorithm, Multi-objective Optimisation, Parallel Genetic Algorithm, Airfoil Design

1. Introduction

Airfoil shape optimisation plays a major role in the determination of lift an aircraft can produce. However, determining the lift is only a part of the design problem. Aircraft designs are a compromise imposed by several conflicting design factors. A higher angle of attack produces more lift than a lower angle, but it also produces more drag. The lift to drag ratio is an important design factor for the aircraft because it is directly related to the angle at which a glider descends in flight. Increasing the wing area increases the lift, but it also increases the weight that has to be lifted. Higher speed produces more lift, but it also increases drag. To provide higher thrust for a powered aircraft a larger engine is needed, which typically increases weight. All of these trade offs must be considered to arrive at a final design.

This trade off based nature of airfoil shape design practice makes it preferable to obtain a set of optimum solutions each with its own blend of satisfaction of different criteria, rather than a single solution optimum in one criterion. In this context, the use of multi-objective optimisation algorithms is particularly suitable to the problem of balancing multiple performance criteria. Multi-objective Optimisation (MOO) is defined as the problem of finding a vector of decision variables that optimises a vector function whose elements represent multiple objective functions. Various performance measures such as the maximisation of lift and minimisation of drag may be brought together by modelling the problem with many objective functions. Recently, the usage of Evolutionary Algorithms (EA) in MOO has become particularly popular. The success factors of EMO (Evolutionary Multi-objective Optimisation) have been summarised by Deb [1] and thus are not included here.

EA have been applied to airfoil optimisation on various occasions. Obayashi *et al* compared airfoil optimisation with gradient-based method, with simulated annealing and genetic algorithms (GA), a branch of EA. They reported that although the GA is time-consuming, it provides results that are superior to those of the others [2]. On the other hand, airfoil design with EMO has also been experimented. A review of reports on applications EMO of to airfoil design can be found in [3].

Adding to the multi-objective nature of the airfoil shape design problem, another complexity is hinted by Zores *et al*, who reported that judgement on the shape of the airfoil is not only determined by common measures such as coefficient of lift and drag, but also by expert systems that encode knowledge from airfoil design experts [4]. The success of human expertise in shape judgement lays in the ability of humans to grasp and approximate shapes faster than a lengthy and accurate mathematical calculation performed by the computer. While the accurate and lengthy calculation needs to take place at the secondary design stage the expert opinion of the shape is typically gathered at the conceptual development stage. Similarly, Parmee *et al* noted that the conceptual stage of aircraft development is the stage where expert intuition and creativity on the shape of aircraft is mostly used [5].

A previous survey conducted by the authors suggested the lack of flexible frameworks that enable the designer to incorporate his qualitative opinion on the airfoil shape design during the optimisation process [6]. The wording “flexible framework” is intended for frameworks that support the incorporation of qualitative judgement without the need for a lengthy modelling or coding process. It is often found that modelling of expert judgement remains too rigid in an optimisation problem. As more detailed information about the solution space is gathered during an iterative search, it is often likely that objective preferences and their relative importance are reconsidered. Constraints may also soften, and search may move to areas that were initially thought unsuitable with discovery of new solution properties. When expert judgement is modelled any desired change would result in the revision of a coded expert system.

A comparative analysis of adaptive computing based methods for the flexible incorporation of expert judgement brings a relatively new field of evolutionary computing: Interactive Genetic Algorithms (IGA). IGA is widely defined as a GA where a human evaluator assigns fitness values to population members instead of a built-in fitness evaluation function. A broader definition of IGA is the optimisation of a target system based on human-machine interface [7].

Although IGA have not been applied to airfoil shape design, the closest design study is Parmee et al.’s application of co-evolutionary GA to conceptual aircraft optimisation [5]. Here interaction was partial as interactivity was used to gather user preferences on quantitative objectives which were then translated into weightings of objectives. In other words qualitativeness was not modelled as an objective.

Building on the two complex dimensions of the airfoil shape design optimisation, i.e. its multi-objective nature and its need for qualitative expert opinions, we apply our previously developed parallel IGA and multi-objective IGA [6] to conceptual airfoil shape design. Both parallel IGA and multi-objective IGA use evolutionary multi-objective philosophy to reach to trade off solutions and interactivity to gather expert opinions during the optimisation process. This paper compares the results obtained by each algorithm and reports on the performance of the airfoil design using three selected performance metrics.

Section 2 introduces multi-objective and parallel IGA platforms, Section 3 outlines the airfoil shape optimisation problem and experimental parameters, Section 4 presents the results and Section 5 concludes the paper.

2. Interactive Multi-objective Design Optimisation

This section briefly reviews the two algorithms that are applied to airfoil shape design. A comprehensive review of the parallel IGA and multi-objective IGA are given in the authors’ previous work [6] and hence they are not elaborated in detail here.

2.1 Multi-objective IGA

Multi-objective IGA is a modified version of the popular multi-objective optimisation algorithm, the non-dominated sorting GA 2 devised by Deb *et al* [8]. The non-dominated sorting GA 2 enhances the usual non-domination-based multi-objective optimisation techniques by introducing the concepts of elitism and diversity. Elitism ensures the preservation of globally good solutions from generation to generation. Diversity ensures achieving a set of well-spread solutions in the objective space, thereby providing the decision maker with a set of solutions that cover a wide spectrum of the Pareto front. Diversity is encouraged by performing the crowding distance calculation and promoting evenly spread solutions.

In the non-dominated sorting GA 2, elitism is achieved by combining parent and offspring populations before sorting them for non-domination. Non-domination shows how many solutions are better in all criteria then a particular solution.

We included interactive fitness assignments in the non-dominated sorting GA 2, which resulted in the new algorithm multi-objective IGA. The qualitative objective rating for a solution is obtained from the user, whereas the quantitative fitness of a solution is assessed by the built-in fitness functions.

2.1. Parallel IGA

We propose that the use of parallelisation and interactivity together is advantageous and natural for our problem as solutions to multiple objectives can be evolved in separate populations with elite migrants exchanged between one another i.e. following the island model. There is a limited amount of literature on the use of parallelisation in EMO [9]. On the other hand, the use of parallelisation techniques in IGA has not been reported except in our previous work [6].

In the parallel IGA the qualitative fitness of a solution on the qualitatively evaluated population island (P_{QL}) is obtained through user interaction, while another population on the quantitatively evaluated population island (P_{QN}) is evolved through a quantitative fitness function. Using this method a compromise decision can be encouraged by the migration of elites between populations. However, it takes much longer for a user to evaluate designs than a computer. As the objectives are optimised on separate populations, the P_{QN} can pursue more numbers of generations while the P_{QL} is optimised. Similarly, a bigger population size can be used with P_{QN} resulting in faster convergence, whereas this is generally not possible with P_{QL} due to the burden on the user.

3. Airfoil Shape Optimisation Problem

This section describes how the airfoil shape optimisation problem is modelled as a multi-objective problem to include qualitative opinions. First the objective functions and the genetic representation are given. This is followed by an overview of experimental GA parameters.

3.1 Problem Description

The following flight conditions are set constant to optimise the airfoil shape design:

The length of foil chord *L* is 1. Speed of flight *U* is specified to be 30 m/s in standard atmospheric conditions. A constant coefficient of lift, C_l is set to 0.6. These conditions lead to a *Reynolds number (Re)*, of 7.1e06, defined in Eq.1 and a *Mach number* (*M*), 0.23, defined in Eq.2.

$$Re = \frac{U \cdot L}{\nu} \qquad (1)$$

where is the kinematic viscosity of air.

$$M = \frac{U}{c} \qquad (2)$$

where *c* is the speed of sound at 340 m/s.

The specified conditions lead to a subsonic flight. The objective functions f_1 and f_2 are then defined:

$$f_1(X, Y_{SRF}) = C_d \qquad (3)$$

where X and Y_{SRF} are the *(x, y)* coordinates of the two dimensional airfoil surface representation and C_d is the coefficient of drag. The aerodynamic simulation to obtain C_d under the above flight conditions is performed using the open source Computational Fluid Dynamics (CFD) software, XFOIL [10].

$$f_2(\exp) = f_{user}(\exp) \qquad (4)$$

where f_{user} denotes the user given rating from a scale of 0 to 9 which is a function of the user's expert judgement *(exp)* of the design.

3.2 Genetic Representation

A commonly used method for genetic representation of airfoil shape is the simple encoding of the coordinates of the airfoil [11]. An alternative encoding scheme is representation using design variables [12].

With coordinate based representation, the higher the number of coordinates the smoother is the airfoil shape, and thus coordinate based representation could mean the generation of a very large chromosome. It was thus concluded that representation using design variables would be less computationally demanding and would result in a smoother graphical user illustration in this study.

The seven gene long real string chromosome was encoded with seven design variables. The design variables are substituted into the Hicks and Vanderplaats shape functions, which are used generate coordinates without increasing the computational cost and memory [12]. The airfoil shape is given by Eq.5:

$$Y^{j}_{SRF} = Y^{j-1}_{SRF} + \sum a_i g_i(X) \qquad (5)$$

where Y^{j}_{SRF} is the set of y coordinates, normal to the aifoil chord, the superscript j indicates the generation number, g_i are the shape functions below, and a_i are the design variables encoded in the chromosome.

$$g_i(X) = X^{n_i}(1 - X\ )/e^{m_i x}, i = 1 \qquad (6)$$

$$g_i(X) = \sin^3(\pi X^{n_i}), i = 2,3,4 \qquad (7)$$

$$g_i(X) = \sin^3\lfloor \pi(1 - X)^{n_i} \rfloor, i = 5 \qquad (8)$$

$$g_i(X) = \sin\ \lfloor \pi(1 - X)^{n_i} \rfloor, i = 6,7 \qquad (9)$$

Where X is the coordinate along the chord of the airfoil, m_1 =10, n_1 = 0.4, where $n_5 = n_2$, and

$$n_i = \frac{\log 0.5}{\log X_i}, X_i = 0.2,0.4,0.6,0.06,0.13, i = 2,3,4,6,7 \qquad (10)$$

Random foils could not be used as a start point as this would increase the time to reach to a resolvable solution considerably. 12 random re-generates of a single airfoil, the NACA0012 are used instead.

3.3 Experimental Parameters

We carried out 6 runs for the parallel IGA and 10 runs for the multi-objective IGA. For each qualitative run on the parallel IGA P_{QL} there are 10 generations on the P_{QN} making a total of 66 generations to be pursued. On the other hand as qualitative and quantitative optimisation is pursued simultaneously in the multi-objective IGA 10 generations are pursued in total. The parallel IGA P_{QL} contains 12 individuals as in the multi-objective IGA, whereas parallel IGA P_{QN} of contains 50 individuals.

All algorithms were real-coded, used tournament selection, mutation with a rate of 0.01 and a distribution index of 10, one-point simulated binary crossover with a rate of 0.9 and a distribution index of 20. The distribution index is any nonnegative real number, which is used to derive the probability distribution used to create a child solution. A large distribution index results in a higher probability for creating near-parent solutions and conversely a small value allows distant solutions to be selected. These parameters were kept constant throughout to allow a valid comparison of the two algorithms. Each run of any given algorithm started with a different randomization seed, which was reused in the other algorithms. Designers are 2 females and 3 males of ages 24–32, whose expertise range over design engineering and aerospace engineering. The users continued to run the programs until qualitative generation 6 in parallel IGA or 10 in multi-objective IGA was reached. Each user conducted one test for each of parallel IGA, and multi-objective IGA.

4. Results

This section evaluates the results of the multi-objective and parallel IGA in terms of three performance metrics: fitness convergence [13], diversity [13] and qualitative user preference. While the first two metrics are commonly used for multi-objective problems, the last one is a new metric proposed in this study. The final set of solutions obtained by each algorithm are compared and ranked by the user. The algorithm with highest percentage of solutions is in the final pool is declared to be winner. All three metrics carry equal significance in determining the success of an algorithm.

4. 1 Fitness convergence

Figure 1 shows fitness convergence in the qualitative space. The parallel IGA displays a smoother and more consistent qualitative convergence than the multi-objective IGA.

Figure 2 shows the quantitative fitness minimisation obtained by the two algorithms. During optimisation with multi-objective IGA a local minimum is observed for four generations.

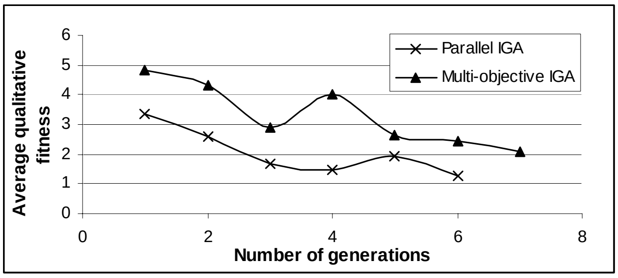

Fig. 1. Qualitative fitness in airfoil design with multi-objective and parallel IGA

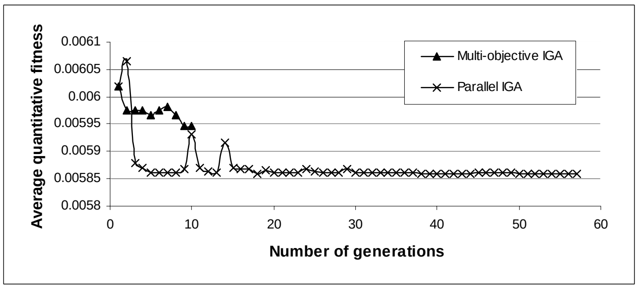

Fig. 2. Qualitative fitness in airfoil design with multi-objective and parallel IGA

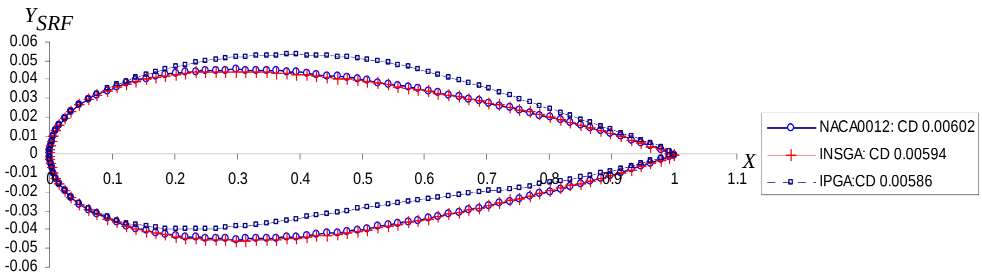

Fig. 3. Original airfoil shape: NACA0012, design using multi-objective IGA: INSGA, design using parallel IGA: IPGA

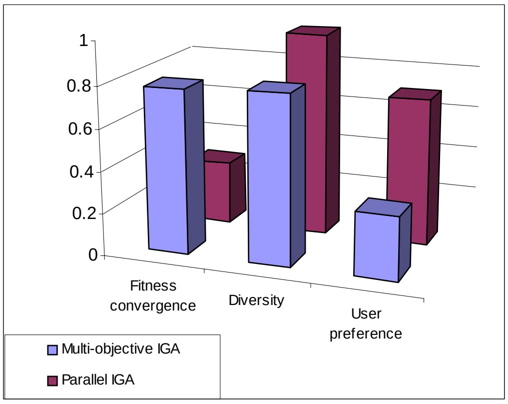

Fig. 4. Overview of performance metrics

When iterations are continued, the local optimum is eventually overcome. With the parallel IGA there is rapid improvement in the quantitative fitness until the 50th generation which stabilizes around the 60th generation and overcomes the local optimum observed in the multi-objective IGA. Parallel IGA significantly outperforms the multi-objective IGA when the fitness convergence metric is applied to evaluate the overall convergence, providing better fitness in both the qualitative and quantitative objectives.

4.2 Diversity

Figure 3 shows sample designs obtained from the multi-objective and parallel IGA. Although there is little difference between the original NACA0012 airfoil and the multi-objective IGA generated airfoil in terms of shape the coefficient of drag is significantly improved. This can help explain the impact of expert opinion on performance and illustrates the high sensitivity of the problem to slight variations in geometry. Although the multi-objective IGA outperforms the parallel IGA, the diversity metric shows a less dramatic difference than the fitness convergence metric.

4.3 Qualitative preference

The users significantly prefer the parallel IGA generated solutions in both the qualitative and quantitative spaces according to the preference metric. Although the users evaluate the same number of designs in both algorithms the users reported fatigue with the multi-objective IGA. The preference of the majority of the users was to interact through a separate population island and they articulated that the impact of user evaluation could be observed clearer with parallel IGA than the multi-objective IGA.

5. Conclusions

This paper presented a novel application of the multi-objective and parallel IGA algorithms to the airfoil shape design problem and compared the two algorithms in terms of fitness convergence, diversity and designer preference. While the multi-objective IGA provided more diverse results, the designers overwhelmingly preferred the parallel IGA solutions. The fitness convergence in both qualitative and quantitative objective spaces was significantly better with the parallel IGA. It is hypothesised that the variability of population sizes and numbers of generations in different objective spaces in the parallel IGA provides an ideal platform for airfoil design optimisation. The designers articulate that interaction through a separate population island is preferable in the case of computationally demanding problems as the airfoil design.

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