Conceptual design of UAV using Kriging based multi-objective genetic algorithm

S. Rajagopal
Aeronautical Development Establishment
DRDO
Bangalore, India

R. Ganguli
Department of Aerospace Engineering
Indian Institute of Science
Bangalore, India

ABSTRACT

This paper highlights unmanned aerial vehicle (UAV) conceptual design using the multi-objective genetic algorithm (MOGA). The design problem is formulated as a multidisciplinary design optimisation (MDO) problem by coupling aerodynamic and structural analysis. The UAV considered in this paper is a low speed, long endurance aircraft. The optimisation problem uses endurance maximization and wing weight minimisation as dual objective functions. In this multi-objective optimisation, aspect ratio, wing loading, taper ratio, thickness-to-chord ratio, loiter velocity and loiter altitude are considered as design variables with stall speed, maximum speed and rate of climb as constraints. The MDO system integrates the aircraft design code, RDS and an empirical relation for objective function evaluation. In this study, the optimisation problem is solved in two approaches. In the first approach, the RDS code is directly integrated in the optimisation loop. In the second approach, Kriging model is employed. The second approach is fast and efficient as the meta-model reduces the time of computation. A relatively new multi-objective evolutionary algorithm named NSGA-II (non-dominated sorting genetic algorithm) is used to capture the full Pareto front for the dual objective problem. As a result of optimisation using multi-objective genetic algorithm, several non-dominated solutions indicating number of useful Pareto optimal designs is identified.

NOMENCLATURE

AR	wing aspect ratio
$\overline{g}$	inequality constraint
HCR	loiter altitude in m
ROC	rate of climb in ms^{-1}
t	endurance in hrs
TC	thickness to chord ratio of wing in percentage
TR	wing taper ratio
UAV	unmanned aerial vehicle
VCR	loiter velocity in kmph
$VMAX$	maximum speed in kmph
VS	stall speed in kmph
W_O	all up weight of UAV in kg
WL	wing loading in kg/m^2
WW	wing weight in kg
$\overline{x}$	design variable

1.0 INTRODUCTION

Aircraft design takes inputs from various disciplines such as aerodynamics, structures, control and propulsion. Since the inputs from various disciplines are inter linked, aircraft design provides considerable opportunities for MDO. The greatest challenge in aircraft design lies in handling these inputs and performing the interdisciplinary tradeoff necessary to obtain a good design. The conventional aircraft design process starts with aerodynamic design to satisfy the performance requirements followed by design iterations and checks to satisfy the requirements from other disciplines. With advances in computing power, designers are investigating the optimum aircraft design process and looking for an overall optimal solution in what is called MDO.

Paper No. 3241. Manuscript received 2 October 2007, revised version received 3 April 2008, accepted 15 May 2008.

https://doi.org/10.1017/S0001924000002621 Published online by Cambridge University Press

Several research activities[1,2,3] have been carried out on the application of MDO to aircraft design. The survey of developments by Sobieski and Haftka[1] reports that MDO methodology has transcended its structural optimisation roots and is growing in scope and depth toward encompassing the complete set of disciplines required by applications. According to that survey, the two major obstacles in realizing the full potential of MDO technology appear to be the high computational demands and complexities arising from organization of the MDO task. The computational issue has been alleviated by the enormous growth of computing power.

Bartholomew[2] provides a definition of MDO incorporating state of the art analysis tools and discusses the function of MDO as a key tool in the context of concurrent engineering. He also says that MDO permits the constraints of a diverse range of disciplines to be addressed from the early stage of the design process. Kroo[3] highlights some interesting aspects of MDO applications in the preliminary design phase and summarises how the field is developing. Kroo also covers the evolution of computational tools, strategies and challenges. Much research has focused on applying MDO for conventional commercial transport aircraft and current generation fighters. For example, Ref. (4) describes the wing planform optimization for a subsonic aircraft. The different methods and approaches for carrying out the MDO problem is discussed in detail by Kroo *et al*[5] who also investigate new architectures for MDO applied to the preliminary design of complex systems.

Most MDO works are based on the traditional gradient-based methods in engineering optimisation. Recently, some researchers have used non-traditional optimisation methods and Hajela[6] presents the status and potential of the application of such non-gradient methods in MDO. The use of evolutionary algorithms such as genetic algorithms and novel multi-objective optimisation methods in a MDO framework for aircraft applications has been researched. Raymer and Crossley[7] compare the merits and demerits of the conventional steepest descent method with that of genetic algorithm as applied to design of a supersonic fighter aircraft. They conclude that for the fighter design problem with less number of design variables, the orthogonal steepest descent algorithm gives the optimum value in much fewer computations as compared to the genetic algorithm. However, they also report that for a different optimization problem and different set of design variables, the advantages of genetic algorithm are worth pursuing.

Marta[8] studied the effect of various genetic algorithm parameters on the efficiency of the algorithm using aircraft design problems and examples. Jun *et al*[9] studied the usage of GAs and RSM to an aircraft wing design by collaborative optimisation. Clayton *et al*(10) address the application of genetic algorithms in aerodynamic optimisation design process. They studied three methods namely truncated Newton (Gradient based) algorithm, simplex approach (Direct search method) and a genetic algorithm for a specific diffuser problem. They conclude that the direct search approach requires a smaller number of evaluations than GA. The gradient method performs as well as the simplex method but is not able to provide a solution for problems with higher number of design variables. Also, the level of robustness obtained by the use of GA is superior to the other methods.

In the MDO process, the number of function evaluation is limited by computation time and cost. On the other hand, if GA is adopted as the optimisation algorithm, then it requires many function evaluations. As a result, in general, MDO using GA is time consuming and becomes impractical if the analysis codes are employed for function evaluation. The organisational complexity can be simplified by replacing the analysis codes with the polynomial based approximations, response surface approximations and other meta-modeling methods. Meta-models are models that seek to provide a simple mathematical representation of a complex physical system. Reisenthel *et al*[11] describe the key role played by meta-models in surrogate based optimisation. They show how the global meta-models can be used for data fusion. They present a methodology that provides simultaneously a meta-model and uncertainty of the model. Polynomial based approximation[12] model is a widely accepted meta-model because of its simplicity. However, this model is limited in representing the non-linearities in aircraft design optimisation problems. Recently, researchers focused on a reduced order model called the kriging model[13,14] basically developed for use in spatial statistics and geostatistics for use in aircraft design problems. This model captures the non-linearity present in most engineering problems with sufficient flexibility and with less computation time. For example, Ref. 15, describes the wing shape and planform optimization for jet transport aircraft and transonic wing planform. In order to avoid the complexities due to organisational tasks and computational demands, Ref. 15 uses the kriging model.

As far as the multi-objective optimisation problems are concerned, Lu and Zhenghong[16] provide a comparison of conventional weighted sum and genetic algorithm and Arora and Marler[17] present an exhaustive list of various multi-objective optimisation methods. Arora and Marler categorise all the methods into three different pools namely methods with prior articulation preferences, methods with post articulation preferences and methods with no preferences. In prior articulation of preferences, the user selects the relative importance of the objective functions. In post articulation preferences, a single solution is selected from a set of mathematically equivalent solutions. In methods with no articulation of preferences, the user continuously provides inputs during the running of the algorithm. Genetic multi-objective algorithms provide post articulation preferences by seeking to capture the complete Pareto optimal set. Arora and Marler conclude that in general, multi-objective optimisation requires more computational effort than single objective optimisation. They also point out that genetic multi-objective algorithms provide a relatively new approach and depending on the application, these methods can be effective in obtaining the Pareto optimal set. Classical multi-objective optimization approaches have difficulties in obtaining the full Pareto set. Very recently, novel and powerful multi-objective evolutionary algorithms have been proposed which show superior performance in obtaining the full Pareto optimal front[18].

The works discussed until now typically involve conventional manned aircraft design. Some special opportunities are provided by UAV design as compared to the conventional manned aircraft design. UAV's are not governed by the strict airworthiness requirements of manned aircraft and provide more flexibility in the selection of wing design parameters. The conceptual design of UAV can be formulated as an optimisation problem and the initial aircraft sizing can be performed by the optimisation approach. Some recent research activity has focused on UAV applications[18-20] of optimisation. Gonzalez *et al*[18] discuss the use of evolutionary algorithms for a single and multi-objective aerofoil optimisation. They bring out the demerits of applying the traditional gradient based approach for problems involving multi-objective, multi-modal and non-differentiable functions. Also, they show that EAs can find global optima and can be executed in parallel by adapting to arbitrary solver codes. Gonzalez *et al*[19] present the design and development procedure of UAV using evolutionary computing approach. They highlight the difficulties in the design of UAVs arising due to the varied and non-intuitive nature of the configurations and missions that can be performed by these vehicles. An MDO framework[19] is applied to two case studies using high fidelity analysis codes. The first case study involves dual objective UAV airfoil section optimisation. Detailed design of a single element airfoil for a small UAV application similar to RQ-7A Shadow 200 tactical UAV is performed with the two fitness functions defined as minimisation of drag at two different flight conditions. Three constraints for maximum thickness, maximum thickness location and pitching moment are used. In the second case study, multicriteria wing design optimisation for a UAV with the two fitness functions defined as minimisation of wave drag and minimisation of the spanwise cap weight is performed. Constraints are imposed on minimum thickness and position of

https://doi.org/10.1017/S0001924000002621 Published online by Cambridge University Press

maximum thickness. In another work, Sobester and Keane[20] studied and constructed a multidisciplinary analysis for UAV airframes. They look at a blended wing body design and illustrate optimisation of the geometry using a constraint analysis.

We see that some works have been done on the design optimisation of UAVs. However, the use of MDO in UAV designs is much less compared to its use in conventional manned aircraft. This is especially true for the application of evolutionary algorithm to UAV design. Also, most works have used simple GA for the optimisation problem and not exploited the power of evolving multi-objective GAs. The advantages of evolutionary methods over classical gradient based algorithms in single and multi-objective optimisation problems are well highlighted by Goldberg[21] and Deb[22,23]. In this paper, the design problem posed as a multi-objective optimisation problem is solved using the evolutionary algorithm and two approaches. An example of conceptual design of low speed long endurance UAV using the two different approaches is illustrated.

2.0 FORMULATION

2.1 Description of the design problem

Maximising endurance and minimising wing weight is the main goal of the UAV conceptual design. Only the wing design parameters are considered. The amount of the fuel to be carried and the volume of systems such as payload and equipment usually govern the fuselage design. The UAV under consideration is a low speed long endurance UAV that is required to loiter over the target area for long hours at a medium altitude. The optimisation problem involves objective functions, design variables and constraints.

2.1.1 Objective functions

In general, the objective functions are identified from the design mission of the aircraft. Dual objectives are considered in this paper. The first objective function is the maximisation of the endurance ($t(x)$). The second objective function is minimisation of the wing weight ($WW(x)$). Throughout this paper, the objective functions are normalised and presented as ratios with respect to the maximum value.

2.1.2 Design variables

In order to satisfy the mission design requirement, various wing planform parameters are considered as design variables. The aspect ratio, wing loading, taper ratio, thickness to chord ratio are the wing parameters treated as design variables. The upper and lower bounds for the wing planform are indicated in Table 1.

Table 1
Design variables — upper and lower bounds

Design variables	Lower bound	Upper bound
Wing Aspect Ratio	0·727	1
Wing Loading	0·6	1
Wing Taper Ratio	0·25	1
Wing Thickness to chord Ratio	0·727	1
Loiter Velocity	0·714	1
Loiter Altitude	0·5	1

Apart from these planform design variables, two more parameters, namely the loiter velocity and the loiter altitude of the UAV, are also treated as design variables. Again, throughout this paper, the design variables are normalised and presented as ratios with respect to the upper bound value.

2.1.3 Constraints

Constraints are imposed on the performance parameters of the UAV. The constraints are imposed on (1) rate of climb at that altitude (2) stall speed and (3) maximum speed at sea level condition. These performance constraints arise again from the requirements.

2.2 Mathematical Representation of Optimisation Problem

The dual objective optimisation problem can be formally represented as:

$$\text{Maximize } f(\bar{x}) = \text{Maximize} \begin{bmatrix} t(\bar{x}) \\ -WW(\bar{x}) \end{bmatrix}$$

$$\text{Subject to}$$

$$\bar{g}_1(\bar{x}) = \left[-ROC(\bar{x}) + ROC^*\right] \le 0$$

$$\bar{g}_2(\bar{x}) = \left[VS(\bar{x}) - VS^*\right] \le 0 \qquad \ldots (1)$$

$$\bar{g}_3(\bar{x}) = \left[-VMAX(\bar{x}) + VMAX^*\right] \le 0$$

$$\bar{x}_l \le \bar{x} \le \bar{x}_u$$

$$\bar{x} = \left[AR \quad WL \quad TR \quad TC \quad VCR \quad HCR\right]^T$$

The dual objective problem has three inequality constraints and six design variables. Move limits are placed on each design variable.

3.0 UAV DESIGN OPTIMISATION MODEL

3.1 Approach 1:

The first optimisation approach is illustrated in Fig. 1. The optimisation process is composed of the aircraft design software RDS and the weight module directly coupled to the optimiser.

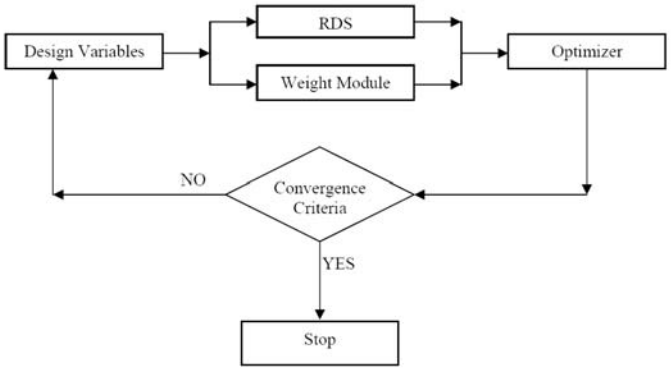


Figure 1. Schematic of optimisation process using direct use of design software (first approach).

https://doi.org/10.1017/S0001924000002621 Published online by Cambridge University Press

RDS professional is a conceptual aircraft design and analysis software developed for use on a personal computer. The algorithm of the software is based on the methods outlined in Raymer's book[24]. RDS features a 3D CAD module for design layout, and has analysis modules for aerodynamics, weights, propulsion, and cost. RDS includes capabilities for aircraft sizing, mission analysis, and performance analysis including takeoff, landing, rate of climb, and acceleration. The RDS professional software is well validated for many aircraft conceptual design stage applications and widely used throughout the world. The structure of RDS is intentionally flexible to allow the user full flexibility to analyse and design. The user can, for example, choose to use some of the RDS modules, while bypassing others in favor of analysis done outside of RDS. In this paper, only three modules namely the aerodynamic analysis module, sizing and mission module and performance analysis module are used from the RDS professional software. The aerodynamic analysis module estimates the lift to drag ratio by calculating the coefficient of lift and drag as per the methods described in Chapter 12 of Ref. 24. The output of the aerodynamic analysis module is written to an aircraft data file. In the sizing and mission analysis module, a mission sizing file is interactively created by selecting mission element types (takeoff, cruise, combat, etc...) and then entering the required data in a matrix format. Then from the aircraft data file, the mission range or endurance is solved for a given aircraft gross weight. RDS performs the mission analysis for a given design, and prints the resulting aircraft takeoff gross weight, fuel weight, empty weight, range and endurance. The performance analysis module uses the data in the aircraft data file to calculate performance such as takeoff, landing, rate of climb, turn rate, maximum speed, stall speed and acceleration.

As far as the weight module is concerned, it is separate and outside the RDS. The weight module calculates the structural weight of the wing of the UAV by using a simple in house developed empirical relation[25] given below,

$$WW = 0{\cdot}642 IW_0 \left(\frac{AR^{0.7103} TR^{0.1224}}{WL^{0.7136} TC^{0.235}} \right) \quad \ldots (2)$$

Most of the design variables are inputs to the aerodynamics analysis module of the RDS. At each iteration, the optimiser varies these design variables using the underlying algorithm. The optimisation model workflow is created in such a way that for a given starting value of the design variables, RDS calculates the aerodynamic characteristics, evaluates the endurance of the vehicle for the mission specified and checks for the performance constraints. For the given design variables, the wing weight is simultaneously estimated by the weight module. This procedure is iterated if the convergence criteria are not met.

3.2 Approach 2:

The second optimisation approach is illustrated in Fig 2. The optimization process is composed of the Kriging model replacing the aircraft design software RDS. The reduced order model is integrated with the weight module and to the optimiser.

3.2.1 Kriging model

Kriging model was basically developed in the field of geostatistics — a hybrid discipline of mining, engineering, geology, mathematics and statistics. In geostastics, Kriging is useful for predicting temporally and spatially correlated data. Kriging meta-models are extremely flexible due to the wide range of correlation function that can be chosen for building the meta-model.

In the first approach, the RDS code is used in the optimisation model for the objective function evaluation. As this design code

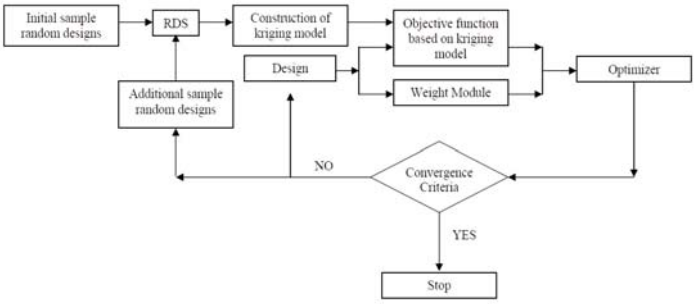


Figure 2. Schematic of optimisation process using Kriging model of design software (second approach).

works in a different operating platform, tremendous time is consumed in all the iterations. Introducing an approximate model in the optimisation algorithm reduces the enormous computation time. The RDS design and analysis solver is replaced with the Kriging model in the objective function evaluation process of MOGA. As the Kriging model introduces uncertainty at the prediction point, the biggest advantage of GA in obtaining the global optimisation may be lost[26]. In order to retain this advantage, both the prediction value and its uncertainty are to be considered at the same time[26]. This is captured by updating the Kriging model during the optimisation. If the optimisation algorithm is not converged, additional random designs are initialised and the Kriging model is reconstructed. The Gaussian correlation function is used in the meta-model interpolates all data points exactly. A brief description of the Kriging model is given next.

Kriging model takes the combination of a polynomial model and a statistical function and is written as follows,

$$\mathbf{y(x)} = \mathbf{f(x)} + \mathbf{z(x)} \quad \ldots (3)$$

where $y(\boldsymbol{x})$ is the unknown function, $f(\boldsymbol{x})$ is the known polynomial function and $z(\boldsymbol{x})$ is the function from a stochastic process with mean zero, variance and non-zero covariance. The polynomial function approximates the design space globally and the localised deviations are created by the function $z(\boldsymbol{x})$. The polynomial function is taken as a constant term for this study. The covariance matrix of $z(\boldsymbol{x})$ that is responsible for the local deviations is given below,

$$\mathrm{Cov}[z(x^i), z(x^j)] = \sigma^2 \mathbf{R}([R(x^i, x^j)]) \quad \ldots (4)$$

where $\mathbf{R}$ is the correlation matrix, and $R(x^i, x^j)$ is the correlation function between any two of the sample data points x^i and x^j. The correlation matrix considered in this paper is the common Gaussian correlation function as described below,

$$\prod_{k=1}^{n} \exp\left(-\theta_k |d_k|\right)^2 \quad \ldots (5)$$

where n is the number of design variables, θ_k is the unknown correlation parameters used to fit the model and d_k is the distance between the k^{th} component of sample points x^i and x^j.

The algorithm of optimisation in this approach is as follows,

- Initially, some random designs are initialised. The procedure to identify these designs is to randomly choose the design points available within 50% on both sides of the initial population.

https://doi.org/10.1017/S0001924000002621 Published online by Cambridge University Press

- The RDS code is run to construct the Kriging model for the two objective functions.
- The MOGA is performed on the Kriging model.
- If the convergence is not achieved, additional random designs are chosen and the optimisation process is repeated till convergence.

Further details of Kriging model are available in Ref 13.

4.0 MULTI-OBJECTIVE GENETIC ALGORITHM

A key feature of this paper is the use of a multi-objective genetic algorithm NSGA-II[27], to solve the dual objective problem. This algorithm can give the full Pareto front for multi-objective problems. The merits and demerits of the classical approaches and evolutionary approaches for a given optimisation problem is extensively discussed in literature[6-9,18-20]. In a nutshell, the difficulties encountered by the classical gradient based optimisation algorithm for a general optimization problem occur in situations with (1) non-smooth variables, (2) nonlinear and discontinuous constraints, (3) noisy functions and (4) multiple minima. However, there are disadvantages in evolutionary optimisation such as (1) no clearly defined convergence criteria, (2) parameter tuning mostly by trial and error, (3) computationally expensive population-based approach and (4) slow convergence to optimum. The main difference between classical gradient based optimisation and the evolutionary algorithm (EA) is that EA uses a population of solutions in each of the iterations, instead of a single solution. Since a population of solutions is processed in each of the iterations, the outcome of an EA is also a population of solutions.

When the optimisation problem involves more than one objective function, the task of finding one or more optimum solutions is termed as multi-objective optimisation[22]. If the objective functions are conflicting in nature, each objective corresponds to a different optimal solution. Thus, there exist a set of optimal solutions where a gain in one objective calls for a sacrifice in some other objective. For a designer, knowing a number of optimal solutions becomes important and it also gives considerable insight into the design thereby providing several feasible and useful design solutions. Therefore, as far as the designer is concerned, the ideal multi-objective optimisation procedure is to find the multiple trade-off optimal solutions with a wide range of values for the objectives and choose one of the obtained solutions using higher-level information. Often this higher-level information would be non-technical, qualitative and experience driven.

4.1 Conflicting objectives

It is well known that there exist multiple Pareto optimal solutions in a problem only if the objectives are conflicting with each other. If the objectives are not conflicting with each other, the cardinality of the Pareto optimal set is one as shown in an example described in Ref. 22. We need to find out whether the dual objectives considered in the conceptual design of UAV are conflicting in nature. To check for this conflict, a design space exploration is done by performing a parametric study. Each of the design variables is allowed to vary and the variation in both the objectives and constraints is observed. For this parametric study, we consider aspect ratio and wing loading as the design variables.

The results of the parameter study are plotted in Figs 3 to 11. The results clearly indicate that the two objectives considered are conflicting in nature. For example, Fig. 3 shows that increasing the wing aspect ratio results in increasing endurance. However, Fig 4 shows that decreasing the aspect ratio could reduce the wing weight. Similarly Figs 5 and 6 present the variation of endurance and wing

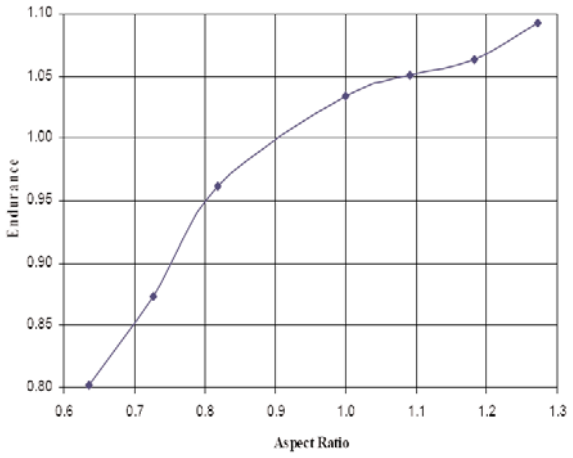


Figure 3. Endurance variation of the UAV with aspect ratio.

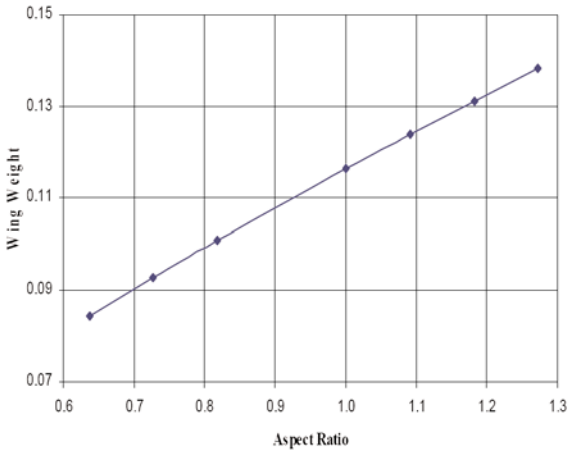


Figure 4. Wing weight variation of the UAV with aspect ratio.

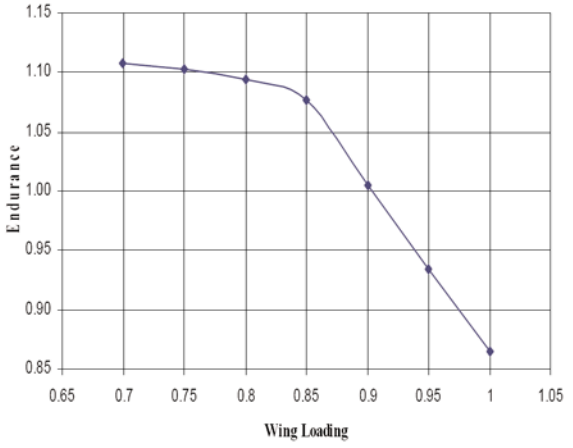


Figure 5. Endurance variation of the UAV with wing loading.

https://doi.org/10.1017/S0001924000002621 Published online by Cambridge University Press

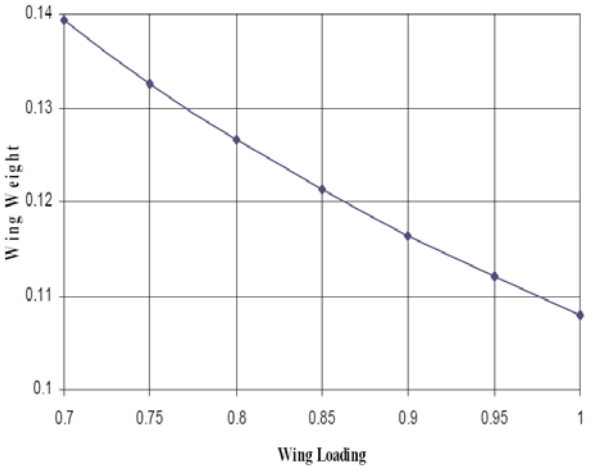


Figure 6. Wing weight variation of the UAV with wing loading.

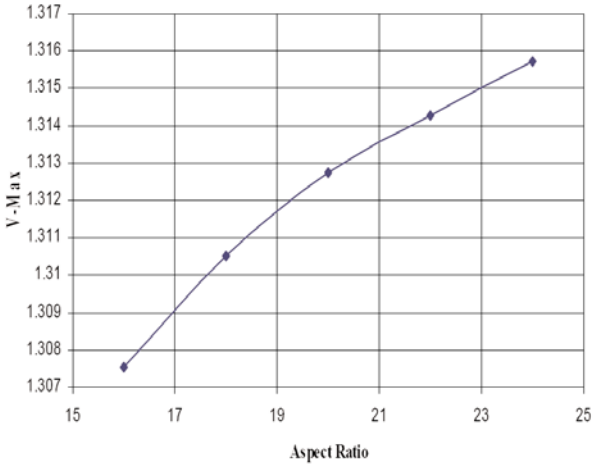


Figure 7. Maximum speed variation of the UAV with aspect ratio.

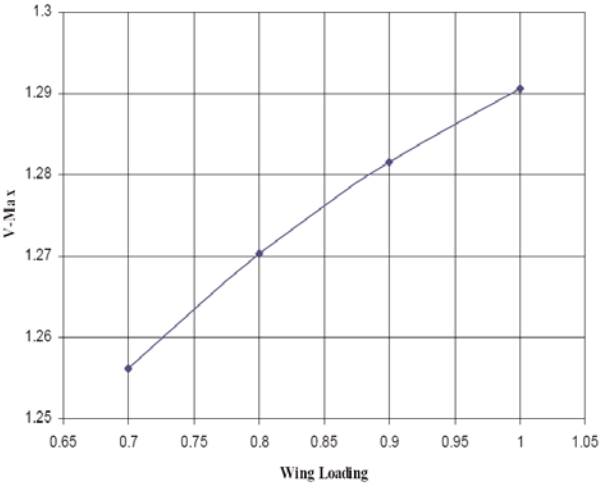


Figure 8. Maximum speed variation of the UAV with wing loading.

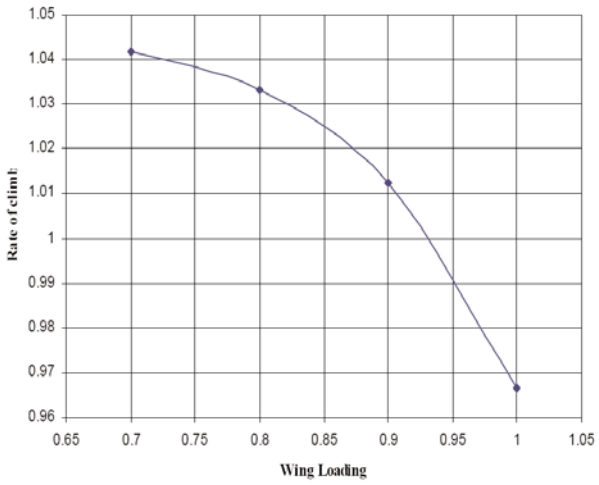


Figure 9. Rate of climb variation of the UAV with wing loading.

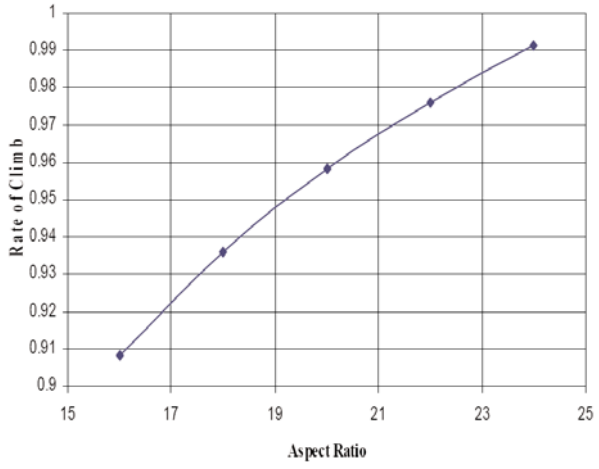


Figure 10. Rate of climb variation of the UAV with aspect ratio.

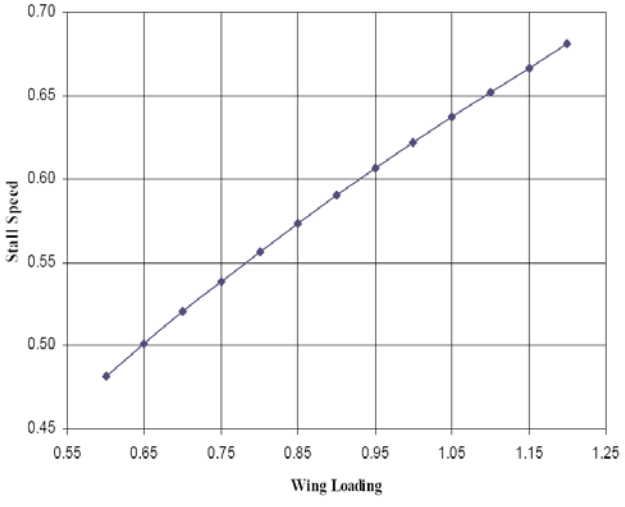


Figure 11. Stall speed variation of the UAV with wing loading.

https://doi.org/10.1017/S0001924000002621 Published online by Cambridge University Press

weight with wing loading, respectively. It shows that when the wing loading decreases, endurance increases and wing weight also increases. Figure 7 and Fig 8 give the variation of maximum speed with aspect ratio and wing weight. It indicates that maximum speed increases with increase in aspect ratio and wing loading. Figure 9 and Fig. 10 show the variation of rate of climb with wing loading and aspect ratio respectively. These two figures show that rate of climb decreases with increase in wing loading whereas it increases with increase in aspect ratio. The variation of stall speed with wing loading is presented in Fig. 11. It indicates that by increasing wing loading, the stall speed increases. We see the conflicting nature of the two objectives. Therefore, a set of Pareto optimal solutions is expected when the multi-objective optimisation problem involving endurance maximisation and weight minimisation is solved. Most of the relationships between the UAV performance parameters and the design variables are also non-linear, making this a non-linear optimisation problem.

Most of the multi-objective optimisation algorithms use the concept of domination. In these algorithms, two solutions are compared on the basis of whether one dominates the other solution or not. A solution $x_{(1)}$ is said to dominate the other solutions $x_{(2)}$ (in other words, $x_{(1)}$ is non-dominated by $x_{(2)}$), if both the following conditions are true[22],

(1) The solution $x_{(1)}$ is no worse than $x_{(2)}$ in all objectives

(2) The solution $x_{(1)}$ is strictly better than $x_{(2)}$ in at least one objective

The non-dominated set of the entire feasible search space S is the globally Pareto optimal set and these solutions are known as non-dominated solutions (Pareto optimal solutions). The rest are called dominated solutions. Since none of the solutions in the non-dominated set is absolutely better than any other, any one of them is an acceptable solution. Since the NSGA-II is based on sorting the non-dominated solutions, it is referred to as non-dominated sorting GA. There are three approaches for determining the non-dominated set[22] namely naive and slow approach, continuously updated approach and Kung *et al*'s efficient approach.

The steps involved in the non-dominated sorting of a population are listed below[22],

- Step 1: Set all non-dominated sets $P_j(j = 1,2\cdots)$ as empty sets. Set non-domination level counter $j = 1$.
- Step 2: Use any one approach to find the non-dominated set P' of population P.
- Step 3: Update $P_j = P'$ and $P = \frac{P}{P'}$
- Step 4: If P ≠ 0 increment j by one and go to Step 2. Otherwise, stop and declare all non-dominated sets P_j for $i = 1,2\cdots$

The binary coded GA's have the following difficulties: (1) search space is discrete, (2) Hamming cliffs problem, (3) search restricted to variable boundaries and (4) arbitrary precision impossible due to fixed length coding. To address these difficulties with binary GA, the NSGA-II uses the real coded GA and the decision variables are coded directly. The idea behind the NSGA-II algorithm is that a ranking selection method is used to emphasise good points and a niche method is used to maintain stable sub-populations of good points. NSGA-II is different from the simple GA only in the way the selection operation works. The mutation operations for NSGA-II are similar to simple GA. The 'Simulated Binary Crossover (SBX)' operator used in NSGA-II is slightly different from the crossover operator of the simple GA and details are given in Ref. (27). The NSGA-II procedure is outlined as follows,

- Step 1: Combine parent P_t and offspring Q_t populations and create $R_t = P_t \cup Qt$. Perform a non-dominated sorting to R_t and identify different fronts: F_i, $i = 1,2\cdots$
- Step 2: Set new population $P_{t+1} = 0$. Set a counter $i = 1$. Until , $|P_{t+1}| + |F_i| < N$ perform $P_{t+1} = P_{t+1} \cup F_i$ and $i = i + 1$. Also 2N is the population size.
- Step 3: Perform the crowding sort procedure and include the most widely spread solutions by using the crowding distance values in the sorted F_i to P_{t+1}.
- Step 4: Create offspring population Q_{t+1} from P_{t+1} by using the crowded tournament selection, cross over and mutation operators.

The NSGA-II algorithm for finding the multiple Pareto optimal solution in a multi-objective optimisation problem has three key features as discussed in Ref. 27: (a) use of an elitist principle (b) an explicit diversity preserving mechanism and (c) emphasis on non-dominated solutions in a population. The NSGA-II requires a non-dominated sorting of a population of size 2N. This requires at most $O(Mn^2)$ computations, where n is the number of solutions and M is the number of function evaluations. Thus the computational complexity of this algorithm is at most $O(Mn^2)$. The greatest advantage of NSGA-II is that the diversity among the non-dominated solutions is introduced by using the crowding comparison procedure, which is used with the tournament selection and during the population reduction phase. Since the solutions compete with their crowding distances, no extra niching parameter is required here. The elitism mechanism does not allow an already found Pareto optimal solution to be deleted.

5.0 UAV OPTIMISATION RESULTS

From the preliminary weight estimation, the empty weight fraction is 0·53 and the useful weight (payload weight and fuel weight) fraction is 0·47. For this study, the following parameters are set for simulations in the optimisation algorithm,

Population size = 50
Number of generations = 100
Crossover probability = 0·9
Crossover distribution index = 20
Mutation probability = 0·1
Mutation distribution index = 100

For the Kriging model construction, the number of random designs chosen is 20 and the number of additional random designs is 10. The optimisation problem is run on a PC with a Windows XP platform and an Intel Pentium IV processor with 2GB RAM and a processor speed of 1·86 GHz.

Applying the two different approaches to the conceptual design of the UAV, no difference is found in the optimisation results. Both the approaches capture the Pareto front fully. The only advantage in second approach is that it is much faster as compared to the first approach. The first approach took 48 minutes to complete all the optimisation runs and arrive at an optimum solution whereas the second approach took only four minutes. The main objective of reducing the computation time in evaluating the objective functions is achieved through the second approach by using the Kriging approximation.

Figure 12 gives the Pareto front obtained for the multi-objective optimization case. The Pareto front has 11 different points with varying combinations of the wing weight and endurance. We call the Pareto point with the lowest wing weight ratio as Pareto point 1 and the point with highest wing weight ratio as Pareto point 11. Table 2 gives the optimum design variables for two extreme members of the Pareto front, which are indicated as Pareto member 1 and 2 in Fig. 12. Thus Pareto member 1 corresponds to Pareto point 1 and Pareto member 2 corresponds to Pareto point 11. The design variables of Pareto member 1 corresponds to the point in Fig 12 which is good

https://doi.org/10.1017/S0001924000002621 Published online by Cambridge University Press

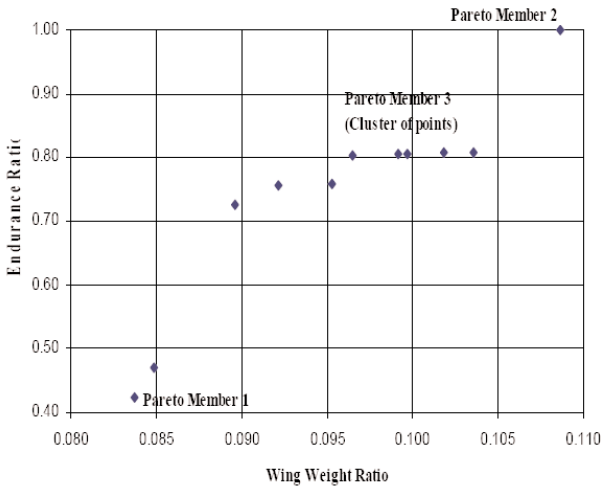


Figure 12. Pareto front of eleven points for the two-objective optimisation problem.

with respect to one objective namely the maximum endurance and the design variables of Pareto member 2 corresponds to the point in Fig. 12 which is good with respect to the other objective namely the minimum wing weight.

In Fig. 12, there is a cluster of five Pareto points, which have almost similar values of the endurance for a small change in wing weight. This cluster of Pareto points is designated as Pareto member 3 and includes Pareto points 6-10. The points in the Pareto member 3 are also actually a smaller Pareto front forming a part of the original Pareto front given in Fig. 12. This smaller Pareto front is expanded and shown in Fig. 13.

Figures 14 to 19 presents the optimal values of the six design variables corresponding to each of the eleven Pareto points given in Fig. 12. The cluster of 5 points in Pareto set 3 (Points 6-10) shows the aspect ratio at the maximum bound. Since aspect ratio is a critical variable for endurance, this may create the cluster like behavior in Pareto set 3. There is a variation of about 30 percent in the aspect ratio as shown in Figure 14 between the different designs. The wing loading in Fig. 15 shows a variation of about 15 percent with two values near the maximum bound. The taper ratio in Fig. 16 shows a large variation of over 60 percent, however, none of the designs show the taper ratio at the upper bound. The thickness to chord ratio shows a variation of about 20 percent between the maximum and minimum values which is shown in Fig. 17 and none of the designs reach the upper limit. The variation of loiter velocity is presented in Fig. 18. There is also a considerable variation in loiter velocity between the Pareto designs of about 25 percent with one design being at the upper limit. Finally, variation of loiter altitude is presented in Fig. 19 and it shows a considerable variation of about 40 percent with no design reaching the upper limit. A lower loiter velocity may be useful for the surveillance applications.

There is a large variation in the design variables between the eleven Pareto points. The different planform shapes corresponding to Pareto members 1, 2 and Pareto point 6 are shown in Fig. 20. Here Pareto point 6 is taken as a representative point from Pareto member 3. We clearly see that these points offer choice to the designer interested in experimenting with different planform shapes and sizing and also for structural design. The identification of the Pareto front gives considerable insight into the design problem. The Pareto points for the conceptual design can now be evaluated for use in detailed structural wing design studies. Various higher-level issues relating to manufacturing ease, strength, aeroelastic stability, stealth etc. can then be factored in before choosing one of the designs.

Table 2
Optimisation Results – Dual Objective Case (NSGA-II)

Description	Pareto Member 1	Pareto Member 2
Aspect ratio	0·73	0·94
Wing loading	0·99	0·874
Taper ratio	0·30	0·475
Thickness to chord ratio	0·94	0·86
Loiter velocity	0·77	0·896
Loiter altitude	0·62	0·75
Endurance ratio	0·4243	1·0
Wing weight ratio	0·083	0·1087

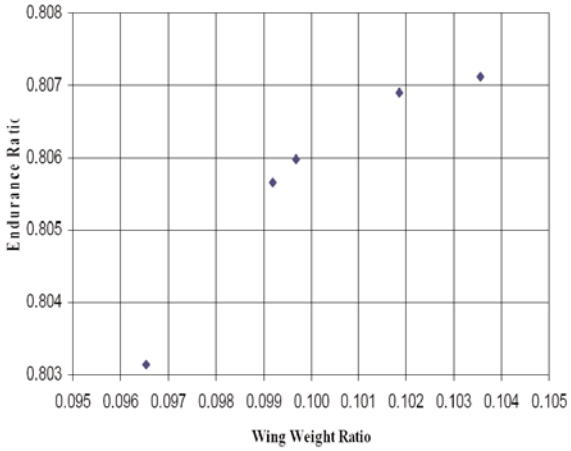


Figure 13. Pareto front corresponding to the cluster of points of Pareto member 3 in Fig. 12.

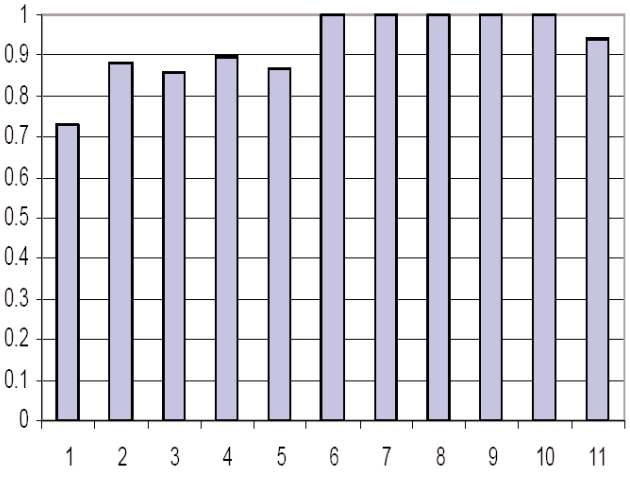


Figure 14. Aspect ratio of different Pareto points.

6.0 CONCLUSION

An evolutionary optimisation algorithm capable of finding the full Pareto front of multi-objective optimisation problems is applied for UAV conceptual design. The conceptual design problem is formulated as a mathematical optimisation problem. A dual objective problem of maximising endurance and minimising

https://doi.org/10.1017/S0001924000002621 Published online by Cambridge University Press

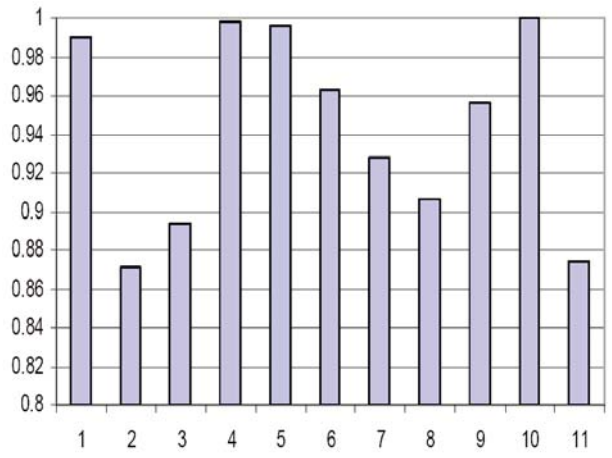


Figure 15. Wing Loading of different Pareto points.

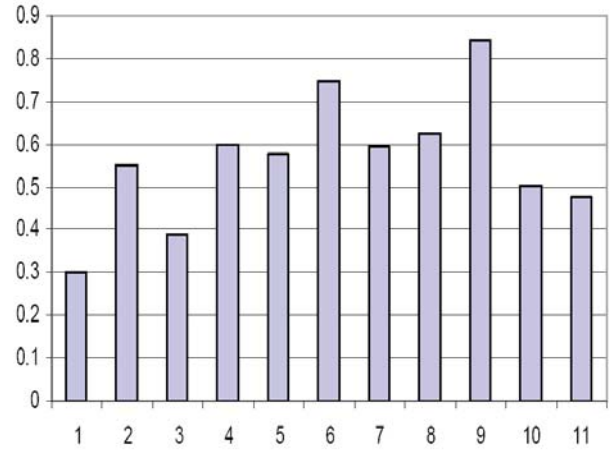


Figure 16. Taper ratio of different Pareto points.

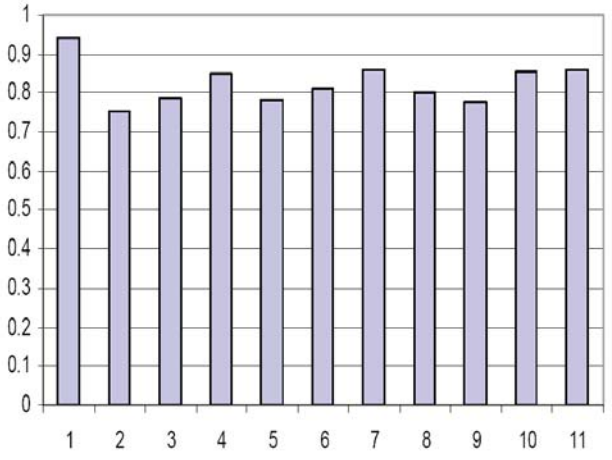


Figure 17. Thickness to chord ratio of different Pareto points.

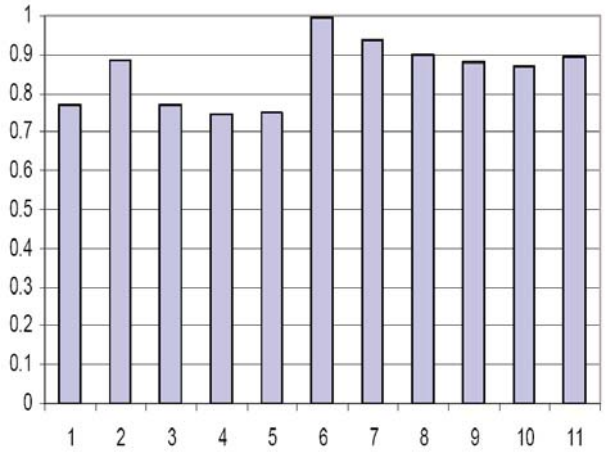


Figure 18. Loiter velocity of different Pareto points.

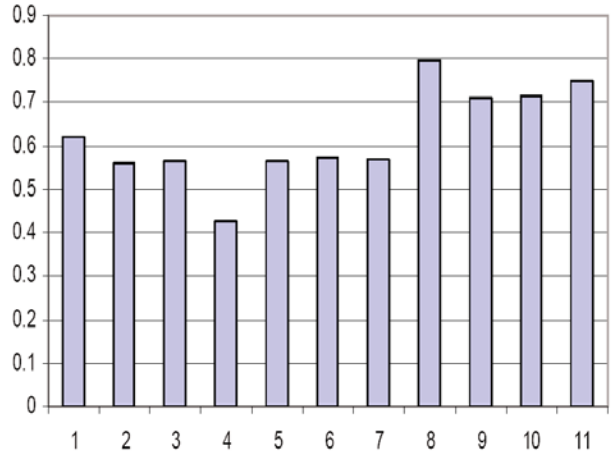


Figure 19. Loiter altitude of different Pareto points.

weight is considered. The formulation and workflow is done in two approaches, initially coupling the analysis code with the optimiser directly. In the second approach, the Kriging approximation model replaces the analysis code. An enormous amount of computation time is involved in the first approach because of use of evolutionary algorithm and analysis codes. Employing the Kriging model in the second approach reduces the computation time by about 90 percent. The robust evolutionary algorithm NSGA-II used to capture the Pareto front is capable of identifying the tradeoff between the conflicting objectives thereby providing alternative useful designs for the designer. It is found that the eleven Pareto designs obtained offer various possibilities to the designer in terms of higher-level requirement and may offer novel and non-traditional solutions to the design problem. The Kriging model employed reduces the computation time without losing any of the Pareto points. The optimisation results confirm the feasibility of the Kriging based MOGA for UAV design optimisation.

https://doi.org/10.1017/S0001924000002621 Published online by Cambridge University Press

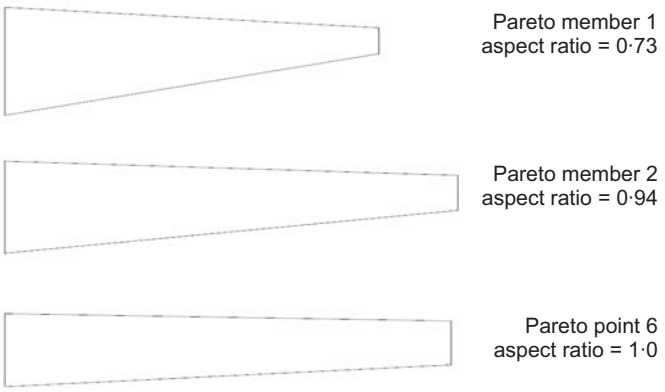


Figure 20. Wing planform corresponding to Pareto members 1, 2 and Pareto point 6.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the support given by all colleagues who helped directly and indirectly in carrying out this work and Director, ADE, DRDO, India for allowing it to be published.

REFERENCES

1. SOBIESKI, I. and HAFTKA, R.T. Multidisciplinary aerospace design optimization: survey of recent development, 1996, AIAA Paper No. 96-0711.
2. BARTHOLOMEW, P. The role of aerospace design and progress towards an MDO capability, 1998, AIAA Paper No 98-4705.
3. KROO, I. Multidisciplinary optimisation applications in preliminary design, 38th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference and Exhibit and AIAA/ASME/AHS Adaptive Structures Forum, Kissimmee, Florida, US, 7-10 April, 1997.
4. WAKAYAMA, S. and KROO, I. Subsonic wing planform design using MDO, *J Aircr,* July-August 1995, **32,** (4), pp 746-753.
5. KROO, I., ALTUS, S., BRAUN, R., GAGE, P. and SOBIESKI, I. Multidisciplinary optimization methods for aircraft preliminary design, AIAA 94-4325, Fifth AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, September 7-9, Panama City, Florida, 1994 Structures, Structural Dynamics and Materials Conference and Exhibit and AIAA/ASME/AHS Adaptive Structures Forum, Kissimmee, Florida, US, 7-10 April, 1997.
6. HAJELA, P. Non-gradient methods in multidisciplinary design optimization — Status and potential, *J Aircr*, January-February 1999, **36,** (1), pp 255-265,
7. RAYMER, D.P. and CROSSLEY, W.A. A comparative study of genetic algorithm and orthogonal steepest descent for aircraft multidisciplinary optimization, AIAA Paper No 2002-0514.
8. MARTA, A.C. Parametric study of a genetic algorithm using a aircraft design optimization problem, Department of Aeronautics and Astronautics, Stanford University, Stanford, California 94305, URL: http://www.cs.ucl.ac.uk/staff/W.Langdon//ftp/public/papers/koza/sp2003/marta.pdf.
9. JUN, S., JEON, Y.H., RHO, J. and LEE, D.H. Applications of collaborative optimization using genetic algorithm and response surface method to an aircraft wing design, *J Mech Sci and Tech*, January 2006, **20,** (1), pp 133-146.
10. CLAYTON, R.P. and MARTINEZ BOTAS, R.F. Application of genetic algorithm in aerodynamic optimization design process, *Aeronaut J,* December 2004, **108,** (1090), pp 611-620.
11. REISENTHEL, P.H., LOVE, J.F., LESIEUTRE, D.J. and CHILDS, R.E. Cumulative global meta-models with uncertainty — a tool for aerospace integration, *Aeronaut J,* 2006, 110, (1108), pp 375-384.
12. CHEN, W., ALLEN, J.K., SCHARGE, D.P. and MISTREE, F. Statistical experimentation methods for achieving affordable concurrent systems design, 1997, *AIAA J,* **35**, (5), pp 892-900.
13. TIMOTHY, W.S., TIMOTHY, M.M., JOHN, J.K. and FARROKH, M. Comparison of response surface and kriging models for MDO, AIAA Paper No. 98-4755, September 1998.
14. ANTHONY, A.G. and LAYNE, T.W. A comparison of approximate modeling techniques: Polynomial versus interpolating models, September 1998, AIAA Paper No 98-4758.
15. KUMANO, T., JEONG, S. and OBAYASHI, S. Multidisciplinary design optimization of wing shape for a small jet aircraft using Kriging model, 2006, AIAA Paper No 2006-932.
16. LU, X. and ZHENGHONG, G. The investigation of multi-disciplinary and multi-objective optimization method for the aircraft configuration design, ICAS Paper No 2002-811.1
17. ARORA, J.S. and MARLER, R.T. Survey of multi-objective optimization methods for engineering, *Structural Multidisciplinary Optimization*, 2004, **26,** pp 369-395,.
18. GONZALEZ, L.F., LEE, D.S., SRINIVAS, K. and WONG, K.C. Single and multi-objective UAV aerofoil optimization via hierarchical asynchronous parallel evolutionary algorithm, *Aeronaut J,* 2006, **110,** (1112), pp 659-672.
19. GONZALEZ, L.F., PERIAUX, J., SRINIVAS, K. and WHITNEY, E.J. A generic framework for design optimization of multidisciplinary UAV Intelligent systems using evolutionary computing, 44th AIAA Aerospace Sciences Meeting and Exhibit, Reno, NV, US, 9-12 January 2006.
20. SOBESTER, A. and KEANE, A.J. Multidisciplinary design optimization of UAV airframes, AIAA 2006-1612.
21. GOLDBERG, D.E. *Genetic Algorithms in search, optimization and machine learning,* Addison Wesley Pub Co, 1989.
22. DEB, K. *Multi-objective optimization using evolutionary algorithms,* Chichester, UK,Wiley, 2001.
23. DEB, K. and SRINIVAS, N. Multi-objective optimization using non-dominated sorting genetic algorithm, *J of Evolut Comp,* 1994, **2**, (3), pp. 221-248.
24. RAYMER, D.P. *Aircraft Design: A Conceptual Approach,* AIAA Education Series, AIAA, Washington DC, 1992.
25. KUPPANAN, M., *et. al*, Weight model of composite wing for MALE UAV, ADE internal report No. ADE/SDET/TM/06 dated 25 July 2006, ADE, DRDO, Bangalore, 2006.
26. JEONG, S., MURAYAMA, M. and YAMAMOTO, K. Efficient optimization design method using Kriging model, *J Aircr*, March-April 2005, **12,** (2), pp 413-420.
27. DEB, K., AGRAWAL, S., PRATAP, A. and MEYARIVAN, T. A fast and elitist multi-objective genetic algorithm: NSGA-II, IEEE *Transactions on evolution comp*, 2002, **6,** (2), pp 182-197.

https://doi.org/10.1017/S0001924000002621 Published online by Cambridge University Press