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Initial Investigation of Aerodynamic Shape Design Optimisation for the Aegis UAV

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Abstract

This paper presents an aerodynamic design optimisation methodology used in further developing an already existing Unmanned Aerial Vehicle (UAV) platform called Aegis. This paper aims to deliver a medium altitude long endurance UAV for civilian purposes. The methodology used is also applicable to conceptual and preliminary design phases of any aerial vehicle platform. It combines a low fidelity aerodynamic analysis tool, Athena Vortex Lattice Code, with a design optimisation tool (Nimrod/O). The meta-heuristic algorithm, Multi-Objective Tabu Search-2 (MOTS2), is used to perform the optimisation process. This new methodological study optimises the UAV wing planform for level flight. It was used successfully to obtain a set of optimal wing shapes for the Aegis UAV flying at different speeds. Prior to the formulation of the design problem, a parametric study was performed to explore the design space and provide an insight into how the objective functions behave with respect to the design variables. The methodology presented here is not finalized, it is a first step to constructing a general framework that can be used to optimise the design of a twin-boom UAV aerodynamic shape. The interfacing of the already successful packages Nimrod/O, MOTS2, and AVL software produces an initial result that shows the capability of the new methodology to provide correct support decisions making for a design optimisation process that will benefit the entire community of UAV researchers and designers when it is complete.

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Keywords: multi-objective optimisation, nimrod/O tool, Tabu search, UAV conceptual design, parallel coordinates;

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1. Introduction

The design of unmanned aerial vehicles (UAVs) has expanded substantially over the past two decades. Although the UAV was initially introduced for military applications, they have now become vital for many civilian uses. The variety of UAV applications requires different UAV configurations. Regardless of the specific UAV configuration, engineers are required to design UAVs that can successfully withstand a wide range of flight conditions, are suitable for long survey periods and have the advantage of low cost. This is made possible by using low fidelity code during the conceptual design phase, which can accelerate the design procedure and enable the design engineers to manipulate large numbers of parameters. Due to the fluid nature of the conceptual design process, it is not recommended to use high fidelity analysis design tools such as Computational Fluid Dynamics (CFD) and Finite Element Methods (FEM) at this stage as they can be costly (Jameson, 1999; Mason et al., 1998). What is required is a tool that strikes a better balance between sufficient accuracy and computational cost. This tool should contain considerable data concerning basic aircraft geometry to minimise the time required for the tens of thousands of necessary computations (Nicolai et al., 2010). At the end of the preliminary design phase, it is possible to utilise more costly and time-consuming software, since by then only one design case is being studied (Raymer, 2002). Ideally, an efficient design configuration of limited cost and less computation time would be achieved by coupling an aerodynamic design code with an optimisation algorithm (Chen et al., 2015; Leifur Leifsson, 2015).

On the other hand, even though the aircraft optimisation process is function of several disciplines; aerodynamics, structural engineering, control theory and aeroelasticity, the design process invariably starts with an aerodynamic shape to satisfy the aerodynamic constraints, and this is followed by satisfying the requirements of the other disciplines (Rajagopal and Ganguli, 2012). Typically, each discipline contains more than one objective, and these objectives commonly conflict with each other. The solution for such a problem is complex and requires a slightly different approach to a single objective optimisation problem. Computational time becomes a significant factor in this case with the final design a trade-off, and it is recommended that a Pareto front should be used to find the optimal decision (Chase et al., 2009; Jones, Mirrazavi, 2002; Tobergte and Curtis, 2013).

To address these needs, we combine the low fidelity flow solver Athena Vortex Lattice (AVL) with a design optimisation tool (Nimrod/O). Nimrod/O is one of the software packages that utilize resources on a global computational grid. It computes the values of objective functions and performs optimisation by parallel processing, so computational time is reduced (Kipouros et al., 2012; Riley et al., 2010). On the other hand, AVL is easy to use and capable of manipulating a large number of design parameters with short computational times and limited cost (Hadjiev and Panayotov, 2013).

The idea of aircraft optimisation design is not new, and much work has been done in this field at last few years. Hicks et al. (1974) optimised the design of an airfoil section by coupling a numerical optimisation method based on the method of feasible directions with an aerodynamic analysis code. This work is considered as the first practical application procedure for aerodynamic shape optimisation (Leifsson et al., 2014). The work of Hicks et al. (1974) has been extended to the design of three-dimensional wing geometry combining an aerodynamic code capable of fully simulating potential inviscid flow, with a conjugate gradient optimisation algorithm based on the methods of feasible direction. Since then, aerodynamic shape optimisation, using either gradient-based optimisers or evolutionary algorithms have been extensively explored. However, use of optimisation techniques for UAVs aerodynamic shape optimisation is much less well developed compared with the optimisation technique used for commercial aircraft design.

Recently, many researchers have started to show an interest in using evolutionary algorithms (EA) instead of gradient base algorithms (Cioppa, 1995). The drawbacks of conventional gradient base methods are the difficulty of getting gradient information on the objective function, and the optimiser usually tends to become trapped in local minima. In contrast, EA has the important ability to compute the global minimum (Jahangirian and Shahrokhi, 2011). Thus, several works have utilised EA to successfully optimise UAV lifting surfaces (González et al., 2005; Rajagopal et al., 2007; Shiau et al., 2010). The reason for investigating different optimisation techniques is to reduce the length of the design cycle, reduce computational cost, and improve the quality of the design (Vanderplaats and Springs, 2001). None of the publications quoted has made a full parametric sweep to explore the design space before the formulation of the optimisation problem. However, by performing a sweeping study, the designer can efficiently explore a range of design scenarios and get a clear idea of how the design variables and objective functions are related (Pratiksha Saxena, Dipti Singh, 2016).

On the other hand, visualisation of data becomes more difficult as the number of variables in the optimisation process increase. To overcome these issues, parallel coordinate techniques for viewing multi-dimensional data are used (Inselberg, 2009; Kipouros et al., 2013). This presents the solution in a multi-dimensional parallel coordinate system, where parallel coordinates represent each variable. It allows observation of relations between design variables and trade-offs between objectives and monitors the evolutionary process (He and Yen, 2016; Novotn, 2006; Weiskopf, 2015).

The remaining part of the paper is organized as follows. In Section 2, the methodology used in this work is described. The description of the design problem and problem formulation setting are presented in Sections 3 and 4, respectively. Finally, Sections 5 and 6 give the optimisation results and conclusions.

2. Methodology

To better accomplish of the best UAV MALE configuration, a new methodology is presented in the schematic shown in Fig. 1, and which consists of three parts: Nimrod/O design optimiser tool, the Athena Vortex Lattice (AVL) aerodynamic code, and an Interface-AVL that controls the interactions. Nimrod/O is a tool for distributed optimisation that combines optimisation, computing, and rapid sweeping (Abramson et al., 2006, 2001; Kipouros, 2012; Riley et al., 2010). The optimisation algorithm used in this work is the MOTS-II (Tsotskas et al., 2015). A meta-heuristic algorithm that searches for the global minimum and does not stop at local ones. It depends on the Hooke and Jeeves (H&J) local search algorithm that couples three different memories; short, medium, and long-term memories for performing Tabu, intensification and diversification searches (Jaeggi et al., 2008; Pirim et al., 2008; Tobergte and Curtis, 2013). The low fidelity flow solver used in this methodology is the Athena Vortex Lattice (AVL) (Drela, M. and Youngren, 2006). This is a well-known code for aerodynamic and flight-dynamic analysis of rigid body aircraft of arbitrary configuration. It uses an extended Vortex Lattice Method for creating wings and tails and slender-body theory for fuselage and nacelle modelling (Hadjiev and Panayotov, 2013).

Defining a new UAV geometry (dimensions and mass properties) using AVL code requires filling two files manually. For the automatic filling and reading of these data, a code (Interface-AVL) that controls the interaction is written. Its purpose is to (i) generate the configuration need to run AVL, (ii) satisfy certain constraints that are required to complete the flight mission, and (iii) compute other quantities that are needed to perform the sweep and evaluate the objective function, such as parasite drag (Sadraey, 2009) and mass properties. The mass of the UAV is the sum of the masses of all the subsystems including the frame structure, propulsion system and payloads, and is parametrized in terms of the wing design variables.

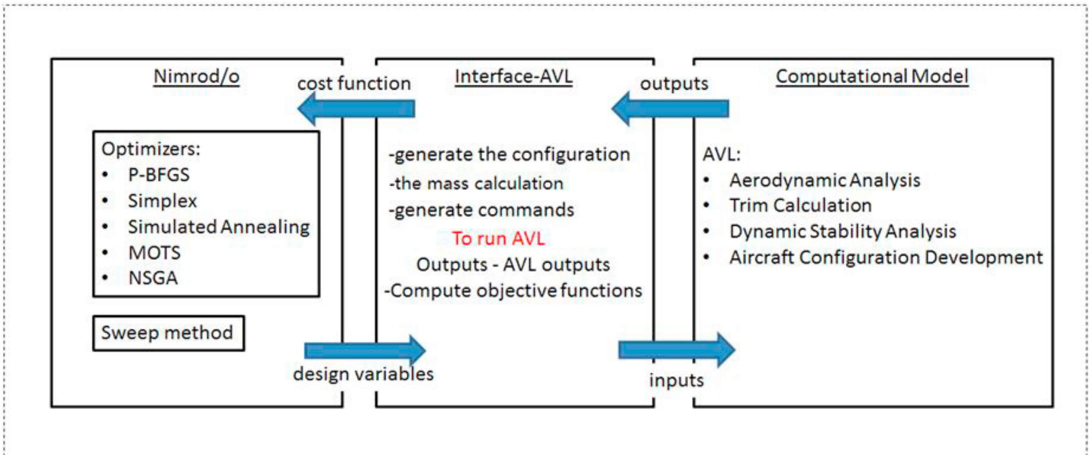

Fig. 1. Schematic of the optimisation methodology

Prior to the formulation of the problem, a parametric sweep study was conducted. It was performed using the Sweep method contained in the Nimrod/O tool. The parametric sweep allows the designer to explore a range of design scenarios and gives a clear idea of how the model behaves. Once the sweep results have been analysed and investigated, the optimisation problem is formulated. The aerodynamic design optimisation problem is formulated as a single and multi-objective function. The optimisation process starts by sending the jobs to the High-Performance Computer (HPC) and stops when the number of evaluations reaches a pre-set number. Penalty functions are applied to solutions that do not satisfy the constraint

3. Description of the design problem

Some four years ago, Cranfield University launched a project to develop a medium altitude and long endurance UAV for surveillance missions and an initial base design configuration was built. The design is not yet fully optimised and there is room for further improvements (D'Auzay, 2011; Keast, 2015). The base UAV consists of a rectangular wing and two different tail configurations; U-Tail and inverted Vee-tail. It is a twin-boom pusher with maximum take-off mass equal to 66 [kg] and capable of carrying 10 to 15 [kg] payload. It flies at an altitude of 2000 [m], where the density of air is 1.007 [kg/m^3]. Using AVL, the lift coefficient (CL) for level flight is found to be 0.304 $(CL_{\propto=0} = 0.304)$ at a cruise speed (v) equal to 43.6 [m/s]. In this work, the wing planform parameters are used to obtain a set of optimal wing configurations for the Aegis UAV in steady flight. Optimal wing configurations will result in maximum UAV endurance. Gudmundsson defined endurance as the time period that UAV will remain in steady flight while consuming a certain amount of fuel. Ideally, the endurance ratio (E) will be an optimum by using flight conditions and configurations that maximize the term $C_L^{3/2}/C_D$ (Gudmundsson, 2014; Gundlach, 2012).

In order to formulate the design problem, we defined the objective functions and design space as shown in Table 1. Two different objectives are included in this study; maximise the endurance ratio and minimise the structural mass (UAV mass). However, since all solvers attempt to minimise objective functions, the endurance ratio is redefined as $(-C_L^{3/2}/C_D)$. Throughout this work, the design variables' upper and lower bounds were amended as a result of parametric sweep results and Pareto front solutions.

Table 1. Design variables and their lower and upper bound

Design Variables, $\overline{x}$	Span [m]	Root chord [m]	Taper ratio, λ_t [-]
Lower bounds, $\overline{x}_l$	2.59	0.42	0.6
Upper bounds, $\overline{x}_u$	4.81	0.78	1.0

In order to maintain the applicability of the design problem, we considered a number of constraints. It is essential to apply appropriate constraints, either linear or non-linear, to the design variables to limit the search space of the optimiser algorithm and to ensure obtaining a feasible solution. However, exploring the design parameter space without applying any constraints is important too. Three different types of constraints are used in this work; equality constraints, inequality constraints, and non-linear inequality constraints. The equality constraints were applied to the weight and lift during level flight, while inequality constraints were applied to the design variables to control their upper and lower bounds. The non-linear inequality constraints were applied to set the upper limit for stall velocity (V_{st}) and lower limit for maximum velocity (V_{max}). Other constraints were imposed on the UAV during its flight, such as fixed air density (ρ_∞), fixed gravity (g) and lift equal to weight. The stall and maximum velocity for the base design were defined by (V_{st}^*) and (V_{max}^*) , respectively.

$$
\begin{gathered}
CL = 0.304 \\
V_{st}(\overline{x}) - V_{st}^* \le 0 \\
-V_{max}(\overline{x}) + V_{max}^* \le 0 \\
\frac{1}{2}\rho_\infty v^2 S_w CL - (UAV\ mass).g = 0 \\
\overline{x}_l \le \overline{x} \le \overline{x}_u \\
\overline{x} = [span \quad root\ chord \quad taper\ ratio]^T
\end{gathered}
$$

4. Problem formulation and settings

Before formulation of the optimisation problem, existing relations between the desired objectives and design variables need to be found (Pratiksha Saxena, Dipti Singh, 2016). To explore the design space and identify any design limitations, a parametric sweep study was performed. Cartesian and parallel coordinate visualisations were used to visualize the sweep results. The analysis and investigation of the results were used as a feedback to formulate the problem.

4.1. Parametric sweep study and results

Prior to the formulation of the design problem, a parametric study was performed to (i) explore the design space, (ii) provide an insight into how the objective functions behave with respect to the design variables, and (iii) validate the Interface-AVL results. It takes all combinations of the variables to explore the entire design space. Whether the design variables have positive or conflicting effects on the objective functions becomes clear after performing the parametric study. If the objectives do not conflict with each other because of design variables variations, the coordinates of the Pareto optima reduce to only one. In contrast, when the objectives conflict, the coordinates of Pareto optima are more than one (Deb, 2001).

The sweep steps were in steps of 0.1 [m], 0.01 [m], and 0.0075 for the design variables span, root chord, and taper ratio respectively. The sweep process was performed seven times to cover all design variable combinations. Firstly, the sweep study began by sweeping each design variable independently to display any dysfunction that may exist in the optimisation algorithms (methodology), and then sweeping different design variables in combinations. The first result of the parametric sweep for level flight subject to a constant lift coefficient showed a slight oscillation existed in the endurance ratio. However, by improving the quality of panel discretization for the lifting surfaces, design variables sweep steps, and precision of some variables in the code, the results were improved and the graph became smoother, see Fig. 2. It is obvious from Fig. 2-A that increasing wingspan (wing root chord and taper ratio fixed at 0.6 and 1.0, respectively) will minimise endurance ratio (i.e. improving). On the other hand, increasing the root chord length (wingspan and taper ratio fixed at 3.7 and 1.0, respectively) caused the endurance ratio to pass through a minimum value at a chord length of about 0.65 m, and then increase; similarly with increase in taper ratio (wingspan and root chord fixed at 3.7 and 0.6, respectively) the endurance ratio passed through a minimum value at a taper ratio of about 0.75 but then increased, see Figs. 2-B and 2-C.

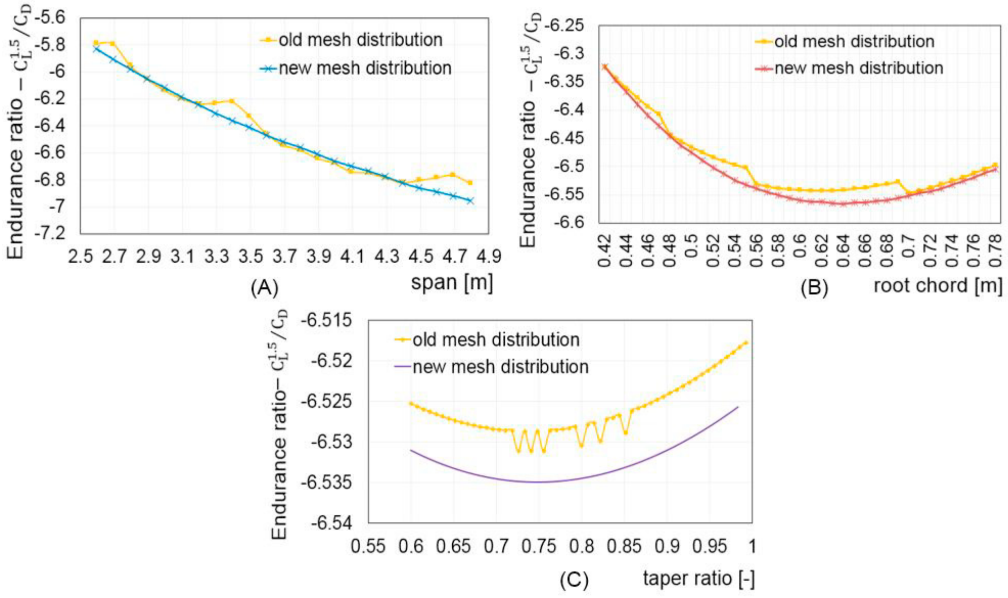

Fig. 2. Sweep results before and after panel discretisation and accuracy improvements for span (A), root chord (B), and taper ratio (C)

To check whether the design parameters have conflicting effects on the objective functions or not, each design variable is allowed to vary as a function of both objectives as shown in Fig. 3. It is clear that a confliction relation exists between wingspan and both of the objectives. Since one of the objectives is decreasing and the other is increasing when the span is increased. However, the aim is to minimise both of the objectives. Thus, a conflict exists, and Pareto optima should be used to optimise the wingspan. On the other hand, increasing either root chord or taper ratio will cause UAV total mass to increase, but will have a varying impact on the endurance ratio as shown in Figs. 3-B and 3-C. Sweeping the root chord in steps of 0.01 [m], gradually improved the endurance ratio until the wing root chord equalled 0.64 [m], after which it slowly declines. Sweeping the taper ratio in steps of 0.0075 produced a maximum absolute value of endurance ratio when taper ratio was about 0.76. Thus, optimising the wing geometry as a function of these three design variables is a trade-off problem. Such a problem requires the correct support for the decision maker to perform the trade-off process accurately.

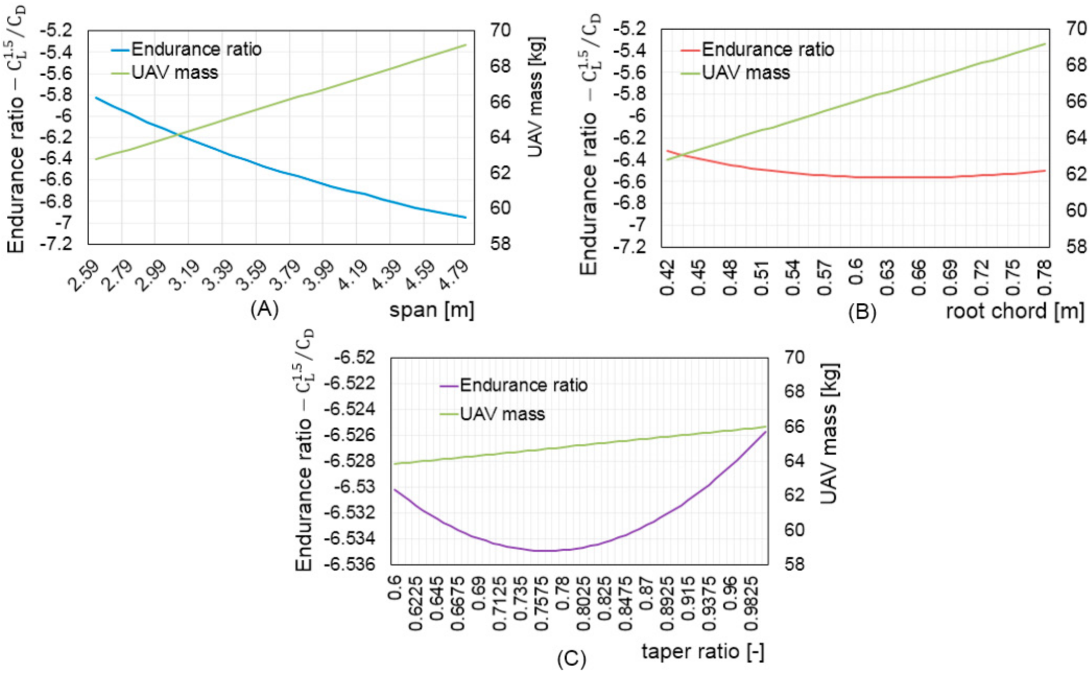

Fig. 3. Design variables varying with both objectives for span (A), root chord (B), and taper ratio (C)

The sweep process was performed by the simultaneous sweeping of the design variables in various combinations (two and three design variables together). Visualization of these results was performed using parallel coordinates. This kind of technique is very effective at highlighting the effects of using different combinations of the design variables in the objective functions. Figs. 4 to 7 show that a trade-off solution is required to improve the values of the objective functions and that only a compromise in the values of the design variables can achieve an optimum result. It is clear that the objective functions are more sensitive to wingspan and less sensitive to taper ratio. Also, objective functions are highly sensitive to span-root chord sweep but less so to root chord-taper ratio sweep. Actually, sweeping the design variables either individually or in combinations provides a better understanding of the design space, design variables, and objective function relations.

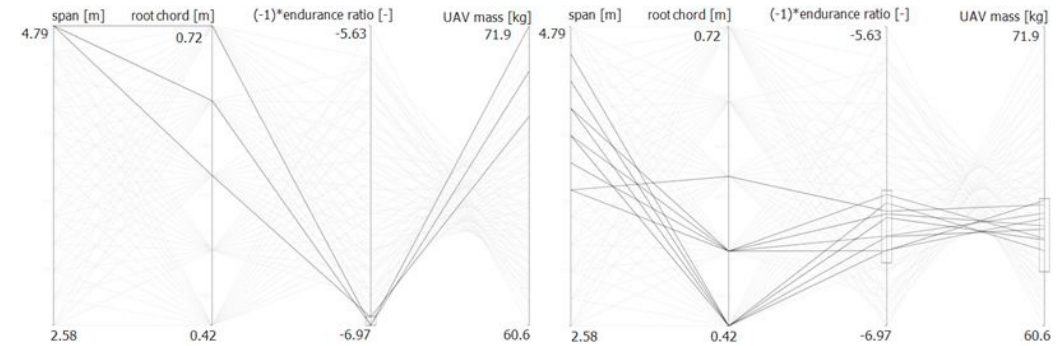

Fig. 4. Span-root chord sweep results

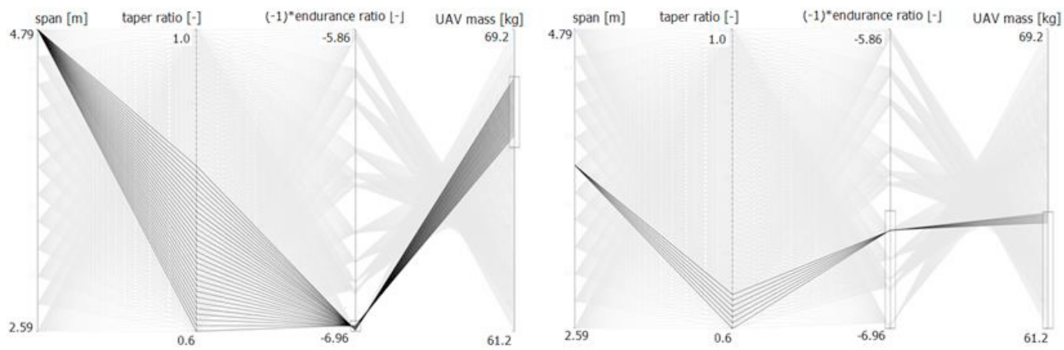

Fig. 5. Span-taper ratio sweep results

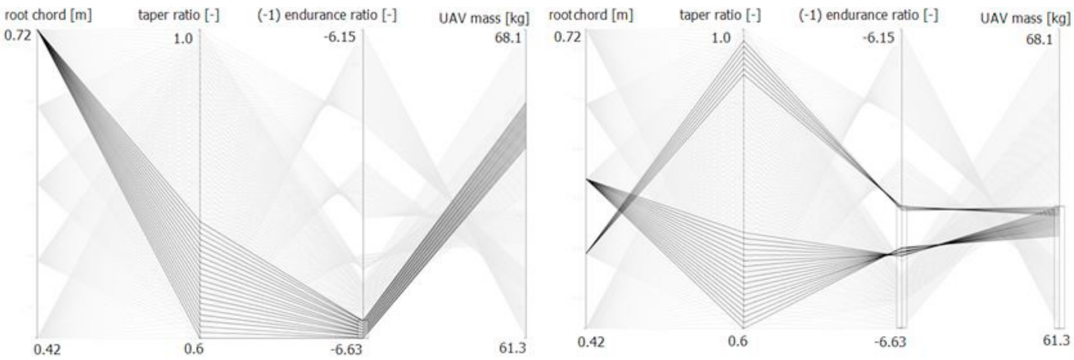

Fig. 6. Root chord-taper ratio sweep results

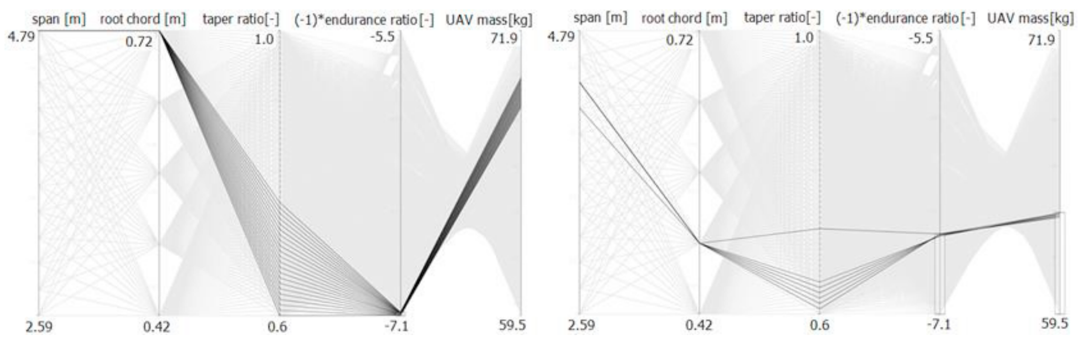

Fig. 7. Span-root chord-taper ratio sweep results

5. Optimisation procedure and results using MOTS-II

Exploring the design parameter space without applying any constraints is an important stage in checking the implementation of the interface using the AVL code, MOTS2 algorithm, and Nimrod/O tool optimizer. The left panel in Fig. 8 shows a section of the Nimrod/O schedule file, where the user can identify the MOTS2 parameters. The optimisation process first starts without applying any constraints and then under constraints. Fig. 8, right panel, shows the feasible solutions without applying a constraint. It shows 56 different Pareto points that have different design variable combinations and unlike aerodynamic characteristics. The optimiser satisfied the maximum requirements of both objectives in point-1 and point-56. Point-56 gives minimum UAV weight, whereas point-1 gives the best endurance ratio. As Pareto optima do not accept the domination of a single objective, different combinations of wing design variables are available for the remaining Pareto points, where there is no absolute domination of one objective above the others.

```
method mots_ii
  starts 1
    resume optimisation 0
    number of regions 4
    size of Short Term Memory 20
    intensification 15
    diversification 25
    stepsize reduction 50
    initial step size 0.1
    stepsize reduction-factor 0.5
    size of sample 2
    number of evaluations 400
    starting method 0
    pattern move mode 1
    tolerance 0.00
    on error ignore
  endstarts
endmethod
```

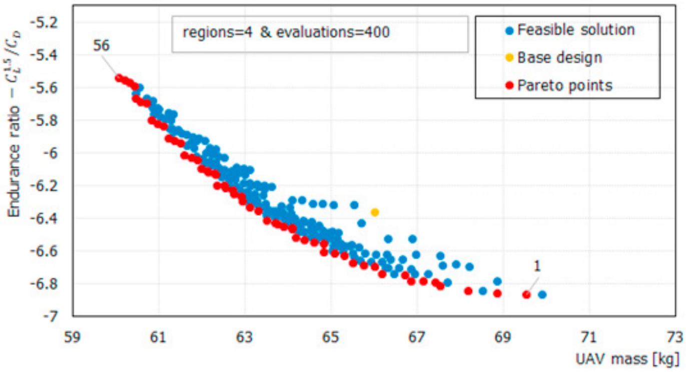

Fig. 8. Left MOTS2 settings and right Optimisation results without constraints

Finally, the optimiser is re-executed under constraints to get more feasible solutions. Fig. 9 shows optimisation results using 5 regions, and different numbers of evaluations. It is clear that the Pareto front results become smoother as the number of evaluations is increased. Since the design variable bounds needed to be redefined, 14 runs were performed using different regions and evaluations. Then, by directly observing the Pareto front of each solution, using the parallel coordinates visualisation technique, the design variables' bounds were efficiently redefined, see Fig. 10.

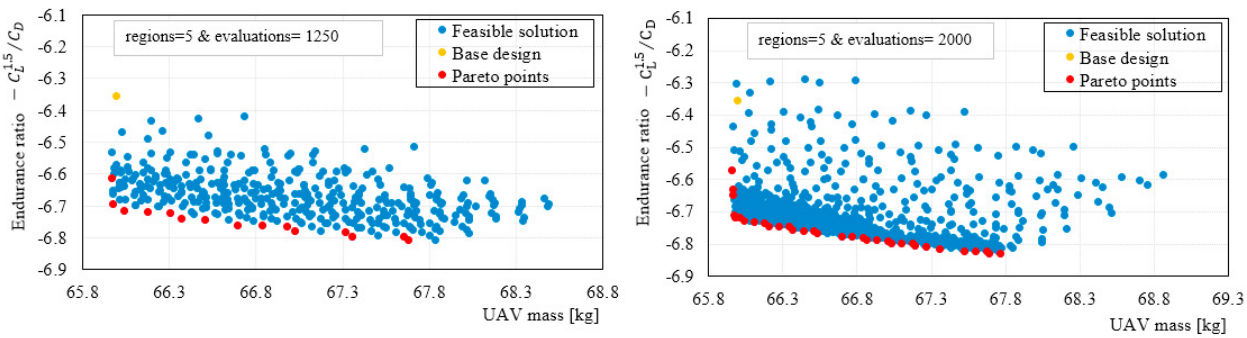

Fig. 9. Initial optimisation results with using constraints; left using 5 regions and 1250 evaluations, and right using 5 regions and 2000 evaluations

It obvious that when the wingspan is a maximum (4.8 m) and taper ratio is a minimum (0.6), the endurance ratio has its best value (-7.0), and the mass values can vary from minimum to maximum. This variation in mass values is due to differences in wing root values. It is clear that wing root values between 0.55 [m] and 0.725 [m] are more efficient, whereas chord root values below 0.55 do not contribute either to best endurance nor minimum weights. Using maximum span value and proper selection of taper ratio and chord root will result simultaneously in a reasonable endurance ratio and UAV mass.

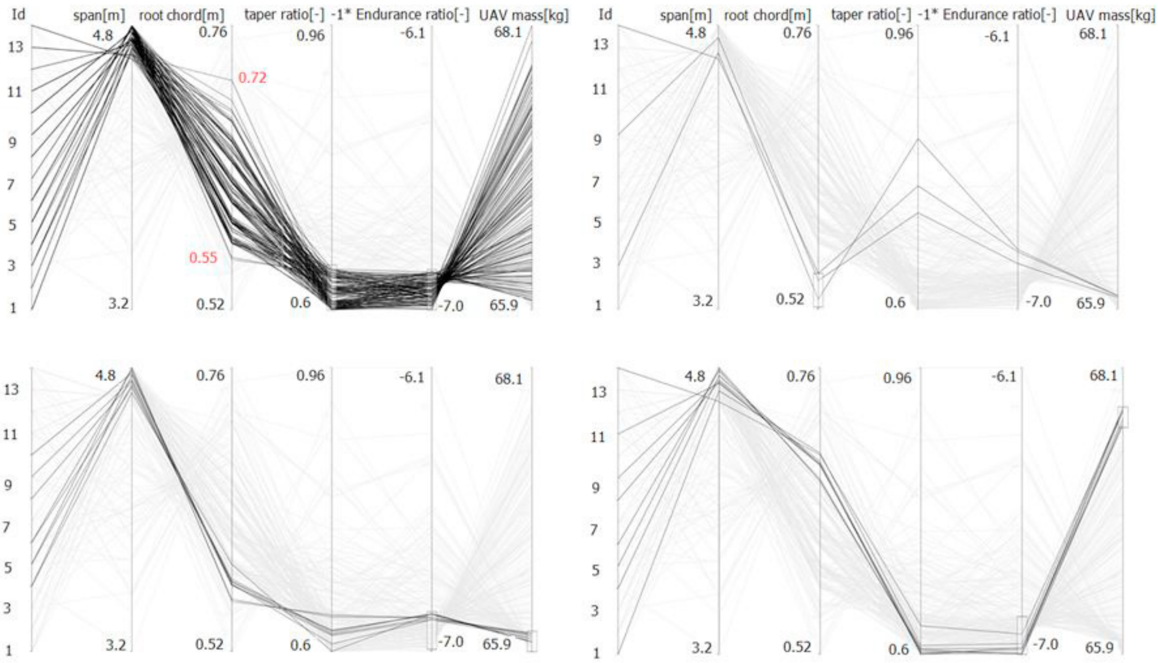

Fig. 10. Pareto front points analysis using parallel coordinates

To investigate the effects of lower values of taper ratio, another case study was performed by merely changing its lower bound from 0.6 to 0.4. It was found that the minimum value of taper ratio that can be assigned to any new configuration was 0.5. The optimiser could not go below this value of taper ratio because of the constraint on stall velocity. However, a minimum taper ratio of 0.6 was selected as a lower bound at this stage of the design to consider the wing surface area required for control surfaces in the next step of the design process. On the other hand, endurance ratio is almost directly proportional to wingspan, so that as wingspan increases, the endurance ratio is also improved. However, the maximum wingspan is restricted to 4.5 [m] due to constraints imposed by material stiffness, the ground effect at landing, and handling requirements.

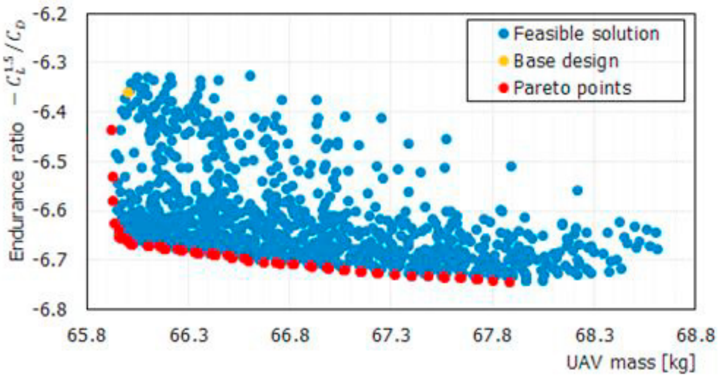

Fig. 11. Optimisation results using 5 regions and 1300 evaluations

On the other hand, to select a sufficient number of suitable regions and evaluations necessary to obtain an efficient and optimal design, the MOTS-II setting was investigated by performing several runs with different sets of regions and evaluations. Since the number of evaluations had a significant impact on the computational time required to find an optimised design or Pareto front (Chase et al., 2009), an adequate number of evaluations should be used. Increasing the number of regions forced the algorithm to explore more areas of the design space (Gendreau, 2003). Consequently, 5 regions and 1300 evaluations were selected. Applying the above changes, Nimrod/O was again used to obtain a set of optimal wing shapes for the Aegis UAV at different flight speeds. Fig. 11 shows the feasible solutions. It shows 64 different Pareto optimal, and there is no absolute dominance of one objective over the others.

For further study, three Pareto solutions were selected (P1, P2, and P3). The performance of the selected shapes were compared with the base design, see Table 2. An improvement of 6.3% endurance ratio was achieved by P3 with only 2.9% mass penalty, whereas P1 with zero mass penalty achieved 2.1% endurance ratio improvement. To examine whether the optimized shapes gave better performance than the BD, simulation of Pareto shapes as a function of the angle of attack (AOA) was performed. This is not included in this work as the focus here is on investigating a new methodology to generate a set of Pareto optimal. However, multi-point optimisation - by including conditions at different lift coefficients - will be taken into consideration in further work to obtain shapes that are more robust.

Table 2. Aerodynamic shapes optimisation results

Pareto front	**Span [m]**	**Wing root [m]**	**λ_t [-]**	**Wing Loading [kg/m^2]**	**AOA [deg]**	**v [m/s]**	**UAV mass [kg]**	**E [-]**
P1	3.90	0.66	0.73	29.64	-0.12	43.54	66.00	6.48
P2	4.35	0.63	0.63	29.57	-0.36	43.49	66.05	6.63
P3	4.50	0.73	0.6	25.84	-0.26	40.65	67.93	6.75
BD	3.70	0.60	1.00	29.73	0.0	43.60	66.00	6.35

6. Conclusion

An aerodynamic design optimisation methodology that will be used in the further development of an already existing Aegis UAV has been described and investigated. The analysis and visualisation of sweep results provide an insight into how the objective functions behave with respect to the design variables. Furthermore, by direct observation of the Pareto front of each solution using parallel coordinates visualisation, the design variables' bounds were redefined efficiently. The optimisation process used is computationally efficient and capable of exploring various design scenarios in a short time. It generates feasible solutions for the design problem under the defined constraints. For confirmation, the authors selected four Pareto optimal solutions. Comparison with the base model showed a better performance for these configurations. Further work is in progress to extend the methodology and develop a complete configuration of the UAV Aegis.

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