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A hyper-heuristic approach to aircraft structural design optimisation

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Abstract The conceptual design of an aircraft is a challenging, highly multidisciplinary problem in which optimisation is of great importance in order to rapidly generate near-optimal solutions. Optimisation of the aircraft structure is critical to the solution in order to design an airframe of minimal mass whilst maintaining strength under load. Hyper-heuristic optimisation is a newly evolving field of research wherein the process applied to an optimisation problem is itself optimised, such that solution quality and process efficiency may be improved. The infancy of hyper-heuristic optimisation has resulted in limited application within the field of aerospace design. This paper describes a framework for the optimisation of the structural layout of an aircraft concept thorough a hyper-heuristic approach, including a case study to illustrate the influence of hyper-heuristics on the problem. Results of the study indicate an improvement in solution quality through the use of hyper-heuristics and increased efficiency of execution **(CHECK RESULTS)**.

Keywords Aircraft conceptual design · Structural optimisation · Hyper-heuristic optimisation

1 Introduction

The structural optimisation of an aircraft concept is a process critical to the quality of the final design to ensure satisfactory performance of the airframe under load. This problem must be solved efficiently through the use of effective tools such that a near-optimal solution may be obtained rapidly without the requirement for excessive computation.

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Methodologies within the field of aerospace design for multidisciplinary optimisation (MDO) were the subject of a review in Sobieszczanski-Sobieski and Haftka (1997), where a growing tendency towards interdisciplinary optimisation was described. These findings were supported by a similar later review in Allen et al. (2010), with a focus on structural design. Aerospace MDO is commonly concentrated on the aerodynamic and structural optimisation of the aircraft, where minimal drag and weight typically form the respective objective functions (Allen et al. 2010, Sobieszczanski-Sobieski and Haftka 1997). An additional consideration of manufacturing and operating costs as a design objective is often considered, albeit typically through a single objective function with costs estimated using empirical formulae (Gantois and Morris 2004, Kaufmann et al. 2010).

Challenges of MDO include increased computational demands and complexities resulting from inherent interdisciplinary tasks, commonly leading to the decomposition or approximation of the problem, or a tendency to focus on a single discipline of optimisation (Allen et al. 2010, Sobieszczanski-Sobieski and Haftka 1997). Such simplifications have often led to the consideration of single aircraft section, e.g. wing, resulting in a failure to obtain a complete aircraft configuration (Allen et al. 2010). An alternative approach to reduce high computational requirements uses a multi-tier framework for optimisation, where an population-based optimisation technique is initially employed to obtain an approximation of a near-optimal solution prior to the application of a gradient-based technique for greater analysis of the solution (Allen et al. 2010, Hansen and Horst 2008). Mathematical modelling of the problem is another method of reducing computational requirements, wherein an approximate solution is obtained through sampling the solution space (Neufeld et al. 2010).

A standard process of optimisation is commonly followed within the field of aerospace design, wherein periods of initialisation, mission definition, and empirical mass estimation are followed by optimisation of the design within the selected disciplines (Allen et al. 2010). Such optimisation is either performed simultaneously or in series, such as through initial optimisation of the aerodynamic profile prior to structural optimisation within; commonly for a single, isolated loading condition. Meta-heuristics such as genetic algorithms (GA) are typically employed due to the typically unpredictable, multi-modal solution space (Allen et al. 2010).

Optimisation of a problem, such as aerospace design, is highly dependent on the process followed, where the development and tuning of high quality, problem-specific optimisation techniques can be of great difficult in unpredictable domains without known solutions. Such development commonly requires extensive investigation for the design and validation of the technique. An emerging area of optimisation research is that of hyper-heuristic optimisation, wherein the application of techniques to a problem is evaluated, such that intelligent application of optimisation techniques to a problem may be performed (Burke et al. 2010). Due to its infancy, hyper-heuristic optimisation has seen limited application to aerospace design, a domain where a standard optimisation procedure is commonly followed.

Hyper-heuristic optimisation is performed across two independent domains: the *problem* and *hyper-heuristic domains*, as illustrated by Fig. 1. Within the problem domain, heuristics (wherein the term considers heuristics and meta-heuristics) search for a near-optimal solution to a given problem, and are labelled *low-level heuristics*. Conversely, *hyper-heuristics* are applied in the higher-level domain to improve the performance of the optimisation process within the problem domain and promote further solution improvement. Data flow between the domains is restricted by a barrier to problem-independent information to inform the hyper-heuristic optimisation (Chakhlevitch and Cowling 2008). As such, a hyper-heuristic was introduced as *"an approach that operates at a higher level of abstraction than current meta-heuristic approaches"* (Cowling et al. 2000).

The actions of hyper-heuristic optimisation are dependent on the hyper-heuristic approach employed, informed through a learning mechanism fed by data passed across the domain barrier. Online reinforcement learning is commonly applied through rewarding improvements in a specified hyper-heuristic objective function; alternatively an offline trial period prior to the main process may be performed in order to establish a set of positive moves to be applied during the main process (Burke et al. 2010). This objective function is formed using measures of process performance within the problem domain, such as through that of a *choice function* to measure improvements in solution and computation effort required (Cowling et al. 2000).

Heuristic selection is a popular hyper-heuristic approach to choose the most appropriate low-level heuristic for application within the problem domain from a set of heuristics, leading to the alternative definition of hyper-heuristics as *"heuristics to choose heuristics"* (Burke et al. 2010). Such hyper-heuristics may be *constructive* or *perturbative heuristics*, where the former creates a low-level heuristic through the intelligent application of the heuristic set whereas the latter repetitively applies the set in a local search approach to determine the best order of application (Burke et al. 2010).

Perturbative heuristics employ *move acceptance* to define rules for the approval of selection, where common methods include all moves (AM), improving or equal (IE), only improving (OI), and Monte Carlo (MC) methods. AM permits selection regardless of perfor-

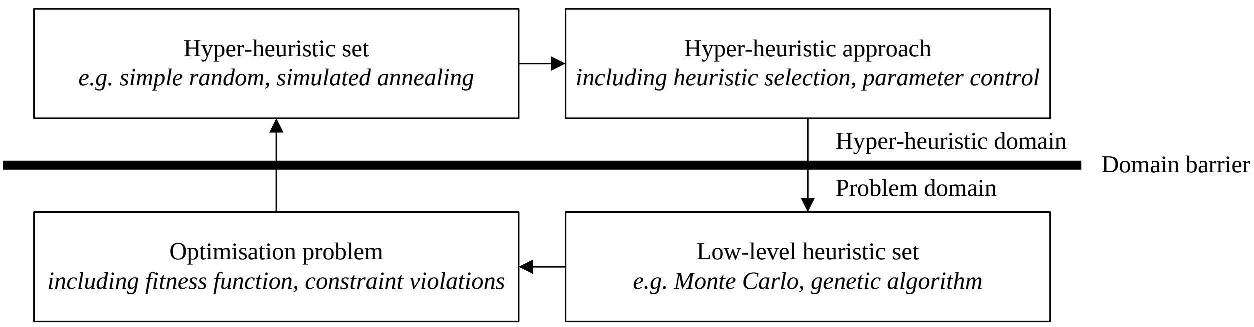


Fig. 1: Domains of hyper-heuristic optimisation

mance, OI only permits selection with an improvement in solution quality, whilst IE permits low-level heuristic selection for solutions of better or equal quality. MC methods allow beneficial moves and randomly permit negative moves with linearly (LMC) or exponentially (EMC) decreasing probability. This method has been combined with a counter of iterations since improvement (EMCQ) with promising results (Ayob and Kendall 2003, Özcan et al. 2008).

An alternative hyper-heuristic approach is *population distribution*, wherein solutions within the a problem domain population are distributed between multiple low-level heuristics for each generation. The distribution may be performance-based, random, or even, such that each low-level heuristic optimises solely the individuals within its assigned sub-population. In the event that single-solution low-level heuristics are employed, each sub-population individual is optimised independently. This approach aims to overcome limitations of individual heuristics through the availability of alternatives (Rafique et al. 2011). However, care must be taken to ensure adequately-sized sub-populations to allow the opportunity for improvement by each low-level heuristic. This concern can be addressed through dynamic populations, such as in Arabas et al. (1994), where the fitness-driven lifetime of individuals enabled variation in population size.

Parameter control provides the ability to intelligently adapt low-level heuristics during process execution, using the history of the problem to inform decisions (Eiben et al. 2007). Such changes may be made either through perturbation of existing values or selection of the better performing settings, where the latter is referred to as *operator selection* and is similar in nature to heuristic selection (Burke et al. 2010, Maturana 2010).

The final hyper-heuristic approach discussed is *perturbation analysis*, wherein learning of the local solution space around a population individual is enabled through the use of a memetic algorithm (Özcan et al. 2008). The frequency and duration of analysis, as well as which solutions to perturb, are key to the success of the approach. Common strategies perturb the entire population, only improved solutions, or a proportion of the population, continuing for a set duration or until no further improvement is made (Ong et al. 2006).

The remainder of this paper is organised as follows: Section 2 describes the hyper-heuristic approach developed to assist aircraft structural optimisation, with a resulting optimisation framework presented in Section 3. A case study demonstration of the framework follows in Section 4 prior to concluding remarks in Section 5.

2 Hyper-Heuristic Approach

A hyper-heuristic approach for application to the problem of aircraft structural optimisation has been developed such that solution quality and process efficiency may be improved. This aims to reduce computational requirements in order to obtain a solution of better quality than that obtainable without the use of hyper-heuristics. The hyper-heuristic approach reduces the limitations of individual low-level heuristics whilst preventing low-level heuristic dominance through heuristic selection and population distribution. Parameter control enables dynamic adaption of the process, whilst perturbation analysis provides the opportunity for learning of local solution space. Perturbative hyper-heuristics are applied, in order to minimise the computational resources required by the hyper-heuristic approach. As such, these functions of the hyper-heuristic approach can be grouped into the following aspects:

1. Selection of appropriate low-level heuristics for use in the problem domain based on past performance;
2. Biased distribution of the population towards better performing low-level heuristics;
3. Control of process parameters for promotion of more efficient optimisation and increased solution quality;
4. Perturbation analysis of newly-discovered optima for learning of local problem domain solution space;
5. Reinforcement learning performed online to enable intelligent application of the above aspects.

The hyper-heuristic approach encourages solution space exploration during early generations prior to later promotion of convergence about the best solution found. This reduces the likelihood of premature convergence on local or infeasible optima, or a failure to adequately sample the design space, whilst permitting analysis of the solution space neighbouring good solutions.

2.1 Heuristic Selection

Heuristic selection ensures application of appropriate low-level heuristics to the problem at a given point during the process. Such appropriate selection enables the encouragement of diversity during early generations and convergence at later stages, achieved through the ranking of low-level heuristics by the objective value of best solution found and weighting based on typical behaviour of the heuristic, i.e. whether the encouragement of exploration or convergence would be expected.

Low-level heuristics within the heuristic set are listed by category in Table 1, chosen from those commonly applied within the domain of aerospace design. Both single-solution and population-based heuristics may be employed as low-level heuristics, where each individual assigned to a single-solution heuristic is optimised independently to maintain the principles of the technique.

Table 1: Low-level heuristics in problem domain

Category	Low-level heuristic
Random	Monte Carlo (MC)
	Random immigration (RI)
Single-solution	Hill climbing (HC)
	Simulated annealing (SA)
	Tabu search (TS)
Genetic algorithm	Roulette wheel (RW)
	Tournament selection (TO)
	Breeder pool (BP)
Evolutionary algorithm	Killer queen (KQ)
	Differential evolution (DE)
Swarm intelligence	Particle swarm (PSO)

A similar list of hyper-heuristics applied within the hyper-heuristic domain is presented in Table 2. The choice of hyper-heuristic for heuristic selection is made by the engineer prior to execution of the process.

Table 2: Hyper-heuristics in hyper-heuristic domain

Hyper-heuristic	Heuristic selection	Parameter control	Perturbation analysis
Simple random (SR)	x	x	
Peckish (PE)	x	x	
Greedy (GR)	x	x	
Hill climbing	x	x	x
Simulated annealing	x	x	x
Tabu search	x	x	x
Roulette wheel	x		
Tournament selection	x		

Move acceptance controls heuristic selection, with the AM, IE, and EMCQ methods available, as well as a SA approach. The latter two are the preferred methods as these permit negative moves with decreasing probability as the process progresses. As such, dominance by a selection of low-level heuristics may be avoided through the probabilistic selection of poorer performing low-level heuristics. This is necessary as convergence-encouraging low-level heuristics would be expected to converge prematurely during early generations, thus perform poorly at this stage, whereas are desired to encourage convergence towards the end of the process.

2.2 Population Distribution

For generations with multiple low-level heuristics, heuristic selection is performed for each individual within the population, leading to individuals possessing a personal low-level heuristic for their optimisation. This permits a population to be distributed between a selection of low-level heuristics, with greater probability of being assigned to those with a better performance history.

The total population size is increased by a factor of the number of permitted low-level heuristics to be selected to ensure a sufficiently large sub-population per low-level heuristic for improvement. This leads to increased problem analysis with a subsequent penalty on computation time, hence a limit is imposed on the maximum number of low-level heuristics per generation.

To prevent excessively large sub-population sizes, a dynamic population size may be used to limit the size of sub-populations and prevent low-level heuristic dominance. For reductions in population size, randomly-selected individuals are rejected from excessively large sub-populations, whilst to increase the population size in generations following such reductions, extra solutions are generated randomly within the sub-population, thus preserving population diversity.

2.3 Parameter Control

The application of the optimisation process is driven through the control of a set of process parameters, listed in Table 3. The prevention of premature convergence on local optima through encouraged solution space exploration, improvement of convergence performance on the obtained best solution, focus on key design variables without requiring excessive computational expense, and prevention convergence on an infeasible solution are the aims of parameter control. As for heuristic selection, the hyper-heuristic used for parameter control is selected from Table 2 by the engineer prior to execution.

Table 3: Hyper-heuristically controlled parameters

Parameter	Affected low-level heuristic	Range Min.	Max.
Penalty coefficient	-	0.25	2.00
Strand length	-	4-bits	16-bits
Crossover probability	RW, TO, BP	0.50	1.00
Crossover points	RW, TO, BP	1	Random
Mutation probability	RW, TO, BP	0.00	0.01
Breeder pool intake	BP	0.10	0.30
Indigenous population	RI	0.10	0.40
Differential weight	DE	0.00	2.00
Crossover probability	DE	0.00	1.00
Cognitive parameter	PSO	1.40	2.10
Social parameter	PSO	0.90	1.80
Inertia weight	PSO	0.55	0.75
Cooling rate	SA	0.00	0.95
Length of tabu list	TS	0	100

The ranges of parameters given in Table 3 are taken from typical values (Clerc and Kennedy 2002, Coello Coello 2000, Grefenstette 1986, Pedersen 2010), and previous experiments to tune the optimisation process to the given problem. The penalty coefficient controls the severity of penalty applied to infeasible solutions to promote convergence within the feasible solution space. The binary chromosome strand length of converging design variables are extended to allow optimisation of greater accuracy, prior to the disabling of variables upon convergence to permit focussed optimisation on those failing to converge. The remaining parameters promote diversity, exploration, or negative moves during early generations of optimisation before discouraging such actions towards the end of the process.

2.4 Perturbation Analysis

Perturbation analysis is performed when better solution are obtained through the use of a memetic algorithm with Lamarckian evolution. This is achieved through repeated perturbation of randomly-selected variables and subsequent re-analysis of performance until no further improvement in objective value is made. Computational requirements are minimised through the use of single-solution low-level heuristics and the limitation of analysis to only newly-discovered optima. The low-level heuristic employed is chosen through heuristic selection based on past performance for perturbation analysis.

2.5 Learning Mechanism

Continuous evaluation of process performance within the problem domain is performed such that the above aspects of the hyper-heuristic approach may be applied intelligently. The objective function within the problem domain is also used within the hyper-heuristic domain for heuristic selection, population distribution and perturbation analysis. During parameter control, process performance over a period of generations is compared against that during previous periods, measured using the following criteria:

1. Objective value of best solution;
2. Mean objective value;
3. Diversity of population;
4. Convergence rate.

These criteria form a choice function similar to that of Cowling et al., albeit focussed on the encouragement of population diversity or convergence rather than computation time, employed as the hyper-heuristic objective function for parameter control. The function is defined by Eq. 1 at generation t of n over a period of Δt generations, where $\Phi(X)$ represents the objective value, $\sigma(X)$ population variance, and $\delta(X)$ convergence rate for $X \in \mu, \Delta t$ with a population of size μ

$$\min \Phi(X) + \overline{\Phi(X)} + \left(1 - \frac{t}{n}\right) \sigma(X) + t\delta(X) \qquad (1)$$

The mean variance of design variables is used in order to measure population variance (Morrison and De Jong 2002), whilst convergence is measured as the mean change in objective value. The coefficients forming the choice function are normalised for equal weighting.

3 Framework for Aircraft Structural Design Optimisation with a Hyper-Heuristic Approach

The hyper-heuristic approach described above has been inserted into a previously-developed framework for aircraft conceptual design optimisation (Allen et al. 2010). Due to the natural increase in computational requirements resulting from the addition of a hyper-heuristic approach, a single discipline of optimisation, that of the structural design of the airframe, is addressed. The key stages within this framework are presented in Fig. 2.

Due to the typically static approach to optimisation employed within the field of aircraft conceptual design, the hyper-heuristic framework provides the opportunity for intelligent dynamic adaption of the optimisation process to better solve the problem presented. Within the framework, the design process is set up through a period of initialisation to define the requirements of the aircraft (indicated by stages 0.1 and 0.2 in Fig. 2), optimisation process (0.3), and FEA (0.4). This enables the engineer to set up the optimisation problem for fully-automated execution of the following modules.

3.1 Mission Definition

Given the requirements input during initialisation, a mission profile is generated (1.1) to permit definition of realistic loading conditions, with those selected in initialisation calculated using the airworthiness requirements (1.2). The aircraft payload is also defined based on the requirements input during initialisation (1.3).

3.2 Mass Estimation

Empirical methods are employed (2.1) for the calculation of payload mass (2.2), and estimation of aircraft mass at various points during the previously-defined mission (2.3) and fuel required for the mission (2.4).

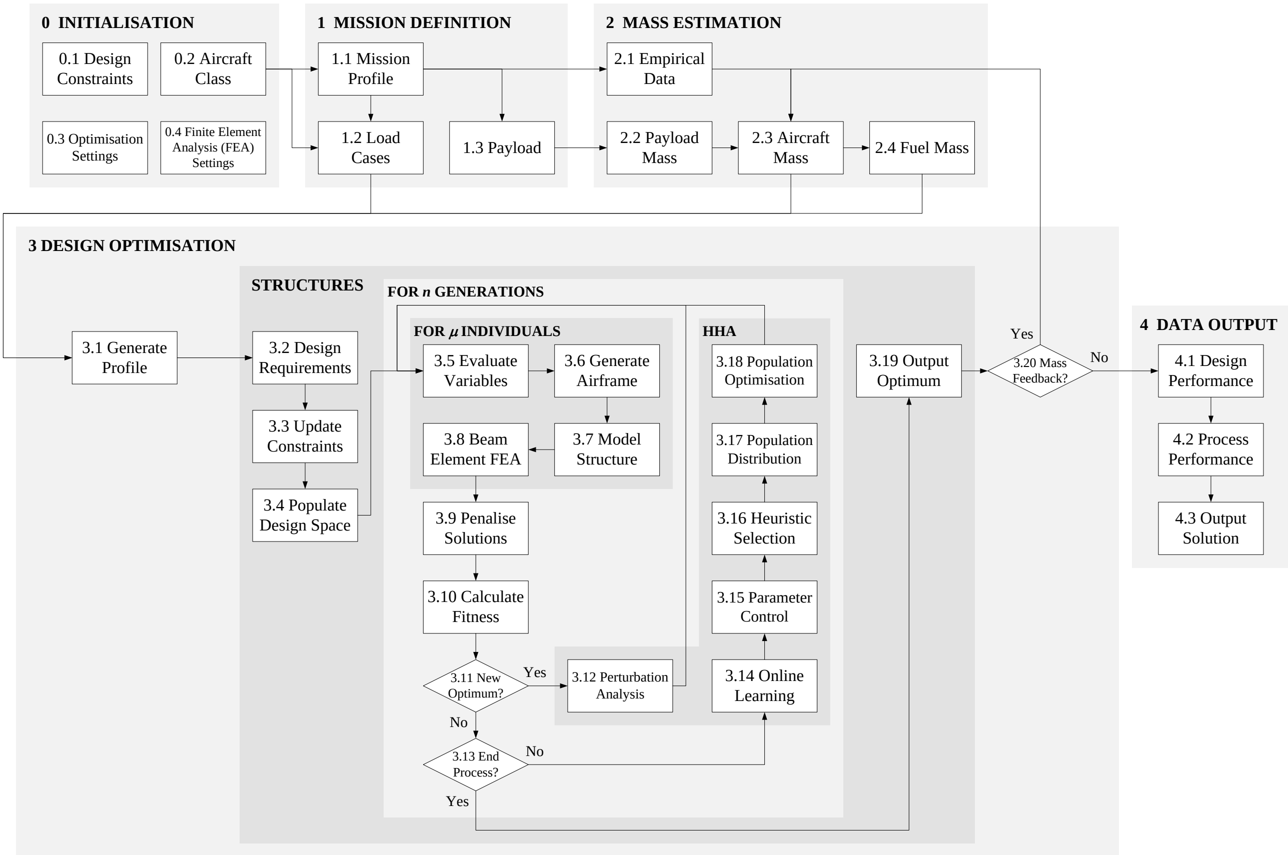


Fig. 2: Framework for optimisation of aircraft structural design with embedded hyper-heuristic approach (HHA)

3.3 Design Optimisation

The outputs of the previous modules drive the constraints within which the optimisation of the aircraft design is conducted, such that empirical formulae are used to generate an external profile of the aircraft such that it meets the requirements for flight dictated by mission definition and mass estimation (3.1). Structural optimisation is then performed within the profile for the problem given by Eq. 2 for minimum structural mass

$$\min_{X \in \mu, n} \Phi(X) \tag{2}$$

subject to constraints for factor of safety and wingtip deflection defined by airworthiness requirements and typical industrial practise. Requirements of the structural design to satisfy geometric constraints imposed by the external profile, such as limits on member positions, are calculated (3.2) prior to evaluation of the ranges of design variables to ensure they comply with such constraints (3.3). Individuals may then be seeded or generated randomly to create an initial population within the solution space (3.4).

Optimisation is performed over a series of generations, where for each generation the population is firstly analysed to determine performance. For each individual, the values of the design variables are obtained such that they may be used to determine the aircraft represented by the individual (3.5). These values dictate the generation of an airframe design (3.6) which is modelled in preparation for analysis (3.7). The finite element (FE) model generated is constructed of one-dimensional beam elements, with multiple structural members combined within elements, and nodes located at key loading positions. This approach reduces the sizes of the matrices within the FEA to provide increased computational efficiency, of great importance when considering many design variations. FEA is performed using the modelled aircraft to establish the feasibility of the design against the design constraints of Eq. 7 (3.8).

An exterior penalty function is applied to penalise infeasible solutions, the severity of which is controlled by the penalty coefficient in order to encourage feasible convergence (3.9). The objective value is calculated in Eq. 3, where ρ, A, and l denote the density, area, and length of member a of $A(X)$ for an individual of the population, with the penalty function given by Eq. 4

$$f(X) = \sum_{a=1}^{A(X)} (\rho A l)_a \tag{3}$$

$$\Phi(X) = f(X) \left\{ 1 + \lambda \sum_{j=1}^{m} g_j^2(X) \right\} \tag{4}$$

where $f(X)$ is the unpenalised objective function of the population set, λ the penalty coefficient, and $g_j(X)$ the measure of violation of constraint j of m calculated by Eq. 5 using the FEA results

$$g_j(X) = \max(0, c_j(X)) \tag{5}$$

Fitness is then calculated by ranking the population in order of objective value, an approach that encourages population diversity over a function based solely on the objective values of the population (3.10)

$$F(X) = \frac{\mu - r(\Phi(X))}{\sum\limits_{X \in \mu} r(\Phi(X))} \tag{6}$$

Improved solutions within the population are then identified through comparison of fitness (3.11). If a better solution is discovered, perturbation analysis is performed to the individual until no improvement is made (3.12). Termination criteria are then checked, including a generation limit, number of generations since last improvement in objective value, and population variance.

The learning mechanism is applied to evaluate the performance of the optimisation process (3.14), leading to guided parameter control (3.15), heuristic selection (3.16), and population distribution (3.17). The population is then optimised using the allocated low-level heuristics (3.18). The optimisation process is repeated until the termination criteria are satisfied, at which point the optimal solution obtained is output (3.19).

As the empirical method of mass estimation can incur inaccuracies in aircraft mass input, intermediate feedback of the obtained structural mass for re-evaluation of aircraft mass is possible (3.20). This leads to an additional termination criterion of convergence in the error between input and output aircraft mass.

3.4 Data Output

Upon the completion of optimisation, the predicted aircraft performance is output to enable analysis of the design (4.1), along with the process performance (4.2). Data provided by the latter include the selection of low-level heuristics, control of parameters, distribution of the population, population feasibility, and process convergence. Finally, the optimum solution is output, including a model of the aircraft and FEA reports (4.3).

4 Case Study

The operation of the framework is demonstrated in a case study using a computational implementation of the framework: AStrO (Aircraft Structural Optimiser). The baseline aircraft design for structural optimisation is the Airbus A340-300, the most popular A340 variant by number of orders, with a selection of properties (Airbus Industrie 2012) are listed in Table 4, alongside those of the mission and load cases to be simulated. The mission profile is for single-cruise between two aerodromes, with simultaneous simulation of cabin pressurisation, engine thrust, and gravitational loads within the load cases.

Table 4: Selected properties of aircraft and mission

Property	Value
Wing span	60.30 m
sweep	30.0°
Tail span	19.40 m
height	16.99 m
Fuselage length	63.69 m
width	5.64 m
Undercarriage track	10.69 m
wheelbase	25.37 m
Power plant	4x CFM International 56-5C4
Mass empty aircraft	130,200 kg
maximum takeoff	276,500 kg
Cruise altitude	35,000.0 ft
range	5,000.0 nm
speed	0.82 M
Number of flight crew	2
passengers	335
Aircraft class	Civil transport
Load case in flight	$+2.5g$ pull-up manoeuvre
on ground	2-point landing

Design constraints imposed for minimum factor of safety, $c_1(X)$, and maximum wingtip deflection, $c_2(X)$, are given by Eq. 7 (European Aviation Safety Agency 2009), where the latter is determined through consideration of allowable deflection without ground strike

$$
\begin{aligned}
c_1(X) &\geq 1.5 \\
|c_2(X)| &\leq 7.5 \text{ m}
\end{aligned}
\tag{7}
$$

The properties in Table 5 provide similar limits on the airframe, such that variables within the case study may focus on the layout the structural members within the airframe. These include the material, section profile, and minimum thickness of the types of members.

Table 5: Constraints on structural members

Structural member	Material	Profile	Thickness
Lifting surface rib	Al 7075-T6	I	10.0 mm
spar	Al 7178-T6	I	4.0 mm
stringer	Al 2014-T6	Z	2.0 mm
Fuselage frame	Al 7075-T6	T	10.0 mm
stringer	Al 2014-T6	Z	5.0 mm
floor beam	Al 7075-T6	I	20.0 mm
Skin	Al 2014-T6	-	3.0 mm
Floor	Al 7075-T6	-	20.0 mm

To minimise the computational requirements, the FE model is designed at a level of detail of 10% fidelity, wherein 1 in 10 structural members are modelled as an element. Remaining members are grouped within the closest element, resulting in smeared member properties. Critical members, such as those with attachments and the lifting surfaces spars, are exceptions to this rule and are modelled in isolation, with lifting surface stringers grouped within the nearest spar element.

Table 6 lists the design variables within the case study, focussing on the structural layout of the aircraft. Each lifting surface is constrained to possess two spars. Variables V9 to V11 give the proportion of frames in the fuselage positioned within the nose, tail, and wingbox, whilst the position of the front wing spar, V12, is calculated as a fraction of the wing chord. V16 and V17 define the increase in height and width of the wing spar at the root relative to the tip, with linear variation along the span. The spanwise distribution of ribs is controlled by variables V13 to V15 as α in Eq. 8, allowing an increasing concentration towards the root where stress concentrations under bending loads are expected. Hence, for a surface of span b with R ribs, the position of the ith. rib from the root is given as

$$
y_i = \frac{i^{\alpha-1}\left(Cb - y_0\right)}{R^{\alpha}} + y_0
$$
$$
\text{where } C = \begin{cases} 0.5 & \text{for wing, horizontal tail} \\ 1.0 & \text{for vertical tail} \end{cases}
\tag{8}
$$

Table 6: Constrained ranges of design variables

ID	Design variable	Range Min.	Max.
V1	Number of wing ribs	10	100
V2	wing stringers	20	120
V3	horizontal tail ribs	10	40
V4	horizontal tail stringers	10	80
V5	vertical tail ribs	10	40
V6	vertical tail stringers	10	80
V7	fuselage frames	20	160
V8	fuselage stringers	30	180
V9	frames in nose	5.0%	15.0%
V10	frames in tail	5.0%	15.0%
V11	frames in wingbox	5.0%	20.0%
V12	Position of wing front spar	$0.2c$	$0.35c$
V13	wing ribs	1.0	3.0
V14	horizontal tail ribs	1.0	3.0
V15	vertical tail ribs	1.0	3.0
V16	Height of wing spars at root	1.0	4.0
V17	Width of wing spars at root	1.0	4.0

The case study is performed through a series of runs, with differing setups to illustrate the effects of the hyper-heuristic approach. Table 7 describes the setup of each run. Parameter control is defined as in Table 3, with initial values generated using the SR hyper-heuristic. Hyper-heuristics for runs with multiple hyper-heuristic aspects are applied as: i) heuristic selection, ii) parameter control, and iii) perturbation analysis.

In order to maintain stable test conditions across the runs, an identical initial population is seeded to all runs, with a binary representation, uniform crossover, and an EMCQ method of move acceptance. No more than three low-level heuristics may be selected for each generation during population distribution to prevent the requirement for an excessively large population, except for the final run where a dynamic population size limits sub-populations to 100 individuals. Termination criteria include a generation limit of 1000, minimum population variance of 2.0 %, and 250 successive generations without improvement in objective function.

4.1 Results

Introduction to results of case study, with best results for each run in Table 8

Discussion of results, effects of hyper-heuristic approach, plot of key runs in Figs. 3 and 4

Plot of progressive changes to aircraft design in Fig. 5 for run generating best results, using stick model from MATLAB

Table 7: Setup of hyper-heuristic approach for runs performed for case study and required population size

	Settings of parameters for selection of runs of case study							
Process parameter	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8
Population size	100	100	100	100	100	300	300	Dynamic
Heuristic selection					x	x	x	x
Population distribution						x	x	x
Parameter control				x			x	x
Perturbation analysis			x				x	x
Low-level heuristics	MC	RW	RW	RW	All	All	All	All
Hyper-heuristics			RW SA	SA	GR	RW	i) RW ii) SA iii) TS	i) RW ii) SA iii) TS

Table 8: Results obtained for iterations generating best design solutions

	Values for best solution obtained by end of run							
	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8
Φ, kg								
c_1								
c_2								
τ, %								
$\Delta\Phi$, %								
β, %								
σ, %								
n								
T, hr								

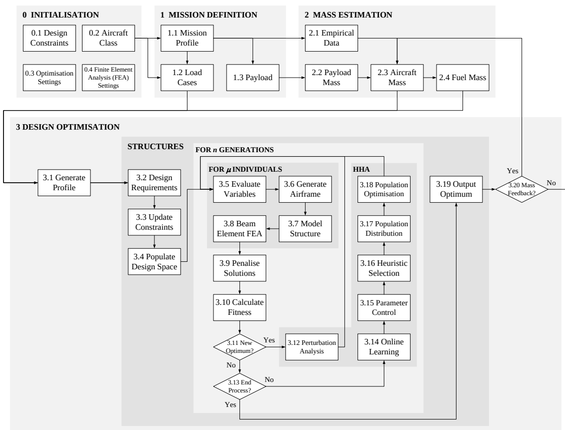


Fig. 3: Objective value for selected case study runs

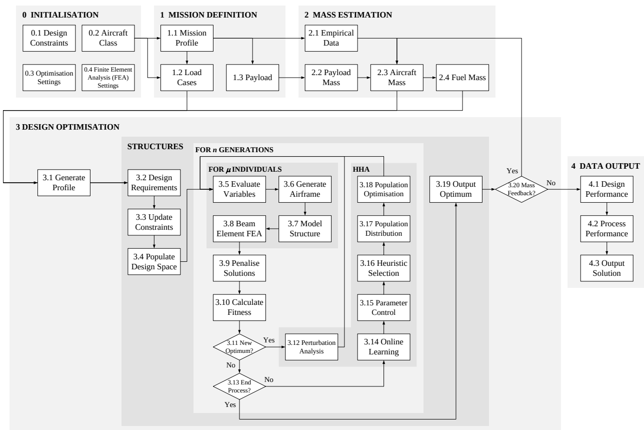


Fig. 4: Population feasibility for selected case study runs

5 Conclusions

Conclusions of paper and case study, plus further work

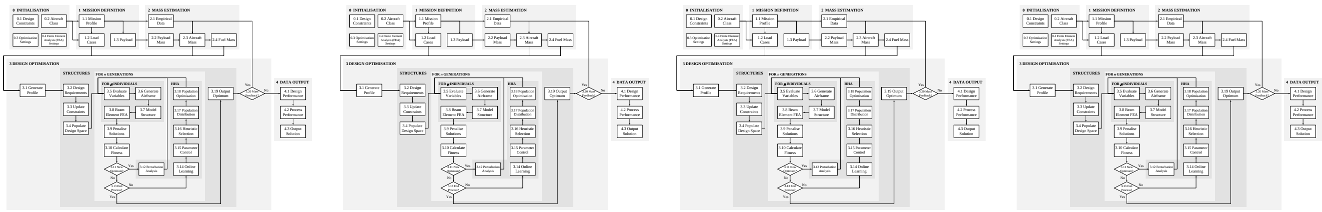
References

Airbus Industrie (2012) A340-200/-300 airplane characteristics for airport planning. Tech. rep., rev. 19

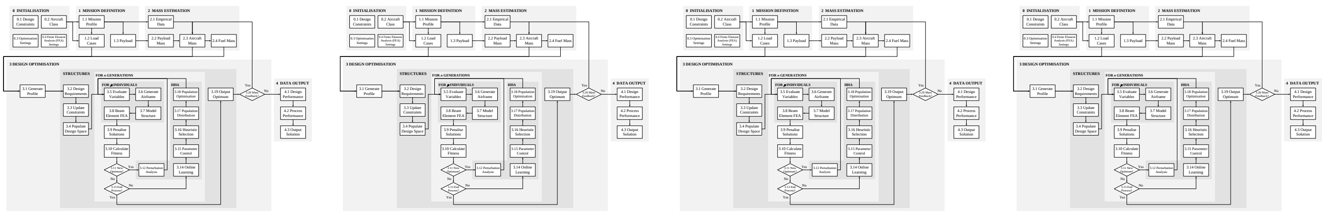
Allen JG, Coates G, Trevelyan J (2010) A theoretical framework for the optimisation of the structural layout of an aircraft using deterministic and stochastic optimisation. In: Proc 8th ASMO-UK/ISSMO Conf, pp 19-25

Arabas J, Michalewicz Z, Mulawka J (1994) GaVaPS - a genetic algorithm with varying population size. In: Proc 1st IEEE Conf Evol Comput, pp 73-78

Ayob M, Kendall G (2003) A Monte Carlo hyper-heuristic to optimise component placement sequencing for multi head placement machine. In: Proc Int Conf Intell Tech, pp 19-25



(a) Generation NUM (b) Generation NUM (c) Generation NUM (d) Generation NUM



(e) Generation NUM (f) Generation NUM (g) Generation NUM (h) Generation NUM

Fig. 5: Maturity of best solution for Airbus A340-300 airframe design during run NUM

Burke EK, Hyde M, Kendall G, Ochoa G, Özcan E, Qu R (2010) Hyper-heuristics: a survey of the state of the art. Tech. rep. NOTTCS-TR-SUB-0906241418-2747, University of Nottingham

Chakhlevitch K, Cowling P (2008) Hyperheuristics: recent developments. Adapt Multilevel Metaheuristics 136:3-29

Clerc M, Kennedy J (2002) The particle swarm - explosion, stability, and convergence in a multidimensional complex space. IEEE Trans Evol Comput 6(1):58-73

Coello Coello CA (2000) Use of a self-adaptive penalty approach for engineering optimization problems. Comput Ind 41:113-127

Cowling P, Kendall G, Soubeiga E (2000) A hyperheuristic approach to scheduling a sales summit. In: Pract Theory Autom Timetabling III, pp 176-190

Eiben AE, Michalewicz Z, Schoenauer M, Smith JE (2007) Parameter control in evolutionary algorithms. Parameter Setting Evol Algorithms 54:19-46

European Aviation Safety Agency (2009) Certification specifications for large aeroplanes, CS-25. Tech. rep., rev. 8

Gantois K, Morris AJ (2004) The multi-disciplinary design of a large-scale civil aircraft wing taking account of manufacturing costs. Struct Multidisc Optim 28:31-46

Grefenstette JJ (1986) Optimization of control parameters for genetic algorithms. IEEE Trans Syst Man Cybern 16:122-128

Hansen LU, Horst P (2008) Multilevel optimization in aircraft structural design evaluation. Comput Struct 86:104-118

Kaufmann M, Zenkert D, Wennhage P (2010) Integrated cost/weight optimization of aircraft structures. Struct Multidisc Optim 41:325-334

Maturana J, Lardeux F, Saubion F (2010) Autonomous operator management for evolutionary algorithms. J Heuristics 16(6):881-909

Morrison RW, De Jong KA (2002) Measurement of population diversity. In: Proc 5th Int Conf LNCS 2310, pp 31-41

Neufeld D, Behdinan K, Chung, J (2010) Aircraft wing box optimization considering uncertainty in surrogate models. Struct Multidisc Optim 42:745-753

Ong YS, Lim MH, Zhu N, Wong KW (2006) Classification of adaptive memetic algorithms: a comparative study. IEEE Trans Syst Man Cybern B 36(1):141-152

Özcan E, Bilgin B, Korkmaz EE (2008) A comprehensive analysis of hyper-heuristics. Intell Data Anal 12(1):3-23

Pedersen MEH (2010) Good parameters for differential evolution. Tech. rep. HL1002, Hvass

Rafique AF, He L, Kamran A, Zeeshan Q (2011) Hyper heuristic approach for design and optimization of satellite launch vehicle. Chin J Aeronaut 24(2):150-163

Raymer DP (2002) Enhancing aircraft conceptual design using multidisciplinary optimization. Dissertation, Kungliga Tekniska Högskolan

Sobieszczanski-Sobieski J, Haftka RT (1997) Multidisciplinary aerospace design optimization: a survey of recent developments. Struct Optim 14:1-23