

TWO ASPECTS OF HUMAN-CENTRIC EVOLUTIONARY DESIGN SYSTEMS

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Abstract: *The paper introduces two examples of user-centric evolutionary design. Each illustrates a differing degree of user interaction. The first example relates to the inclusion of subjective aesthetic criteria to complement quantitative evaluation in the conceptual design of bridge structures. The second relates to the succinct graphical presentation of complex relationships between variable and objective space and the manner in which this can support a better understanding of a design domain. This improved understanding can contribute to the iterative improvement of initial machine-based representations. Both examples complement and add to earlier research relating to interactive evolutionary design systems (IEDS).*

1. INTRODUCTION

The paper presents research and development relating to powerful machine-based search and exploration systems that, through appropriate user-interaction, allow both quantitative and qualitative evaluation of solutions and the extraction of information from complex, poorly understood design domains. The integration and capture of user experiential knowledge in order to support and increase understanding is of particular interest. The objective is the realisation of user-centric intelligent systems that overcome initial lack of understanding and associated uncertainty; support an improving knowledge-base; allow the integration of designer subjective judgement and stimulate innovation and creativity.

Interactive evolutionary computing [1] in the main, relates to partial or complete human evaluation of the fitness of solutions generated from evolutionary search. This has been introduced where quantitative evaluation is difficult if not impossible to achieve e.g. graphic arts [2] and hazard icon design [3]. Such applications rely upon a human-centred, subjective evaluation of the fitness of a particular design, image etc. Partial human interaction that complements quantitative machine-based solution evaluation is also in evidence. For instance, the user addition of new constraints in order to generate solutions that are fully satisfactory within an evolutionary nurse scheduling system [4].

Interactive Evolutionary Design Systems (IEDS) also represent a human centric approach [5, 6] in

that they generate and succinctly present information appertaining to complex relationships between the variables, objectives and constraints that define a developing design space. In this case, solutions generated from stochastic population-based search techniques provide information to the user which supports a better understanding of the problem domain whilst helping to identify best direction for future investigation [7] especially when operating within poorly defined decision-making environments.

In an attempt to categorise these various forms of IEC it is possible to view complete human evaluation as explicit whereas partial evaluation and interaction are less explicit, more subtle forms of human involvement. Completely implicit interaction occurs where users are unaware of their role in the evolution of a system (e.g. Semet's web-based tutorials [8]). A simple implicit/explicit spectrum of interactive evolutionary approaches can thus be developed as shown in figure 1 [9].

Two examples of user-centric intelligent systems that sit at differing points along this spectrum are presented. The first is closer to the more established explicit interaction where user subjective evaluation is in evidence. However, this subjective evaluation complements detailed, machine-based quantitative evaluation. The second is current interactive evolutionary design research relating to problem definition and the iterative interactive improvement of machine-based design representations. This work sits further toward the implicit end of the spectrum.

2. INTEGRATING AESTHETICS WITH INTERACTIVE EVOLUTIONARY DESIGN PROCESSES

This example brings together agent-based machine learning, object-oriented representation, agent-based control, evolutionary computing and user-based subjective evaluation. We are searching for aesthetically pleasing, feasible designs during conceptual design. Figure 1 illustrates the main components of the system. The user defines initial design requirements and aesthetically evaluates the designs generated via an evolutionary search, exploration and optimisation system (ESEO). Agents have tasks relating to initial population creation based on design requirements, the monitoring of evolving designs for feasibility and evaluation of machine-based aesthetic criteria. The ESEO identifies design solutions that can be considered high performance in terms of structural feasibility and stability; materials cost and rule-based aesthetics.

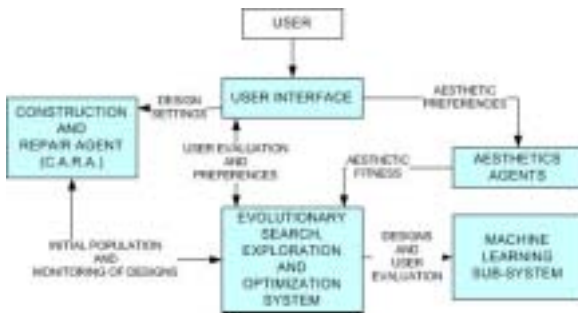


Fig. 1. The User-centric System

Research is now concentrating upon the design of ‘urban furniture’ in the form of interesting and aesthetically pleasing seating arrangements for open areas. However, proof-of-concept has been initially achieved via simple bridge design upon which we concentrate here.

2.1. Representation

A highly flexible and robust component-based representation has been developed in order to accommodate complex design entities with many related sub-systems / components [e.g. 10, 11, 12]. Evolutionary Programming (EP) [13], a purely mutation-based evolutionary algorithm, has been selected to overcome feasibility maintenance problems incurred when using crossover.

The representation must be able to model all possible designs and be robust enough to be manipulated by a stochastic search process. [14]. A collection of primitive elements represents an overall design and elements with different design properties can be included in the set of design primitives. A simple bridge design is divided into a **Span Element** collection which form the span of the

bridge and a **Support Element** collection which form the support of the bridge (figure 2).

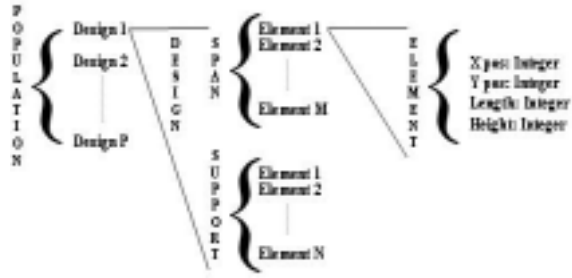


Fig. 2: Details of the object based representation.

Simple beam or angled beam span bridges with and without support require only two basic Elements i.e. the angled section Element (to be used as a span element only) and a simple rectangular Element which can be used as both spanning and supporting element. The principles of object-oriented programming such as inheritance can be utilised i.e. to add a new kind of element the basic properties of Element can be extended.

The representation supports the transition from abstract concepts to well defined specifications as it can represent designs at all levels i.e. at the abstract level by using high level objects / elements and at the well-defined level as a set of specifications.

2.2 Mutation



Fig. 3. Design before mutation

Assume the solution to be mutated is a basic beam bridge supported at each end with a single intermediate support (B3) and two span elements (B1, B2) (figure 3). L = span, H = maximum height of the bridge (figure 4).

Separate mutation rules exist for the two arrays of elements from which a rule is selected randomly. Supports can only move left or right and their height depends upon the thickness of the spanning element. Hence two rules for left and right movement and two for increasing and decreasing width exist for a supporting element. Span element depth can vary but upper surfaces must be level and continuous with no overlap or space between them. Two rules therefore exist i.e. to increase or decrease the span depth. Now, if mutation moves support (B3) two units to the left and decreases the thickness of the B2 support by two units then the X value attribute of the B3 object will be similarly decreased and the height of the B2 object in the span array will be decreased

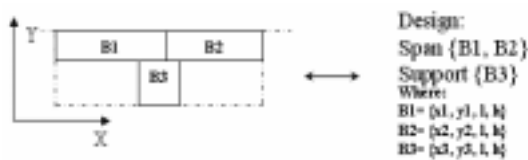


Fig. 4. Structure of a design solution.

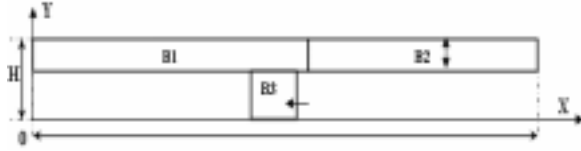


Fig. 5. Design after mutation

by 2 units. The height attribute of the support will be automatically adjusted for continuity and any overlap will be removed. The mutated design is shown in figure 5.

2.3. Introduction of agency

We initially attempted to evolve feasible structures using EP but this proved a difficult and lengthy process. However, rule-based agent assembly is straightforward and rapid. An approach where agents create the initial population and provide a continuing 'repair' capability combined with EP search, exploration and optimisation across the space of possible structures was therefore introduced. The Construction and Repair Agents (CARAs) assemble structures of varying size and shape based upon specifications re restrictions on placement of supports and types of span section. EP provides the SEO process while CARAs keep a check on potential disruption processes and repair the structure where necessary.

2.4. Simple structural criteria

The CARAs can currently create three kinds of bridges:

- Simple beam bridges without supports (Type 1a).
- Simple beam bridges with supports (Type 1b).
- Simple beam bridges with angled span sections and supports (Type 2).

Initial populations comprise a mixture of these designs which are structurally evaluated via simple length/depth ratios and column buckling criteria.

Type 1a is analysed as a simple beam under uniform distributed loading via a simple heuristic where an ideal length to height ratio for a span element of 20:1 is utilised using equations 1 & 2 ie the closer a span section is to the ideal ratio (R) the better its fitness. L_i and H_i are the length and height of the i th span element. It is evident that the closer the dimensions of the span elements are to the ideal ratio (R) the lower will be the value of F_i . At the minimum all F_i 's are equal to zero and thus stability is equal to one.

$$F_i = \left| R - \left(\frac{L_i}{H_i} \right) \right| \quad (1)$$

$$\text{Stability} = \frac{1}{\left(1 + \sum F_i \right)} \quad (2)$$

In **Type 1b** buckling in the columns is also considered using equation 3.

$$P' = \frac{\pi^2 EI}{H^2} \quad (3)$$

Where P' = maximum possible load; E = modulus of elasticity, I = moment of inertia; H = column height.

Columns are assumed to share the loading from the span sections between the end supports. A column satisfying the buckling criteria can either increase or decrease in thickness. Otherwise it can only increase in thickness.

2.5. Example

A basic EP approach is used with a population size of 100 solutions. Tournament selection is utilised with a tournament size of ten and the system is run for 100 generations. A selection of members from the initial population are shown in figure 6. In this first experiment structural criteria alone was utilised.

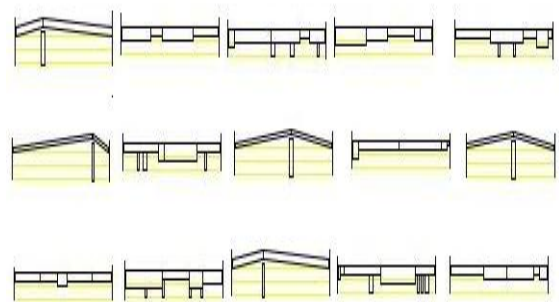


Fig. 6. Sample of mixed initial population of bridge shapes.



Fig. 7. Bridge profiles optimized using structural criteria only.

Examples of the three bridge types are evident. The optimal designs shown in figure 7 are achieved within 100 generations. The angled span bridges turn out to be most efficient in terms of the structural criteria alone. The other two design types have not survived.

2.6. Aesthetics and User Evaluation

Generic guidelines for aesthetic bridge design are available [15, 16] but these only provide a partial

quantification via generic rules. Complete aesthetic evaluation must involve both machine rule-based and designer-led subjective factors. The following aesthetics have been hard coded:

1. Symmetry of support placement (A1).
2. Slenderness Ratio (A2).
3. Uniformity in thickness of supports (A3).
4. Uniformity in thickness of span sections (A4).

Each aesthetic rule is evaluated by a separate 'Aesthetic Agent'. The '**Rule-based Aesthetic Fitness**' is calculated as:

$$Aesthetic_Fitness = \sum_{i=1}^4 w_i A_i \quad (4)$$

Where w_i are weights for each of the aesthetic rules ($A_i = A1$ to $A4$) which can also be modified on-line.

'**User-assigned Aesthetic fitness**' (Ufit) is assessed by the designer on a rising scale of 0 to 10. Overall user evaluation operates thus:

1. User stipulates the frequency of user interaction (e.g. once every 10 generations).
2. User aesthetically evaluates a preset number of population members from the initial population (usually the top 10 members i.e. those with highest fitness re stability, material usage and explicitly defined aesthetic criteria).
3. The EP system runs.
4. Population members are aesthetically evaluated by the user every n generations.
5. Repeat steps 3 and 4 until user terminates the evolutionary process.

The overall fitness function now includes 'Aesthetic Fitness' and 'User Assigned Aesthetic Fitness' (Ufit). Furthermore, weights have been added (w_1 to w_4) to each of the objectives which the user can modify on-line to influence evolutionary direction, i.e:

$$F_t = (w_1 * St) + (w_2 / MU) + (w_3 * AF) + (w_4 * Ufit) \quad (5)$$

Where:

F_t = Solution fitness

MU = Material usage

AF = Aesthetic fitness (rule-based)

$Ufit$ = User-assigned fitness

St = Structural Stability

Figure 8 shows aesthetically pleasing cross-sections after 30 generations with user evaluation every ten generations. The aesthetic objectives (A1 to A4) are clearly reflected in them. The span elements are of the same size. The supports are of nearly uniform thickness and their placement is also symmetric.

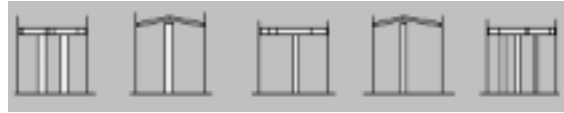


Fig. 8: Aesthetically pleasing bridge profiles.

Due to user interaction, the solutions take on a variety of different aesthetically pleasing shapes that satisfy the explicitly defined aesthetic guidelines (A1 to A4) and the implicit aesthetics of the user (Ufit).

2.6. Integrating aesthetics with more free-form evolutionary design

Current work [17] is extending the capabilities of the user-centric evolutionary system to handle greater complexity in terms of representation and aesthetic evaluation. Proof-of-concept has been provided by the initial work relating to simple bridge design which has allowed us to attempt the interactive design of 'urban furniture' in the form of novel and aesthetically pleasing seating arrangements for parks and other public areas.

Again, simple structural analysis of the resulting forms is combined with both rule-based and user-led aesthetic evaluation but at a more complex level than similar evaluation relating to the previous bridge structures.

Figure 9 shows evolved bench-type seating arrangements that are founded upon a relatively well-structured representation rule-base. Figure 10, however, utilizes a far more flexible rule-base which allows the evolution of more free-form seating arrangements that are practical, interesting and pleasing to the eye. Both designs have utilized the rule-based and user-led aesthetic evaluation procedures.

2.7. Incorporating learning to reduce user fatigue

The purpose of a Machine Learning Sub-system is the on-line assimilation of the designer's subjective aesthetic preferences. This addresses a major problem in interactive evolutionary design systems relating to user fatigue caused by the evaluation of excessive numbers of solutions. The intention is that, as the generations progress, the system reduces its dependence on human interaction and increasingly produces aesthetically pleasing solutions based upon the assimilated user preferences. This would result in a reducing degree of user-interaction and, in later generations, a completely machine-based process once user preferences have been adequately learned by the system.

Supervised learning taking user evaluation into account has been incorporated. Learning is attempted at two levels. Level 1 determines user preference for one of the three types of bridge design through evaluation of the relative difference between user assigned fitness for each type of design. Level 2

assesses features that the user finds pleasing across the different designs.

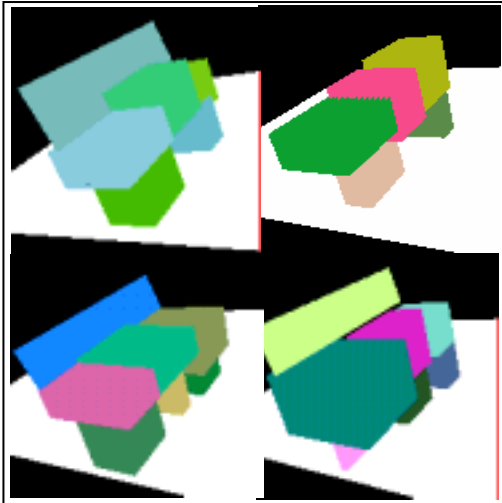


Fig. 9: Evolved bench-type seating arrangements.

Three machine-learning techniques have been implemented within the IEDS namely: Fuzzy rule based learning systems, Radial Basis functions (RBF) and Case based reasoning (CBR). Various authors [18, 19] point out that the learning ability of any algorithm is only as good as the representation of the information to be learned. Thus, the essentially pictorial design has to be represented to suit various machine learning techniques such as back propagation neural networks and fuzzy rule based systems. If the representation is too rich then the machine learning system would be overloaded with the instances to be learned. If the representation is too lean then the system could miss out small but important differences between designs.

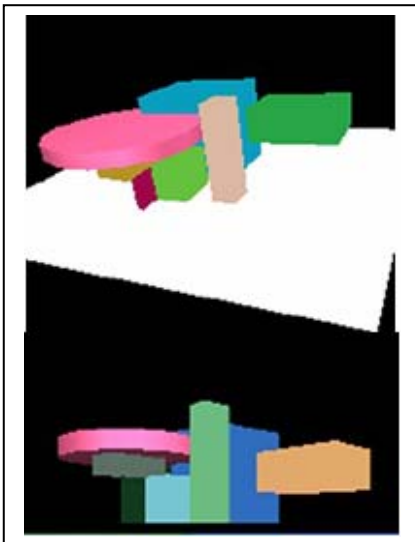


Fig. 10: Evolved free-form seating arrangements

Several important conclusions have resulted from extensive experimentation involving the three approaches. Results confirm that even in the case of machine learning, representation plays an important role. Fuzzy rule based systems require the extraction of complex design properties which are difficult to define using a simple set of variables. A more

comprehensive fuzzy model might lead to better results but would also lead to a loss of information during decomposition. The RBF approach could provide an ideal machine learning sub-system in an offline, profile based interaction but for online learning, using a smaller training data set, the error between expected and actual output is too large. However, the CBR approach avoids the representation and on-line learning problems associated with the other two techniques and is a very promising way forward. Experimentation shows a gradual decrease in user-interaction as generations progress. The reader is referred to [20] for more detail. Further development and experimentation in this area is currently underway.

3. EVOLVING THE DESIGN SPACE VIA INTERACTIVE EVOLUTIONARY PROCESSES

A more implicit form of interaction involves the extraction of high-quality information and its succinct presentation to the designer to support a better understanding of complex relationships between variables, objectives and constraints during conceptual design. This approach attempts to meld user experiential knowledge and intuition with powerful machine-based search, exploration and subsequent information processing.

Initial machine-based design representations can be relatively basic and confidence in the fidelity of their output may be low. However, significant problem insights can be generated from their utilization despite apparent shortfalls. Identified high performance solutions based upon quantitative criteria followed by qualitative human evaluation can provide an indication of concept viability and degree of model fidelity. An iterative user/machine-based process can commence where gradual improvements in understanding contributes to the development of better representations, a growing knowledge-base and the establishment of computational models that support more rigorous analysis i.e. a process emerges that supports the development of representation through knowledge discovery.

An initial variable parameter set may vary in size and content as the sensitivity of the problem to various aspects becomes apparent. Constraints may be treated in the same way with the added option of softening them to allow exploration of non-feasible regions. Included objectives may change as significant payback becomes apparent through a re-ordering of objective preferences. Some non-conflicting objectives may merge whilst difficulties relating to others may require serious re-thinking with regard to problem formulation. The initial design space is therefore a moving feast rich in information [6].

The visualisation of variable and objective space from cluster-oriented genetic algorithm (COGA) output provides a variety of perspectives illustrating complex relationships [21]. This information is further defined by data mining, processing and visualization techniques. The intention is to support implicit learning and reduce complexity by supporting the development of an intuitional understanding of the problem that supports iterative model development.

3.1. COGAs and the MiniCAPs model

Cluster Oriented Genetic Algorithms provide a means to identify high-performance (HP) regions of complex conceptual design spaces and enable the extraction of information from such regions [22]. COGAs identify HP regions through the on-line adaptive filtering of solutions generated by a genetic algorithm. COGA can be utilised to generate design information relating to single and multi-objective domains [7]. The technique has been well documented (see <http://www.ad-comtech.co.uk/Parmee-Publications.htm> for relevant papers).

The research utilises the BAE Systems' MiniCAPs model a simplified version of a suite of preliminary design models for the early stages of military aircraft airframe design and initially developed for research relating to the development of the IEDS concept. The model comprises nine continuous input variables and twelve continuous output parameters relating to criteria such as performance, wing geometry, propulsion, fuel capacity, structural integrity etc.

3.2. Identifying high-performance regions relating to differing objectives

Figures 11a, b & c show HP regions comprising COGA generated solutions relating to three of the twelve MiniCAPs objectives (Ferry Range (FR), Attained Turn Rate (ATR1) and Specific Excess Power (SEP1)) projected onto a variable hyperplane relating to two of the nine variables utilized in the search process. This projection allows the designer to visualize the HP regions, identify their bounds and subsequently reduce the variable ranges as described in previously referenced papers.

These papers also introduce the projection of these differing objective HP regions onto the same variable hyperplane as shown in figure 12 from which the degree of objective conflict immediately becomes apparent to the designer. The emergence of a mutually inclusive region of HP solutions

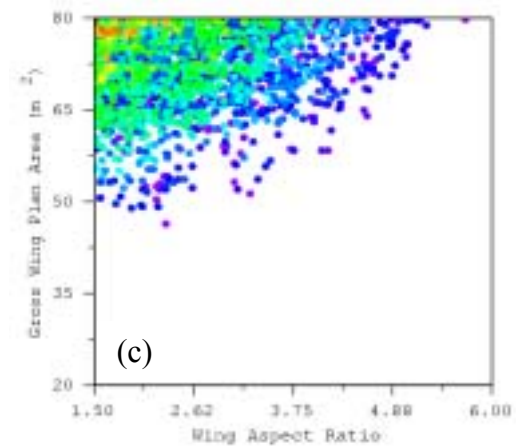
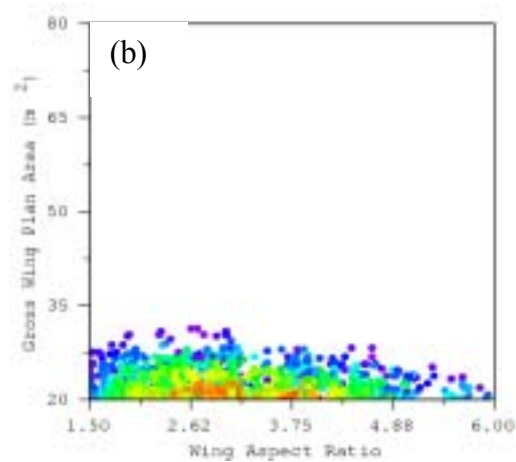
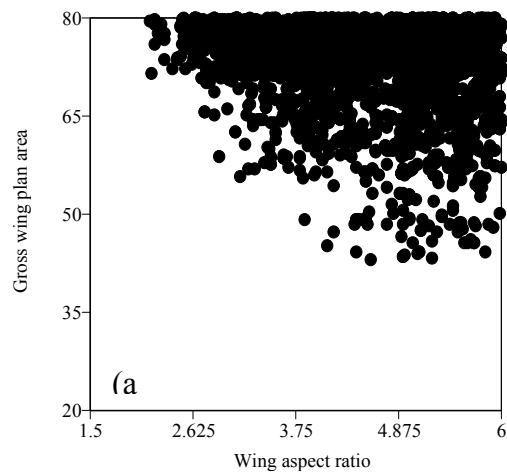


Fig. 11: COGA-generated high performance regions relating to three differing objectives:

- a) FR – Ferry Range
- b) ATR1 – Attained Turn Rate
- c) SEP1 – Specific Excess Power

N.B. Colour versions of figures can be found at: <http://www.ad-comtech.co.uk/cogaplots.htm>

relating to the ATR1 and FR objectives indicates a low degree of conflict whereas the HP region relating to SEP1 is remote (in variable space) to both the ATR1 and FR regions indicating a higher degree of conflict.

There is much information contained in the HP regions relating to appropriate variable ranges for single objectives, degree of conflict between multiple objectives and the emergence and definition of mutually inclusive (common) HP regions. This graphical representation provides an excellent spatial indication of the degree of objective conflict. However, searching through all possible two dimensional variable hyperplanes to visualize such information is not a feasible approach. Recent research has resulted in single graphical representations that can present all variable and objective data whilst providing links to other visual perspectives. The Parallel Co-ordinate Box Plot (PCBP) representation shown in figure 11 is one such graphic that provides a central repository containing much single and multiple-objective solution information.

3.3. Parallel Co-ordinate Box Plots (PCBP)

Parallel Co-ordinate representation [23] displays each variable dimension vertically parallel to each other. Points corresponding to a solution's value of that variable can then be plotted on each vertical axis. It is thus possible to show the distribution of solutions in all variable dimensions and the correlation between different dimensions. In order to allow the clear representation of several objectives three modifications to the standard Parallel Co-ordinate representation have been introduced [21]:

i) Additional vertical axes for each variable so that each objective can be represented.

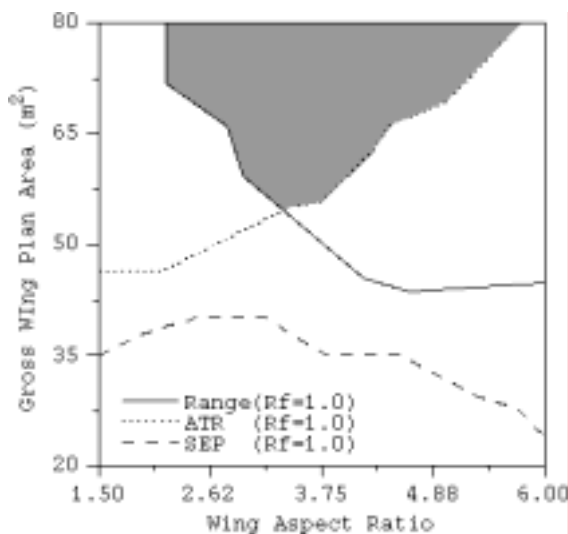


Fig. 12: All HP regions projected onto the GWPA (Gross Wing Plan Area)/WAR (Wing Aspect Ratio) variable hyperplane.

ii) An indication of the degree of HP region solution cover across each variable range.

iii) The introduction of Box Plots to indicate skewness of solutions across each variable range.

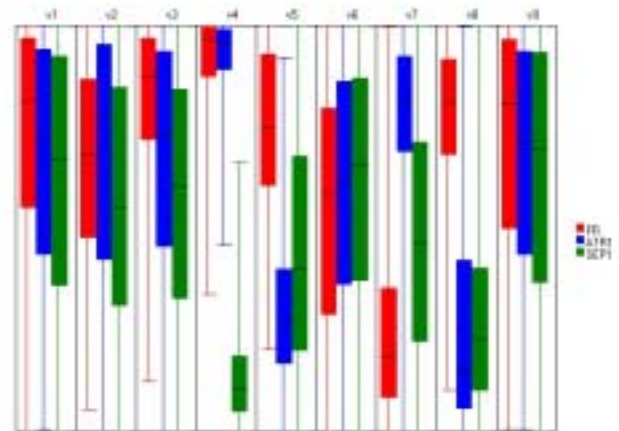


Fig. 13: Parallel Box Plot of solution distribution of each objective across each variable dimension

This Parallel Co-ordinate Box Plot (PCBP - figure 13) provides a succinct and clear graphical indication of the relationships between particular variables and included objectives. The vertical axis of each variable is scaled between the minimum and maximum value of that variable in the HP region solutions of each objective i.e. the length of the axis represents the normalized ranges of variable values present in a HP region. Where a HP solution set does not fully extend across the variable range the axis is terminated by a whisker at the maximum or minimum value of the variable. The colour-coded box plots relate to each objective (i.e. SEP1, ATR1 and FR). The median is marked within the box and the box extends between the lower and upper quartile values within the variable set. The Box Plots clearly visualize the degree of skewness of solution distribution relating to each objective in each variable dimension which provides an indication of the degree of conflict between objectives.

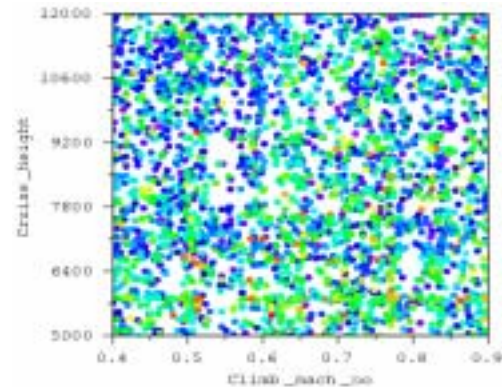


Fig. 14: Projection of results onto variable 1 / variable 2 hyperplane for attained turn rate (ATR) objective.

For instance, it is apparent that all three objective boxes overlap in the case of variables 1, 2, 3, 6 and 9. However, significant differences in the distribution of the boxes are evident in terms of at least one objective where variables 4, 5, 7, and 8 are concerned. Variables 4 and 5 are Gross Wing Plan Area and Wing Aspect Ratio. The conflict between SEP1 and FR / ATR1 evident in figure 12 is strongly reflected in the HP solution distribution indicated by the whisker truncation of variable 4 in figure 13 and in the box plots of that variable. In terms of variable 5 the whisker terminations relating to ATR1 and FR in figure 13 reflect the extent of the solution distribution across their HP regions in figure 12. The box plots also reflect the relative distribution of HP solutions of all objectives along that variable plane as illustrated in figure 12. Figure 14 shows a projection of the ATR1 HP region onto the Cruise Height (variable 1) and Climb Mach No (variable 2) hyperplane. The relatively uniform distribution of HP solutions across the hyperplane is reflected in the appropriate variable plots of figure 13 i.e. the majority of the variable axes fully extend across the variable range and the Box Plots are relatively well aligned when compared to variables 4 and 5.

The PCBP graphic therefore represents a ‘one-stop shop’ from which the designer can select which two dimensional hyperplanes they wish to view to better appreciate the spatial relationship between objectives. This also highlights which variables are causing high degrees of objective conflict. Further reinforcement can be obtained from the perspectives explored in the following section relating to projections of HP solutions upon objective space. Improved understanding can lead to developments of the computational design representation and to appropriate setting of objective preferences.

3.4. Projection of COGA output on to objective space

The HP region solutions for ATR1 and FR can be projected onto objective space as shown in figure 15. A relationship between the HP region solutions and a Pareto frontier emerges along the outer edge of the plot [21] despite the fact that the working principle of COGA does not include the non-dominance aspects of other evolutionary multi-objective algorithms [24]. Using a standard multi-objective GA (MOGA) it is possible to populate a Pareto front but difficult to explore the relationship between variable and objective space. It is also very likely that the designer is interested in high-performance solutions that lie close to particular sections of the Pareto front. For comparative purposes, figure 16 illustrates the distribution of COGA output and SPEA-II [25] Pareto front output in objective space.

It is apparent that the COGA approach provides a good visual indication of the degree of conflict between objectives; an opportunity to explore varying objective preferences and view their effect upon HP region bounds and the ability to generate

an approximate Pareto front relating to the objectives under investigation whilst also providing extensive information re other HP solutions close to the front. A direct mapping is also available from variable space to objective space and vice versa.

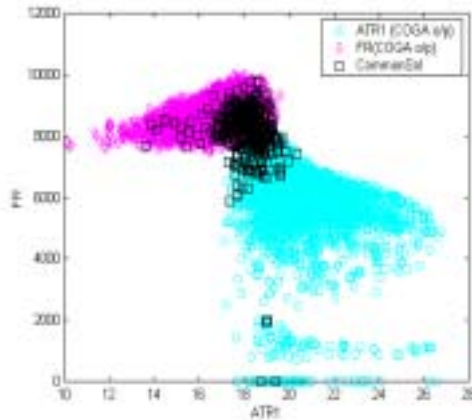


Fig. 15: *Distribution of FR and ATR1 solutions in objective space*

This is in addition to the utility of COGA in single objective space as described in previous referenced papers.

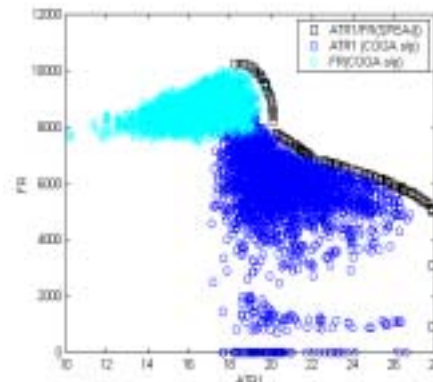


Fig. 16: *Distribution of ATR1 and FR solutions against SPEA-II Pareto front.*

3.5. Summary and conclusions

The aesthetics work reveals a significant potential in terms of the development of systems that include criteria ranging from purely quantitative through to purely subjective. Ultimately the system will be required to give a comparative indication in terms of aesthetically pleasing design and likely cost whilst indicating structural feasibility.

The developing system should be seen as a generic framework for the integration of user-evaluation with any preliminary design/decision-making domain. The CARA-EP representation concept should be portable across many problem domains. The integration of user preference and user-varied objective weights supports the transfer of subjective evaluation from the user to a design / decision-making system. The machine learning work is showing considerable promise in terms of

overcoming the ‘user fatigue’ problem which is, perhaps, the major stumbling block in the development of successful systems. Any system must significantly decrease the load on the user as early as possible in the evolutionary process.

It is apparent from previous research and the research presented here that COGA generated data can provide visual representations in variable space of the degree of conflict between objectives and excellent spatial indications of the distribution of high-performance solution regions relating to a number of objectives. It is also apparent that the COGA HP solution sets, when projected onto objective space provide the designer with an opportunity to explore a wealth of HP solutions that offer varying degrees of objective compromise and a variety of design characteristics. The non-dominance sorting of these solutions also provides an approximate Pareto frontier illustrating succinct available trade-offs. The direct mapping of solutions between objective and variable space facilitates an understanding of the relative utility of solutions in terms of preferred variable ranges and particular design characteristics.

The PCBP of figure 13 offers a first point of call for the designer to get an overview of the varied information available from COGA output. The intention is that the COGA graphical perspectives will be available through simple menu / clicking operations from the central PCBP image. These differing perspectives are seen as essential aids to understanding overall complexities relating to the two dependant design spaces (Variable vs Objective space).

There is a wealth of information available from COGA output relating to single objective solutions that is also inherent within the multi-objective output. Hence the utility of the approach should be assessed across both areas. The information available from single objective HP regions has been fully discussed in previous referenced papers.

We have previously attempted to position this research in terms of cognitive science based upon our current understanding of the field. The reader is referred to [21] which also provides more detail re the research described in this section. It is apparent that further human-centric work requires input from the cognitive science and human factors areas. The recent activities of the research Cluster: ‘Discovery in Design: People-centred Computational Issues’ has addressed these areas to some extent. The Cluster was funded under the AHRC/EPSRC ‘Designing for the 21st Century’ Initiative. An Institute for People-centred Computation involving the Universities of West of England, Cambridge, Cardiff, Bristol and Newport has now been established to continue the Cluster work. The Institute’s activities are currently supported by EPSRC Network funding. Details of the Institute and Cluster activities can be found at <http://www.IP-CC.org.uk>. Membership is open to all.

User-centric techniques described in the chapter and variations of them are also currently being applied in the conceptual design of submersible vehicles [26] pharmaceutical drug design and discovery [27] and conceptual software design [28].

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