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Supporting Implicit Learning via the Visualisation of COGA Multi-objective Data

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Abstract - **The paper speculates upon the development of human-centric evolutionary conceptual design systems that support implicit learning through the succinct visual presentation of data relating to both variable and objective space. Various perspectives of multi-objective design information support a constantly improving understanding of both subjective and quantitative relationships between variables and objectives. This information emerges from cluster-oriented genetic algorithm (COGA) output and is further defined by appropriate data mining, processing and visualization techniques. The intention is to support implicit learning and reduce complexity through the presentation of differing perspectives relating to solution / objective interaction and dependencies. It is proposed that the developing systems could support intuitional understanding of the problem domain. Further proposed agent-based support and interactive elements for the various processes are also introduced.**

I. Introduction

Multi-objective satisfaction is an inherent aspect of conceptual design when many initial objectives can be in evidence. Some will be quantifiable using an appropriate evaluation functions upon which the designer will have varying degrees of confidence whilst others will rely solely upon subjective human judgement. Although some perception of the relative importance of these objectives will be evident this is subject to change. Initial uncertainties create a need for design search and exploration with regard to rather vague performance criteria. This will involve multiple re-ordering of objective preferences as acceptable trade-offs are sought that satisfy both the quantitative and qualitative goals considered important at a particular time. As trade-offs are accepted many objectives may become redundant as conflicts disappear. Indeed, the problem itself may be reformulated to reduce objective conflict in order to take advantage of particular significant potential paybacks [1].

Decision-making processes therefore relate to two high-dimensional spaces i.e. the variable space defined by the values of the constituent variables plus the objective space comprising solutions relating to all objectives. Understanding complex variable interactions in single objective space presents great difficulty but understanding interactions between this space and a dependant objective space would seem relatively impossible. However, designers concurrently negotiate these spaces assisted by experience, assumption and intuition to locate solutions that satisfy requirements that appear most relevant at a particular time.

The paper introduces developing approaches that support the designer during these early investigations of variable and objective space. High-performance (HP) solutions relating to a number of design objectives are generated and high-quality information is extracted and succinctly presented to the designer. The intention is that such information, combined with user experiential knowledge and intuition will support decision-making and problem reformulation leading to eventual identification of high-performance solutions. Cluster-oriented Genetic Algorithms (COGAs) [2, 3] identify HP solution regions relating to various objectives whilst data-mining and presentation techniques extract information from these regions. Various graphical representations of the results are under investigation and initial representations are included. The work follows on and complements the interactive evolutionary design (IED) concept which attempts to meld experiential knowledge and intuition with powerful machine-based search, exploration and information processing [4, 5].

Cognitive aspects relating to the described approaches are initially discussed. COGAs are then briefly described before data visualization techniques that support a better understanding of the complex relationships between variable and objective space are introduced. An experimental approach emerges which could be utilised to investigate the manner in which designer understanding of dependant design spaces can be supported by graphical representations of complex variable / objective relationships from a variety of perspectives. We propose that this approach could support the designer in developing an intuitional map of a multi-objective design space that will subsequently support initial design decision-making.

II. Cognitive Aspects

Much of the authors' previous IED research has been based upon an intuitive understanding of designer requirement during early design stages. Personal design experience and close collaboration and discussion with designers from a variety of disciplines have supported the various approaches. We now attempt to position our research in terms of cognitive science based upon our current (and probably rather naïve) understanding of the field. It is apparent that further IED work requires input from this area and we welcome constructive comment and assistance to help clarify this position.

It has been shown experimentally that the regular achievement of high performance solutions to complex problems through the manipulation of multiple input variables becomes far easier as familiarity with the problem domain increases [6]. This learning process appears to be implicit as, upon interview, those participating in the experiment had great difficulty in describing how they achieved such results. Similarly, it has been shown that we can unconsciously recognize repeated patterns in data sets that support success in certain tasks [7]. Again, subsequent investigation revealed that such patterns could not be consciously detected by the subjects of this particular experiment even when given the opportunity to extensively study the data.

The overall intention of research relating to the IED concept is to provide an environment that supports designer/machine interaction. Such interaction allows the user to explore multi-variate problem space and to view complex relationships from a variety of perspectives. The intention is that this approach will support such implicit learning and that some proportion of a developing implicit learning capability would be transferable to other problem domains. In other words, designers using this interactive search and exploration approach would become inherently better at handling high-dimensional problem domains.

Although anecdotal, the first author's personal experience of the capability of human schedulers to handle far greater dimensions of information that would seem possible in order to achieve a satisfactory schedule appears to support the implicit learning concept. It seems apparent that experiential knowledge and the possibly unconscious recognition of subjective constraints and objectives plays a major role in this problem-solving process. If this is the case, computer-aided conceptual design systems that support implicit learning could represent a new approach. Such systems may allow the development of an overall capability to unconsciously handle far more dimensions of information whilst consciously manipulating and attempting to understand those of prime importance at any particular moment.

This is a very different approach to that of attempting to understand complexity via mathematical analysis. Although some would find such analysis the best way forward others may find it restrictive in that it channels thought and lowers the probability of innovation and discovery from seemingly unrelated sources of information. Although some designers would be far more comfortable with a more deterministic methodology others may prefer a more holistic approach especially during the early stages of design where intuition can play a major role. Westcotts's work [8] relating to intuition and sub-groups of people requiring differing amounts of information to solve problems appears to support this. His 'successful intuitives' are those who require very little information in order to achieve correct solutions. Such people are very comfortable in their exploration of uncertainty and confident in arriving at correct solutions whereas another sub-group, 'cautious successes', have a greater preference for structure, certainty and control and require far more information and data to arrive at a successful conclusion. Current computer aided design, especially in the engineering domain, caters primarily for the latter group rather than the former. Unfortunately, it is only during the later stages of the design process that sufficient data/information is available to satisfy both current computer-aided design tools and the 'cautious successes'. The earlier stages of design remain poorly supported by much of the powerful computational capability available.

In order to support intuitive creativity it is essential that fresh perspectives are presented to an existing experiential body of knowledge. Such perspectives allow the designer to escape from well-worn paths of thinking and to explore associated new concepts and possibilities [9]. A major contributing element is the time available to explore alternatives and discover and develop new concepts. In order to satisfy the requirements of budgets and deadlines it is essential that the designer can rapidly access diverse, high-quality information. Various developing aspects of the IED approach are attempting to support this capability through the powerful search and exploration capabilities of evolutionary computation allied with data-mining and agent-based data processing.

The above conjectures seem to also be supported by findings in neuroscience where familiar routine, analytical tasks cause high-levels of neural activity. The identification of problem relationships appears to utilize relatively well-defined regions of the brain in a conscious process. Conversely, less routine, but related creative tasks cause lower, more widespread neural arousal activating a greater range of neural clusters from which solutions appear to unconsciously emerge [10]. Our understanding from this is that areas of the brain can be primed by appropriate learning from concentrated, routine tasks and that insights, intuition and creative concepts arise from seemingly unconnected links whilst we unconsciously 'surf' what we already know. Again, there is a requirement here for external stimulation (perhaps from diverse problem perspectives) to provoke changes in well-established neural pathways in order to identify links, associations and novel 'solutions'.

It is hoped that the further development of systems similar to those described in the paper would seem to support the cognitive aspects identified in this section. It is intended that, initially, the developed systems will be utlised in an experimental manner to further clarify many of the aspects discussed above.

III. COGAs and The BAE Systems MiniCAPs model

Cluster Oriented Genetic Algorithms were developed in the early 1990s to provide the means to identify high-performance (HP) regions of complex conceptual design spaces and enable the extraction of information from such regions relating, initially, to solution sensitivity [2, 11]. COGAs identifies HP solution regions through the on-line adaptive filtering of solutions generated by a genetic algorithm [12]. Further work resulted in several variations of COGA and also identified and illustrated the manner in which the COGA approach can be utilised to generate highly relevant design information relating to single, multi-objective and constrained problem domains [13, 14].

COGA comprises two primary components: the diverse search engine which utilises a genetic algorithm to search the design space identifying regions of high performance relating to a particular objective and the adaptive filter (AF) which extracts and stores information relating to each identified region. The Adaptive Filter (AF) copies high fitness designs from the evolving population to the Final Clustering Set (FCS). The user can vary the severity of the filtering mechanism in order to identify regions ranging from succinct groupings of very high performance solutions to larger regions of high and lower performance solutions. Sufficient regional set-cover (in terms of number of solutions) can be achieved to allow significant qualitative and quantitative design information to be extracted. COGA development and application has been well documented and is widely referenced within the text. Many of the COGA and IED papers referenced can now be downloaded from http://www.ad-comtech.co.uk/Parmee-Publications.htm

Table 1: MiniCAPS Input Variables

1. Climb Mach Number (CLMN)	4. Gross Wing Plan Area (GWP)	7.Wing Lead Edge Sweep (WLES)
2. Cruise Height (CH)	5. Wing Aspect Ratio (WAR)	8.Wing T/C Ratio (WTCR)
3. Cruise Mach Number (CRMN)	6. Wing Taper Ratio (WTR)	9. By Pass Ratio (BPR)

Earlier IED research has utilised the BAE Systems MiniCAPs model, a simplified version of the British Aerospace CAPS (Computer Aided Project Studies) suite of preliminary design models for the early investigation stages of military aircraft airframe design. MiniCAPS was initially developed for research purposes relating to the development of the IED concept. It comprises nine continuous input variables and twelve continuous output parameters. MiniCAPs subroutines calculate properties relating to criteria such as performance, wing geometry, propulsion, fuel capacity, structural integrity etc. Input variables are listed in Table 1.

IV. Identifying High-performance Regions Relating to Differing Objectives

Figures 1a, b & c show HP regions comprising solutions from the FCSs 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

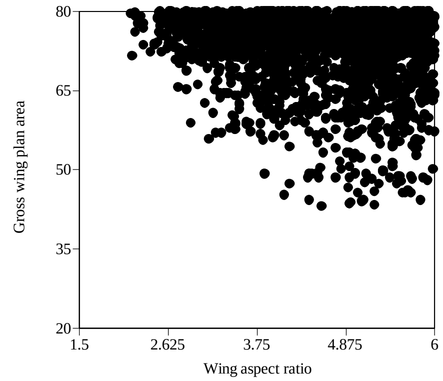


Figure 1a: HP region for Ferry Range

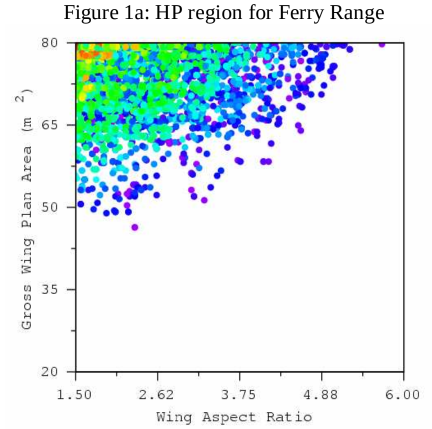


Figure 1b: HP region for ATR 1

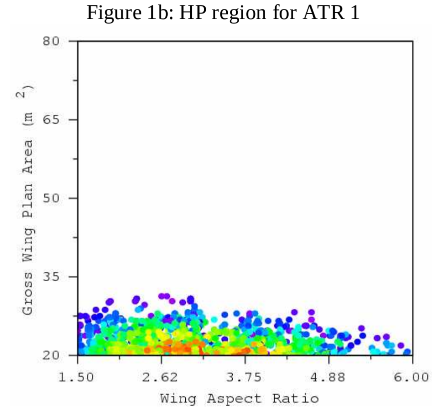


Figure 1c: HP Region for SEP 1

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

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 previous papers [1,4,13].

The projection of a number of HP regions relating to different objectives onto the same variable hyperplane as shown in figure 2 has also been previously illustrated [4, 5, 13]. The degree of objective conflict immediately becomes apparent to the designer i.e. the emergence of a mutually

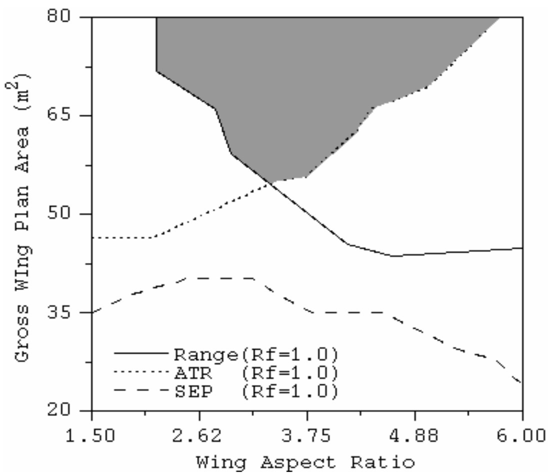


Figure 2: All HP regions projected on to GWPA / WAR variable hyperplane.

inclusive region of HP solutions 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 HP regions indicating a high degree of conflict. The Adaptive Filter setting has been kept constant across the COGA runs relating to each objective.

It is apparent that there is a deal of information contained in the FCS solution sets relating to appropriate variable ranges for single objectives, degree of conflict between multiple objectives and the emergence and definition of mutually inclusive regions. Although such graphical representation provides an excellent spatial indication of the degree of conflict, having to search through all two dimensional variable hyperplanes to visualise such information is not a feasible approach. Recent research has resulted in graphical representations that can present all objective data whilst providing easily utilised links to other visual perspectives. The parallel co-ordinate box plot representation shown in figure 3 is one such graphic that provides a central repository containing much relevant single and multiple-objective information.

V. Parallel Co-ordinate Box Plot

Parallel Co-ordinate representation [15] 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 variable axis. It is thus possible to show the distribution of solutions in all variable dimensions and the correlation between different dimensions. A combination of Box Plot representation and Parallel Co-ordinates is shown in figure 3. The vertical axis of each variable plane is scaled between the minimum and maximum value of the variable found in the FCS of each particular objective i.e. the length of the axis represents the normalized ranges of variable values present in a HP region. If the HP solution set does not extend across the whole of 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. This Parallel Co-ordinate Box Plot (PCBP) clearly visualizes the skewness of solution distribution relating to each objective in each variable dimension. Differing degrees of skewness provide an indication of the degree of conflict between objectives.

For instance, it is immediately apparent that all three objective boxes largely overlap in the case of variables 1, 2, 3, 6 and 9. However, significant spatial 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. Referring back to Table 1, variables 4 and 5 are Gross Wing Plan Area and Wing Aspect Ratio. The conflict between SEP1 and FR / ATR1 evident in figure 2 is strongly reflected in the HP solution distribution indicated by the whisker truncation of variable 4 in figure 3 and in the box plots of that variable. In terms of variable 5 the whisker terminations relating to ATR1 and FR in figure 3 reflect the extent of the solution distribution across their HP regions in figure 2. The box plots also reflect the relative distribution of HP solutions of all objectives along that variable plane as illustrated in figure 2.

Figure 4 shows a projection of the ATR1 HP region onto the Cruise Height (v1) and Climb Mach No (v2) variable hyperplane. Again, the relatively uniform distribution of HP solutions across the hyperplane is reflected in the appropriate variable plots of figure 3.

Extensive variable attribute relevance analysis [16] utilising the COGA-generated HP solutions has been carried out in addition to standard skewness calculations to verify the visual information available in the PCBP [17]. Variable attribute relevance analysis quantifies the relevance of an attribute (i.e. variable) with respect to a given class or concept by measures such as information gain and correlation co-efficient. Using the above procedure the information gain of each variable is calculated and variables are ranked in terms of the degree of effect they have across the set of objectives. The resulting ranking identifies variables 4, 5, 7 and 8 as those variables to which the objective set is most sensitive. Skewness analysis also confirms the visual information available in the plot. Further details of this work can be found in [17]. Skewness analysis also confirms the visual information available in the plot.

VI. Utilising PCBP Information

Taking into account the information available within the PCBP with regard to **multi-objective (MO) space** the designer can:

i) Rapidly identify variables which least affect solution performance across the full set of objectives (i.e. those

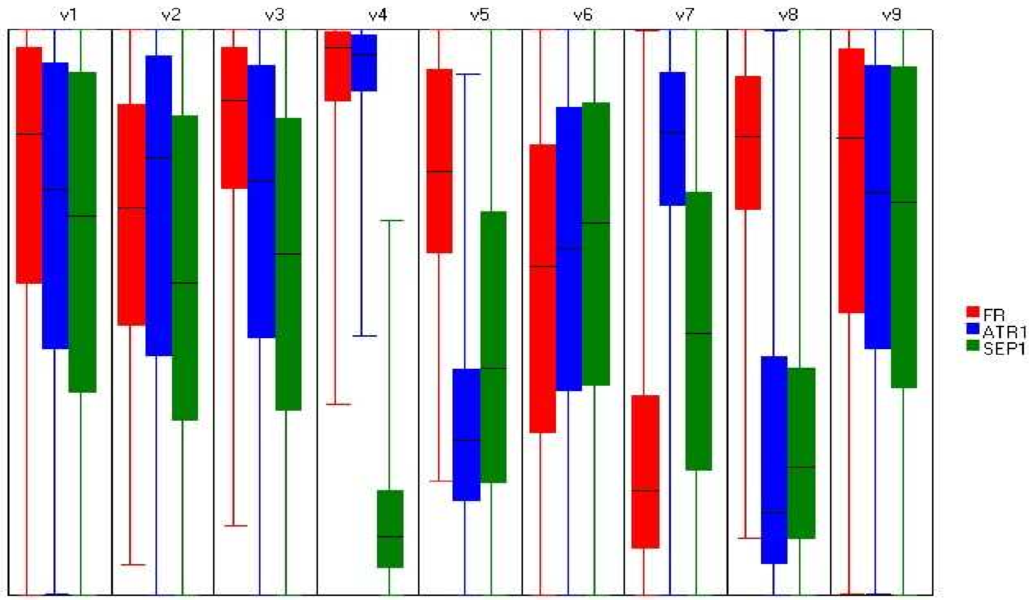


Figure 3: Parallel Box Plot of solution distribution of each objective across dimensions. Colour plot available at: http://www.ad-comtech.co.uk/cogaplots.htm

variables where the full axis relating to each objective largely overlap e.g. 1, 2, 3, 6, & 9).

ii) Further identify where minimum objective conflict is evident (i.e. where box plots relating to each objective largely overlap).

iii) Rapidly identify which objectives conflict which is evident from the diverse distribution of box plots along some axes.

iv) View those related variable hyperplanes where conflict is evident in order to see a different perspective of the spatial distribution of the objectives' high-performance regions (as illustrated in figure 2). Access to such hyperplanes will be driven by simple clicking operations on selected variable axis.

v) View projections of high-performance regions on objective space as shown in figure 5.

vi) View approximate Pareto frontiers generated from the non-dominated sorting of HP region solutions as shown in figure 6.

The development of the graphics supporting activities (iv) and (v) are now described in the following section.

VII. Comparing COGA and MOGA Output

If we take the FCS solutions and the identified common region solutions for ATR1 and FR (see figures 1 &2) and plot them in objective space the distributions shown in figure 5 emerge. We have always assumed a relationship between the solutions in the FCSs and a Pareto frontier and the outer edge of the plot would seem to support this assumption. The working principle of COGA for a multi-objective problem is different to that of standard Pareto dominance based evolutionary MO algorithms [18]. The principle of COGA is to generate as much information as possible concerning high performance regions relating to various objectives within a problem space. Using a standard multi-objective GA (MOGAs) it is possible to obtain solutions lying upon the Pareto front but difficult to explore the relationship between variable and the objective space. COGA identifies high-performance MO solutions

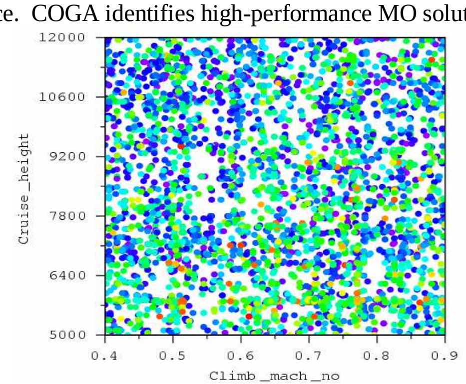


Figure 4: Comparison of a projection of results onto v1 / v2 variable hyperplane for Attained Turn Rate objective

that may offer significant utility and satisfy currently perceived multi-objective, interdisciplinary requirements. Many of these HP solutions may not be available in a non-dominated Pareto set. A direct mapping also exists

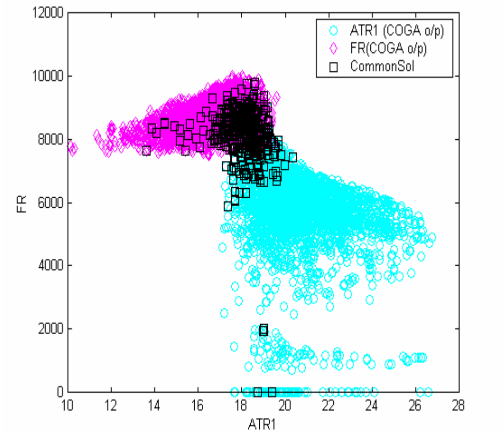


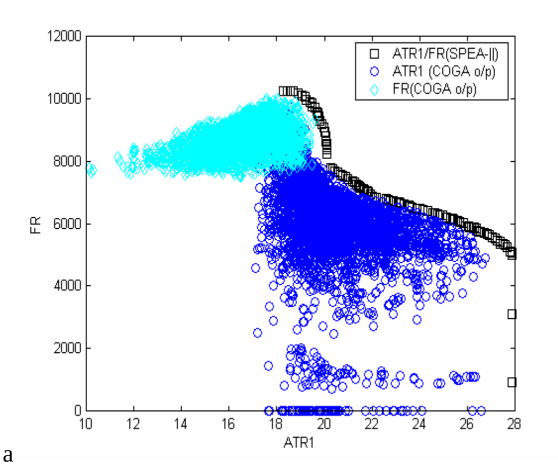
Figure 5: Distribution of HP and common region solutions objective space (FR and ATR)

between variable and objective space allowing designers with differing requirements to further investigate particular characteristics of any HP solutions. The identification of multi-objective HP regions whilst also identifying approximate Pareto frontiers through on-line non-dominance sorting of solutions within them offers the combined advantages of COGA and MOGA approaches.

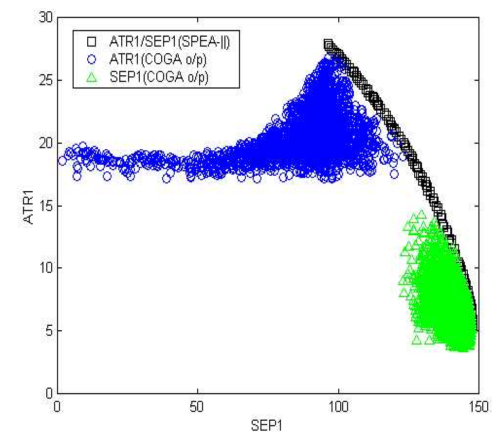
The COGA capability to generate an approximated Pareto front relating to the objectives under investigation in addition to HP solutions around the Pareto frontier has been further investigated [17]. Comparison has been made to output from the Strength Pareto Evolutionary Algorithm (SPEA) [19]. SPEA has been shown to perform comparatively well against other evolutionary Pareto approaches [20]. The SPEA-II algorithm has been utilised to generate Pareto fronts for the objectives SEP1, ATR1 and FR.

Figures 6a, 6b & 6c illustrate the distribution of COGA output and SPEA-II output in objective space. Figures 5b & 5c show the conflicting relation between the objectives ATR1 and SEP1 and between objectives FR and SEP1. Figure 5a shows complete approximate COGA cover of the SPEA Pareto front for objectives FR and ATR1 further indicating less conflict between them.

Figure 7 shows that COGA can provide a good approximation to the non-dominated front identified by SPEA-II. This figure also shows how conflict between the objectives can be reduced by lowering the adaptive filter threshold. The COGA solutions in figure 7 have been obtained by identifying the non-dominated solutions in the ATR1 and SEP1 final clustering sets. The darker, non-dominated solutions are from the FCSs generated with a higher adaptive filter threshold whereas the lighter non-dominated solutions have been generated using a lower filter threshold. It is clear from the figure that by lowering the filter threshold it is possible to obtain a continuous Pareto front. The front only breaks down with an increase



a



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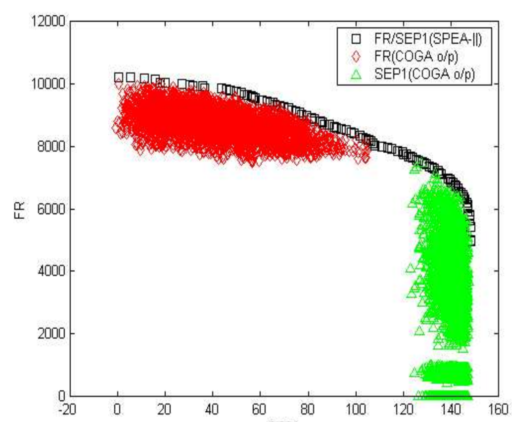

c

Figure 6a. Distribution of solutions for objective ATR1 and FR against SPEA-II Pareto front

Figure 6b. The distribution of solutions for objective ATR1 and SEP1 against SPEA-II Pareto front.

Figure 6c. The distribution of solutions for objective ATR1 and SEP1 against SPEA-II Pareto front.

in adaptive filter threshold severity indicating the conflict between the objectives in a high information gain variable space e.g. GWPA(variable 4) and WA (variable 5). This confirms earlier results relating to the identification of mutually inclusive HP regions relating to all three objectives through the relaxation of the adaptive filter threshold in the COGA run relating to SEP1 as shown in figure 8.

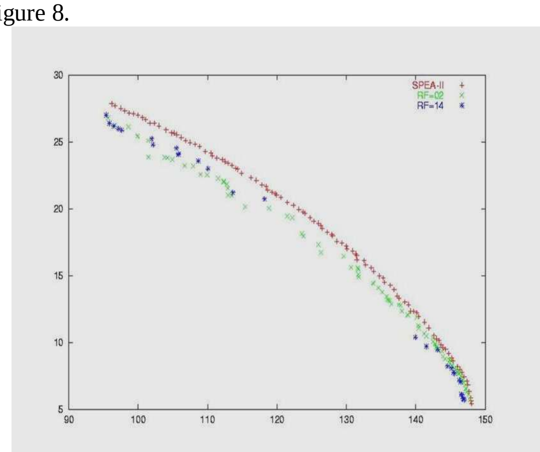

Figure 7. Comparing Pareto front of SPEA-II with that of COGA for low and high AF threshold

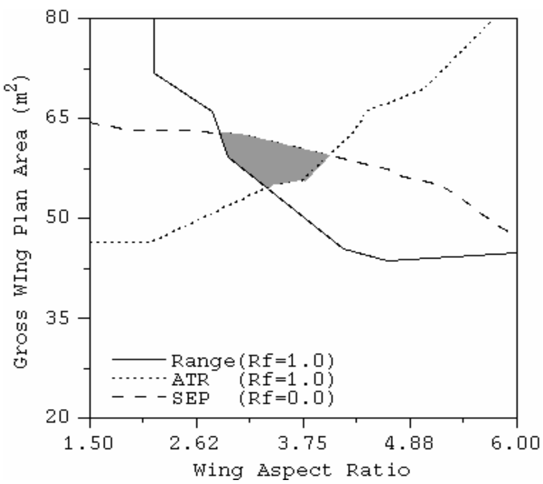

Figure 8: Emergence of a mutually inclusive region relating to all objectives through the relaxation of the adaptive filter setting in the SEP COGA run

As has been previously stated, this filter relaxation, which allows lower performing solutions to enter the SEP1 final clustering set, is analogous to lowering the importance (preference / weighting) of the SEP1 objective.

VIII. Future Research - Agent-based Activities

Data mining procedures described in previous sections could provide sufficient information to an agent-based system to support a degree of autonomous activity to supplement designer interaction with the system. Such activity may relate to for instance data processing, designer interrogation and / or the provision of textual advice. Appropriate agency should reduce the amount of information presented to the designer thereby reducing cognitive load and allowing greater concentration upon primary design characteristics. Agent activity must not, however, reduce designer interaction with the system in terms of search and exploration to the extent that the 'hands on' and implicit learning aspects are diminished. Agent activity should enhance rather than replace understanding by improving clarity and revealing differing perspectives whilst minimising more mundane tasks facing the designer.

Many activities could benefit from agent support. For instance, identifying the degree of filter relaxation required to overcome objective conflicts. Only three of the possible twelve miniCAPS objectives have been involved in the research presented here. Several more objectives will be involved in an objective preference determination exercise. Such an exercise will be human-centred with a high degree of agent support. Previous negotiating agent work [21] provides an initial basis for this interaction to further discover objective relationships and identify 'best' compromise regions that satisfy all objectives. The approximate Pareto frontier generation from COGA output may also provide support in the determination of objective preferences and ranking. This overall interactive process in itself is likely to provide extensive and significant insight relating to overall design characteristics and future direction.

The entire IED concept revolves around the melding of machine-generated high-quality design information with designer experiential and arising knowledge and intuition. Any resulting user development and / or reformulation of the design problem therefore represent an integration of this knowledge and intuition. A degree of inherent knowledge capture is therefore evident in subsequent search and exploration of the reformulated space and the designer / machine loop is closed as further high-quality design information is generated. It is proposed that a degree of machine-learning is inherent in this cyclic human / machine interaction. A major objective is the appropriate development of multi-agent based systems that can identify primary characteristics of this captured designer knowledge. Semi-autonomous interpretation and utilization of these characteristics (i.e. with user guidance and support when necessary) will greatly support the understanding of design complexities in further iterative user / machine interactions.

IX. Conclusion

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 3 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 other 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.

The graphical representations are experimental at this point in time and other alternatives are under development. COGA performance itself is also receiving a deal of research effort to improve solution set cover of the HP regions whilst minimising computational effort.

It is not currently possible to assess effect relating to the implicit learning aspects discussed in section II. Further development of the data generation and presentation techniques will result in an experimental tool that can be utilised to explore the cognitive and HCI aspects of the work..

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.

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

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