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USER-CENTRIC EVOLUTIONARY DESIGN

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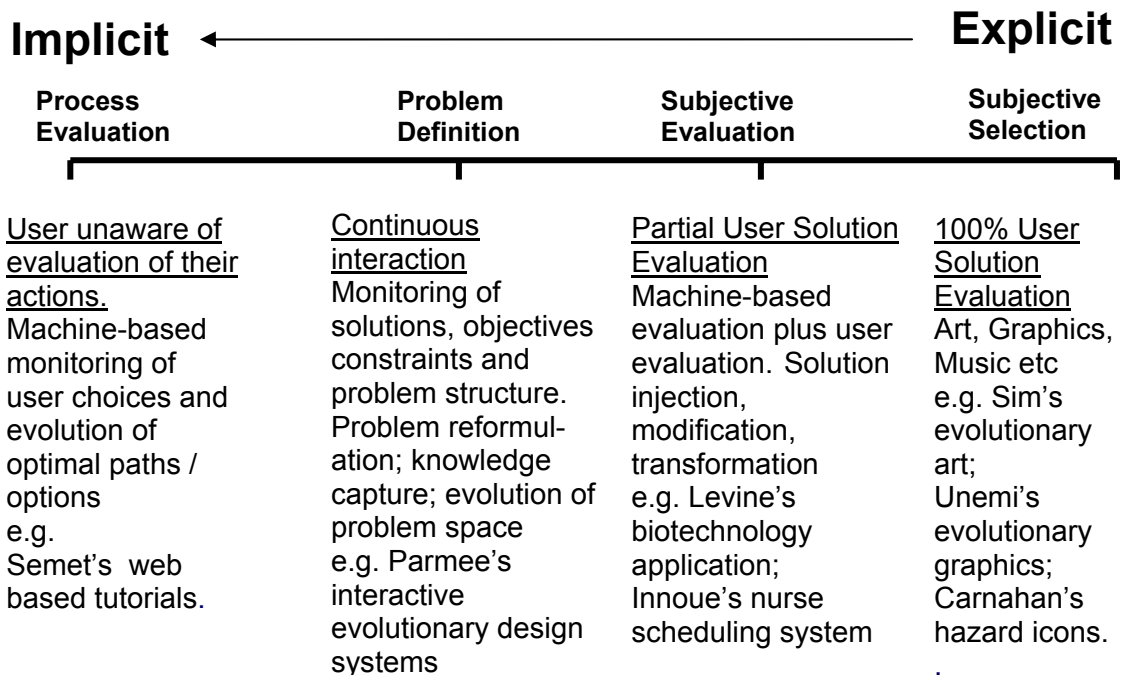*Keywords: interactive evolurionary design, user- centric intelligent systems*

1. Introduction

Interactive evolutionary computing (IEC) relates to partial or complete human evaluation of the fitness of solutions generated from evolutionary search. It has generally been introduced where quantitative solution evaluation is difficult if not impossible to achieve. Examples of application include graphic arts and animation, musical composition and food engineering. Such applications rely upon a human-centred, subjective evaluation of the fitness of a particular design, image, taste etc as opposed to an evaluation developed from some analytic model. An interesting industrial engineering example in graphical design is the work of Carnahan and Dorris [2003] relating to the design and validation of warning sign icons.

Examples of partial human evaluation / interaction include an evolutionary nurse scheduling system where a schedule model provides a quantitative evaluation of a solution where the user must add new constraints in order to generate solutions that are fully satisfactory. In computational biology, genetic algorithms (GA) can provide the search process for the identification of optimal biomolecule combinations but the process can be much enhanced by the user-introduction of new combinations into selected GA generations. Further details and/or references to all the above examples can be found at: http://www.ad-comtech.co.uk/Workshops.htm. Parmee [2002] proposes that interactive evolutionary design processes when operating within ill-defined and uncertain design domains provide information that can improve problem definition, increase confidence and identify innovative / creative design direction.

It is possible to view complete human evaluation as explicit whereas partial evaluation and interaction could be viewed as a less explicit, more subtle degree of human involvement. Recent work involving the on-line assessment of the manner in which students navigate a web-based tutorial system [Semet et al 2003] and the utilization of this data to optimize web layout to facilitate future student usage could be viewed as a more implicit form of interaction as the users are unaware of their role in the evolution of the system. A spectrum of interactive evolutionary approaches can therefore be developed based upon their explicit /implicit nature as shown in figure 1. It is suggested that there is significant utility to the engineering / product / industrial designer across this spectrum both in terms of direct utilization of IEC and in the integration of various IEC elements within suites of computer-aided design tools. Several projects within the ACDDM Group are exploring various IEC aspects within both design and manufacturing environments building upon previous related user-oriented evolutionary design research and application [Parmee 2001].

The following sections concentratte upon the manner in which evolutionary design search and exploration can generate high quality information from complex, multi-objective design environments. that can be utilized interactively to modify and refine design problem representation i.e. the problem definition aspect in the explicit / implicit spectrum of figure 1.

Implicit ←——————————————————— **Explicit**

Process Evaluation	Problem Definition	Subjective Evaluation	Subjective Selection
User unaware of evaluation of their actions. Machine-based monitoring of user choices and evolution of optimal paths / options e.g. Semet's web based tutorials.	Continuous interaction Monitoring of solutions, objectives constraints and problem structure. Problem reformul-ation; knowledge capture; evolution of problem space e.g. Parmee's interactive evolutionary design systems	Partial User Solution Evaluation Machine-based evaluation plus user evaluation. Solution injection, modification, transformation e.g. Levine's biotechnology application; Innoue's nurse scheduling system	100% User Solution Evaluation Art, Graphics, Music etc e.g. Sim's evolutionary art; Unemi's evolutionary graphics; Carnahan's hazard icons. .

Figure 1. Possible spectrum of interactive evolutionary approaches offering utility to the designer. (please visit http://www.ad-comtech.co.uk/Workshops.htm for further details / references relating to examples)

2. Information extraction from multi-objective space

The techniques introduced in the paper generate high-performance data relating to multiple design objectives. Information relating to both solution and objective space is extracted and graphically presented to the designer. Cluster-oriented Genetic Algorithms (COGAs) [Parmee 1996] identify high performance regions relating to various objectives. The work complements the Interactive Evolutionary Design (IED) concept where a human-centric evolutionary approach attempts to meld experiential knowledge and intuition with powerful machine-based search, exploration and agent-assisted information processing [Parmee 2001, 2002].

Many design objectives may be evident during the early stages of design, some are quantifiable whilst others may be largely subjective. Initial uncertainties introduce the need for search and exploration of an initial design space with regard to vague performance criteria. Multiple re-ordering of objective preferences may be required in order to satisfy both quantitative and qualitative goals considered important at the time. Some objectives may become redundant as conflicts disappear due to such preference re-ordering and problem reformulation whereas the perceived importance of others may vary considerably as beneficial trade-offs become more apparent.

The complex decision-making process relates to two dependant multi-variate spaces i.e. the solution space comprising solutions defined by the constituent variables and the objective space comprising some n dimensional surface relating to n objectives. Cluster-oriented Genetic Algorithms (COGAs) identify high performance regions of the design space relating to differing individual objectives and succinct visual representations of this information, projected onto both variable and objective space, are presented. The intention is that these differing perspectives will support the designer in better understanding complex variable / objective relationships. This better understanding coupled with experiential knowledge should support intuitive decision-making relating to appropriate development

of the design space and design direction. COGA output is also compared to the Pareto frontiers generated from an established evolutionary multi-objective approach

3. Cluster-oriented Genetic Algorithms (COGAs) and the MiniCAPS Model

Cluster Oriented Genetic Algorithms identify high-performance (HP) regions of complex design spaces enabling the extraction of relevant information from such regions. [Parmee 1996]. HP regions are identified via the on-line adaptive filtering of solutions generated by a genetic algorithm (GA). The manner in which COGAs can be utilised to generate highly relevant design information relating to single, multi-objective and constrained problem domains has been illustrated [Parmee and Bonham 1999]. Such information supports a better understanding of complex variable, solution and performance trade-off relationships and contributes to the knowledge-base appertaining to the problem.

COGA comprises two primary components: a GA which searches the design space identifying regions of high performance and the adaptive filter (AF) which extracts and stores information relating to each region. The adaptive filter copies high performance solutions from the evolving population to a Final Clustering Set (FCS). The severity of the adaptive filter can be varied to support its utilisation in an exploratory manner to identify either succinct groupings of very high performance solutions or larger regions of high and lower performance solutions.

Earlier IED research utilised the BAE Systems MiniCAPs model, a simplified version of the British Aerospace CAPS (Computer Aided Project Studies) suite of preliminary design models utilised during the early investigation stage of military aircraft 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.

Table 1. MiniCAPS Input Variables

1. Climb Mach Number	4. Gross Wing Plan Area	7. Wing Lead Edge Sweep
2. Cruise Height	5. Wing Aspect Ratio	8. Wing T/C Ratio
3. Cruise Mach Number	6. Wing Taper Ratio	9. ByPass Ratio

## 4. Identifying High-performance Regions Relating to Differing Objectives

Typical COGA output has been fully illustrated in several previous papers and the reader is refered to them for completeness. Figure 2 shows COGA generated HP region relating to one of the twelve
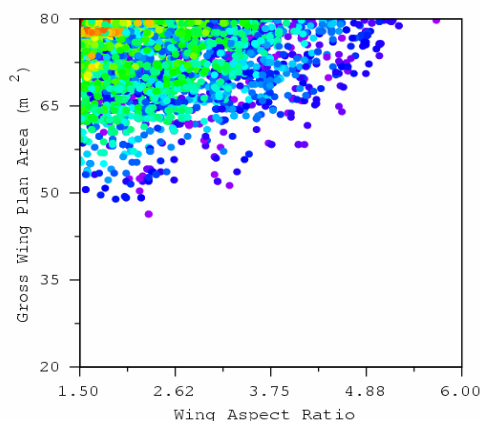
Figure 2. COGA generated HP region (ATR objective)

MiniCaps objectives: Attained Turn Rate (ATR1) projected onto a particular hyperplane relating to variables 4 and 5 of the nine variables utilized in the search process. This projection allows the designer to visualize the regions, identify their bounds and subsequently reduce the variable ranges as described in previous papers.

Figure 3a shows HP regions relating to Ferry Range (FR), Attained Turn Rate (ATR1) and Specific Excess Power (SEP1) objectives projected onto the same hyperplane (Parmee and Bonham 1999). Objective conflict immediately becomes apparent i.e. the emergence of a common region of HP solutions relating to ATR1 and FR indicates a low conflict whereas the remote HP region relating to SEP1 indicates a high degree of conflict. This

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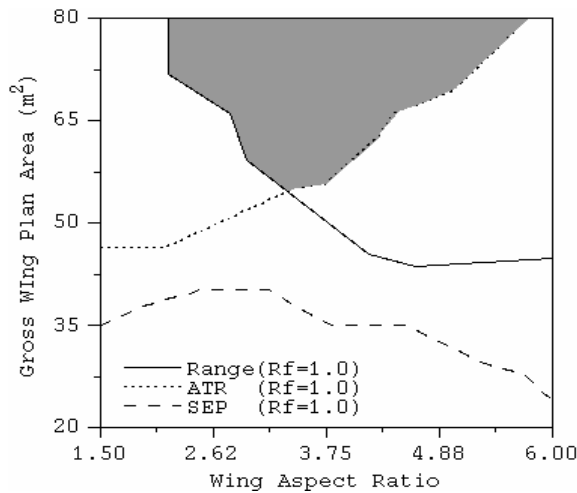
**Figure 3a. Three objective HP regions projected on to variable 4/5 hyperplane**
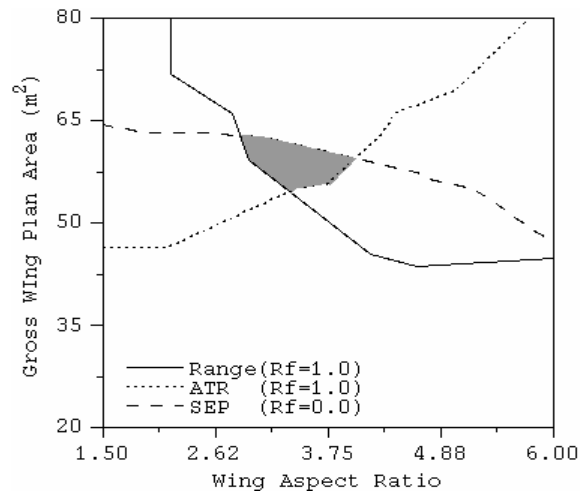
Figure 3b. Relaxing the filter threshold for SEP1 - common region for all three objectives emerges

conflict can be resolved by reducing adaptive filter severity relating to the SEP1 COGA run as shown in figure 3b. Lower performance solutions now enter the SEP1 Final Clustering Set (FCS) which lowers the average solution performance in the HP region. This can be considered analogous to introducing a lower weighting or preference to the SEP1 objective as described in Parmee and Bonham [1999].

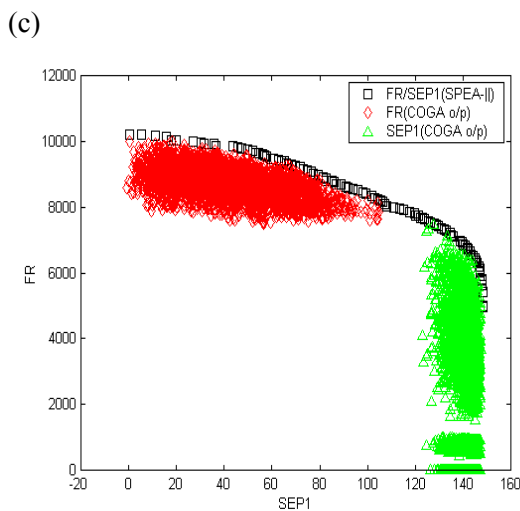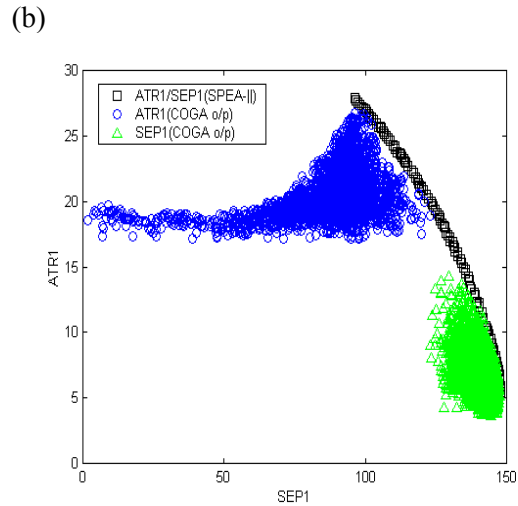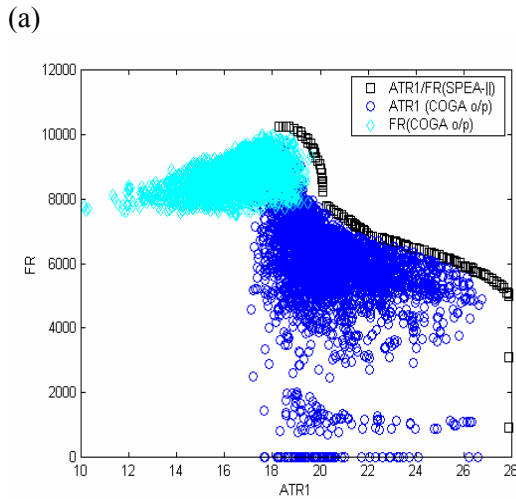## 5. Exploring the relationship Between COGA and MOGA Output

If we take the FCS solutions and the identified common region solutions for ATR1 and FR and plot them in objective space the distributions shown in figure 4 emerge. We have always assumed a relationship between the solutions in the FCSs and a Pareto frontier and the outer edge of the plot
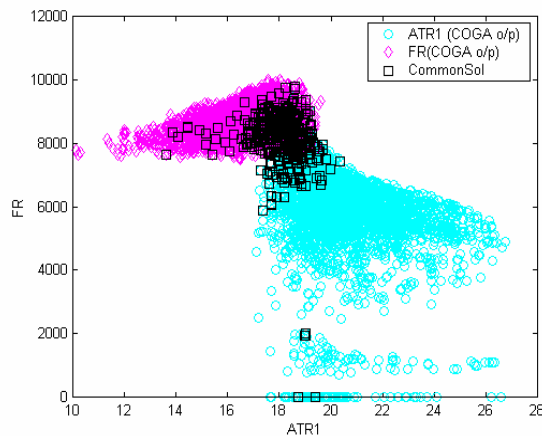
Figure 4. Distribution of HP and common region solutions in objective space (FR and ATR)

would seem to support this assumption . The working principle of COGA for a multi-objective problem is different to that of standard evolutionary multi-objective algorithms [Deb 2001] which tend to use a Pareto dominance based approach. 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 along the Pareto front but difficult to explore the relationship between variable and the objective space and to discover what is available close to the frontier. During the early stages of design it is quite possible that the designer is also interested in such solutions and solutions that lie around particular sections of the Pareto front. The multi-objective 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; the

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(a)

(b)

(c)

Figure 5a. Distribution of solutions for objective ATR1 and FR against SPEA-II Pareto front

Figure 5b. The distribution of solutions for objective ATR1 and SEP1 against SPEA-II Pareto front

Figure 5c. The distribution of solutions for objective ATR1 and SEP1 against SPEA-II Pareto front

NB: Colour versions of these plots can be viewed at:

http://www.ad-comtech.co.uk/cogaplots.htm

capability to generate an approximated Pareto front relating to the objectives under investigation and also to identify high performance solutions around the Pareto frontier.

Most multi-objective genetic algorithms use the concept of Pareto dominance. The Strength Pareto Evolutionary Algor-ithm (SPEA) [Zitzler et al. 2002] performs comparatively well. SPEA's strength lies in its use of elitism (the concept of storing and using the good solutions in earlier generations for future search). The SPEA-II algorithm has been utilised to generate Pareto fronts for the objectives SEP1, ATR1 and FR for comparative purposes.

Figure 10a, 10b & 10c illustrate the distribution of COGA output and SPEA-II output in objective space. Figures 10b &10c show the conflicting relation between the objectives ATR1 and SEP1 and between objectives FR and SEP1. Figure 10a shows complete COGA cover of the SPEA Pareto front for objectives FR and ATR1 further indicating less conflict between them.

Figure 6 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 6 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 filter threshold whereas the lighter non-dominated solutions have been generated using a lower filter threshold. It is clear from the figure that with a low filter threshold is possible to obtain a continuous Pareto front and the front only breaks down with an increase in filter threshold indicating the conflict between the objectives in a high information gain variable space i.e. GWPA(variable 4) and WA (variable 5).
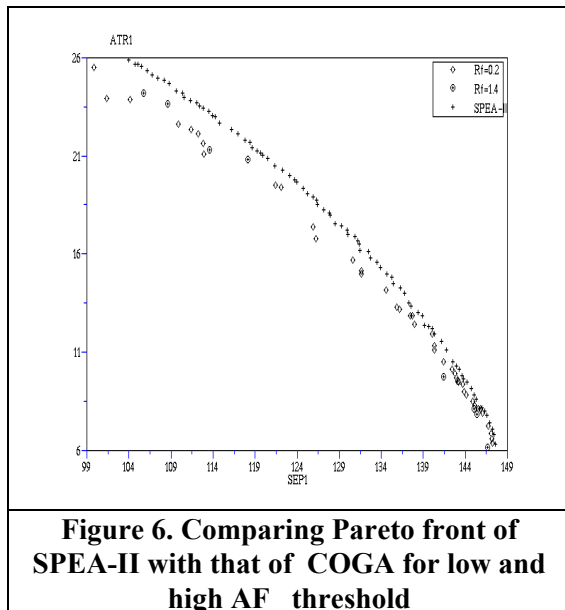
Figure 6. Comparing Pareto front of SPEA-II with that of COGA for low and high AF threshold

6. Conclusion

COGA provides a visual representation in variable space of the degree of conflict between the variables. The designer can interact with the system to explore how changes to the relative importance of objectives relate to these conflicts. An opportunity to explore complex solution relationships across both variable and objective space is therefore available. Various visual perspectives of these relationships presented in a succinct manner to the designer can support a clearer understanding of the design problem space and its characteristics in terms of multi-objective characteristics. Overall, this information supports the designer with respect to the continuous development of the problem representation and the interactive evolution of the design space. Further technical detail relating to the the research described here can be found in Abraham and Parmee [2004].

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

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