Evolutionary Design Search, Exploration and Optimisation

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Setting the Scene

1. Design Search, Exploration and Optimisation
2. SEO Spectrum across Conceptual, Embodiment and Detailed Design
3. Design Attributes of EC
4. Search and Exploration during Conceptual Design

Design Search

- Search across space of design solutions

i.e. across all possible variable combinations

- Driven by single criteria or by multiple criteria (qualitative and quantitative) which may conflict
- Relatively fixed design space - variables, constraints and objectives are pretty well defined
- Designer not necessarily interested in 'best' solution - wishes to better understand what solutions are available and their characteristics.

Exploration

- Search moves outside initial variable bounds, constraints soften, objective preferences change - any combination of these actions.

i.e. Introduces change to *design space and fitness landscape*

- Design *exploration* - seeking and selecting solutions from new space evolved from initial definition.
- Primarily takes place during conceptual stages of design – leads to innovation and creativity?

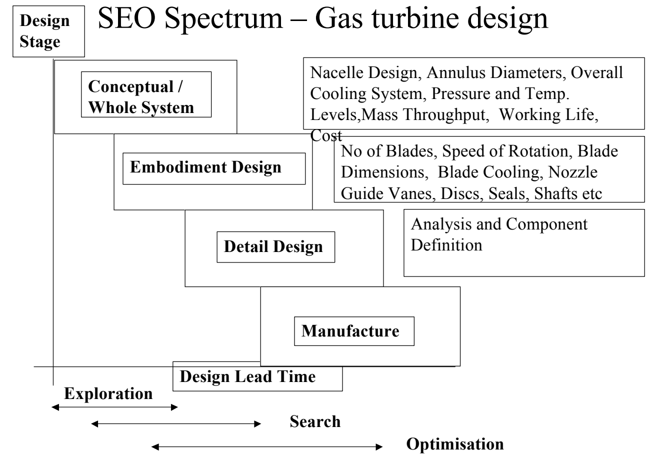
Optimisation

- Attempted identification of highest performing solution within a design space

or, more realistically, a better solution within a restricted time period than those found before

- Very well-defined evaluation functions (FAE / CFD?), fixed quantitative objectives and constraints
- Computationally expensive
- Exploration and search provide high performing starting points for this final optimisation

SEO Spectrum – Gas turbine design



- Degree / extent of exploration far greater where subjective evaluation plays a major role

e.g. product design, architectural / structural design

- Aesthetics must be taken into consideration – largely explorative, innovative and creative.
- Satisfying aesthetic considerations necessitates engineering exploration

- innovative structural developments?
- innovative considerations for services etc?

Why Evolutionary Computing?

Common attributes of the techniques of particular relevance to design SEO include:

- no requirement for apriori knowledge relating to problem.
- Wide range of model type eg. discrete, continuous, mixed-integer, quantitative, qualitative, etc. can be utilised.
- excellent exploratory capabilities – diverse sampling of design space continues throughout search process

• ability to avoid local optima - continuing random sampling prevents premature convergence.

• ability to handle high dimensionality.

• robustness across wide range of problem class - can outperform deterministic optimisation algorithms across wider range of problem classes where high modality, high dimension, conflicting criteria and heavy constraint are in evidence.

• provision of multiple good solutions - can identify multiple high-performance solutions

• multi-objective approaches easily and successfully integrated with various EC techniques;

• can locate region of global optimum - extensive local search may be required to isolate the optimum. Introduction of deterministic gradient-based optimisers or local search techniques can be of considerable utility.

• can be utilised in an interactive search and exploration manner to capture user experiential knowledge and intuition

Agent-based technologies can be easily integrated to further support search and exploration, knowledge extraction and visualisation.

Although all techniques offer utility individually ***appropriate combinations of them can provide very powerful complementary global and local design search, exploration and optimisation capabilities***

Evolutionary Search and Exploration during Conceptual Design

• Tutorial concentrates upon integration during early stages of design

• Early stages characterised by poor definition, uncertainty, multiple qualitative and quantitative objectives, problem reformulation and moving goalposts.

• High degree of user involvement - varying degrees of subjective solution evaluation.

•Evolutionary systems required that can capture designer experiential knowledge and intuition

Primary area of my research since late 1980's with projects relating to:

• Design of novel pneumatic hydropower systems;

• Cluster-oriented GAs - integration with gas turbine design, preliminary air-frame design, drug design and discovery, ROV design;

• Whole system design - structured GA representations for exploration of discrete/ continuous problem spaces;

•Various hybrid techniques for constraint satisfaction in aerospace and power engineering domains;

• Use of GP for systems identification – evolution of approximate design representations to aid search and exploration;

Further details of all these projects in

Evolutionary and Adaptive Computing in Engineering Design. Parmee I. C., Springer Verlag, 2001.

More recent work concentrates upon development of interactive evolutionary design systems (IEDS) involving:

• Cluster-oriented GAs for high-performance solution generation and extraction (both single and multi-objective)

• Co-evolutionary multi-objective satisfaction;

• Fuzzy preferences techniques for objective / constraint ranking;

• Software agent-based systems for data processing and visualisation and objective / constraint negotiation.

What is Interactive Evolutionary Computing?

• Generally relates to partial or complete human evaluation of fitness of solutions generated from evolutionary search.

• Quantitative evaluation difficult if not impossible to achieve. Examples of application:
Graphic arts and animation (Sims K ,1991); Automotive design (Graf J., Banzhaf W.,1995); Food engineering (Herdy M., 1997.)
Database retrieval (Shiraki H., Saito H., 1996.) All rely upon a human-centred, subjective evaluation of the fitness of a particular design, image, taste etc

Partial human evaluation also in evidence, e.g.

• User interaction relating to an evolutionary nurse scheduling system - schedule model provides quantitative evaluation but model not adequate in terms of changing requirements, qualitative aspects etc. User must add new constraints to generate satisfactory solutions (Inoue T., 1999).

• Design of biomolecular systems enhanced by partial interactive evolution. Optimal bio-molecule combinations improved by user-introduction of new combinations into selected genetic algorithm generations (Levine D. 1997).

Recent examples of IEC in engineering domains:

- Carnahan and Dorris's work [2003] graphical design of industrial warning sign icons.
- Development of hearing-aid signal processing capabilities - user's evaluation of hearing utilised during fitting process [Takagi et al, 1999].
- Caleb-Solly and Smith (2002) – IEC identifies regions of interest in sets of images during hot rolled steel surface inspection – supports defect classification
- Parmee (2001) - IEC provides information to user which supports better understanding of design domain and iterative improvement in problem representation

Complete human evaluation could be viewed as **explicit interaction**

Partial evaluation could be considered **less explicit interaction**

Implicit interaction? -
Recent work: on-line assessment of student navigation of web-based tutorial systems [Semet et al 2003] - data then utilised to optimize web layout to facilitate future student usage -
Users unaware of their role in the evolution of the system.

Spectrum of IEC approaches based upon explicit /implicit nature [Parmee 2003] :

Implicit ← **Explicit**

Process Evaluation	**Problem Definition**	**Subjective Evaluation**	$\boxed{\textbf{Subjective Selection}}$
<u>User unaware of evaluation of their actions.</u> Machine-based monitoring of user choices and evolution of optimal paths / options e.g. Semet's web based tutorials.	<u>Continuous interaction</u> 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	<u>Partial User Solution Evaluation</u> Machine-based evaluation plus user evaluation. Solution injection, modification, transformation e.g. Levine's biotechnology application; Innoue's nurse scheduling system	<u>100% User Solution Evaluation</u> Art, Graphics, Music etc e.g. Sim's evolutionary art; Unemi's evolutionary graphics; Carnahan's hazard icons.

Significant utility to engineering / product / industrial designer across this spectrum in terms of direct utilization of IEC and in the integration of various IEC elements within suites of computer-aided design tools.

In this instance, we will concentrate upon interactive / user-centric aspects relating to:

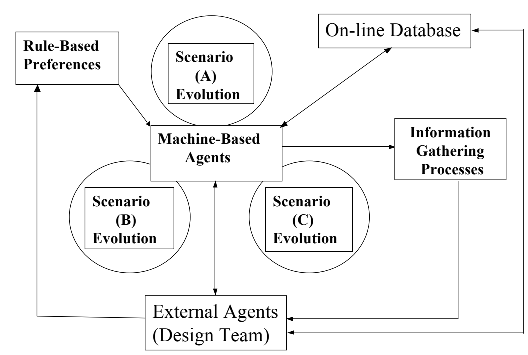
- evolutionary design search and exploration;
- high-quality information generation;
- knowledge discovery;
- knowledge capture and integration;
- design space evolution.

Interactive Evolutionary Design

- Major potential - utilisation of EC algorithms as gatherers of optimal / high-quality design information
- Info can be collated and integrated with human-based decision-making processes.
- Approach can capture designer experiential knowledge and intuition within further evolutionary search
- Supports exploration outside of initial constraint, objective and variable parameter bounds

- Off-line analysis of search data supports iterative designer/machine-based refinement of design space [Parmee, I.C., 1996].
- Immersive system? - designer part of iterative loop
- Multi-disciplinary aspects considered at early stage
- Global considerations represented simply as objectives with associated preferences
- Effect upon emerging solutions identified during iterative development of design space.

Generating Design Information - Initial IEDS concept [Parmee, I.C. et al, 2000] :



Initial IEDS Components

Information extraction:

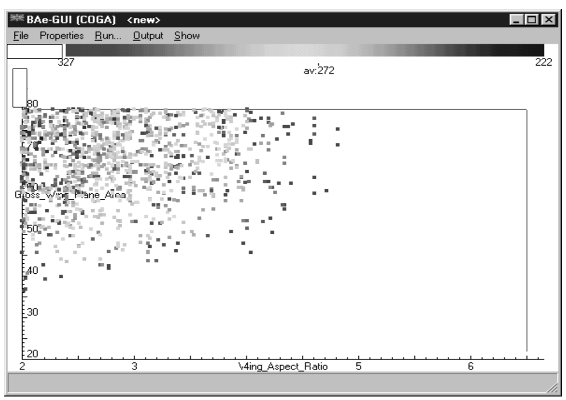
COGAs rapidly identify high performance (HP) design regions relating to single or multiple objectives.

Good solution set cover of identified regions supports extraction of relevant design information

Information mined, processed and presented to the designer in succinct graphics .

Info relates to: Solution robustness, revision of variable ranges, conversion from variable to fixed parameters, degree of objective conflict, sensitivity of objectives to each variable

Solutions describing HP regions can be projected onto any 2D variable hyperplane:

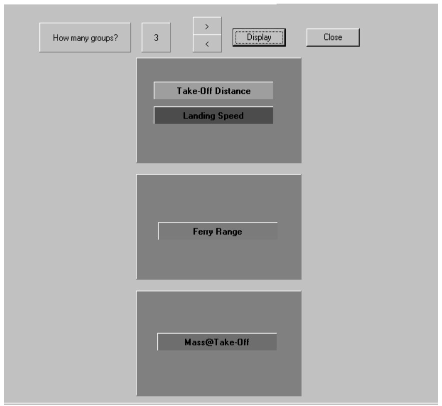


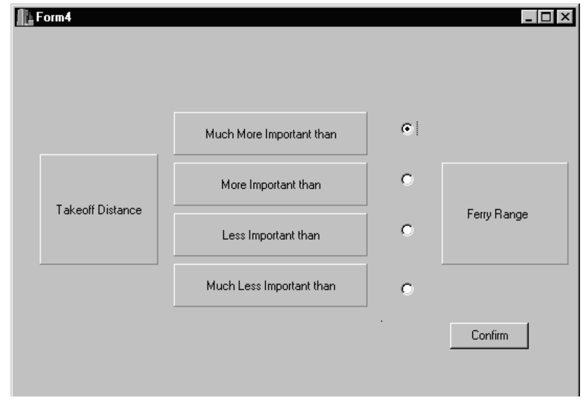
ii)Rule-based preferences:

Designer utilizes rule-based preferences to vary importance of constraints or objectives [Cvetkovic D., Parmee I. C., 2001]

Avoids setting of numeric weightings - Fodor and Reubens' method of fuzzy preferences and induced preference order

Designer inputs qualitative ratings e.g. ' Objective A is much more important than objective C; Objective B is equally important as objective D etc'. Machine-based maths transformation gives appropriate numeric weightings.



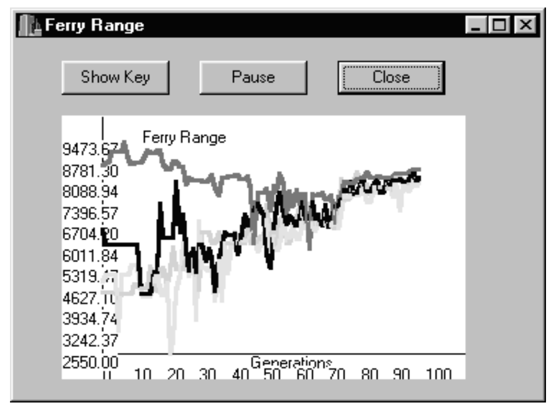


iii) Co-evolutionary Multi-objective convergence:

Co-evolutionary MO strategy developed where each evolutionary process attempts to converge upon a particular objective [Parmee I., Watson A., 1999]

Penalty functions penalize best solutions in each process relative to Euclidean distance i.e. HP solutions far apart design space have their fitness reduced.

Results in all processes converging upon best compromise regions in the design space i.e. regions containing best solutions for all objectives.

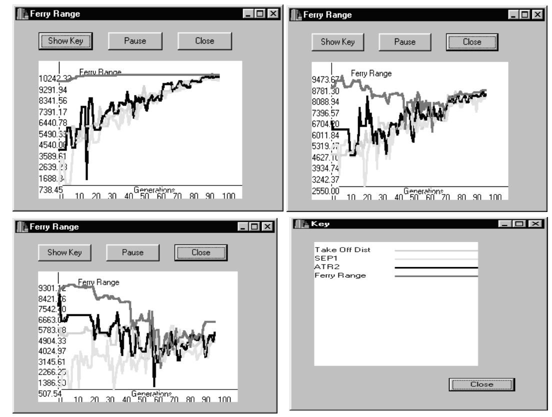


Approach operates in variable space

Graphical visualization of each process tracking across approximate Pareto surface is generated

Direct mapping between solutions on the Pareto surface and their location in variable space readily available.

Integration of Preference component allows designer to interact with the system and to converge upon differing regions of Pareto surface



iv) Software Agents:

Software agents monitor co-evolutionary processes

Recognise states relating to degree of convergence, constraint satisfaction and multi-objective satisfaction

Negotiating agent systems utilising Preference module have been established

Identify solutions satisfying range of design scenarios re multiple objectives and ideal variable values [Cvetcovic D., Parmee I. C., 2002] .

Where do we go from here?

Can we develop user-centred intelligent systems that during conceptual design:

Support exploration of multi-variate problem space?

Provide succinct graphical representation of complex relationships from various perspectives?

Support a better (intuitional?) understanding of complex relationships?

Cognitive Aspects

Can we position these approaches in terms of cognitive science?

Regular achievement of HP solutions to complex problems through manipulation of multiple input variables becomes easier as familiarity with problem increases [Berry D. C., Broadbent D. E., 1984].

Learning process is implicit as subjects have great difficulty in describing how they achieved such results.

Other research shows that repeated patterns in data sets that support success in certain tasks can be recognized [Lewicki P., Hill T., Czyzewska M., 1992].

Subsequent investigation revealed that patterns could not be consciously detected by the subjects even when given opportunity to extensively study the data.

- Westcotts's 'successful intuitives' and 'cautious successes' - sub-groups who require differing amounts of information to solve complex problems.
- Former group comfortable exploring uncertainty - confident in arriving at correct solutions based upon small amounts of information
- Latter group prefer structure, certainty, control and far more information to arrive at successful conclusion.

CAD caters for latter group rather than former. Sufficient data only available during later stages of design - satisfies CAD tools and 'cautious successes'.

Early design and 'successful intuitives' poorly supported

Need to redress this imbalance.

A Step Further: Data Mining COGA Output

Recent research further concentrating upon info generation / extraction

Focuses upon variable / objective space interaction

How can we support designer when concurrently negotiating these two *n*-dimensional spaces?

Current COGA utilisation in combinatorial drug design and in early design of underwater vehicles.

Results shown based upon previous IEDS design domain:

Preliminary military airframe – BAE Systems

- Characterised by uncertain requirements and fuzzy objectives
- Long gestation periods between initial design brief and realisation of product.
- Changes in operational requirements + technological advances
- Demand for responsive, highly flexible strategy - design change / compromise inherent features.

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)
MiniCAPS Input Variables		

Cluster-oriented Genetic Algorithms

COGAs identify high performance regions of complex preliminary / conceptual design spaces

Approach can be utilised to generate highly relevant design information relating to single, multi-objective and constrained problem domains

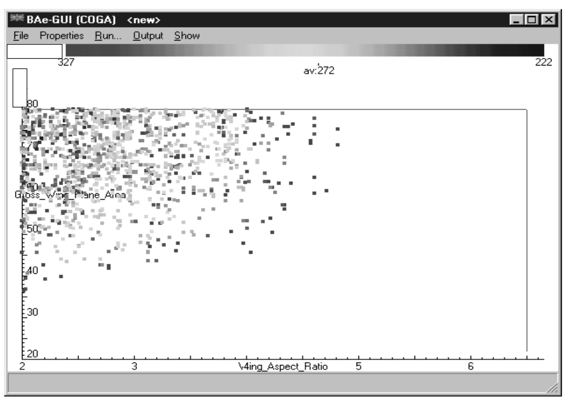
How do COGAs operate?

- Highly explorative GA / GAs

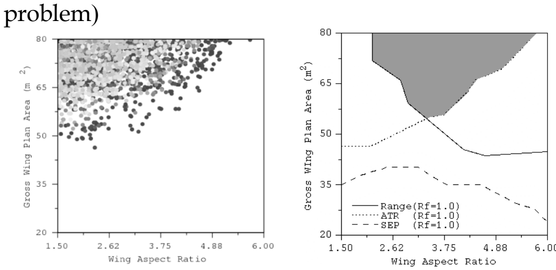
- Solutions extracted and passed through Adaptive Filter

- Better solutions pass into Final Clustering Set - defines HP regions

[Parmee, I.C., 1996, Parmee I. C., Bonham C. R., 2000, Bonham C. R., Parmee I. C., 1999a, Bonham C. R., Parmee I. C., 1999b]



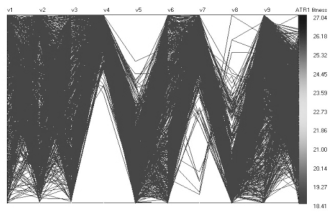
Projection of COGA single and multi-objective output on 2D variable hyperplanes (data from nine variable problem)



Single objective Multiple objectives

Not feasible to search through all 2D hyperplanes – single graphic required.

Parallel Co-ordinate plots [Inselberg, A., 1985] show each variable dimension vertically parallel to each other. Points corresponding to solution's variable values can be plotted on each vertical variable axis.



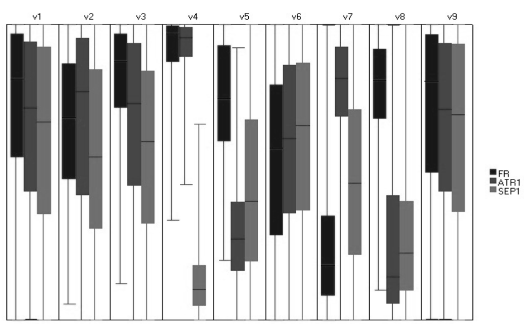
Distribution of ATR1 HP region solutions across all variable dimensions

Distribution of solutions in all variable dimensions and correlation between dimensions can be shown

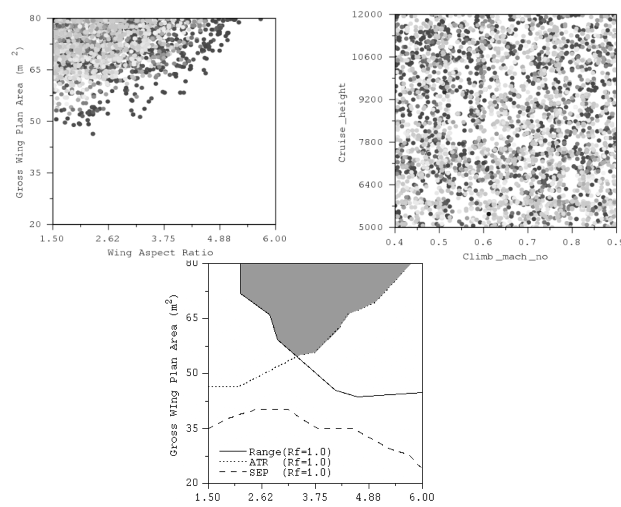
Information too dense when dealing with multi-objectives

Combination of Box Plot representation and Parallel Co-ordinates relating to all objectives contains several layers of design information

Developed Parallel Co-ordinate Box Plot –PCBP [Parmee and Johnson, 2004] provides all information in single graphic



PCBP of solution distribution of each objective across each variable



Variable attribute relevance plus standard skewness analysis of [Han, J., Kamber, M., 2001] COGA-generated HP solutions verifies visual information available in the Parallel Co-ordinate Box Plot.

Information gain ranking identifies variables 4, 5, 7 and 8 as those variables to which the objective set is most sensitive

Skewness analysis also confirms visual information available in the plot. Further details of this work can be found in [Johnson and Parmee, 2004].

Input Variable	Skewness			Correlation Coefficient			Inform-ation Gain	Rank
	ATR1	FR	SEP1	ATR1	FR	SEP1	ATR1, F R & SEP1	
1. CLMN	-0.481	-0.888	0.013	0.095	0.136	-0.086	0.026	7
2. CH	-0.566	-0.193	-0.430	0.059	0.307	0.043	0.068	6
3. CMN	-0.475	-1.123	-0.151	0.051	0.181	0.049	0.118	5
4. GWPA	-1.653	-1.758	1.280	0.170	0.463	-0.566	0.953	1
5. WAR	0.501	-0.404	0.761	-0.257	0.251	-0.207	0.255	4
6. WTR	-0.230	0.172	-0.008	0.013	0.001	-0.018	0.013	9
7. WLES	-1.351	1.098	0.315	0.478	-0.349	-0.071	0.265	3
8. WTCR	1.059	-0.922	1.073	-0.55	0.249	-0.521	0.419	2
9. BPR	-0.460	-0.757	-0.127	0.141	0.119	0.019	0.014	8
Mean of Information Gain							0.237	

Utilising PCBP Information
Using information available within the PCBP designer can:

i)Identify variables least affecting solution performance across full set of objectives (i.e. variables where full axes relating to each objective overlap e.g. 1, 2, 3, 6, & 9).

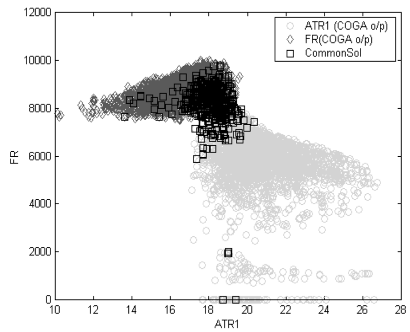
ii) Further identify minimum objective conflict i.e. where box plots relating to each objective largely overlap

iii) Identify conflicting objectives - evident from diverse distribution of box plots along some axes

iv) View related variable hyperplane projections for a different perspective of spatial distribution of objectives' high-performance regions

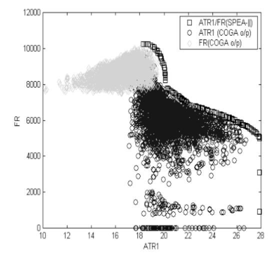
Access to such hyperplanes driven by simple clicking operations on selected variable axes

v) View projections of high-performance regions on objective space – direct mapping between variable and objective space

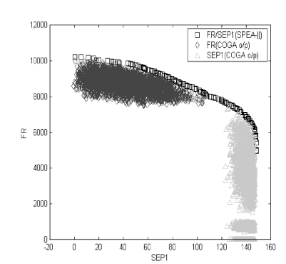


Projection of ATR / FR regions on objective space

vi) View approximate Pareto frontiers generated from the non-dominated sorting of HP region solutions



Distribution of solutions for objective ATR1 and FR against SPEA-II Pareto front



Distribution of solutions for objective ATR1 and SEP1 against SPEA-II Pareto front.

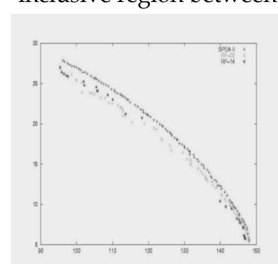
Approximate Pareto frontiers generated through non-dominated solution sorting within the objectives' HP regions

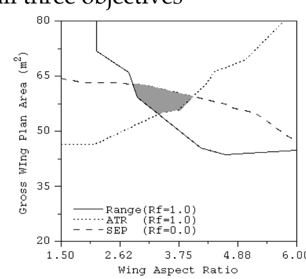
Comparisons to SPEA generated Pareto fronts [Zitzler E., et al 2002] are good

Pareto approximations are all that are required during conceptual design

COGA potentially offers more information than standard Pareto based methods (but not considered a better approach!)

Relaxing the COGA adaptive filter allows lower performance solutions into the HP regions and 'closes the gap' in the approximate Ferry Range / Specific Excess Power Pareto front – also results in mutually inclusive region between all three objectives





COGAs can provide much high-quality information relating to solution distribution in both variable and objective space

• A direct mapping can be achieved between these two spaces

• Good approximations to relevant Pareto fronts can be identified.

Current Research - Agent-based Activities

Established data mining and statistical analysis tools drive agent-based activity

Support degree of autonomous action which supplements designer interaction with system.

e.g. data processing, designer interrogation and / or the provision of textual advice

Agency should reduce amount of information and cognitive load, allowing greater concentration upon primary design characteristics.

Agency mustn't reduce designer interaction with the system to the extent that 'hands on' and implicit learning aspects are diminished.

Agency should enhance rather than replace understanding by improving clarity through provision of differing perspectives relating to complex dependencies whilst minimising mundane tasks

Questions posed:

Can unconscious recognition of variable, constraint and objective relationships play a role in design problem-solving processes?

Supports 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?

Computer-aided conceptual design systems that support implicit learning could represent a new approach.

Possibly best way forward?

THANKYOU!

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