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Computational Steering of a Multi-Objective Evolutionary Algorithm for Engineering Design

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Abstract

The execution process of a evolutionary algorithm typically involves some trial-and-error. This is due to the difficulty in setting the initial parameters of the algorithm - especially when little is known about the problem domain. This problem is magnified when applied to many-objective optimisation, as care is needed to ensure that the final population of candidate solutions is representative of the trade-off surface. We propose a computational steering system that allows the engineer to interact with the optimisation routine during execution. This interaction can be as simple as monitoring the values of some parameters during the execution process, or could involve altering those parameters to influence the quality of the solutions produced by the optimisation process. The implementation of this steering system should provide the ability to tailor the client to the hardware available, for example providing a lightweight steering and visualisation client for use on a PDA.

Key words: Computational Steering, Evolutionary Multi-Objective Optimisation, Decision Making, Engineering Design.

1. Introduction

Decision making in engineering design can often be aided by using evolutionary algorithms to solve multi-objective optimisation problems. Typically, these multi-objective evolutionary algorithms are run non-interactively. The decision-maker (DM) will set the initial parameters of the algorithm and then execute it. During this execution process, which can often take hours or days to complete, user interaction, if any, is limited to the occasional plotting of the intermediate solutions and the possible termination of the algorithm if it appears to have failed (for example, if the algorithm does not show convergence). When the execution has finished the solutions produced by the algorithm are assessed and, if the results are not satisfactory, the parameters of the algorithm are adjusted and it is run again. This process of repeated execution of the multi-objective evolutionary algorithm leads to an inefficient use of resources, and possibly also to inferior solutions.

As the process of setting the initial parameters of the algorithm can be difficult, especially if little is known about the problem domain, the re-execution of the algorithm with altered parameters is common. Unfortunately, the evolutionary computation community is still some way from possessing anything more useful than ‘rules-of-thumb’ when it comes to the setting of these initial parameters (Bullock et al., 2002). One potential solution to this problem is to allow the decision maker to interact with the optimisation routine during execution. This is known as computational steering, and may be as simple as allowing the decision maker to monitor the values of some parameters in the optimisation process and, if necessary, to adjust others. In this way, the decision maker could influence the quality of the solutions produced by the optimisation process.

Research into interactive evolutionary computation has mostly focussed on partial or complete human evaluation of solutions produced by an evolutionary search (Parmee, 2002). This technique has mainly been applied to those problems that rely on a subjective evaluation of the fitness of a particular solution, such as the evolutionary design of computer graphics (Sims, 1991) or music (Biles, 2003). There is little research into the computational steering of evolutionary computation at run-time, and the research

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that exists (Bullock et al., 2002) focuses solely on the single-objective case.

This paper aims to show that computational steering of a multi-objective evolutionary algorithm can provide improved performance in both the execution speed of the algorithm and in the quality of the solutions the algorithm produces. Section 2 briefly outlines the ideas behind computational steering, and then, in section 3, evolutionary algorithms are introduced and their suitability to multi-objective optimisation is highlighted. Section 4 describes the implementation of our computational steering system. In section 5 our computational steering system is applied to a many-objective (see section 3.3) aircraft controller design problem. The main results from section 5 are summarised in section 6 and some conclusions about the use of our computational steering system in optimisation using multi-objective evolutionary algorithms are drawn.

2. Computational Steering

Computational steering is defined as an approach that improves the integration of simulation and visualisation in the computational process, allowing the engineer or scientist to control the succession of steps required to solve engineering and computational science problems (Johnson et al., 1999). The desire to interact with their simulations is nothing new for engineers and scientists. In 1987, the Visualization in Scientific Computing Workshop reported:

“Scientists not only want to analyse the data that results from super-computations; they also want to interpret what is happening to the data during super-computations. Researchers want to *steer* calculations in close to real time; they want to be able to change parameters, resolution, or representation, and see the effects. They want to drive the scientific discovery process; they want to *interact* with their data.” (McCormick et al., 1987)

Currently, the majority of computational steering systems are applied to large simulations involving compute-intensive models. One area of application is in computational fluid dynamics (CFD) where lattice-Boltzmann simulations can be used to understand the behaviour of meso-scale fluid systems (Chin et al., 2003). Examples of such systems occur in everyday life, for example in detergents, milk and blood. In this application, computational steering is used to overcome the limitations of the simulate-then-analyse approach, such as having a fixed number of time steps in the simulation. Another area of application of computational steering is in medical science. The SCIRun computational steering system (SCIRun, 2006) has been used in EEG simulation and visualisation (Johnson et al., 2004)

and to plan operations by performing interactive visualisation of tumours. This planning and simulation is of great benefit to surgeons as it allows them to practice the operations they are to perform.

The visualisation of the intermediate results of the computational process is extremely important. It must allow the engineer or scientist to efficiently extract the relevant information from the data (Parker et al., 1997), so as to be able to make an informed choice about which aspects of the process to adjust. The complexity of the visualisation should be able to be tailored to the hardware available to the user (for example, a lap-top computer, Personal Digital Assistant (PDA), etc.) (Brooke et al., 2003).

For an application to be ‘steerable’ it must have a point in the control loop of the program where it can be interrupted and steering tasks can be performed. This point is commonly termed a break-point and should allow some or all of the following tasks to occur (Brooke et al., 2003):

- (i) The retrieval of the current parameter set.
- (ii) The alteration of one or more parameters.
- (iii) The retrieval of the current results set (which can then be passed to a visualisation routine).
- (iv) The taking of a ‘snap-shot’ of the application (often referred to as a checkpoint) to allow the system to be restarted from this point.

The first three tasks in this list form the basis of the computational steering process (i.e. the alteration of simulation parameters in response to the results currently being produced by the simulation). The support of checkpointing in large-scale complex simulations may be difficult, however, and this decision should be left up to the application user.

3. Evolutionary Algorithms in Engineering Design

3.1. Background on Evolutionary Algorithms

Evolutionary Algorithms (EAs) are a stochastic optimisation technique utilising some of the mechanisms of natural selection (Goldberg, 1989). They offer an iterative, population-based method, capable of both exploring the solution-space of the problem and exploiting information contained in previous generations of candidate solutions. The exploration of the solution-space is typically carried out by a variation operator such as mutation, whilst the exploitation of previous candidate solutions is mostly performed by the selection operator. The recombination operator can arguably be said to perform both exploration and exploitation. The trade-off between the exploration of undiscovered regions of the solution-space and the exploitation of promising areas already discovered is extremely important for the performance of the algorithm. Obtaining a

good balance between exploration and exploitation for the problem faced is a ‘black-art’ (Purshouse, 2003). One solution would be to use *a priori* knowledge about the problem landscape; however this may not be possible for many real-world problems, as this information may be unknown.

The stochastic nature of the exploration operators helps to ensure the robustness of the algorithm by preventing it from becoming stuck in local optima. This, combined with the use of objective function pay-off information (rather than derivative information or other auxiliary knowledge) ensures that EAs are applicable to many areas in which conventional optimisation methods struggle.

3.2. Multi-Objective Optimisation and EAs

Many real-world optimisation problems involve the satisfaction of multiple, often conflicting, objectives. The general form of a multi-objective optimisation problem can be described by an objective vector f and a corresponding set of design variables x ; as can be seen in (1). Note that here minimisation can be assumed with no loss of generality.

$$\min_f(x) = (f_1(x), \dots, f_n(x)) \quad (1)$$

In this case it is unlikely that a single ideal solution will be possible. Instead, the solution of a multi-objective optimisation problem often leads to a family of Pareto optimal points, where any improvement in one objective will result in the degradation of one or more of the other objectives.

A set of non-dominated solutions¹ generated by the optimiser is known as an *approximation set* (Zitzler et al., 2003). Three measures of the quality of this approximation set can be considered (Purshouse, 2003). These are illustrated graphically in Figure. 1, and listed below.

- Proximity. This is a measure of how close the approximation set is to the true Pareto front.
- Diversity. This is a measure of the distribution of the approximation set both in the extent and uniformity of that distribution.
- Pertinency. This criteria measures the relevance of the approximation set to the decision maker (see section 3.4).

Conventional multi-objective optimisation techniques often fail to satisfy these criteria. For example, the goal-attainment method (Gembicki, 1974) and the weighted-sum method (Hwang and Masud, 1979) both only provide single solutions to the optimisation problem - thus failing to provide a diverse distribution of solutions. However, EAs are well suited to this kind of multi-objective optimisation,

¹ A solution is termed non-dominated if there is no other solution in the solution set that is superior in all objectives.

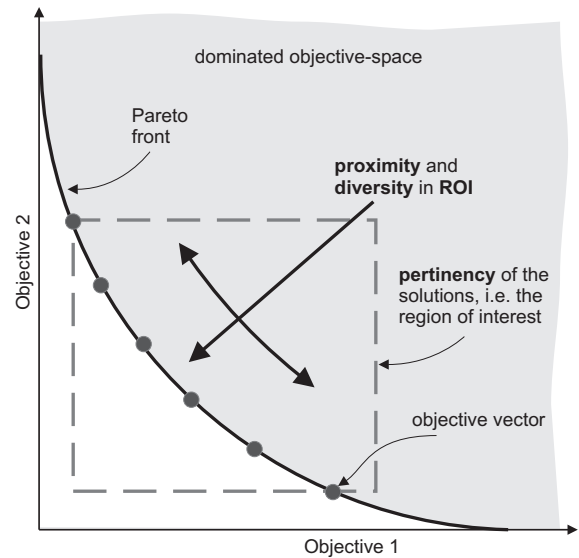


Fig. 1. The Ideal Solution to a Multi-Objective Optimisation Problem

because they search a population of candidate solutions (Deb, 2001). This enables the EA to achieve diversity in its solution-set.

3.3. Many-Objective Optimisation

Theoretical evolutionary multi-objective optimisation (EMO) studies generally consider a small number of objectives, with most of the published literature in the EMO field focussing on the bi-objective case. However, real-world applications of optimisation in engineering design often require a large number of objectives to be dealt with, leading to a growing interest amongst the research community in the area of *many-objective optimisation*². The increased scale of a many-objective optimisation problem means that the *pertinency* (see Figure. 1) of the candidate solutions, i.e. focussing on those solutions in the decision maker’s region of interest (ROI), is especially important so as to avoid overwhelming the decision maker. This is a major issue because a global trade-off surface for a problem with many conflicting objectives would contain many Pareto-optimal solutions, most of which may not be in the decision maker’s ROI (Purshouse, 2003).

3.4. Decision Making in Engineering Design

The main role of the decision maker in evolutionary multi-objective optimisation is usually to select a single

² The phrase *many-objective* has been suggested in the Operations Research (OR) community to refer to problems with more than the standard two or three objectives (Farina and Amato, 2002).

solution from the potentially infinite Pareto-optimal solution set, according to some criteria. In practice the DM is usually only interested in a sub-set of the trade-off surface, thus there is little or no benefit in representing parts of the trade-off surface that lie outside this region of interest. Allowing the DM to focus the search on relevant areas of the solution space increases the efficiency of the optimisation process and reduces the amount of irrelevant information that the DM has to consider (Fleming et al., 2005), thus preventing the DM from becoming overwhelmed (see section 3.3).

DM preferences can be incorporated into the optimisation process in three ways; *a posteriori*, *a priori*, and progressively. *A posteriori* methods of preference articulation involve the DM selecting a compromise solution from the global set of Pareto-optimal solutions. *A priori* preference articulation and progressive preference articulation aim to achieve a good representation of the trade-off surface in the DM’s ROI. They do this by concentrating the optimiser on a sub-set of the global trade-off surface. In *a priori* articulation of preferences the DM expresses their preferences before the start of the optimisation process. However, often the DM may not be sure of their preferences prior to optimisation, and by stating preferences *a priori* the DM may not investigate some areas of the search space that merit attention. A better method is progressive articulation of preferences, where the DM can express preferences during the search and thus incorporate information that becomes available during the search process.

The first scheme for progressive preference articulation in multi-objective evolutionary algorithms was introduced by Fonseca and Fleming (1998). It extended the Pareto-based ranking scheme to allow preferences to be expressed during the run of a multi-objective evolutionary algorithm. These preferences are used in a modified version of dominance which combines Pareto-optimality with a preference operator to rank the candidate solutions in a multi-objective evolutionary algorithm. This progressive articulation of preferences is a limited form of computational steering. The preferences can be altered during the running of the algorithm. However, these are the only variables in the optimisation process it is possible to alter.

The ability for the DM to computationally steer the optimisation routine is desirable due to the large amount of time such optimisation routines often take to complete. By giving the DM the ability to observe the progress of the optimisation process and to alter the parameters as the algorithm runs, the DM can act to improve the quality of the solutions produced by this optimisation process. For example, if the optimisation routine is struggling to find solutions of interest to the DM, then the DM could alter the mutation rate, change the bounds on the decision variables, or express design preferences to try to improve the quality of the solutions produced by the algorithm.

4. Implementation

4.1. Steering of the Multi-Objective Evolutionary Algorithm

Before we can implement computational steering in our application, we need to check that the application is ‘steerable’. In section 2 it was noted that for computational steering to be applied to an application there must be a suitable break-point in its control loop where the program can be interrupted and the steering operations performed.

Our optimisation routine contains an ideal break-point due to its iterative nature. This point occurs between the generations of the algorithm, and provides a convenient place to retrieve the current candidate solutions and parameter set, and to alter those parameters that are appropriate (see Figure. 2). However, if there are no steering tasks to be performed then the optimisation routine will continue to the next generation.

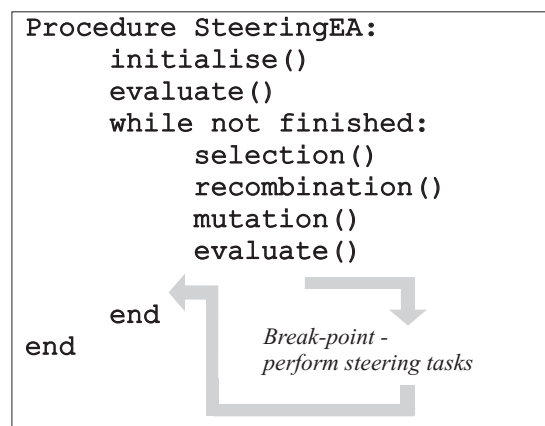


Fig. 2. Pseudo-Code Illustrating the Positioning of a Break-Point in the Control Loop of the Optimiser

Because the next generation of candidate solutions produced by our optimisation routine only relies on the current generation of candidate solutions and the current parameter set it is also simple to implement a checkpointing system. This will take the form of a ‘snap-shot’ of our algorithm, taken at the break-point, consisting of the current parameter set and the current generation of candidate solutions. If the optimisation routine is to be restored from this point it is a simple matter to reload this ‘snap-shot’ and continue the optimisation process.

The actual computational steering of our optimisation process can be achieved in two ways. The first of these is by adjusting the parameters of the algorithm. These parameters control the behaviour of the algorithm and can affect both the rate of convergence and the quality of the solu-

tions produced. For example, reducing the exploratory effects of mutation in the algorithm by lowering the mutation rate will reduce the amount of new genetic material coming in to the population in each new generation, and thus increase convergence. However this increase in the rate of convergence will come at the risk of converging to a local optimum.

Some other parameters that we can adjust in our steering system are the upper and lower bounds on the decision variables, the population size (either by increasing the number of immigrants or increasing the number of solutions produced by selection), and the fitness assignment method. These parameters all affect the behaviour of the algorithm in different ways. For instance, tightening or loosening the bounds on the decision variables allows the engineer to focus or widen the search in decision space, while increasing the number of immigrants in the population can force the algorithm out of local optima because it introduces new genetic material.

The engineer can alter the probability of a solution being carried over to the next generation by changing the method by which fitness is assigned. For example, if an exponential fitness assignment method is used, then the highest ranked solution will form a proportionally larger part of the next generation compared to a linear fitness assignment method.

The second way of steering the optimisation process is to use progressive preference articulation (see section 3.4) to alter the goals and priorities for the objectives, and thus affect the areas of the search space that the algorithm focuses on. The areas of the search space that the algorithm focuses on are defined by the ROI of the DM. This ROI is defined by the preferences specified by the DM, and the algorithm focuses on this ROI by assigning a higher rank to those solutions that are in this region. Once a satisfactory value has been achieved for one of the objectives, the objective in question can be constrained to be at least as good as that value. All the potential solutions that do not meet this criterion are ranked worse than those that do, and therefore the algorithm is steered away from values that violate that constraint. Reducing the region of interest in this way can accelerate the optimisation process and improve the quality of useful solutions.

One possible alternative to computational steering for tuning key parameters in evolutionary computation is the concept of Nested Evolution. This was introduced for a differential evolution (DE) algorithm in Babu et al. (2004), and consists of an inner optimisation loop and outer optimisation loop. The inner loop aims to solve the problem, whilst the outer loop optimises the key parameters of the inner loop (with the objective of minimising the number of generation the inner loop runs for). The main drawback of this method is that, as the inner loop is a population based evolutionary optimiser, a large number of function evaluations may be needed to tune the key parameters in the

inner loop. Many non-trivial, real-world problems require the use of computationally intensive computer simulations to evaluate the candidate solutions produced by the optimiser, and it is therefore desirable to keep the number of function evaluations to a minimum. For this reason it was felt that computational steering was a better choice than nested evolution.

4.2. Visualisation

As mentioned in section 2, visualisation is a key component of computational steering. The visualisation method of any computational steering system must be able to present the user with enough relevant information for the user to guide the process. Therefore, the visualisation method for the intermediate results of our multi-objective evolutionary algorithm must be able to display high-dimensional data sets, as we are dealing with many objectives.

The visualisation of high dimensional data sets in an intuitive manner is extremely difficult. While scatter diagrams provide a fundamental tool for visualisation of lower dimensional data - allowing the eye to see such features as clustering, outliers and linearity/nonlinearity - they do not generalise easily to more than three dimensions (Wegman, 1990). Many techniques have been proposed to solve this problem (ATKOSoft, 1997), but this paper will focus on two of the most common techniques.

Scatter plot matrices (see Figure. 3) are a commonly used technique in the visualisation of high dimensional data sets. They provide a visualisation technique that facilitates rapid scanning of many dimensions; however discovery of high dimensional patterns can be complicated by the disconnected representation of multiple aspects of the same point in high dimensional space (Carr et al., 1986). The representational complexity of these scatter plot matrices is high ($O(n^2)$), because they project n dimensions onto $n \times (n - 1)$ scatter plots. This means that this technique will not scale well to large numbers of variables. This high representational complexity also means that this technique will be unsuitable for on a device with limited screen size, for example that of a PDA.

Parallel Coordinate Plots (Inselberg, 1985) are another commonly used technique for visualising high dimensional data. They allow the visualisation of high dimensional data in a simple two dimensional representation. Instead of having the axes orthogonal to each other, as in Cartesian geometry, the axes are placed in parallel. Thus a point in n dimensional space will be represented as a line that bisects n parallel axes (see Figure. 4). Figure. 5 illustrates the mapping between the Cartesian system and the corresponding representation in parallel coordinates, where points A and B in the Cartesian system are represented by lines in the parallel coordinate plot.

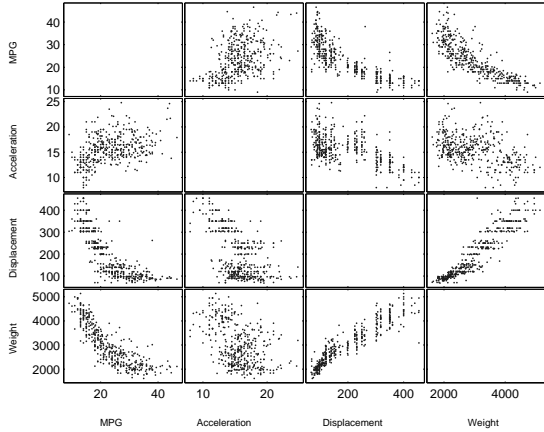


Fig. 3. A Scatter Plot Matrix Representation of a Four Dimensional Data Set

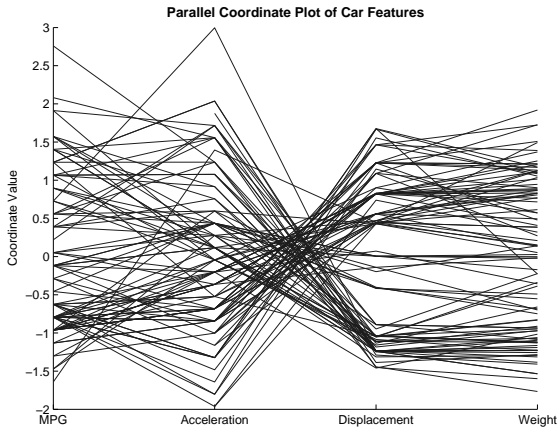


Fig. 4. A Parallel Coordinate Plot Representing a Four Dimensional Data Set

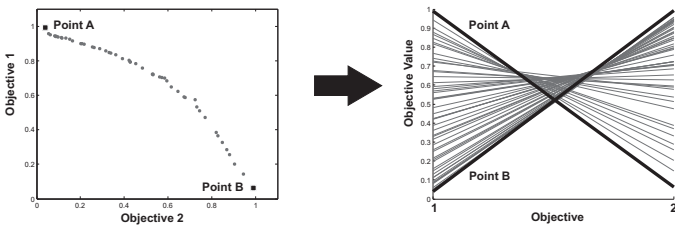


Fig. 5. Mapping Between the Cartesian System and the Corresponding Parallel Coordinate Plot

Parallel Coordinate plots have a lower representational complexity than scatter plot matrices. The representational complexity of parallel coordinates is $O(n)$ (where n refers to the dimensionality of the data), as each line bisecting the axes of the plot represents a single point in high dimensional space. Parallel coordinates lose no data in the representation process; this in turn ensures that there is a unique representation for each unique set of data. The main weak-

nesses of this method are that it requires multiple views to see different trade-offs and it can be difficult to distinguish individual points if many data points are represented.

Parallel Coordinate plots were chosen to perform the visualisation of the data in our computational steering system due to their ease of interpretation and the ability to display all the appropriate data on a screen of limited size, for example on a PDA. To overcome the potential problem of having difficulty distinguishing individual points when the display is cluttered, we will only represent those candidate solutions that fit our modified definition of Pareto optimality (see section 3.4). This will prevent the plot from becoming cluttered without removing any of the useful data, i.e. the candidate solutions in the ROI of the DM.

4.3. A PDA Implementation

In our application domain of Engineering Design, it would be especially useful for an engineer working on a many-objective optimisation problem to be able to check on the progress of the algorithm from the field. An ideal client for this computational steering system would provide low-cost, portable access to the system.

The implementation of this steering client can be effectively realised by using a PDA enabled with a wireless connection. The low cost involved in the use of a PDA-based client would allow a wide uptake of this steering system by engineers in the field, whilst the portability of a PDA-based client would enable the engineer to check on the progress of the optimisation routine and alter parameters from anywhere with access to the internet. This would be especially useful in the case of a long running optimisation process that may take days to complete.

This PDA-based steering system was implemented in two parts. The first part was the design of a steering-enabled multi-objective evolutionary algorithm web service. This service provides the ability to adjust the parameters of the optimisation routine as well as allowing the execution of the multi-objective evolutionary algorithm for a given number of generations. The second part of the implementation was the development of a PDA-based client to interface with the steering-enabled multi-objective evolutionary algorithm web service. Due to issues with scarcity of memory and computational power, this client has to be lightweight whilst still providing the desired functionality.

The PDA-based client connects wirelessly to the steering-enabled multi-objective evolutionary algorithm web service. The decision maker can then choose whether to initiate a new optimisation routine or continue a previous one. The DM can then adjust the parameters of the optimisation process and run the multi-objective evolutionary algorithm for a given number of generations. The results are displayed in the PDA client as a parallel co-ordinate plot

of the objectives (see Figure. 6). The DM can then use this information to improve the optimisation process.



Fig. 6. A PDA Based Implementation of the Steering Client for our Multi-Objective Evolutionary Algorithm

5. Results

A many-objective aircraft controller design problem from literature (Tabak et al., 1979) was chosen to illustrate the computational steering process of the multi-objective evolutionary algorithm. This problem involves the design of controller gains to obtain rapid and precise roll response to aileron inputs. There are 8 objectives:

- (i) Control Effort
- (ii) Bank Angle at 2.8 seconds
- (iii) Side Slip Deviation
- (iv) Spiral Root
- (v) Roll Damping Root
- (vi) Dutch Roll Damping Ratio
- (vii) Dutch Roll Damping Frequency
- (viii) Bank Angle at 1 second

Firstly we attempted to solve this problem using a multi-objective evolutionary algorithm with common values for the parameters. We ran this algorithm for 100 generations with no preference articulation (see Figure. 7 and Figure. 8). We then reduced the mutation rate and tightened the bounds on some of the decision variables (those that can be seen to contribute to an unsatisfactorily large value for Objective 3) and reran the algorithm (again for 100 generations - see Figure. 9).

Altering the parameters of the multi-objective evolutionary algorithm improved the results produced by the algorithm, but the solutions are still not satisfactory. We then

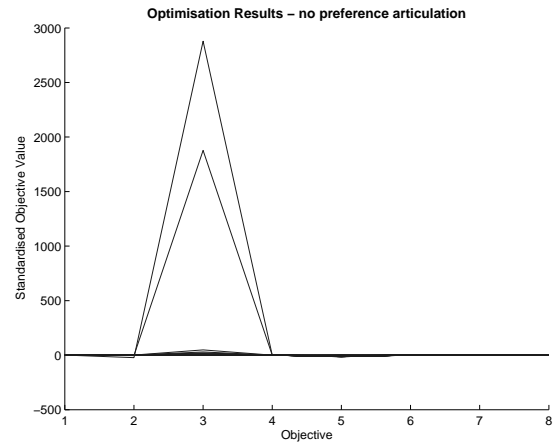


Fig. 7. Results of the Initial Execution of the Multi-Objective Evolutionary Algorithm

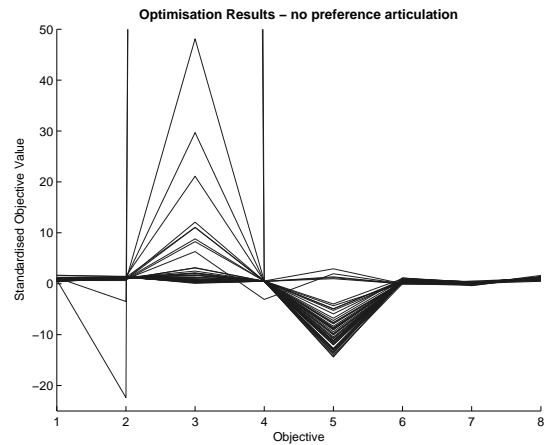


Fig. 8. A Close Up View of the Results of the Initial Execution of the Multi-Objective Evolutionary Algorithm

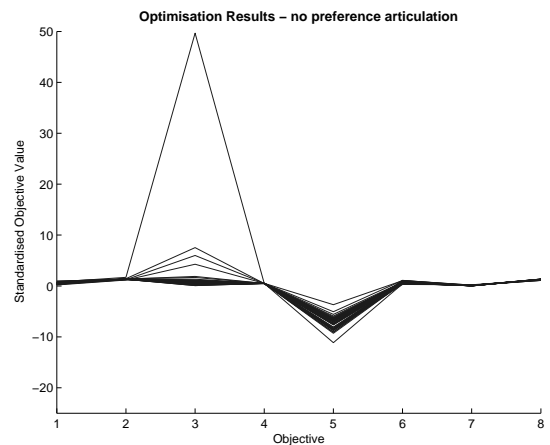


Fig. 9. Results of the Re-execution of the Multi-Objective Evolutionary Algorithm

incorporated *a priori* preference articulation into the multi-objective evolutionary algorithm (see section 3.4) and ran this MOEA with *a priori* preference articulation for 100 generations. The results produced by the algorithm with *a priori* preference articulation are shown in Figure. 10.

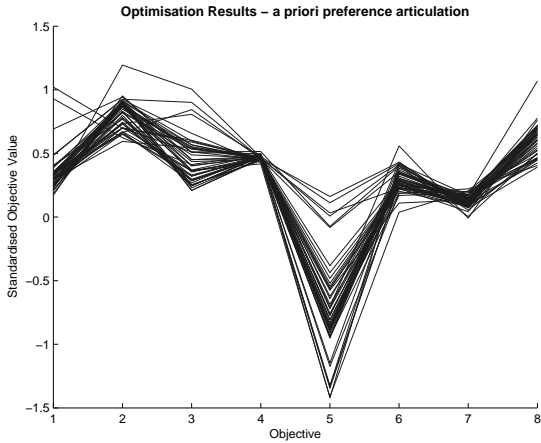


Fig. 10. Results of the Multi-Objective Evolutionary Algorithm with *a priori* Preference Articulation

As we can see, the incorporation of *a priori* preference articulation helps the algorithm to achieve better results. This is because the initial preferences given to the algorithm impose a strict ROI (see section 3.4) on which to focus the search. However, these solutions can be further improved by computational steering of the optimisation process. The computational steering of our MOEA was carried out using the steering-enabled web service described in section 4.3, however a desktop implementation of the steering client was used so as to produce the figures in this publication. The results were confirmed using the PDA client.

Figure. 11 is a parallel co-ordinates representation of the 8 objectives after having executed the steering-enabled multi-objective evolutionary algorithm for 20 generations. The dashed line represents the initial goal values for the algorithm and therefore the solutions shown on the plot are those that satisfy the initial design specifications, i.e. are within the ROI defined by the DM.

We know from domain knowledge that it is important to keep the control effort (Objective 1) small. This is because high gains can cause sensitivity to sensor noise and may lead to saturation of control actuator response. We will therefore constrain this objective to be at least as good as it is at the moment. This plot also shows that we can tighten the goals on objectives 5, 6, 7, and 8. We then run the multi-objective evolutionary algorithm for another 10 generations (see Figure. 12).

A decision is now made to isolate the best solution (see Figure. 13) with respect to the Roll Damping Root (Objective 5). This objective is of primary importance for aileron response. We would like to have this objective provide a

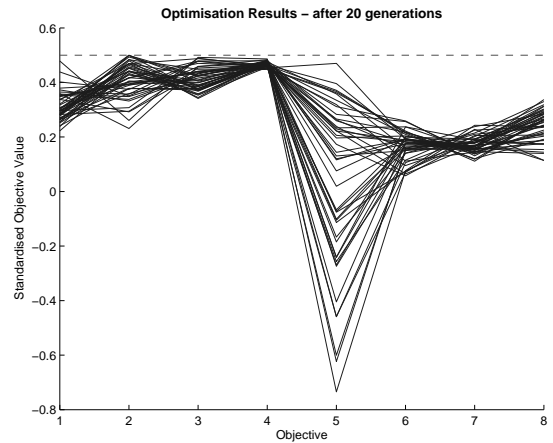


Fig. 11. Results of the Multi-Objective Evolutionary Algorithm after 20 Generations using our Computational Steering Client

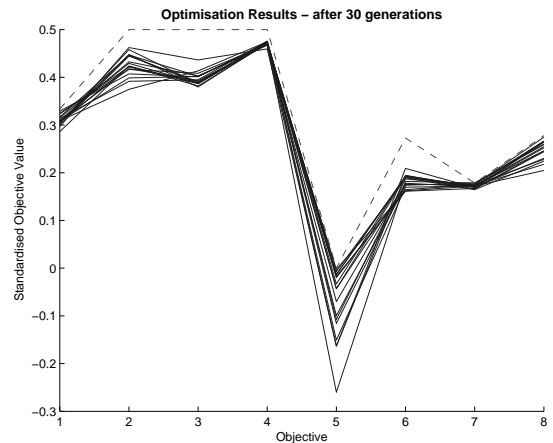


Fig. 12. Results of the Multi-Objective Evolutionary Algorithm after 30 Generations using our Computational Steering Client

fast well damped response. The mutation rate of the multi-objective evolutionary algorithm is then turned down so as to generate multiple solutions that are close to this (see Figure. 14).

This provides the decision maker with multiple solutions to choose from. The DM then picks the best solution with respect to the Bank Angle at 2.8 seconds (Objective 2) as this ensures that the speed and steadiness of the basic roll response does not drop off with time (see Figure. 15).

6. Conclusions and Further Work

Figure 16 shows the ‘best’ solution produced by each of the runs of the multi-objective evolutionary algorithm³.

³ The results presented in this paper are from a single run of each MOEA, however similar results were obtained from repeated experiments

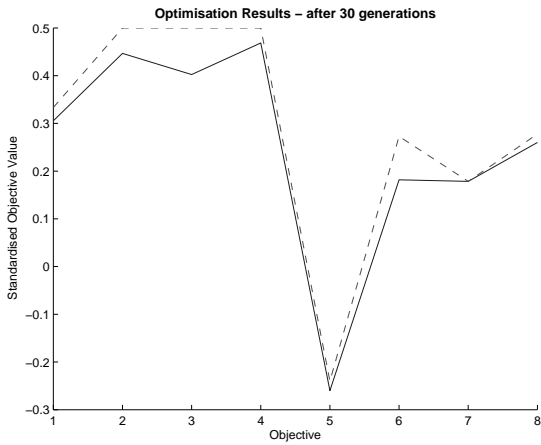


Fig. 13. Isolating a Solution from our Steered Multi-Objective Evolutionary Algorithm

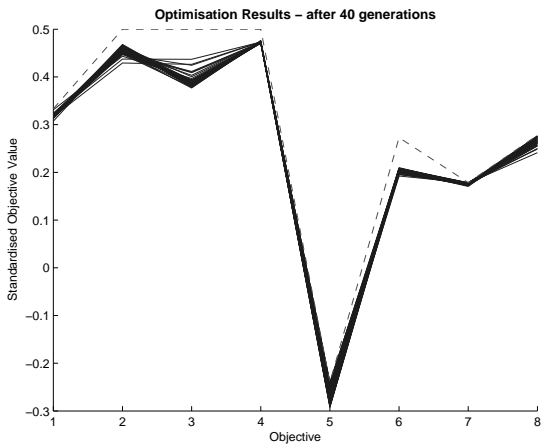


Fig. 14. Results of the Multi-Objective Evolutionary Algorithm after 40 Generations using our Computational Steering Client

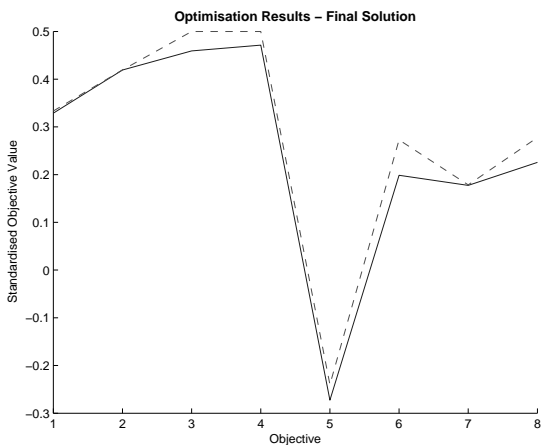


Fig. 15. The Final Solution Chosen by Decision Maker from our Steered Multi-Objective Evolutionary Algorithm

The solutions plotted for the first three MOEA runs are those chosen by the decision maker *a posteriori* (see section 3.4) according to the preferences of the DM. The fourth solution plotted on the graph is the final solution achieved by our computational steering system (see Figure. 15).

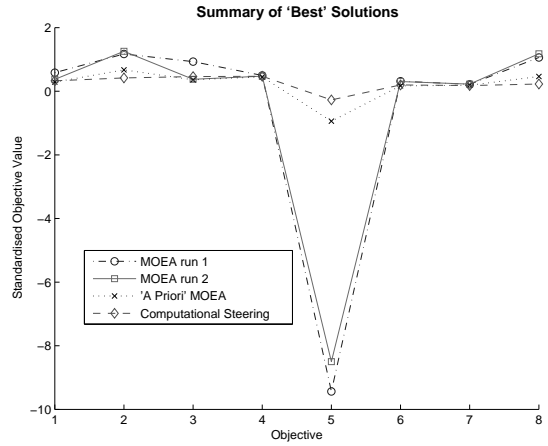


Fig. 16. The Solutions Chosen by the Decision Maker from the Pareto optimal sets produced by each of the MOEAs

As we can see from Figure 16, both of the runs of the MOEA with no preference articulation have produced solutions that minimise objective 5 very well. However, this is at the expense of achieving satisfactory values for objective 2 (bank angle at 2.8s) and objective 8 (bank angle at 1s). These objectives are important to ensure a good response from the controller.

The solution selected by the DM from the run of the MOEA with *a priori* preference articulation is a superior solution (from the DMs point of view) because, although objective 5 is larger, objectives 2 and 8 are much more satisfactory.

The solution achieved using our computational steering system provides the best response of all the solutions. It is the most successful solution in minimising objectives 2 and 8, whilst still achieving good values for the other objectives. Our computational steering system also produced this solution in fewer generations than the other MOEA runs (40 generations, compared to 100 generations from each of the other algorithms).

Therefore we can conclude that significant gains in both the execution speed of the MOEA (i.e. the number of generations needed to find good solutions) and the quality of the solutions produced by the MOEA can be achieved by using computational steering to guide the optimisation routine. By using both progressive preference articulation (Fonseca and Fleming, 1998) and steering of parameters, such as population size and mutation rate, we can avoid the need for repeated execution of the multi-objective evolutionary algorithm. This improves the efficiency of the optimisation process.

The results produced by computational steering of the optimisation routine are an improvement over those achieved without using steering. This is largely due to the ability to alter the goals progressively. However, being able to alter the mutation rate and other parameters is also an important factor. For instance, in order to produce multiple solutions in close proximity to each other (see Figure. 14), we were able to reduce the mutation rate which decreased the amount of variation produced in the next generation of candidate solutions.

The ability to control the population size of the algorithm also proved useful, as we were able to use large population sizes initially, so as to cover a large area of the search space, and then reduce the population size to allow for quicker execution of the algorithm.

Although altering the bounds on the decision variables was unnecessary in the case of our example, providing the ability to do so is potentially useful. By changing the upper and lower bounds the decision maker is able to guide the search in decision space, as well as guiding the search in objective space using preference articulation. By loosening the bounds on certain decision variables, the DM can expand the search to include previously ignored areas, whereas by tightening the bounds the DM can constrain the area of decision space searched by the optimiser.

This computational steering process for evolutionary optimisation may allow the user to gain some insight into the optimisation process. As has been noted in the introduction to this paper, the evolutionary computation community possesses little more than ‘rules-of-thumb’ when it comes to setting the initial parameters of an evolutionary algorithm (Bullock et al., 2002). By using computational steering of the evolutionary optimisation process, it may be possible to further understand the effects and interactions of the different parameters in the algorithm. This is an area for further work.

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