A FAST MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM APPLIED TO INDUSTRIAL PROBLEMS

G. Leyland, A. Molyneaux, D. Favrat

Laboratoire d’Energétique Industrielle
Ecole Polytechnique Fédérale de Lausanne
CH 1015 Ecublens, Switzerland
email: geoff.leyland@epfl.ch
web page: http://leniwww.epfl.ch/

Abstract. The CPEA, an Evolutionary Algorithm that preserves diversity by finding clusters in the population, has had its convergence performance improved by a technique tentatively called ‘evolutionary operator selection’. Performance is compared to results found in the literature, though at the moment it is not entirely clear how the evolutionary operator selection mechanisms work. The resulting algorithm has been applied to a number of problems—including a hybrid vehicle configuration and coke production in Shanxi Province, China.

Key words: multi-objective optimisation, clustering, evolutionary operator selection, hybrid vehicles, plant siting.

1 Introduction

The Laboratoire d’Energétique Industrielle (LENI) has been involved in the optimisation of thermal systems for some years. In general, the optimisation techniques used attempt to find solutions that consider both economic and environmental factors: we would not only like a cheap solution, but a clean one as well.

In the past a combination of single-objective optimisation and aggregation of cost and pollution into a total cost—termed ‘environomics’—has been used so solve such problems. Unfortunately, the weights (or ‘pollution factors’) used to add pollution to other costs are poorly known, and estimates vary widely. Consequently, an optimisation is often run many times, with a range of values for pollution factors, in order to see their effect.

A multi-objective optimisation approach, which effectively provides (in the environomic case) a tradeoff curve between cost and pollution, is thus extremely attractive. Even more so, as recent results indicate that LENI’s multiobjective algorithms can find an entire tradeoff curve faster than algorithms used earlier could find a single environomic solution.

Another of the main focuses of LENI’s optimisation research is on multi-modal...
optimisation. Here, we wish to find not only the global optima of a model, but as many local optima as possible. The reason for this is related to the models to be optimised: they are complex, frequently imperfect, and often approximative. Hence the value of a single optimal choice to the engineer is limited—what is needed is description of all the ‘interesting regions’ of the model. It may well be that an unexpected local optima in a region where the model is not very accurate will prove to be a global optima once the model’s accuracy has been improved in that region. Multi-modality also gives the engineer more choices—the final solution chosen for a design problem will quite likely not be the global optima of a model as found by an optimisation algorithm, but something chosen from the region of one of the optima, based on other, non-quantifiable criteria.

2 Clustering

The CPEA, LENI’s algorithm that uses clustering techniques to find several local optima is introduced in. Figure 1 show the results of a multi-modal multi-objective optimisation on a test problem with four local Pareto-optimal frontiers. In this case, the frontiers are well-defined by the final population. However, while these graphs are typical of results obtained over a number of runs, they are no substitute for statistical results based on a surface coverage measure such as that proposed by.

3 Evolutionary Operator Choice

Once the work on clustering had achieved its initial goals, we focused improving the local convergence performance of the algorithm.

One of the features that has greatly increased convergence speed is evolutionary operator choice. Here, there is a choice of combination and mutation operators and each individual is labelled with the operators that created it. When an individual is used as the ‘first parent’ for a new individual, the operators used to create the new individual are highly likely to be those of the parent (and are otherwise chosen randomly from the available operators).

This approach provides a large performance gain over the CPEA, which only used blend crossover operators, even when the number of operators is limited. The combination operators used in tests so far are ‘none’, blend crossover ($\alpha = 0.5$), and single and uniform crossover, while mutation is ‘none’, uniform across twice the span of the population, or normally distributed in a small portion of a single cluster.

Many aspects of how evolutionary operator choice improves performance are not yet clear - we do not know how evolutionary operator choice might compare to an
‘optimal operator choice’ for each problem, whether the operators chosen change in a regular manner throughout the course of an optimisation, or if some combination of the available operators is exploiting aspects of the test problems. Preliminary results do show, however, that higher probabilities of inheriting operators result in faster convergence.

4 Performance on Test Problems

The algorithm has been tested on a large number of multi-objective test problems, particularly those proposed by.\textsuperscript{4–6} Zitzler kindly made final populations from the ‘Strength Pareto Evolutionary Algorithm’ (SPEA) for a number of test problems available for download. These populations are the results of 30 runs of 25,000 function evaluations each of his test problems 1-6.

<table>
<thead>
<tr>
<th>Test</th>
<th>Runs</th>
<th>( E_w )</th>
<th>( E_b )</th>
<th>( E_{all} )</th>
<th>( E_{95} )</th>
<th>Speed up</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>140</td>
<td>4339</td>
<td>4639</td>
<td>4694</td>
<td>6200</td>
<td>4.03</td>
</tr>
<tr>
<td>2</td>
<td>140</td>
<td>4342</td>
<td>4105</td>
<td>4384</td>
<td>5600</td>
<td>4.46</td>
</tr>
<tr>
<td>3</td>
<td>140</td>
<td>4166</td>
<td>4438</td>
<td>4476</td>
<td>5900</td>
<td>4.24</td>
</tr>
<tr>
<td>4</td>
<td>140</td>
<td>3842</td>
<td>3255</td>
<td>3884</td>
<td>6000</td>
<td>4.17</td>
</tr>
<tr>
<td>6</td>
<td>140</td>
<td>3398</td>
<td>3038</td>
<td>3406</td>
<td>5400</td>
<td>4.63</td>
</tr>
</tbody>
</table>

Table 1: Performance figures for the Algorithm

Table 1 shows the number evaluations taken by our algorithm to pass the fourth best population from the SPEA results (ie all but the best 10%) for problems 1-4 and 6\textsuperscript{1}. \( E_w \) is the average number of evaluations for the worst point in our population to pass the SPEA’s worst, \( E_b \) those required for our best to pass SPEA’s best, \( E_{all} \), those required for our worst to pass SPEA’s best, \( E_{95} \) is the number of evaluations for 95% of our runs to pass both \( E_w \) and \( E_b \), and the speed up is the number of times faster our algorithm is based on \( E_{95} \).

5 Real-World Applications

To date, the algorithm has been applied to four ‘real world’ problems.

The primary problem has been a comparison of models of conventional and hybrid drivetrains for vehicles.\textsuperscript{7} Hybrid vehicles offer advantages over conventional vehicles because they can use their electric drive in a manner such that the internal combustion engine (ICE) always runs near its optimal point, and because they don’t use any energy while the car is stopped. They can even recuperate energy otherwise lost when braking. However, hybrid vehicles have more complex drive trains, and thus higher losses, and are often heavier than conventional vehicles. Thus, the advantages of hybrid vehicles are only really clear themselves in city and urban driving—on a highway at constant speed a conventional drivetrain’s higher efficiency may give it an advantage.

We performed a two objective optimisation of the vehicle model ADVISOR\textsuperscript{2} with respect to a number of parameters. The two objectives were fuel efficiency on an urban (EUDC ECE) and a highway (US06 HWY) drive cycle, and the results are

\textsuperscript{1}Problem 5 is a binary problem of quite a different nature than the others that hasn’t been implemented yet

\textsuperscript{2}©NREL and Midwest Research Institute
shown in Figure 2. As the simulation model takes a long time to evaluate, the algorithm was implemented ‘in parallel’, using PVM, and the optimisation problem was spread around the lab’s computers, to run overnight. The results show that all

![Figure 2: Urban and Highway Fuel Economy](image)

the vehicles in the Pareto-optimal set are hybrid vehicles, even the best performers on the highway. Why? Although a conventional vehicle can perform well at a steady high speed on the highway, it still has to be able to accelerate up the on-ramp. Thus the conventional vehicle’s ICE is dimensioned for acceleration, not efficiency. The hybrid vehicles, on the other hand, can use the electric motor for the acceleration, and have an ICE that is optimally dimensioned for cruising on the motorway.

A second problem concerns the placement and sizing of cokemaking plants in Shanxi Province, China. In this problem, the plants must be placed so as to minimise plant construction costs (preferring a few large plants) and raw material and product transport costs (preferring many small plants). Given a set of plant sizes, a Linear Program is used to find a minimum transport cost solution from coal mines to coke plants, and from coke plants to coke consumers. Candidate sets of plant sizes are generated by the EA. Once more data becomes available on emissions from the coke plants, and from the diesel trucks and trains generally used to transport coke and coal, the optimisation will be reformulated in order to minimise emissions from various parts of the production chain.

The problem is notable because in order to improve convergence to the low construction cost solutions ‘problem specific’ mutation operators were added to the operator pool, greatly improving convergence to some solutions, with no negative impact on convergence to any of the other solutions.

Figure 3 shows ‘extreme’ solutions from the problem. Round dots are coke plants, triangles are
6 Conclusions

Multi-modal, multi-objective optimisation can be an extremely useful tool for the engineer, as it provides a large range of interesting solutions, rather than a single optimal point. The engineer is then free to study the solutions proposed in order to better understand the problem, to find any transition regions in the problem, or to choose one of the solutions based on qualitative criteria.

The recent focus on the performance of the algorithm has been extremely fruitful, even if at this stage it is not entirely clear what aspects of the evolutionary operator choice make it successful.

7 Future Work

In the near future, tests will be performed on a wide range of test problems, using each permutation of combination and mutation operators. Hopefully, results from this, and from studies of the evolution of operator choice, will shed some light on the mechanisms behind evolutionary operator choice, and its relation to ‘optimal operator choice’. It will also be very interesting to implement more ‘special case’ operators (for example a quadratic search step, or hill climbing) and see if these have positive or negative effects on local convergence rates and overall global convergence.

The algorithm is currently implemented in MATLAB, which makes it slow for large-scale statistical studies. Reimplementation in C is being investigated.

Acknowledgement

The authors gratefully acknowledge the support of the Alliance for Global Sustainability\(^3\), which funds this work as part of the Holistic Design Project.

REFERENCES


\(^3\)The Alliance for Global Sustainability (AGS) is a collaborative research foundation formed by the Swiss Federal Institutes of Technology, MIT, and the University of Tokyo.


