A Multi-Objective Window Optimisation Problem

Alexander E. I. Brownlee
a.e.i.brownlee@lboro.ac.uk

Jonathan A. Wright
j.a.wright@lboro.ac.uk

Monjur M. Mourshed
m.m.mourshed@lboro.ac.uk

Department of Civil and Building Engineering
Loughborough University
Leicestershire, LE11 3TU, UK

ABSTRACT

We present an optimisation problem which seeks to locate the Pareto-optimal front of building window and shading designs minimising two objectives: projected energy use of the operational building and its construction cost. This problem is of particular interest because it has many variable interactions and each function evaluation is relatively time-consuming. It also makes use of a freely-available building simulation program *EnergyPlus* which may be used in many other building design optimisation problems.

We describe the problem and report the results of experiments comparing the performance of a number of existing multi-objective evolutionary algorithms applied to it. We conclude that this represents a promising real-world application area.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search; I.2.1 [**Artificial Intelligence**]: Applications and Expert Systems; I.6.3 [**Simulation and Modeling**]: Applications

General Terms

Algorithms, Performance, Experimentation

Keywords

Evolutionary Algorithm, Multiobjective Optimization, Building Design, EnergyPlus Simulation

1. INTRODUCTION TO THE PROBLEM

Window positioning and shading are important considerations in the design of a building envelope, having a large impact on the energy use associated with the building's artificial lighting, heating and cooling, as well as the its cost. We present a two-objective optimisation problem, extending previous work [7] which presented promising results for a single-objective genetic algorithm minimising energy use.

We seek to optimise the size, shape and position of windows on the southern façade of a commercial building located in Chicago, USA. The goal is a design which minimises energy use and (new for this paper) cost. We also add possibility of overhangs on each window: physical shades which can reduce the light and heat entering the building via a window, but with a corresponding increase in overall cost.

The wall is divided into a 15 x 8 grid of cells, each of which may be either glazed or unglazed solid wall. Adjoining cells constitute a single window, with a constraint applied to limit each window's aspect ratio to between 1.5 and 1.75 (tall and narrow in shape). The problem naturally lends itself to a binary representation; a 120 variable bit string where a bit is set true for a glazed cell and false for an unglazed one. A second string of 120 bits represents the presence of shading overhangs on each window. The objectives are as follows:

- **Building energy use.** Unweighted sum total of the energy used by heating, cooling and lighting over a pair of design days for Chicago weather. Computed by the EnergyPlus building simulation package[1], commonly used by the building design community.
- **Cost of construction.** A straightforward linear function of the number of windows n_w and overhangs n_o: $c = 112(120 - n_w) + 350n_w + 128n_o$

2. ALGORITHMS

We made use of the JMetal suite [3] for experimental runs and the algorithm implementations were as provided by the suite. We give results five existing algorithms (IBEA [8], MOCell [6], NSGA-II [2], SPEA 2 [9] and PAES [5]), in addition to a random search.

3. EXPERIMENTS AND RESULTS

An initial set of experiments was run for each algorithm to tune population size (PS), crossover & mutation rates (CR & MR) and bisection number (B), settling on the values in Table 1. Where the constrained / unconstrained problems had different optimal parameters, these are given as c/u respectively. Mutation rates MR mean the actual rate is MR/l where l is the bit string length. All algorithms used single point crossover, bit-flip mutation and an archive size of 100 where such operators / features were required.

Tables 2 and 3 give the mean hypervolume (S) and spread [1] (std. dev. in brackets) for the Pareto fronts found in 5000 evaluations for the constrained and non-constrained versions of the problem over 32 runs. Figures for the constrained problem only include runs which found feasible solutions (meeting the aspect ratio constraint). The percentage of runs finding feasible solutions is given under SR (success

GECCO'11, July 12–16, 2011, Dublin, Ireland.
ACM 978-1-4503-0690-4/11/07.

[1]http://apps1.eere.energy.gov/buildings/energyplus/

Table 1: Chosen Algorithm Parameters

	IBEA	MOCell	NSGA-II	PAES	SPEA2
PS	50	100	50	N/A	50/100
CR	0.99/0.9	0.5/0.9	0.5/0.99	N/A	0.5/0.99
MR	0.5/1	2	2	2/0.5	1
B	N/A	N/A	N/A	3/5	N/A

Table 2: Algorithm comparison (constrained)

Algorithm	SR	HV (SD)	SPREAD (SD)
IBEA	6	0.220 (0.080)	1.000 (0.000)
NSGA-II	**47**	**0.587 (0.090)**	**0.911 (0.078)**
SPEA 2	6	0.215 (0.014)	1.000 (0.000)

rate). The true Pareto optimal front for this problem is unknown, so we took the reference point for S to be the minimum and maximum value for each objective from the complete set of solutions evaluated over all the experiments; 287.65–346.29 for energy and 19902–33644 for cost.

Only IBEA, NSGA-II and SPEA 2 found solutions meeting the constraints within the allowed number of evaluations; so only these algorithms have hypervolume and spread figures in Table 2. Of these, NSGA-II attained the highest hypervolumes and closest to zero spread as IBEA and SPEA 2 found only single feasible solutions, which were dominated by the fronts found by NSGA-II. (Higher values are desirable for S; values near zero are preferable for spread.)

It is unsurprising that random search was unable to find feasible solutions within the allowed number of evaluations, however it is unclear why the other algorithms also failed to do so. Both MOCell (using neighbourhood-based reproduction) and PAES (a 1+1 ES generating individuals one at a time) would be inclined to make smaller individual moves around the search space which may prove a hindrance attempting to find feasible regions. If this is the case, SPEA 2 and IBEA may simply be more successful by not having this limitation. Further, the selection methods in these algorithms (Pareto strength and hypervolume) may be beneficial for this problem. In any event, it appears that meeting the constraint is particularly difficult for evolutionary algorithms; in future we aim to report on our current experiments investigating biased mutation and seeding the initial population as means to overcome this.

A flaw may be the initial parameter setting experiment; being limited to 1000 evaluations none of the runs found feasible solutions. Hence the best runs were those having found high hypervolume fronts of infeasible solutions and the parameters may be biased towards achieving the best hypervolume ignoring constraints. It is however interesting that this did not similarly impede NSGA-II.

4. SUMMARY

We have presented a new real-world problem with some interesting characteristics. Based around a freely-available building simulation package the window shading problem requires an efficient optimisation algorithm being costly to run with many variable interactions (a run of the Linkage Detection Algorithm [4] found all pairs of variable to interact). Future work includes improving the ability of algorithms to find feasible solutions, the use of fitness surrogates or approximations to improve run time, and using algorithms which exploit variable interactions such as estimation of distribution algorithms. As well as further many-objective building design problems a logical future step would also be extension to the many continuous problems existing in this domain.

Table 3: Algorithm comparison (unconstrained)

Algorithm	HV (SD)	SPREAD (SD)
IBEA	0.487 (0.024)	0.889 (0.010)
MOCell	0.342 (0.039)	0.927 (0.013)
NSGA-II	**0.686 (0.012)**	**0.882 (0.016)**
PAES	0.550 (0.046)	0.897 (0.025)
SPEA 2	0.488 (0.027)	0.916 (0.015)
Random	0.485 (0.022)	0.916 (0.014)

We conclude that evolutionary multi-objective optimisation offers a practical solution to this problem, and there is much potential for investigation of other building design problems using a similar approach.

5. ACKNOWLEDGEMENT

This research was funded under the UK EPSRC grant TS/H002782/1.

6. REFERENCES

[1] K. Deb. *Multi-Objective Optimization using Evolutionary Algorithms.* Wiley-Interscience Series in Systems and Optimization. John Wiley & Sons, Chichester, 2001.

[2] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6:182–197, 2002.

[3] J. Durillo, A. Nebro, and E. Alba. The jMetal framework for multi-objective optimization: Design and architecture. In *CEC 2010*, pages 4138–4325, Barcelona, Spain, July 2010.

[4] R. B. Heckendorn and A. H. Wright. Efficient linkage discovery by limited probing. *Evolutionary Computation*, 12(4):517–545, 2004.

[5] J. D. Knowles and D. W. Corne. Approximating the nondominated front using the pareto archived evolution strategy. *Evol. Comput.*, 8:149–172, June 2000.

[6] A. J. Nebro, J. J. Durillo, F. Luna, B. Dorronsoro, and E. Alba. Mocell: A cellular genetic algorithm for multiobjective optimization. *International Journal of Intelligent Systems*, 24(7):726–746, July 2009.

[7] J. Wright and M. Mourshed. Geometric optimization of fenestration. In *Building Simulation 2009 - the Eleventh International IBPSA Conference*, pages 920–927, Glasgow, Scotland, July 2009.

[8] E. Zitzler and S. Künzli. Indicator-based selection in multiobjective search. In *Proc. 8th International Conference on Parallel Problem Solving from Nature (PPSN VIII*, pages 832–842. Springer, 2004.

[9] E. Zitzler, M. Laumanns, and L. Thiele. SPEA2: Improving the Strength Pareto Evolutionary Algorithm for Multiobjective Optimization. In K. Giannakoglou et al., editors, *Evolutionary Methods for Design, Optimisation and Control with Application to Industrial Problems (EUROGEN 2001)*, pages 95–100.