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A Multi-Objective Window Optimisation Problem

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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 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 package¹, 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], MOCCell [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

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¹<http://apps1.eere.energy.gov/buildings/energyplus/>

Table 1: Chosen Algorithm Parameters

| | IBEA | MOCcell | 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 MOCcell (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 approxi-

Table 3: Algorithm comparison (unconstrained)

| Algorithm | HV (SD) | SPREAD (SD) |
|-----------|----------------------|----------------------|
| IBEA | 0.487 (0.024) | 0.889 (0.010) |
| MOCcell | 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) |

mations 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.

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

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