

Multi-criteria Decision Making for the Design of Building Facade

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ABSTRACT

Most engineering designs involve evaluation of several performance criteria. Usually these criteria conflict with each other and identifying good compromise solutions is difficult. While multi-criteria optimization approaches such as Pareto filtering have been applied to this task, not much attention has been paid to the selection of a single best solution. A new algorithm for selecting the best compromise solution that closely corresponds to the human decision making process is presented in this paper. This algorithm called RR-PARETO3 iteratively eliminates worst solutions according to multiple criteria from a population of possible solutions. A facade design example is selected for illustration and to evaluate the performance of the algorithm. It is shown that the algorithm is capable of identifying good compromise solutions that achieve reasonable trade-offs among conflicting criteria.

INTRODUCTION

Building facade design has to satisfy multiple criteria such as energy efficiency, indoor environment quality and aesthetics. When designs are optimized with respect to these criteria individually, the solutions are usually not acceptable with respect to other criteria. Nevertheless, single objective optimizations of building systems have been performed by a number of researchers. For example, Bouchlaghen (2000) used a simplified building thermal model for the optimization of building envelopes. Wang et al (2006) presents an approach to optimizing the shape of a building for energy efficiency. Energy consumed by electrical and mechanical building systems was minimized using a genetic algorithm by Wright et al. (2002). Many other examples can be found in the literature. Today researchers are increasingly adopting the multi-criteria optimization approach. In multi-criteria optimization, several objectives are considered simultaneously and these usually conflict with each other. For example, minimizing the lighting energy might require increasing the window area which would increase the radiant heat entering into the building. Therefore, in multi-objective optimization the emphasis is on identifying solutions that achieve the best trade-offs among multiple objectives. An early application of this concept can be found in Radford and Gero (1987) where they applied dynamic programming in the multi-criteria design optimization with four

performance criteria namely, thermal load, daylight availability, construction cost and usable area.

A popular approach to multi-objective optimization is the generation of a Pareto Front. In this approach, a population of solutions known as the Pareto set is generated in which all the solutions are Pareto optimal or non-dominated. By definition, there is no solution better than a Pareto optimal solution with respect to all the criteria simultaneously. Several applications of this concept are found in the literature (Horn 1997, Deb 2001, Grierson and Khajepour, 2002). El-Rayes and Kandil (2005) generated Pareto surfaces in order to extend traditional two-dimensional time-cost trade-off analysis to three-dimensional time-cost-quality trade-off analysis. Some of these techniques have already been used in the optimization of building systems. Caldas (2008) studied the trade-off between the initial cost of a building and the energy performance of the building using a multi-objective optimization approach. In another experiment described in this paper, the trade-offs were analyzed in terms of environmental impacts: the system considered both the energy saved locally in the building by using better construction terms, and the embodied energy of materials, that is, the energy spent to manufacture them. In these experiments, Pareto genetic algorithms were used as the optimization technique.

While the Pareto approach is useful for design tasks in helping engineers make decisions, it does not support the selection of a single best solution. Automatic selection of solutions is needed in tasks such as control where decisions have to be taken several times a minute or second. The issue of selecting a single solution from the Pareto set has been largely ignored by previous researchers. This paper presents a new algorithm called RR-PARETO3 for selecting the best solution that makes reasonable trade-offs among conflicting objectives.

RR-PARETO3 ALGORITHM

RR-PARETO3 algorithm is the third generation of the multi-criteria decision making algorithm presented in Raphael (2010). In this algorithm, the solution with the best trade-offs among all the objectives is chosen using two pieces of information:

- Order of the objectives according to their importance
- The sensitivity of each objective

The sensitivity of an objective specifies what level of increase in its value is acceptable to the user. For example, consider the objective of minimizing the power consumption. If increasing the power consumption above 10% is not acceptable to the user, the sensitivity of this objective is defined as 10%. In this case, the algorithm attempts to select solutions that are within 10% of the best solution. The sensitivity may also be specified in absolute terms as the maximum increase instead of as a percentage. The sensitivity value is an important piece of domain knowledge which can only be provided by the design consultants who are specialists in the domain. It

reflects the experiential knowledge, priorities and preferences of the designers. In the following discussion, the term solution point or point is used to denote a set of values of all the objectives as well as the decision variables (optimization variables).

The RR-PARETO3 algorithm works by iteratively eliminating the worst points according to maximum number of criteria. This filtering is done in two stages. In the first stage, the solution point with the best value for the current objective is chosen from among all the points. All the points that lie outside the sensitivity band of the chosen point are eliminated from the set. If the sensitivity is not specified for any objective, no filtering is done for this objective and all the solutions are retained. At the end of Stage 1, one or more points might remain in the solution set. If a unique solution is not identified, Stage 2 filtering is performed.

In Stage 2 filtering, the hypercube containing all the remaining solutions is trimmed. This is done by dividing the hypercube volume into half by bisecting each objective axis one by one according to their order of importance. Let y_{\min_i} and y_{\max_i} be the minimum and maximum values of the i -th objective among all the solutions in the current set. The threshold is computed as $(y_{\min_i} + y_{\max_i})/2$. In the minimization problem, the region containing values greater than this threshold is considered as the bad half with respect to this objective. Worst solutions are eliminated using the algorithm described below:

- Stage 2.1: Points that lie within the bad half of most objectives are eliminated, taking combinations of k most important objectives at a time (repeated for $k = N - 2$)
- Stage 2.2: Points that lie in the bad half of individual objectives are eliminated according to the order of importance of objectives
- Stage 2.3: Iteratively remove the worst point according to each objective based on the order of importance

The process of bisection of hypercube helps to remove visibly obvious bad solutions. When there are still many points left, each objective is given a chance to remove the worst candidate in Stage 2.2. The most important objective is given the first chance. Stages 2.1 and 2.2 use values of objective function for elimination, while Stage 2.3 uses ranking of solutions. The process stops when a single solution remains in the set or all the remaining solutions have the same values for all the objective functions. By repeating Stage 2.2 for each objective, each criterion is given an opportunity to eliminate bad solutions and the final selection is a trade-off among all the objectives. It is emphasized that the process does not favor the best solution according to any objective. For example, if the best solution according to the first objective lies within the bad half of the second objective, this solution is eliminated. Since the process is driven by the order of importance of objectives, the users' preferences in the selection process are also respected.

The algorithm can be used to filter a set of solution points that are generated by any optimization algorithm or even pure random sampling procedures. The initial

set need not be Pareto optimal. In fact, it is recommended not to perform initial Pareto filtering since this might remove important solutions which are likely to become Pareto optimal when existing points are eliminated through the addition of new constraints.

ILLUSTRATIVE EXAMPLE

In order to illustrate the application of the algorithm an example of façade design is presented here. A simple layout of an office space of dimensions 8m by 6m is considered in this example. Only the first floor of the building is studied. This has a total height of 4.1m with the false ceiling at a height of 2.7m. There are windows on the east and west. The windows on the west are shaded by two horizontal overhangs at different elevations. The parameters related to the window and the shading on the west side are taken as design variables. The optimization variables and their ranges of values are given in Table 1. All dimensions are in meters.

Table 1. Optimization variables

Variable	Description	Min value	Max value
W1_H	Sill height of the window	0.1	2
W1_W	Width of the window	0.4	5
SHADE1_Z	Height of the first shade	1.8	2.3
SHADE1_W	Width of the first shade	0.01	1
SHADE2_Z	Height of the first shade	2.4	2.7
SHADE2_W	Width of the first shade	0.01	1

1500 solutions were generated by pure random search. Each solution was evaluated for lighting and energy performance using EnergyPlus software version 8.1 (EnergyPlus 2013). Yearly simulations were conducted using the weather data file of Chennai, India. The initial set of solutions obtained through random sampling is shown using parallel axis plot in Figure 1. A parallel axis plot is a method of visualizing multi-dimensional data. Each variable is represented by a vertical axis and a sequence of lines connecting these axes represent a point. For example, the point highlighted in Figure 1 using white dots has the following values of variables:

Table 2. A solution point for illustration

Lighting (WHr)	Cooling (WHr)	W1_H	W1_W	SHADE1_Z	SHADE1_W	SHADE2_Z	SHADE2_W
2172	13447	0.967	4.978	2.033	0.115	2.428	0.254

The effects of conflicting objectives are clearly seen in the plot. Inclined lines that start from low values of lighting load and touch upper regions of the cooling load axis indicate that minimizing one of these objectives would result in high values for the other objective. The compromise solution obtained through RR-PARETO3 filtering is shown in Figure 2. In this filtering, the sensitivity of both objectives is specified as 5% and lighting is given higher priority over cooling. In order to show

how the compromise solution changes by modifying the sensitivity parameter, the design obtained using 1% sensitivity for both objectives is shown in Figure 3. Since in this case, large increase in the lighting load is not acceptable, the windows are larger and the shades are smaller.

In order to illustrate the point that single objective optimization is inappropriate for the design of facades, the optimal solutions obtained using lighting and cooling as individual objectives are shown in Figures 4 and 5. Even though the solution in Figure 4 looks reasonable, the first shade has minimum width and the cooling load for this design has the maximum value which is 63% more than the minimum value. When the thermal load was minimized (Figure 5), the width of the window was reduced to the minimum value and the shades were made wider to further block solar radiation. A single objective optimization process moves towards larger shades even though the improvements in cooling load are marginal when the windows are small. Such nearly insignificant improvements in the value of a single objective are ignored by a multi-objective algorithm such as RR-PARETO3.

DISCUSSION

The illustrative example shows that reasonable trade-offs among conflicting objectives can be achieved through RR-PARETO3 filtering. The compromise solution obtained with a sensitivity of 5% had a lighting load 4.1% higher than the minimum and a cooling load 10.6% higher than the minimum. The cooling load is higher because the lighting objective was given higher priority and no solution having lighting load within the 5% threshold had a better performance with respect to cooling load. If the compromise solution is compared with the optimal solution according to the lighting load objective, 30.3% decrease in the cooling load was achieved by a mere 4.1% increase in the lighting load. This shows the quality of trade-off that has been achieved.

Several papers have discussed the use of traditional trade-off analysis in value engineering. Feng et al. (1997) concluded that traditional techniques using heuristic and mathematical programming are not efficient or accurate enough to solve real-life construction projects. They state that many methods have limitations such as assuming linear relationships and cannot accommodate discrete variables. Researchers who have used multi-objective optimization for trade-off analysis usually stop at producing the trade-off curves and leave decision making to domain experts (El-Rayes and Kandl, 2005). RR-PARETO3 algorithm captures users' preferences for acceptable trade-offs indirectly using a sensitivity parameter which specifies the acceptable maximum increase in the value of objective function. This is easy to input compared to pair-wise ratios of benefit to cost. In general it is difficult to convert all the benefits into a single utility function having the same units. For example, the value of amount of daylight obtained through unit increase in material

cost cannot be compared with potential energy savings since they have different units. It is easier to set constraints on the levels of acceptable increase (or decrease) in the values of light levels and energy. Within these constraints, the algorithm identifies best compromises through elimination of worst solutions iteratively.

CONCLUSIONS

A new algorithm for identifying the best compromise solution according to multiple criteria has been developed. This has been applied to a facade design task. The results show that reasonable trade-offs between conflicting objectives have been achieved through the application of this algorithm.

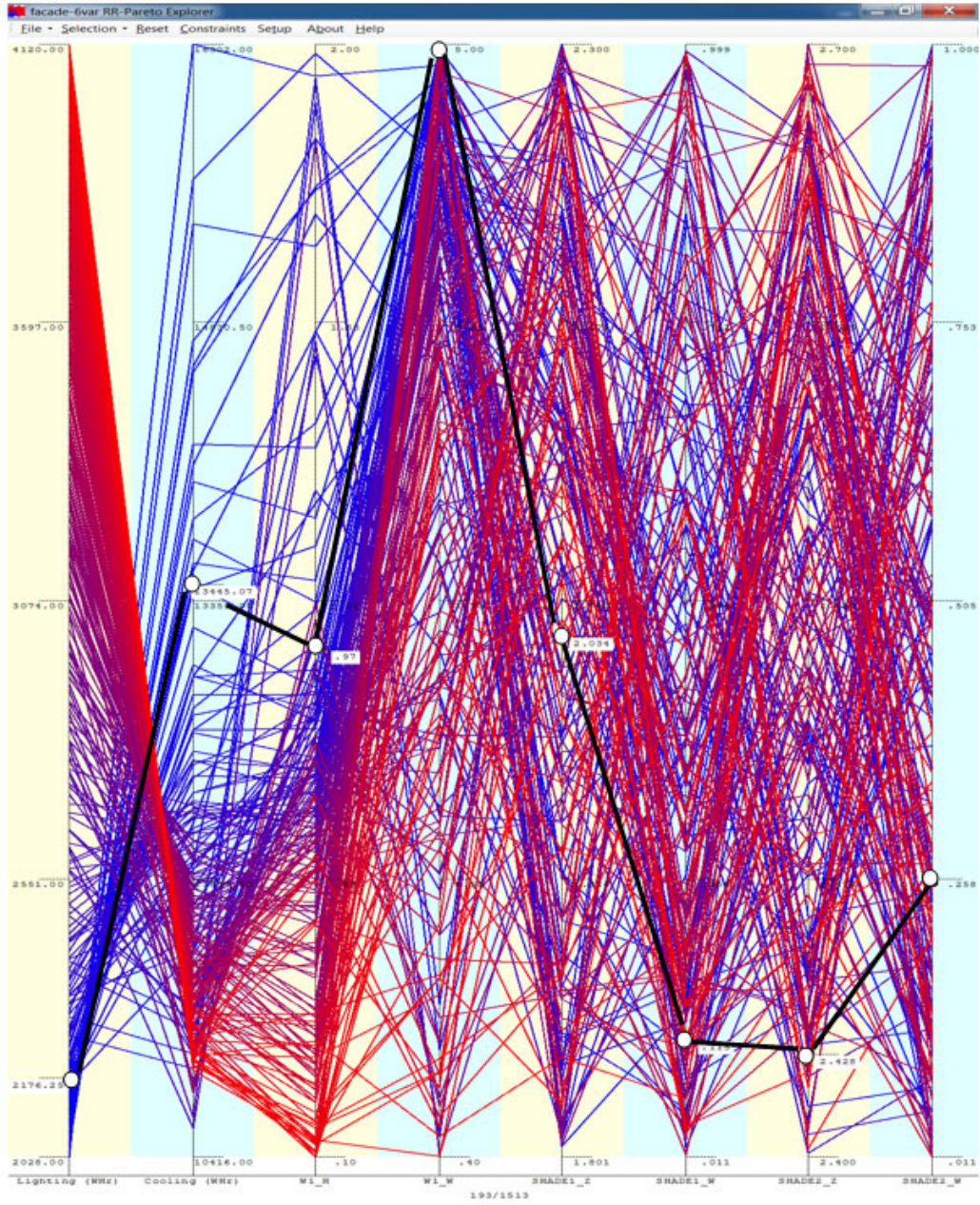


Figure 1. Parallel axis plot of the solution points

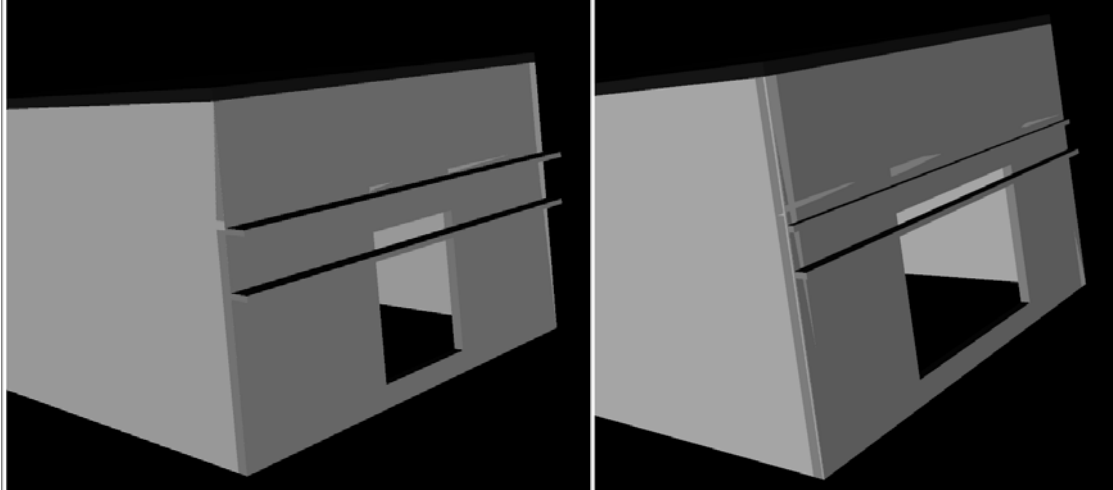


Figure 2. Compromise solution obtained by the RR-PARETO3 algorithm with sensitivity of 5%

Figure 3. Compromise solution obtained by the RR-PARETO3 algorithm with sensitivity of 1%

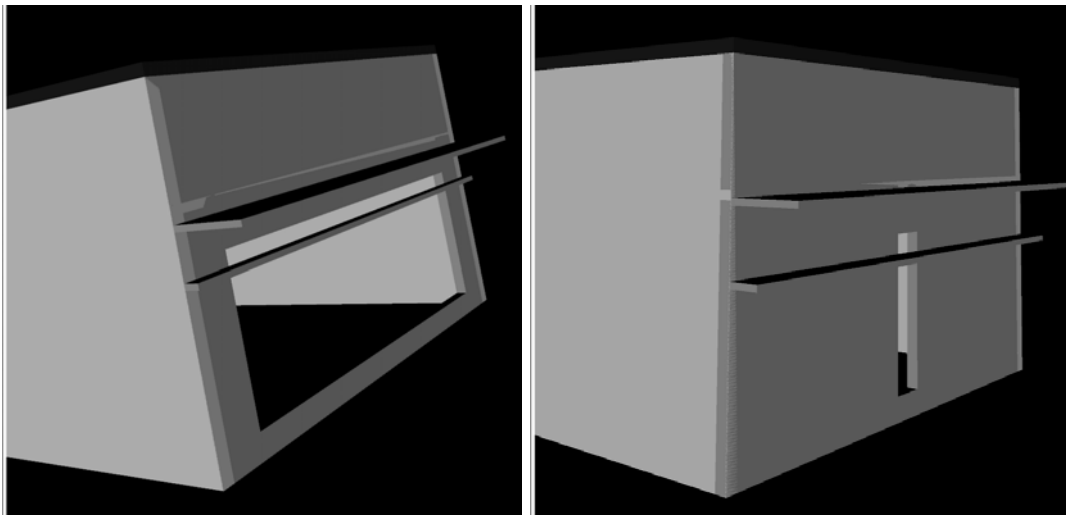


Figure 4. Optimal solution with respect to lighting energy

Figure 5. Optimal solution with respect to thermal load

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