THE MULTI-CRITERION OPTIMIZATION OF BUILDING THERMAL DESIGN AND CONTROL

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ABSTRACT

The design of buildings is a multi-criterion optimization problem, there always being a trade-off to be made between capital expenditure, operating cost, and occupant thermal comfort. This paper investigates the application of a multi-objective genetic algorithm (MOGA) search method in the identification of the optimum pay-off characteristic between the elements of the building design problem.

Results are presented for the pay-off characteristics between daily energy cost and zone thermal comfort, and for building capital cost and energy cost. It was concluded that the MOGA was able to find the optimum pay-off characteristic between the daily energy cost and zone thermal comfort, but that the characteristic between the capital cost and energy cost was sub-optimal. However, it can be concluded that multi-criterion genetic algorithm search methods offer great potential for the identification of the pay-off between the elements of building thermal design, and as such can help inform the building design process.

INTRODUCTION

It is common for buildings to be designed and constructed to a fixed capital cost. Within this capital expenditure, there may be some optimization of the design in an attempt to reduce running costs without prejudicing the thermal comfort of the building occupants. This approach however, pays no attention to the impact that a marginal increase in capital cost might have on the reduction in running costs or the improvement in occupant comfort. The coupling between these design criteria and its impact on the design solutions can be evaluated through the application of multi-criterion decision making (MCDM) methods. The MCDM process has two elements:

1. the designer must make a *decision* as to which pay-off between the criteria results in the most desirable design solution;

2. a procedure to *search* for one or more solutions that reflect the desired pay-off between the criteria.

The relationship between *decision* and *search* has three forms (Van Veldhuizen and Lamont, 2000; Miettnen, 2001):

A Priori preference articulation (decide → search), in which the decision maker (DM) defines the preferred pay-off between the criteria in advance of the search (for instance, the designer may say that the capital cost of the building is twice as important as the operating cost).

Progressive preference articulation (decide ↔ search), in which the DM and search are intertwined, with the DM using progressive solutions to inform the decision making process and the final choice of pay-off.

A Posteriori preference articulation (search → decide), in which the DM is presented with a set of solutions and then chooses a final design solution from that set.

The most common *a priori* approach is one in which the DM assigns weights to each of criteria, the weighted sum of the criteria then forming a single design criterion. An optimization algorithm is then used to find the single design solution that minimizes the weighted sum of the criteria. For instance, the capital cost $f_c(\mathbf{X})$, and the operating cost $f_o(\mathbf{X})$, of a building could be transformed into a single design objective by assigning a weight (w_c and w_o), to each of the criteria and summing them (Equation 1). The sum of the criteria could then be minimized to produce a single design solution that provided a weighted payoff between the capital and operating costs. The choice of weights may be arbitrary, although the weights could be defined through the life-cycle cost of a building since this is in principle a weighted sum of the capital and operating costs.

$$f(\mathbf{X}) = w_o\ f_o(\mathbf{X}) + w_c\ f_c(\mathbf{X}) \qquad (1)$$

Figure 1 illustrates a possible pay-off between the capital cost of the building and the operating cost of the building. Suppose that the designer (DM), decided that minimizing capital cost was twice as important as minimizing the operating cost. Minimizing a single weighted criteria would result in one design solution on the pay-off curve. However, this does not provide the designer with information about how sensitive the operating cost is to changes in capital cost. For instance, the designer would not be able to evaluate the potential reduction in operating cost due to say a 50% increase in the capital cost.

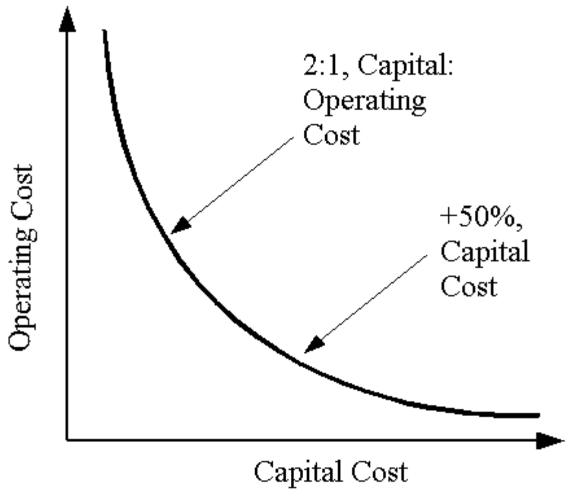

Figure 1: Example Pay-off Characteristic

The *progressive* preference articulation approach in part solves this problem, by generating at least one alternative to the single design solution (for instance, by assigning different weights and repeating the optimization). However, information available to the designer is restricted since the complete pay-off curve is not available . Further, this approach is likely to be computationally too intensive for building thermal design, since each new optimization would require repeated optimization and simulation of the building thermal performance. Therefore, in this paper, the *a posteriori* preference articulation approach is advocated, in which the complete pay-off characteristic is determined in one optimization of the building design (thus minimizing the need for repeated optimization and associated simulation of building thermal performance).

Pareto Optimization

The optimum pay-off characteristic is represented by the Pareto optimum set of solutions. Each solution in the set is said to be non-dominated by any other solution. This concept is illustrated in Figure 2, which shows a set of 7 sample solutions for two criteria ($f_1(\mathbf{X})$ and $f_2(\mathbf{X})$). The non-dominated solutions in the set are indicated by a ranking of 0. For each of the non-dominated there is no other solution in the set that has a lower value in any criteria. The solution ranked 3 however, is "dominated" by three other solutions in the set; that is, three other solutions have a lower value in both criteria.

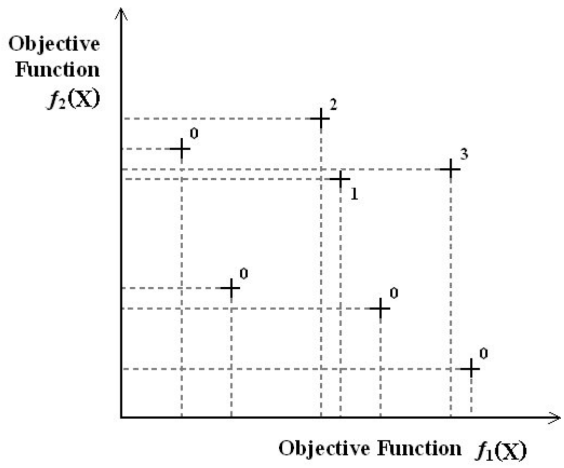

Figure 2: Example Pareto Ranking

The Pareto multi-criterion optimization has been applied previously to the design of buildings (D'Cruz and Radford, 1987). The criteria considered where the thermal load, daylight availability, planning efficiency, and capital cost. The optimization problem was solved using a dynamic programming optimization algorithm, which although solutions where obtained, did not provided a sufficient number of solutions to allow the pay-off between the criteria to be examined. A solution to this deficiency is examined in this paper through the use of a multi-criterion Genetic Algorithm optimization method. Note therefore, that the focus of this paper is on the *search* element of the MCDM process rather than the *decision* making element. The effectiveness of the search method is examined in relation to the simultaneous design of the building fabric construction, the size of heating ventilating and air conditioning (HVAC) system, and the HVAC system control strategy.

THE OPTIMIZATION ALGORITHM

The search method advocated for finding the Pareto, non-dominated, set of solutions is based on a Genetic Algorithm (GA). Although several "traditional" methods exist (Miettnen, 2001), these often require a sequential and therefore computationally intensive approach to finding the Pareto set of solutions. However, rather than progressively minimizing a single possible solution, GA's operate with a set of possible solutions (known as the *population*). This enables several members (if not all members) of the Pareto optimum set to be found in a single run of the algorithm (Ceollo Coello, 2001).

GA's often begin with randomly initialized *population* of solutions. The GA then seeks to maximize the *fitness* of the population by selecting the "fittest" *individuals* from the population and using their "genetic" information in "mating" and "mutation" operators to create a new population of solutions. The form of GA implemented in the work is derived from the simple GA described by Goldberg (1989). A detailed description is beyond the scope of this paper, but the form of the GA implemented can be summarized as being, a simple binary encoded GA with "roulette wheel" selection, single point cross-over, and a non-overlapping population.

This GA is an unconstrained search method originally designed to optimize a single criterion, represented by the fitness of each individual in the population. Many of the variations to the basic GA are concerned with the description of the individuals *fitness*, and this is particularly the case for the multi-criterion optimization. Several approaches to defining the fitness for a multi-criterion GA optimization exist (Coello Coello, 2001); the approach implemented here is the Multi-Objective Genetic Algorithm (MOGA) by Fonseca and Fleming (1995, 1998). This algorithm employs the Pareto ranking scheme illustrated in Figure 1, the Pareto rank then being used to form the fitness of each solution (solutions of equal rank having equal fitness). However, since GA's seek to *maximize* fitness and we seek to find the pay-off that *minimizes* the criteria, the Pareto rank is inverted to form the fitness of the individuals. An exponential weighting is also applied during the inversion to give extra weight to the non-dominated (Pareto 0) solutions.

Since many problems are constrained (as is the case in thermal design of buildings), the MOGA includes an approach to handling the constraint functions. In short, the constraints are treated as criteria and "goal restraints" applied to force the solutions into the desired feasible region (by penalizing the Pareto rank of the infeasible solutions). Treating the constraints as criteria has the advantage that the pay-off between constraint function bounds and the true design criteria can be examined, but has the disadvantage that the pay-off characteristic becomes increasingly difficult to interpret as the number of criteria increases (the pay-off *curve* becomes a pay-off *surface* as the number of criteria is increased from 2 to 3 for instance). For this reason, a means of aggregating the constraints into a single criteria has been developed (Wright and Loosemore, 2001). As well as reducing the number of criteria, the method also allows the aggregated constraint "criterion" to be removed from the search once feasible solutions are obtained, further reducing the dimensionality of the pay-off information.

Finally, in order to maintain a spread of solutions across the Pareto "front", it is necessary to employ a "sharing" function. These functions prevent clustering of solutions by re-assigning the fitness of the individuals in relation say, to how close a given solution is to a similar solution. The proximity of the solutions to each other can be measured in the variable space or the criterion space. A criterion space sharing function has been implemented here (Deb, 1989).

EXAMPLE PROBLEM FORMULATION

The multi-criterion optimization of building thermal systems is investigated here through the design of a single zone "all outside air" heating, ventilating and air conditioning (HVAC) system (Figure 3). Traditional single criterion optimization problems are defined in terms of the problem variables, the design criterion, and the design constraints (Wright and Farmani, 2001). For instance, for the system in Figure 3, the design would be optimized for either operating cost, capital cost, or life-cycle cost; with the optimization being subject to constraints on the zone thermal comfort and the HVAC system design. However, in the multi-criterion problem described here, all potential objective criteria are included in the problem formulation; the design constraints are also treated as criteria (by aggregating them to form a single criterion). The choice and form of the problem variables, design criteria, and design constraints, is only summarized here, but a more detailed description is available in Wright and Farmani (2001).

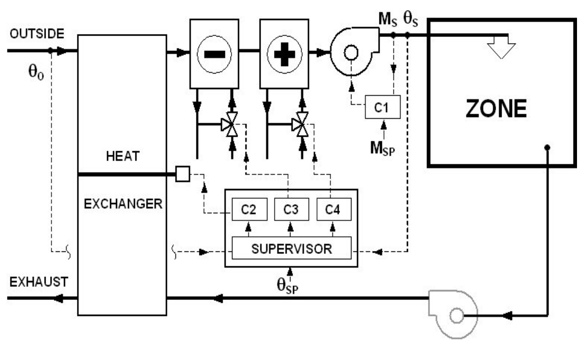

Figure 3: The Example HVAC System

Problem Variables

In order to account for the coupling between the fabric thermal storage, the HVAC system size, and the HVAC system control strategy, the optimization problem must include variables that represent:

- the choice of building fabric construction;
- the size or capacity of the HVAC system;
- the HVAC system supervisory control strategy.

In this paper, the building fabric construction is defined for three weights of building ("light", "medium" and "heavy"), two types of glass (clear and low emissivity glass), and three glazed areas (10%, 20%, 30%).

Since the capital cost of the building is a criteria of interest, the "size" of the HVAC system is described by the physical dimensions of the system components rather than just the system thermal capacity. The system size is therefore represented by the width, height, number of rows and number of water circuits for each coil, and the supply fan diameter (the extract fan is not explicitly included in the problem formulation). The hot and chilled water maximum flow rates to the coils are also problem variables, since these govern the peak capacity of the coils.

Finally, the HVAC system supervisory control variables are described as the supply air setpoint temperature and flow rate (M_s and θ_s, Figure 3), in each hour of the day, giving 48 setpoints for each day of operation. The ON/OFF operation of the system outside of the occupied period is controlled by a further 15 system status (ON/OFF) variables, giving a total of 63 variables for each day of operation. The number of control variables could be significantly reduced (Ren and Wright, 1997), but this has not been implemented here in order to allow the performance of the MOGA to be investigated for a large solution space.

This gives a total of 77 problem variables (63 control variables, 11 HVAC system size variables, and 3 building construction variables). Optimizing for three design days of operation (a winter day, "swing" season day, and a summer day), would increase the number of variables to 203 (Wright and Farmani, 2001).

Design Criteria

Three design criteria have been specified:

1. the capital cost of the construction and the HVAC system;
2. the operating cost of the HVAC system over a design day;
3. and the maximum thermal discomfort during occupancy for the design day.

The capital cost has been calculated as a function of the building construction, (building weight, glass type, and window area), and the physical size of the coils and supply fan (coil width, height and number of rows, and fan diameter).

The operating cost of the HVAC system is defined here simply as the system energy cost over the design days. The hot water supplied to the heating coil is considered to have originated from a gas fired boiler and the chilled water from an electric powered chiller. A two part electricity tariff has been applied, the high tariff occurring from 8:00am to 12:00pm. The gas is charged at a flat rate over the day.

The zone comfort criteria are represented here by the "predicted percentage of dissatisfied" (PPD). It is not necessary to include a comfort criteria for every hour of the day, it is only necessary to specify the maximum PPD occurring at any point in the day (this representing the maximum discomfort). Hence one comfort criteria is specified for each design day.

Design Constraints

The design constraints are derived from restrictions on the design of the coils, the performance envelop of the supply fan, and the need to ensure that the system has sufficient capacity to meet the supply air temperature and flow rate setpoints.

The design of the coils is restricted by 3 constraints (giving 6 constraints for both coils). First, the air face velocity is restricted to limit noise, and moisture carry-over in the cooling coil. Second, the water velocity per water circuits is limited to prevent excessive pipe erosion. Finally, the coil water circuits configuration is restricted to ensure that the flow and return headers are on the same side of the coil.

The supply fan is restricted to remain within the manufacturers performance envelop by 4 constraints, the first two constraints restricting the fan speed and the second two restricting the volume flow rate through the fan.

The ability of the system to meet the supply air setpoints has been described by 2 constraints, one on the error in the supply air temperature, and a second on the error in the supply air flow rate.

The constraint functions are aggregated by a normalized sum of their violations (Wright and Loosemore, 2001), to form a single design criterion.

Evaluation of Trial Solutions

Each trial solution is evaluated by running a simulation of the building performance. The simulation is based on a finite difference model of the building (Ren and Wright, 1998), and a steady state model of the HVAC system (Wright and Farmani, 2001). The boundary conditions have been taken from UK weather data (also in Wright and Farmani, 2001).

RESULTS AND ANALYSIS

In order to investigate the performance of the MOGA in identifying the pay-off characteristic for building thermal design problems, two sub-problems have been optimized. The first is for a fixed building construction, but with the pay-off characteristic between daily operating cost and occupant thermal discomfort. The problem variables in this sub-problem are the control variables and the HVAC system size variables. The characteristic is identified for a medium weight construction, with low emissivity glass and 20% window area. The system operation is only optimized and simulated for a summer day.

The second sub-problem includes the building construction in the problem variables, and seeks to identify the pay-off characteristic between the capital and running cost of the building. In this sub-problem, the comfort criteria have been defined as constraints, with a maximum PDD of 10% allowed during the occupied period. In this optimization, the operating cost is defined as the sum of the energy cost for the three design days (winter, "swing" season, and summer).

Operating Cost versus Thermal Comfort

Figure 4, gives the optimum pay-off characteristic between the daily energy cost and occupant thermal discomfort for a summer design day. As would be expected, an improvement in thermal comfort requires an increase in energy use.

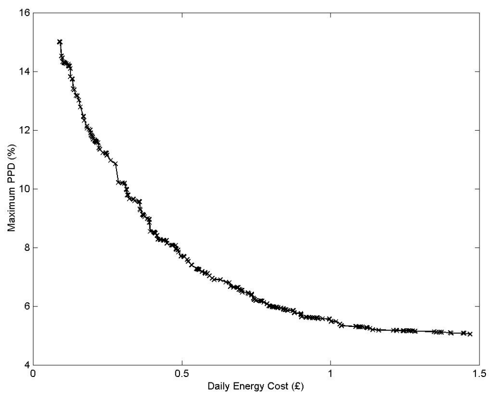

Figure 4: Summer Day Energy Cost versus PPD Pay-off

A comparison between Figures 5 and 6 illustrates that the higher energy cost is driven largely by changes in plant operation during the afternoon. The solid lines on both figures represent the variable bounds in the optimization; the dashed line for the temperature setpoints is the ambient temperature at that hour.

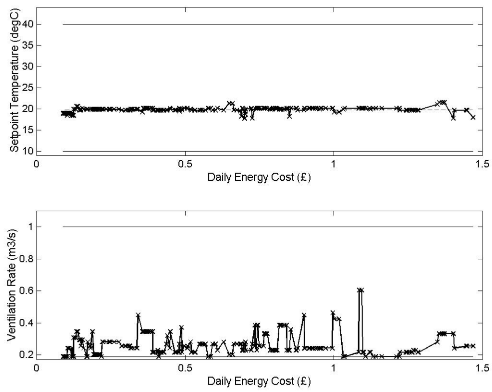

Figure 5: Setpoints versus Energy Cost at 10:00am

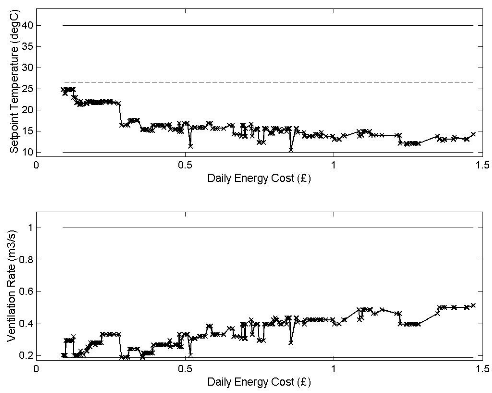

Figure 6: Setpoints versus Energy Cost at 4:00pm

Figure 5 illustrates that the energy cost is practicably unaffected by the system operation at 10:00am, with the temperature setpoint being equal to the ambient temperature and the flow rate tending to the minimum allowable flow rate. Conversely, the changes to both setpoints at 4:00pm (figure 6), are clearly contributing to the increase in energy cost (the increase in flow rate resulting in more fan power and the supply air temperature demanding increasing levels of mechanical cooling). The trend of little change in setpoints during the morning and increased cooling in the afternoon is driven by the load characteristic for the building. In general, the building is comfortable during the morning, and it is not until the afternoon that the thermal loads increase to a level where mechanical cooling is necessary to maintain comfort (Wright and Farmani, 2001). Hence, the greatest coupling between the thermal comfort and the energy use occurs during the late afternoon when the thermal loads are the highest.

It is informative to investigate the setpoint solutions for the extreme points on the curve, since this gives an insight to the extremes of system operation and to some extent, the degree to which the solutions are optimal. Figure 7 illustrates the supply air setpoints for the lowest energy cost solution (and the highest discomfort solution). It would be expected that the lowest energy cost would result from a setpoint schedule that demanded no mechanical cooling and set the flow rate to the minimum allowable value. Figure 7 illustrates that this is the case for the solution obtained from the optimization. Note that the occupied period is between 8:00am and 5:00pm.

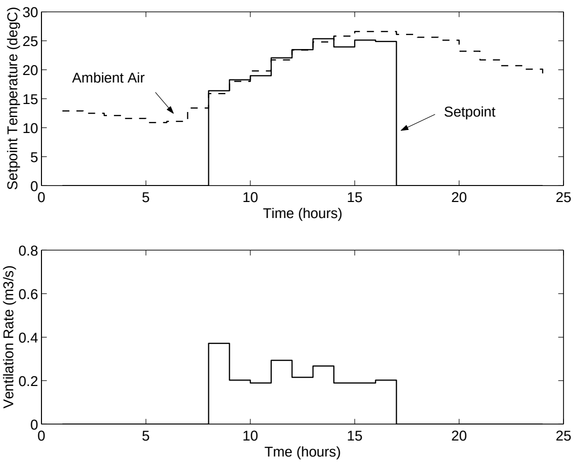

Figure 7: Lowest Energy Cost Setpoints

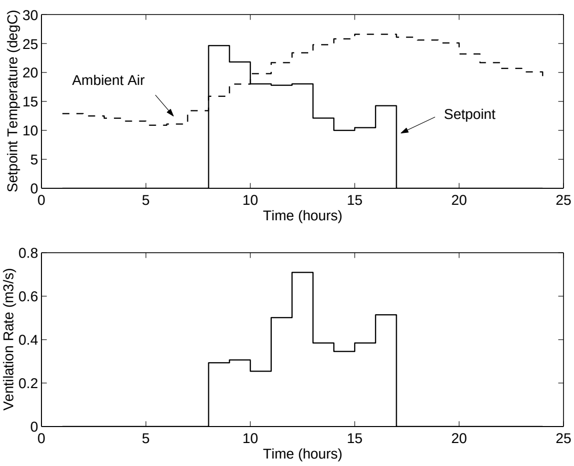

Figure 8: Highest Energy Cost Setpoints

The solution for the highest energy cost (and lowest thermal discomfort) is somewhat harder to predict, although it would be expected that energy use would increase during the afternoon as the thermal load increases (hence more mechanical cooling is required in order to minimize the thermal discomfort). Figure 8 indicates that this is the case, with the increase in thermal load first being offset by an increase in flow rate. As the load increases further however, it can only be offset by a lower supply air temperature. This occurred at 1:00pm, the change in temperature setpoint being so marked that the supply air flow rate was also reduced so as to not over-cool the building. Note also that the supply air temperature during the early part of occupancy is above the ambient temperature; this occurs since during summer operation, the building maybe slightly cool during the early part of occupancy until the thermal gains increase. Hence the supply air temperature is above cool morning ambient temperature so as to not over-cool the building.

The optimality of the extreme points has not been confirmed, although they appear to be consistent with the perceived operation of the HVAC system. This is examined further through a mid-range solution, the solution closest to a 10% PPD.The solution obtained from the MOGA has been compared to the corresponding solution obtained from a single criterion optimization for the same building (the procedure being described in Wright and Farmani, 2001). This optimization was performed to minimize only the energy cost, with the maximum thermal discomfort of 10% PPD set as a constraint on the optimization.

The energy cost and the thermal discomfort are very close for the two optimizations. The MOGA led to an energy cost of £0.3125 and the single criterion search, £0.3120; clearly an insignificant, if not unquantifiable difference. The maximum thermal discomfort was 9.99% PPD for the MOGA search, and 9.96% for the single criterion search, again very little difference.

Figure 9, illustrates the supply air setpoints for the MOGA solution closest to 10% PPD. As expected, the highest demand for mechanical cooling is in the late afternoon, the temperature setpoints following the ambient temperature during the early part of occupancy. Figure 10 illustrates the corresponding solution obtained from the single criterion optimization. The main differences between the two solutions is that the single criterion optimization has made some use of free cooling during the off-peak period, whereas the MOGA solution has not. The MOGA solution is also using more energy through a generally higher flow rate setpoint, although this is compensated for by a slightly higher supply air temperature setpoint in the late afternoon.

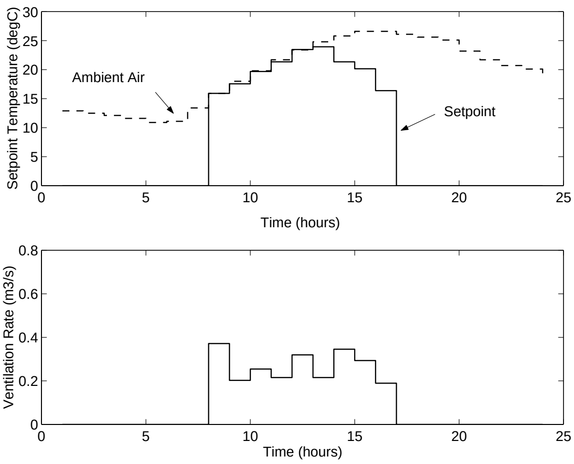

Figure 9: Setpoints for 10% PPD (MOGA Search)

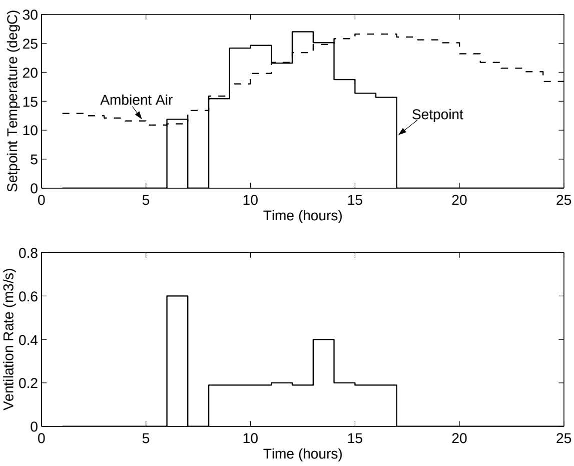

Figure 10: Setpoint for 10% PPD (Single Criterion Search)

It can be concluded, that for this example, the MOGA is finding a near optimal pay-off characteristic between the daily energy cost and zone thermal discomfort. The extreme points on the curve are consistent with the expected behaviour of the system, and comparison with a solution found from a single criterion optimization confirmed that the difference in energy cost was unquantifiable. As to which solution the "decision maker" should choose, it would seem that the solution with the lowest energy cost is a good solution, considering that this corresponded to a 15.0% PPD, (this not withstanding that the sensitivity of the solution has not been investigated).

Capital Cost versus Operating Cost

The Pareto "optimal" solutions found for the capital versus operating cost pay-off are illustrated in Figure 11. Only five solutions have been found,

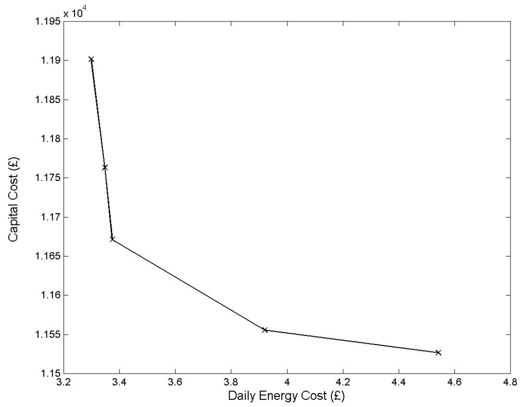

Figure 11: Capital Cost versus Energy Cost

with all of the solutions corresponding to a "heavy weight" construction (the variation in cost being due to a combination of HVAC system size and window type and area). Inspection of the capital versus energy cost solutions indicates that there are very few non-dominated solutions for other constructions. It can therefore be concluded that the MOGA has found a good proportion of the non-dominated solutions available, although the Pareto set is sub-optimal.

Performance of the MOGA

The search results indicate that the MOGA has the potential to find Pareto optimal solutions for building design problems. It is however, prudent to examine the computational effectiveness of the algorithm in finding these solutions. In order to determine the pay-off characteristic between the energy cost and zone thermal discomfort, the MOGA was run with a population of 200 sample solutions, and was allowed to run for a 1000 generations. It is common to allow a GA based search to run for a fixed number of generations since defining stopping rules for these stochastic optimizers is difficult. The fixed number of generations could result in a total of 200,000 trial solutions. However it is likely that the number of trial solutions required to find the Pareto optimum set was much less, since GA based optimizer exhibit an exponential convergence towards the solution. This is illustrated in Figure 12, in which starting from an initial randomly generated population of solutions, the search has converged to the region of the optimum within 20 generations. It should also be noted that all solutions in the initial population were infeasible, but that feasible solutions was found within 4 generations.

CONCLUSIONS

The design of buildings is a multi-criterion optimization problem, there always being a trade-off

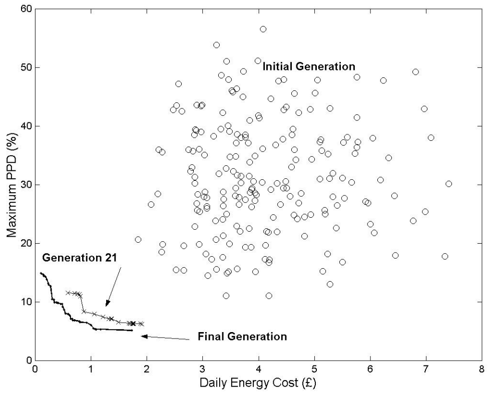

Figure 12: "Convergence" of the MOGA Search

to be made between capital expenditure, operating cost, and occupant thermal comfort. Such a design process can be informed by the application of multi-criterion decision making (MCDM) techniques. The MCDM process has two elements, the *search* for viable solutions, and the *decision* as to which solution is the most desirable. This paper investigates that application of a multi-objective genetic algorithm (MOGA) in the search for a non-dominated (Pareto) set of solutions to the building design problem.

The results indicate that the MOGA was able to identify the pay-off characteristic between daily energy cost and zone thermal comfort. The MOGA was also able to identify a pay-off characteristic between capital cost and energy cost, although inspection of the results suggests that the solution set was incomplete and was therefore sub-optimal. The MOGA exhibits fast progress towards the Pareto optimal solutions, and in particular is able to find feasible solutions within a very few trail solutions.

It can be concluded that multi-criterion genetic algorithm based optimizers can be used to solve multi-criterion building optimization problems, particularly with respect to aiding the understanding of the characteristic behaviour of the design problem.

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