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A preference driven multi-criteria optimization tool for HVAC design and operation

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ABSTRACT

This paper discusses the issue of selecting the design solution that best accords with an articulated preference of multiple criteria with an acceptable performance band. The application of a newly developed multi-criteria decision-making tool called RR-PARETO2 is presented. An example of HVAC design is used to illustrate how solutions could be selected within a multi-criteria optimization framework. In this example, five criteria have been selected, namely, power consumption, thermal comfort, risk of airborne infection of influenza and tuberculosis and effective differential temperature (Δt_{eq}) of body parts. The goal is to select the optimal air exchange rate that makes reasonable trade-offs among all the objectives. Two scenarios have been studied. In the first scenario, there is an influenza outbreak and the important objective is to prevent the spread of infection. In the second scenario, energy prices are high and the primary objective is to reduce energy. In both scenarios, RR-PARETO2 algorithm selects solutions that make reasonable trade-offs among conflicting objectives. The example illustrates how objectives such as reduction of airborne disease transmission and maximizing thermal comfort can be incorporated in the design of a practical, full-scale HVAC system.

1. Introduction

Optimization techniques are increasingly being used for the design of building systems. Huh and Brandemuehl [1] optimized HVAC system performance using five systems variables to minimize energy consumption while meeting building loads and maintaining thermal comfort. Wemhoff [2] used multi-dimensional interpolation between optimized control configurations for several steady-state load distributions to reduce energy consumption of an HVAC system. Other examples can be found in [3–5]. Realizing the importance of optimization of building systems, some simulation softwares such as Ecotect [6] already provide options for design optimization.

The development of direct search methods [7] has contributed to the use of optimization in design. These techniques use the concept of black box optimization in which the objective function need not have an explicit mathematical representation. The objective function might involve executing external programs which are treated as black-boxes by the optimization algorithm. Unlike traditional mathematical optimization, mathematical characteristics of the evaluation function including convexity, expression for the gradient, etc. are not needed. Examples of direct search methods include Genetic Algorithms [8], Simulated Annealing [9] and PGSL [10]. These algorithms make it possible to minimize objective functions such as energy which require running simulations as external programs.

While minimizing the energy consumption of HVAC system has been the primary goal of several building related optimization studies, recent studies have highlighted the importance of other factors. After the emergence of Severe Acute Respiratory Syndrome (SARS) in 2003 and the resurgence of Influenza in 2009, airborne infection transmission became one of the most important concerns in densely occupied indoor environments. HVAC system has a large impact on airborne transmission [11,12]. Hence reduction of airborne disease transmission is a very important consideration that has to be taken into account besides minimizing energy consumption. Optimization of HVAC systems using this criterion has not been attempted so far.

When factors such as disease transmission are considered along with energy consumption, design becomes a multi-objective optimization problem. The multi-objective approach to design optimization has been applied by several researchers. Wright et al. [13] investigated application of a multi-objective genetic algorithm to find pay-off characteristic between the energy cost of a building and the occupant thermal comfort. Djuric et al. [14] performed optimization of HVAC system based on energy consumption, investment cost and thermal comfort using generic

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optimization program. Hamdy et al. [15] used multi objective genetic algorithm to optimize HVAC system performance for primary energy conservation. However, the decision-making process involving multiple criteria is still not well established. For example, a building design that maximises natural day lighting may not perform well with respect to the total energy consumption, since it might have high cooling loads in tropical climates. Decision-making in such situations is not straightforward because trade-offs have to be made between user's preference for natural day lighting and the goal of reducing energy consumption.

This paper discusses the issue of evaluating design alternatives according to multiple criteria and selecting the solution that best accords with user defined preferences and performance bands in a design process. A recently developed algorithm called RR-PARETO2 is applied to the design of an air distribution system in order to illustrate the concept of multi-criteria decision-making. The decision variable is the air exchange rate (ACH). Five criteria have been selected, namely, power consumption, thermal comfort, risk of infection of influenza and tuberculosis and manikin based equivalent temperature difference of the facial region (Δt_{eq}). The goal is to select the optimal ACH that makes reasonable trade-offs among all the objectives. The example illustrates how these objectives are computed in a practical, full-scale air delivery system, and how a design decision is made through multi-criteria optimization.

2. Methodology and experimental design

2.1. Multi-criteria optimization

Currently, single objective optimization is used in most design applications (for example see [3–5]). However, complex engineering artefacts such as building systems have to be necessarily evaluated according to multiple criteria. The task of selecting the best design is complex since it involves making trade-offs among conflicting objectives. Rarely, we find solutions that perform equally well with respect to all the criteria. One approach for accommodating multiple criteria in evaluation is the use of weight factors to combine the effects of all the criteria into a single utility function. A variation of this is presented in [16], in which a multiplicative utility function is used and the weights are determined through an opinion based survey conducted on experts in the domain. The difficulties with this approach are the subjectivity of the importance factors and the efforts required to obtain a reasonable survey sample to improve the accuracy of assessment. Several other methods for multi-criteria decision-making involving the use of weight factors are summarized in [16–18].

Another approach to managing multiple criteria is Pareto optimization in which a population of solutions that are non-dominated is generated. Such techniques have already been used in the design of building systems. For example, Jelle and Arnold [19] used genetic algorithms to find and select Pareto optimal solutions for the trade-off between energy and the risk of exposure to pollutants. However, they do not present a well-defined algorithm for selecting a single solution from the Pareto front. Instead, it is recommended that the practical selection of system configuration should be limited to the midrange spectrum of the Pareto front, where the curvature is the maximum. In fact, researchers have not paid much attention to the problem of selecting the best solution from the Pareto set. In many applications, the final selection of the solution is usually left to the designer (for example see [20,21]).

This work uses a recently developed algorithm called RR-PARETO2 [22,23] that aims to select a single solution with the best trade-offs within a multi-objective framework. In this algorithm, the solution with the best trade-offs among all the objectives is chosen using two pieces of information, ranking of the objectives according to their importance; and the sensitivity of each objective.

The sensitivity of an objective refers to the threshold which determines whether the differences in the objective function values are significant. All the points lying within the specified sensitivity band are considered to be equivalent with respect to that objective. In order to illustrate the concept of sensitivity, consider the objective of minimizing the power consumption. The user might specify that reduction in power below 10% is not significant, and therefore, the sensitivity of this objective is defined as 10%. All the solutions lying within the sensitivity band are considered to be equivalent. These solutions are further filtered using other objectives.

The algorithm starts off with a set of solutions that are generated by any optimization process (Fig. 1). Each solution point contains the values for all the objectives as well as decision variables (optimization variables). The set of solutions are sequentially filtered according to the order of importance of objectives. 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 $ymin_i$ and $ymax_i$ be the minimum and maximum values of the ith objective among all the solutions in the current set. The threshold is computed as $(ymin_i + ymax_i)/2$. In the minimization problem, all the solutions that have a value greater than this threshold are removed from the set. After completing all the objectives, the process is repeated starting from the first objective. 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.

Within each iteration of Stage 2 filtering, the inferior half of the solution space according to a criterion is eliminated as shown in Fig. 2. The area **V1** contains solutions with high values of the first objective and this is eliminated in the first iteration. From among remaining solutions, the inferior half of the space **V2** according to the second objective is identified. The solutions that lie within **V2** are then eliminated and the process is repeated until a single solution remains in the set. It should be noted that this process need not necessarily eliminate exactly half the number of solutions in each iteration, since the inferior half of the hypercube might contain fewer solutions. The iterative process is aimed at removing relatively high values at each stage, irrespective of how the points are clustered within the space. By repeating this process for each objective, each criterion is given an opportunity to eliminate inferior solutions and the final selection is a trade-off among all the objectives. It is further emphasized that the process does not favour the best solution according to any objective. For example, if the best solution according to the first objective lies within the inferior half of the second objective, this solution is eliminated. A solution with a better trade-off is one which lies within the better half of the first objective as well as the better half of the second objective. Since the process is driven by the order of importance of objectives, the users' preferences in the selection process are also respected.

An interactive process with good computer support for decision-making is proposed for the selection of the most attractive solution according to multiple criteria. Appropriate visualization of the solution space allows designers to appreciate the range of possibilities and judge the trade-offs that need to be made. It helps them define the sensitivities of objectives by visually evaluating what might