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Sustainable building envelope design by considering energy cost and occupant satisfaction

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ABSTRACT

The built environment is a major contributor to the world's carbon dioxide emissions, with a considerable amount of energy being consumed in buildings due to heating, ventilation and air-conditioning, space illumination, use of electrical appliances, etc., to facilitate various anthropogenic activities. The development of sustainable buildings seeks to ameliorate this situation mainly by reducing energy consumption. Sustainable building design, however, is a complicated process involving a large number of design variables, each with a range of feasible values. There are also multiple, often conflicting, objectives involved such as the life cycle costs and occupant satisfaction. One approach to dealing with this is through the use of optimization models. In this paper, a new multi-objective optimization model is developed for sustainable building design by considering the design objectives of cost and energy consumption minimization and occupant comfort level maximization. In a case study demonstration, it is shown that the model can derive a set of suitable design solutions in terms of life cycle cost, energy consumption and indoor environmental quality so as to help the client and design team gain a better understanding of the design space and trade-off patterns between different design objectives. The model can be very useful in the conceptual design stages to determine appropriate operational settings to achieve the optimal building performance in terms of minimizing energy consumption and maximizing occupant comfort level.

Introduction

Climate change caused by global warming is said to be one of the most important challenges facing society today, with a major contributor being excessive greenhouse gas (GHG) release into the environment. Carbon dioxide (CO_2) emissions are a particular problem (Masters, 1998) and an attempt to reduce atmospheric CO_2 concentration is inevitable worldwide (Scheffer et al., 2006). In pursuit of this, a cut in energy consumption is one of the most effective ways to achieve significant emission reduction in the immediate future. A way to reduce emissions is by switching to clean energy sources as this can minimize the CO_2 emitted from the oxidation of carbon embodied in fossil fuels. Meanwhile, however, primary energy consumption and CO_2 emissions grew by 49% and 43% respectively from 1984 to 2004 (IEA, 2006) and 81% of the world's total primary energy supply in 2008 was generated by fossil fuel (IEA, 2010) with no evidence of any reduction since that time. Indeed, the escalated demand for energy, especially in developing countries due to increasing industrialization, rapid urbanization and rise in living standards, is only aggravating the situation (Dakwale et al., 2011).

The built environment is a major culprit with a considerable amount of energy being consumed in buildings due to heating, ventilation and air-conditioning (HVAC), space illumination, use of electrical appliances, etc., to facilitate various anthropogenic activities. Studies indicate that the energy consumed by buildings were 39% in the United Kingdom, 37% in the European Union (Perez-Lombard et al., 2008), 40% in the United States (USDOE, 2010), 31% in Japan and 40% in Hong Kong (Juan et al., 2010). The main reasons for high building energy consumption include an increase in population, greater reliance on building services equipment, amelioration of comfort level of indoor environment, and increase in time spent inside buildings (Perez-Lombard et al., 2008).

As a major energy consumer, buildings are also one of the most significant CO_2 emitters. Studies have shown that over a third of the world's CO_2 emissions emanate from the combustion of fossil fuels in order to satisfy the energy demand of buildings (Filippin, 2000; Levermore, 2008). Therefore, buildings have a significant role to play in lowering CO_2 emissions. Improving the energy efficiency of buildings not only does this, but can also help preserve non-renewable energy sources (Lee & Yik, 2004). Over the years, sustainable building has gained increasing attention and popularity from stakeholders in the

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construction industry such as architects, engineers, developers, contractors and government. Sustainable building is designed, constructed, operated, renovated and disposed of in accordance with ecological principles for the purposes of minimizing the environmental impact of the built environment and promoting occupant health and resource efficiency (Kibert, 2003). In addition to benefitting the environment and occupants, sustainable buildings can also produce substantial economic benefits by reducing operating expenses, enhancing building marketability and market value, improving the productivity of occupants and thus the revenue-generating ability of corporate tenants of office buildings, minimizing potential liability due to poor indoor environment, and optimizing life cycle economic performance (USGBC, 2010; USEPA, 2012).

In many sustainable building guidelines and evaluation methods, the design phase is the most comprehensively emphasized and addressed phase of the life cycle (Bunz et al., 2006). Although some forms of minor energy conservation could be achieved via relatively simple and individual measures during the operational phase, significant reduction in energy consumption is made possible only if design solutions are generated and fully assessed during the design stage. The most effective point of incorporating sustainable features is in the early design stage (Wang et al., 2005). For instance, a typical feature of sustainable building design is good insulation of the building envelope to lower heat loss and thus decrease the energy demand for heating and cooling.

However, sustainable building design is a complicated process involving a large number of design variables, each with a range of feasible values. Seen this way, a design solution is basically a result of choosing a value for each design variable and combining them together. This creates a very broad space of all possible design solutions. A simple example is a sustainable building design problem involving five design variables: north south, east and west wall window types, and exterior wall insulation thickness. Assume that the windows on each façade can be chosen from 10 different types and the insulation thickness takes discrete values ranging from 10 mm to 170 mm in 10 mm steps, which amounts to 17 feasible values for insulation thickness. The design space therefore consists of 170,000 ($10^4 \times 17$) possible solutions.

Another aspect in sustainable building design is its multiple, and often conflicting, objectives—the simultaneous minimization of cost and environmental impact for example. This involves a trade-off in which the aim is to locate a set of diversely distributed Pareto-optimal solutions rather than single best solution as occurs in single objective optimization.

Acting as a boundary separating indoor and outdoor environment, the building envelope plays a critical role in determining the energy performance of a building. The building envelope consists of various elements including exterior walls, roofs, doors, windows, skylights, and walls and floors in contact with the ground (EMSD, 2007b). Building operational settings, such as lighting power density, air temperature, relative humidity, air velocity, and outdoor air exchange rate, determine the occupants' comfort level of indoor environmental quality (IEQ) as well as affecting the building's energy performance. Although such settings belong to the building's operational stage, deciding on their appropriate values must be considered during the design stage as, together with other physical building configurations and external climate conditions, they determine energy performance as a complete system. For example, to achieve the same level of thermal comfort, if the building envelope has higher thermal resistance, the cooling temperature setting can be increased accordingly, which will also reduce energy consumption and energy cost.

One approach to dealing with such issues is through the use of optimization models. Although rarely used in building design practice, these powerful tools have the potential to identify better design solutions and provide a more comprehensive knowledge of the whole design space. Quite a number of optimization models for sustainable building design have been developed in past research, but they are limited in either not including consideration of occupant comfort level or using only thermal comfort to partially represent occupant comfort level. In this paper, a new multi-objective optimization model is developed for sustainable design of office buildings in Hong Kong, a Special Administrative Region of China, by considering the design objectives of cost and energy consumption minimization and occupant comfort level maximization. In a demonstration on a hypothetical case study, it is shown that the model could be a useful tool for designers at the conceptual design stage to derive a set of suitable design solutions and help gain a better understanding of the design space and trade-off patterns between different design objectives.

Optimization of sustainable building design

Many sustainable building design optimization models have been developed considering only one objective. The optimization model developed by Saporito et al. (2001), for example, minimizes just the energy consumption for heating requirement. This utilizes computer thermal simulations to understand the dynamic interaction of different parameters and the lattice method for global optimization to uniformly search the highly multi-dimensional design space. Similarly, Al-Homoud (1997) and Coley & Schukat (2002) consider energy consumption only but expand the coverage of energy consumption to include both the heating and cooling requirement. Al-Homoud (1997) applies a computer-based detailed hourly energy simulation model for evaluating energy performance and a direct search method for optimization. Coley & Schukat (2002) couple the genetic algorithm (GA), a population-based optimization technique, to a simplified dynamic energy model with characteristic equations solved analytically in order to identify a large number of distinctly different low-energy design solutions. Lighting energy is included in addition to heating and cooling energy in evaluating the single design objective of energy performance in the model developed by Caldas & Norford (2002) for optimizing the placing and sizing of windows in an office building. Energy behavior is assessed using a sophisticated BEPS program (DOE2.1E) and GA is employed to guide the solution generation and search process. However, considering energy performance alone tends to produce high-cost design solutions. For instance, when optimizing building envelope configurations, the final design solution can involve the extensive, but financially infeasible, use of wall insulation. Generally speaking, therefore, although single objective models are able to pinpoint the best design solution with respect to the designated design objective, they cannot be put into use in practice as multiple design objectives are usually considered simultaneously in sustainable building design. Multi-objective models can more accurately reflect real life situations and are therefore more suitable.

Financial impact and environmental impact are the two commonly adopted design objectives in existing studies. In the multi-objective optimization model developed by Shi (2011), EnergyPlus, a sophisticated and widely used BEPS software tool, was integrated into modeFRONTIER, an optimization suite that contains a series of preprogrammed optimization algorithms. This was done with the goal to minimize the energy demand for space conditioning and insulation usage of office buildings in Southeast China. With only one insulation material, insulation usage is essentially equivalent to initial cost. A multi-objective genetic algorithm (MOGA) which is based on concept of Pareto-optimality was used in the study. Wang (2005) developed a simulation-based optimization system aimed at minimizing the life cycle cost (LCC) and life cycle environmental impact of a building. Life cycle environmental impact was evaluated using the indicator 'expanded cumulative energy consumption', calculated by summing the cumulative energy consumption in resource inputs and the abatement energy consumption due to waste emissions. The model was later applied in other studies (Wang et al., 2005; Wang, 2005) to optimize the floor shape and building envelope with the same set of design objectives. Likewise, Hamdy

et al. (2011) propose a simulation-based multi-objective optimization approach to combine a BEPS program IDA_ICE 3.0 with GA. A modified three-phase multi-objective optimization approach (PR_GA_RF) was implemented to reduce the randomness of GA and to speed up fast convergence. Minimization of operational carbon emissions and initial investment costs are the two design objectives. In addition, thermal discomfort was incorporated into the model as a design constraint as represented by the level of summer overheating, which is quantitatively assessed by summing up the hours in which the operative temperature exceeds 24 °C in the hottest zone during a one-year simulation period. Verbeeck & Hens (2007) perform a life cycle optimization for extremely low energy dwellings aiming at reducing financial costs and ecological impact over the life cycle. The life cycle ecological impact was evaluated through life cycle assessment (LCA). Operational energy simulations were executed using the sophisticated BEPS software TRNSYS. Optimization was conducted with a Pareto-based GA. Diakaki et al. (2008) optimize window type, wall insulation materials and thickness with the aim of reducing initial acquisition costs and energy consumption. Energy consumption was evaluated indirectly from the thermal transmittance of the building envelope with relevant mathematical formulas. Three optimization methods were applied, namely compromise programming, global criterion, and goal programming. However they either consider only one design objective at a time or integrate the two objectives into an aggregated one, and because none are based on a Pareto-optimality concept, only one single design solution can be identified. As a result, it is not surprising that they reported that no optimal solution exists due to the conflicting nature of the design objectives involved. Tuhus-Dubrow & Krarti (2010) also develop a simulation-optimization tool based on DOE-2 and GA to minimize the energy consumption and LCC of residential buildings.

On the other hand, cost and occupant comfort level have been considered in a few studies. Wright & Alajmi (2005) develop a multi-objective model to optimize HVAC system design and control parameters with two design objectives: to minimize the operating cost for the design days and to minimize thermal discomfort. A single zone lumped capacitance model is used to represent thermal response, and thermal discomfort is represented by the index of predicted percentage of dissatisfied occupants (PPD) (ISO, 2005). In a study by Magnier & Haghighat (2010), thermal discomfort and energy consumption are the two design objectives. Thermal discomfort is represented by the PPD index and energy consumption is assessed from an artificial neural network trained and validated from a dataset of base building model created in TRNSYS. This evaluation approach for energy consumption is much faster than directly running TRNSYS.

Although the optimization models reviewed above could contribute to the better design of sustainable buildings, two major limitations undermine their application in practice. The first is that the design objectives adopted in previous studies are incomplete. Cost, environmental impact and occupant comfort level in terms of IEQ are critically important criteria in sustainable building design. However, the previous related optimization models reviewed so far consider only a maximum of two design objectives from within the abovementioned three essential design objectives. Occupant comfort level is largely neglected in previous optimization models compared with the other two design objectives probably due to its difficulty in quantification, as the human sensation of comfort is inherently uncertain and vague. Therefore, most previous relevant optimization models do not reflect the whole picture. The second limitation is that the IEQ representation of occupant comfort level is incomplete. For the studies that have incorporated occupant comfort level into optimization models, only thermal comfort is included, as quantitatively evaluated by the indexes of predicted mean vote (PMV) and PPD. This is incomplete because thermal comfort contributes only partially to the overall comfort level towards IEQ. Other aspects such as visual comfort and indoor air quality are also important dimensions constituting IEQ.

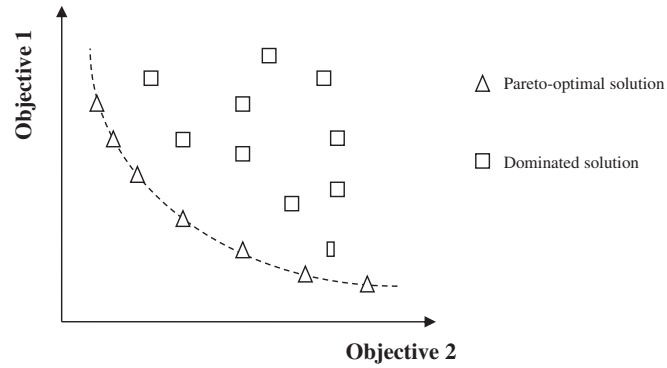

Fig. 1. Pareto-optimal and dominated solutions (two objective functions).

Multi-objective optimization

The design problem presented in this paper is a multi-objective optimization problem. Multi-objective optimization, as its name implies, is the process of systematically and simultaneously seeking one or more best solutions with respect to two or more objective functions. Multi-objective optimization problems are fundamentally different from single objective optimization problems. Single objective optimization identifies only one globally optimal solution. However, multi-objective optimization problems often involve multiple competing, conflicting and incommensurate objectives, i.e. improvement in the performance of one objective unavoidably incurs deterioration in the performance of another objective. Therefore, it is impossible to find one globally perfect solution that simultaneously achieves the optimal value of each objective function. In the multi-objective context, a solution Y is said to be dominated by another solution X, if (i) X is not worse than Y in all objectives; and (ii) X is strictly better than Y in at least one objective (Deb, 2001). A solution is said to be non-dominated or Pareto-optimal if it is not dominated by any other solutions in the entire solution space. All the Pareto-optimal solutions in the entire solution space constitute the Pareto-optimal set of solutions, or Pareto front, and they are located on the boundary of the solution space (Fig. 1). As a result, the aim of multi-objective optimization is to locate the Pareto-optimal set of solutions.

The GA is adopted to solve the sustainable building design optimization problem in this paper. The GA borrows the concept and principle of natural selection and utilizes it in optimization. In GA terminology, a solution is called an individual or a chromosome. A chromosome consists of discrete units called genes. The decision variables that comprise the solution are likened to the genes that the chromosome consists of. For sustainable building design optimization, the equivalence between a design solution and the chromosome representation in GA is schematically shown in Fig. 2. The objective functions are similar to the environmental conditions controlling natural selection and thus determining the fitness of a chromosome. The GA starts by randomly generating an initial population of solutions within the solution space, encodes them into chromosomes, and then uses genetic operators to approach the global optima based on fitness (Goldberg, 1989). The GA is particularly suitable for solving multi-objective optimization problems because it deals with a set of solutions simultaneously that enables it to locate a

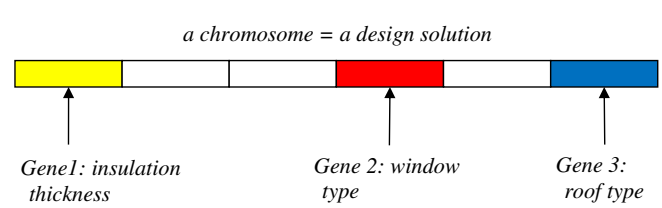

Fig. 2. Sustainable building design solution represented in a chromosome in GA.

series of Pareto-optimal solutions in a single run, which is superior to classical methods. In addition, the proficiency and efficiency of the GA are not affected by the shape and continuity of the Pareto front of the optimization problem, no matter whether convex or non-convex, continuous or discontinuous (Coello, 1999). Moreover, the GA is also capable of handling complex problems with other features such as multimodality (with multiple optimal solutions, many of which are local optima), disjoint feasible spaces and noisy function evaluations (Fonseca & Fleming, 1995).

In this paper, NSGA-II, a MOGA method developed by Deb et al. (2002), is selected for the optimization model. NSGA-II has two major innovations in comparison with other multi-objective GA methods. The first innovation is that non-dominated fronts are identified through a fast non-dominated sorting algorithm with much higher computational efficiency than the conventional sorting algorithm. The second innovation is that it introduces a crowding distance comparison to preserve diversity and eliminates the need for user-specified sharing parameters such as niche size so that the optimization outcome is not affected by the values of sharing parameters (a major drawback in other multi-objective GA approaches). In addition, NSGA-II utilizes elitism to enhance the probability of creating better offspring solutions and thus increase searching efficiency. It has been shown that NSGA-II outperforms other widely used contemporary MOGAs embedded with diversity preservation and elitism features in terms of nearness to the true Pareto front and diversity of the solutions (Deb et al., 2002).

Building energy performance simulation

The energy performance of a building is dependent upon the characteristics and dynamic interaction of building elements, external weather conditions, internal climate settings, mechanical and electrical systems, and occupant behavior. Such characteristics and interaction are usually very complicated and building energy performance simulation (BEPS) is the only means available to assess energy performance characteristics of a building design scheme (Thomas, 2002). Hong Kong performance-based BEC also stipulates the use of a "computer-based hour-by-hour, full-year, multiple-zone" BEPS program for modeling and simulating design energy and the energy budget (EMSD, 2007a, 2007b).

Taking cooling energy demand as an example to illustrate the concept of BEPS, the cooling load of a building originates from two sources—external and internal. A building absorbs external heat from solar radiation, conductive heat gains and infiltration of hot air. On the other hand, the occupants, lights, computers and other electrical equipment within the building also generate heat. Therefore, energy is demanded for cooling the building to maintain a comfortable and productive indoor environment (Hui, 2011). The amount of energy needed to maintain a stable indoor temperature under the exposure of various forms of heat gain can be computed via a heat balance calculation that takes into account all types of heat flows from the building envelope, fenestration, people, equipment, air movement, etc., into and out of the building (Thomas, 2002). To obtain a measure of annual energy consumption, the heat balance calculation has to be repeated over the year at a selected time step, usually one hour, amounting to a total of 8760 hourly repetitions. In addition, the heat balance equations are usually in the form of complex partial differential equations that can only be solved by numerical methods. Due to the iterative and complex nature of the process, computer programs must be used to forecast the energy use of a building design scheme (EMSD, 2007b). In this case, energy consumption is estimated by a BEPS program, EnergyPlus 7.1.

Model development

Design variables

The design variables of the model are related to either the building envelope or an operational setting of the indoor environment. The building envelope consists of exterior walls, roofs, doors, windows, skylights, and walls and floors in contact with the ground (EMSD, 2007b). Typical envelope-related design variables include the type of window, window-to-wall area ratio and exterior wall insulation. Typical operational setting-related design variables include air temperature, air velocity, ventilation rate with outdoor air and relative humidity.

The exact formation of design variables varies case-by-case and may be dependent on the specific requirements imposed by the design team. For instance, in the later design stages when the configurations and values for all building elements and operational settings except for the type of window have already been decided, then the type of window is the only design variable to solve. However, at a much earlier design stage, the design team is faced with a plethora of envelope elements and operational settings of which the configurations and values are undecided, so that everyone is a design variable. Therefore, the first step of optimization modeling is to establish the exact formation of the design variables.

Previous research suggests that, in building design optimization, the design variables can be divided into two groups, discrete and continuous. Discrete variables only take a finite number of values from a discrete set such as the type of window, while continuous variables take infinite number of values from the real line, such as the temperature setting for air conditioning and wall insulation thickness (Wang et al., 2005; Hamdy et al., 2011; Magnier & Haghighat, 2010). However, classifying design variables as continuous is infeasible in practice due to lack of precision of the installation machinery and systems. In practice, the so-called continuous variables change in steps and are therefore essentially discrete. For example, the minimum step of change in a temperature setting that we can be made to most split-type air conditioners for residential apartments is 1 °C. Hence, all design variables are assumed to be discrete.

Design objectives and the evaluation methods

The model considers three design objectives: (i) minimization of cost; (ii) minimization of energy consumption; and (iii) maximization of occupant comfort level in terms of better IEQ. This section examines approaches to representing, assessing and quantifying these three design objectives.

Design objective 1—cost

Cost is an eternal concern for any projects that involve initial capital outflow. One unique feature of sustainable buildings is that the initial capital investment is usually higher than conventional, and merely code-compliant counterparts (Kibert, 2008). However, in the long run, the extra expenditure incurred in the initial capital outlay of sustainable buildings can be recouped within a relatively short period due to reduced energy consumption (Kibert, 2008).Therefore, in the model, the evaluation of cost takes into account all of types of cost incurred throughout the building's life cycle. This starts with the initial capital investment in design and construction of the building, through operating and maintenance expenses, and ultimately end-of-life expenses or salvage value associated with the disposal of the building. By evaluating economic performance over the course of a building's useful life span, LCC provides a comprehensive and consistent framework for discerning the true economic benefits of sustainable building (Kats et al., 2003).

The underlying principle of LCC is to discount costs incurred in different life stages back to the present level using a discount factor and thus create common ground for comparing the costs associated with different design alternatives of sustainable buildings. The general LCC equation (Fuller & Peterson, 1995) is expressed as Eq. (1).

$$LCC = C_0 + \sum_{1}^{N} \frac{C_i}{(1+d)^i} - \frac{R_N}{(1+d)^N} \tag{1}$$

where

C_0	initial capital investment.
N	life span of the building, in years.
C_i	sum of all relevant costs occurring at year *i*.
R_N	end-of-life residual value of the building.
d	discount rate used to adjust cash flow to present value.

Design objective 2—energy consumption

In this model, operational energy consumption is used as the sole surrogate for the environmental impact of a building as it contributes approximately 80% of energy usage (Wong & Mui, 2009a) and releases 90% of the carbon emissions of the whole life cycle of a building (Ayaz & Yang, 2009). The embodied energy of construction materials, energy consumed in transportation, construction and demolition are not considered in the model. As electricity is the predominant energy source for office buildings in Hong Kong (EMSD, 2010), operational energy consumption is represented by electricity consumption in the model. EnergyPlus version 7.1 is adopted for evaluating electricity consumption.

Design objective 3—occupant comfort level in terms of IEQ

The basic function of a building is to serve its occupants by providing and maintaining a safe, healthy and acceptably comfortable indoor environment (Wong & Mui, 2009b). The IEQ of a building, therefore, is closely associated with the well-being of its end users. For example, poor indoor air quality increases the prevalence of Sick Building Syndrome (WHO, 1983; Pommer et al., 2004). On the other hand, improved IEQ can produce various economic benefits. Taking office buildings as an example, in terms of increasing employee productivity, a good IEQ could ultimately improve a tenant corporation's profit. Past studies estimate that the yearly monetary gain of productivity increase due to improved IEQ to be as much as US$38 billion in USA (Fisk & Rosenfield, 1998) and a loss of 2.7 billion Euros due to poor IEQ in Finland (Seppanen, 1999). Other economic benefits from improved IEQ include appreciation of building's market value and probable enhancement of the building's image (Hui et al., 2008). Furthermore, IEQ forms part of the environmental performance evaluation and diagnosis in building environmental assessment and rating tools such as LEED (USGBC, 2009) and HK-BEAM Plus (BEAM Society, 2012). Therefore, due to its importance, the comfort level of the indoor environment is included as a design objective in the model.

The model uses an empirical-based multivariate-logistic regression method developed by Wong et al. (2008) to predict the overall occupant IEQ comfort level of air-conditioned office buildings in Hong Kong. The regression model recognizes that occupant comfort level in terms of IEQ is jointly determined by four separate aspects of thermal environment. These are thermal comfort, indoor air quality (IAQ), acoustic environment and visual environment. The next sections present the formulas for calculating occupant comfort level for each of these together with overall comfort level in terms of IEQ.

Thermal comfort: Thermal comfort, ϕ_1, is calculated using the well-established index of PPD and PMV as Eqs. (2) & (3). Based on a 7-point scale rating system of −3 (cold) to +3 (hot), the PMV index measures the subjective thermal comfort level of indoor thermal environment. The PPD index measures the percentage of people who are dissatisfied with the thermal environment. The relationship between PMV and PPD is plotted in Fig. 3. The PMV and PPD indexes were first proposed by Fanger (1972) to quantify the average sensation of a large group of people concerning the indoor thermal environment. This later developed into an international standard (ISO, 2005). PMV is determined by six factors of (i) indoor air temperature; (ii) relative humidity; (iii) mean radiant temperature; (iv) indoor air movement; (v) occupant metabolism rate; and (vi) clothing level. The formulas for calculating PMV from the six factors are contained in ISO (2005). The formulas for both PMV and PPD are built into EnergyPlus and

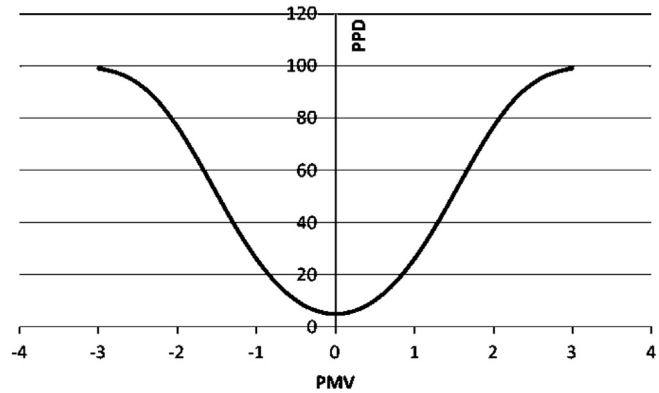

Fig. 3. Relationship between PPD and PMV.

therefore their values can be obtained directly from the simulation output file (Big Ladder Software, 2014).

$$\phi_1 = 1 - \frac{PPD}{100} \tag{2}$$

$$PPD = 100 - 95 \times e^{-\left(0.03353PMV^4 + 0.2179PMV^2\right)}; -3 \le PMV \le 3 \tag{3}$$

Comfort level and IAQ: The comfort level associated with IAQ, ϕ_2, is calculated from CO_2 concentration ζ_2 (in ppm) by

$$\phi_2 = 1 - \frac{1}{2}\left(\frac{1}{1 + exp(3.118 - 0.00215\zeta_2)} + \frac{1}{1 + exp(3.230 - 0.00117\zeta_2)}\right);$$
$$500 \le \zeta_2 \le 1800. \tag{4}$$

CO_2 concentration is used because it is a good indicator of ventilation although not regarded as an indoor air pollutant (Wong et al., 2006).

Acoustic comfort: Acoustic comfort, ϕ_3, is related to the equivalent noise level ζ_3 (in dBA) by

$$\phi_3 = 1 - \frac{1}{1 + exp(9.540 - 0.134\zeta_3)}; 45 \le \zeta_3 \le 72. \tag{5}$$

As this formula is derived from a survey of existing Hong Kong office buildings, whereas the model focuses on new office buildings that are yet to be built, the equivalent noise level of a design solution is hard to predict. As a result, the average value of noise level in Hong Kong office buildings of 56dBA (Wong & Mui, 2009b) is used in the model.

Visual comfort: Visual comfort, ϕ_4, is related to the illumination level ζ_4 (in lux) by:

$$\phi_4 = 1 - \frac{1}{1 + exp(-1.017 + 0.00558\zeta_4)}; 200 \le \zeta_4 \le 1600. \tag{6}$$

Overall comfort: Combining ϕ_1 to ϕ_4, the overall comfort level, θ, is calculated according to:

$$\theta = 1 - \frac{1}{1 + exp(-15.02 + 6.09\phi_1 + 4.88\phi_2 + 4.74\phi_3 + 3.7\phi_4)}. \tag{7}$$

Combining the design objectives

The aim of the optimization model is two-fold: (i) the solutions should be located on the Pareto front (namely Pareto-optimal solutions) or in close proximity to the Pareto front (namely quasi-Pareto-optimal solutions); and (ii) the solutions should be diversely distributed so as to inform the decision-makers of the various design outcomes that can be achieved as well as the trade-off relationship between different design objectives.

This two-fold aim is realized by the process of selection in GA optimization. By denoting a design solution as a chromosome in GA terminology, selection is the process of choosing the better chromosomes for the mating pool and eliminating the worse ones, with the anticipation that two good parent chromosomes can reproduce better offspring chromosomes. In the present model, the selection method adopted is tournament selection, with the size of tournament being 2. This means that for each selection, two chromosomes are randomly chosen from the current generation and entered into the arena for comparison and the better one is selected for the mating pool for the subsequent reproduction process generating the next generation. During the 2-chromosome tournament selection, the two chromosomes are compared in terms of the non-domination rank and the crowding distance, following NSGA-II. The concept of non-domination rank and crowding distance is briefly explained as follows.

For non-dominated solutions, meaning that they are not dominated by any solutions, they are said to belong to the first non-domination front—the Pareto front, and their non-domination rank is set to 1. For those solutions that are only dominated by the solutions in the first non-domination front but not otherwise, they are said to belong to the second non-domination front and, accordingly, their non-domination rank is set to 2. Following the same rule, all the solutions in the same generation can be sorted based on non-domination front and their non-domination rank is set accordingly.

As a major innovation of NSGA-II, crowding distance is capable of well preserving the diversity of the solutions without of the need to specify the value of any diversity preservation-related parameters, for instance, niche size, as commonly adopted in other MOGA methods. Simply speaking, crowding distance measures the average distance of a chromosome from its neighboring chromosomes, i.e. the crowdedness of the neighborhood of a chromosome. The procedure of calculating crowding distance is:

1) Identify each non-dominated front by the Pareto ranking process.
2) For front F_i, assume it contains n solutions: $n = |F_i|$.
3) For each objective f_m, $m = 1, 2, \cdots, M$ (in the present model, $M = 3$
   a. Sort F_i in ascending order with respect to f_m and label them with 1 to n.
   b. The two boundary solutions with minimum and maximum value of m are always assigned infinite crowding distance:

$$f_m(1) = \min(f_m) \, and \, f_m(n) = \max(f_m), cd(1) = cd(n) = \infty \tag{8}$$

For other solutions, the crowding distance is the absolute normalized difference in the objective values of two adjacent solutions:

$$cd(i) = \frac{f_m(i+1) - f_m(i-1)}{f_m(n) - f_m(1)}, \mathrm{i} = 2, 3, \ldots, n-1. \tag{9}$$

```
window =

    'window1'    [1000]    [1400]
    'window2'    [2000]    [1400]
    'window3'    [3000]    [1400]
```

Fig. 5. Demonstration of how cell arrays can be used to store the design variable database.

4) The total crowding distance of a solution is the sum of individual crowding distances for every objective.

After obtaining the non-domination rank and crowding distance of each chromosome in the present generation, the 2-chromosome tournament selection is conducted in the following way. For the two chromosomes, if they have different non-domination ranks, select the one with higher non-domination rank, otherwise select the one with higher crowding distance.

Constraints

The constraints on design variables essentially delineate the bounds of the feasible range of each variable, which is influenced by the market availability of relevant products and applicable codes and regulations.

The constraints on design objectives specify the range of the desired outcome. For instance, the cost objective is usually constrained by a budgetary cap on initial capital investment. In the Hong Kong performance-based building energy code, the constraint imposed on the energy consumption objective is that the designed building must consume less energy than that of a reference building (EMSD, 2007b).

Model framework

The model consists of five modules, namely a design variable database, design objectives evaluation, optimization engine, BEPS program and results storage. Detailed descriptions of the composition and function of each module and the interaction and data flow between different modules are presented in the following subsections.

Module 1—design variable database

The design variable database of contains three forms of data: (i) feasible domains; (ii) unit initial costs; and (iii) quantities. With respect to a specific design variable, the feasible domain consists of the feasible values that it can take, i.e. the types of configuration into which an envelope element can be constructed, or the values to which

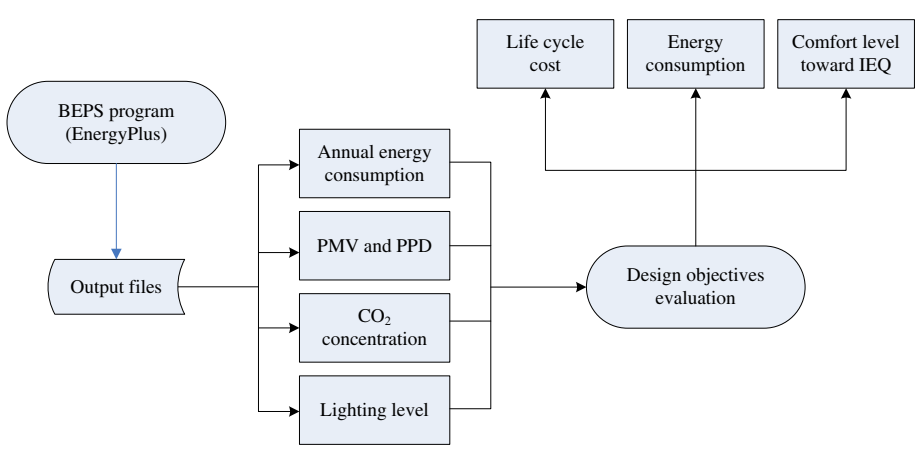

Fig. 4. Data flow between BEPS program and design objectives evaluation.

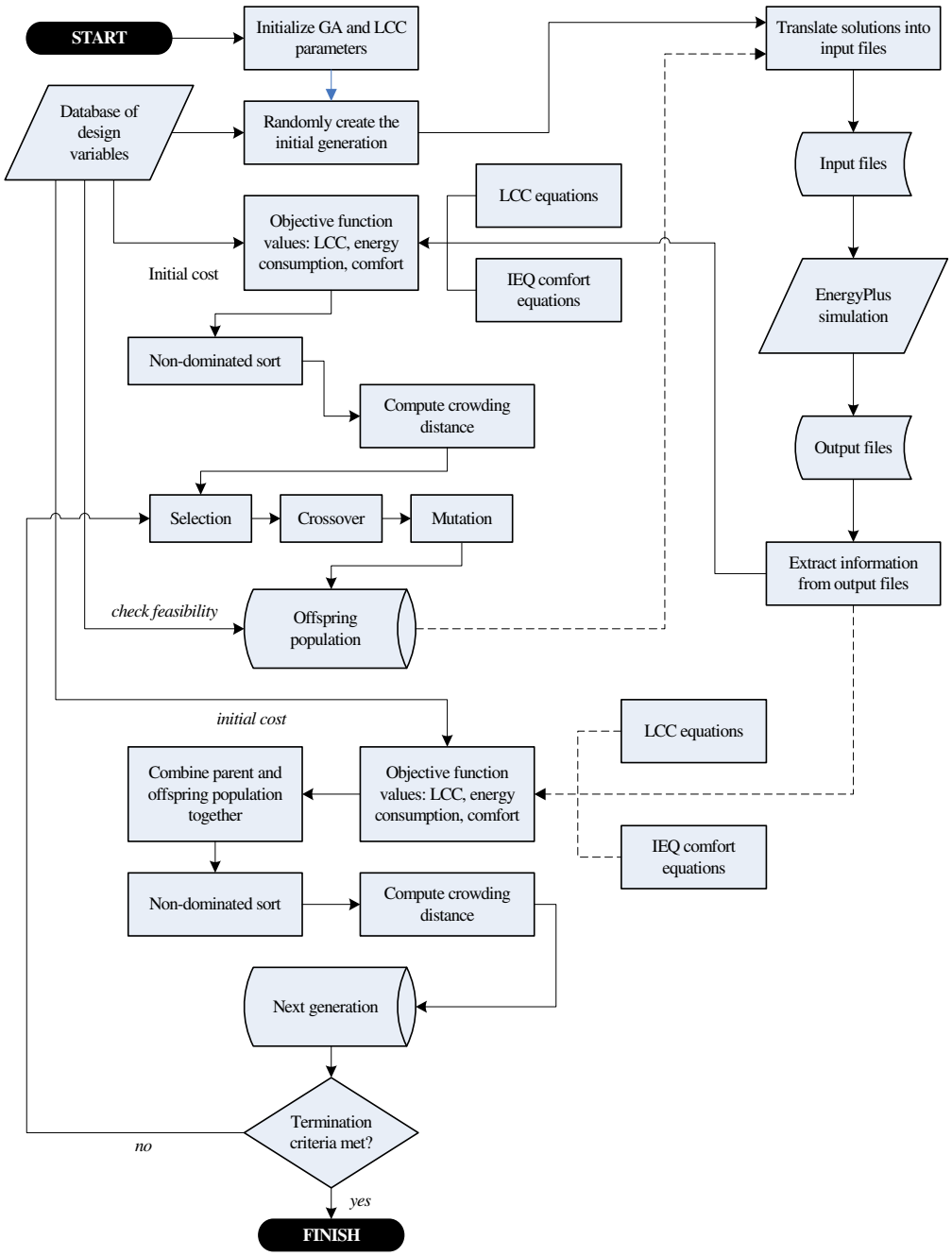

Fig. 6. Flow chart of the BEPS-based optimization process.

an operational setting can be set. Then, for each feasible value, the initial unit cost is the cost required to realize this feasible value for a unit of the design variable and includes the purchasing cost, transportation cost and labor cost of installation. The quantity of the design variable is also stored in the database. However, as operational setting-related variables are non-cost-based, their unit initial costs and quantities are set as zero.

After the design variable database is established, the design space comprising all possible design solutions is also implicitly formed. A possible solution is formed by simply choosing a feasible value for each design variable and combining them together. The size of design space (the number of possible design solutions), is equal to the number of possible combinations of feasible values for each design variable.

Module 2—evaluation of design objectives

The module for evaluating design objectives is responsible for quantitatively evaluating LCC, energy consumption and comfort level in terms of IEQ.

Module 3—optimization engine

The non-dominated sorting genetic algorithm II (NSGA-II), a powerful and efficient multi-objective optimization method developed by Deb et al. (2002), is used as the optimization engine for the model. The optimization engine module is responsible for searching for design solutions that are as close to the true Pareto front and as diversified as possible.

Table 1
Design variables defined in the demonstration.

Design variable	Name	Feasible domain	Unit initial cost	Quantity	No. of feasible values
Envelope-related (type of windows on each façade)					
1	South	Type 1 to type 8 (refer to Table 3)	Refer to Table 3	1391 m^2	8
2	East	As above	As above	927 m^2	8
3	North	As above	As above	1391 m^2	8
4	West	As above	As above	927 m^2	8
Operational setting-related					
5	Cooling temperature set point	19 to 28 °C, step of change is 0.5 °C	0	0	19
6	Relative humidity set point	30% to 80%, step of change is 10%	0	0	6
7	Designed outdoor air ventilation rate	0.008 to 0.015 m^3/s/person, step of change is 0.001 m^3/s/person	0	0	8

Module 4—BEPS program

EnergyPlus version 7.1 is the BEPS program for the building performance simulation. It is responsible for simulating the design solution generated by the optimization engine and outputting the energy consumption simulation results of PMV, PPD, lighting level and CO_2 concentration levels. These are later used to calculate the values of the three design objectives.

Module 5—results storage

The results storage module saves the values of the design variables and design objectives for each design solution of each simulation throughout the GA optimization process.

Inter-module interaction and data flow

Between design variable database and design objectives evaluation: Data relating to unit initial costs and quantities is passed from the design variable database to the design objectives module of evaluation to compute the initial cost, which is subsequently used in the LCC calculation.

Between the design variable database and optimization engine: As the optimization engine is based on the GA, it extracts information on feasible domains from the design variable database to carry out two tasks of the optimization process. The first of these is to create the initial generation randomly. The second task is to check if the variable values of newly formed solutions are within the corresponding feasible domains.

Table 2
Thermal properties and unit initial cost of feasible window types.

Feasible window type	U-value (W/m^2 °C)	Solar heat gain coefficient (SHGC)	Unit initial cost (HK$/$m^2$)
1	6	0.9	780
2	3	0.8	1170
3	1.8	0.75	1500
4	1.4	0.55	1890
5	1.1	0.65	2340
6	0.85	0.4	3100
7	0.55	0.3	3500
8	0.2	0.4	4200

Table 3
Values of LCC and GA parameters.

LCC parameters	GA parameters
o Life span = 10 years (this is the life span of the windows) o Discount rate = 6% o No end-of-life salvage value o Electricity price = $1.446/KWh in 2012 o Escalation rate of electricity price = 3% p.a. o Annual maintenance cost = 10% of initial cost	o Population size = 20 o Maximum number of population = 50 o Mutation rate = 0.02 o Encoding method = binary encoding o Selection method = tournament selection o Size of tournament selection = 2

Between optimization engine and BEPS program: The optimization engine translates the new generation of solutions created through crossover and mutation into corresponding ASCII text input files of the BEPS program. Subsequently, the input files are executed by the optimization engine calling the BEPS program remotely.

Between BEPS program and design objectives evaluation: The output files are generated after simulation by the BEPS program. Relevant information regarding annual energy consumption, PMV and PPD, lighting levels, and CO_2 concentration is extracted from the

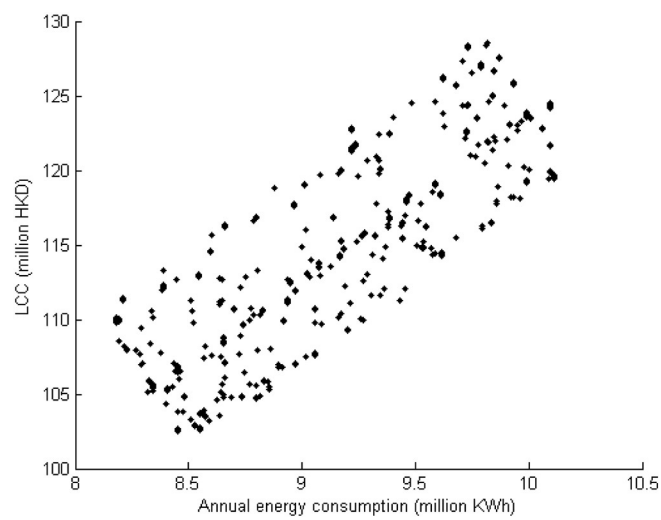

Fig. 7. Trade-off pattern between annual energy consumption and LCC.

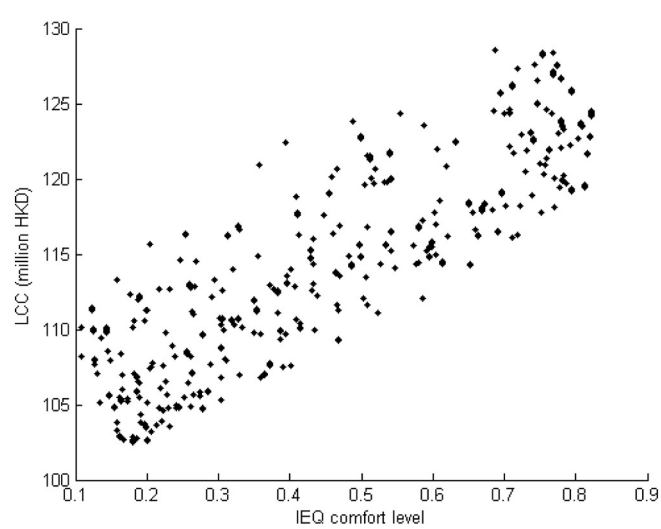

Fig. 8. Trade-off pattern between IEQ comfort level and LCC.

output files and used in the design objectives evaluation module (Fig. 4).

Between optimization engine and design objectives evaluation: The design objectives evaluation module passes the values of the three design objectives to the optimization engine. The fitness of the design solutions is then determined.

Model implementation

Implementation platform

MATLAB is used as the implementation platform as its fundamental data type is a matrix. This is especially useful for GA programming because the main data in GA are chromosomes and objective function values. Therefore, a generation of chromosomes can be represented by a single matrix of size $N \times L$ where N is the number of chromosomes in each generation and L is the length of a chromosome. In C/C++, N one-dimensional arrays of size L are needed to represent a generation. Likewise, the objective function values of a generation can be stored in a single matrix of size $N \times M$ where M is the number of objective functions. Moreover, the objective function matrix can be further appended to the chromosome matrix to form an aggregate matrix of size $N \times (L + M)$. Secondly, MATLAB comes with an extensive library of predefined functions aimed at solving many basic technical tasks, including writing to and reading from ASCII text-based files (Chapman, 2004). This makes coding for the model much easier and more convenient. Thirdly, there is the advanced data type of cell arrays in MATLAB, which are capable of storing data of different types and/or sizes (MathWorks, 2014) and thus all the information of a problem can be grouped together and accessed using a single name (Chapman, 2004). Cell arrays are particularly useful in the model to act as the storage media for the design variable database because feasible values are stored as text strings, while unit initial cost and quantity are stored as numbers. Taking the design variable of type of window as an example, and supposing that it has three feasible types, named 'window1', 'window2', and 'window3'. If the initial unit costs for the three types of window are \$1000/m^2, \$2000/m^2, and \$3000/m^2 respectively, and the total window area is 1400 m^2, then a 3×3 cell array named 'window' can be constructed as illustrated in Fig. 5. Here, the first column contains the feasible window types, the second column contains the unit initial cost for each window type. The third column contains the quantity for each window type which, for this problem, is the same for all three types of window and equal to the total window area.

Elaboration of the BEPS-based optimization process

Fig. 6 provides the flow chart of the BEPS-based optimization process. First, the values of the various GA and LCC parameters are defined. The GA parameters include population size, maximum number of generations, size of tournament, size of mating pool and mutation rate. The LCC parameters include lifespan, discount rate, end-of-life salvage value, energy unit price, annual maintenance cost and inflation rate.

After all relevant GA and LCC parameters are defined, the main loop of the NSGA-II process commences:

1) Randomly create the first generation (size N).
2) Every design solution in the initial population is translated into the EnergyPlus input file and then simulated by EnergyPlus. Useful results such as annual electricity consumption, PMV and PPD values, lighting and CO_2 concentration levels are extracted from the output file generated by EnergyPlus simulation.
3) The values of the three design objectives of LCC, energy consumption and occupant comfort level in terms of IEQ are calculated. LCC is based on initial cost, annual energy consumption and relevant LCC parameters. Energy consumption is simply equal to the annual electricity usage predicted by EnergyPlus. Occupant comfort level in terms of IEQ is obtained from the noise level, lighting level, PMV and PPD values, and the CO_2 concentration level using Wong et al.'s (2008) multivariate-logistic regression method.
4) Subsequently, based on the design objective values, a non-dominated sort is applied to the current generation to divide it into several non-domination fronts.
5) Within each non-domination front, the crowding distance of each solution is computed.
6) Tournament selection is then performed on the current generation to form the mating pool.
7) Crossover and mutation are applied to the mating pool to form the offspring population (size N) and the feasibility of each solution in the offspring population is checked.
8) Every solution in the offspring population is then simulated by EnergyPlus to obtain the values of the three design objectives.
9) The offspring population and the parent population are combined to form a single population (size $2N$).
10) A non-dominated sort is applied and the crowding distance of each solution within each non-dominated front is obtained. The best N solutions in the combined population survive and form the next generation.

Steps (6) to (10) are reiterated until the GA termination criteria are met (the maximum number of generations is reached). The final generation is the desired set of Pareto-optimal solutions.

Model demonstration

A hypothetical case of a Hong Kong office building is used to demonstrate the model. The details of the building are:

- o Building location: Hong Kong
- o Weather file: Hong Kong (available at Department of Energy, US, http://apps1.eere.energy.gov/buildings/energyplus/cfm/weather_data.cfm)
- o Simulation period: whole year (Jan 1 to Dec 31)
- o Number of stories: 12 floors plus a basement
- o Building shape: rectangle
- o Total floor area: 46,320 m^2
- o Aspect ratio: 1.5
- o Azimuth: 0
- o Floor to floor height: 3.96 m
- o Floor to ceiling height: 2.74 m
- o Thermal zoning: core zone with four perimeter zones
- o Exterior walls: mass wall, U-value = 0.85
- o Roof: built-up flat roof, insulation entirely above deck (IEAD), U-value = 0.36
- o Floor: slab on grade
- o Foundation: basement, 100 mm slab with carpet, U-value = 1.85
- o Interior partitions: 50 × 100 mm steel-frame with gypsum board
- o Window to wall ratio: 0.38 for all four facades, all fixed windows, equally distributed
- o Window area
  - ▪ South = north = 1391 m^2
  - ▪ East = west = 927 m^2
  - ▪ Total = 4636 m^2
- o Skylight: none
- o External shading device: none
- o HVAC
  - ▪ System type: MZ-VAV
  - ▪ Heating type: gas boiler
  - ▪ Cooling type: 2 water cooled chillers
  - ▪ Fan control: variable
- o Internal gains
  - ▪ Occupant density: 13 m^2/person
  - ▪ Lighting power density: 20 W/m^2

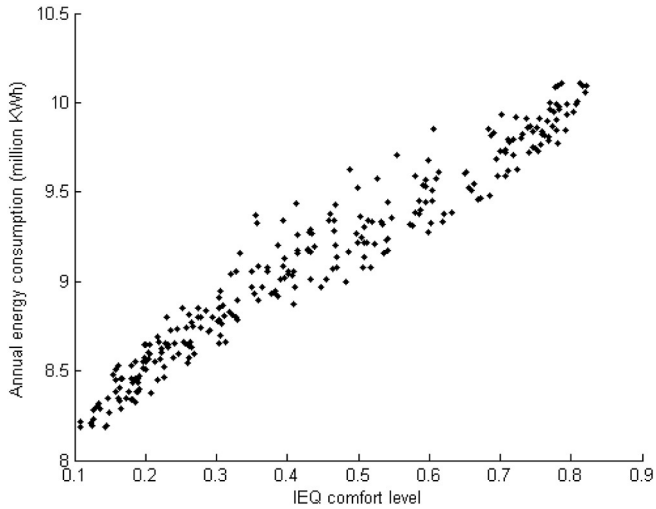

Fig. 9. Trade-off pattern between IEQ comfort level and annual energy consumption.

- Equipment power density: 10 W/m^2
- Operating schedule: see Al-Homoud (1997)

As summarized in Table 1, seven design variables are defined in this problem with 4 being (Nos. 1–4) related to the building envelope and the remaining 3 (No. 5–7) related to operational setting. To simplify the illustration, the envelope-related design variables would consider the type of exterior windows on each façade only, i.e. south, east, north and west. One implicit but conspicuous requirement for the design variable of window types is that the windows should be of the same type on the same façade. Taking the west facing façade as an example, decision-makers cannot select type 1 windows for G/F while using type 2 windows for the floors above. Besides, the three operational setting-related variables are: (i) cooling temperature set point; (ii) relative humidity set point; and (iii) ventilation rate.

The type of windows on each façade can be selected from the following eight feasible types as shown in Table 2.

As a result, the total number of design solutions is $8^4 \times 19 \times 6 \times 8 =$ 3,735,552.

The LCC and GA parameters are summarized in Table 3.

The case project was performed on a computer with the following configurations:

Table 5
Results of design objectives of the final generation solutions.

Solution#	*LCC* (*$ millions*)	*Annual energy consumption* (*million KWh*)	*Comfort level of IEQ*
1	124.14	10.09	0.82
2	102.53	8.45	0.18
3	109.80	8.18	0.14
4	119.46	10.11	0.81
5	124.57	9.59	0.71
6	109.80	8.18	0.14
7	104.78	8.65	0.24
8	110.61	8.83	0.32
9	122.19	9.72	0.71
10	113.44	9.08	0.51
11	118.15	9.96	0.77
12	106.82	8.90	0.36
13	109.96	9.27	0.43
14	103.81	8.47	0.19
15	114.33	9.31	0.58
16	107.75	8.38	0.21
17	107.55	9.06	0.40
18	123.54	9.40	0.59
19	109.90	8.92	0.39
20	116.59	9.51	0.66

- CPU: Intel® Core™ 2 Duo 2.66GHz
- RAM: 1.96GB
- Operating system: Microsoft® Windows XP Professional
- Implementation platform: MATLAB version R2008a

Results and discussion

No constraints are imposed on the design objectives in this demonstration and therefore some extreme trade-off patterns can be observed, e.g. the solution with a high comfort level in terms of IEQ, which also has a high energy consumption value. The time required to perform the optimization for this demonstration problem was approximately 8.4 h, with the majority of the time being spent on EnergyPlus simulation.

Trade-off pattern

Combining the total 1000 solutions generated and evaluated in the GA evolution process, the pair-wise trade-off patterns are plotted in Figs. 7–9. This shows that, pair-wise speaking, the design objectives are positively and linearly related: higher IEQ comfort level demands

Table 4
Values of design variables of the final generation solutions.

Solution#	*South wall window*	*East wall window*	*North wall window*	*West wall window*	*Cooling temperature* (*°C*)	*Relative humidity* (*%*)	*Outdoor air ventilation rate* (*m^3/s/person*)
1	'window8'	'window1'	'window1'	'window5'	'19'	'60'	'0.015'
2	'window1'	'window4'	'window1'	'window6'	'27'	'60'	'0.008'
3	'window7'	'window8'	'window7'	'window7'	'27'	'60'	'0.008'
4	'window1'	'window1'	'window1'	'window5'	'19'	'60'	'0.015'
5	'window7'	'window8'	'window7'	'window5'	'19'	'60'	'0.014'
6	'window7'	'window8'	'window7'	'window7'	'27'	'60'	'0.008'
7	'window1'	'window4'	'window1'	'window6'	'27'	'60'	'0.009'
8	'window1'	'window8'	'window7'	'window1'	'19'	'60'	'0.009'
9	'window1'	'window8'	'window7'	'window5'	'19'	'60'	'0.014'
10	'window7'	'window4'	'window1'	'window6'	'19'	'60'	'0.011'
11	'window1'	'window2'	'window1'	'window5'	'19'	'60'	'0.014'
12	'window1'	'window4'	'window1'	'window5'	'19'	'60'	'0.009'
13	'window1'	'window1'	'window1'	'window5'	'27'	'60'	'0.011'
14	'window1'	'window4'	'window1'	'window8'	'26.5'	'60'	'0.008'
15	'window7'	'window1'	'window1'	'window5'	'19'	'60'	'0.011'
16	'window7'	'window8'	'window1'	'window6'	'19'	'60'	'0.008'
17	'window1'	'window1'	'window1'	'window5'	'19'	'60'	'0.009'
18	'window7'	'window8'	'window7'	'window7'	'27'	'60'	'0.014'
19	'window7'	'window1'	'window1'	'window5'	'19'	'60'	'0.009'
20	'window7'	'window1'	'window1'	'window5'	'19'	'60'	'0.012'

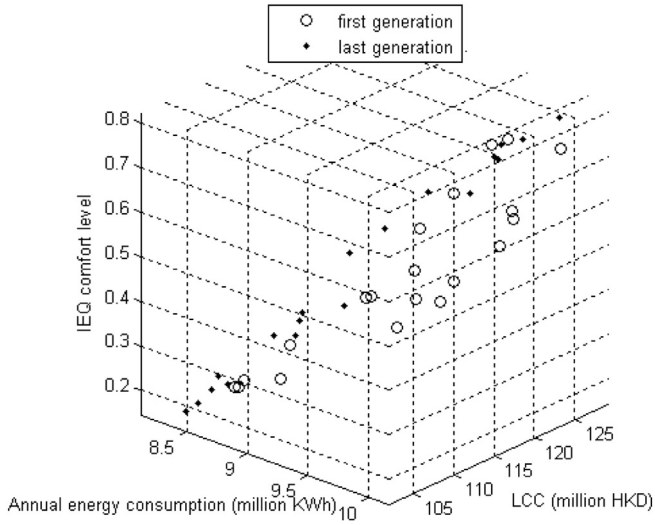

Fig. 10. Comparison of solutions of the first generation and final generation.

higher energy consumption, which then incurs higher LCC. However, compared with the energy consumption—LCC and IEQ comfort levels—LCC pairs, the IEQ comfort level—the energy consumption pair is less scattered and has a higher correlation.

Solutions of the final generation

The values of the design variables and the results of design objectives of the final generation solutions are listed in Tables 4 and 5. These solutions are all Pareto-optimal.

From Table 5, it can be found that some rather extreme design solutions are included, due to no constraints being imposed in this demonstration case. For example, for Solution #3, although it is a very environmentally friendly (8.18 KWh annual energy consumption) and low-budget (109.8 m HKD) design solution, its IEQ comfort level index is only 0.14, the operational settings of which are a 27 °C cooling temperature, 60% relative humidity, and 0.008 m^3/s/person ventilation rate, which is very unrealistic and impossible to implement in Hong Kong's hot and humid sub-tropical climate. On the other hand, decision makers can utilize the final generation solutions in Table 5 for further decision making such as screening out unfeasible solutions by setting a threshold for the design objectives such as a limit on LCC, or locating the ultimate design solution by assigning weights to the three design objectives. For example, if the decision maker provides that the LCC should not exceed 120 m HKD, solutions no. 1, 5, 9 and 18 can be effectively screened out. The trade-off picture as exhibited in the final generation solutions can also provide a referential value to the decision maker when assigning weightings to the design objectives. For example, with respect to solutions no. 1 and 4 both with high IEQ comfort level, the decision maker can see that, in order to slightly increase the comfort level (from 0.81 to 0.82) and decrease energy consumption (from 10.11 KWh to 10.09 KWh), an extra 4.68 m HKD (from 119.46 m to 124.14 m HKD) would be incurred throughout the building life cycle. With the aid of such trade-off information, the decision maker can decide whether it is worthwhile to spend more to ameliorate the environmental-friendliness and IEQ comfort level and this in turn would help shape the decision maker's perception of the relative importance of the three design objectives.

A comparison between the first generation and final generation solutions is made in Fig. 10. This shows that, overall, the last generation outperforms the first generation that is randomly created. However, due to the limitations in showing a 3D plot on 2D paper, the superiority of the last generation over the first generation is not clearly visible.

Conclusions

Optimization as a powerful tool is rarely utilized in practice for building design, despite the benefits of obtaining better design solutions and of providing a more comprehensive knowledge of the whole design space. Although quite a number of optimization models for sustainable building design have been developed in the past, they suffer from the limitation of either not including consideration of occupant comfort level in the optimization process or of using only thermal comfort to partially represent occupant comfort level. In this paper, a new multi-objective optimization model is developed for the design of sustainable Hong Kong office buildings by considering the three design objectives of minimization of cost, minimization of energy consumption and maximization of occupant comfort level in terms of IEQ. The IEQ comfort level is evaluated with a comprehensive statistical model by aggregating the effects of thermal comfort, visual comfort, acoustic comfort and indoor air quality. The case study demonstration indicates that the model could be a useful tool for designers at the conceptual design stage of Hong Kong office buildings. It can be used to derive a set of suitable design solutions in terms of LCC, energy consumption and IEQ occupant comfort level. A further benefit is that, with the help of this tool, building designers can also gain a better understanding of the design space in addition to the trade-off patterns between different design objectives, which is important for interactive design and decision-making. Furthermore, the model can also be used to determine appropriate operational settings to achieve the optimal building performance in terms of minimizing energy consumption and maximizing occupant comfort level.

As the GA process is influenced by the values of relevant GA parameters, such as mutation rate, size of tournament and maximum number of generations, further refinement of GA parameter values is desirable. The performance of other approaches for selection, crossover and mutation also need to be tested to see if better results can be obtained.

As the final output of the model is a set of Pareto-optimal solutions, further research needs the selection of an appropriate design solution from this set. One possibility is that, after the building designers use the model to understand the trade-off pattern between different design objectives from the set of Pareto-optimal solutions, they are able to make an informed judgment on the relative importance of each design objective. In doing this stage, the analytical hierarchy process could be used to determine the pair-wise relative importance matrix and weightings involved. Future research could also extend the optimization process to the whole building design by including more design objectives such as structural robustness and safety.

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