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REPORT

Title: Coupling of Whole-Building Energy Simulation and Multi-Dimensional Numerical Optimization for Minimizing the Life Cycle Costs of Office Buildings

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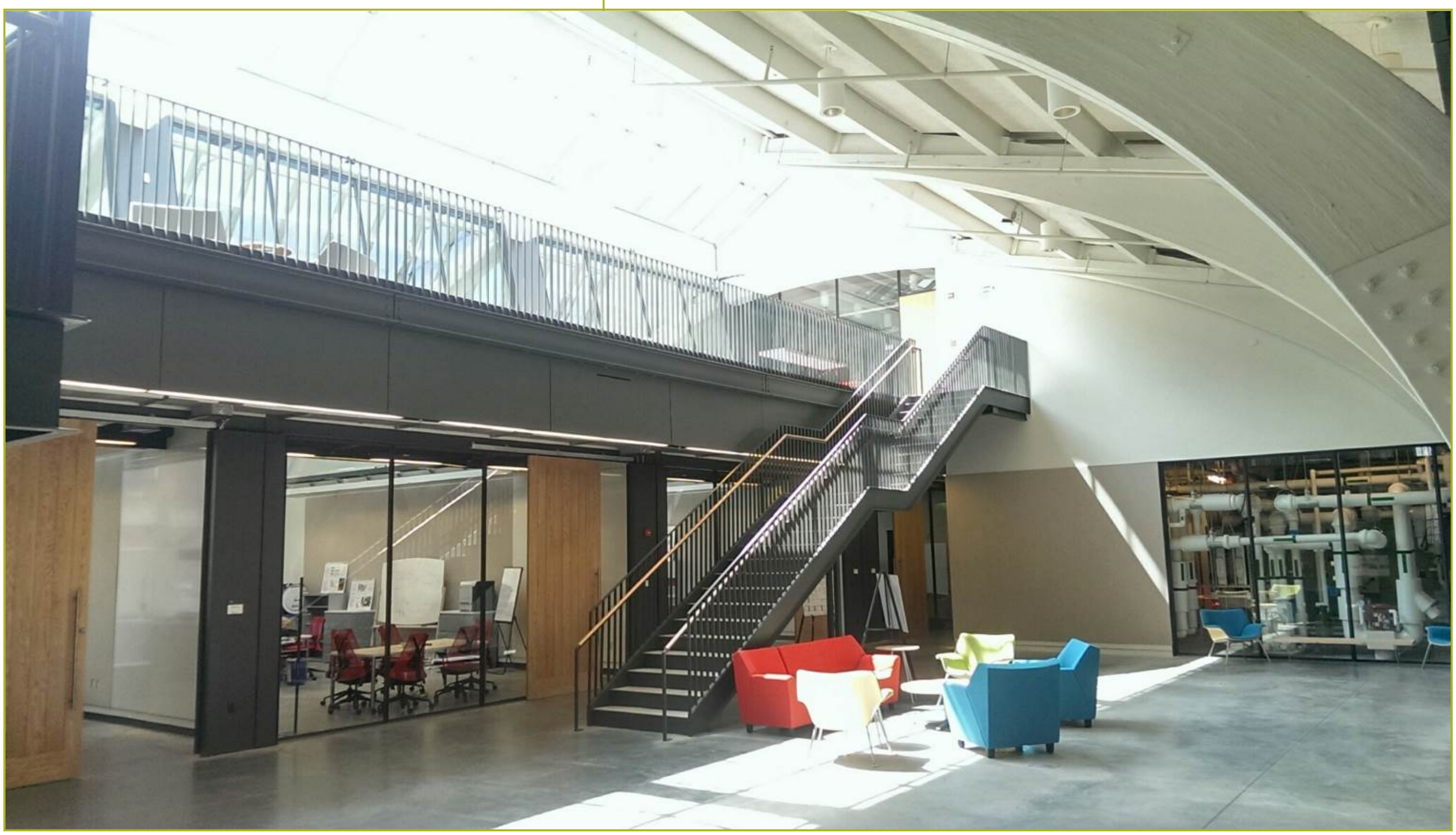

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REPORT

Report Abstract

The paper presents a detailed study on the influence of building envelope upon the building's life cycle performance and optimizes the design of the building envelope con-figurations, based on the detailed results obtained from a computational framework in which the whole-building energy simulation program of EnergyPlus v6.0 is coupled with GenOpt v3.0 generic optimization tool.

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Disclaimer

Research Article

Coupling of whole-building energy simulation and multi-dimensional numerical optimization for minimizing the life cycle costs of office buildings

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Abstract

The minimization of life cycle costs for building materials and operational energy consumption of a reference commercial office building model is achieved through the optimization of envelope design parameters by the use of integrated energy simulation and multi-dimensional numerical optimization techniques. The whole-building energy simulation program EnergyPlus v6.0 is coupled with GenOpt v3.0 generic optimization tool to automatically compute the optimal values of thermal insulation thicknesses for external walls and roofs in addition to glazing unit types for vertical fenestration. A life cycle cost (LCC) model is implemented within the GenOpt program for the objective function evaluation using simulation outputs pertaining to energy consumption and associated utility costs. A stochastic population-based and multi-dimensional optimization technique of Particle Swarm Optimization (PSO) is utilized for searching the parameter space. This algorithm can result in a 36.2% reduction in the computational effort to converge to the global minimum point with a very high degree of accuracy compared to the full enumeration technique. The results indicate that the annual total site energy consumption of the optimized building model is reduced by 33.3% with respect to the initial baseline case. The optimized envelope parameters can yield 28.7% life cycle cost reduction over a 25 years life span with a simple pay-back period of 4.2 years.

Keywords

whole-building energy simulation,
multi-dimensional numerical optimization,
coupling framework,
life cycle cost,
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Building Thermal, Lighting, and Acoustics Modeling

1 Introduction

The building industry is the largest energy consuming sector in many countries and has a substantial impact on the environment. According to the statistics from the U.S. Department of Energy, buildings are currently responsible for approximately 41% of the total primary energy use in the U.S., including 19% for commercial buildings and 22% for residential buildings. Buildings are also responsible for 40% of carbon dioxide emissions in the U.S. (DOE 2011). It is therefore critical and essential for the building industry to improve the energy efficiency levels and provide means for sustainable developments in the built environment. The building delivery process typically involves several complex actions with different characteristics and generally spans a long time period in the magnitude of decades (Braun 2002). In such a lifespan, the building envelope plays a critical role due to its lasting influence on the building's energy and environmental performance throughout the whole life cycle. The selection of construction materials for the building envelopes not only changes the building's primary cost at the construction phase but also impacts the HVAC (heating, ventilating, and air conditioning) systems' energy consumption and costs during the building operation phase.

In conventional building design, the specifications of building envelopes are determined based on either the requirements given in building energy efficiency standards or the rule-of-thumb guidelines gained through the experience of architects (Bichiou and Krarti 2011). Such design approaches which lack parametric and analytical feedbacks tend to ignore the influence of the optimized building envelope features on building's life cycle energy performance. Furthermore, the simulation-based parametric analysis for the determination of optimum design choices for the building

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envelopes is at best conducted using a one-factor-at-a-time (OAT) approach. This is a single-dimensional approach where the designer tries to optimize an objective function with respect to changing a single variable while keeping all the other variables as constant. Such a parametric procedure is then iterated for another variable. However, as indicated by Wetter (2001), each time a variable is changed other variables typically become non-optimal and also need to be adjusted. This time and labour intensive procedure becomes impractical for multi-parameter/multi-dimensional optimization approaches (e.g., building envelope optimization) where interactive effects of multiple design parameters on building energy performance need to be evaluated. The building envelope specifications implemented in the conventional and/or simple parametric building design approaches may not be the optimal choice and have potentials for further improvements in both accuracy and computational effectiveness in terms of number of simulation iterations for convergence on the global optimal point.

As computational performance modelling become more prevalent in building research, simulation-based multi-dimensional building design optimization techniques have been increasingly studied in recent years. Al-Homoud and Degelman (1994) proposed one of the earliest examples of an optimization framework which identifies best design solutions satisfying minimum energy requirements while maintaining thermal comfort in the occupied spaces. This framework was exemplified by linking simple transient thermal simulation engine with a relatively simple optimization technique of Nelder and Mead suitable for unconstrained optimization problems. Peippo et al. (1999) introduced an optimization scheme which involves a large number of different design options including building shape, thermal insulation, windows, daylighting, and photovoltaic systems. Optimal design options are identified where a cost analysis (for material investments and energy costs) is used to evaluate objective functions values. Demonstrated simulation models are relatively simple in terms of building geometry (shoe-box models) and calculations of heat transfer through the envelope. The optimization technique was Hooke and Jeeves which is deterministic in nature and requires increased number of simulation iterations resulting in slow convergence. Similar approaches are also seen in the works of Bouchlaghem (2000) and Al-Homoud (1996). Some researchers also investigated optimization problems using integrated and whole-building simulation programs. For instance, Christensen et al. (2003) utilized DOE-2.1E program in a life cycle cost (LCC) optimization problem for net zero energy buildings. In their study, the cost optimization technique was aimed at balancing increased first costs in the building enveloped with the reduced future costs (net present value of the costs) from operational energy consumption. The iterative simulations can only be controlled by Visual Basic programming without resorting to well-structured numeric optimization methods. Mertz et al. (2007) also utilized a similar optimization technique introduced by Christensen et al. (2003) which is a hybrid and modified version of parallel and sequential search. They calculated life cycle costs for alternative energy efficiency strategies under the constraint of net-zero and CO_2-neutral energy levels. Energy simulations are conducted using ESim software which is based on fundamental thermodynamic and psychrometric and heat-transfer algorithms. Verbeeck and Hens (2007) introduced a global multi-objective optimization methodology which takes into account multiple objective functions of energy savings, environmental impact and financial costs over a specified life cycle of low energy buildings. The proposed method relies on the use of commercial TRNSYS thermal engine as well as the Matlab mathematical programming tool. This can be costly in terms of required expertise and investments on these commercial tool sets. The economic and computational cost issues can also be seen in the work of Tuhus-Dubrow and Kararti (2010) where the solution to a building design optimization requires similar complex mathematical tools of Matlab and Perl. On the other hand, Wetter and Wright (2004) introduced the platform of GenOpt which allows coupling the state-of-the-art energy simulations engines (e.g., EnergyPlus) with sophisticated and effective optimization techniques in an extensible and open-source environment where all incorporated tools are non-commercial and non-propriety. Exemplified methods only focus on the design optimization for reduced annual energy consumption for HVAC and lighting. Current version of this platform does not contain functions for life cycle costing. Hasan et al. (2008) achieved minimization of the life cycle costs of a single family detached house through coupled simulation (using IDA ICE 3.0 software) and optimization using GenOpt platform. However, their approach accomplishes the calculation of LCC within the simulation tool throughout the iterative simulations which limits the application of the approach to other tools and restricts the extension of the proposed optimization framework.

This paper presents a detailed study on the influence of building envelope upon the building's life cycle performance and optimizes the design of the building envelope configurations, based on the detailed results obtained from a computational framework in which the whole-building energy simulation program of EnergyPlus v6.0 (BTP 2011) is coupled with GenOpt v3.0 generic optimization tool (LBNL 2011). Coupling tools for the solution of the selected optimization program are highly automated (thereby saving user effort), non-commercial, open-source and readily extensible. The optimization technique used in this study is the population-based stochastic particle swarm optimization (PSO) which is an effective technique (for building design problems) evolved through several decades (Wetter and Wright 2004). An office building case for the U.S. context (DOE 2011) is purposely selected to generate results that have a higher level of generalizability (instead of one-of-a-kind solution set with limited usability). Furthermore, this study provides a new approach of extending the source code of GenOpt platform with a standard and well-known life cycle costing model. Hence, the updated GenOpt tool can be linked to any simulation engine (having a text-based input-output structure) and applicable to a wide-range of building design optimization problems as opposed to methods that are functional only within a specific setting. The proposed framework can be executed using the existing user interface of GenOpt requiring no additional scripting to automate the iterative simulations.

With the introduced framework, this study exemplifies specifying the optimized values of thermal insulation thicknesses for external walls and roofs as well as the glazing unit types for vertical fenestration. Life cycle cost analysis is used to quantify the impact of building envelopes in both the building construction phase and the operational phase. The optimization problem in this study is formulated as a multi-dimensional single-objective optimization type which addresses the sum of life cycle costs over a 25-year time period for building materials and operational energy as the objective function value to be minimized. Validation of the optimization algorithm is then conducted by comparisons with results obtained from a brute-search method in which full enumeration of the parameter space is realized. The proposed approach can be applied to an increased number of design variables to generate guidance for both the new building design and existing building retrofit projects.

2 Reference building model

As mentioned, the building model implemented in this study is a medium-sized commercial reference office building provided by the U.S. Department of Energy Building Technologies Program. This model is selected from a database containing 16 hypothetical reference building definitions developed to represent new commercial building stock meeting the minimum requirements given in ANSI/ASHRAE/IESNA Standard 90.1 (ASHRAE 2004). These building definitions are given in the form of whole-building energy simulation models that are compatible with the EnergyPlus program (Deru et al. 2006).

This reference model is a three storey commercial office building with a total conditioned floor area of 4982 m^2. As shown in Fig. 1, the building shape is rectangular with an aspect ratio of 1.5 with long axis facing north-south orientation. Vertical fenestrations are in the form of horizontal strip windows uniformly distributed to each orientation and window-to-wall ratio is about 33%.

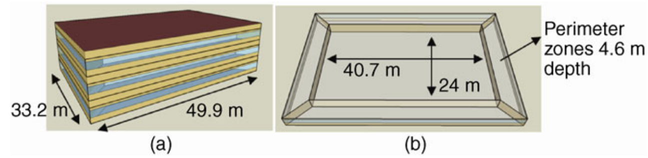

Fig. 1 Overall geometry of the building: (a) 3D exterior view; (b) plan layout from a typical floor indicating the perimeter vs. core thermal zoning approach

The model consists of 15 thermal zones configured according to perimeter–core zoning approach. The HVAC system is a packaged single duct multi-zone variable air volume (VAV) type with three gas furnaces, 15 electric terminal reheats, and three differential dry-bulb economizers. Gas burner efficiency is 80% and cooling coils have a rated COP of 3.2. System fans are variable volume type with efficiency of 0.59 at maximum 1109 Pa pressure rise. The heating set-point is 21℃ with a setback of 15.6℃, while the cooling set-point is 24℃ with a setback of 26.7℃ during unoccupied times of the day. The total office occupancy is 268 people with a maximum density of 5.38 per 100 m^2 which is modulated at each simulation time step to represent typical hourly occupancy schedules, as shown in Fig. 2.

The reference model is assumed to be equipped with electric lighting system with a power density of 10.76 W/m^2 which is also assumed for electric plug loads. Two elevators at 20 HP are deployed for vertical transportation within the building with a total power of 32.1 kW. Occupancy, electrical equipment and lights are the sources of office space heat gains following the occupancy profiles indicated in Fig. 2. Air infiltration is assumed only for exterior facade area of perimeter zones at the rate of 0.002 $m^3/(sec{\cdot}m^2)$. This rate is assumed to be 25% of its maximum during operation of the mechanical ventilation system. The reference office model is simulated under the environmental boundary conditions for the location of Chicago, IL, USA (41°N, 87°W) which is

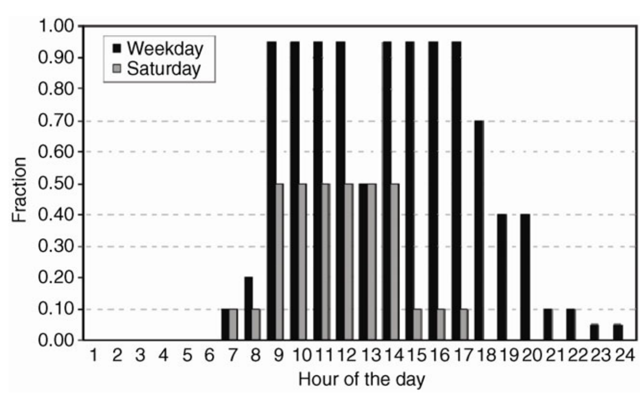

Fig. 2 Hourly occupancy profiles for typical medium-sized office buildings

classified as ASHRAE Climate Zone 5A. According to the TMY III (Typical Meteorological Year) weather file, Chicago has a heating dominated, cool and humid weather conditions with annual heating and cooling degree days of 506 and 3430, respectively (with respect to 18℃ baseline). Annual average of maximum solar radiation on a horizontal surface is reported as 8.12 and 1.8 kWh/m^2 for direct and diffuse components, respectively.

3 Investigated design variables

The objective of this study is to propose an open-source computational approach for minimizing the life cycle costs of building envelope system investment and building energy system operation. Focus is given to key components of external envelope assemblies constituting the building systems of external walls, roofs, and vertical fenestration. The design variables subjected to the optimization procedures are thermal insulation thickness (cm) of external walls and roofs and glazing unit types with varying U-factor (W/(m^2·K)), Solar Heat Gain Coefficient (SHGC), and Visible Transmittance (V_T) performance specifications. Among other possible design measures, the specific ones mentioned above are chosen as a result of preliminary multi-variate sensitivity analyses which indicated that thermal insulation thicknesses and glazing types are responsible for the significant portion of variability in the output of heating and cooling energy consumption for medium-sized offices under heating dominated climates along with infiltration rates (Karaguzel and Lam 2012). However, infiltration rate variable is excluded from this study due to a lack of cost data associated with envelope air tightness measures. The proposed computational framework has the flexibility of being applied to a wider range of design variables with increased cardinality at the expense of computational resources.

3.1 Thermal insulation of external walls and roof assemblies

External wall construction of the reference model is composed of an insulated steel frame with wood siding and gypsum wall board (GWB) finish on the outer and inner surfaces, respectively. Thermal insulation layer is positioned at the core of this assembly, the thickness of which is varied from 0.00 cm to 15.24 cm with 2.54 cm intervals while keeping all other external wall layers unchanged during parametric perturbations. Extruded polystyrene (XPS) rigid insulation is chosen to be the insulation material, the properties of which are derived from ASHRAE material data set (ASHRAE 2005). The insulation layer has a thermal conductivity of 0.028 W/(m·K), density of 29 kg/m^3 and a specific heat of 1210 J/(kg·K). This layer is assumed to have a medium smooth surface characteristic with solar and visible absorptance of 0.6 while the thermal absorptance is assumed as 0.9 for EnergyPlus models.

So as to conduct life cycle cost minimization, the optimization inputs are defined as the unit material cost for each different design variant obtained from the U.S. RS Means Cost Database (Cost Works 2012) as shown in Table 1.

Cost items for XPS rigid insulation are identified with three distinct categories for material thicknesses from 2.54 cm to 7.62 cm associated with varying thermal resistance values (i.e., R-factors). Identified costs in Table 1 only represent "bare material" costs excluding the items of labor and overhead costs and benefits. R-0.0 resistance level represents existing buildings that may be subjected to energy retrofit studies. R-0.8 resistance level achieved with 2.54 cm of XPS rigid insulation represents ASHRAE 90.1-2004 (ASHRAE 2004) compliance for external walls for the Climate Zone 5A. Preliminary multi-variate parametric simulations revealed R-5.2 as the critical thermal resistance level beyond which increment in insulation thickness produces marginal efficiency gains in space heating energy consumption. Therefore, R-5.2 level and a corresponding thermal insulation thickness are taken as the upper limit of the parametric set for the variable category of external wall insulation.

Roof construction of the reference office model is built-up flat roof type with insulation entirely above deck (IEAD) configuration according to ASHRAE 90.1-2004 specifications. XPS insulation for roof decks with varying thicknesses from 2.54 cm up to 15.24 cm is assumed for the simulation models. Unit costs of insulation materials are obtained from the U.S. RS Means Cost Database (Cost Works 2012) which provides unit costs for four different XPS roof deck insulation materials (Table 2). Existing office buildings that need energy retrofit are represented by R-0.8 resistance level. ASHRAE 90.1-2004 compliant roof assemblies are identified with R-2.6 level and the upper limit is selected as R-5.2 representing the critical point after which diminishing returns on energy efficiency gains are observed during preliminary parametric analysis.

Table 1 Material cost structure for external wall thermal insulation variants

Parametric expression	Thickness (cm) (inch)	Configuration (cm)	Unit cost ($/m^2)	R-factor (m^2·K/W)
W_0	0.00 (0″)	0.00	0.00	R-0.0
W_1	2.54 (1″)	2.54	5.40	R-0.8
W_2	5.08 (2″)	5.08	10.75	R-1.7
W_3	7.62 (3″)	7.62	15.50	R-2.6
W_4	10.16 (4″)	7.62+2.54	20.90	R-3.5
W_5	12.70 (5″)	7.62+5.08	26.25	R-4.4
W_6	15.24 (6″)	7.62+7.62	31.00	R-5.2

Table 2 Material cost structure for roof thermal insulation variants

Parametric expression	Thickness (cm) (inch)	Configuration (cm)	Unit cost ($/m^2)	*R*-factor (m^2·K/W)
R_1	2.54 (1″)	2.54	4.74	R-0.8
R_2	5.08 (2″)	5.08	9.48	R-1.7
R_3	7.62 (3″)	7.62	10.79	R-2.6
R_4	10.16 (4″)	10.16	12.10	R-3.5
R_5	12.70 (5″)	7.62+5.08	18.45	R-4.4
R_6	15.24 (6″)	7.62+7.62	24.80	R-5.2

3.2 Glazing unit types

Six different glazing unit types are taken into consideration to cover a range of systems from single clear monolithic to double clear and low-E coated insulated glazing units (IGUs) with varying overall thicknesses. Unit material costs (bare material only) are obtained from the U.S. RS Means Cost Database (Cost Works 2012). Within the glazing alternatives, single clear type represents existing buildings that need energy retrofit measures. ASHRAE 90.1-2004 compliance can be achieved with double clear 16 mm glazing unit. 25 mm thick double low-E on both panes represents the high-performance glazing unit alternative for vertical fenestrations of office buildings.

The required EnergyPlus simulation model inputs for window assemblies equipped with the optimization alternatives given in Table 3 are first generated within WINDOW 6.3 program (LBNL 2012) by selecting representative glass panes and gas types from the current International Glazing Database (IGDB v22). Developed window assembly model definitions are then exported to EnergyPlus as individual text-based IDF (Input Definition File) blocks which are integrated with whole-building models to be used alternatively during parametric perturbations. Table 4 lists the selected glass and mid-pane gas types from IGDB with their database identifier numbers so as to develop window assembly models within WINDOW 6.3 program.

Table 3 Material cost structure for glazing unit type variants

Parametric expression	Glazing unit alternative	Unit cost ($/m^2)	Center-of-glass *U*-factor (W/(m^2·K))	Performance indices: SHGC	Performance indices: V_T
G_1	Single clear glazing	58.0	5.82	0.817	0.886
G_2	Double clear—16 mm thick	140.0	3.44	0.699	0.791
G_3	Double clear—25 mm thick	168.0	2.68	0.703	0.791
G_4	Double low-E—16 mm thick	276.0	2.97	0.600	0.763
G_5	Double low-E—25 mm thick	280.0	1.80	0.596	0.763
G_6	Double low-E—25 mm both panes coated	320.0	1.38	0.557	0.737

Table 4 IGDB glass and mid-pane gas types for selected glazing unit alternatives

Parametric expression	Glazing unit alternative	Glazing unit combination with IGDB ID number (#)
G_1	Single clear glazing	5012
G_2	Double clear—16 mm thick	5012+1(4mm air)+5012
G_3	Double clear—25 mm thick	5012+1(13mm air)+5012
G_4	Double low-E—16 mm thick	5235+1(4mm air)+5012
G_5	Double low-E—25 mm thick	5235+1(13mm air)+5012
G_6	Double low-E—25 mm both panes coated	5235+1(13mm air)+5235

4 Methodology: Integrated-simulation based optimization

4.1 EnergyPlus–GenOpt coupling framework

The integrated-simulation based optimization procedure proposed in this study is accomplished by coupling the whole-building energy simulation program of EnergyPlus v6.0 with GenOpt v3.0 (Wetter 2011), a JAVA-based extensible generic optimization program. GenOpt incorporates a range of multi-dimensional numerical optimization algorithms that can be coupled to any simulation program that has a text-based input/output (I/O) structure (e.g., EnergyPlus). GenOpt avoids modifying the source code of the coupled simulation programs through the use of such a text-based I/O integration approach. This program is designed for numerical optimization problems where the evaluation of objective function is computationally expensive (as in the case of whole-building energy simulation) and derivatives of this function (non-existing formula for determination of the gradient) are not available or not even existing (i.e., treating the simulation program as a black-box in the optimization set-up). Independent design variables accepted by GenOpt can be continuous, discrete (integer programming), or a combination of both. Constraints of independent variables are implemented as constraint sets (i.e., box constraints) while dependent variables can be constrained using penalty or barrier functions. GenOpt is a single-objective optimization program and does not provide functionality for extracting the Pareto front through a single optimization run under multi-objective criteria.

The framework of EnergyPlus–GenOpt coupling for iterative simulation runs is given in Fig. 3. The GenOpt kernel requires a number of input files that have to be customized by the user following a predefined syntax, so as to launch the coupling simulation program which is responsible for calculating the objective function and the model response on the specified grid points. After a

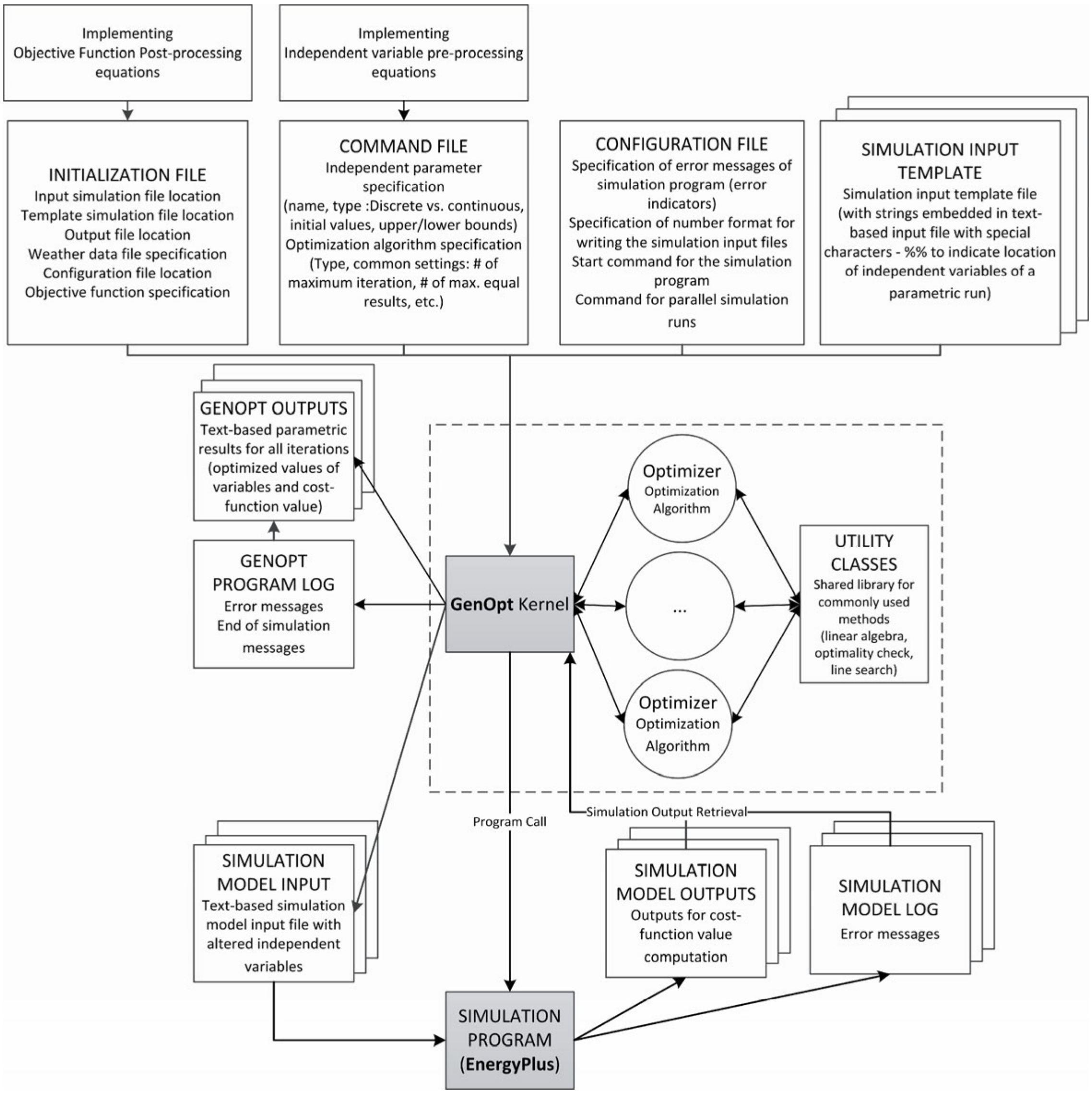

Fig. 3 EnergyPlus–GenOpt coupling framework for simulation-based optimization (Adapted from (Wetter 2011))

simulation cycle, GenOpt reads the objective function value from the text-based outputs of the program in various file types (e.g., CSV, ESO, or HTML files of EnergyPlus outputs) after checking possible simulation errors which can be used to terminate the iterative cycle. This process is followed by GenOpt's specification of another set of input design variables for the next simulation cycle. The built-in optimization search algorithms are responsible for the specification of this new parameter set. The entire process is repeated until a minimum objective function value is found or after a certain stopping criterion imposed on the system.

In the current optimization set-up, EnergyPlus is iteratively called by GenOpt for the calculation of objective function value which is in turn evaluated by the internal numerical optimization methods for the determination of the values of independent variables, as shown in the coupling framework in Fig. 3. With the integration of these techniques, this study proposes a systematic and automated optimization platform with multi-dimensional optimization algorithm coupled to a detailed and integrated energy simulation program.

4.2 Formulation of the optimization problem

The office envelope design problem of the study is taken as a single objective multi-dimensional optimization problem which can be stated as

$$\text{Given} \quad f : \boldsymbol{X} \to \mathbb{R}(f : \mathbb{Z}^{n_\mathrm{d}} \to \mathbb{R}) \tag{1}$$

$$\text{Find} \quad \min_{x \in X} f(x) \tag{2}$$

$$\text{Subject to} \quad \boldsymbol{X} \triangleq \{ x \in \mathbb{Z}^{n_\mathrm{d}} \mid x^i, i \in \{1, \ldots, n_\mathrm{d}\} \} \tag{3}$$

where $x \in \boldsymbol{X}$ is defined as the vector of independent variables, $f : \boldsymbol{X} \rightarrow \mathbb{R}$ is the objective function to be minimized and $\boldsymbol{X} \subset \mathbb{Z}^{n_d}$ is the constraint set. All envelope design parameters are specified as discrete independent variables that can only take pre-defined discrete values defined in $\mathbb{Z}^{n_d}$. The optimization problem can be defined as box-constrained integer programming without equality or inequality constraints on the dependent variables. Since GenOpt conducts single-objective optimization, the solution is the minimum value of $f(\cdot)$ in the domain of $\mathbb{R}$. Three categories of building envelope measures (wall insulation, roof insulation and glazing types) are involved in the analysis, so this optimization set up is three-dimensional ($n_d = 3$).

Constraint sets for the independent variables are defined as

$$x^1 = \{W_j, j \in \{0,...,6\}\} \tag{4}$$

$$x^2 = \{R_k, k \in \{1,...,6\}\} \tag{5}$$

$$x^3 = \{G_l, l \in \{1,...,6\}\} \tag{6}$$

External wall insulation alternatives are factored into the optimization problem as 7 discrete independent variables represented as a constraint set with a finite number of elements, as stated in Eq. (4). Similarly, roof insulation and glazing unit type alternatives are represented as 6 discrete independent variables, as stated in Eq. (5) and Eq. (6), respectively.

The number of intervals (sizes of sets for box constraints) for each independent variable category can theoretically be unlimited. However, the dimension of the current optimization problem (number of different independent variable categories) can be increased to the limit of $n_d = 9$ at most due to the computational limitations of the existing algorithms within GenOpt program's optimizer library (Wetter 2011).

The objective function equation is given as

$$f(x) = \mathrm{IC_M} + \mathrm{LCC_E} \tag{7}$$

The LCC of the building case is taken as the present value of material investments and operational energy costs of HVAC and other building systems over a specified life span. This model excludes the material replacement costs due to relatively shorter life span for this LCC analysis. Replacement costs calculations are usually factored in the LCC analyses with longer than 25 years life span, which can be investigated with an alternative model we have already developed and implemented within the GenOpt program. The mathematical model for the calculation of $f(\cdot)$ is adapted from (Hasan et al. 2008) as the sum of initial material investment costs ($\mathrm{IC_M}$) and energy life cycle costs ($\mathrm{LCC_E}$). $\mathrm{IC_M}$ is the sum of all initial unit bare material costs multiplied by applicable building surface area (opaque or transparent) and is automatically calculated by EnergyPlus. $\mathrm{LCC_E}$ is the net present value of operational energy costs over a specified time period and calculated as below (Hasan et al. 2008):

$$\mathrm{LCC_E} = a e_p E \tag{8}$$

$$a = 1 - (1 + r_e)^{-n} / r_e \tag{9}$$

$$r_e = (i - f / 1 + f) - e / 1 + e \tag{10}$$

where:

a is the discount factor for inflation and escalation in energy prices (different a-factors are defined for natural gas and electricity consumption),

e_p is the current utility rate for a fuel source ($/kWh),

E is the simulated annual cumulative energy consumption for the building case alternatives (kWh),

n is the life span of the building, i.e., the life cycle cost analysis period (year),

r_e represents the real interest rate (including the effect of escalation in energy prices),

i is the nominal interest rate,

f is the inflation rate.

Input parameters for the LCC model of this study are summarized in Table 5.

The LCC model explained above is implemented into the GenOpt algorithm library by source code extensions and re-compiling this program as an executable JAR file. The updated GenOpt is capable of computing LCC of a building case by the use of a number of user-defined constant variables as shown in Table 5 and post-processing of dependent variables including simulated energy cost values and material costs.

EnergyPlus object "ComponentCost:LineItem" is used to define unit bare material costs for each discrete design variable. These entries are then associated with specific building surfaces containing respective material. This allows EnergyPlus to automatically calculate total building material cost taking into consideration all the building surfaces. The calculated costs are obtained from CSV (Comma Separated

Table 5 Input parameters of the LCC model

LCC model variable	Expression	Value	Unit
Life span	n	25	year
Inflation rate	f	2	%
Escalation rate	e	1	%
Utility rate*	e_p	0.154 (electricity) 0.0291 (natural gas)	$/kWh
Nominal interest rate	i	7	%

* Obtained from (BLS 2011)

Value) files that are provided by EnergyPlus and then parsed by GenOpt using specific pre-defined delimiters at each cycle of the automated optimization set up.

4.3 Optimization algorithm

The optimization algorithm utilized in this study is Particle Swarm Optimization (PSO) in the optimizer library of GenOpt. This algorithm is a type of meta-heuristic population-based and stochastic optimization techniques proposed by Eberhart and Kennedy (1995).

The principal reasons for selecting PSO algorithm for the current optimization problem can be listed are:

1) PSO makes no assumption about the problem being optimized (does not require approximate gradient of the objective function).
2) PSO can handle non-linear, non-differentiable functions. Therefore, PSO is a suitable algorithm to couple with EnergyPlus simulation engine which includes heat balance solution algorithms (for the calculation of the objective function value) which can be discontinuous and not provide derivatives at every point.
3) PSO appears to be more suitable for problems with discrete variables (due to the concept of particles). Due to the nature of building based design decisions, all independent variables of this study are discrete which can take on certain values.
4) PSO has a computationally less intensive mathematical structure and shows relatively faster convergence.

The basic PSO formulation can be given as (Wetter and Wright 2004):

$$v_i(t+1) = v_i(t) + c_1 r_1[\hat{x}_i(t) - x_i(t)] + c_2 r_2[g(t) - x_i(t)] \quad (11)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (12)$$

The position of a particle randomly generated particle (i) at the current iteration (t) is updated to the next iteration ($t+1$) by the addition of a velocity component ($v_i(t+1)$), a cognitive component ($c_1 r_1[\hat{x}_i(t) - x_i(t)]$), and a social component ($c_2 r_2[g(t) - x_i(t)]$). The velocity component is updated based on inertia component ($v_i(t)$) that keeps particle moving in the same direction that it was previously moving; the cognitive component is affected by the particle's own memory (cognitive behaviour) for the regions of the search space in which it experiences lowest objective function values; and the social component forces particle to move to regions which contain the smallest objective function experienced by all members of the swarm (social behaviour). r_1 and r_2 are random values for stochastic operations. c_1 and c_2 are user defined coefficients that can affect the movement of particles with respect to social and cognitive influences. PSO evaluates the objective function value at a finite set of points (coined as *particles*) which are randomly generated. The social behaviour of flocks of birds or schools of fish are used as a guiding principle for the change of each particle from one iteration to the next. The movement of a particle is a combined effect of its cognitive and social behaviour. Each new generation of particles is formulated by individual velocity and position updates until a stopping criterion is reached. The mechanism of particle update in PSO algorithm is illustrated in Fig. 4 (Mikki and Kishk 2008).

Since all enclosure design options are represented by discrete independent variables in this study, PSO on Mesh algorithm is used within GenOpt v3.0 environment. Table 6 summarizes the PSO algorithm parameters used for the optimization runs.

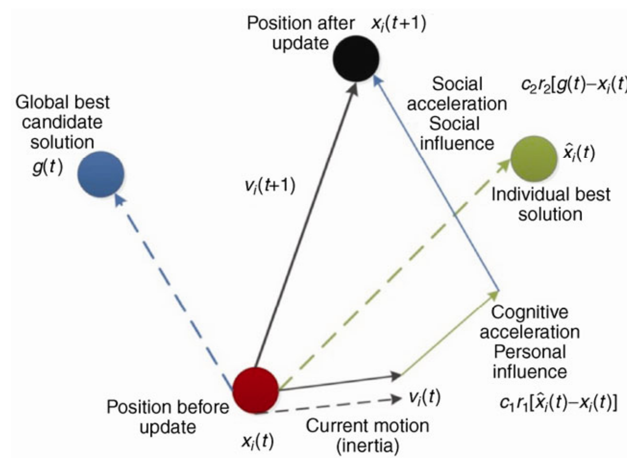

Fig. 4 The mechanism of particle update in the PSO algorithm (Adapted from (Mikki and Kishk 2008))

Table 6 PSO algorithm parameters for the optimization

Algorithm parameter	Value/ attribute	Algorithm parameter	Value/ attribute
Neighbourhood topology	Von Neumann	Cognitive acceleration	2.8
Neighbourhood size	3	Social acceleration	1.2
Number of particles	12	Constriction gain	0.5
Seed for random number generator	0	Maximum velocity (discrete PSO)	4
Number of generations	10		

5 Optimization results and discussions

Since the current study is focused on single-objective optimization of the total LCC of a reference office building case, a single solution is generated as the outcome. This is the design combination that provides the lowest LCC and can be referred as the best iterate (x^*). In this case, the best iterate is found as

$x^* = \{W_6, R_5, G_5\}$ (global minimum point)

This is the design option having 15.24 cm (6″) of external wall insulation, 12.70 cm (5″) of roof insulation and equipped with 25 mm thick double low-E IGU. The total life cycle cost (over a 25 years period) for this solution is $3 054 576 which is composed of life cycle natural gas and electricity cost (associated with all building energy systems) and initial material investment costs, as shown in Fig. 5.

The global optimum model solution demonstrates that for an office building case, choosing the "best" material specification alternative for all design choices (such as the model with W_6, R_6 and G_6 combination) does not necessarily provide the best overall design choice in terms of life cycle costs over a long run. Hence, the optimal point (combination of W_6, R_5, G_5) indicated by this simulation-based optimization study (with a relatively lower dimensionality) can be unintuitive to the designers and such a solution may not be reached through simple heuristics and/or expert judgment. The unique contributions of such analytical feedbacks can be enhanced in more extensive optimization studies with increased degrees of freedom as well as cardinality.

It can be seen from Fig. 5 that about 91% of the LCC is due to the electricity consumption over the analysed life span. This is due to the fact that about 95.1% of total annual site energy consumption of this case is from electricity. Natural gas is only used partly for space heating and service water heating systems. Furthermore, material LCC only includes initial investments and no replacement is taken into account during the 25-year analysis period.

Results of optimization runs revealed that initial/baseline case (x_b) and the maximum point (x_{max}) are the same for this study:

$x_b = x_{max} = \{W_0, R_1, G_1\}$ (global maximum point)

The initial case model has external walls with R-0 thermal insulation, 2.54 cm (1″) of R-0.8 roof insulation, and windows with single clear glazing units. The total LCC for this model

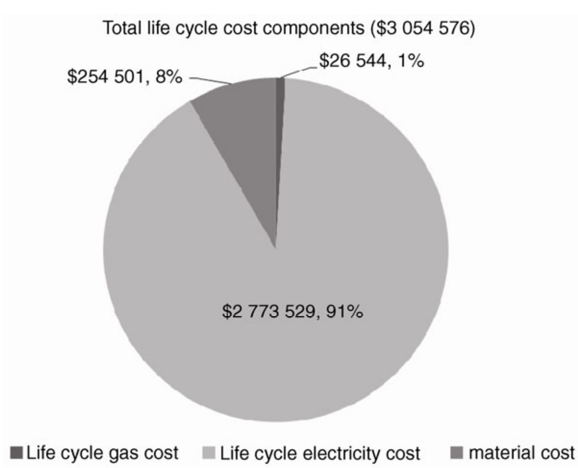

Fig. 5 LCC components of the global minimum point x^* (best iterate)

alternative is about $4 289 633 as shown in Fig. 6. Both the best and worst iterate (global minimum and maximum points) have the LCC for electricity as the largest portion of the total LCC.

After identification of maximum point and the best iterate we can provide the normalized cost reduction (NCR) value (Wetter and Wright 2004) computed from

$$\mathrm{NCR} = [f(x_b) - f(x^*)]/f(x_b) \quad (13)$$

The normalized cost reduction (NCR) is found to be 0.287 through optimization of building envelope parameters discussed in this study. Further cost analysis reveals that the optimum design case has a construction material cost differential of 208 766 USD over the initial case. However, such an investment can provide a savings (net present value) of 1 235 057 USD. Such a cost structure indicates a simple pay-back period of 4.2 years for the extra investment dedicated to improvements on wall, roof thermal insulation and glazing unit types. The comparison of annual site energy consumptions of the best iterate and the initial case (which is also the maximum point) from EnergyPlus simulation results is shown in Table 7.

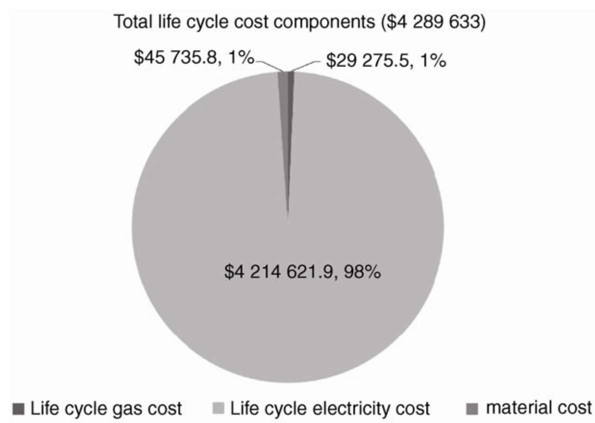

Fig. 6 LCC components of the global maximum point x_{max} (worst iterate)

Table 7 Comparison of annual site energy consumption (by end-use breakdowns)

End-use category	Energy use intensity (kWh/m^2) x^* (minimum point) (best iterate)	Energy use intensity (kWh/m^2) x_{max} (maximum point) (worst iterate)	Percent deviation (worst to best iterate) (%)
Space heating	22.0	89.1	−75.3
Space cooling	18.3	24.8	−26.2
Fans & pumps	4.61	7.41	−37.8
Lights & equipment	46.8	46.8	0.0
Service water heating	2.0	2.0	0.0
TOTAL BUILDING	153.1	229.6	−33.3

Optimized design solution shows 75.3% energy use reduction for space heating and 26.2% for space cooling with respect to the maximum point. An energy reduction up to 33.3% can be achieved with optimized design at total building level due to the fact that building envelope measures only affect space heating, cooling and fan energy consumptions while all other end-uses remain constant between different design alternatives. Electricity is the main energy source for both cases and all end-uses except space heating and service water heating relies on electricity. 93.3% of energy consumption is from electricity source for the maximum point/initial case and 75.5% for the best case, which is due to the specified HVAC system configuration for the reference building model.

6 PSO algorithm verification and computational resource costs

To check the effectiveness of PSO algorithm in finding the global optimum instead of sticking to local minima, the full enumeration method is applied in this study by the use of MESH algorithm of GenOpt v3.0 (Wetter 2011). Given the dimension of optimization problem ($n_{\mathrm{d}} = 3$) and the number of the discrete independent variables (7 walls, 6 roofs, 6 glazing unit types), the full enumeration (exhaustive search) of the design parameter space requires 252 EnergyPlus simulation runs. The MESH algorithm simply spans a multi-dimensional grid in the space of the independent parameters and evaluates the objective function at each and every grid point (Wetter 2011). The PSO algorithm identified the global optimum (with given variable set and using the algorithm parameters in Table 6) with 161 EnergyPlus simulation runs. Therefore, only 63.8% of the entire design parameter space is necessarily enumerated to locate the population minimum point.

Comparison of PSO optimization with full enumeration results showed that the global minimum can be detected by PSO with a very high degree of accuracy for this particular case. Multiple runs of the same problem with PSO provide the same minimum point to the one that is obtained through full enumeration of the search space. A single annual EnergyPlus simulation run takes about 88.7 seconds on a PC with 2.67 GHz CPU and 16.0 GB installed RAM. So as to reduce the time dimension of the computational effort to execute optimization models, parallel processing functionality of GenOpt program was used. GenOpt provides a batch file (RunEPlusParallel.bat) which can initiate multiple EnergyPlus program simultaneously with a minor code modification needed to indicate the correct version of the program being initiated. Meanwhile, a necessary setting within EnergyPlus executable model was made such that the number of allowable simultaneous EnergyPlus processes is equal to the number of CPU cores existing in the computer executing the optimization model. Multiple threads can then be assigned to a single optimization task that can significantly reduce the computation time. In this study, the full enumeration runs executed on an 8-core machine result in about 46.5 minutes of total iteration run time, while the PSO algorithm requires only 29.75 minutes to converge to the global minimum point, which means that the computing time can be reduced by 36.0%.

7 Conclusions

Minimization of total building life cycle cost (including initial material costs and life cycle operational energy costs) of a reference medium size office building over a 25-year time period is conducted through integrated simulation-based optimization technique in this study. A computational coupling framework for the EnergyPlus whole-building energy simulation program and GenOpt generic optimization tool is implemented to achieve the goal. Three main categories of building envelope retrofit measures are taken into consideration as discrete independent variables to be investigated, namely, external wall thermal insulation thickness (from zero to 15.24 cm with 2.54 cm increments), roof thermal insulation thickness (from 2.54 cm to 15.24 cm with 2.54 cm increments) and glazing types (from single clear to double, with/without low-E with different overall thickness).

Main findings of this study can be listed are:

1) Design option with 15.24 cm (6″) and 12.7 cm (5″) of wall and roof insulation and 25 mm thick double low-E IGU is found to be the optimum design solution for the medium-sized commercial reference office building in the ASHRAE Climate Zone 5A.
2) The optimum design solution can yield a 28.7% life cycle cost reduction ($1 235 057 reduction) over a 25 years life span. Simple pay-back time for the investment differential imposed by the optimum solution is 4.2 years.
3) The PSO algorithm implemented in the parametric setup shows satisfactory performance in terms of accuracy and efficiency. It can result in a 36.2% reduction in the computational effort to converge to the global minimum point with a very high degree of accuracy compared to the full enumeration technique.
4) The optimal design solution suggested by the implemented approach indicates that choosing the “best” specification from all design options does not necessarily provide the best overall design solution in terms of life cycle costs over a long run. This implies the possible potentials of simulation-based optimization as a design decision support method in terms of detecting the global optimum design choices which are otherwise ignored or unrecognized due to inefficient and conventional methods of simple heuristics or even certain “expert” judgments.

This integrated simulation-based optimization framework can be applied to any type and size of building case for new construction and advanced energy retrofit (AER) projects. The tools utilized in this framework are open-source and non-commercial products. The modular and open-source programming architecture can be extended and/or updated to calculate customized objective functions values in order to serve different aspects of building design decision making. Future development work for this study will include further refinement of the PSO algorithm parameter so that the optimization can converge to global minimum with even less number of simulation iterations. Cardinality and dimensionality of the problem can be expanded by increasing the number of intervals for the constraint sets of existing variables and by adding other building envelope measures to the formulated design optimization problem.

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References

Al-Homoud M, Degelman LO (1994). The framework of an optimization model for the thermal design of building enveloped. In: Proceedings of the 9th Symposium on Improving Building Systems in Hot and Humid Climates. Arlington, TX, USA, pp. 100 – 109.

Al-Homoud M (1996). Optimum thermal design of air-conditioned residential buildings. *Building and Environment*, 32: 203 – 210.

ASHRAE (2004). ANSI/ASHRAE Standard 90.1-2004: Energy standard for buildings except low-rise residential buildings. Atlanta: American Society of Heating, Refrigeration and Air-Conditioning Engineers.

ASHRAE (2005). ASHRAE Handbook of Fundamentals. Atlanta: American Society of Heating, Refrigeration and Air-Conditioning Engineers.

Bichiou Y, Krarti M (2011). Optimization of envelope and HVAC systems selection for residential buildings. *Energy and Buildings*, 43: 3373 – 3382.

Braun JE (2002). An inverse gray-box model for transient building load prediction. *HVAC&R Research*, 8: 73 – 99.

BLS (2011). Focus on Prices and Spending. US Bureau of Labor Statistics. http://www.bls.gov/opub/focus/home.htm. Accessed 10 Nov. 2012.

Bouchlaghem N (2000). Optimising the design of building envelopes for thermal performance. *Automation in Construction,* 10: 101 – 112.

BTP (2011). EnergyPlus Energy Simulation Software. U.S. DOE Building Technologies Program. http://apps1.eere.energy.gov/buildings/energyplus/. Accessed 10 Nov. 2012.

Christensen C, Stoltenberg B, Barker G (2003). An optimization methodology for zero net energy buildings. In: Proceedings of 2003 International Solar Energy Conference, Hawaii, USA, pp. 93 – 100.

Cost Works (2011). Online RS Means Building Construction Cost Data-book. http://www.meanscostworks.com/. Accessed 15 Jan. 2012.

Deru M, Griffith B, Torcellini P(2006). Establishing Benchmarks for DOE Commercial Building R&D and Program Evaluation. California: National Renewable Energy Laboratory.

DOE (2011). Building Energy Data Book.U.S. Department of Energy. http://buildingsdatabook.eren.doe.gov/.Accessed 10 Nov. 2012.

Eberhart RC, Kennedy J(1995). A new optimizer using particle swarm theory. In: Proceedings of the6th International Symposium on Micro Machine and Human Science. Nagoya, Japan, pp. 39 – 43.

Hasan A, Mika V, Siren K(2008). Minimization of life cycle cost of a detached house using combined simulation and optimization. *Energy and Buildings*, 48: 2022 – 2034.

Karaguzel OT, Lam KP (2012). Simulation-based parametric analysis, Part II: Multi-variate exhaustive evaluation of enclosure measures for Building 661. Technical Report Submitted To: Greater Philadelphia Innovation Cluster (GPIC) for Energy-Efficient Buildings (The U.S. DOE Award # EE0004261). Carnegie Mellon University. Pittsburgh, PA, USA.

LBNL (2011). GenOpt–Generic Optimization Program. Lawrence Berkeley National Laboratory. http://simulationresearch.lbl.gov. Accessed 10 Nov. 2012.

LBNL (2012). Window 6.3 Program. Lawrence Berkeley National Laboratory. http://simulationresearch.lbl.gov. Accessed 10 Nov. 2012.

Mertz GA, Raffio GS, Kissock K (2007). Cost optimization of net-zero energy house. In: Proceedings of Energy Sustainability 2007 Conference, Long Beach, CA, USA, ES2007 – 36077.

Mikki SM, Kishk AA(2008). Particle Swarm Optimization: A Physics-Based Approach. San Rafael, CA, USA: Morgan & Claypool Publishers.

Peippo K, Lund PD, Vartiainen E (1999). Multivariate optimization of design trade-offs for solar low energy buildings. *Energy and Buildings*, 29: 189 – 205.

Tuhus-Dubrow D, Krarti M(2010). Genetic-algorithm based approach to optimize building envelope design for residential buildings. *Building and Environment*, 45: 1574 – 1581.

Verbeeck G, Hens H (2007). Life cycle optimization of extremely low energy dwellings. *Journal of Building Physics*, 31: 143 – 177.

Wetter M (2001). GenOpt—A generic optimization program. In: Proceedings of 7th International IBPSA Conference. Rio de Janeiro, Brazil, pp.601 – 608.

Wetter M (2011). GenOpt—Generic Optimization Program User Manual Version 3.1.0. Simulation Research Group, Building Technologies Department, Lawrence Berkeley National Laboratory, Berkeley, CA, USA.

Wetter M, Wright J (2004). A comparison of deterministic and probabilistic optimization algorithms for non-smooth simulation-based optimization. *Building and Environment*, 39: 989 – 999.