Energy and Buildings 79 (2014) 223–231

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

Variability of optimal solutions for building components based on comprehensive life cycle cost analysis

Guiyuan Han [a,*], Jelena Srebric [a], Elena Enache-Pommer [b]

[a] Department of Architectural Engineering, Pennsylvania State University, University Park, PA, USA
[b] Dow Building Solutions R&D, Midland, MI, USA

A R T I C L E I N F O

Article history:
Received 6 February 2013
Received in revised form
30 September 2013
Accepted 8 October 2013
Available online 31 December 2013

Keywords:
Life cycle cost
Building energy
Optimization
Enclosure system
Mechanical system

A B S T R A C T

Building energy contributes to a significant fraction of the total energy cost during all processes of its life span. Buildings are dynamic, non-linear systems with a large number of components that strongly influence total building energy consumption. Therefore, it is challenging to find an optimal combination of building components to minimize the building life cycle cost (LCC). This paper proposes a framework of building systems optimization designed to minimize life cycle cost by combining optimization algorithms and a comprehensive building life cycle cost model. A case study based on an office building demonstrates that annual energy costs and initial construction costs are major contributors to the whole building life cycle cost. A case study of an office building shows that when the building lifespan is greater than 30 years, the cumulative annual energy consumption cost is projected to be higher than the initial construction cost. Finally, optimal component combinations vary with different lengths of a building's life span. For instance, wood window frames become the optimal component for less energy and maintenance cost when the building lifespan changes from 14 to 60 years.

1. Introduction

Building energy contributes to a significant fraction of the total national energy cost during a building's lifetime. In developed countries, building energy consumption represents 20–40% of total national energy use and this percentage is above the industry and transportation figures in EU and the US. The growing trend in building energy consumption will continue during the coming years due to building floor area expansion and associated energy needs [1]. Buildings have relatively long life spans. In the U.S., the median lifetime of commercial buildings is 50–65 years [2]. In addition, buildings are dynamic, non-linear systems with a large number of components that strongly affect building energy consumption. This complicates optimizing total building energy consumption. Several specific components that contribute strongly to total building life cycle cost (LCC), most notably building enclosure and mechanical systems [3].

Life cycle assessment (LCA) is a methodological framework for estimating and assessing the environmental impacts attributable to the lifecycle of a product [4]. Following the definition and guidance in the International Organization for Standardization (ISO) 14040 [5], building life cycle includes construction, annual operation and maintenance, and demolition. The cash flow during these phases contains construction capital cost, transportation cost, annual operating energy consumption, maintenance cost, and demolition cost.

2. Literature review

2.1. Building life cycle analysis

A large number of LCA tools have been developed for designers and researchers to analyze life cycle cost, such as BEES, ATHENA EcoCalculator, ATHENA Impact Estimator, and SimaPro [6]. The existing LCA tools are designed for different levels of flexibility and detail. However, as shown in Table 1, every existing LCA tool is missing one or more analysis aspects of building life cycle analysis. Therefore, this study proposes a comprehensive methodology that covers all the phases of the building life cycle.

The data used in the existing LCA tools are mostly based on built-in life cycle inventory databases. However, building energy consumption is not only determined by building materials, but also by building profile and location. The proposed methodology combines a dynamic building energy simulation for annual operating energy consumption and a built-in database containing information regarding other costs. The building energy simulation will consider envelope profile, mechanical system type, and building location.

* Corresponding author. Tel.: +1 8147532821.
E-mail addresses: goh5067@psu.edu, hanguiyuan@gmail.com (G. Han).

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http://dx.doi.org/10.1016/j.enbuild.2013.10.036

Table 1
Life cycle assessment tools.

LCA tools		BEES	ATHENA EcoCalculator	ATHENA impact estimator	SimaPro	Proposed methodology
Development organization		EPA (US)	ATHENA (Canada)	ATHENA (Canada)	PRé Consultants (Netherlands)	–
Analysis level		Material	Assembly	Building	Variable	Building
Program complexity		Low	Low	Medium	High	Depend on users
Analysis aspect	Capital cost	Y	N	Y	Y	Y
	Operational energy	Y	N	N	Y	Y
	Transportation	Y	N	N	Y	Y
	Maintenance	N	N	Y	N	Y
	Demolition	N	N	N	N	Y
	Life cycle economic cost	Y	N	Y	Y	Y

2.2. *Building optimization methods*

A large number of research projects have developed methodologies for building optimization. In the following literature review, they are divided into two categories: simple method and advanced optimization method.

2.2.1. *Simple method*

Simple methods are the straightforward methodologies based on derivation and simple iteration.

2.2.1.1. Derivation. There are many optimization problems in the field of building energy. Simple optimization projects usually focus on only one component of building. Hasan [7] selected the insulation thickness as the optimization parameter. This optimization method is based on a life cycle cost analysis, which is a function of degree days and wall thermal resistance. The optimum insulation thickness is obtained by minimizing the total cost. Hence, the derivative of total life cycle cost (Ct) with respect to insulation thickness (X) is set equal to zero, obtaining the optimum insulation thickness (X_{op}). Dombaycl et al. [8] used a similar method to optimize insulation-thickness of the external wall for five different energy-sources (coal, natural gas, LPG, fuel oil, and electricity), and two different insulation materials (expanded polystyrene and rock wool).

This is the most straightforward way to obtain the optimum. This method is effective in simple problems that have one or two optimized parameters with countable options and one objective. If one function cannot define the problem objective, the derivation method is not adequate to achieve the optimum. The optimization problem needs more advanced methods when the objective is too complex to describe as a function of variables.

2.2.1.2. Simple iteration. Another simple method is based on iteration. A choice between two options is made at each step of the iteration according to a comparison of the energy consumption results. In every iteration, the option of variables gives a better solution of the objective, and the optimal variable is chosen for the next iteration. In 1989, Gustafsson and Karlsson developed an OPtimal Energy Retrofit Advisory (OPERA) to implement the optimal retrofit combination for multi-family buildings [9]. The process, showed in Fig. 1, starts with calculation of LCC for the existing building, followed by several iterative comparisons and choices.

In this case, the aim of the retrofit is to decrease the existing LCC. The model focuses on envelope and ventilation retrofits: attic floor insulation, floor insulation, external wall insulation, glazing type, weather-stripping, and exhaust-air heat pumps. The method requires significant computational resources that increase exponentially with the number of the optimized parameters in one problem. Therefore, when the problem becomes more complex with many parameters, the efficiency of this method to make an optimal decision could decrease.

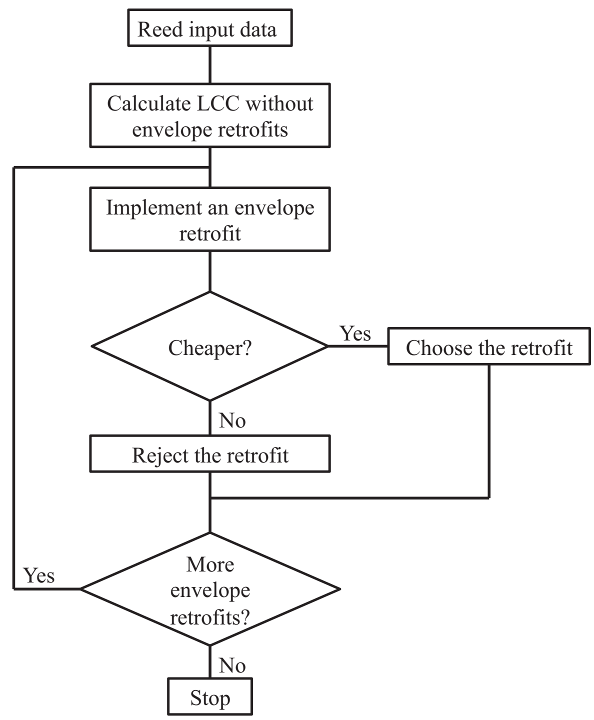

Fig. 1. Flow chart of iteration.

2.2.2. *Advanced optimization methods*

The limitations of the simple methods have encouraged more advanced methods to solve building energy optimization problems, such as neural network sequential search and genetic algorithms.

2.2.2.1. Neural network. A study to optimize office building shape is accomplished by Ouarghi and Krati [10]. In this study, the objective is minimizing annual building energy cost. The building shape is described by its relative compactness, with a cube as the reference building. Relative compactness is defined as the ratio of the building volume to its surface area. The study used a Bayesian neural network to optimize building energy performance, trained by results from simulations using the DOE-2 engine.

The neural network is a reliable method in optimization problems, but requires training to guarantee reliability. Furthermore, simulation of the real project is needed for the training since the network must learn to react realistically. Unfortunately, in design projects, decisions must be made within a certain time frame, which means there is rarely sufficient time and material to train the network.

2.2.2.2. Sequential search. Another optimization method used in building issues is sequential search. Christensen et al. [11] used sequential optimization with iteration to optimize selection for different building envelope categories. The optimization is based on marginal cost of energy, which is the cost of saved energy for a discrete option. Each successive category uses the optimal options from previous categories optimizations. The process begins a new iteration once all categories optimized. A candidate optimum solution has been found when the results remain unchanged upon successive iterations.

2.2.2.3. Genetic algorithms. Genetic algorithms (GA) are the most frequent choice method for multi-objective optimization. Wang et al. [12,13] established an optimization model based on genetic algorithms to consider shape-related parameters and envelope-related design parameters, such as window ratios and overhangs. In their study, life cycle cost and life cycle environmental impact are the two objective functions used to evaluate the performance of a green building design.

For building energy issues, there are often conflicting objectives, such as initial investment cost and annual operating cost. Initial investments in building material usually conflict with the energy cost during operation. There is a trade-off to achieve the optimum. Verbeeck and Hens [14] developed a global methodology to optimize designs for extremely low energy dwellings, taking into account energy use, environmental impact, and financial costs over the life cycle of the buildings. Energy simulations are carried out with TRNSYS. The ecological impact is evaluated through a cost-benefit analysis. The multi-objective optimization problem is solved by combining genetic algorithms and the Pareto concept.

The initial cost is not the only factor which conflicts with energy cost. Thermal comfort can be another conflicting objective against energy cost. Research by Wright [15] identifies the optimum payoff characteristics between the energy cost of a building and the occupant thermal comfort. The paper investigates the application of a multi-objective genetic algorithm method to identify the optimum trade-off characteristic between daily energy cost and zone thermal comfort for three design days (summer, winter, and swing design day) and three building weights (light, medium, and heavy weight). The optimization criteria are specified into three aspects: operating cost of the HVAC system for the design days, maximum thermal discomfort of occupancy on each design day, and the infeasibility objective. For the particular conditions in this study, the optimization results are robust. However, the result of this study is not a representative analysis for an entire year, as it is limited by its particular design days.

2.2.3. Comparison study of different optimization methods

As demonstrated in the discussions above, although the previous optimization studies are significant to explore effective ways for optimizing building systems, several limitations may undermine their practical application.

2.2.3.1. Accuracy and efficiency. In the study of Tubus-Dubrow and Krarti [16], researchers compared three different optimization methods: genetic algorithm approach, sequential search technique, and particle swarm technique. In this study, the performance of these methods was compared in terms of accuracy and efficiency for various sets of building envelope parameters. The GA method was found to be more efficient than the sequential search and particle swarm optimization methods when more than 10 parameters are considered in one case. With the robustness of 1%, the GA method is generally more efficient than the sequential search method and saves more than 50% of simulation efforts, especially for medium and large optimization cases.

2.2.3.2. Calculation time. Building optimization problems include a mixture of many discrete and continuous variables, non-linear inequality and equality constraints, a discontinuous objective function, and variables embedded in constraints but not in the objective function. Such characteristics make gradient-based optimization methods inappropriate and restrict the applicability of search methods [17]. The calculation time of mixed integer programming, which was used to optimize the operation of a district heating and cooling plant, increases exponentially with the number of integer variables. It was shown that normal programming takes about two times longer than a GA for a 14-hr optimization window and 12 times longer for a 24-h period [18].

Wetter and Wright [19] compared the performance of nine optimization algorithms using numerical experiments, including four direct search algorithms, a simple genetic algorithm (GA), two particle swarm optimizations (PSO), a hybrid particle swarm Hooke–Jeeves algorithm and a gradient-based algorithm. They also discussed a different optimization based on cost function with different smoothness. The best solution had been found with the hybrid particle swarm and Hooke–Jeeves algorithm. However, the simple GA was still recommended as a good choice if the user is willing to accept a slight decrease in accuracy at the benefit of less simulation time.

2.3. Building optimization case studies

Many research projects have demonstrated building optimization using case studies. Tables 2 and 3 show a general review of the optimized parameters and objectives in previous building optimization studies, and also the comparison with this study.

As shown in Tables 2 and 3, only a few studies focus on optimization and life cycle analysis of commercial buildings [12,19,20]. In fact, commercial buildings consume large amounts of energy during their life span [21]. In the USA, energy consumption in the service sector, which covers all commercial and public buildings, has expanded from 11% to 18% since the 1950s. Both economic growth and population growth increase the demand of services (health, education, culture, leisure, etc.) and energy consumption [1]. Therefore, the building used in this particular case study is an office building.

The optimized parameters shown in Table 2 include building type, building azimuth, HVAC system size, and enclosure properties. In this study, building type and building azimuth, which are determined in a very early phase of most projects, are not considered as optimized parameters. This study will optimize the parameters of both enclosure system and HVAC system. Table 3 indicates that building optimization studies have different optimization objectives. To evaluate building performance from a comprehensive life cycle perspective, the optimization criteria in this study will include all aspects of building LCC.

3. Methodology

3.1. Scope

The choice of building component material and dimensions (i.e. thickness) are primary contributors to embodied energy [22], LCC [8], and life cycle environmental impacts (LCEI) [23]. In addition, material and thickness choices extend to many aspects of building performance, such as occupant productivity [24], internal health effects [25,26], and ecosystems [27]. However, according to the existing literature, neither current life cycle analysis tools nor previous building system optimization studies created a comprehensive model to cover all phases through the building life cycle. Therefore, this study focuses on building life cycle cost to develop

Table 2
Optimized parameters in previous building optimization studies.[a]

	Building type	Building shape	Building azimuth	HVAC system size	Enclosure properties			
					Wall assembly	Window to wall ratio	Glazing	Insulation
[7]	N/A	N	N	N	N	N	N	Y
[8]	N/A	N	N	N	N	N	N	Y
[11]	N/A	N	N	N	N	Y	Y	Y
[15]	N/A	N	N	Y	N	Y	N	N
[9]	R	N	N	N	N	N	Y	Y
[20]	R	N	N	N	N	N	Y	Y
[21]	R	Y	Y	N	N	Y	Y	Y
[12]	O	Y	N	N	Y	Y	Y	N
[19]	O	N	Y	N	N	Y	N	N
[22]	O	Y	N	N	N	Y	Y	Y
[23]	O	Y	Y	N	N	Y	Y	N
This study	O	N	N	Y	Y	Y	Y	Y

[a] N/A: not available; R: residential building; O: commercial office building; Y: yes, considered; N: no, not considered.

Table 3
Objectives in previous building optimization studies.[a]

	Building type	Capital cost	Operating energy	Transportation	Maintenance	Demolition
[7]	N/A	Y	Y	N	N	N
[8]	N/A	Y	Y	N	N	N
[11]	N/A	Y	Y	N	N	N
[15]	N/A	N	Y	N	N	N
[9]	R	Y	Y	N	N	N
[20]	R	Y	Y	N	Y	N
[21]	R	Y	Y	N	N	N
[12]	O	Y	Y	N	N	N
[19]	O	N	Y	N	N	N
[22]	O	Y	Y	N	N	N
[23]	O	Y	Y	N	N	N
This study	O	Y	Y	Y	Y	Y

[a] N/A: not available; R: residential building; O: commercial office building; Y: yes, considered; N: no, not considered.

an optimization framework based on a comprehensive building life cycle analysis.

The scopes of this study are: (1) to develop a comprehensive framework of building life cycle cost analysis considering cash flow during the building life cycle, and (2) to propose a building optimization procedure based on the comprehensive building life cycle cost analysis. A case study based on a medium size office building is used to demonstrate the proposed life cycle optimization procedure.

3.2. Building life cycle cost analysis framework

Previous studies have identified several categories that are useful in measuring the life cycle performance of buildings. These categories include global warming potential [28], human health impacts [25], embodied energy [22], energy consumption [29], and financial cost, among others. Although the authors recognize the importance of all of these categories in comprehensively assessing building performance, this methodology considers only financial cost during the building life cycle.

The building life cycle includes construction, annual operation and maintenance, and demolition phases. Fig. 2 schematically shows the complete life cycle of a typical building, which is included in this study. The framework contains all the phases of a building life span in terms of financial cost.

3.3. Building components optimization framework

Genetic algorithm (GA) is a technique used to search for optimal solutions. In GA terminology, a solution to a problem is an individual and a group of individuals is a population. A generation is a new population generated in iteration. The fitness of any particular individual corresponds to the value of its objective function. The iterations continue until the solution set reaches satisfactory convergence criteria or reaches the maximum number of generations.

GA starts from a random sample within an optimization solution space, and then uses stochastic operators to direct a process based on objective function values [30]. Operators in GA control the evolution of successive generations. There are three main genetic operators used in GA, which are selection, crossover, and mutation, shown in Fig. 3.

1. Selection: The populations in the generation are ranked according to the fitness value, which is the value of the objective function calculated by each individual. The better rank the individual has, the greater the chance it will be selected.
2. Crossover mating: Once the population for reproduction is selected, the individuals are paired off and "mated" using a crossover procedure. After this step, a new population is formed.
3. Mutation: This is the last step to form the population of the next generation. The purpose of mutation is to prevent the individuals stuck in a local optimum solution. Finally, this mutated population becomes the population of the next generation, and this process is repeated until the convergence is met.

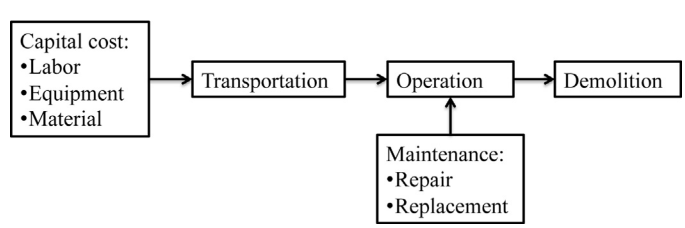

Fig. 2. Building life cycle phases included in the proposed life cycle cost analysis framework.

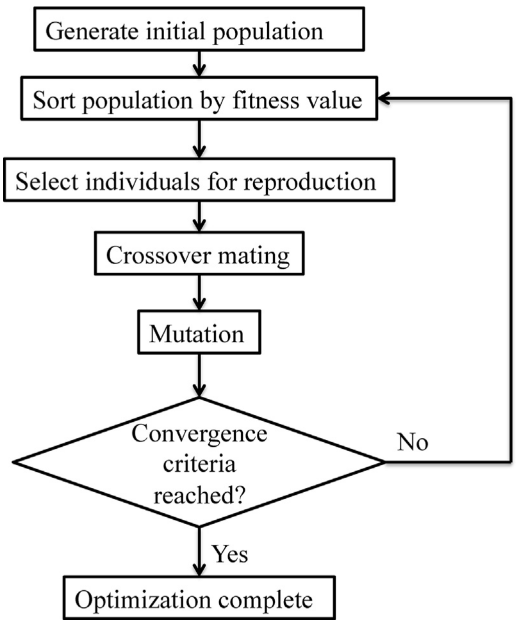

Fig. 3. Flow chart of the evolutionary algorithms.

Based on genetic algorithm, an optimization–simulation model is developed and applied to select optimal values of a comprehensive list of parameters associated with the enclosure features in order to optimize building performance. The model to optimize the building enclosure consists of two main sections: building performance analysis section and optimization section, shown as Fig. 4.

The model starts with several sets of building enclosure components. Through building performance analysis, different results are obtained according to various building enclosure components. The optimization procedure calls the data from the building performance analysis program. According to analysis output, the optimization solver will select the optimal set(s) of building enclosure components. When the optimization solver reaches the convergence criterion, which is fixed by users, the set(s) of components in use at that point is the final solution that establishes the best building performance. If the convergence criteria are not reached, the set(s) of components will become the analysis input of the next iteration.

As stated above, the objective in this optimization procedure is the building life cycle cost calculated by a comprehensive LCA methodology. Correspondingly, the building performance analysis in Fig. 3 is the building life cycle assessment in this study.

Fig. 5. Visualization model of the case study building.

Table 4
Options of parameter values.

Parameter	Options
Window frame	Wood, aluminum
Window glazing	Standard, double, low-E
Insulation material	Fiberglass, foamglass, XPS, EPS
Insulation thickness	1, 1.5, 2, 3
Wall assembly	Concrete block, Masonry

4. Case study

Simulations are built for a two-story office building in Saginaw, MI, USA. The building is a medical office building with a total conditioned floor area of 14,702 ft^2 (1366 m^2). Fig. 5 presents the visualization model of the building.

In this case study, the objective is to minimize the building LCC, calculated by the model proposed in Fig. 4. The optimization is carried out with five parameters, which influence building energy consumption significantly: window frame, window glazing type, insulation product, insulation layer thickness, and wall assembly. The detailed options of the parameter values are show in Table 4.

RS Means is used for initial cost of building material and construction [31–33], regular maintenance [34], and demolition [32]. The transportation cost is calculated by the database of Simapro. The operating energy simulation is established by DesignBuilder, an interface of EnergyPlus. The envelope materials could have great impacts on building thermal load, which is an important factor for HVAC system sizing. In this study, the capital cost not only considers the investment in the enclosure system, but also the capital cost of the HVAC system. The calculation is using the average local energy price in 2012 with two financial scenarios: (1) the future energy prices remain the same as the present prices, and (2) the future

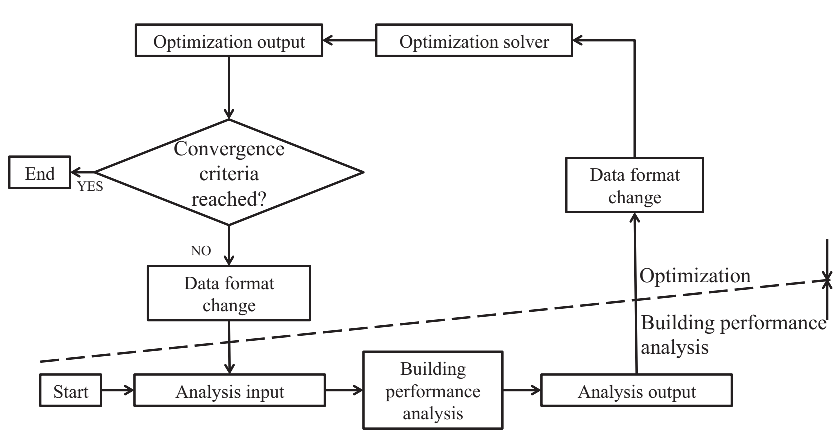

Fig. 4. Model construction.

energy prices are calculated based on the projections provided by EIA [35].

Present value (PV), also known as present discounted value, is the value on a given date of a payment or series of payments made at other times. In finance the net present value (NPV) of a time series of cash flows, both incoming and outgoing, is defined as the sum of the present values of the individual cash flow of the same entity. The NPV is given by:

$$NPV(i, N) = \sum_{t=1}^{N} \frac{C_t}{(1+r)^t} \tag{1}$$

where *NPV* is present value, t is the time of the cash flow, N is the lifetime of system, C_t is net cash flow (the amount of cash, inflow minus outflow) at time t, and r is discount rate.

In this study, the net present value is applied to evaluate cash flows during different phases of the building life span.

5. Results and discussions

The case study building is analyzed to first implement the building life cycle cost analysis and then to find the building enclosure components that result in minimal life cycle costs, accounting for both enclosure performance as well as HVAC system capacity and cumulative energy consumption.

5.1. Building life cycle cost analysis

Fig. 6 shows the maximum, median, and minimum LCC net present value with different combinations of building enclosure components.

The life cycle cost could be broken down into costs in each of the building periods. Fig. 7 shows the breakdown detail of the net present value in minimal cases when the building has different life span (1–60 years). Operational energy cost and initial construction cost are primary costs during the whole building life cycle. When the building life span is longer than 30 years, operating energy consumption becomes the primary cost instead of building capital cost.

The results in Fig. 7 are based on a calculation strategy of net present value (NPV). The NPV method provides an easy way to evaluate projects by moving all cash flows to the present. It examines the cash flows of a project over a given time period and resolves them to one equivalent present date cash flow [36]. Due to a discount rate, the absolute value of future spending is decreased when being converted to present spending. Therefore, when building has a longer life span, the cumulative energy cost flattens off and the demolition cost also contributes less in the total LCC.

5.2. Building optimization of minimal life cycle cost

Table 5 indicates that an optimization objective could vary the combination of optimal building system components. The result shows an optimal solution for operating energy emphasis on the combination of the best materials in terms of thermal properties.

The life cycle analysis in this study considers both building envelope and mechanical system in use. The lowest investment of building systems is not always the cheapest envelope component. The difference between optimal combinations for envelope capital cost and total capital cost states that the investment of better envelope components could reduce HVAC system size, saving total capital cost.

The optimization result aiming to minimize LCC compromises all phases of building life cycle, which provides good insulation material with medium price, thick insulation layer, low maintenance of windows, and cheap wall assembly.

Using the life cycle optimization framework, shown in Fig. 3, the optimal combinations of the parameters minimizing building life cycle costs are shown in Table 6. For different lengths of building life spans, minimal LCC is obtained by configuring different combinations of building components.

As stated before, better envelope could reduce the size of the mechanical system as well the investment. Consequently, the optimized parameters for lowest investment, and also the optimal components for a one year building life span, is a combination of an aluminum window frame, low-E glazing, and concrete walls with 1″ EPS insulation.

The breakdown result of building LCC (shown in Fig. 7) indicates that when a building has a relatively longer life span, annual energy consumption is a major cost in building life cycle and more capital cost is worthwhile for better and thicker insulation material with a larger *R*-value. Therefore, the optimal insulation during the building life cycle is 3″ fiberglass.

Double glazing, relatively high *R*-value with reasonable cost, is the optimum choice. Aluminum window frames are ideal for buildings with 2–13 years life span because of the requirement of less investment.

The building components require regular maintenance as the life span becomes longer. For instance, according to RSMeans Facilities Maintenance and Repair Cost Data [34], the wood versus aluminum window units require different maintenance in various lengths of operating years, as shown in Table 7.

Frame conductance could influence annual energy consumption in a relatively long term. Consequently, for a building with a 14–60 year life span, wood window frames become the optimal component for less frame conductance and maintenance cost.

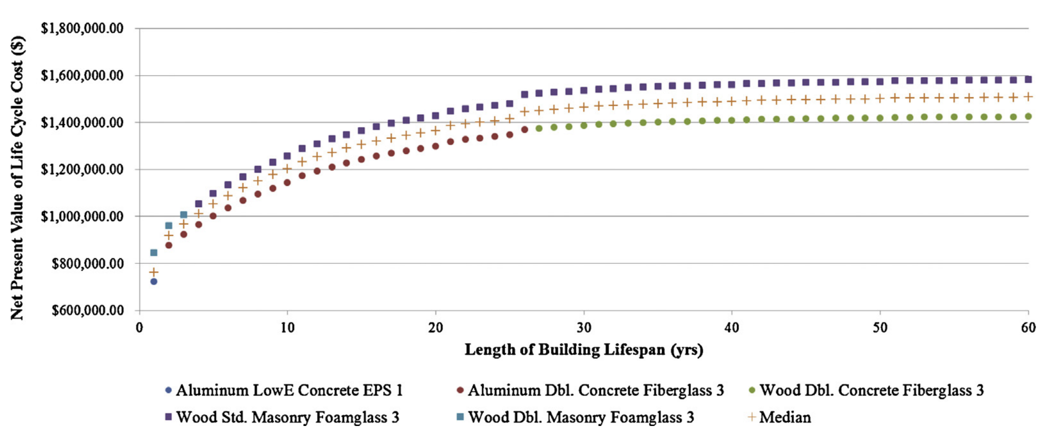

Fig. 6. Cases with maximum, median, and minimal life cycle cost.

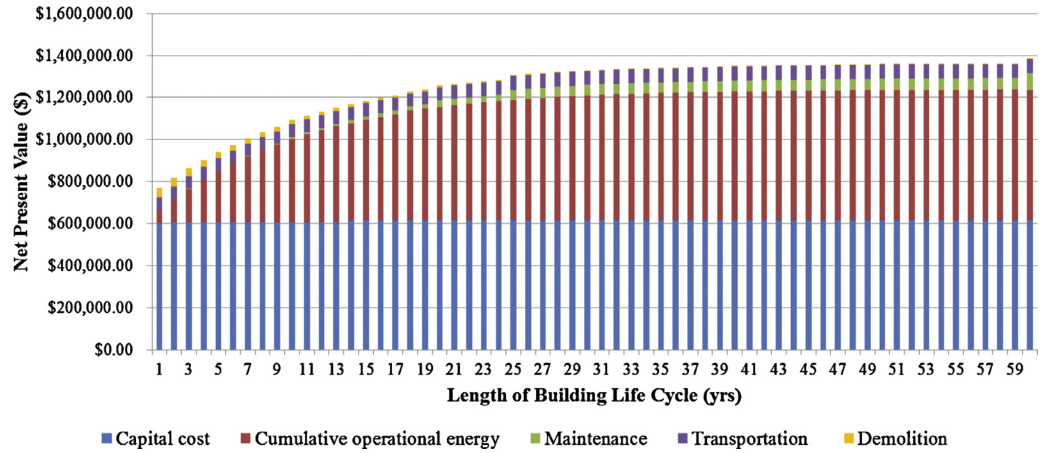

Fig. 7. Cost breakdown in minimal cases.

Table 5
Optimal components with different objectives.

Objective	Optimal components				
	Window frame	Window glazing	Insulation material	Insulation thickness	Wall assembly
Operational energy	Wood	Low-E	XPS	3	Masonry
Envelope capital cost	Aluminum	Standard	EPS	1	Concrete
Total capital cost (envelope + HVAC)	Aluminum	Low-E	EPS	1	Concrete
LCC (10 years)	Aluminum	Double	Fiberglass	3	Concrete

Table 6
Optimal values of parameters with different building life span.

Length of building life span (years)	Window frame	Window glazing	Insulation material	Insulation thickness (in)	Wall assembly
1	Aluminum	Low-E	EPS	1	Concrete block
2–26	Aluminum	Double	Fiberglass	3	Concrete block
27–60	Wood	Double	Fiberglass	3	Concrete block

Table 7
Window unit maintenance.

Window unit	Maintenance cost							
	Annual replace		Refinish		Repair		Replace	
	Cost ($/unit)	Freq. (years)	Cost ($/sf)	Freq. (years)	Cost ($/unit)	Freq. (years)	Cost ($/unit)	Freq. (years)
Wood frame with standard glazing	9.17	1	68.65	4	180.6	15	287.45	40
Wood frame with double glazing	9.17	1	68.65	4	180.6	15	304.58	40
Wood frame with lowE glazing	9.17	1	68.65	4	180.6	15	288.29	40
Aluminum frame with standard glazing	9.17	1	–	–	240.39	20	385.23	50
Aluminum frame with double glazing	9.17	1	–	–	240.39	20	402.36	50
Aluminum frame with lowE glazing	9.17	1	–	–	240.39	20	386.06	50

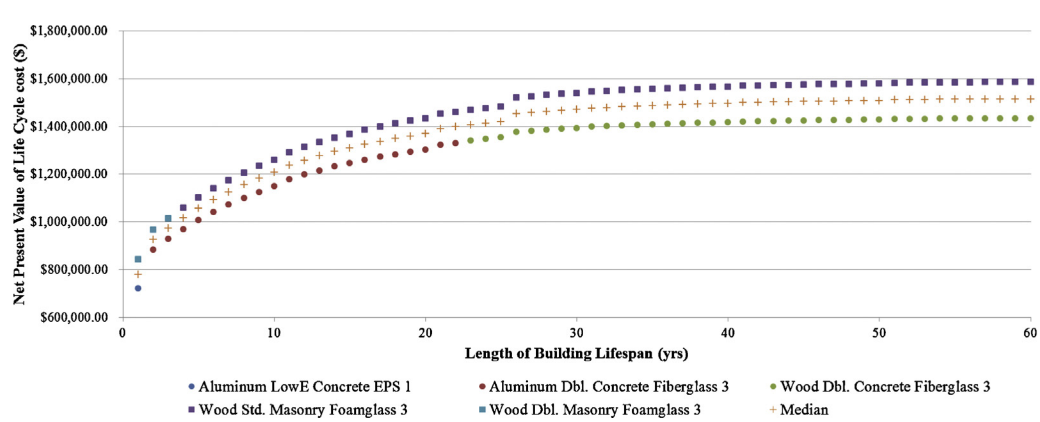

Fig. 8. Net present value of life cycle cost of minimal, maximal and median cases calculated based on consideration of future energy prices.

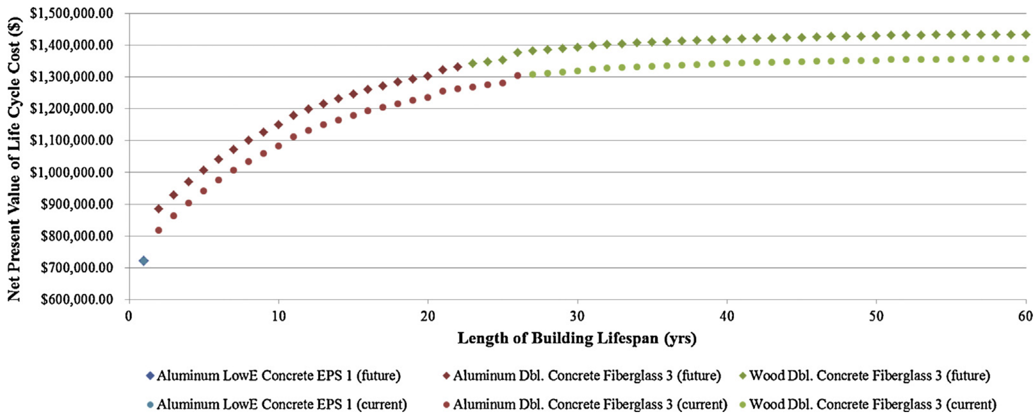

Fig. 9. Comparison of the minimal life cycle cost based on current energy prices and future energy.

Table 8
Optimization results based on future energy prices.

Length of building life span (years)	Window frame	Window glazing	Insulation material	Insulation thickness (in)	Wall assembly
1	Aluminum	Low-E	EPS	1	Concrete block
2–22	Aluminum	Double	Fiberglass	3	Concrete block
23–60	Wood	Double	Fiberglass	3	Concrete block

5.3. *Uncertainty associated with future energy prices*

During a calculation period of 60 years, the projection on energy prices is associated with uncertainties. According to the energy price projections published by U.S. Energy Information Administration (EIA), the annual growths of electricity and natural gas prices for commercial sector are 0.2% and 1.4%, respectively [35].

Fig. 8 shows the net present value of life cycle cost of minimal and maximal cases based on the projection of energy prices provided by EIA [35]. The results associated with dynamic energy prices are following the same trend as the calculation results based on the assumption that the energy prices will be the same as the current ones.

Fig. 9 shows the comparison of the minimal life cycle cost based on these two financial scenarios. The comparison indicates that the annual growth of energy prices will have a significant impact on building LCC. The difference of minimal life cycle cost between the two financial scenarios ranges between 5.7% and 8.2%.

Table 8 shows the optimization results calculated based on future energy prices provided by EIA. The optimal option of window frame changes from aluminum to wood when building lifespan is longer than 22 years, which is four years earlier than the case based on constant energy prices (shown in Table 6). This indicates that the growing energy prices are giving the operational energy cost a more important role in the early years of the building lifespan.

6. Conclusions

This study determines a framework to optimize building components using genetic algorithms with the objective of optimizing building life cycle cost. Different from previous studies, the life cycle analysis methodology proposed here covers all phases of the building life cycle. The annual energy consumption – an important aspect of life cycle cost – is calculated by an energy simulation tool instead of referring to a fixed database.

The case study based on a medium size office building demonstrates the proposed life cycle optimization framework. The results show that the capital cost and operating energy consumption are both major parts of life cycle cost. The annual energy consumption becomes more important when the building has a longer life span. In this case study, the operating energy cost takes the largest percentage of the life cycle cost when the building has more than 30 years life span. It also demonstrates that the optimal building components are very different according to different objectives. Optimal combination for annual energy cost highlights the material with best thermal properties, while cheap materials and smaller HVAC system size are emphasized in optimization of capital cost. Therefore, a comprehensive life cycle analysis model provides a better understanding of objectives for building systems optimization. It also suggests that combinations of optimized building components are dependent on the building life span. There are two energy pricing scenarios considered in this study. The results indicate that the increasing prices will influence life cycle cost and optimization results.

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