INVESTIGATION OF THE IMPACT OF ELECTRICITY RATE AND MIX ON OPTIMUM GREEN BUILDING DESIGN

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ABSTRACT

This paper presents an optimization model that minimizes life cycle cost and life cycle environmental impact. Impact categories considered in this study are expanded from operating energy consumption to non-fuel natural resources and waste emissions with global/continental and long-lasting impacts such as global warming and acidification. Design variables are building envelope-related parameters usually determined at the conceptual design phase. Using the optimization model, the impact of electricity rate and mix on the optimum building design is studied. The investigation is carried out for Montreal using three electricity scenarios with different rates and mix. It is found that the electricity rate and mix have a large impact on the optimum design.

INTRODUCTION

Buildings are major energy consumers. In Canada, residential and commercial/institutional buildings account for about 30 percent of the total secondary energy use (NRC 2003). As a direct result, they are responsible for nearly 29 percent of CO_2 equivalent greenhouse gas emissions along with many other wastes (NRC 2003). As the close relationship between buildings and energy-related environmental issues become more apparent, it is important to explore ways for a better building design that considers environmental performance. Green building is a recent design philosophy that requires the consideration of a number of aspects such as resources conservation, waste emissions reduction, and cost minimization, during the whole life cycle of a building.

Optimization can help in obtaining the most promising solution for green building design. Many studies have been made in this respect. Operating energy consumption or life-cycle cost is used as the single performance criterion in many optimization models (Wetter 2001; Coley and Schukat 2002; Nielsen 2002). Although the previous studies have explored effective ways for better building design, they have the following two major limitations.

Incomplete environmental performance criterion. This can be seen from the following two aspects. First, only the operation phase is considered. The life cycle of buildings, however, covers all processes from natural resource extraction, through material production, construction, and operation, until demolition. The environmental impacts will be underestimated if the scope is limited to the operation phase only. Secondly, only energy consumption is considered. However, environmental impacts for the same amount of consumed energy vary with the fuel types, and many environmental impacts associated with material production are not energy-related. Therefore, it is necessary to distinguish different energy sources and to incorporate their impacts such as natural resource depletion and global warming into the objective function.

Difficulty in making cost-effective decisions accounting for environmental performance. Most previous studies deal with either economical or environmental performance separately. Hauglustaine and Azar (2001) combined them together using the weighted sum technique. Only one optimal solution is obtained for each run if the two performance criteria are treated separately or coupled together into one meta-criterion. The designer cannot learn about the impact of the marginal change of one criterion on another just from a single optimal solution. It is difficult to make cost-effective decisions without knowing the trade-off relationship between economical and environmental performance.

In order to avoid the above limitations, a new optimization model is developed and presented in the next section of this paper. Then, the simulation program used to evaluate the objective functions is discussed. A case study is presented in the fourth section to find the optimum design for three scenarios with different electricity rates or mix.

OPTIMIZATION MODEL AND ALGORITHM

Model Considerations

The phases considered in this study are pre-operation phase (including natural resource extraction, building material production, on-site construction, and transportation associated with the above phases) and operation phase. Maintenance and demolition are not included for two reasons. First, the corresponding environmental impact data are unavailable for many building materials or assemblies. Second, they account for only a small portion of life cycle environmental impacts (Cole and Kernan 1996).

Global/continental, long-lasting impact categories (e.g., global warming) usually have characteristics that can be dealt by life cycle assessment (LCA) with acceptable theoretical accuracy (Barnthouse et al. 1998). Therefore, impact categories considered in this optimization study include natural resources depletion, global warming, and acidification. Environmental impacts characterized as being local or transient such as ecotoxicity and photochemical smog are not considered. Waste emissions considered in this paper are restricted to three major greenhouse gases (CO_2, CH_4, N_2O) and two major acidic gases (SO_x and NO_x).

Exergy is employed in this paper for the life cycle assessment of buildings. It is "the amount of work obtainable when some matter is brought to a state of thermodynamic equilibrium with the common components of the natural surroundings by means of reversible processes, involving interaction only with the common components of nature" (Szargut 1988).

Cumulative exergy consumption proposed by Szargut et al. (1988) expresses the sum of the exergy of all natural resources consumed in all the steps of a production process. Unlike cumulative energy consumption, it also takes into account the chemical exergy of the nonfuel raw materials extracted from the environment. Therefore, cumulative exergy consumption can be used to measure natural resource depletion. Exergy can also be a measure of waste emissions. Because exergy can evaluate the degree of disequilibrium between a substance and its environment, the abatement exergy is employed in this study to evaluate the required exergy to remove or isolate the emissions from the environment. As indicated by Cornelissen (1997), it is feasible to determine an average abatement exergy for each emission based on current available technologies.

Thus, by extending the cumulative exergy consumption to include abatement exergy, the expanded cumulative exergy consumption can consider both resource inputs and waste emissions to the environment, across all life cycle phases. The main advantages of using the expanded cumulative exergy consumption for life cycle optimization with respect to environmental performance can be summarized as:

- It can combine resource depletion and waste emissions together, and therefore, the life cycle environmental impacts can be condensed into one single objective function.
- It can combine fuel and nonfuel materials together to characterize the resource depletion.

Optimization Model

Variables

Two types of variables are used to define a building design alternative: discrete and continuous. Some variables such as window type can only be discrete with a list of available types of windows. Some variables can be either continuous or discrete. Orientation, for example, may assume any value between 0^o and 90^o, or it may take one from a pre-set list such as 0^o, 15^o, or 30^o.

In this study, buildings are limited to a rectangular shape with a known total floor area. The following variables have been defined with their corresponding names in parenthesis:

- Building orientation (*orientation*) in degrees with clockwise direction being positive.
- Aspect ratio (*aspectRatio*) of a building plan.
- Window type (*winType*) defines the window construction. An example is a double glazing window with 13 mm airspace in between.
- Window-to-wall ratio (*winRatio*) for each building façade.
- Wall type (*wallType*) defines the wall configuration with a sequence of layers. Masonry cavity wall, for example, consists of the following sequence of layers from outside to inside: cladding, cavity, insulation, vapor barrier, masonry structure, and finish.
- Each layer of wall (*wallLayer*) defines the actual material selected. For example, the insulation layer in a wall type can be 76.2 mm fiberglass batts or 101.6 mm mineral wool batts.
- Roof type (*roofType*) defines the roof configuration with a sequence of layers.

- Each layer of roof (*roofLayer*) defines the actual material selected.

Constraints

Two types of constraints are considered in this optimization model. They are box constraints for continuous variables and selection constraints for discrete variables. Box constraints give the boundary values of continuous variables. Selection constraints give a predefined set of alternatives for discrete variables.

Objective Functions

Both life cycle cost (LCC) and life cycle environmental impact (LCEI) are selected as the two objective functions to be minimized. Let **X** denotes a variable vector, the general expressions to calculate LCC and LCEI are:

$$LCC(\mathbf{X}) = IC(\mathbf{X}) + OC(\mathbf{X}) \qquad (1)$$

$$\begin{aligned} LCEI(\mathbf{X}) &= EE(\mathbf{X}) + OE(\mathbf{X}) \\ &= \left[CExC_{PP}(\mathbf{X}) + AbatEx_{PP}(\mathbf{X})\right] \\ &\quad + \left[CExC_{OP}(\mathbf{X}) + AbatEx_{OP}(\mathbf{X})\right] \end{aligned} \qquad (2)$$

The items in the above formulas are explained in the nomenclature section at the end of this paper.

Optimization Algorithm

Genetic algorithm, a stochastic global search technique inspired from the principles of biological evolution (Goldberg 1989), is employed in this paper to solve the above established optimization problem. In genetic algorithm, a variable is usually coded into a fixed number of bits consisting of “1” and “0”. The binary codes of all variables are concatenated to form a binary string (chromosome), representing a potential solution to the optimization problem. Genetic algorithm maintains and operates on a set of potential solutions (chromosomes), called a population of individuals. The first generation of population is randomly generated while the remaining generations are produced through genetic operations such as selection, crossover, and mutation. Selection is biased towards those robust individuals by giving them higher opportunity to reproduce. The robustness or fitness of each individual is related with the value of its objective function(s), which are LCC and LCEI in this study. One of the commonly used selection operators is the binary tournament selection that works as follows: two individuals are randomly selected from the current generation and the stronger one survives to the next generation. Crossover and mutation operations are applied on the selected individuals to form a new generation of population. Based on the predefined probability, crossover recombines two individuals by exchanging part of their binary strings, starting from a randomly chosen crossover point. This leads to two new solutions that most probably inherit desirable qualities of their parents. The mutation operator flips the values of some bits according to the mutation probability. This can prevent premature convergence by exploring new regions in the search space. The above genetic operations, namely selection, crossover, and mutation, are applied on the new population and repeated until the maximum number of generations is reached.

Although some previous studies (e.g., Goldberg 1989) indicate that a large crossover probability and a small mutation probability usually perform well, many parameters of genetic algorithm are problem dependent. Based on a number of trial runs, the following parameter settings are found to achieve better results in this study. They are specified as: crossover probability=0.9, mutation probability=0.02, maximum number of generations=200, population size=40, the selection operator is the binary tournament selection.

A particular characteristic of the predefined optimization problem lies in the hierarchical variables. For example, *wallType* and *wallLayer* are variables at different levels because the configuration of wall depends on the applicable wall type. Therefore, the structured genetic representation, as proposed by Dasgupta and McGregor (1993), is employed to represent the chromosome as hierarchical genomic structures. This means that dominant and recessive genes for low-level variables may coexist in a chromosome. High-level genes will determine which low-level genes are active.

Considering that two objective functions are minimized simultaneously, a multi-objective genetic algorithm is used to locate a set of Pareto solutions. A solution is said to be Pareto optimal if and only if it is not dominated by any other solution in the performance space. For this study, a solution $\boldsymbol{X_1}$ dominates another solution $\boldsymbol{X_2}$ implies that either LCC or LCEI of $\boldsymbol{X_1}$ is less than that of $\boldsymbol{X_2}$ but none of them is greater than that of $\boldsymbol{X_2}$. The multi-objective genetic algorithm proposed by Fonseca and Flemming (1998) is implemented in this study. This algorithm uses a rank-based fitness assignment strategy, where the rank of an individual is equal to one plus the number of solutions in the current population that dominate it.

External population is also used in this study because this elitist strategy can improve the performance of multi-objective genetic algorithm (Deb 2001).

SIMULATION PROGRAM AND DATA PREPARATION

A simulation program based on the ASHRAE toolkit for building load calculations (Pedersen et al. 2000) has been developed to calculate both life cycle cost and life cycle environmental impact. Using the heat balance method, the ASHRAE toolkit calculates hourly heating or cooling loads of two typical days per month, which correspond to (1) the average weather condition, for the calculation of energy consumption; and (2) the extreme weather condition, for peak load calculation. Based on the hourly loads, the simulation program estimates the operating energy consumption accounting for the efficiency of the heating and cooling system. The operating energy consumption is then used to calculate the operating cost (*OC*), and the environmental impacts due to the operation phase (*OE*). The initial construction cost (*IC*), and the environmental impacts due to the pre-operation phase (*EE*) are derived directly from the building description, construction cost and embodied impact data of building materials/products.

Initial construction cost data are taken from the R.S. Means cost databook (2002). The life cycle operating cost is derived from the annual operating cost which is discounted to the present worth considering the time value of money (NRC 1997):

$$OC(\mathbf{X}) = AC(\mathbf{X}) \cdot \left[1 - \left(\frac{1+i}{1+r} \right)^{-n} \right] \cdot \frac{1+r}{i-r} \qquad (3)$$

Cumulative exergy consumption (*CExC*) is evaluated as the sum of the exergy, from both nonenergetic resources (e.g., mineral ore) and energetic resources (fuel), consumed in all the steps of a production process. Nonfuel exergy can be calculated as the product of mass and its chemical exergy. Fuel exergy can be obtained by multiplying the amount of energy consumption with the ratio α between the fuel's exergy and its energy content. Thus, the cumulative exergy consumption for pre-operation phase and operation phase can be expressed as:

$$CExC_{PP} = \sum_j (\alpha_j \cdot EN_j) + \sum_k (e_k \cdot m_k) \qquad (4)$$

$$CExC_{OP} = n \cdot \sum_j (\alpha_j \cdot \frac{ON_j}{\eta_j}) \qquad (5)$$

The value of α is taken from (Szargut et al. 1988; Wall 1977). For instance, α is equal to 1.07 and 1.04 for oil and natural gas, respectively, and 1.0 for both nuclear energy and electricity. The η value is used to convert on-site operating energy to primary sources, taking into account the production and transportation losses. Its values are taken from (Zhang 1995) with the following two exceptions. First, generation loss is not considered for renewable energy sources such as hydro. Second, the applicable local electricity mix is used to calculate the η value of electricity.

Embodied energy (EN_j) and the mass of nonfuel resources (m_k) for a building material or assembly can be obtained from life cycle assessment programs. ATHENA (2002) program is used in this study.

Abatement exergy consumption (*AbatEx*) is calculated as the product of mass of waste emissions and its unit abatement exergy. That is:

$$AbatEx = \sum_w u_w \cdot m_w \qquad (6)$$

The unit abatement exergy (u_w) is usually determined according to the particular processes used to remove or separate waste emissions (e.g., decarbonisation of flue gases after combustion). In this paper, the values of unit abatement exergy for CO_2, SO_x, and NO_x are taken as 5.86, 57, and 16 MJ/kg, respectively (Cornelissen 1997). Since the values of unit abatement exergy for CH_4 and N_2O have not been found in the literature, they are derived by assuming that the abatement exergy is proportional to the global warming potential (GWP) index. Hence, they are calculated by multiplying the GWP index (over a 100-year period) by the unit abatement exergy for CO_2.

The mass of each waste emission (m_w) generated in the pre-operation phase is calculated by multiplying the emission per unit area by the applicable envelope area. The emissions per unit area for different materials construction are stored in the program data files, which are prepared in advance with the aid of the ATHENA program. The mass of each waste emission generated in the operating phase is calculated by multiplying the on-site operating energy consumption with an emission factor. The emission factor of delivered electricity is calculated from the electricity mix and the emission coefficients due to electricity generation from different fuel types (Gagnon et al. 2003).

CASE STUDY AND RESULTS

Case Description

A single-story office building located in Montreal is employed in this paper as a case to investigate the impact of electricity rate and mix on the optimum design. The building has a total above-basement floor area of 1000 m^2 with a 40-year life expectancy. The floor type is an open web steel joists (OWSJ) on beam system with concrete topping. The floor to roof height is 3.6 m. The energy consumption due to lighting is kept constant according to a given schedule. Only heating and cooling energy consumptions are considered in this case study. Heating season is from November to March, and cooling season from June to August. The indoor design temperatures are 21^{o}C and 23^{o}C in the heating and cooling season, respectively, without night setback or setup. Rooftop units (coefficient of performance of 3.0) are assumed to be used for cooling, and electric baseboard heaters for heating. Internal loads and daily operating schedule take the default values for office buildings according to the Model National Energy Code of Canada for Buildings (NRC 1997). The discount rate and the expected energy cost escalation rate (both including general inflation) are 9% and 3%, respectively (NRC 1997).

The list of variables used in this study is given in Table 1. There are two possible wall types. The first wall type is a masonry cavity wall, composed of the following layers in sequence from outside to inside: clay brick cladding, air space, rigid insulation, vapor barrier, masonry structure, and finish. The second wall type is a steel-frame wall composed of clay brick cladding, air space, air barrier, sheathing, steel-stud with cavity insulation, vapor barrier, and finish. Only one roof type is considered in this case study: a compact conventional roof system composed of ballast, roofing membrane, insulation, structure, and finish. Two rigid insulation materials: expanded polystyrene (EPS) and extruded polystyrene (XPS), are used in the masonry cavity wall and the roof. Two types of insulation batts: fiberglass batts (FG) and rockwool batts (RW), are used in the steel-frame wall. Each insulation layer can take one of six possible discrete values.

The above described variables are optimized for three scenarios with different electricity rates or mix for building operation (Table 2). The first scenario has low rate and low waste emissions. It corresponds to Quebec data in the year of 2003. The second scenario has high electricity rate based on New York City data. The third scenario has high waste emissions. It assumes that the electricity is totally generated from oil while keeping the same rate as the first scenario.

Table 1 Variable instantiation

Variable Name		**Variable Type**	**Range or Value**
orientation		Continuous	[0, 90]
aspectRatio		Continuous	[0.1, 1.0]
winType		Constant	Double Low-e
winRatio1		Continuous	[0.2, 0.8]
winRatio2		Continuous	[0.2, 0.8]
winRatio3		Continuous	[0.2, 0.8]
winRatio4		Continuous	[0.2, 0.8]
wallType		Discrete	(1, 2)
roofType		Constant	Compact conventional roof
Layer of wall Type1	cladding	Constant	Brick veneer
	other	Constant	20 mm air space
	insulation	Discrete	*W1-1.* 102 mm EPS *W1-2.* 127 mm EPS *W1-3.* 152 mm EPS *W1-4.* 102 mm XPS *W1-5.* 127 mm XPS *W1-6.* 152 mm XPS
	membrane	Constant	6 mil polyethylene
	structure	Constant	100 mm concrete block back-up
	finish	Constant	12.7 mm Gypsum
Layer of wall Type2	cladding	Constant	Brick veneer
	other	Constant	20 mm air space
	membrane	Constant	Asphalt sheathing paper
	sheathing	Constant	12.7 mm oriented strand board
	insulation (stud)	Discrete	*W2-1.* 152 mm FG *W2-2.* 203 mm FG *W2-3.* 254 mm FG *W2-4.* 152 mm RW *W2-5.* 203 mm RW *W2-6.* 254 mm RW
	membrane	Constant	6 mil polyethylene
	finish	Constant	12.7 mm Gypsum
Layer of roof Type	other	Constant	ballast
	membrane	Constant	4-ply Built-up
	insulation	Discrete	*R-1:* 178 mm EPS *R-2:* 203 mm EPS *R-3:* 229 mm EPS *R-4:* 178 mm XPS *R-5:* 203 mm XPS *R-6:* 229 mm XPS
	structure	Constant	OWSJ and steel decking
	finish	Constant	12.7 mm Gypsum

Results and Discussion

Due to the inherent randomness of genetic algorithm, the program is run three times for each scenario. Since the three runs for a particular scenario have similar results, only one of them is used for further analysis.

For the first scenario, the distribution of the initial, final, and external population in the performance space is presented in Figure 1. One can notice the following:

- The initial randomly produced individuals are widely distributed, while the final population is clustered to the lower left corner. The final population is close to the external population. Both observations indicate that a good convergence has been achieved.
- The role of optimization is noticeable. Every solution in the initial population is dominated by some solutions in the final external population. The minimum values of the life cycle cost and the life cycle environmental impact are $3.59*10^5$ \$ and $1.55*10^7$ MJ in the initial population, while they reached $3.35*10^5$ \$ and $1.39*10^7$ MJ in the external population after the optimization.
- The Pareto front, consisting of all the points in the performance space for Pareto solutions, is composed of two isolated regions which are indicated as zones *A* and *B* in the figure. Solutions in Pareto zone *A* have lowest cost, and solutions in zone *B* have lowest environmental impact.

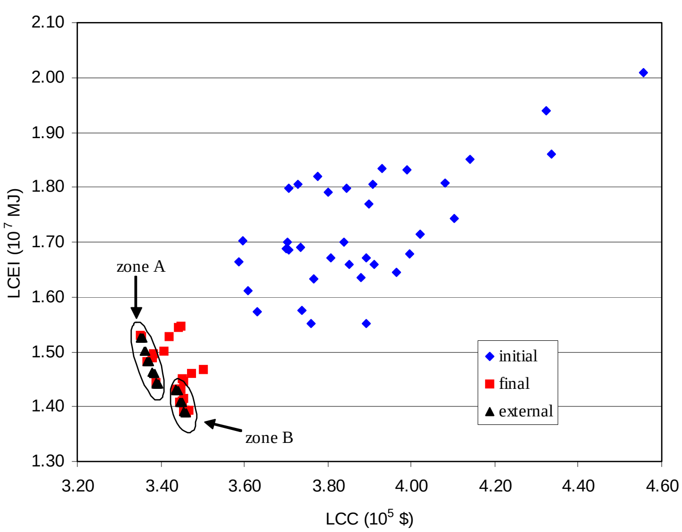

Fig. 1 Distribution of initial, final and external population in performance space (scenario 1)

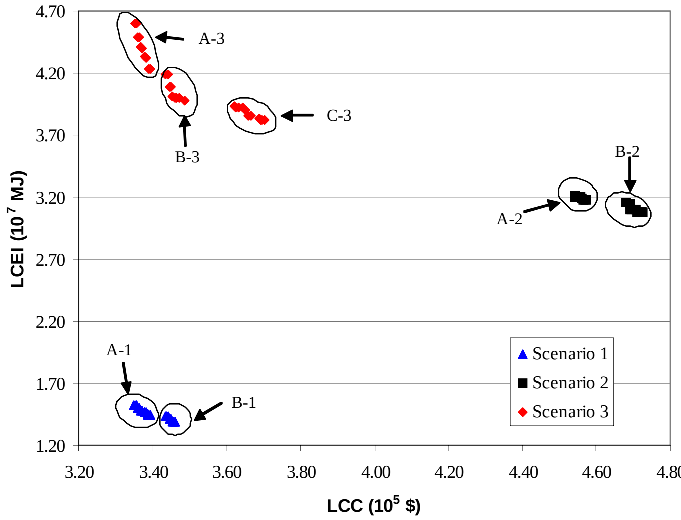

Fig. 2 Comparison of Pareto fronts for all three scenarios

The general trend of convergence is similar for all three scenarios. However, the final Pareto fronts are different in terms of the location and the number of isolated Pareto zones in the performance space (Figure 2).

Optimal solutions and the corresponding objective function values for each scenario are given in Table 3. Due to space limitation, the range is presented if a variable does not converge to a fixed value in a Pareto zone. Because window-to-wall ratios on all the four sides take the same value, it is indicated in the table without distinction about façade. The actual insulation materials presented in Table 3, were defined in Table 1. The following observations can be made:

- For all Pareto solutions in each scenario, orientation converges to zero; window ratio on each façade converges to the low bound value which is equal to 0.2 in this case study. This indicates that orientation and window ratio will converge to the same point even if the two objective functions are optimized separately.
- Scenarios 1 and 3 have located the Pareto zone (*A-1* and *A-3*) with steel-frame wall as the optimal wall type in terms of cost. However, the high electricity rate of scenario 2 make the steel-frame wall no longer a cost-effective solution.
- The optimal insulation for Pareto solutions is dependent on electricity rate and mix. Due to the low rate and low emissions of electricity, scenario 1 has limited the optimal roof insulation material to EPS, which has less initial cost than XPS. The high rate of scenario 2 has made the

insulation with high thickness and thermal resistance values (e.g., *R-3* and *R-6*) the optimal roof insulation. Because of the high emissions of electricity in scenario 3, optimal roof insulation varies from the least (*R-1*) to the highest (*R-6*) thermal insulation levels for different Pareto zones.

- The situation of insulation changing with the two performance criteria can be observed in each Pareto zone and between Pareto zones. In Pareto zone *A-3*, for example, the wall insulation changed from *W2-1* (152 mm fiberglass) to *W2-3* (254 mm fiberglass). From Pareto zone *B-3* to *C-3*, the insulation in roof changed from expanded polystyrene to extruded polystyrene which has lower thermal conductivity and higher density.

CONCLUSIONS

The multi-objective optimization model proposed in this paper can be used to locate optimum or near optimum green building designs for given conditions. Using expanded cumulative exergy consumption as the indicator for life cycle environmental performance, the optimization problem can be simplified by incorporating all considered impact categories into one objective function. The obtained Pareto front is important in helping designers to understand the trade-off relationship between the economical and the environmental performance.

The case study has demonstrated that the electricity rates and mix have a large impact on the configuration of Pareto fronts and the optimal variable values. High electricity rates lead to more energy efficient design. The low electricity rates and low emissions produce several different Pareto zones that may be favorable for initial construction cost or operating energy performance. Some variables such as orientation and window ratio on each façade converge to the same value for all Pareto solutions. However, optimal values for some variables such as aspect ratio and insulation materials vary with different Pareto solutions or Pareto zones.

It would be worthwhile in the future to study the impact of utility rates and utility structures on optimum design in different climates and for different fuel types.

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NOMENCLATURE

AbatEx: Abatement exergy (MJ)
AC: Annual operating cost ($)
CExC: Cumulative exergy consumption (MJ)
EE: Environmental impacts in pre-operation phase (MJ)
EN: Embodied energy (MJ)
IC: Initial construction cost ($)
LCC: Life-cycle cost ($)
LCEI: Life-cycle environmental impact (MJ)
OC: Life-cycle operating cost ($)
OE: Environmental impacts in operation phase (MJ)
ON: Annual on-site operating energy (MJ)
e: Chemical exergy of nonfuel material (MJ/kg)
i: Discount rate
m: Mass (kg)
n: Building life expectancy
r: Energy price escalation rate
u: Unit abatement exergy (MJ/kg)
α: Ratio between exergy and energy content
η: Overall efficiency of production and delivery of fuel

Subscripts:

j: Fuel type
k: Nonfuel material type
op: Operation phase
pp: Pre-operation phase
w: Waste emission type

Table 2 Electricity rates and mix for three scenarios

Scenario	Electricity Rates		Electricity Mix
	Demand Price ($ CAN/KW)	Consumption Price ($ CAN/KWh)	
1	11.97	0.0372 (0- 210000 KWh) 0.0242 (>210000 KWh)	96% hydro; 2% oil; 2% nuclear
2	27.04 (0-100 KW) 26.08 (100-900 KW) 25.15 (900-2000 KW) 23.98 (>2000KW)	0.1023	15% hydro; 12% oil; 16% coal; 27% gas; 28% nuclear; 2% other
3	11.97	0.0372 (0- 210000 KWh) 0.0242 (>210000 KWh)	100% oil

Table 3 Comparison of Pareto solutions for three scenarios

Scenario	Pareto Zone	orien.	aspect Ratio	winRatio	wall Type	wall Insu.	roof Insu.	LCC ($10^5$$)	LCEI (10^7 MJ)
1	A-1	0	0.79~ 0.97	0.2	2	W2-1, W2-3	R-1, R-2, R-3	3.35~ 3.40	1.53~ 1.44
	B-1	0	0.77~ 0.98	0.2	1	W1-3	R-1, R-2, R-3	3.44~ 3.46	1.43~ 1.39
2	A-2	0	0.71~ 0.94	0.2	1	W1-3, W1-6	R-3	4.54~ 4.57	3.21~ 3.18
	B-2	0	0.70~ 0.94	0.2	1	W1-3, W1-6	R-5, R-6	4.68~ 4.73	3.16~ 3.08
3	A-3	0	0.77~ 0.97	0.2	2	W2-1, W2-3	R-1, R-2, R-3	3.35~ 3.39	4.60~ 4.23
	B-3	0	0.70~ 0.99	0.2	1	W1-3, W1-6	R-1, R-2, R-3	3.44~ 3.49	4.19~ 3.98
	C-3	0	0.70~ 0.94	0.2	1	W1-3, W1-6	R-5, R-6	3.62~ 3.70	3.93~ 3.82