FINDING THE COST-OPTIMAL MIX OF BUILDING ENERGY TECHNOLOGIES THAT SATISFIES A SET OPERATIONAL ENERGY REDUCTION TARGET

Brian Simmons[1], Matthias H.Y. Tan[1], C.F. Jeff Wu[1], Youngdong Yu[2], and Godfried Augenbroe[1]
[1]Georgia Institute of Technology, Atlanta, Georgia
[2]Research Institute of Industrial Science and Technology, Seoul, Korea

ABSTRACT

This paper presents the development of an optimization methodology for selecting the lowest monetary cost combinations of building technologies to meet set operational energy reduction targets. The developed optimization algorithm comes from the fact that the actual properties of building technologies have a discrete nature and seeing their selection as a combinatoric problem. The optimization algorithm searches the discrete combinatoric space by maximizing the objective function: calculated energy savings divided by premium cost. The algorithm is codified into a custom MATLAB script and when compared to prescriptive methodologies is shown to be much more cost effective and can be generically applied given a palette of building technology alternatives and their corresponding cost data.

INTRODUCTION

The manufacturers of building materials, systems, and technologies continue to create larger palettes of products and levels of accomplishment within them. Each instance of a technology or system is considered to have effectiveness in its own right which can be ranked against others in its class. For example, the level of accomplishment of HVAC systems, boilers, and heat recovery units would be their macro system efficiency which can be ranked in order by each level of accomplishment. The level of accomplishment of a certain property or technology parameter is an important distinction from the performance of the whole building. Although each accomplishment level (expressed as values of a technology parameter) can be ranked in order, its role in the resulting performance of the whole building is only comprehensible in the outcome of the whole building system.

The diversity of technologies and discrete technology solutions exponentially increase the already broad spectrum of available design alternatives. The vast array of alternatives available for buildings can be seen as a discrete combinatorial space made up of all the possible combinations of levels of accomplishment from each technology category. Surveying this combinatorial design space reveals a dizzying number of possible technology combinations. For example, given 16 technology types with between 2 to 7 levels of accomplishment each, there exist more than 170 million unique combinations. The motivation to explore this combinatorial space of technology options is to develop a rigorous methodology for finding low cost solutions that meet the energy saving goals required by the local energy codes which enforce better performing buildings.

The American Institute of Architects created the 2030 challenge with the goal that all new buildings designed in the year 2030 and after will use net-zero site energy. The Korean government is currently pursuing even more aggressive legislation that will require all new buildings to use net-zero energy by 2025. In this instance, the net-zero building uses zero energy at the site meaning the energy produced at the site must meet or exceed the energy consumed by the building. The pathway towards this goal requires an incremental and affordable energy saving strategy. Many prescriptive building codes and guidelines such as LEED, ASHRAE Advanced Energy Design Guide in the US and Passivhaus in UK present a step by step method to reduce building energy use. These guides do not necessarily result in the selection of financially viable technology combinations and hence do not provide a cost-effective path for owners to meet the energy saving goals enforced by governing energy codes. To meet energy reduction targets, an optimization process is developed as the most efficient way to find sets of technology mixes that meet the energy saving constraints, and do so at minimal cost.

For this study we have focused on three levels of energy reduction, 30%, 50% and 100%. It is expected that each level can be reached by applying different combinations of technology solutions, with different extents and different accomplishment levels. At the 30 and 50 % levels a comparison with design guides and procedures that target the same goals will be performed.

METHODOLOGY

Case Study Buildings

Two buildings have been selected to study the application of the optimization methodology and compare its ability to reach lowest-cost technology mixes with the way current existing prescriptive techniques achieve energy savings. A 10 story 8,467 square meter office and a 15 story 60 unit 6,028 square meter apartment building have been selected as representations of prototypical Korean buildings.

Figure 1 Elevations of Apartment and Office Buildings

For this case study, the buildings are situated in the urban capital city of Seoul, Korea. The weather data used in the study is from the Incheon airport at latitude 37.48 degrees and longitude 126.55 degrees.

The two prototypical buildings are modeled with a normative energy modelling tool, EPC, which calculates the yearly energy use intensity (EUI) of each building with the given climate data. The following sections show the development and application of the optimization framework to meet the energy reduction targets. We then compare the resulting optima with the results we would obtain by following the procedures laid out in prescriptive design guides. Our optimization approach and the prescriptive techniques are then compared in their ability to reach the desired energy targets of 30% and 50% energy savings whereas the monetary cost of the suggested best mix will be compared across alternative approaches as well.

Modelling Approach

This study uses a normative energy calculation approach which is defined by ISO 13970 and CEN 15603. The ISO-CEN whole building energy modelling approach has been coded into an excel calculator that solves algebraic heat balance equations with averaged monthly weather data. The calculator's output is an energy use intensity, i.e. the yearly energy used per unit floor area in kilo-watt hours per square meter per year (kWh/m^2/year) and is mostly used in benchmarking the building's performance rating as an energy performance coefficient or EPC. This approach offers significant advantages over dynamic simulation based tools such as those promulgated by ASHRAE 90.1 and its Apendix G based LEED scoring of the EA credits. The main advantages are reduced modelling effort, increased transparency and avoidance of modeler's bias, increased model accountability and reduction or absence of computation time. The normative model this study utilizes is composed of algebraic heat balance equations and is therefore more transparent than a corresponding dynamic simulation model which numerically solves partial differential equations that describe the full complexity of dynamic physical behavior. Obviously the latter requires much more computation time that the simplified calculations encoded in the standard. The normative modelling methodology has been shown to lead to the same ranking of alternatives as the detailed dynamic simulation models. The reason for this surprisingly good behavior is the fact that simplified calculations do much better in comparative analysis than in predicting absolute outcomes. Recent work shows for example that a normative model produces the correct ranking and prioritization of energy conservation measures. (Heo et al 2011). When testing different competing technologies against each other, we are basically performing a comparative analysis. This substantiates that the underlying engine for finding the optimal mix of technologies is based on the normative model. A specially adapted version was developed for this purpose, making sure that all technologies and solutions were adequately represented in the energy performance calculation.

The resulting EPC calculation tool is used by the optimization algorithm to evaluate the combinatorial space of technology parameters in the two selected prototypical buildings. It should be stressed that the optimization problem is only well posed at the whole building level. As a consequence, optimality can only be defined at the whole building energy outcome level. Any attempt at a prescription of subset technology parameters will likely lead to a sub-optimal building because the performance of any single technology cannot judged on its own but only as part of the whole building system. Augenbroe (2011) asserts that the method of optimizing the building or a building system by simply selecting the components with the highest achievement is inadequate for many system theoretic problems. Rather the whole building's performance must be evaluated as a function of all technology parameters.

Prescriptive energy codes and guidelines bias the technologies that the design team selects because guidelines by definition trail developments available in the market. Therefore, they list only a segment of the technologies available at the time of application. Any list of prescribed technologies is inherently reflective of the regulators' bias and limits the number of acceptable strategies. Instead, a whole building energy performance indicator like energy use intensity that can account for the complexities and interactions between different technologies, should be used to benchmark buildings.

A performance based approach allows for compliance through innovation and does not restrict the path selected to reach the energy performance requirement. For example, if a design space of 16 parameters has 170 million possible combinations, the prescriptive compliant building is just one data point in a vast array of possible solutions that meet an energy reduction target and most likely is not the monetary cost optimal one. If these possible combinations are seen as a potential population of typical buildings then a Monte-Carlo random sampling method can be used to enumerate a portion of this population. Figure 2 shows an example population of virtual realizations of Korean office buildings as a probability density function from 10,000 random technology combinations. In this population, the mean building has a EUI of 135 kWh/m^2/year, of which there are almost 280 instances (each instance representing a particular mix in the considered building). The developed optimization methodology searches the combinatorial space, or potential population of instances of technology mixes applied to the considered building, for the single instance that meets the energy saving objective at the lowest monetary cost.

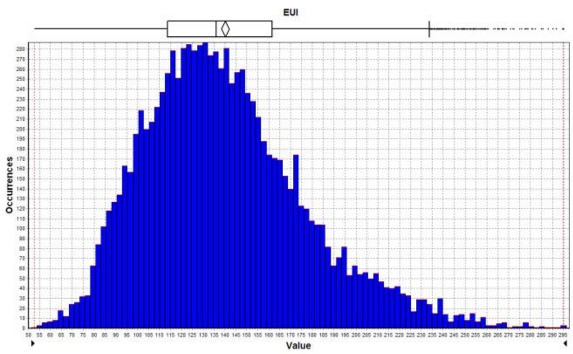


Figure 2 Population of Potential Buildings

Baseline Definitions

The baseline building performance for the apartment and office building are calculated by applying the prescriptive Korean building code to each building. Amongst others, the code dictates minimum allowable U-values for the building's envelope and overall system efficiencies. The Korean building code varies for each of its three regions; Central, Southern and Jeju Island. Seoul is in the Central Region of Korea so the building codes that apply there are used to determine the baseline buildings' properties. (Table 1)

Table 1
Korean Building Codes

Korean Standards for Envelope Conductivity	Roof U-Value W/m^{2}K	Wall U-Value W/m^{2}K	Window U-Value W/m^{2}K
Central Region	0.2	0.36	2.1
Southern Region	0.24	0.45	2.4
Jeju Island Region	0.29	0.58	3.1

The occupancy schedule for the office building is defined as 100% occupancy for normal weekday operation: Monday - Friday, 9:00am - 6:00pm, with no other occupied times. The occupancy schedule for the apartment building is interpolated at hourly points from a continuous model. (Richardson 2008) The baseline office and apartment buildings' yearly energy use intensity as calculated with the normative model includes energy consumed for heating, cooling, ventilation, ligthing, plug loads and hot water is 320 and 346 kWh/m^2/year respectively. The heating and cooling demand, before efficiencies of mechanical equipment is considered, for the baseline office building is 66 and 49 kWh/m^2/year respectively while the demands for the baseline apartment building are 69 and 35 kWh/m^2/year which demonstrates that the Central Region of Korea is a heating dominated climate zone.

Cost Function

The cost function this study aims to minimize is a linear sum of the premium monetory costs of 16 technologies (identified by technology parameters) at their levels of achievement. The premium monetary cost is defined as the cost of any technology's level of achievement cost minus baseline cost. For each technology we define a cost evaluation function with the technology parameters and certain building specific parameters as its arguments. For each evaluation of the cost function the cost of all applied technologies are summed to calculate total premium cost.

Any technology that is not included in the baseline building but is added later as in the case of renewables and heat recovery, the premium cost is just the total cost of the technology since the baseline cost of that parameter is zero. Since the baseline cost is subtracted from the cost of each added technology the "premium" cost of the baseline building equals zero.

The cost function can be written as:

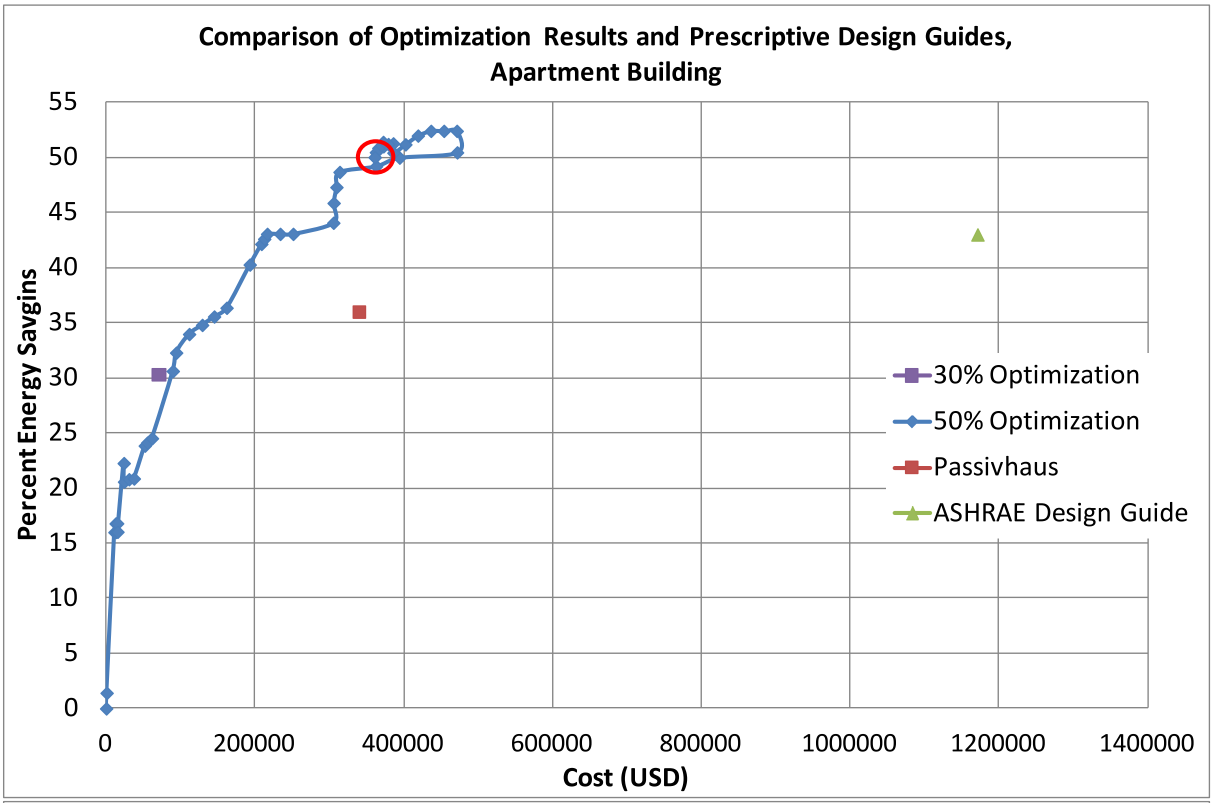
$$C(\boldsymbol{x}) = \sum_{i=1}^{p} A_i(x_i),$$

where $x_i \in \{0,1,\ldots,n_i\}$, $x_i = 0$ represents the baseline, $x_i = 1,2,\ldots,n_i$ represents the achievement levels ordered along increasing cost (i.e., if $j < k$, $A_i(j) < A_i(k)$). For each technology, $A_i(0) = 0$; therefore, $C(\boldsymbol{0}) = 0$.

It should be noted that this method of costing removes the time sensitivity of technology cost and excludes Net Present Value or return on investment calculation because the main goal of the optimization algorithm is to meet an instantaneous energy reduction target at the time of construction at minimum capital investment cost. The 16 technology parameters considered and their corresponding levels of accomplishment with individual premium costs based on system size are given in (Figure 3).

Energy Saving Technologies and Accomplishment Levels	Premium Cost for Apartment	Premium Cost for Office	Apartment		Office	
			30% Energy Savings	50% Energy Savings	30% Energy Savings	50% Energy Savings
A0 (NULL) Daylight Sensor	0	0	■	■	■	■
A1 Partial Daylight Sensor	1635	230725.75				
A2 Fully Automated Daylight Sensor	2068.8	291942.16				
B0 (NULL) Occupancy Sensor	0	0	■		■	■
B1 Partial OccupancySensor	1635	230725.75		■		
B2 Fully Automated Occupancy Sensor	2068.8	291942.16				
C0 (NULL) Baseline Dimmer Switch	0	0	■		■	
C1 Partial Dimmer Switch	661.8	93391.01		■		■
C2 Full Dimmer Switch	992.4	140044.18				
D0 Two-Pipe FCU, Standard Boiler and Chiller	0	0	■	■	■	■
D1 Two-Pipe FCU, Improved Boiler	280844.52	394477.53				
D2 Two-Pipe FCU, Air Source Heat Pump	593577.16	833745.49				
D3 Two-Pipe FCU, Ground Source Heat Pump	2692044.52	3781277.53				
E0 (NULL) Heat Recovery	0	0	■		■	■
E1 Loading Cold with Air-Conditioning	31140	439437.3				
E2 Two-Elements-System	46710	659155.95				
E3 Heat Exchange Plates or Pipes	50602.8	714106.78				
E4 Slowly Rotating Heat Exchangers	54495.6	769057.61		■		
F0 Exhaust Air Recirculation (NULL)	0	0	■	■	■	
F1 Exhaust Air Recirculation (20%)	17408.4	24554.3				■
F2 Exhaust Air Recirculation (40%)	34816.8	49108.6				
F3 Exhaust Air Recirculation (60%)	52225.2	73662.9				
G0 Baseline Air Tightness - Medium	0	0				
G1 Baseline Air Tightness - Low	10525.168	11910.872	■	■	■	■
H0 Baseline Standard Boiler	0	0	■	■	■	■
H1 Electric Boiler	186000	63248.49				
H2 Co-Generation Boiler	260400	130984.49				
I0 (NULL) Building Energy Management System	0	0	■	■	■	■
I1 User Adaptive BEMS	301400	423350				
I2 Controller Optimized BEMS	452100	635025				
I3 Fault Detection Diagnosis BEMS	602800	846700				
J0 (NULL) Photovoltaic Modules	0	0	■		■	■
J1Photovoltaic Modules 25% Roof	17493.25	35350.56		■		
J2 Photovoltaic Modules 50% Roof	33558.65	70716.15				
J3 Photovoltaic Modules 75% Roof	50338.81	106045				
K0 Baseline Equipment	0	0				
K1 Energy-Star Baseline	14727	24545		■		
K2 Energy-Star Top 10%	17999.4	29999			■	
K3 Energy-Star Top 5%	24352.8	40588	■			■
L0 Code Compliant Florescent Lighting	0	0	■		■	■
L1 T-10 Florescent	77459.8	108800.95		■		
L2 T-8 Florescent	232319.12	326318.18				
L3 Compact Florescent	586644.96	824008.44				
L4 LED	782193.28	1098677.92				
M0 Metal Decking with Insulation	0	0	■	■	■	
M1 Metal Roof, Extruded Polystyrene (139.7mm)	6478.628	13648.804				■
M2 Metal Roof, Extruded Polystyrene (190.5mm)	13146.149	27695.557				
N0 EFIS Wall	0	0	■		■	
N1 Build Block ICF 4" 101.6mm + Acrylic Surfacing	54162.187	48785.315				
N2 Ray Core SIP 3.5" (88.9mm) + Acrylic Surfacing	54622.088	49199.56				
N3 Build Block ICF 6" + Acrylic Surfacing	58372.05	52577.25				
N4 Build Block ICF 8" + Acrylic Surfacing Systems	62546.536	56337.32				■
N5 Ray Core SIP 5.5" (139.7mm) + Acrylic Surfacing	111649.812	100565.94				
N6 Ray Core SIP 7.5" (190.5mm) + Acrylic Surfacing	142993.834	128798.33		■		
O0 Double Glazing	0	0				
O1 Double Air Low-E	28012.952	46166.692	■			
O2 Triple Air Low-E	32513.976	53584.596		■	■	
O3 SouthWall Super Glass QUAD Clear/Air/41mm	156543.838	257991.773				■
O4 SouthWall Super Glass QUAD Clear/Argon/41mm	158128.08	260602.68				
O5 SouthWall Super Glass QUAD Clear/Argon/51mm	164509.466	271119.511				
O6 SouthWall Super Glass QUAD Clear/Krypton/51mm	307890.77	507418.795				
P0 (NULL) Solar Boiler	0	0			■	■
P1 Solar Boiler 25% of Roof	2199.75	4445.28	■	■		

Figure 3 Accomplishment Levels of Technology Parameters (First/Leftmost Column), Their Premium Costs (Second and Third Columns), and Technology Levels Selected by Optimization Algorithm (Fourth Column to Seventh/Rightmost Column), Korean Apartment and Office Buildings. Selected technology levels are indicated by the shaded cells.



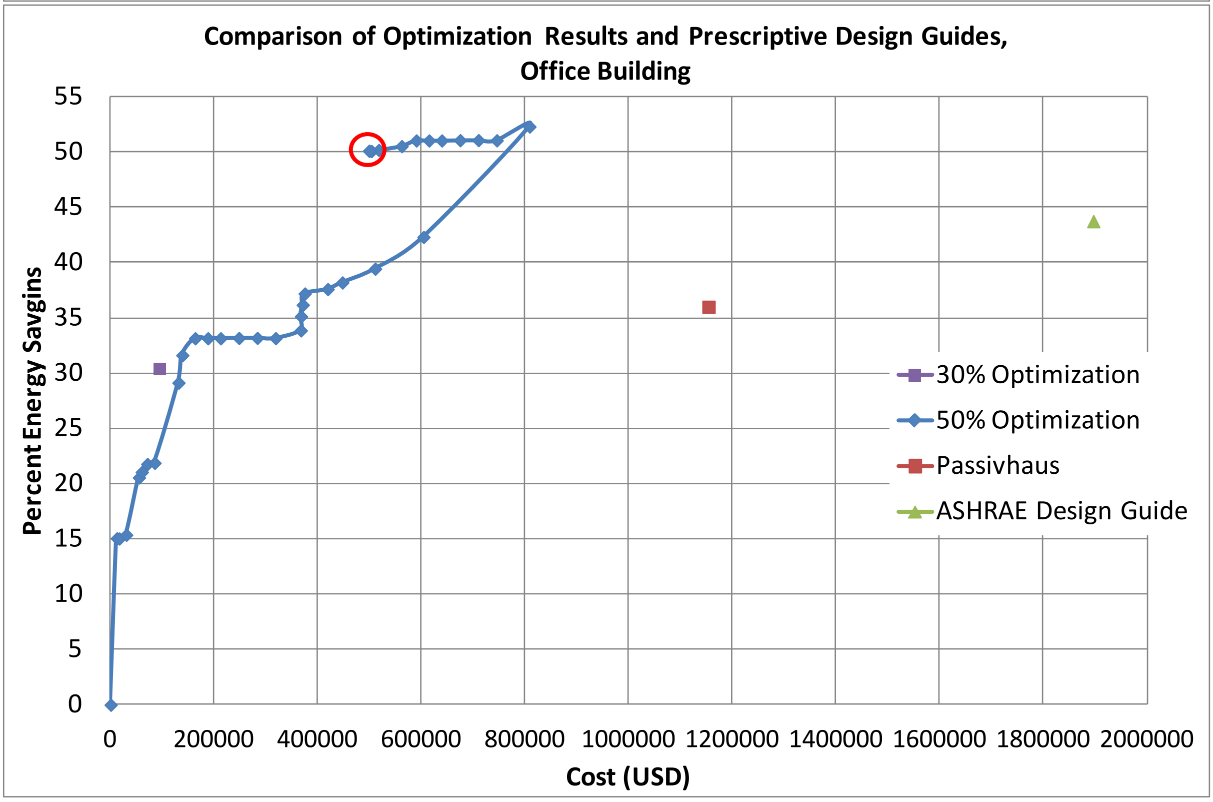


Figure 4 Comparison of Optimization Results and Prescriptive Design Guides for Korean Apartment and Office Buildings. Blue lines plot the percent energy savings versus cost for technology level combinations visited by optimization algorithm when the energy savings target is set to 50%. The starting point is the origin. The algorithm increases the technology level of a technology parameter at each step until the energy savings exceed the target. Then, it reduces the technology levels and terminates when further reduction causes the energy savings target constraint to be violated (termination point is indicated by a red circle).

Optimization

To search the large discrete combinatorial space of technology alternatives an optimization algorithm is developed into a MATLAB code which automates the testing of combinations of technologies in a combined ascent and descent method which can be initialized at any point, i.e. at any specific set of technologies to begin the search for an optimum. In this paper, we initialize the combined ascent-descent procedure from the baseline building where all technologies are equal to the lowest or baseline level of accomplishment. The algorithm then ascends in steps by selecting the single alternative that maximizes the objective function, energy savings divided by monetary cost or E/C ratio, until the energy saving target is reached directly or exceeded. When the energy savings target is exceeded, the algorithm performs the procedure in reverse, by stepping down levels of accomplishment (in such a way that the E/C ratio is maximized and the energy saving constraint is satisfied) until any further step would result in the violation of the energy saving constraint. In this study the switch to the descent procedure can be seen in Figure 4 at the ridge where the optimization path reverses and steps down to reach the final value of the E/C Ratio.

The developed combinatorial optimization approach is unlike previous optimization studies because it does not reduce the discrete nature of technology accomplishments by continualizations between minimum and maximum property values but retains the ability to produce unique solutions from currently available discrete technology options and products. One reason to support the creation of custom MATLAB code for optimization is that even powerful off-the-shelf software such as Phoenix Integration's Model Center is unable to execute optimization algorithms with discrete input parameter values. Even with an automated process in MATLAB, enumerating the full factorial set of combinatoric options is computationally prohibitive; the main computation burden is the evaluation of the energy savings of the 170 million technology achievement level combinations utilizing our Excel implementation of the normative building energy model.

Optimization Algorithm

The optimization algorithm is specified below.

$$C(\boldsymbol{x}) = cost\ function$$

$$E(\boldsymbol{x}) = energy\ savings\ function$$

$$\chi = \{0, \ldots, n_1\} \times \cdots \times \{0, \ldots, n_p\}$$

$$T = minimum\ required\ energy\ savings$$

$C(\boldsymbol{x}) = \sum_{i=1}^{p} A_i(x_i)$, where $x_i \in \{0,1, \ldots, n_i\}$ and the A_i's are increasing functions, i.e., $A_i(x_k) > A_i(x_l)\ if\ k > l$.

Assume that $E(\mathbf{0}) \leq T \leq E\left((n_1, \ldots, n_p)^T\right)$ and $E\left((n_1, \ldots, n_p)^T\right) = \max\{E(\boldsymbol{x}) : \boldsymbol{x} \in \chi\}$.

Initialize**:** Specify a starting solution $\boldsymbol{x}_0$. Compute $E(\boldsymbol{x}_0)$. Set $\boldsymbol{x} = \boldsymbol{x}_0$. If $E(\boldsymbol{x}_0) > T$, use Descent Procedure. If $E(\boldsymbol{x}_0) < T$, use Combined Ascent and Descent Procedure.

Descent Procedure:

1. Set $\Omega = \{1, \ldots, p\}$.
2. For $i \in \Omega$, set $\boldsymbol{x}^i = \boldsymbol{x}$. If $x_i^i > 0$, set $x_i^i = x_i^i - 1$ and compute $S(\boldsymbol{x}^i) = E(\boldsymbol{x}^i)/C(\boldsymbol{x}^i)$. Otherwise, set $\Omega = \Omega \backslash \{i\}$.
3. If $\Omega = \emptyset$, **stop** and return $\boldsymbol{x}$. Otherwise, find $k = \mathrm{argmax}\{S(\boldsymbol{x}^i) : i \in \Omega\}$.
4. If $E(\boldsymbol{x}^k) \geq T$, set $\boldsymbol{x} = \boldsymbol{x}^k$ and return to Step 2. Otherwise, set $\Omega = \Omega \backslash \{k\}$ and return to Step 3.

Combined Ascent and Descent Procedure:

1. Set $\Omega = \{1, \ldots, p\}$.
2. For $i \in \Omega$, set $\boldsymbol{x}^i = \boldsymbol{x}$. If $x_i^i < n_i$, set $x_i^i = x_i^i + 1$ and compute $S(\boldsymbol{x}^i) = E(\boldsymbol{x}^i)/C(\boldsymbol{x}^i)$. Otherwise, set $\Omega = \Omega \backslash \{i\}$.
3. Find $k = \mathrm{argmax}\{S(\boldsymbol{x}^i) : i \in \Omega\}$ and set $\boldsymbol{x} = \boldsymbol{x}^k$.
4. If $E(\boldsymbol{x}^k) \geq T$, find $l = \mathrm{argmin}\{C(\boldsymbol{x}^i) : i \in \Omega, E(\boldsymbol{x}^i) \geq T\}$, and set $\boldsymbol{x} = \boldsymbol{x}^l$. Otherwise, return to Step 2.
5. Apply Descent Procedure with $\boldsymbol{x}$ as starting point.

OPTIMIZATION RESULTS

The energy saving targets for the optimization are set for 30% and 50% of the EUI for the prototypical apartment and office building. The energy saving target forms the constraint whilst the objective is the minimization of the premium cost function. Analysis of the optimization routine shows that the algorithm selects more photovoltaics to generate renewable energy in the middle of the process but after the building envelope's level of accomplishment is raised the enegy demand decreases and the value of the photovoltaics for energy production diminishes thus the solar panels are actually removed during the descent procedure. The ridge at the end of each of the optimization procedure, seen in each of the two optimization graphs in Figure 4 , are sets that are very close to the optimal point but happen to be located where technology accomplishment levels can still be decreased. The optimization algorithm's descent procedure continues to step down the level of technology accomplishment until the energy savings target as a constraint is violated.

This study assumes that given two technology achievement level combinations that achieve energy savings greater than the target, the decision maker prefers the one with the smaller cost. Thus, even though the technology combinations on the ridge of the final descent procedure are very close to the optimum, the technology levels are stepped down until any further stepping down would violate the energy saving constraint.

To highlight the insights that can be garnered from our approach we present a few salient results. (Figure 3) The technology parameters that the optimization algorithm selects for the 30% energy savings target apartment building are: improved sealants (ACH = 0.20), Energy Star appliances, Double Low-E Glazing, and Solar Hot-Water installed on 25% of the roof area. For the office building with the 30% target, the optimization algorithm selected improved sealants (ACH = 0.13), Energy Star equipment, and Triple Low-E Glazing. In the optimization process to reach the 50% energy savings target for the apartment building the algorithm selected Occupancy Sensors, Dimmer Switches, Rotating Heat Exchangers, improved sealants (ACH = 0.20), Photovoltaics on 25% of the roof area, Energy Star Equipment, T-10 Florescent Lighting, SIP wall panels with 190.5mm polystyrene insulation, Triple Low-E Windows, Solar Hot Water on 25% of the roof area. In the optimization process to reach the 50% energy savings target for the office building the algorithm selected Dimmer Switches, 20% Exhaust Air Recirculation, improved sealants (ACH = 0.13), Energy Star Equipment, 139.7mm Extruded Polystyrene Roof Insulation, 203.2mm Insulated Concrete Form Work, and 41mm Quadruple Glazing.

PRESCRIPTIVE METHOD RESULTS

Passivhaus

The Passivhaus ideology and rating system is interesting because it is composed of both prescriptive requirements and a performance rating. The performance rating in this system is set up such that certification can only be awarded after the building is operational, where as our study only considers design specifications. To rate the outcome of the Passivhaus compliant designs in this study the impact of the Passivhaus guidelines on the office and apartment building's EUI are calculated with our nornmative model. For the office and apartment buildings in this case study the Passivhaus guidelines required selecting the technologies: slowly rotating heat exchangers, improved sealing (ACH = 0.13/0.20 office/apartment), 139.7mm polystyrene roof insulation, SIP wall panels with 139.7mm polystyrene insulation, and 41mm quadruple glazing. The office and apartment buildings recorded a 35.6% and 36.0% energy savings respectively, as a reduction in EUI in our calculations.

ASHRAE Advanced Energy Design Guide

The ASHRAE Advanced Energy Design Guidelines were developed as a prescriptive methodology for small to medium office buildings to achieve 50% energy savings with variations provided for each of the US climate zones. The document also includes conceptual ideas about integrated design frameworks and workflow arrangements that will help facilitate the production of energy efficient buildings. In this case study we assume that the prototypical Korean apartment and office buildings have been through the design development stage and are being optimized for materials, lighting, and heating and cooling systems so the focus of the application is the specific level of achievement for each of the associated technology parameters. For this study the recommendations are applied for US climate zone 4, Baltimore, which is a coastal city two degrees of latitude north of the Korean Capital, Seoul.

The technologies that were required for the apartment and office to meet ASHRAE Energy Design Guide standards are Daylight Sensors, Occupancy Sensors, High Efficiency Boiler for heating and hot water, improved sealants (ACH = 0.13/0.20 office/apartment), Energy Star Equipment, High Efficiency Florescent Lighting, 139.7mm polystyrene roof insulation, SIP wall panels with 88.5 mm polystyrene insulation. The office and apartment buildings both recorded a 43.75% and 43.0% reduction in EUI respectively as calculated by our model.

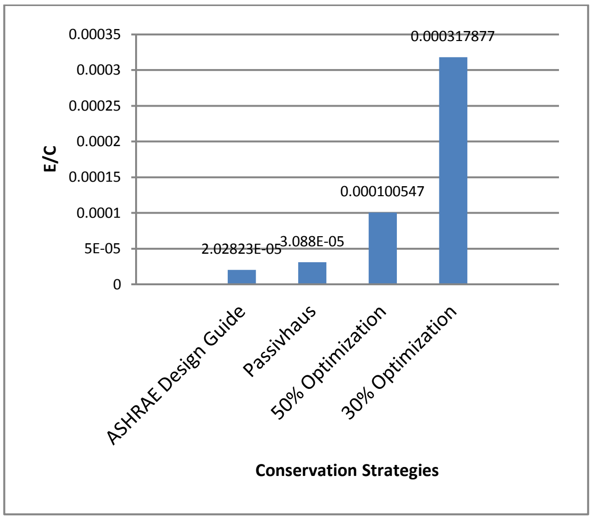


Figure 5 Energy Savings / Premium Cost: Office Building

CONCLUSION

We introduced an optimization algorithm to maximize the ratio of energy savings divided by cost (E/C) of an energy saving technology mix. The evaluation of the (E/C) ratio is applied to an apartment building and an office building located in Korea. The (E/C) ratio ranking demonstrates that existing (semi-)prescriptive methodologies are much less efficient than the optimization algorithm at reducing the prototypical buildings' EUI at the lowest premium cost. (Figure 5) The optimization methodology is shown to produce superior performance in terms of finding the lowest cost solutions to energy saving targets for prototypical apartment and office buildings. (Figure 4) This result further reinforces the concept of performance based thinking in that the performance indicator, EUI, is a function of all the building parameters and can only be optimized at the whole building level rather than sub-optimizing (or prescribing) a subset of technology components. Furthermore, this result identifies the weaknesses of prescriptive energy saving methodologies in that they do not provide cost efficient solutions to meet the energy saving targets imposed by international energy codes and desired by building owners.

Further Applications

The optimization algorithm developed in this study could be extended as a tool to study hypothetical situations based on trends in technology development and price forecasting. The tool can be used to answer the questions such as: how much will the cost of a certain technology have to fall before its selection is advantageous over others of the same type? The optimization process could be made an integral part of performative based energy codes such that building owners would have more design alternatives than those listed in current (partly prescriptive) codes to develop energy efficient buildings.

In the briefing and developing requirements stage the optimization process could also be used to determine appropriate energy saving targets given the owner's budget limit to spend on premium energy conservation measures.

The optimization tool could be even more powerful and widely applicable if cost data were published by manufacturers as openly as the physical characteristics of their systems. If the availability of cost data increased then it would be possible to make more accurate longitudinal projection for cost increases such that Net-Present Value could be transparently calculated along with the lifetime cost of operational energy use of the building. These lifetime costs could then be aggregated to transparently find total operations and maintenance cost for each technology combination.

The results from the optimization can also be used to make more informed general predictions about which combinations will produce cost-optimal solutions in buildings of similar size, type, function, and climate given a similar palette of technology parameters and cost information. The optimization approach could also be extended to select technologies for retrofit strategies also to demonstrate a more cost-effective path to bringing existing buildings up to current levels of energy code compliance than generic prescriptive guidelines.

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