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ABSTRACT

Optimizing the life cycle cost of a building typically involves a large number of variables due to the many options that exist at the time that a building is being designed. Such large-scale optimization problems are often prohibitive within the building industry because of the excessive computational time required by the building energy modeling software; therefore, any optimization studies that are performed during a building design are typically only completed using a small number of variables. To achieve the goal of performing a life cycle building optimization in an acceptable time frame, this paper proposes an accurate and efficient method using singular value decomposition on the design variables. Through the use of singular value decomposition a large number of design variables can be reduced to a smaller subset of design variables that can be solved more quickly by the optimization algorithm. In this paper the authors apply this methodology to a case study of a typical residential building in six separate locations across the U.S. and compare the results with those of the full optimization process over the entire design space.

1. INTRODUCTION

As energy consumption in the U.S. continues to increase, building energy modeling and simulation software is being incorporated more regularly into the building design process to simulate thermal loads and energy consumption, and to predict the energy performance characteristics of the building prior to construction. Energy simulation programs typically require hundreds of design parameters as inputs, which means they are not often employed at a very early design stage because a large number of the design parameters are still uncertain (Augenbroe, 2002). Since any given building project can include a large number of design variables, and each variable may take on many different values, it is impossible to do an exhaustive search of the entire design space to find the variables that optimize the building design subject to various project constraints and objectives, such as construction cost, energy cost, and environmental impact.

The current study proposes an accurate and efficient method to perform the optimization, using detailed energy calculation with existing energy simulation software, and using actual construction costs. This optimization is normally prohibitive because of calculation time and therefore it is processed with only a limited number of variables. The main reason for the long running process is that there are too many input variables and the building energy simulation software takes a long time to predict energy consumption. To perform the optimization within an acceptable time frame, several approaches can be made. The focus of this study is on reducing the number of design variables that are considered during the optimization process. Many approaches to reduce the number of design variables have been studied in the past. Bettonvil and Klenijnen (Bettonvil & Klenijnen, 1997) applied a group screening method by detecting the important factors using sequential bifurcation to the building energy model. The author asserts that important factors need to be further explored in a later phase, for example in the optimization stage. Rahni (Rahni, et al., 1997) partitioned factors into groups and tested which group demonstrates a significant effect. Only 6% of the input variables were identified as important variables for analyzing the output model.

However, not many studies have been performed to further examine the trade-offs between accuracy of the optimization study and the efficiency of the optimization algorithm with a reduced number of design variables.
To achieve the goal of performing a life cycle building optimization in an acceptable time frame, this paper proposes an accurate and efficient method using singular value decomposition on the design variables. Through the use of singular value decomposition a large number of design variables can be reduced to a smaller subset of design variables that can be solved more quickly by the optimization algorithm. In this paper the authors apply this methodology to a case study of a typical residential building in six separate locations across the U.S. and compare the results with those of the full optimization process over the entire design space.

2. METHODOLOGY

To have an accurate methodology for determining the optimized building system, a detailed energy consumption model using energy simulation software needs to be utilized to evaluate the energy cost along with a detailed cost model of the building. This study is focused on reducing the variables in the design space by eliminating insignificant design variables through a variable selection method. Significant variables are considered to be those that demonstrate the strongest contribution to the output results. Using this approach, significant variables are identified for use in the optimization process while redundant variables and insignificant variables are discarded prior to optimization. To validate the accuracy of this methodology, two optimization processes are set. The processes are described in Figure 1. The first is the original optimization process, which is performed using all available design variables. The second is a reduced optimization process, which is performed with a smaller subset of only the significant design variables based on the variable selection approach. In this study, singular value decomposition is used to explore the design space and determine the most significant variables for use in the optimization study.

To perform an optimization study on the buildings and compare the alternatives, minimizing life cycle cost (LCC) is used as the objective function. To have an accurate analysis, the first step is to develop a detailed building energy simulation model and cost database. To develop a detailed building model, the energy simulation software EnergyPlus is selected and used. For the cost database, RSMeans (RSMeans, 2011) is used for construction cost, while HVAC equipment cost data is taken from online equipment suppliers.

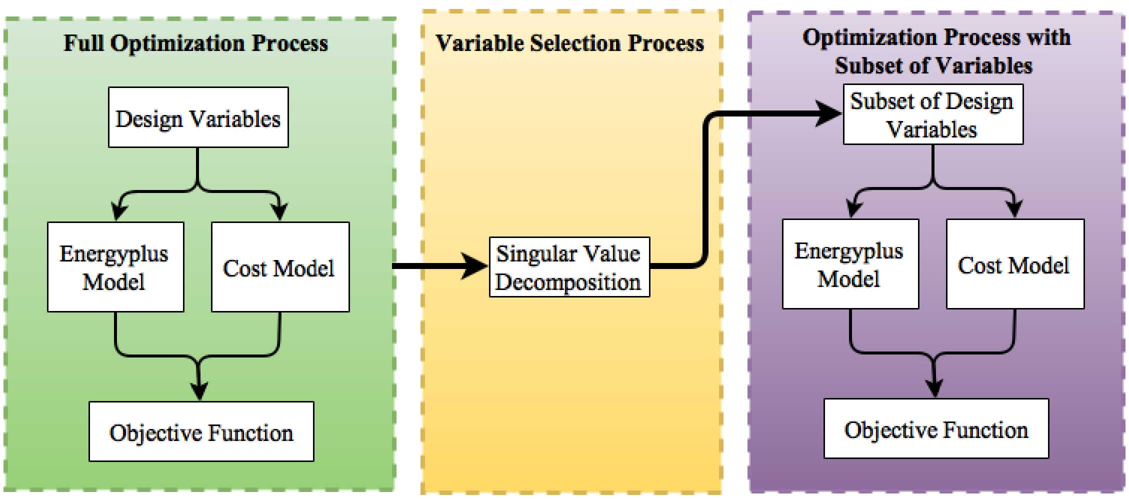

Figure 1: Description of methodology

3. CASE STUDY

3.1 Case study building characteristics

The case study building is assumed to be a typical U.S residential single family home (Cooper, 2011) with a crawl space and attached garage. Gross floor area of the house is 139.1m^2 (1497 ft^2) and detailed dimensions are shown in Figure 2. To investigate the impact of different climates on building energy consumption and optimization results, six different locations are considered; including, Denver, CO, Indianapolis, IN, Minneapolis, MN, Phoenix, AZ, Seattle, WA, Tampa, FL. The house has four different thermal zones, which include a living space, garage, crawl space, and attic. The living space, which is 111m^2 (1194 ft^2) is the only actively conditioned zone in the home while the remaining zones are unconditioned.

All of the major building construction elements are defined on a layer-by-layer basis to emulate typical residential house construction. The primary HVAC system for the house is modeled as a single-zone unitary system and the heating and cooling capacities are sized based on calculated building thermal loads. The heating set point temperature is fixed at 21.1°C (70°F) and the cooling set point temperature is set to 23.3°C (74°F). For realistic seasonal control of the HVAC system, a seasonal on-off schedule is set for all locations. Since each location has a different heating/cooling season, a generalized approach to cover all location is assumed as follows: a) the heating system is on from August 22 to May 1 and b) cooling system is on from March 21 to October 21. The overlapping dates allow both the heating and cooling systems to be active during the shoulder months when any given day may require heating during one portion of the day and cooling during another.

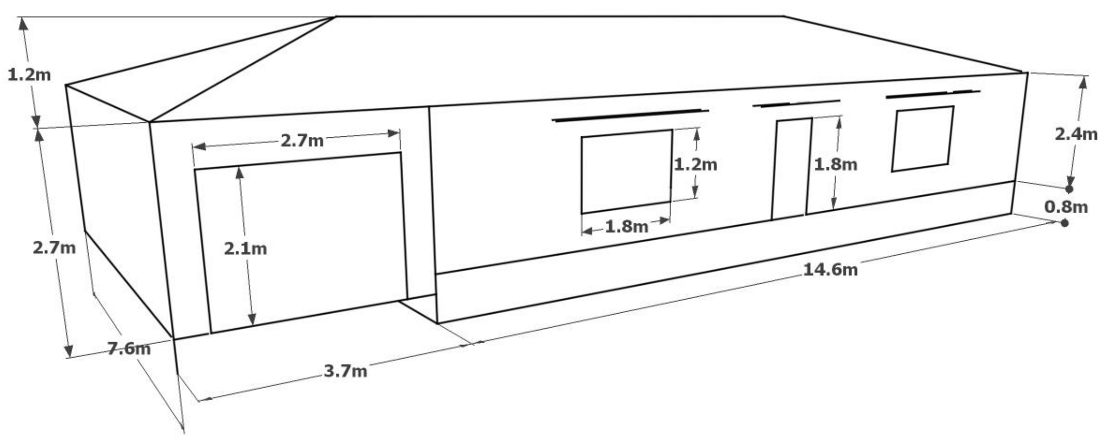

Figure 2: Model dimension

3.2 Selected design variables for optimization

The following considerations are made in selecting the design variables for the study: 1) select elements that may have a high impact on house energy consumption, 2) select elements that may have a strong influence in the construction cost, 3) select elements that may have energy saving or cost saving but whose influence is not strictly known beforehand. Based on these considerations, 13 different construction design variables were selected to investigate their impact on life cycle cost of the residential building. The first nine variables are related to the building envelope and the remaining variables are related to the HVAC system. Only those design variables relative to the envelope and the HVAC system that are commercially available have been selected for inclusion in the current study. As a result, the design variables can only take on discrete values or categorical values, which are listed in Table 1. Each variable can take anywhere from two to 16 values shown in the second column. For example, roofing material can take on a value of asphalt shingles, metal surface, or concrete tile roof. Design variables of the wall core can be a given stud dimension and filled with any type of insulation shown in the table. Structural insulated panels or insulated concrete forms with various thicknesses are also considered as wall core material for this study.

Table 1: Design variables and values

<table>
<tr><th>Design variables (Number of options)</th><th colspan="2">Values</th></tr>
<tr><td>Roofing Material (3)</td><td colspan="2">Asphalt shingles, Metal surface, Concrete tile roof</td></tr>
<tr><td>Roof Eave overhang Depth (3)</td><td colspan="2">305mm, 457mm, 610mm</td></tr>
<tr><td rowspan="2">Attic Insulation Material (12)</td><td colspan="2">Loose fill cellulose: SI-R3.3, 4.4, 5.3, 6.7, 8.6, 10.6</td></tr>
<tr><td colspan="2">Fiberglass batting: SI-R3.3, 4.4, 5.3, 6.7, 8.6, 10.6</td></tr>
<tr><td>External Wall Siding Material (4)</td><td colspan="2">Vinyl siding, Wood siding, Fiber cement siding, Brick</td></tr>
<tr><td rowspan="3">Wall Core (16)</td><td>Stud: 38mmx89mm (2”X4” nominal) studs at 400mm (16”) on center, 38mmx140mm (2”X6” nominal) studs at 600mm (24”) on center, 38mmx184mm (2”X8” nominal) studs at 600mm (24”) on center</td><td>Insulation: Filled with fiberglass batting insulation, Sprayed on foam insulation, Loose fill cellulose insulation</td></tr>
<tr><td colspan="2">Structural Insulated Panels (SIPS) [mm]: 114, 165, 210, 260</td></tr>
<tr><td colspan="2">Insulated Concrete Forms (ICF) [mm]: 228, 278, 328</td></tr>
<tr><td>External Foam Board Insulation (6)</td><td colspan="2">Board insulation [mm]: 12.7, 25.4, 38.1, 50.8, 63.5, 76.2</td></tr>
<tr><td rowspan="2">Foundation Wall Insulation (9)</td><td colspan="2">Foundation board insulation [mm]: 12.7, 25.4, 38.1, 50.8, 63.5, 76.2</td></tr>
<tr><td colspan="2">Foundation spray foam [mm]: 25.4, 50.8, 76.2</td></tr>
<tr><td rowspan="2">Under Floor Insulation (7)</td><td colspan="2">Spray on polyurethane foam [mm]: 25.4, 50.8, 76.2</td></tr>
<tr><td colspan="2">Fiberglass batting: SI-R2.3, 3.3, 5.3, 6.7</td></tr>
<tr><td>Window Type (2)</td><td colspan="2">Double pane window, Triple pane window</td></tr>
<tr><td>Garage Door (4)</td><td colspan="2">1 Layer with no insulation, 2 Layer with polystyrene, 3 Layer with polystyrene, 3 Layer with polyurethane</td></tr>
<tr><td>Heat Recovery Type (2)</td><td colspan="2">None, Sensible heat recovery</td></tr>
<tr><td>Air Conditioner Seasonal COP (6)</td><td colspan="2">3.81, 4.10, 4.40, 4.69, 4.98, 5.28</td></tr>
<tr><td>Natural Gas Furnace Efficiency (4)</td><td colspan="2">80%, 85%, 90%, 95%</td></tr>
</table>

3.3 Life cycle cost

To assess the total cost associated with any given building construction permutation, a life cycle cost analysis (LCCA) approach is performed using a 20-year time horizon. The true life cycle cost of a building includes the initial construction cost, annual energy utility cost, and ongoing maintenance cost. However, in the current study only construction materials and annual energy costs are considered since it is anticipated that these will have the strongest influence on the LCCA. The impact of construction labor and maintenance costs will be considered in a later study. Equation (1) shows the method that is used to calculate life cycle cost in this study.

$$LCC = C_{Mat} + C_{Equip} + C_{Elec} + C_{Ng} \tag{1}$$

C_{Mat}: *Material cost*

C_{Equip}: *HVAC equipment cost*

C_{Elec}: *Electricity cost*

C_{Ng}: *Natural gas cost*

A database of material costs for the envelope was developed on a regional basis across the U.S. to accurately capture not only the physical structure and energy consumption of the home but also the material cost of the various components. Several available sources were used in developing the material cost database. The primary tool utilized for estimating cost is RSMeans residential cost data. HVAC equipment costs are modeled using multiple linear regression to fit cost data taken from online equipment suppliers. To determine an appropriate model for the cost of the air conditioner and furnace, several factors are taken into account. In this study the system cost is correlated to both its heating/cooling capacity as well as its efficiency.

3.4 Singular Value Decomposition

To reduce the dimensionality of a design space, the focus is on trying to find only those significant variables that need to be considered as optimization input variables, which means they are the variables that most strongly affect the life cycle cost. The next thing to be considered is that in many cases involving nonlinear systems, including categorical variables and discrete variables, a linear approach cannot be applied or will not have an accurate result. To overcome these problems, a new index is introduced. Each material is converted into an insulation value per unit cost, and the materials are then ordered from least to greatest and assigned an index. Using the methodology described in the previous section, 100 data samples with a different combination of design variables for each location is generated to explore the design space and identify the most significant variables to be used later in the optimization study. After generating the initial 100 data samples, singular value decomposition (SVD) is applied to the data set. Singular value decomposition is one method that can identify the most significant input variables by transforming correlated variables to uncorrelated variables. By selecting the first few dimensions or variables that explain most of the variance within the data set, the input variables can be reduced from a higher dimensional space to a lower dimensional space (Baker, 2005). After applying SVD to matrix A, which is the data sample, matrix A is broken into an orthogonal matrix U, and a diagonal matrix S with the singular values in decreasing order; and the transpose of an orthogonal matrix V. By selecting the first k dimensions on the diagonal matrix S, matrix A can be approximated as follows.

$$A = USV^T = U_1S_1V_1^T + U_2S_2V_2^T \simeq U_1S_1V_1^T \tag{2}$$

3.5 Optimization

The optimization of the building design based on energy simulations may require large scale computing resources to properly explore the numerous variables (both discrete and continuous) and nonlinear functions, which also leads to discontinuous outputs. To deal with these characteristics, a discrete binary version of the particle swarm optimization methodology (Kennedy & Eberhart, 1997) has been selected and used for this study based on its ability to efficiently explore the design space and arrive at an optimal solution. To prevent fast convergence to a local optimum, the inertial version (Eberhart, et al., 2001) is used.

The first optimization study is a full optimization in which the life cycle cost is optimized using all 13 of the initial variables. The second optimization study is performed with a subset of design variables based on the results of the singular value decomposition. After finding the significant variables for the optimization, the remaining variables can be fixed to any values since they have only a minor affect on the life cycle cost. In this study, the cheapest material is chosen as the value of the insignificant variables during the optimization process.

According to Parsopoulos and Vrahatis (Parsopoulos & Vrahatis, 2002) when there are up to 15 variables under consideration, the recommended swarm size is the number of variables multiplied by 5. Based on this suggestion, the swarm sized is set to 64 and a von Neumann topology is selected having a neighborhood size of eight for the first study. For the second study, a swarm size of 36 and neighborhood size of six is used. The total number of generations are set to 500 and 300 respectively to make sure the particles are converged fully.

4. RESULTS

4.1 Singular Value decomposition result by location

After applying singular value decomposition on the sample data, the most meaningful components are identified based on the singular values. Figure 3 shows the singular values in descending order in Indianapolis. Engineering judgement is used to determine how many components need to be selected. There is a trade-off between the speed of the optimization process and the accuracy of the optimization result depending on the number of components that are selected. If only the first few components are selected, the optimization process will be considerably faster; however, the optimum point that is determined using a reduced number of design variables could be significantly further away from the true optimal point. In this study, the first four components are chosen as significant components to explain the most of the data samples and rest of the components are considered insignificant for all six locations.

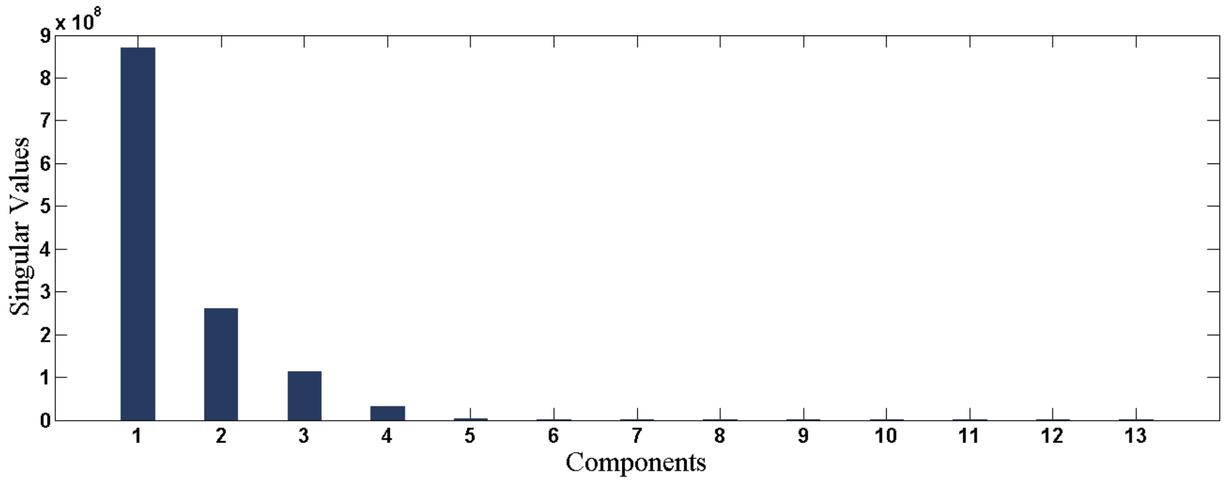

Figure 3: Result of singular values in Indianapolis

The first four singular vectors of the matrix are examined to identify the significant variables for the optimization study. As shown in Table 2, external foam board insulation is a strong contributor to the first singular vector, while a linear combination of roofing materials, window type, and heat recovery type are significant variables for the second singular vector. Wall core and under floor insulation are chosen as the main contributors for the third and fourth vectors.

Table 2: Indianapolis result of first four singular vectors

	1	2	3	4
Roofing Materials	-0.009	**0.238**	0.007	0.001
Roof Eave Over Hang Depth	-0.001	0.002	-0.001	0.002
Attic Insulation Material	0.006	-0.004	0.025	0.033
External Wall Siding Material	**-0.999**	-0.033	-0.019	-0.017
External Foam Board	0.004	-0.054	-0.019	-0.011
Wall Core	-0.018	-0.032	**0.999**	-0.008
Foundation Wall Insulation	0.000	-0.021	-0.012	0.006
Under Floor Insulation	-0.018	0.003	0.007	**0.999**
Window Type	-0.029	**0.875**	0.025	-0.003
Garage Door	0.004	-0.061	-0.010	-0.002
Heat Recovery Type	0.013	**-0.401**	-0.012	0.004
Air Conditioner Seasonal COP	0.002	-0.085	-0.005	0.006
Natural Gas Furnace Efficiency	0.002	-0.020	-0.004	-0.015

The same approach is applied to all six locations, and the selected significant design variables for each location are summarized in Table 3. Some items such as wall core, window type, heat recovery, external wall siding material, and under floor insulation are chosen for all locations, which indicates that LCC will be affected greatly by these variables, which means they should be included in the optimization process. The result also shows variation of the significant variables by location. In Denver and Seattle, the air conditioner seasonal COP is significant, while natural gas furnace efficiency is significant in Phoenix and Tampa. This occurs because there is no significant energy savings to annual utility cost by increasing the natural gas furnace efficiency in these warmer climates, and as a result the LCC is greatly increased as the efficiency goes up while air conditioner seasonal COP is not selected because there is a significant trade-off between air conditioner seasonal COP and LCC.

Table 3: Selected design variables for each location

<table>
<tr><td>Location</td><td>Denver</td><td>Indianapolis</td><td>Minneapolis</td></tr>
<tr><td rowspan="7">Selected design variables</td><td>Roofing Materials</td><td>Roofing Materials</td><td>Roofing Materials</td></tr>
<tr><td>External Wall Siding Material</td><td>External Wall Siding Material</td><td>External Wall Siding Material</td></tr>
<tr><td>Wall Core</td><td>Wall Core</td><td>Wall Core</td></tr>
<tr><td>Under Floor Insulation</td><td>Under Floor Insulation</td><td>Under Floor Insulation</td></tr>
<tr><td>Window Type</td><td>Window Type</td><td>Window Type</td></tr>
<tr><td>Heat Recovery Type</td><td>Heat Recovery Type</td><td>Heat Recovery Type</td></tr>
<tr><td>Air Conditioner Seasonal COP</td><td></td><td></td></tr>
<tr><td colspan="4"></td></tr>
<tr><td>Location</td><td>Phoenix</td><td>Seattle</td><td>Tampa</td></tr>
<tr><td rowspan="7">Selected design variables</td><td>External Wall Siding Material</td><td>Roofing Materials</td><td>External Wall Siding Material</td></tr>
<tr><td>Wall Core</td><td>External Wall Siding Material</td><td>Wall Core</td></tr>
<tr><td>Under Floor Insulation</td><td>Wall Core</td><td>Under Floor Insulation</td></tr>
<tr><td>Window Type</td><td>Under Floor Insulation</td><td>Window Type</td></tr>
<tr><td>Heat Recovery Type</td><td>Window Type</td><td>Heat Recovery Type</td></tr>
<tr><td>Natural Gas Furnace Efficiency</td><td>Heat Recovery Type</td><td>Natural Gas Furnace Efficiency</td></tr>
<tr><td></td><td>Air Conditioner Seasonal COP</td><td></td></tr>
</table>

4.2 Optimization result comparison

With the original 13 variables, or the selected six to seven variables from the previous section, the two optimization studies are performed. The optimized LCC for a 20-year horizon are compared in Table 4. Results show that the overall optimized LCC using only a subset of significant design variables are close to the original optimal point by 3.2 to 6.2%.

Table 4: comparison of optimized LCC

	Optimized LCC [$]	Optimized LCC with subset of variables [$]	Absolute Cost Difference [$]	Percentage Difference [%]
Denver	17,850	18,722	873	4.9
Indianapolis	20,097	21,025	928	4.6
Minneapolis	22,046	23,206	1,160	5.3
Phoenix	17,892	18,999	1,107	6.2
Seattle	16,543	17,182	639	3.9
Tampa	16,655	17,181	527	3.2

Using a 6-core processor and 6 gigabytes of RAM, the first (13 variable) optimization process requires approximately 36 hours per each location to complete the study while the second (reduced number of design variables using SVD) optimization process requires an average of 4 hours and 20 min per each location, which includes one hour for data generation that is used in the variable selection procedure. This significant reduction in computational calculations is mainly caused by the reduced design space and as a result, the number of evaluations requested by the optimization algorithm is significantly reduced. Also, the reduced swarm size due to a smaller number of design variables allows the optimizer to more quickly search the design space. Table 5 shows the comparison of time requirements and evaluation time between original full optimization and reduced optimization process. The total number of evaluations is decreased by 60% and the time requirement is decreased by 88% of the original computational time.

Table 5: comparison of two optimization methodologies

	Full optimization	**Optimization with subset of variables**
Number of evaluations	32,000	12,200
Time requirement[hrs]	36	4.35
Average LCC	18,514	19,386

5. CONCLUSION

The primary focus of this paper was to develop a methodology to perform an efficient and accurate life cycle building optimization in an acceptable time frame and apply the methodology to a case study of typical residential building and compare the results with those of the full optimization process over the entire design space. The result of the optimization process with a subset of design variables after performing singular value decomposition on the data sample for the design space shows a significantly shortened time requirement for the optimization process of 88%, while the optimized life cycle cost is close enough to the original optimum point by 3.2 to 6.2 %.

In the future, a more detailed study will be carried out to determine the relationship between accuracy and computational time based on the criteria selection as well as the optimization methodology to improve the efficiency and accuracy proposed in this paper.

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