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# Multi-objective optimization of building's life cycle performance in early design stages

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# Multi-objective optimization of building's life cycle performance in early design stages

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**Abstract.** The early design stages of buildings have the highest potential for optimizing energy efficiency. From the aspect of architectural design, the architects can hardly make the best decisions of the complexed variables of geometries and materials. The choice and weighting of different optimization objectives also have no reference while considering the impacts from the whole view of the life cycle. In this paper, a simulation-based parametric approach through the use of multi-objective optimization method is framed. The extraction of geometry variables from the original design and the principles of explaining optimization results obtained from different objective combinations are discussed.
This process is carried out in Rhino and Grasshopper. To fully consider the aesthetic and building performance step by step in early design stages, the geometry and material parameters are tested simultaneously. The life cycle inventory data of materials and energy resources are imported by programming, and local data is partly used. Life cycle environmental impacts (PED and GWP), life cycle cost, and operating energy consumption are used as optimization objectives. A case study is verified on a project of a small campus museum building in northern China. The results indicate that the combination of geometry and material values in the optimal solution set is various and needs to be artificially selected according to actual needs. The optimization objectives should be considered comprehensively; an incomplete set may result in poorly behavior of the unselected objectives.

## 1. Introduction

The construction, operation, and demolition of buildings are the essential reasons for the consumption of resources and energies worldwide, which also lead to vast amounts of pollutions. In 2016, China's total building energy consumption was 899 million tons of standard coal, accounting for about 20.6% of the country's total energy consumption[1]. The resource conversion rate of construction waste is lower than the average level of developed countries. Less than 5% of the construction waste is recycled[2]. It is necessary to consider the environmental impacts of buildings from the early design stages. The International Standards Organization identifies the Life Cycle Assessment (LCA) and Life Cycle Cost (LCC) methods as an essential method for building sustainability assessment (ISO TS 21929-1). The optimization which aimed at life cycle environmental impacts and costs plays a vital role in improving the overall performance of the building[3].

In the process of building design, due to the variety of parameters, the influence of these parameters (such as orientation, layout, geometry, structure, equipment, etc.) on the performance of the building is not intuitive[4]. The concept generation will become too complicated for designers while considering environmental impact, economic performance and aesthetics requirement at the same time. Questionnaire research also points out that time-consuming and none available workflow are the two main factors that the design companies do not run simulation and optimization in the concept generation[5].

Most of the decisions related to building performance occurred in the early stages of design[6]. At these stages, the variable range of the building geometry parameters is broad, and the material selection often comes from conventional construction practice. The parametric modelling platform can take care of these two demands. It can effectively complete the modelling of simple mass and combine the geometry with life cycle inventory (LCI) data to achieve multi-objective optimization of building's life cycle performance.

## 2. Framework
This paper proposes a framework for performing multi-objective optimization of building design using parametric modelling platform. Figure 1 shows an overview of the frame.

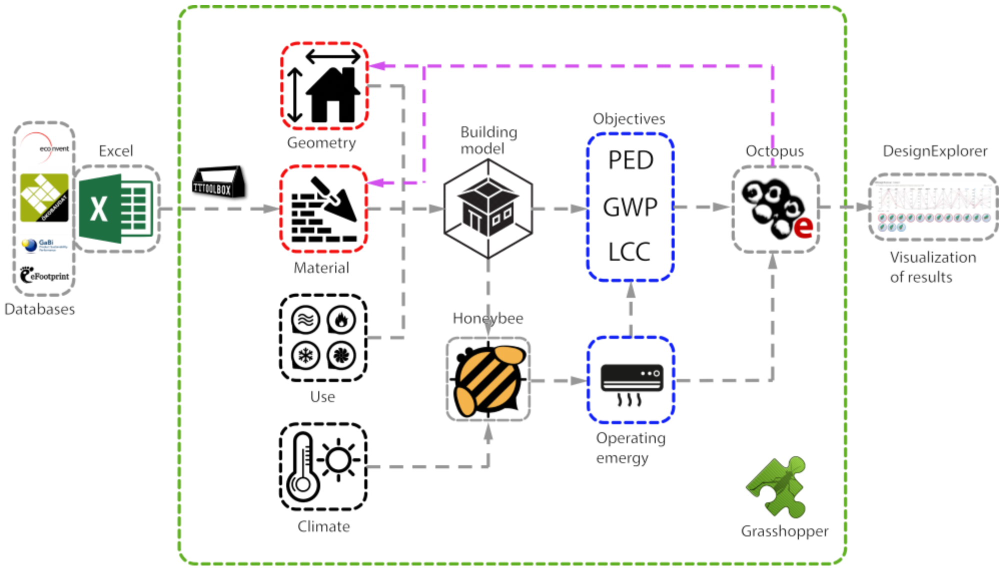


**Figure 1.** Framework for performing multi-objective optimization.

The framework is based on Rhino's plugin Grasshopper[7] and its components. Firstly, the physical and LCI information of materials are collected from the database and imported into GH as an Excel file. Then the data is compared with a geometric model to generate the building model containing the complete information. Secondly, the Honeybee[8] component is used after completing the geographical location, equipment, running time and other information of the model to calculate the energy consumption of the building. Then the environmental impact and LCC of the project is estimated by comparing the material quantity and energy consumption with the LCI information. Finally, the objectives are optimized by the genetic algorithm through the Octopus[9] component to obtain the optimal parameter combination. The combinations of parameters and results can be exported to Design Explorer[10] for visual visualization of further guidance on architectural design.

## 3. Case study
This study selects a public building with a strong diversity of geometric variables. The small museum is located in Tianjin (39°N), a northern city in China. The air conditioning in summer is run by electricity and the central heating in winter is powered by burning natural gas. It is used to display the dinosaur skeleton donated by alumni of a university, four floors above ground and a total area of 5,200 square meters. The building is located on an east-west narrow site on campus. The main exhibition hall is designed on the north side. The curtain wall of the exhibition hall has a wrinkled shape to simulate the geological effect of the rock formation（Figure 2）. Designed for a service life of 50 years, the price

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index and discount rate of the material are 2.0%/2.3%, of the energy are 3.0%/2.3%[11]. Table 1 shows the variables.

**Table 1.** Input variables and their ranges for optimization.

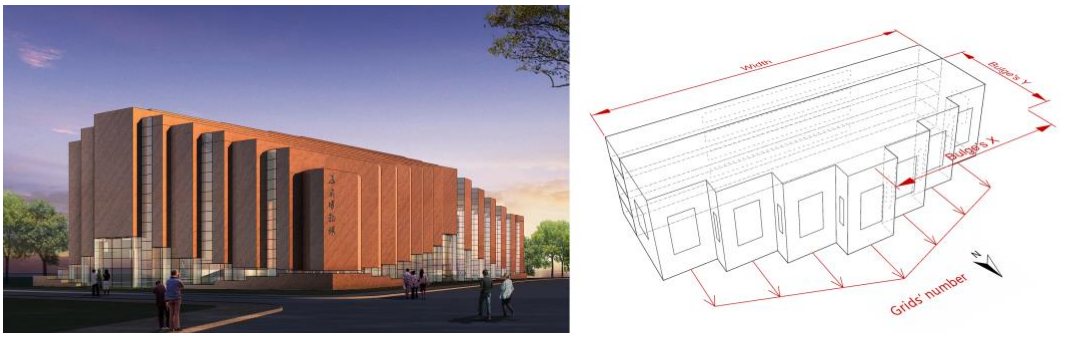


**Figure 2.** The rendering(left) and energy analyse model(right).

| Categories | Description of variables | Unit | Distribution | Sampling ranges |
|---|---|---|---|---|
| Building geometry | Width | m | Uniform | (70.0,80.0) |
| | Bulge's X | % | Uniform | (0,100) |
| | Bulge's Y | m | Uniform | (40.0,60.0) |
| | Grid's number | - | Discrete | (3,5,7,9,11,13,15) |
| Window to wall ratio (WWR) | North WWR | % | Uniform | (20,40) |
| | West WWR | % | Uniform | (10,30) |
| | South WWR | % | Uniform | (20,30) |
| | East WWR | % | Uniform | (10,30) |
| Building element | Window | - | Discrete | (1-5) |
| | Exterior wall | - | Discrete | (1-21) |
| | Roof | - | Discrete | (1-19) |

Table 2 shows the physical properties of the building elements.

**Table 2.** Building elements in this case study.

| Index number (Window) | Glass type | Frame type | U-value [W/m$^2$·K] | SHGC | Visible transmittance |
|---|---|---|---|---|---|
| 1 | Double Low-E | Aluminum alloy | 2.16 | 0.4767 | 0.76 |
| 2 | Triple Low-E | Aluminum alloy | 1.78 | 0.4759 | 0.72 |
| 3 | Triple Low-E (Argon filled) | Aluminum alloy | 1.51 | 0.4721 | 0.68 |
| 4 | Double Low-E | Wood-aluminum | 1.30 | 0.4767 | 0.76 |
| 5 | Triple Low-E | Wood-aluminum | 0.80 | 0.4759 | 0.72 |
| **Index number (Exterior wall)** | **Layers (from outside to inside)** | **Thickness [m]** | **Thermal conductivity [W/m·K]** | **Density [kg/m$^3$]** | **Specific heat capacity [J/kg·K]** |
| | Curtain (Stone panel) | 0.005 | 3.5 | 3300 | 920 |
| | Curtain (Aluminum frame) | 0.02 | 203 | 2700 | 900 |
| | Cement mortar | 0.01 | 0.93 | 1800 | 1050 |
| 1-11 | Rock wool panel | 0.05-0.15 [a] | 0.048 | 140 | 1220 |
| 12-21 | XPS panel | 0.04-0.13 [a] | 0.0384 | 30 | 1380 |

| | | | | | |
|---|---|---|---|---|---|
| | Autoclaved aerated con crete block | 0.2 | 0.175 | 500 | 1050 |
| | Cement mortar | 0.01 | 0.93 | 1800 | 1050 |
| Index number (Roof) | Layers (from outside to inside) | Thickness [m] | Thermal conductivity [W/m·K] | Density [kg/m$^3$] | Specific heat capacity [J/kg·K] |
| | Polymer waterproofing membrane | 0.002 | 0.15 | 580 | 1680 |
| | Thermal insulation mortar | 0.065 | 0.08 | 400 | 1050 |
| | Perlite insulating concrete | 0.002 | 0.435 | 800 | 1320 |
| 1-11 | Rock wool panel | 0.1-0.2 [a] | 0.048 | 140 | 1220 |
| 12-19 | XPS panel | 0.08-0.15 [a] | 0.0384 | 30 | 1380 |
| | Reinforced concrete | 0.1 | 1.74 | 2500 | 920 |

[a] Due to the consideration of the actual product specifications, the thickness of the insulation material is not set as uniform but discrete with a span of 0.01 m. Study has also pointed out that too many uniform variables will produce a near-infinite combination, reducing the efficiency of the optimization process[12].

Table 3 shows the environmental data of the building materials.

**Table 3.** Environmental data of materials used.

| Categories | Components | Unit | PED [MJ] | GWP [kg CO2 eq] | Database | Initial cost [Yuan] | Initial cost's unit | RSL [a] |
|---|---|---|---|---|---|---|---|---|
| Insulation material | Rock wool panel | kg | 14.96 | 1.13 | Ecoinvent | 474.61 | m$^3$ | 30 |
| | XPS panel | m$^3$ | 3020.1 | 96.37 | ÖKOBAUDAT | 747.2 | m$^3$ | 30 |
| Structure | Autoclaved aerated concrete block | kg | 4.00 | 0.47 | Ecoinvent | 463.93 | m$^3$ | ＞50 |
| | Reinforced concrete | kg | 0.50 | 0.13 | ÖKOBAUDAT | 743.66 | m$^3$ | ＞50 |
| Cladding | Curtain (Stone panel) | m$^2$ | 535.76 | 35.92 | ÖKOBAUDAT | 805.56 | m$^2$ | 30 |
| | Curtain (Aluminum frame) | kg | 48.22 | 11.12 | ÖKOBAUDAT | 340.44 | m$^2$ | 30 |
| | Cement mortar | kg | 1.47 | 0.18 | ÖKOBAUDAT | 49.23 | m$^2$(10mm thickness) | 20 |
| | Polymer waterproofing membrane | kg | 4.18 | 0.08 | ÖKOBAUDAT | 5.69 | m$^2$ | 30 |
| | Thermal insulation mortar | kg | 2.05 | 0.29 | ÖKOBAUDAT | 33.72 | m$^2$ | 30 |
| | Perlite insulating concrete | kg | 14.58 | 1.23 | Ecoinvent | 366.26 | m$^3$ | 30 |
| Window | Double Low-E(A) | m$^2$ | 1792.07 | 131.54 | Gabi | 756.78 | m$^2$ | 30 |
| | Triple Low-E(A) | m$^2$ | 2362.21 | 172.58 | Gabi | 963.61 | m$^2$ | 30 |
| | Triple Low-E(A) (Argon filled) | m$^2$ | 2387.27 | 174.53 | Gabi | 1313.61 | m$^2$ | 30 |
| | Double Low-E(WA) | m$^2$ | 3301 | 180 | Gabi | 3104 | m$^2$ | 30 |
| | Triple Low-E(WA) | m$^2$ | 3520.52 | 193.91 | Gabi | 3311 | m$^2$ | 30 |
| Energy | Electricity | kW·h | 14.98 | 1.18 | CLCD[13] | 0.9 | kW·h | - |
| | Natural gas | m$^3$ | 15.49 | 0.28 | CLCD | - [a] | - | - |

[a] There is a starting fare 12Yuan/m$^2$ on the whole building and 0.25Yuan/kWh fee for the actual cost.

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### *3.1. Variables' preparation*

Based on the original design, geometry parameters that can make a significant change in the shape are selected. All the extreme combinations of geometric variables have been tested to prevent modelling errors during the optimization process and to meets the requirements from the site and function.
A pre-optimization artificial selection of the material variables has been made to make sure the material be chosen is not performing poorly at either thermal property or embodied energy than the others, as shown in Table 4. If insulation material A is poorly at all three factors ( $\lambda \cdot$PED, $\lambda \cdot$GWP, $\lambda \cdot$LCC) than material B, it means A has a more significant environmental impact and cost than B while providing the same thermal resistance. Only material that has its own strength in at least one factor can be chosen.

**Table 4.** Insulation variables pre-optimization compare.

| Compared variables | Thermal conductivity $\lambda$ [W/m·K] | $\lambda \cdot$PED | $\lambda \cdot$GWP | $\lambda \cdot$LCC |
|---|---|---|---|---|
| Rock wool panel | 0.0480 | 100.50 | 7.60 | 22.78 |
| XPS panel | 0.0384 | 115.97 | 3.70 | 28.69 |

### *3.2. Genetic algorithm parameters and computational efficiency*

The optimization process uses the HypE[14] algorithm within Octopus. The following parameters are used: population size = 50, crossover rate = 0.8, mutation rate = 0.5, and elitism = 0.5. Five optimization scenarios are performed with the objectives of Operating energy(OE, kWh/m$^2$/a), Life cycle cost(LCC, Yuan/m$^2$), Primary energy demand(PED, GJ/m$^2$), Global warming potential(GWP, t CO2 eq/m$^2$) and any of the three among the four. The convergences of the objective functions in all these five scenarios complete within 50 generations. It takes a desktop computer with a 3.6 GHz Intel® I9-9900K CPU 20-22 hours for one single scenario.

### *3.3. Results*

In the five optimization scenarios, the objective functions converge to the Pareto optimal solution set in four out of the results. Only in the case of OE, PED, and GWP, the only optimal solution is approached in the 30th generation, as shown in Figure 3.

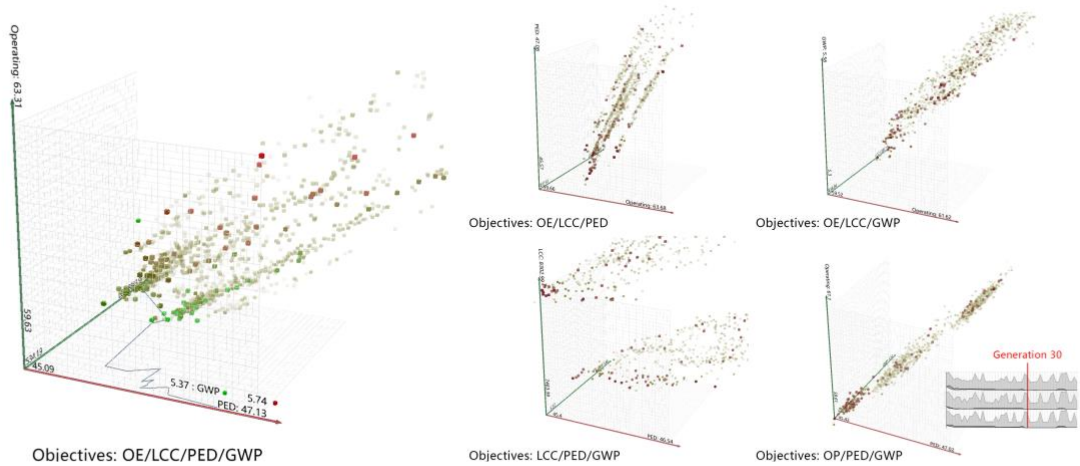


**Figure 3.** The scatter charts of all scenarios.

Due to the different dimensions and units of optimization objectives, the 50th generation Pareto optimal solution sets is standardized by SPSS[15] to make a comparison. It can be seen from Figure 4 that the objectives' value of OE, PED, and GWP is inversely related to LCC and there is not a clear trade-off relationship between the operating energy and embodied energy (PED, GWP) as some previous studies[16, 17].

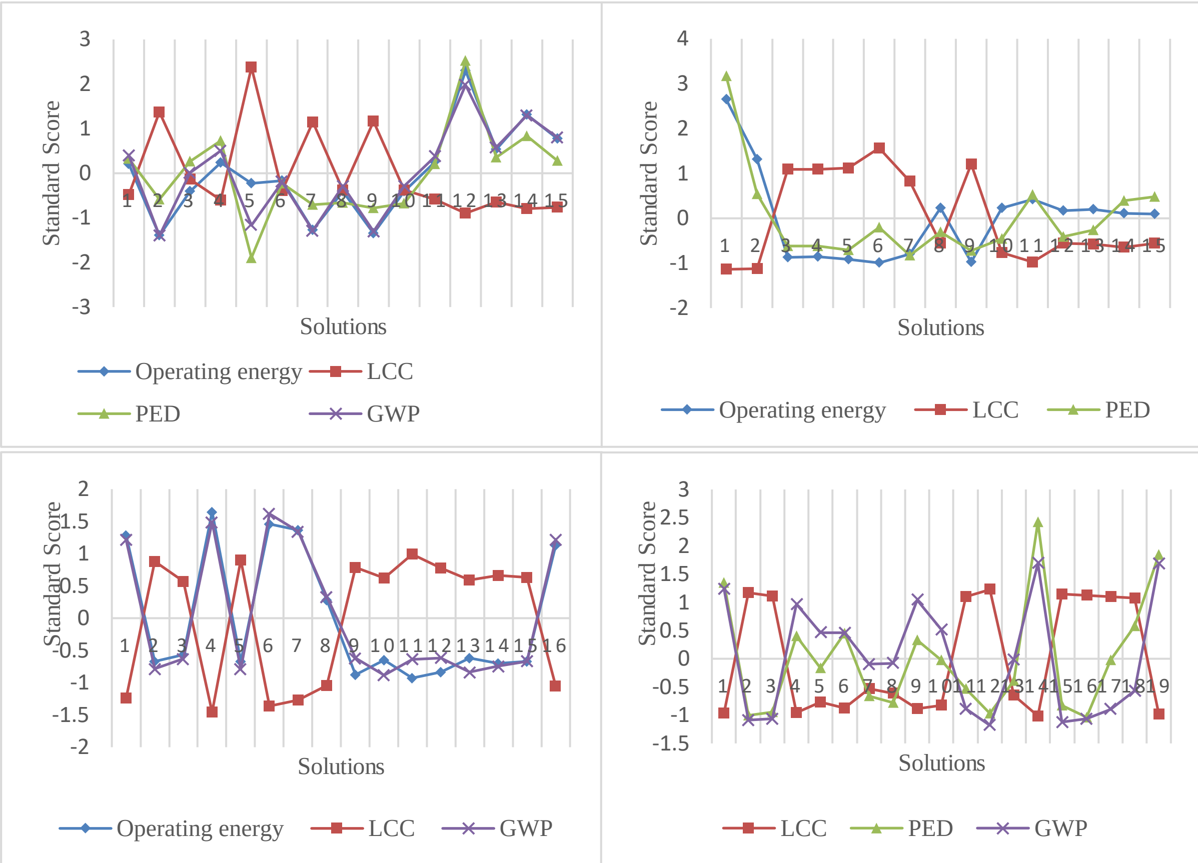


**Figure 4.** The standardized Pareto optimal solution sets.

By using Design Explorer[10] to visualize the optimal solution set and the related 3D models, it can be seen from Figure 5 that the solution space of geometric and material parameters are scattered. Architects need to make a subjective choice.

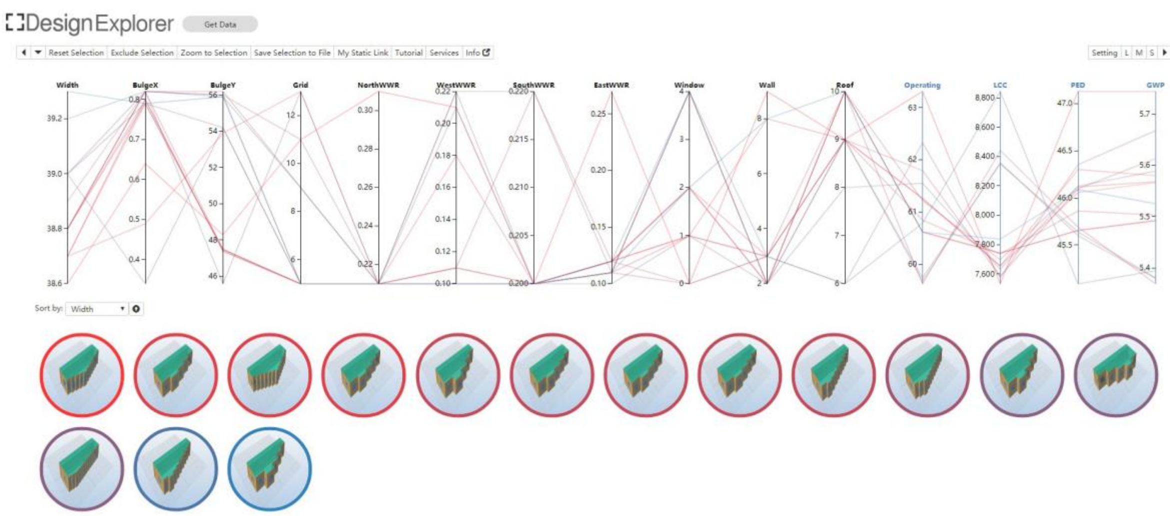


**Figure 5.** Pareto optimal solution set of OE/LCC/PED/GWP scenario.

## 4. Discussion

For each scenario, the optimal solution set obtained by this experimental framework is only more than ten, which can be used for manual comparison. The selection process by the architect can be based on specific values. For example, each objective is normalized in the set and summed to obtain a total score (the lower the better) for comparison, or only the LCC (or initial cost) which below the average cost is selected (Figure 6). Also, it can be considered from the architectural form: whether the optimal solution geometry meets the size of the exhibits or the site and surroundings.

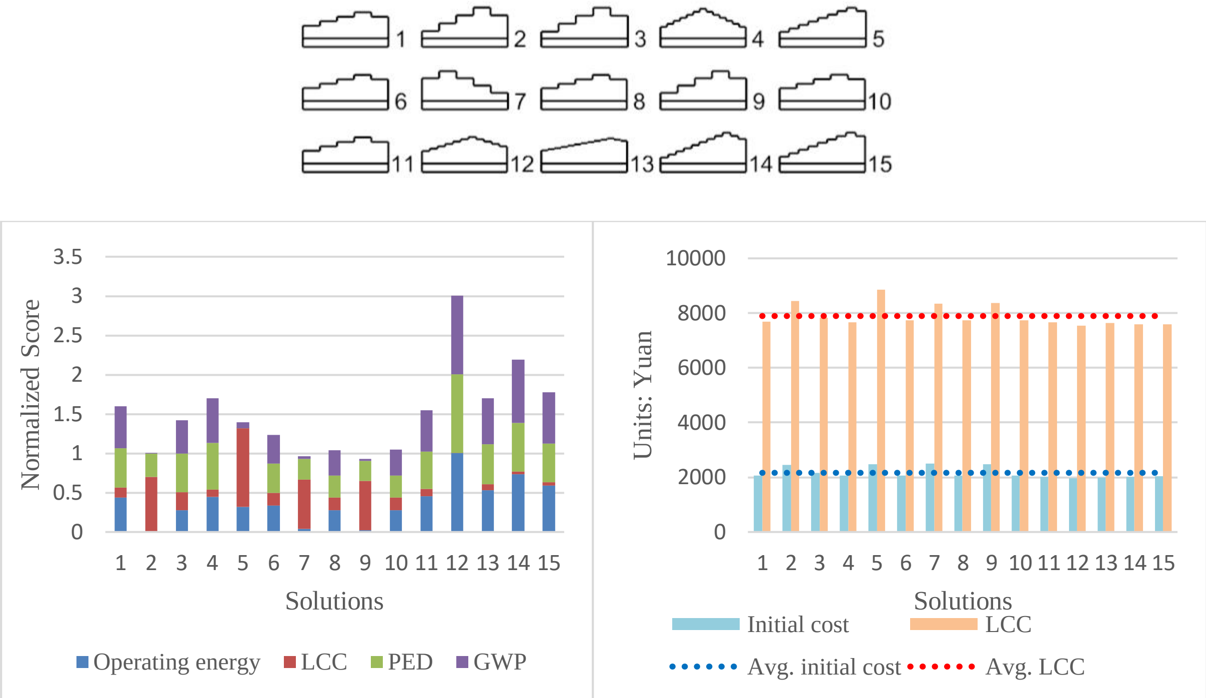


**Figure 6.** The OE/LCC/PED/GWP scenario's optimal solution set. Solution No.9 has the lowest sum normalized score (left) and solution No. 1/3/4/6/8/10/11/12/13/14/15's initial cost and LCC are both under the average (right).

The interpretation of the same optimization objective in different optimization scenarios is also different. When there is no explicit requirement, including as many optimization objectives as possible can ensure the generation of the optimal solution set after the multi-objective optimization process. Otherwise it can lead to poor performance of the unconsidered objective. In this study, the LCC value of the optimal solution from the OE/PED/GEP scenario is 8652.74 Yuan/m$^2$. The average LCC of the optimal solution set from the OE/LCC/PED/GEP scenario is 7893.48 Yuan/m$^2$, and the minimum value is 7534.19 Yuan/m$^2$. When comparing the values of the parameters between the optimal solution sets in different scenarios, it is found that there is no set of solutions with all eleven variables close to each other. This also proves that there is no clear linear relationship between the optimization objectives.

## 5. Conclusions and future work

This study attempts to optimize the parameters of building performance, environmental impact and LCC from the process of the initial stages of the architectural design. It is more detailed than the previous research in the geometry of the shape, but it also leads to a problem that the model is only for this project and cannot be reused. The relationship between the objective functions and the consistent and inconsistent among the optimizations with different objectives also requires more case studies to prove its universality.

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Future work should be broken down into the early stages of design and deepened into the late stages, combined with BIM models and databases for detailed calculations. Another issue is that the original plan is to use local LCA data, but the Chinese database currently only has a small number of basic building materials, the EPD data from the manufacturers is also lacking, which is necessary for improvement in the future.

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