A Multi-Stage Framework for Building Energy Optimization: Key Factors and Prototypes

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Abstract

In traditional building energy optimization, usually only a certain design stage is concerned, and once the optimization model is determined, it is rarely changed. However, design is a process of continuous change and improvement. As a part of the design process, optimization should evolve throughout the whole process.

The goal of this research is to find the key factors affecting the sequential building energy optimization process. According to the three factors proposed (availability, dependency and sensitivity), three multi-stage optimization prototypes are proposed, which group variables based on different decision factors: design phase, design objects and variables' sensitivity. Each prototype consists of three optimization models, which are computed sequentially. In the case study for optimizing the energy consumption of an office building, the performance of these three multi-stage optimization prototypes and traditional optimization methods are compared. The results illustrate that the optimization prototype based on variables' sensitivity is superior to others. This research only used one case study to valid the effectiveness of key factors, however, it still can guide the sequential optimization for other cases since the impact of the key factors are identical. The result of this study is expected to improve the design process, by demonstrating that the integrated design process is able to produce better designs from the energy performance point of view.

Introduction

Building energy accounts for approximately 40% of the total energy consumption in the European Union, the United States, and other developed countries. In China, the figure was 19.1% in 2012 and increased approximately 8.3% annually from 2001 to 2012. Conserving energy and developing energy efficient building designs have been a major concern for researchers in many countries (Tian, 2018). Optimization as an effective tool to support decision-making, especially in sustainable design, attracts more and more attentions.

Currently, building energy optimization is usually applied to a model that only focuses on a certain stage of the design process. However, as a part of the design process, optimization should be evolving throughout the whole process. As a global evaluation criterion, energy consumption is affected by many building components in different design phases. Gagnon et al. (2018) provided an

evaluation of the most influential variables and their impacts of interactions for the present reference building, and illustrated the impact of changing these variables on the final building performance during the building design process. Therefore, the key to implement the process of building energy optimization lies in how to organize the design variables to correspond to the nature of sequential design stages.

Some papers about multi-stage design is reviewed below. Most of these studies propose different models at different design phases, which proves to be effective. Most of them alter the optimization model according to the requirements of variables and their precision at different design phases. Shiel et al. (2018) classified the optimization model into 9 types based on variables and their precision so that the optimization model can adapt to the needs of different design stages. Carlucci Salvatore et al. (2013) proposed a two-step optimization prototype for near-zero energy buildings: 1) passive design with an adaptive model; 2) active design with Fanger's thermal comfort model. There are also studies that focus on changes of design objects. Zhou et al. (2014) proposed an optimal natural ventilation optimization method that consists of a three-stage procedure: 1) building-orientation optimization at the community level; 2) wind-path design at the floor level, and 3) fenestration design at the room level. Other studies consider the effect of the variables on the result as a factor in guiding the sequential optimization. Evins et al. (2012) proposed an energy optimization method with two steps: 1) optimize all variables over a big range of values; 2) a more detailed optimization using greater precision is conducted on all variables that exhibit complex behaviour, i.e. Hester et al. (2017) applied the results of the sensitivity analysis of the variables to the calculation of meta-model in each generation to improve the stability of the meta-model.

From a global viewpoint, design can be seen as a linear process, indicating that the later procedure must be affected by the former decision. This requires an appropriate division of process to guarantee the decision of every step to be as beneficial as possible. It is the same for integrating optimization into the design process. The key to make a series of sequential optimization models lies in how to group the design elements and decide their priority in optimization. As such, this study identifies three key factors from prior research to construct different multi-stage building optimization prototypes. A series of analysis about their performance and comparison between

them and a benchmark model, are conducted, with the energy consumption optimization of an office building as the case study. The results pose a challenge to the traditional design process, suggesting that additional factors should be considered to gain the most benefits from optimization.

Key factors determining the sequential optimization process

In order to get the key factors affecting the sequential optimization process, based on our literature review, we have identified 31 papers (as shown in Appendix) related to building optimization. All the variables mentioned in these papers are divided into 27 types, each containing more specific variables. Their corresponding design processes, design objects as well as their occurrences are summarized in Figure 1, where clear clusters including different variables can be found based on design phases and design objects. Vertically, all variables can be classified according to the design object, such as building, room, wall etc. Horizontally, some variables span multiple design phases. For example, for the marked #1 (number of story) and #12 (building dimension), the higher their value is, the more frequently they appear in all variable types. #12 has a greater radius than #1, which means that #12 contains more specific variables compared to #1. The rectangle surrounding them and the corresponding abscissa represent that they are generally applied to the Conceptual Design and Schematic Design phases, and their corresponding ordinate indicates that the design object they belong to is the building. This reveals two major factors of optimization: availability and dependency of decision variables.

Figure 1: The classification of variables (Darker colour means lower frequency of occurrences in the selected papers, lighter means higher frequency; radii of circles represent the numbers of specific variables included in their corresponding classes of variables, and rectangles represent possibilities to be involved in multiple design stages).

In addition, some prior works also suggest to make an effective optimization model based on sensitivity analysis, specifically, to identify the most important variables, and prioritize them in the optimization process. The

sensitivity of variables is not a design-related consideration that most architects are familiar with. As such, we investigated some related research and compared the variables' sensitivity ranking with their order of availability in the design process. The results in Figure 2 presents many discrepancies (marked by red rectangles) between them. For example, the SHGC of glass has a great impact on building energy consumption, but it is usually considered at the Design Development, rather than the earlier Conceptual Design stage, when the variable could play a more significant role. The introduction of optimization into a complete design process not only requires to fit into the architects' design workflow, but also to utilize the benefits of optimization algorithms in searching the large solution space. Therefore, sensitivity, as a guide to improve the optimization efficiency and effectiveness, should be considered to optimize the optimization process.

Figure 2. Sensitivity ranking in 21 papers presenting sensitivity analyses from literature review (The abscissa represents the number of the review articles, and the ordinate represents the sensitivity ranking of the variables. Each column represents a sensitivity rank in a test. The lighter colour the less sensitivity. The numbers on the colour block correspond to their variable names in Figure 1).

In summary, this study takes three factors into account, as the basis to divide the building energy optimization process into several sequential optimization models:

- Availability:** availability of the design data. This comes from the traditional design process, and implies a natural division of optimization procedures. Thus, the prototype only considering availability is used as a benchmark.
- Dependency:** the dependency relationships between variables. This usually manifests as some variables have the identical subordinate design object. This factor is used to indicate the relevance of the design objects corresponded to the optimization variables.
- Sensitivity:** the influence of the design variables to energy consumption. Variables' sensitivity ranking will determine the order in which they are adjusted for optimization.

Methodology

In an optimization stage, all variables are divided into two types: refined variables which are the target ones of this stage, and rough variables which are the focus in the next stage(s). The main difference between them lies in the granularity of values. Large granularity is used to discretize the rough variables so that the search space can

be significantly narrowed. For example, when the window to wall ratio (WWR) is a refined variable, its value range is [0.1, 0.5], however, when it is a rough variable, its value is among (0.1, 0.2, 0.3, 0.4, 0.5).

The establishment process of the multi-stage optimization prototype is as follows:

- All of the variables are grouped according to the number of optimization stages, and each set of variables are the refined variables corresponding to the optimization stage. Each prototype has its own principle to decide how to divide the refined variables into each stage. And this principle will be explained in detail below.
- In every prototype, the optimal solutions obtained from a prior stage will be fed into the next stage of optimization. Specifically, for each one of the top half solutions, its corresponding values of refined variables at a certain stage are grouped into a combination, which are named Partial Solutions. And these Partial Solutions would be assigned an index for each one. All these indices constitute a set of special variables in the next optimization stage, that are, Partial Solutions.

In the multi-stage optimization, the grouping principle of variables is based on the mentioned key factors in the three prototypes:

Prototype 1: multi-stage optimization prototype based on design process. It divides the whole optimization process into three stages: Conceptual Design, Schematic Design, and Design Development. The refined variables for each stage are the variables that may be involved in this design phase.

Prototype 2: multi-stage optimization prototype based on design objects. All variables are grouped according to the design objects corresponding to the variables, such as building form, building opaque envelope structure and building transparent envelope. The refined variables for each stage are the variables contained in the design object that need to be optimized for this stage.

Prototype 3: multi-stage optimization prototype based on variables' sensitivity. There are three levels of variables' sensitivity: high, medium and low. The classification criterion can be the sensitivity value of each variable or the ranking of the variables' sensitivity.

In summary, the optimization schema can be described as Figure 3, which describes what type of variable is composed of each optimization stage.

Stage1	Refined variables of stage1	Rough variables	
Stage2	Partial solutions of stage1	Refined variables of stage 2	Rough variables
Stage3	Partial solutions of stage1	Partial solutions of stage2	Refined variables of stage 3

Figure 3: The optimization schema.

The above prototypes are applied to the case described in the next section.

Case Study

The proposed multi-stage optimization prototype is tested with an energy optimization case of a hypothetical office building, located in Tianjin, China. There are 29 variables from three design phases (Conceptual Design, Schematic Design and Design Development). For Prototype 1 that is based on design phase, the multi-stage optimization method tries to match with the design phases to optimize those variables that are generally regarded significant in the corresponding phases. For example, the space layout parameters are examined in Stage 1, window design is examined in Stage 2, and material properties are examined in Stage 3. Meanwhile, the main principle of Prototype 2 (prototype based on design objects) is to examine the variables belonging to the same design object in one optimization stage, although these variables may belong to several stages in the traditional design phase. And the design objects are optimized sequentially according to the principle from the whole to the detail. Specifically, in the Prototype 2, building form parameters are examined in Stage 1, building opaque envelope parameters are examined in Stage 2, and building transparent envelope parameters are examined in Stage 3. However, for the purpose of studying the actual sensitivities of the variables, the parameters are examined at different phases in the optimization process, as in Prototype 3.

A building generation method proposed by Dino (2016) is adopted to create a variety of 3D space layouts. The steps of generating the building design are given below and shown in Figure 4:

Figure 4: The generation steps of the test building.

Step1: Obtain building dimensions by using the building aspect ratio (variable) and building ground floor area (fixed). Red line shows the boundary of a building, and each grid cell inside has 4 m² area;

Step2: Generate room dimensions according to the room aspect ratio (variable), the room area (fixed), and the centre coordinates of rooms (room location x and room location y).

Step3: Determine the owner of intersection grid cells according to the derivation of a room's current and its required area. The largest one has a priority;

Step4: Determine the owner of the unoccupied grid cells. This adopts the same rule as Step 3;

Step5: Calculate the number of floors and total height for each type of the functional space represented by a unique colour in Figure 4, with each floor height being 4m.

The generation process of the building helps establish a parametric model that can generate valid design options for the optimization study.

In this case study, there are 29 variables involved building dimensions, layout and materials. In particular, some variables are identified as discrete because the increments between every two values are not equal. For example, for the aspect ratio of the building, 0 represents the aspect ratio of 1/3, and 1 represents the aspect ratio of 1/2. And the objective function is the annual energy load per square meter of the building.

The operation schedule and system parameters for energy simulation are set according to the relevant specifications (JGJ67-2006, GB 50189-2015).

In order to obtain the impact of these variables on building energy consumption, a global sensitivity analysis of all variables has been performed, as shown in Table 1. The sampling method used is the Latin Hypercube Sample (Iooss, 2015, Mc Kay, 1979). And the standardized regression coefficient (SRC) has been chosen as the evaluation index (Nguyen, 2015).

Table 1: Specifications of optimization variables.

Variable	Type	Range	Description	Sensitivity Ranking
building ratio	Discrete	0, 1, 2, 3, 4	the aspect ratio of the building	15
room1 ratio	Discrete	2, 3, 4	the aspect ratio of room1	22
room2 ratio	Discrete	1, 2, 3, 4, 5	the aspect ratio of room2	21
room3 ratio	Discrete	1, 2, 3, 4, 5	the aspect ratio of room3	24
room4 ratio	Discrete	0, 1, 2, 3, 4, 5, 6	the aspect ratio of room4	18
room5 ratio	Discrete	0, 1, 2, 3, 4, 5, 6	the aspect ratio of room5	23
room1_location_x	Discrete	0, 1, 2, 3	the parameters which determine the location of room 1	26
room1_location_y	Discrete	0, 1, 2, 3	the parameters which determine the location of room 1	28
room2_location_x	Discrete	0, 1, 2, 3	the parameters which determine the location of room 2	25
room2_location_y	Discrete	0, 1, 2, 3	the parameters which determine the location of room 2	16
room3_location_x	Discrete	0, 1, 2, 3	the parameters which determine the location of room 3	29
room3_location_y	Discrete	0, 1, 2, 3	the parameters which determine the location of room 3	14
room4_location_x	Discrete	0, 1, 2, 3	the parameters which determine the location of room 4	9
room4_location_y	Discrete	0, 1, 2, 3	the parameters which determine the location of room 4	12
room5_location_x	Discrete	0, 1, 2, 3	the parameters which determine the location of room 5	8
room5_location_y	Discrete	0, 1, 2, 3	the parameters which determine the location of room 5	11
orientation	Continuous	[0, $\pi/2$]	orientation of the building	13
WWR_n	Continuous	[0, 0.25]	window and wall ratio in north	10
WWR_w	Continuous	[0, 0.3]	window and wall ratio in west	5
WWR_e	Continuous	[0, 0.3]	window and wall ratio in east	4
WWR_s	Continuous	[0, 0.7]	window and wall ratio in south	2
distance	Continuous	[0.01, 0.03]	distance of louver blades	27
w	Continuous	[0, 2.5]	width of louver blades in west	19
s	Continuous	[0, 2.222]	width of louver blades in south	20
U_Value	Continuous	[1, 3]	heat transfer coefficient of glass	7
SHGC	Continuous	[0.11, 0.83]	solar heat gain coefficient of glass	1
wall_R	Continuous	[1.5, 10]	heat insulation coefficient of wall	3
roof_R	Continuous	[0.1, 0.45]	heat insulation coefficient of roof	6
floor_R	Continuous	[0.2, 0.45]	heat insulation coefficient of floor	17

According to the multi-stage optimization prototypes mentioned in prior section, refined variables of each stage are shown in Table 2. For each prototype, in each optimization stage, the range of refined variables is shown in Table 1. This study selects the particle swarm optimization algorithm (Kennedy and Eberhart, 1995). The number of generations is 50 at each optimization stage. The PSO's global best (gBest) is obtained at each stage is passed to one of the particles in the initial population of the next stage. A comparison study was

conducted for the performances of these multi-stage optimization prototypes versus the traditional optimization method with indiscriminately considering all the 29 optimization variables in single step. In order to avoid the particles becoming trapped in local optimum, a mutation was performed for each generation of particles. The parameter settings of the PSO algorithm can be seen in Table 3.

Table 2: The refined variables of each stage.

	Prototype 1 (based on design phase)	Prototype 2 (based on design objects)	Prototype 3 (based on variables' sensitivity)
Stage 1	building ratio, room1 ratio	building ratio, room1 ratio	
	room2 ratio, room3 ratio	room2 ratio, room3 ratio	SHGC, WWR_s
	room4 ratio, room5 ratio	room4 ratio, room5 ratio	wall_R, WWR_e
	room1_location_x, room1_location_y	room1_location_x, room1_location_y	WWR_w, roof_R
	room2_location_x, room2_location_y	room2_location_x, room2_location_y	U_Value
	room3_location_x, room3_location_y	room3_location_x, room3_location_y	room5_location_x
	room4_location_x, room4_location_y	room4_location_x, room4_location_y	room4_location_x
Stage 2	room5_location_x, room5_location_y	room5_location_x, room5_location_y	
	orientation	orientation	
			WWR_n, room5_location_y
Stage 3	WWR_n, WWR_w	wall_R, roof_R, floor_R	room4_location_y, orientation
	WWR_e, WWR_s		room3_location_y, building ratio,
	distance, w, s		room2_location_y
Stage 3			floor_R, room4 ratio, w
	U_Value	WWR_n, WWR_w	s, room2 ratio, room1 ratio
	SHGC	WWR_e, WWR_s	room5 ratio, room3 ratio
	wall_R	Distance, w, s	room2_location_x
	roof_R	U_Value, SHGC	room1_location_x, distance
	floor_R		room1_location_y, room3_location_x

Table 3: The parameter settings of the PSO algorithm.

	inertia weight (ω)	individual learning factor (ϕ_1)	sociology learning factor (ϕ_2)
Value	0.99^{t-1} (t: the current generation)	2.0	2.0

Result Analysis

Figure 5 shows the comparison of the population's average fitness values of each stage in the different optimization prototypes. The average value represents the trend of the PSO particles. Regardless of the prototype, the values improve along with the stages. The average values of Prototype 1 and 2 are similar in each stage. Compared to the other two optimized prototypes, the average of Prototype 3 in Stage1 is smaller, Stage2 is closer, and Stage3 is much higher than other prototypes.

The gBest value represents the best value found by all particles in this generation, that is, the lowest average energy consumption. Figure 6 shows the comparison of the gBest value of each stage in different optimization prototypes. It can be seen from the results that the gBest values of the particles found in each stage is either the

same or, in most cases, getting better along the stages. In Prototype 1, since the global best value found in Stage 2 is already very good, it remained unchanged in Stage 3.

Figure 7 shows the comparison of the average fitness values of each prototype in each optimization stage. In the Stage 1, because the optimization variables for Prototype 1 (phase-based prototype) and Prototype 2 (objects-based prototype) are the same, the lines of the two completely overlap, indicating that they share the same result. In Stage 1, the average value of Prototype 3 (sensitivity-based prototype) is much lower than the other two prototypes, but in the latter two stages, Prototype 3 is partially or completely higher. Also, the decreasing trend of Prototype 3 is much smaller than the other two. The variation trend and amplitude of the average values of Prototype 1 and Prototype 2 are always close to each other, but Prototype 1 performs better in Stage 2, and worse in

Stage 3. After the total 150 generations, the average value of Prototype 2 is the lowest, followed by Prototype 1, and Prototype 3 is the highest.

Figure 8 shows the comparison of the gBest values of each prototype in different stages. In Stage 1, because the optimization variables for Prototype 1 and Prototype 2 are

the same, the lines of the two again completely overlap. The gBest value found by Prototype 3 is the best of the three optimization prototypes at any stage, and the final gBest values of Prototype 1 and Prototype 2 are very close. The trend of the gBest in the last two stages is quite different from the trend of the average (Figure 6), especially for Prototype 3.

Figure 5: The average value each stage in every multi-stage prototype.

Figure 6: The gBest value in each stage of each prototype.

Figure 7: The average value of each prototype in each stage. (Note that in Stage 1, Prototype 1 and 2 share the same result because their variables are the same.

Figure 8: The global best value of each prototype in each stage (Note that in Stage 1, Prototype 1 and 2 share the same result because their variables are the same).

Figures 9-10 show the comparison of the multi-stage optimization prototypes and the traditional optimization methods. For the average fitness (Figure 9), Prototype 1 and Prototype 2 showed more significant drops near the 100th generation than the other two. After 150 generations, the traditional optimization method has the highest average value, the Prototype 3 is slightly smaller, followed by Prototype 1, and the average value of Prototype 2 is the lowest. In terms of gBest values (Figure 10), the performance of Prototype 3 is the best, and the gBest values obtained by the other two prototypes and the traditional method are very close to each other. In terms of optimization efficiency, the numbers of generations required for Prototypes 1–3 and traditional method to find their gBest are: 75, 123, 148, 75, respectively. Prototype 3 shows an unexpected results when compared to other prototypes, that is, towards the 150th generation, its gBest value is the lowest among all the prototypes, but its average value is higher than the other two. In other words, Prototype 3 (sensitivity-based prototype) performs poorly on the population average, but performs the best on the gBest.

Because the PSO algorithm used in this study contains mutation factors, in order to reduce the influence of the contingency of mutation on the results, five repeated experiments on Prototype 3 have been performed, and Figures 11 - 12 show the experimental results. It can be seen from the experimental results that the five repeated experiments all showed the consistent results: the population averages of Prototype 3 were higher than other prototypes, but the gBest was lower.

Figure 9: the average fitness of each prototype and the traditional method.

Figure 10: the gBest fitness of each prototype and the traditional method.

Figure 11: the average fitness of each prototype and the traditional method.

Figure 12: the gBest fitness of each prototype and the traditional method.

Discussions

This paper mainly evaluates the behaviour of multi-stage optimization prototypes from two aspects: 1) the

usefulness of the results, reflected by the gBest value of each prototype; 2) the behaviour of optimization algorithm, reflected by the average value of each prototype.

Among the three prototypes, the one based on the design processes (Prototype 1) and design objects (Prototype 2) are similar, whether in the population average or the gBest value, but Prototype 2 can find the lower gBest value. For the sensitivity-based Prototype 3, the population average and the gBest value show two opposite outcomes: the average value is much higher than the other two prototypes, but the gBest value is lower than the other two. Five extra repeated experiments show that the outcomes are consistent. This phenomenon may be caused by the following reasons. In Stage 3 of Prototype 3, most of the refined variables are discrete variables which have less impact on energy consumption, that is, they will not have a great impact on the objective function if their values have been changed. Therefore, the average value of Stage 3 is a little different with Stage 2. In the earlier optimization stage, when the low-sensitivity variables (rough variables with large granularity) are optimized along with the high-sensitivity variables, the population will proceed in a better direction, but this trend is most likely due to the fact that the high-sensitive variables are taken better values. At this time, although the low-sensitive variables play a smaller role, they still have a larger space that has not been searched. Therefore, in Stage 3, a more detailed search can be performed in a larger range to find a better value of objective function. Therefore, although the average value of Prototype 3 is higher in Stage 3, a better gBest value can still be found in the end. To summarize, in terms of practical applications, Prototype 3 is the better multi-stage optimization prototype.

Conclusions

In this paper, we proposed three key factors affecting the sequential building energy optimization process: availability, dependency and sensitivity of decision variables. According to these factors, three multi-stage building energy optimization prototypes are created based on design processes (Prototype 1), design objects (Prototype 2) and variables' sensitivity (Prototype 3). The entire optimization process for each prototype is divided into three stages, and the optimization model of each stage is constantly changing as the design progresses. Specifically, each stage includes different refined variables and rough variables, and the same variable has different granularity when its impact is different at different stages of optimization.

Through experiments using these prototypes, our main conclusion is that the performance of the multi-stage optimization prototypes is much better than the traditional one-stage optimization method, in terms of both the gBest solution or the population average fitness found. Therefore this research suggests further investigation of multi-stage optimization methods and their potential applications in building energy performance optimization.

In future studies, we plan to conduct more experiments and analyses to test the thoughts in Discussion, and find the reasons for the interesting results presented in Results Analysis. We also plan to investigate a more comprehensive approach integrating analysis and optimization, to achieve the optimization procedures in a more efficient way.

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Appendix

Title	Year	Author	Journal Volume / Conference Name
Multi-objective optimization for building retrofit strategies: A model and an application.	2012	Asadi, E., Da Silva M. G. Antunes C. H., Dias L.	Energy and Buildings
Multiobjective optimization model for maximizing sustainability of existing buildings.	2016	Abdallah M., El-Rayes K.	Journal of Management in Engineering
Multi-objective optimization analysis for high efficiency external walls of zero energy buildings (ZEB) in the Mediterranean climate.	2014	Baglivo C., Congedo P. M. Fazio A., Laforgia D.	Energy and Buildings
Optimization of envelope and HVAC systems selection for residential buildings.	2011	Bichiou Y., Krarti M.	Energy and Buildings
Multi-objective optimisation of a modular building for different climate types.	2012	Evins R., Pointer P. Burgess S.	In First building simulation and optimization Conference
A multi-objective optimization model for energy-efficiency building envelope retrofitting plan with rooftop PV system installation and maintenance.	2017	Fan Y., Xia X.	Applied energy
Design of low-emission and energy-efficient residential buildings using a multi-objective optimization algorithm.	2012	Fesanghary M., Asadi S. Geem Z. W.	Building and environment
A generative facade design method based on daylighting performance goals.	2012	Gagne J., Andersen M.	Journal of Building Performance Simulation
Applying a multi-objective optimization approach for design of low-emission cost-effective dwellings.	2011	Hamdy M., Hasan A. Siren K.	Building and environment
A multi-stage optimization method for cost-optimal and nearly-zero-energy building solutions in line with the EPBD-recast 2010.	2013	Hamdy M., Hasan A. Siren K.	Energy and Buildings
Minimisation of life cycle cost of a detached house using combined simulation and optimisation.	2008	Hasan A., Vuolle M. Sirén K.	Building and environment
Optimum design for indoor humidity by coupling genetic algorithm with transient simulation based on contribution ratio of indoor humidity and climate analysis.	2012	Huang H. , Kato S. Hu R.	Energy and Buildings
Facade renovation for a public building based on a whole-life value approach.	2012	Jin Q., Overend M.	In Proceedings of Building Simulation and Optimisation Conference
Optimization of a free-form building shape to minimize external thermal load using genetic algorithm.	2014	Jin J. T., Jeong J. W.	Energy and Buildings
Hybrid single objective genetic algorithm coupled with the simulated annealing optimization method for building optimization.	2015	Junghans L., Darde N.	Energy and Buildings
Optimization of building window system in Asian regions by analyzing solar heat gain and daylighting elements.	2013	Lee J. W., Jung H. J., Park J. Y., Lee J. B. Yoon Y.	Renewable energy
Multi-objective optimization for energy performance improvement of residential buildings: a comparative study.	2017	Li K., Pan L., Xue W. Jiang H., Mao H.	Energies

Passive designs and strategies for low-cost housing using simulation-based optimization and different thermal comfort criteria.	2014	Nguyen A. T., Reiter S.	Journal of Building Performance Simulation
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