Optimizing Buildings' Life Cycle Performance

Subjects: Construction & Building Technology
Contributor: Hanze Yu , Wei Yang , Qiyuan Li , Jie Li

The main considerations in the early stage of architectural design are usually related to form and function. At the same time, with the growing concern regarding energy saving and carbon emission reduction, the parameters for the construction and physical quality of buildings are receiving more attention at the conceptual and schematic design stages. Diverse design options can emerge with the large number of variables to be considered in these stages. Moreover, the combined efforts to reduce buildings' life cycle environmental impacts and cost, as well as the non-linear and often tradeoff relationship between the two objectives, make finding optimal design solutions for buildings' life cycle performance complicated. Previous studies have established workflows to optimize buildings' life cycle energy consumption, GWP and/or cost; however, architectural design diversity has not been sufficiently discussed at the same time. A parametric optimization design process is established, aiming at minimizing the building's operational energy consumption, life cycle environmental impacts, and life cycle cost here. The setting of variables, as well as the workflows of the optimization process, is discussed from the perspective of both life cycle performance and architectural design diversity.

simulation-based multi-objective optimization | life cycle assessment | life cycle cost | design process | diversity

1. Introduction

Currently, CO_2 emissions from the worldwide operation and construction of buildings account for around 37% of the total CO_2 emissions [1]. In a highly dynamic built environment, as in China, the proportion of the building-related greenhouse gas emissions in all of the life cycle processes to the national total is even higher (up to 51% in 2018 [2]). With the ever stricter standards for energy conservation and emissions reduction in the building sector, the relative proportion of the embodied energy and environmental impacts of buildings' components and materials has also increased [3]. At the same time, technical measures for green buildings may increase the cost of initial construction. The economic benefits of building construction should be examined from a long-term perspective. The application of the life cycle assessment (LCA) and life cycle cost (LCC) methods in the built environment have gained significant traction as essential methods for building sustainability assessment following the publication of ISO 14040 [4] and ISO 21929 [5].

There are often differences between a green building's life cycle environmental and economic benefits [6]. Previous studies have shown that there is a tradeoff relationship between a building's operational and embodied energy [7], and between its investment cost and LCC. Therefore, an optimization subjected to LCA and LCC, taking the life cycle environmental impacts and cost as the coupling objectives, can improve a green building's overall performance by maintaining balance between the objectives.

Decisions in the early stage of the architectural design process are crucial to reducing a building's life cycle impacts, because 70% of the decisions related to the project's sustainability are made at this stage [8]. Traditional building performance simulation lags behind this stage, and it is not easy to perform comprehensive simulations on various parameter combinations. Meanwhile, the integrated LCA method is generally not applied to help architects to select design solutions at the early design stage because it is time and information consuming [9]. The information integration function of building information modelling (BIM) software helps to conduct LCA and LCC analysis, such as One Click LCA [10] for the early comparison and selection of the design schemes, and the Revit Plugin program Tally [11], which can assist in the selection of building material solutions in a BIM model, and conduct a complete building LCA. However, due to the limitation of manual variable settings, it is difficult to support the automatic feedback of calculation results and the screening of a large number of design parameter combinations. The parametric design platform can support the automatic generation of design variables and the linkage to the life cycle inventory (LCI) data and to the energy simulation program [12]. It can significantly improve the efficiency and accuracy of performance optimization through the combination with the optimization algorithm.

2. Optimizing Buildings' Life Cycle Performance

Decisions in the early design stage are essential to reducing buildings' life cycle environmental impacts and cost [13]. The studies reviewed are all concerned with multi-objective optimization processes that target building performance in the early design stage. In terms of summarizing the variables, the varieties of the material variables are not analyzed because building performance design based on LCA/LCC methods necessarily involves material selection. In this stage, geometric design parameters are the most intuitive elements to consider, and it is found through the review that studies with life cycle impacts or cost as targets tend to consider the geometric variables in a simple way, while studies that consider building form diversity as an innovative point often do not include the target of calculating life cycle performance (**Table 1**). The studies reviewed are grouped into two categories. The first category focuses on the generation of geometric forms. The second category focuses on the design process of the project.

Table 1. Review of the literature on classification based on design diversity and LCA relevance.

Category	Year	Authors	Geometric Variables				Life Cycle Objectives			Others
			Basics			Characteristics	Operational Energy	Embodied Energy	Economy	
			Orientation	Plan	wwr					
Geometry: free-form	2019	Si et al. [14]				Eave depth by 10 variables	√ [a]			predicted percentage dissatisfied
	2015	Negendahl et al. [15]				Amplitude of façade fold	√		cost	daylight

Category	Year	Authors	Geometric Variables				Life Cycle Objectives			
			Basics			Characteristics	Operational Energy	Embodied Energy	Economy	Others
			Orientation	Plan	wwr					
Geometry: mass-box	2014	Jin et al. [16]				Free-form mass controled by 5 variables	√			
	2009	Yi et al. [17]				Controlling points of surface	√			
	2020	Harter et al. [18]	√	√		7 different plans	√	primary energy		
	2019	Shadram et al. [19]	√	√	√		√	embodied energy		
	2017	Yang et al. [20]			√	Sunshade board length	√		envelope construction cost	
	2016	Brunelli et al. [21]				Building footprint	√	CO_2 emission	net present value of the investment	comfort level
	2013	Basbagill et al. [9]		√	√	Number of buildings, number of floors	√	CO_2 emission		
Design process	2021	Abbasi et al. [22]					√	embodied energy, renewable energy	operation cost, embodied cost	
	2019	Ascione et al. [23]	√				√	primary energy, CO_2 emission	global cost	
	2019	Li et al. [24]	√		√		√	primary energy	global cost, investment cost	
	2018	Shadram et al. [7]					√	primary energy		
	2017	Ascione et al. [25]			√	Overhang projection ratio	√		LCC	
	2016	Hollberg et al. [12]						non-renewable		

e to the uniqueness of the solutions, and some of these studies do not include life cycle objectives. In Section 2.1.2, the form generation logic is weaker than that described in Section 2.1.1. The geometric models are based on operational energy consumption calculation zones (mass-box). Life cycle performance is considered in all of the studies in the second part.

2.1.1. Free-Form Geometry

The geometric design parameters of a building have a significant effect on its appearance and performance. To support the diversity of architectural design, while considering the concision of the model required for the energy

Category	Year	Authors	Geometric Variables				Life Cycle Objectives			
			Basics			Characteristics	Operational Energy	Embodied Energy	Economy	Others
			Orientation	Plan	wwr					
								primary energy		

a “√” indicates that the content is included in the study.

eometric

Jin et al. [16] defined the shape of the building as a polygon, controlling the shape by changing the polygonal shape and twisting angle of the upper and lower bottom surfaces; Si et al. [14] controlled the generation of the roof using the degree of deviation of ten points of the irregular polygonal roof from the center coordinates, in order to affect the indoor environment objectives. Negendahl et al. [15] investigated the relationship between the number and amplitude variables of façade folds and building energy consumption. Yi et al. [17] controlled building forms by defining the hierarchical relationship between geometry points to explore the building geometry without being restricted to a box or simple form.

2.1.2. Mass-Box Geometry

The above studies used specific geometric variables to study specific building models without LCA- or LCC-related objectives. In studies involving LCA, the formulation of geometric variables is often simplified from “free-form” to “mass-box”.

Basbagill et al. [9] took an H-shaped plane as a prototype and generated building plans with different proportions and shapes by adjusting each side’s parameters. The geometric parameters of this plan’s outer contour and the envelope structure’s construction layers and their thickness were used as variables that were subjected to a sensitivity study. Shadram et al. [19] classified the plan shapes of typical residential buildings into six types (“□”, “U”, “H”, “L”, “T”, “×”), the geometric variables of the outer contour and the inner contour were set for each basic shape, and optimization was carried out with the objectives of building’s operational and embodied energy consumption. Harter et al. [18] investigated the uncertainty of variables regarding the life cycle total energy under seven plan shapes (“□”, “+”, “L”, “U”, “H”, “T”, “□ with basement”). Yang et al. [20] set the windows’ number, unit width, unit length and sunshade board length as geometric variables to optimize the envelope construction cost and thermal energy demand. Brunelli et al. [21] studied a case with alternative building footprints to optimize thermal energy demand, and net present value of the investment and CO_2 emissions.

The above studies set the building plan’s geometric variables, elevation, or spatial position relationship based on the “mass-box” model and obtained a more diverse early design stage simplified model. This way of defining geometric variables appears in a large number of studies involving building performance. Some of them also added variables such as the shape of shading components and the verandas that do not change the main form of the building. Because the “mass-box” modelling approach is commonly used, this entry only exemplifies studies that involve life-cycle impacts or cost in the objective.

2.2. Design Process Focused Life Cycle Performance Optimization

Due to the large decision space formed by the variables and objectives, searching for the best solution is inefficient and complicated for architects. Because of the complexity of the LCA and LCC methods, improvement of the design process is a more important part of the optimization. Geometric forms are not the focus in these following studies.

Hollberg and Ruth [12] designed a single-objective optimization process with the objective of non-renewable primary energy consumption by using the parametric platform Grasshopper (GH) and the optimization plug-in Goat. Several plans pre-set by the architects were analyzed and compared, and then insulation material, thickness, and external window alternatives were set as variables to be automatically optimized. The authors pointed out that the current LCA calculation is a time-consuming task, and architects usually did not have relevant knowledge and experience. Meanwhile, the information about the materials, the structures, and the service system required for LCA is often not available in the early design stages.

Shadram et al. [7] combined the comprehensive advantages of building information in the BIM platform with the mature energy analysis tool and the optimization capabilities of the parametric platform to study a small apartment building in one country under four different climate zones. This process used gbxml format files to transfer geometric information, using the MySQL database to transfer material information, linking BIM software and the multi-objective optimization module in GH to achieve a fully automatic optimization process. This method required a higher level of development (LOD) of the model, and the geometric parameters such as building shapes were not set as variables. It was more suitable for the later stages of the design process.

Abbasi et al. [22] also combined BIM and parametric platforms. The building was originally developed in Revit, containing geometric component information. The geometrical data and amount of materials were extracted as input data in the Athena software to calculate embodied energy, renewable energy consumption, and other LCA indicators such as GWP. The three-dimensional model was introduced into GH to regenerate the model for operational energy optimization of the building, using Ladybug and Honeybee plugins. The optimized results were then added to Navisworks, another BIM platform, in the format of database information to create a higher LOD model. In the above-mentioned workflows, the geometric parameters were defined in the original Revit model. The overall design process enhanced the model's information, but the method was unidirectional and could not reverse the early concept of the project. The optimization focused on materials and equipment rather than aesthetic design.

The studies mentioned above adopted the idea of optimizing building performance in one step. Ascione et al. [25] performed the optimization in stages. In the first stage, the objectives of optimization were the minimization of thermal energy needs for space heating and cooling. In the second stage, an intelligent search strategy was carried out to identify the robust cost-optimal retrofit solutions of the whole building system. Finally, a careful decision-making process was performed to find a recommended retrofit package among the 12 cost-optimal solutions found in stage two. This approach was applied to the design of a building energy retrofit. The variables were limited to material and equipment.

Another study from Ascione et al. [23] presented a three-phase framework for multi-objective optimization. Phase One was a three-objective (annual thermal energy demand for space conditioning, annual electrical energy demand for artificial lighting, annual percentage of discomfort hours) Pareto optimization of building geometry, HVAC operation, and the envelope. Phase Two was a smart exhaustive sampling running within Pareto solutions provided by Phase One with another three objectives (primary energy consumption, global cost, investment cost). Phase Three selected the design solutions provided by decision-makers according to the optimal solution sets as well as the other performance indicators. Due to the calculation of objectives in phases, the optimal solutions in each phase were not global. The building geometric variables considered in the study were not as detailed as the HVAC or material ones.

Li et al. [24] proposed a coordinated optimal design method. An iterative approach was adopted to coordinate multi-stage optimizations of the building envelope and the energy systems. The envelope design and the energy system design were optimized iteratively using the updated design of each other until the coordinating design variables converged. A zero-carbon building was tested and the objectives’ results were better compared with existing multi-stage design methods. The premise of this method was that there existed a clear trade-off relationship between the objectives in the different steps of the optimization process.

References

1. United Nations Environmental Programme. 2021 Global Status Report for Buildings and Construction. Available online: https://www.unep.org/resources/report/2021-global-status-report-buildings-and-construction (accessed on 1 June 2022).
2. China Building Energy Consumption Research Report 2020. Build. Energy Effic. 2021, 49, 1–6, (In English and Chinese).
3. Dixit, M.K. Life cycle embodied energy analysis of residential buildings: A review of literature to investigate embodied energy parameters. Renew. Sustain. Energy Rev. 2017, 79, 390–413.
4. ISO 14040:2006; Environmental Management—Life Cycle Assessment—Principles and Framework. International Organization for Standardization: Geneva, Switzerland, 2006.
5. ISO 21929-1:2011; Sustainability in Building Construction—Sustainability Indicators—Part 1: Framework for the Development of Indicators and a Core Set of Indicators for Buildings. International Organization for Standardization: Geneva, Switzerland, 2011.
6. Ostermeyer, Y.; Wallbaum, H.; Reuter, F. Multidimensional Pareto optimization as an approach for site-specific building refurbishment solutions applicable for life cycle sustainability assessment. Int. J. Life Cycle Assess 2013, 18, 1762–1779.
7. Shadram, F.; Mukkavaara, J. An integrated BIM-based framework for the optimization of the trade-off between embodied and operational energy. Energy Build. 2018, 158, 1189–1205.
8. Fu, Y.; Wang, L.; Li, L. Conceptual design scheme automatic generation and decision-making considering green demand. Procedia Manuf. 2020, 43, 407–414.

9. Basbagill, J.; Flager, F.; Lepech, M.; Fischer, M. Application of life-cycle assessment to early stage building design for reduced embodied environmental impacts. Build. Environ. 2013, 60, 81–92.
10. One Click LCA Ltd. One Click LCA. Available online: https://www.oneclicklca.com/ (accessed on 1 December 2021).
11. Building Transparency, KT Innovations, Thinkstep, Autodesk. Tally. Available online: http://choosetally.com/ (accessed on 1 December 2021).
12. Hollberg, A.; Ruth, J. LCA in architectural design—A parametric approach. Int. J. Life Cycle Assess 2016, 21, 943–960.
13. Negendahl, K. Building performance simulation in the early design stage: An introduction to integrated dynamic models. Autom. Constr. 2015, 54, 39–53.
14. Si, B.; Wang, J.; Yao, X.; Shi, X.; Jin, X.; Zhou, X. Multi-objective optimization design of a complex building based on an artificial neural network and performance evaluation of algorithms. Adv. Eng. Inform. 2019, 40, 93–109.
15. Negendahl, K.; Nielsen, T.R. Building energy optimization in the early design stages: A simplified method. Energy Build. 2015, 105, 88–99.
16. Jin, J.-T.; Jeong, J.-W. Optimization of a free-form building shape to minimize external thermal load using genetic algorithm. Energy Build. 2014, 85, 473–482.
17. Yi, Y.K.; Malkawi, A.M. Optimizing building form for energy performance based on hierarchical geometry relation. Autom. Constr. 2009, 18, 825–833.
18. Harter, H.; Singh, M.M.; Schneider-Marin, P.; Lang, W.; Geyer, P. Uncertainty Analysis of Life Cycle Energy Assessment in Early Stages of Design. Energy Build. 2020, 208, 109635.
19. Shadram, F.; Mukkavaara, J. Exploring the effects of several energy efficiency measures on the embodied/operational energy trade-off: A case study of swedish residential buildings. Energy Build. 2019, 183, 283–296.
20. Yang, M.-D.; Lin, M.-D.; Lin, Y.-H.; Tsai, K.-T. Multiobjective optimization design of green building envelope material using a non-dominated sorting genetic algorithm. Appl. Therm. Eng. 2017, 111, 1255–1264.
21. Brunelli, C.; Castellani, F.; Garinei, A.; Biondi, L.; Marconi, M. A Procedure to Perform Multi-Objective Optimization for Sustainable Design of Buildings. Energies 2016, 9, 915.
22. Abbasi, S.; Noorzai, E. The BIM-Based multi-optimization approach in order to determine the trade-off between embodied and operation energy focused on renewable energy use. J. Clean. Prod. 2021, 281, 125359.

23. Ascione, F.; Bianco, N.; Mauro, G.M.; Vanoli, G.P. A new comprehensive framework for the multi-objective optimization of building energy design: Harlequin. Appl. Energy 2019, 241, 331–361.
24. Li, H.; Wang, S. Coordinated optimal design of zero/low energy buildings and their energy systems based on multi-stage design optimization. Energy 2019, 189, 116202.
25. Ascione, F.; Bianco, N.; De Masi, R.F.; Mauro, G.M.; Vanoli, G.P. Resilience of robust cost-optimal energy retrofit of buildings to global warming: A multi-stage, multi-objective approach. Energy Build. 2017, 153, 150–167.