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Towards adoption of building energy simulation and optimization for passive building design: A survey and a review

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ABSTRACT

Integrating optimization algorithms into simulation-based design processes is a promising approach for achieving energy efficient buildings. Building Energy Simulation and Optimization (BESO) is an emerging innovative technique that shows promise but is not yet a widely adopted design practice. To identify the needs, benefits, and hindrances of applying BESO to sustainable building design, particularly passive design, a two-part survey was conducted. A significant amount of attention was dedicated to analyzing the opinions of early adopters. Out of nine potential hindrances of the BESO technique, *long calculation time, lack of adequate advertisement,* and *lack of a standard method or procedure* are in the top three. Based on the survey results, a review was conducted to categorize a general procedure for the BESO technique. The application of the BESO technique to passive building design was investigated. The passive design components covered building forms, opaque envelopes, fenestrations, shadings, natural ventilation, and thermal mass materials. The review concludes that the three-phase optimization method was the most widely used method. Currently, compared to other passive design methods, BESO proved to be a more efficient method for helping designers (especially architects) explore various design territories.

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1. Introduction

1.1. Building energy simulation and optimization

Building energy accounts for approximately 40% of the total energy consumption in the European Union, the United States, and other developed countries [1]. In China, the number was 19.1% in 2012 and increased approximately 8.3% annually from 2001 to 2012 [2]. Conserving energy and developing energy efficient building designs has been a concern for researchers in many countries. In order to tackle this problem, different energy efficient design methods have been proposed. Building energy efficient design requires a collaborative effort between architects, heating, ventilation, and air conditioning (HVAC) engineers, energy consultants, and other relevant professionals. Because of its intrinsically multi-objective and non-linear nature, building energy efficient design is not an easy task [3]. Recently, Building Energy simulation and Optimization (BESO) has been developed as a new technique to assist architects and other relevant professionals in their daily design practice [4].

BESO automatically conducts energy simulation and optimization until the optimal solution is found based on the pre-defined design criteria. Using optimization algorithms, BESO aims at finding the optimal solution among a large number of candidate solutions. Fig. 1 shows the general workflow of BESO. Designers propose different energy efficient measures but do not know which one is the best. Based on the original baseline model and proposed energy efficient measures, the optimization engine is able to generate a new design. The energy simulation engine then calculates the energy performance of the new design. Next, the optimization engine evaluates whether the pre-defined design criteria are met. If the design criteria are not met, the simulation and optimization process will be repeated.

Energy efficient measures for buildings can be categorized into several types; namely, passive design measures, reduction of HVAC energy, usage of renewable energy, and energy management, among which passive design is one of the most fundamental and effective methods [5,6]. An excellent passive building design can decrease HVAC and lighting energy by reducing heating/cooling loads and daylighting needs [7–9].

Several efforts have been made to review state-of-the-art of BESO [4,10,15,16]. Attia et al. [10] conducted a building performance optimization interview with 28 experts who conducted research in this field. They also conducted a review to reintroduce the most commonly used optimization tools. Shi et al. [16] emphasized reviewing and analyzing state-of-the-art of BESO from the perspective of architects. When developing a linear programming method for building energy efficient design, Üçtuğ and Yükseltan [17] analyzed the issue of building energy efficiency from the point of view of the household consumer. Nguyen et al. [4] subdivided a design optimization process into three phases: the preprocessing phase, the optimization phase, and the post-processing phase. They then reviewed the major tasks in each phase.

The present work differs from these previous reviews in several aspects. First, it is built upon a survey aimed at architects, engineers, and other professionals who are potential users of BESO. The results gained from the survey help us understand their needs, benefits, and possible hinderances with respect to BESO. Secondly, the survey results have revealed several issues that are likely hinderances to BESO application. These issues are the focus in the review part that follows the survey. Thirdly, the application of BESO on passive design is an important subject and of particular interests to architects. However, this matter is not adequately addressed in the previous previews. The present work is intended to bridge this gap.

1.2. Aims of this study

The objective of this study is to conduct a survey to understand user opinions on BESO as an emerging technology, and to review the application of BESO to passive building design. The survey consists of two parts. The first part is directed to general stakeholders including architects, mechanical engineers, and green building consultants. The second part is more focused in that selected professionals with experience in adopting BESO technology are asked to determine the benefits and hindrances of adopting BESO. Based on the survey results, several key problems are discovered.

The review follows the survey and addresses BESO procedures and passive building design optimization. The following points are highlighted:

- Classification of BESO procedures.
- Applying optimization to building form design, opaque envelopes, fenestrations, shadings, natural ventilation, and thermal mass materials.
- Discussions about standard BESO procedures and whether previous studies satisfy the needs of designers. In addition, future research areas are discussed.

2. Survey and results

2.1. Survey

Although BESO is a research subject that has been extensively studied over the past two decades [11,12], it is not yet widely applied in the building design community. According to statistics, more than 30 energy efficient optimization programs have been developed, most of which are research tools and cannot be readily used by practicing designers with little training [18]. To understand the needs, benefits, and hindrances of adopting BESO to the building designer, and for the further development of BESO, a survey was developed and conducted for relevant professionals. The first part of the survey is intended to identify what the building designer needs from BESO. The second part focuses on exploring the opinions of early adopters as they relate to the benefits and hindrances of adopting BESO. Early adopters are a group of people who use a product or service earlier than others. They can provide feedback to help refine the product or service. Potential adopters look to early adopters for advice and information about the innovation. The early adopter is considered by many as “the individual to check with” before using a new idea. This adopter category is generally sought by change agents to be a local missionary for speeding up the diffusion process [19]. Therefore, it is necessary to explore the

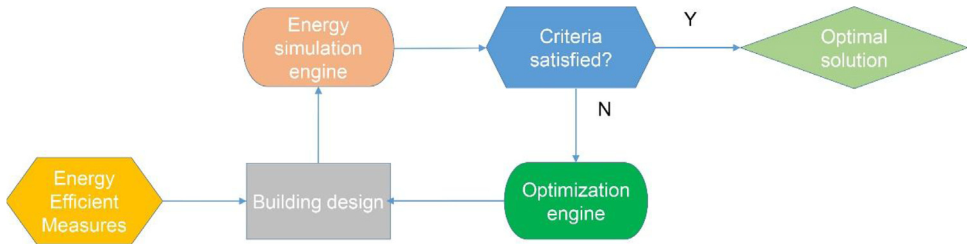

Fig. 1. General workflow of BESO.

opinions of early adopters on BESO. The insight gained from such a survey can be used to determine what improvements need to be made in the next generation of BESO tools.

2.2. The first part of the survey and results

The first part of the survey includes nine questions. The main focus of this part is to identify the needs for conducting BESO. A total of 119 Chinese participants answered the nine questions, and the participants included architects, mechanical engineers, green building consultants, and other relevant professionals. By analyzing the survey results of the first five questions (Questions 1–5), the following general findings are obtained:

- Of the 119 participants, 58 (48.7%) are green building consultants, 29 (24.4%) are postgraduate students, and 19 (16.0%) are mechanical engineers. Only 9 (7.7%) are architects.
- 106 (89.1%) participants have some experience working on different aspects of green building projects.
- The most frequently used building modeling tool in the early design stage is SketchUp [20] (52.7%), followed by Autodesk Revit [21] (24.3%) and Rhino [22] (14.3%).
- In terms of energy simulation programs, EnergyPlus [23] (50.4%) and eQUEST [24] (49.6%) are the most commonly used, followed by DesignBuilder [25] (40.3%), which uses EnergyPlus as the simulation engine, BECS (35.3%), T-BEC (26.9%), and PKPM (34.4%), three of which are DOE-2 based tools specialized for building envelope compliance of China building energy efficiency standard, TRNSYS [26] (12.6%), IES-VE [27] (10.9%), HY-EP [28] (8.4%) a EnergyPlus-based software developed by a Chinese company and others (10.0%). Because these data are summarized from a multiple choices questions, sum of these numbers exceeds 100%.
- The optimization module in DesignBuilder is the most commonly used BESO tool (31.1%), followed by the MATLAB optimization toolbox [29] (18.5%). 52 (43.7%) participants never used any BESO tools.
- It is confirmed that BESO is an attractive technique because 87.4% of participants would like to use BESO tools to perform building design optimization.

Questions 6–9 in the first part of the survey are intended to gain insight into the needs of the designer with respect to three important passive design measures: opaque envelope, fenestration, and shading. The participants are requested to rate the significance level by selecting one of four grades: "never need" (0 point), "seldom need" (1 point), "often need" (2 point), and "always need" (3 point). Fig. 2 summarizes the average points for different passive design measures. Using Fig. 2, the following findings can be concluded:

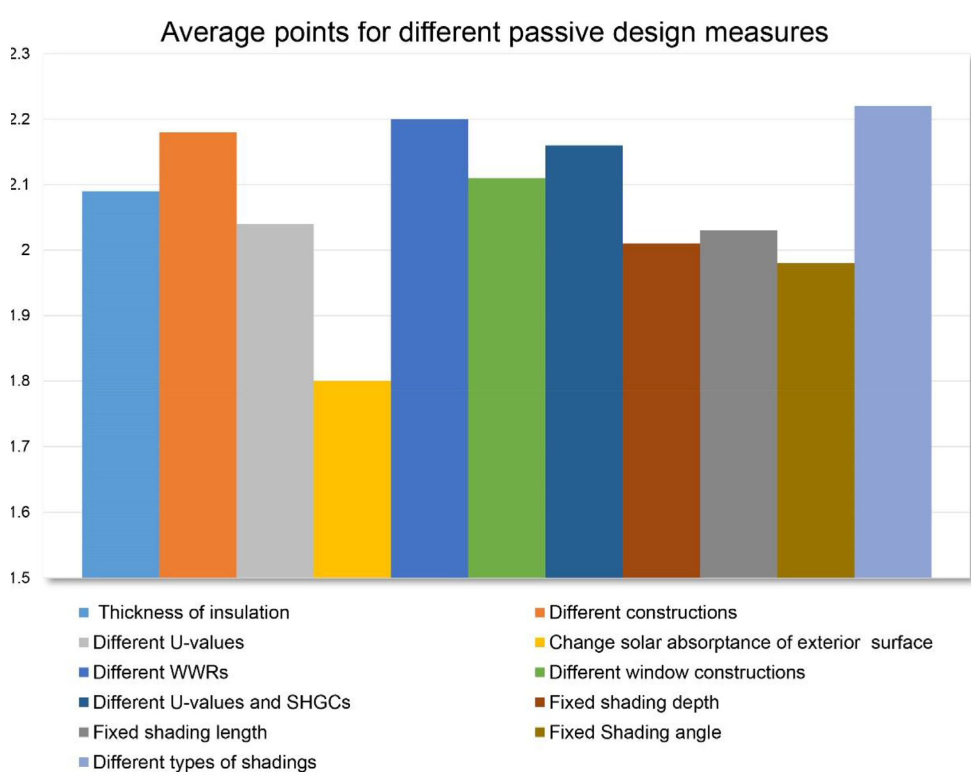

Fig. 2. Degree of respondent preference on different passive design measures.

Table 1
Benefits of applying BESO.

	Completely disagree	Disagree	Unclear	Agree	Completely agree	Average value
Automatically adjust the value of design variables	0(0.0%)	3(10.7%)	1(3.6%)	10(35.7%)	14(50.0%)	4.25
BESO tools are embedded with optimization algorithms	0(0.0%)	2(7.1%)	1(3.6%)	10(35.7%)	15(53.6%)	4.36
Determines the optimal solution, and helps to make decisions	0(0.0%)	1(3.6%)	3(10.7%)	15(53.6%)	9(32.1%)	4.14
Sensitivity analysis	0(0.0%)	6(21.4%)	2(7.1%)	10(35.7%)	10(35.7%)	3.86
Conducts multi-objectives optimization	1(3.57%)	2(7.1%)	2(7.1%)	13(46.4%)	10(35.7%)	4.04
Help design zero energy buildings	1(3.57%)	3(10.7%)	10(35.7%)	7(25.0%)	7(25.0%)	3.57

- Comparison of different types of shadings is the most needed function.
- When conducting BESO, the designer prefers to compare different constructions rather than the parameters in one construction, such as the thickness of the insulation of an exterior wall.

2.3. *The second part of the survey and results*

Because a significant portion of the participants in the first part of the survey do not have any experience using BESO tools, it is inappropriate to ask them questions about the benefits and hindrances of applying BESO. We conducted the second part of the survey by sending it to a group of 28 early BESO adopters who are experts from 11 different countries.

2.3.1. *Benefits of adopting BESO*

Many researchers identify energy simulation as the best way to test ideas for improvement, and optimization as the best way to select the best idea [30]. The first question in the second part of the survey is 'Which benefit(s) can the current BESO technique offer?' Six benefits of adopting BESO were provided as possible answers: (1) Automatically adjust the value of design variables, (2) BESO tools are embedded with optimization algorithms, (3) Determines the optimal solution and help make decisions, (4) Sensitivity analysis, (5) Conduct multi-objective optimization, (6) Help design zero energy buildings (ZEBs).

The participants were asked to rate each benefit on a scale of 5. The scale ranged from "completely disagree" (1) to "completely agree" (5). To examine the overall opinion and vote distribution, a simple arithmetic average value and response percentage rate were used.

As shown in Table 1, the participants rate the benefit that "BESO tools are embedded with optimization algorithms" (choice 2) as the most significant one. Furthermore, the other five benefits are largely agreed upon by the participants because the average ratings are all above 3.5, suggesting somewhere around "agree."

2.3.2. *Hindrances of adopting BESO*

In addition to identifying the benefits of adopting BESO, the hindrances are also investigated. The second question in the second part of the survey is "Which of the following do you believe hinders the application of the BESO technique?" Nine choices are provided: (1) Long calculation time, (2) Lack of a standard method or procedure, (3) The optimal solutions determined by the BESO software are inconsistent with the real optimal solutions, (4) Because I took over the project in the late design phase, there are only a few variables that need to be adjusted, therefore I do not need to use BESO software, (5) Shortage of optimization algorithms, (6) Lack of a user-friendly interface, (7) Poor results analysis ability, (8) Not certain that the effort and time spent using the BESO technique is worthwhile from an overall project perspective, (9) The BEEDO technique is not adequately advertised. Similar to the previous question, a five-level scale ranging from "completely disagree" to "completely agree" is used.

Table 2 shows the opinions of the respondents regarding the possible hindrances of applying BESO tools. Different from the responses regarding the benefits of BESO, respondents had a more diverse range of opinions on the hindrances. Using Table 2, the following results and conclusions are obtained:

- "Long calculation time" ranks first with an average value of 4.04. The respondents agreed that long calculation time was the main reason why users were reluctant to use BESO tools.
- "The BEEDO technique is not adequately advertised" obtained an average value of 3.68 and ranked second place. This is understandable because this method has not been widely applied.
- "Lack of a standard BESO method or procedure" received an average value of 3.57. More than half of the respondents voted agree (including completely agree) and only 21.4% voted disagree. Most of the respondents argued that they did not know what the best routine is to conduct design optimization. They expect a standard method that is easy to operate and can effectively determine the optimal design.
- "Shortage of optimization algorithms" received minimal grades of 2.64. Out of all the hindrances, respondents care the least about the optimization algorithms.

Table 2
Hindrances of adopting BESO.

	Completely disagree	Disagree	Unclear	Agree	Completely agree	Average value
Long calculation time	0(0.0%)	3(10.7%)	0(0.0%)	18(64.3%)	7(25.0%)	4.04
Lack of a standard BESO method or procedure	0(0.0%)	6(21.4%)	7(25.0%)	8(28.6%)	7(25.0%)	3.57
The optimal solutions determined by the BESO software are inconsistent with the real optimal solutions	1(3.6%)	10(35.7%)	10(35.7%)	7(25.0%)	0(0.0%)	2.82
Because I took over the project in the late design phase, there are only a few variables that need to be adjusted, therefore I do not need to use BESO software	5(17.9%)	7(25.0%)	7(25.0%)	8(28.6%)	1(3.6%)	2.75
Shortage of optimization algorithms	5(17.7%)	10(35.7%)	5(17.9%)	6(21.4%)	2(7.1%)	2.64
Lack of a user-friendly interface	2(7.1%)	7(25.0%)	2(7.1%)	12(42.7%)	5(17.9%)	3.39
Poor results analysis ability	3(10.7%)	6(21.4%)	1(3.6%)	17(60.7%)	1(3.6%)	3.25
Not certain that the effort and time spent using the BESO technique is worthwhile from an overall project perspective	3(10.7%)	5(17.9%)	4(14.3%)	11(39.3%)	5(17.9%)	3.36
The BEEDO technique is not adequately advertised	0(0.0%)	4(14.29%)	7(25%)	11(39.29%)	6(21.43%)	3.68

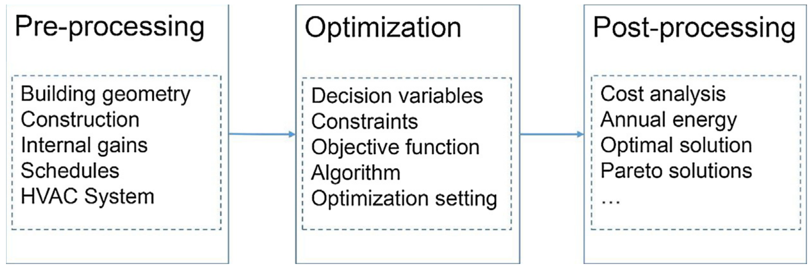

Fig. 3. Three-phase optimization procedure.

- "The optimal solutions determined by the BESO software are inconsistent with the real optimal solutions" received an average value of 2.82, which is close to 3 (unclear). If the optimal solution is inconsistent with the best solution proposed by designers with their analysis and intuition, which solution should be used?
- "Because I took over the project in the late design phase, there are only a few variables that need to be adjusted, therefore I do not need to use BESO software" received an average value of 2.75. More than half of the respondents disagreed with this viewpoint. It can be concluded that designers tend to use optimization methods to solve problems.
- "Lack of a user-friendly interface", "Poor results analysis ability", "Not certain that the effort and time spent using the BESO technique is worthwhile from an overall project perspective" received a value between "unclear" and "agree." 32.1% of respondents disagreed that the BESO tools lack of a user-friendly interface, while 60.6% of respondents agreed that it did. This discrepancy may be because some of the respondents have used optimization software with user-friendly interfaces, such as DesignBuilder, while others have not. "Poor results analysis ability" had a similar situation. It can also be concluded that most of the respondents are unclear whether the time spent to optimize the project is worthwhile or not.

3. BESO procedures

In the previous section, "long calculation time," "The BEEDO technique is not adequately advertised" and "Lack of a standard BESO method or procedure" were revealed as the top three reasons why designers are reluctant to utilize BESO. As there were already many papers dedicated to the reduction of computation time for optimization [13,31–33], and as described in the previous section, if this technique is truly a preferable innovation, early adopters will recommend it to other designers which means they help speed up the innovation diffusion process. Therefore, we pay a significant amount of attention to questions regarding standard BESO methods or procedures.

As shown in Fig. 1, the BESO technique involves multiple steps. Each step performs a different function, and each step works together to form a coherent procedure. In general, the BESO procedure can be divided into three categories: three-phase optimization, multi-time optimization, and sensitivity analysis and optimization. Table 3 gives simple summaries of typical BESO procedures.

3.1. Three-phase optimization

BESO is also known as automatic simulation-based optimization [34]. Therefore, simulation and optimization are the two key components in BESO. Whether it is explicitly stated or not, the BESO procedure is often divided into three stages: the pre-processing stage, the optimization stage, and the post-processing stage. Hasan et al. [35] coupled IDA-ICE [36], a building performance simulation program, with GenOpt [37], a generic optimization program, to explore retrofit strategies for single-family detached houses. A baseline energy model was built in the pre-processing stage using IDA-ICE. The objective functions, design variables, and optimization algorithms were defined and set in the optimization stage that follows. In the post-processing stage, the optimization results were presented and interpreted. This work represents a typical three-phase optimization procedure, as shown in Fig. 3.

3.2. Multi-time design optimization

It is very rare, if not impossible, for designers to achieve an optimal design in the first trial. The design usually requires many rounds of revisions, sometimes minor and other times significant, to reach a satisfying result. From another perspective, as a system design problem, building energy efficient design is completed by multi-discipline background experts. For example, the design of natural ventilation performance requires the use of a computational fluid dynamics (CFD) model, while the design of opaque enclosures always utilizes a detailed energy simulation model. Multi-time design optimization is the process of using many time optimization techniques to solve different energy efficient design sub-problems. Choudhary et al. [38] proposed a multi-level simulation-based optimization framework called Analytical Target Cascading (ATC), which divided the original design problem into a set of sub-problems. These sub-problems include the constituting system, subsystems, and components. Carlucci et al. [39,40] proposed a novel two-step procedure for the design optimization of comfort-optimized nZEB: (1) passive design with adaptive model; (2) active design with Fanger thermal comfort model. Konis et al. [41] proposed a method called the Passive Performance Optimization Framework (PPOF) to improve building passive performance in the early design stage, and a series of validation experiments were also created to compare the PPOF results with an ASHRAE 90.1 compliant benchmark building. This work also demonstrated a unique workflow for conducting optimization in different phases. Site analysis and daylighting analysis are two examples of such phases. Zhou

Table 3
Summaries of typical BESO procedures.

Optimization procedures	Description
Three-phase optimization	Optimization process can be summarized into three phases: pre-processing, optimization, and post-processing.
Multi-time design optimization	At each stage of building energy design, the BESO method is applied.
Sensitivity analysis and optimization	Use sensitivity analysis to narrow the range of variables, determine the significant variables and at the same time filter those variables with little impact on the objectives. Then optimization is conducted with a narrow variables range.

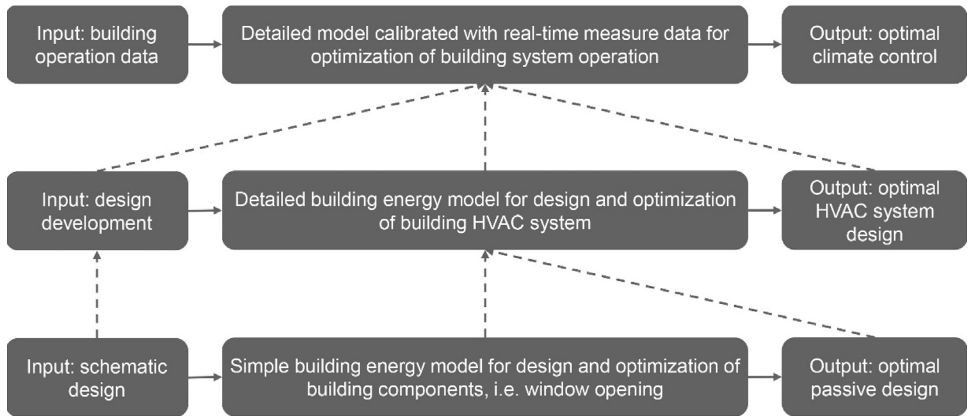

Fig. 4. A multi-time energy simulation and optimization framework for building design and operation.

et al. [42] proposed an optimal natural ventilation design method that consists of a three-stage procedure: (1) building-orientation optimization at the community level; (2) wind-path design at the floor-plan level, and (3) fenestration design at the room level. Magnier and Haghighat [43] coupled the Artificial Neural Network (ANN) with a multi-objective genetic algorithm (NSGA-II) to optimize building design. This process is divided into two steps. In the first optimization process, all of the variables are set. In the second optimization, the variable that has the lowest impact on the global performance is removed. Fig. 4 gives a multi-time optimization design process that applies optimization in building energy efficient design and operation.

3.3. Sensitivity analysis and optimization

If there were many design variables that needed to be considered because of their ability to influence performance, the optimization process could take an excessively long time to obtain the optimal design. In the process of comparing seven commonly used multi-objective evolutionary optimization algorithms to solve the design problem of a nearly ZEB, Hamdy et al. [44] found that 1400–1800 evaluations were the minimum number required to stabilize the optimization results of the building energy model. Similar studies [45–47] concluded that 400–3000 simulations were required depending on the number of design variables. An effective way to deal with the challenge of having too many design variables is to conduct a sensitivity analysis, which can be used to identify the significant variables and narrow the range of values [48].

Sensitivity analysis and optimization refers to the narrowing of the range of values before conducting optimization to determine the optimal design. Evins et al. [49] developed a four-stage optimization framework that was intended to maximize the benefit gained from optimization. Firstly, all variables have been analyzed using the design-of-experiments approach, which aimed at identifying significant variables while at the same time filtering variables that have a low impact on the objectives. Secondly, significant variables were analyzed to eliminate variables that remain constant for all optimum solutions. Finally, a detailed multi-objective optimization analysis is performed. Hamdy et al. [50] divided the optimization into two steps: (1) the first optimization step aimed at narrowing the solution space and (2) the second optimization step aimed at determining the optimal solution among the most sensitive variables. Gong et al. [8] proposed an approach that integrated the orthogonal method to determine the preferable level. In addition, this method analyzed the significance of candidate parameters using the listing method to select the optimal combination, based on thermal load simulation. Prior to implementing optimization, Eisenhower et al. [13] performed a sensitivity analysis of 1009 parameters to determine the 10 parameters that significantly influenced either energy or comfort. Similar research can be found in [51].

In addition to conducting a sensitivity analysis to study the impact of design variables on energy performance, cost is another performance index that must be studied. Krarti and Deneuville [52] implemented a sensitivity analysis to explore the impact of economical parameters, including discount rate, life cycle period, and capital costs on optimization results in the post-processing stage of the optimization design process. Bornatico et al. [53] presented an optimization method to produce the optimal components of a solar thermal system, in which a sensitivity analysis was conducted to explore the influence of certain system parameters.

3.4. Discussion

The review of research papers on BESO procedures showed that the three-phase optimization process is the classic optimization method. Sensitivity analysis plays a crucial role in identifying the significant variables and narrowing the range of values. The majority of studies applied the three-phase optimization procedure, which accounts for 61.5% of the reviewed optimization design literature [14,17,18,30,33,35,45,47,63–68,72–77,80,82–92,97,98,101–103,107–117]. The multi-time design optimization procedure is used in [38–42,54–56], and sensitivity analysis and optimization is used in [8,13,49–53,57–62]. Fig. 5 shows the distribution of optimization procedures found in reviewed literature.

4. Passive design optimization

The survey presented above confirms that there is a clear need to apply the BESO technique to the passive design of buildings. Numerous studies have been conducted to show the potential of BESO to help designers explore large design spaces[64–66]. An effective passive design can improve the performance of energy, daylighting, and natural ventilation. In the early design stage, BESO can explore and optimize building variables that are often outside of the common choices of the designer. To design a highly efficient building, a variety of passive design optimization strategies can be adopted. These optimization strategies may focus on building components such as roofs, wall insulation, window types, natural ventilation, and infiltration [65,67,68]. This section presents a detailed review of the application of the BESO technique on the passive design of buildings. The variables being designed and optimized include building form, opaque envelope, fenestrations, shadings, natural ventilation, and thermal mass materials.

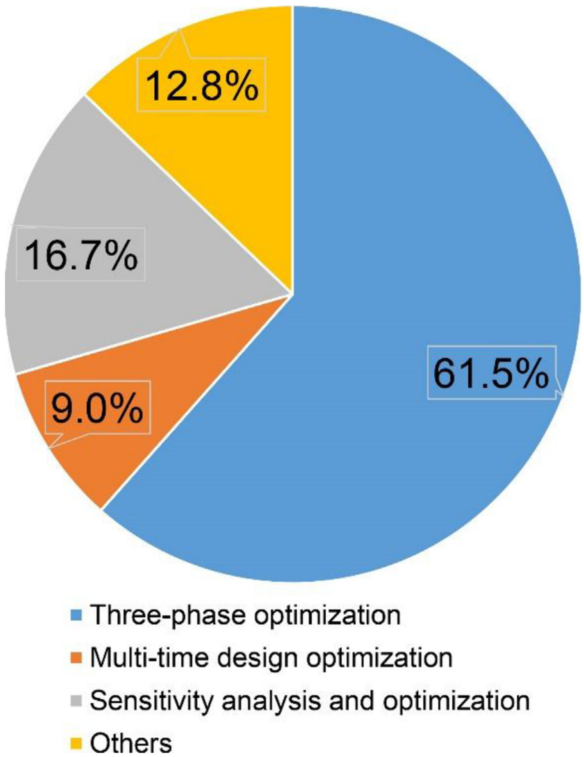

Fig. 5. The percentages of different BESO procedures used.

4.1. Building form

To design an energy efficient building does not mean that important design considerations such as the building form and the aesthetics, which is largely dependent on the form, can be overlooked. In fact, the building form can significantly affect the energy performance. Tuhus-Dubrow and Krarti [61] used a simulation-optimization tool to optimize building shape as part of optimizing the building envelope. The alternative building shapes included a rectangle, L, T, cross, U, H, and trapezoid. Jin and Jeong [69] proposed an optimization methodology to generate a free-form building shape with a minimum external thermal load. Rhinoceros was used to model the generated free-form buildings. HORIKOSHI et al. [70] developed a building energy calculation model coupled with a shape optimization program using a genetic algorithm (GA). In the case study, the shape and zone plan of a building were optimized to minimize energy consumption for lighting and air-conditioning. To break through previous shape optimization that is restricted to simple building form, Yi and Malkawi [71] developed a new optimization method to generate a complex building arrangement. This method introduced hierarchical relationships between geometry points to generate complex building arrangements. Rakha and Nassar [72] proposed a genetic algorithm design and optimization method to help architects generate and find the optimal curvilinear and mesh ceiling forms. Loonen et al. [73] explored the design method of climate adaptive building shells by using a building performance simulation in combination with multi-objective optimization and advanced control strategies. The results showed that the performance of optimally designed building shells was well beyond the level of the best statically designed building shell. Shi and Yang [74] discussed selecting a basic platform suitable for architects, upon which the performance-driven architectural design tool can be developed. They also demonstrated a technical framework by using Rhinoceros as the architectural modeling tool and Grasshopper as the algorithm provider, and by incorporating three performance simulation programs: Ecotect, Radiance, and EnergyPlus. Turrin et al. [75] discussed the benefit of combining parametric modeling and GAs to achieve a performance oriented process in design. They also developed a corresponding design tool that has four basic steps: (1) selection of variables, (2) generation of forms, (3) evaluation of the generated forms, and (4) solution storage and analysis. Marsault [76] demonstrated a multi-objective and interactive GA program to optimize the building form in the early design stages with an objective of bridging the gap between architectural design and energy analysis. The proposed program, EcCoGen, couples a morphogenetic engine, which provides an interactive genetic algorithm, a graphical user interface, and Rhinoceros with its Grasshopper plug-in. Yi et al. [77] proposed an integrated energy-emergy approach to building form optimization that consists of three modules: the Building Energy Simulation (BES) module, the Building EMergy Analysis (BEMA) module, and the MetaModel Development (MMD) module. The building form optimization results were validated with an analytical test. A case study indicated that the proposed method facilitates practical use of emergy simulation in the environmental design process.

The optimization design methods for building floor plan designs are presented by research. Wang et al. [78] presented a GA-based methodology to optimize building floor shape that is based on a multi-sided polygon building footprint. Krarti et al. [79] proposed an integrated approach involving a neural network (NN) and GA to optimize the selection of an office building shape. The optimization results showed that the hybrid NN-GA approach offers a robust and efficient method for selecting an office building shape. Rodrigues et al. [80] proposed an approach to automatically generate a building floor plan design by using a hybrid evolutionary approach. Once generated, an optimization algorithm is used to improve the thermal performance of each solution. Kämpf et al. [81] designed a hybrid CMA-ES/HDE algorithm in order to optimize building and urban geometric forms to determine the optimal usage of solar irradiation, which is predicted by RADIANCE in conjunction with a cumulative sky model for fast computation. Yi and Kim [82] proposed an optimization method that uses an agent-based geometry control system that sets parameters to control a building in a hierarchical manner. The proposed method allows for the building layout and geometry to be repositioned, with direct sunlight as the criterion.

4.2. Opaque envelopes

Opaque envelopes have various types, such as common multi-layer walls, Trombe walls, ventilation walls, green roofs, photovoltaic roofs, and phase change envelops, etc. [5]. Several studies focus on the investigation of wall insulation. For heating dominated buildings, Bojić et al. [83] optimized the insulation thickness of a small residential house using EnergyPlus and the Hooke–Jeeves direct search method. For cooling dominated buildings, Shi [84] optimized the thickness of the exterior wall insulation in four orientations to minimize the space conditioning load of an office building. This is a typical example of utilizing cooling load as a design criterion, which can help mechanical engineers design small HVAC systems. Hamdy et al. [85] applied a modified multi-objective optimization approach to three cases with different summer overheating levels, and a set of optimal combinations were found. The findings indicated that to avoid summer overheating, dwellings that have insufficient natural ventilation measures could require less insulation than the standard required. To minimize CO2 emissions and life cycle costs, Fesanghary et al. [86] employed predefined construction material and glazing type as the design parameters, and thus explored a wide range of design options other than just the U-value of the opaque envelope. Lin et al. [87] conducted a design and optimization of office building envelope configurations for energy conservation using an uncommon building performance predictive model. The optimization produced a 41% cost reduction compared to the original design. Kuznik et al. [88] proposed a meta-model-based, phase change material, wall optimization method for heating that can be used to form the optimal material properties and test different material solutions. Schwartz et al. [89]. used MOGA (multi objective GAs) to find optimal designs for a refurbishment of a residential complex case study, in terms of LCCF (life cycle carbon footprint) and LCC (life cycle cost). This work analyzed the lifecycle impacts of insulating thermal bridges Because of its easy implementation, the optimization of the construction of opaque envelopes is a common practice in energy efficient building design.

4.3. Fenestrations

Fenestration plays a crucial role in providing daylighting, natural ventilation, and heat gain or loss. Lartigue et al. [90] set the window-to-wall ratios (WWRs) and 13 types of windows as the variables, used TRNSYS as the energy engine, and used Daysim as the daylighting simulation engine. The optimization results indicated that their easy-to-set-up methodology was able to find the optimal solutions for multiple antagonistic objective problems. Gagne and Andersen [91,92] demonstrated a GA-based generative façade design method for a high daylighting performance goal. A case study showed a successful goal-driven design exploration process. Lee et al. [93] optimized a building window system for low heating, cooling, and lighting energy consumption in five typical Asian climates. By means of a regression analysis, detailed charts and tables for the relationship between window properties and building energy performance are presented as a function of U-value, SHGC, Tvis, WWR, solar aperture, effective aperture, and orientation. Ferrara [67] conducted an optimization design case study on a low-consumption house using an integrated tool of TRNSYS and GenOpt. Different envelope systems with different window types were set as the optimization variables, and a particle swarm optimization algorithm was used to find the cost-optimal building configuration. Wright and Jonathan [94] proposed a multi-objective optimization method for fenestration that divides the façade into a number of small, regularly spaced cells. Using this façade design method, innovative architectural forms can be found.

Skylights are popular in commercial complexes and large office buildings because of their excellent daylighting performance. Ghobad et al. [95] conducted a design optimization of horizontal roof apertures in office buildings and their results showed a suggested optimum aperture area, energy savings, and operational cost. Acosta et al. [96] optimized the shape of lightscoop skylights, which have a vertical opening oriented in the opposite direction to the solar trajectory, and determined the optimal height/width ratio and other characteristics. Futrell et al. [97] demonstrated an optimization design method to design a real building with high daylighting performance with dynamic climate-based lighting simulations. Seven parameters were considered, including ceiling shape, ceiling height, clerestory window area, daylight window light transmittance, view window light transmittance, and exterior shade length.

4.4. Shadings

The primary function of shadings is to reduce the solar heat gain in summer. However, shadings affect other performance considerations as well, such as natural lighting, illumination comfort, natural ventilation, etc. Therefore, designing and optimizing shadings is a complicated task. Wetter et al. [98] optimized the passive design of a three thermal zone office building with five independent variables. These variables included the widths of southern and northern windows, the overhang of the southern window, and two shading control set points. Torres and Sakamoto [99] set 21 design variables, which included the size, number, and optical properties of the window and shading slat to optimize an exterior window fixed shading using Radiance as the simulation engine. The optimization goals were set to maximize energy savings and to reduce daylight discomfort and daylight penetration. However, this study did not use any energy simulation program. Andersen et al. [100] proposed a daylighting design approach called Lightsolve, which uses dynamic daylighting metrics, the time-segmented method, and Spatio-Temporal Irradiation Maps (STIMAPs) as the main methods. Manzan [101,102] conducted a genetic optimization to determine the optimal design of an externally fixed shading device using DAYSIM to calculate lighting loads, and used ESP-r to calculate energy consumption. ModeFRONTIER, a general commercial optimization tool was used to drive the genetic optimization iterative loop. As daylight has a manifold impact on indoor environments, criteria are very important to the design optimization process. Ochoa et al. [103] demonstrated how the solution space is affected by different optimization criteria when different WWRs were set as the design variables. Gianluca and Saro [104] conducted a sensitivity analysis upon different shading devices and a glazing system. The results indicated that the size and type of glazing has a greater impact on the performance than on the spacing of the louvers.

Another interesting problem related to shadings is to find the optimal control strategy. The real-time control of shading devices is a complex optimization problem that aims to obtain acceptable energy performance, visual comfort, thermal comfort, and airflow. Le et al. [105] formulated a blind optimal control approach using a hybrid model predictive control approach. To decrease the computing capacity requirement, a logic controller whose rules and parameters are based on learning from the behavior of the optimal controller by using support vector machines (SVMs) was proposed. Furthermore, the learned controller was assessed by with SIMBAD, a Matlab toolbox. Park et al. [106] developed a web-based real-time optimal control system for a double-façade system. The comparison of a smart façade system with a manually controlled facade system showed that the smart façade system will yield better performance.

4.5. Natural ventilation

By introducing outdoor air into buildings, natural ventilation has the benefit of promoting indoor air quality (IAQ) and the utilization of free cooling. Zhou and Haghighat [107,108] proposed a simulation-based optimization method that uses the CFD technique, GA, and an ANN for response surface approximation (RSA), and for speeding up fitness evaluations inside the GA loop. The optimization results showed the proposed optimization approach is able to help improve the design and operation of a ventilation system in an office building. Lee [109] demonstrated an optimization design tool that couples a GA and CFD. Random variables (fluctuating outdoor conditions), passive design elements (model variables), and active design elements (HVAC system) were set up to represent a realistic building environment. When implementing an optimization process, all of the above parameters are sent to the CFD program as boundary conditions to simulate the static heat environment. Using the CFD results, objective functions are evaluated and feedback is sent to the GA. The above process repeats until the optimal solutions are found. Stavrakakis et al. [54] optimized the ventilation performance of window-openings using CFD to predict the airflow pattern. Furthermore, optimization input-output data pairs were used to produce meta-models that formulate the optimization problem.

Using a CFD technique to simulate ventilation performance is a time-consuming process that impedes its application in optimization design. Sun et al. [110] developed an integrated method of Lagrangian relaxation and stochastic dynamic programming within the surrogate optimization framework to control shading blinds, natural ventilation, and HVAC systems simultaneously for energy saving and human comfort, rather than using the traditional separated control method. They tested the methodology for a single-room model equipped with a set of shading blinds, lights, a window for natural ventilation, and a fan coil unit (FCU). The methodology extrapolates a single-room model to an entire building with multiple rooms using the surrogate sub-gradient model. To design low-cost houses for low-income urban residents, Nguyen and Reiter [111] used the multi-zone airflow network model, and set 18 continuous variables (including thermal mass, floor type, and natural ventilation scheme, type of roof, window, and external wall) together with six ventilation strategies. The optimization results unveiled the difference between the preferable design strategies for natural ventilation buildings and air-conditioning buildings. For example, natural ventilation buildings require a cool-wind-dominant orientation, but air-conditioning buildings require a solar-preferred orientation. Stephan et al. [63] presented a natural ventilation optimization method that uses a multi-zone airflow network algorithm that models dynamic natural ventilation, and sets the opening height as the variable. This is based on an analogy with a mechanically ventilated building. Finally, an inverse calculation was conducted to determine a series of optimal opening heights. The multi-zone airflow network model is also used in [108] to simulate ventilation performance. Favre and Peuportier [61] used an optimization method to determine the optimal natural ventilation and mechanical ventilation control strategies. A simplified energy simulation with natural ventilation is simulated using a simplified energy simulation model, which is coupled with a multi-zone airflow network model. The case study showed that natural ventilation is more efficient than mechanical ventilation at maintaining comfort in the building during a heat wave.

When to assess the airflow in buildings, several studies hypothesized a static ventilation rate instead of a varied airflow rate. Using indoor air quality and energy as the criteria, Rackes and Waring [112] set up multi-objective optimization to determine the optimal time-resolved mechanical outdoor airflow and zone temperature setpoints. Bambrook et al. [113] optimized a detached house in Sydney with the insulation thickness of a wall and roof, the window type, the thickness of an internal mass wall, and the night ventilation air change rate as the variables. The optimization results showed that in winter, ventilation and infiltration are responsible for the largest energy losses. And in summer, with large internal mass walls and large night ventilation, the case building will have a lower LCC. Salminen et al. [114] set the night ventilation start and end times one of the optimization variables when they optimized a LEED-candidate building. The layout of a building in a district also has a significant impact on the natural ventilation performance. Zhou et al. [42] optimized the orientation of a high-rise residential building and the space between it and neighboring buildings in Chongqing, China. The optimal results indicated that the age of air was less than 6 min in 90% of the rooms, as compared to an age of greater than 30 min in 50% of the rooms in a conventional design.

4.6. Thermal mass materials

Thermal mass material is always used to hold temperature variations and store heat. Baglivo et al. [115] conducted a multi-objective optimization analysis of external walls for ZEBs in the Mediterranean climate that focused on thermal mass and thermal inertia of the envelopes. The results showed that high performance can be reached by utilizing light and thin walls in warm climates. This is quite different from external wall design strategies used to decrease winter heating losses. Li and Malkawi [116] developed a multi-objective, optimization-based, model-predictive control method for building thermal mass that was aimed at shifting cooling load from peak hours to off-peak hours. Using the proposed model prediction control schemes, the energy cost savings ranged from 20%–60% for different cities with different pricing conditions. Huang et al. [117] developed an optimization design method for a humid indoor environment using a GA and a humidity transient simulation method. The amount and arrangement of moisture-buffering materials were set as design variables. The results showed that the proposed method is useful for optimizing indoor humidity.

4.7. Discussion

The design of a building shape requires compliance with standards and creative thinking that is far beyond the ability of current design optimization techniques. Half of the building form design optimization studies are restricted to simple building forms. All of the generated complex roofs have weird shapes [72,74,75] that may not be acceptable to civil engineers and clients because of the extra cost. Currently, optimization methods may only be used to provide an alternative method. That is why this approach is not common in building design. Because of easy to implement, design optimization of opaque envelopes, fenestration, and fixed shading is commonly practiced. However few studies compare different types of shadings, especially fixed and operable shadings. The multi-zone airflow network model is the predominantly used model for dynamic natural ventilation simulation.

5. Conclusions

To accelerate the process of adopting BESO in the design phase, the needs of the designer are considered and the negatives and positives of the method are analyzed. The first part of the survey results showed that architects were reluctant to use BESO tools. In the early design phase, SketchUp is found to be the most widely used geometric modeling tool, and EnergyPlus and eQuest are the mostly widely used energy simulation software packages. The optimization module of DesignBuilder is the most widely used optimization tool. Designers prefer to compare different energy efficient measures instead of optimizing one specific building component. In the second part of the survey, early adopters approve the benefits of BESO, but they hold different view towards the hindrances. The additional key conclusions are summarized below:

- Respondents agreed that long calculation time is the main hindrance and there were no sufficient methods available to advertise BESO methods.
- Half of the respondents agreed that there is not a standard BESO method or procedure.
- BESO users are unclear whether the time spent to optimize the project was worthwhile or not

Three-phase optimization is the most widely used procedure among researchers, accounting for 61.5% of the reviewed optimization design literature [14,17,18,30,33,35,45,47,63–68,72–77, 80,82–92,97,98,101–103,107–117]. In the early design stage, due to a wide range of candidate variables, the implementation of a sensitivity analysis prior to conducting optimization may be a preferable strategy.

Researchers have applied optimization techniques to almost all aspects of passive building design. Designing a building form is a complicated job that requires intelligence beyond the reach of currently available optimization design methods. Compared to other passive design strategies, BESO proved to be an efficient method to help designers, especially architects, to explore various design territories. However, only some of the results were confirmed by real building operation data.

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