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A review on building energy efficient design optimization rom the perspective of architects

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Energy efficiency is a mandatory requirement and integral part of green and sustainable buildings. Energy efficient design optimization is both a design philosophy and a practical technique that has been proposed and used by architects and other professionals for several decades, especially in the past few years. In this review, a set of selection criteria are proposed and 116 works are identified as the core literature. Taking the perspective of architects, analysis is conducted to the core literature to reveal the state of the art of building energy efficient design optimization. The analyzed subjects include the general procedure, the origin and development, the classification, the design objectives and variables, the energy simulation engines, the optimization algorithms, and the applications. The review findings confirm that building energy efficient design optimization is a promising technique to design buildings with higher energy efficiency and better overall performance. However, obstacles still exist and future research is needed.

Contents

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1. Introduction

1.1. Background

After the two oil crisis in the 1970's [1], the energy cost sharply rose, which led to a paradigm shift to a more energy efficient society. Building energy efficient design started becoming mainstream among government, developers, architects, engineers, and other stake holders around the same time. This trend has been ongoing for more than three decades and only recently strengthened by a more profound awareness of climate change and other environmental challenges. One evidence among many is that a variety of green building standards, adopted by many countries, all have energy efficient design as an integral part with a heavy weight, examples being LEED of the US [2], BREEAM of the UK [3], and Green Building Label of China [4].

The emphasis on building energy efficiency would be merely a design philosophy and thus could not be materialized if designers, i.e., architects, mechanical engineers, lighting engineers, plumbing engineers, and others have no suitable technique at their disposal. Building energy simulation and its tools are developed to serve the purpose of providing such technique to designers. It is a broad and active research field. According to the Department of Energy of the United States, there are more than 400 building energy simulation models and/or programs available [5]. Some of them are powerful programs that are widely recognized and used all over the world and across disciplines such as EnergyPlus [6], TRNSYS [7], and DOE-2 [8]. The building energy simulation technique has greatly helped architects and engineers to achieve building energy efficient design by offering capability to accurately and rapidly calculate the loads and actual energy consumption of buildings.

Starting from the 1990 s and really gaining momentum since 2000, a new technique that combines building energy simulation with optimization has emerged. New terms are given to this technique such as "computational optimization" [9], "simulation-based optimization" [10], "building performance optimization" [11], "performance driven design" [12], etc. It should be pointed out that the term "performance" covers a broader range than just energy efficiency. Nevertheless, energy efficient design optimization for buildings is clearly an emerging technique that is being actively studied. The technique relies on optimization algorithms to generate new designs based on simulation results and user-defined design objectives. Compared with the conventional "trial-and-error" design methodology guided by designers' knowledge and experience, this new technique is more efficient, more powerful, and more likely to find the optimal or near-optimal design solution. Post-processing methods such as Pareto frontier is often called for to locate the optimal or near-optimal design solution [13]. The building energy efficient design optimization technique seems promising and yet is not free of limitations. Hence, it has been becoming a very active research field as shown by several important review works published lately [9,10,14].

Building energy efficient design requires a multi-disciplinary design team. Architects and mechanical engineers are probably the two professionals who take the most responsibility in achieving an energy efficient building design. It can be reasonably argued that between the two the architect carries more weight in determining the final quality of the design in terms of the energy performance for several reasons. First, the architect designs the shape, space, and functions of a building, which are the most fundamental aspects of a building design and the most important features to the client. Furthermore, these aspects also greatly influence the energy performance of the design. Secondly, the architect is responsible of making decisions on building envelope, fenestration, and materials, which largely determine the heating and cooling loads of the building. Therefore, as the leading profession in a design team, the architect should be familiar with the latest development in the field of energy efficient building design. However, the reality is far from being ideal. Many architects, purposefully or not, tackles the energy efficient design with traditional, outdated, and inefficient techniques. They are not capable of using energy simulation programs to assist their design, let alone the design optimization technique that incorporates energy simulation and optimization algorithms. Therefore, the role of architects in building energy efficient design and their perspective on the design optimization technique have been studied [14,15].

1.2. Objectives of this review

The primary objective of this paper is to conduct a comprehensive and in-depth review of the building energy efficient design optimization technique. The emphasis is placed on reviewing and analyzing the state-of-the-art from the perspective of architects. The reasons why a review of such kind is both valuable and timely are multi-folds. First and foremost, as the leading profession in a design team, architects often find themselves in an awkward position when it comes to using the building energy efficient design optimization technique. It is clear to them that the conventional architectural design methodology, which in essence is an approach involving design principles mainly based on functions, forms, and spaces, would not suffice since building energy efficient design requires scientifically rigorous energy simulation, which most architects are not familiar with. The problem is further exacerbated when optimization is added. After all, how would you expect a traditionally trained architect to be familiar with optimization algorithms and complex programs, let alone computer coding which is required in many instances. This dilemma has been realized by many such as Flager et al. [16]. Secondly, the existing works in the field of building energy efficient design optimization cannot adequately address the needs of architects. Many of the research works focus on developing the technique and applying it to buildings. Few articles published discuss how the existing technique fits into the overall workflow of an architectural design project and how architects view it. Building service engineers and other professionals also play an important role in designing and optimizing energy efficient buildings. They can benefit from this review as well.

The objective of this review is to collect relevant literature in accordance with a set of clearly defined criteria and then analyze them to understand the evolution and current status of the building energy efficient design optimization technique. An emphasis is placed on how the technique, while achieving the goal of energy efficient design optimization, addresses particular needs of architects. The analysis of the literature is performed to focus on: (1) general procedure, (2) origin and development, (3) classification, (4) optimization objectives and optimized design variable, (5) energy simulation engineers, (6) optimization algorithms, and (7) application. Note that some of these subjects are of interests to other building professionals too.

1.3. Scope of this review

This review is conducted based on collecting and analyzing relevant works in the field of building energy efficient design optimization. These works are referred as the "core literature". The following criteria are proposed to define the core literature.

- The literature must report research work that deals with building energy related matters directly or indirectly. If a paper discusses minimizing the cooling and heating energy consumption, it is obviously qualified as dealing with building energy related matters. However, subjects such as CO2 emission, thermal comfort, and life cycle cost are also qualified because they are indirectly related to building energy. For instance, the calculation of CO2 emissions and life cycle costs require the knowledge of energy consumption.
- The research work must use one or multiple clearly defined algorithms to optimize the design or the performance of the building. Those works studying building energy efficient design but not utilizing algorithms to drive the optimization process are excluded.
- The literature must at least partially deal with the architectural features of buildings such as building shape and form, building envelope, building materials, etc. Research works that exclusively study mechanical systems or energy systems are not considered as the core literature. For example, if a paper only discusses the design and optimization of a geothermal heat pump system, it is excluded.
- Works that primarily focus on the comparison of optimization algorithms are excluded despite that some of them meet the above three criteria. It should be noted that the study of the effectiveness and efficiency of optimization algorithms in building energy efficient design is a valuable subject. Readers can refer to Machairas et al. [14], Wetter and Wright [17,18], Hamdy et al. [19], and Wright and Alajmi [20] for further knowledge.
- Literature that was published before 1980 is excluded. There may be pre-1980 literature that satisfy the above four criteria, but they should be very few. In fact, the number of core literature did not show significant increase until 2000.

Based on the above selection criteria, a total of 116 works are reviewed as the core literature [16,20,27–139]. The majority of them are journal papers and conference proceeding papers.

1.4. Previous reviews

Several previous reviews that focus on performance-based building design optimization or similar methods are available. Evins conducted a review on computational optimization methods applied to sustainable building design [9]. Nguyen et al. reviewed simulation-based optimization methods in building performance analysis [10]. Machairas et al. took a different angle and reviewed the algorithms used in performance-based building design optimization [14]. Attia et al. reviewed the gaps and needs for integrating building performance optimization tools in net zero building design [11]. These works are closely related to this review. Nevertheless, the scope, the selection criteria of the core literature, and especially the perspective of architects taken by the review are different, new, and valuable.

Other review works that are broadly relevant to this review include those focusing on building energy efficient design [21], building energy simulation [22–24], and optimization techniques in other engineering disciplines [25,26].

2. Analysis

2.1. General procedure

Although the building energy efficient design optimization techniques found in the literature may vary in details, they typically follow a similar general procedure as illustrated in Fig. 1. The general procedure shown in Fig. 1 consists of multiple steps, with the ones operated by the designer marked in green and the ones operated by the computer marked in pink. Two engines, namely the optimization engine and the energy simulation engine, drive the design process and function as the most critical components in the procedure. The design and optimization process starts with a design task, based on which an initial design is developed by the designer, usually the architect. This initial design is imported into the energy simulation engine to calculate the energy consumption or other energy related variables. The designer needs to define a single design objective or multiple design objectives. The computer compares the energy simulation results with the design objectives defined. If the design objectives are satisfied, the design process will be terminated and the optimal design will be determined. Otherwise, the design process calls for the optimization engine to generate a new design and the above steps are iterated.

It is clear that in the general procedure shown in Fig. 1, the optimization and energy simulation engines provide the main force to drive the design and optimization process. Once the work flow is set up and automated, the designer's task is reduced to mainly two things. First, he needs to propose an initial design that can be calculated for energy and input it into the work flow to start the process. Secondly, he needs to define a single design objective or multiple design objectives to guide the work flow. In essence, the design objectives determine when to terminate the work flow and when to continue. Ideally, after performing these two tasks, the designer can simply let the process run until it finds the

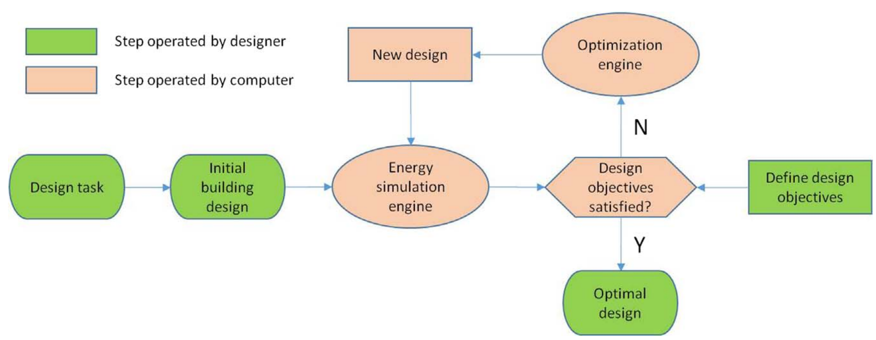

Fig. 1. General procedure of the building energy efficient design optimization technique.

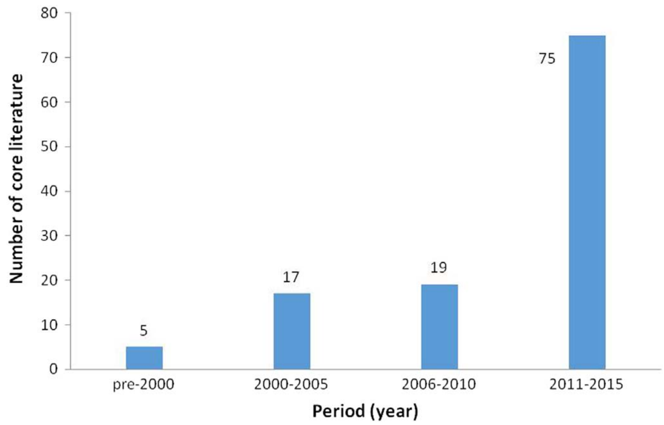

Fig. 2. The number of the core literature in five periods: pre-2000, 2000–2005, 2006–2010, and 2011–2015.

optimal or near-optimal design without his interference. Similar procedures of the building energy efficient design optimization technique are illustrated in Ref. [10,17,18,69]. They differ in presentations and some minor details but are essentially the same.

2.2. Origin and development

The first paper presenting a design and optimization study that meets the five criteria established previously was published in 1983 [27], more than 30 years ago. D'Cruz et al. formulated a Pareto optimization problem of determining the fenestration, insulation, shape, massing, and orientation for thermal, daylight, cost, and spatial efficiency design objectives of an air-conditioned office building. Although no dynamic energy simulation or advanced optimization algorithm was employed, the technique described in [27] generally follows the procedure depicted in Fig. 1.

Throughout the 1980s and 1990s, the research on building energy efficient design optimization was not an active field as evidenced by only 5 works occurring before 2000. The situation made a sharp turn after 2000. More and more journal papers, conference papers, and technical reports are published to study the building energy efficient design optimization technique from different angles. Fig. 2 illustrates the number of core literature published in five periods, namely pre-2000, 2000–2005, 2006–2010, and 2011–2015. As shown in Fig. 2, there is a clear upward trend in the number of core literature published over time, especially in the past five years. This upward trend is caused by a combination of several reasons. First and foremost, in the grand scheme of green and sustainable movement, all stake holders in the building industry, including architects, realize the importance and necessity of designing buildings for higher energy efficiency. This paradigm shift is probably the fundamental reason behind the popularity of the building energy efficient design optimization technique and other design techniques with similar natures. Secondly, the rapid development of building energy simulation makes the technique easier to be implemented. As shown in Fig. 1, the energy simulation engine is a key component of the technique. Today, hundreds of building energy simulation programs are available such as EnergyPlus [7], TRNSYS [8], etc. These building energy simulation programs can be readily integrated into the design process to achieve energy efficient design and optimization. Last but not least, the exponentially increasing power and capability of computers enables architects and other professionals to incorporate the building energy efficient design optimization technique into their design practice. The technique requires fast calculation especially when optimization is needed. Running a complex design optimization on a slow computer is very time consuming, which makes it impossible to be used since the design practice is often time sensitive. Therefore, it is not surprising that the number of publications on building energy efficient design and optimization has been rapidly increasing, especially in the past five years. Between 2011 and 2015, a total of 75 works are published, averaging 13 publications per year.

2.3. Classification

Although the building energy efficient design optimization techniques found in the core literature all share the same general procedure shown in Fig. 1, they differ from each other in terms of energy simulation engine, optimization algorithm, optimization objective, optimized variables, etc. From an architect's perspective, to examine how the design optimization is achieved is a sensible and intuitive way to differentiate and classify them. On the other hand, architectural design in essence is a problem solving process and thus, requires creative thinking [140]. Since the 1950s, computer-aided architectural design has become a major trend in the field of architecture. Nowadays, architects rely heavily on a variety of computer tools to assist them in design, examples being drafting programs such as AutoCAD [141], modeling tools such as Sketchup [142], simulation softwares such as Ecotect [143], etc. Therefore, when encountering the building energy efficient design optimization technique, architects tend to first look at what kind of operating environment they need to use to perform such a technique. Based on this thinking, the building energy efficient design optimization techniques can be categorized into two groups: (1) techniques that integrate energy simulation programs into generic optimization platforms, (2) techniques integrating energy simulation programs into special purpose optimization platforms, (3) customized techniques.

2.3.1. Techniques integrating energy simulation programs into generic optimization platforms

It is obvious that the general procedure of the building energy efficient design optimization technique illustrated in Fig. 1 needs to realized in an integrated operating package. Otherwise the work flow cannot be established or automated. One way to achieve it is to integrate energy simulation programs into generic optimization platforms that are commercially available. A generic design optimization platform provides a user-friendly environment in which designers can set up the design work flow, define optimization objectives, choose optimization algorithms, link performance simulation programs, and visualize optimization results. Such platforms typically originate from a specific science or engineering field and then gradually permeate into others. ModelCenter, modeFRONTIER, GenOpt, and Matlab are four generic optimization platforms that are successfully used in realizing building energy efficiency design optimization.

ModelCenter and modeFRONTIER are two similar software solutions in that they enable users to create model-based engineering frameworks to perform simulation and optimization [144,145]. Flager et al. reviewed several commercially available PIDO (Process Integrated Design Optimization) software frameworks and selected ModelCenter to optimize the energy performance of a classroom building [16]. Lee et al. used modeFrontier as the optimization platform to investigate the impact of varying demand-side parameters such as thermal resistance of the roof and wall insulation on the energy consumption for space conditioning and lighting for a typical industrial hall [123]. A similar study can be found in [107]. Shi selected modeFRONTIER as the design optimization environment to find the best insulation strategy to minimize the space conditioning load of an office building while keeping the insulation usage at minimum [69]. Manzan and Pinto optimized the design of an external shading device in an office with a window and different glass characteristics considering heating, cooling, and lighting energy consumption using modeFRONTIER [57]. One advantage of modeFRONTIER, the same for ModelCenter, is its vast selection of optimization algorithms and its flexible connectivity to energy performance simulations and post-processing tools [107,123].

Different from ModelCetner and modeFRONTIER, Matlab, developed by MathWorks, is a numerical computing environment widely used by scientists and engineers across the world [146]. It has found extensive applications in the field of building energy efficient design optimization mainly because it offers optimization algorithms via its toolbox and integration capability with simulation programs. Petri et al. developed a modular optimization model for reducing energy consumption in large scale buildings, in which Matlab was used as a platform to find the best configuration for Artificial Neutral Network (ANN) based optimization module [117]. Asadi et al. combined the energy simulation program TRNSYS with a Tchebycheff optimization algorithm developed in Matlab to perform a multi-objective optimization task for building retrofit [83]. Hamdy et al. introduced a multi-phase and simulation-based method to find the cost-optimal and nearly-zero-energy building solution in accordance with European energy performance of buildings directive (EPBD-recast 2010) [103]. In the preparation phase, a single-objective deterministic algorithm called Fmincon from Matlab tool box was used. A related work was conducted and both the genetic algorithm and FMINCON algorithm in Matlab toolbox were called for [66]. Tresidder et al. used the surrogate modeling routines offered in Matlab tool box to test the performance of Kriging surrogate modeling optimization techniques on a building design problem with discrete design choices [92]. Evins conducted a building solar gain optimization assisted by the genetic algorithm in Matlab toolbox [64]. Taheri et al. calibrated the thermal simulation model for an existing university building [102]. In this case, Matlab was used to incorporate the values of time-varying input parameters into the thermal model rather than to achieve optimization. Other works in the core literature that achieve the building energy efficient design optimization technique via Matlab include [60,63,72,85,87,99,101,112,127–129,133–135,137].

GenOpt is another generic optimization platform that is extensively used to achieve energy efficient design optimization for buildings. GenOpt, developed by the Lawrence Berkely National Laboratory of the US, is an optimization program for the minimization of a cost function that is evaluated by an external simulation program [147]. Taheri et al. selected GenOpt and used the hybrid generalized pattern search with particle swarm optimization algorithm to arrived at a calibrated simulation model of an existing university building [102]. Palonen et al. used GenOpt to optimize the life cycle cost of a detached house [61]. Asadi et al. combined GenOpt with Matlab to find the optimal solution for building retrofit strategies [83]. Carlucci et al. developed an optimization procedure to support the design of a comfort-optimized net zero energy in GenOpt [104]. Salminen et al. combined energy simulation with GenOpt to optimize the energy and economic performances of a two-story LEED certified building [82]. Karaguzel et al. used GenOpt to minimize the life cycle material cost and operational energy consumption of a commercial office building [121]. Hamdy et. al. compared three optimization algorithms in finding the cost-optimal and nearly-zero-energy solutions for a problem that has a large discrete solution-space with a modified version of GenOpt [91]. Zhou et al. developed an optimization module in EnergyPlus and benchmarked its performance against GenOpt [39]. Hasan et al. coupled a building performance simulation program with GenOpt to find optimized values of five selected design variables in the building construction and HVAC system [55]. Djuric et al. integrated EnergyPlus into GenOpt to optimize the thermal comfort and total costs of a school building [50]. Other works in the core literature that achieve building energy efficient design optimization via GenOpt include [42,58,65,78,86,88,109,110,115,122].

2.3.2. Techniques integrating energy simulation programs into special purpose optimization platforms

The aforementioned ModeCenter, modeFRONTIER, Matlab, and GenOpt are all generic optimization platforms in that they can be linked with various simulation programs and perform design optimization for tasks that are not associated with building energy efficiency. On the contrary, jEPlus+EA is developed solely for carrying out building energy efficient design optimization. It is in essence a Java shell to perform parametric study and optimization with EnergyPlus and a modified non-sorting genetic algorithm. Tresidder et al. used jEPlus+EA to benchmark the performance of Kriging optimization [92] and surrogate modeling optimization [75]. Carreras et al. presented a methodology for determining the optimal insulation thickness for external building surfaces using jEPlus+EA [139]. Naboni et al. conducted design optimization for a nearly zero-energy prototype building with jEPlus+EA [105].

In two papers [114,130], Grasshopper, a graphical algorithm editor tightly integrated with Rhino's 3-D modeling tools, is used to link energy simulation programs, EnergyPlus in both cases, with optimization algorithms and conduct design optimization. Other special purpose optimization platforms found in the core literature include MOBO [111], ENEROPT [59], GENE_ARCH [49,74].

2.3.3. Customized techniques

The building energy efficient design optimization technique does not have to rely on commercially available optimization programs. One can write his own computer program to integrate energy simulation with optimization algorithms. In the core literature, the examples of such customized techniques are not rare. The customized design optimization can be written in Fortran [28,32,45], C++ [46,117,132], Visual Basic in Microsoft Excel [96].

2.3.4. Pros and cons of the three categories of the building energy efficient design optimization technique

The aforementioned three categories of the building energy efficient design optimization techniques have their pros and cons. The first category, which integrates energy simulation programs into generic optimization platforms, is probably the most powerful one in terms of optimization process and algorithms and post-processing capabilities. The generic optimization platforms such as ModelCenter, modeFRONTIER, etc. offer a variety of optimization algorithms and a graphical, user-friendly interface to establish the design optimization workflow. The post-processing capabilities are strong in that the designer can view, analyze, and compare the optimization results in various ways. The cons are mainly about the challenge of integrating energy simulation programs into the generic optimization platforms. Some computer coding, usually not much, may be needed [69]. The second category of the technique, which integrates energy simulation programs into special purpose optimization platforms, does not offer nearly as many optimization algorithms as the first one. However, like jEPlus+EA, the energy simulation programs can be conveniently integrated and therefore, very little computer coding is needed. The last category of customized techniques is the most technically challenging one in that a significant amount of computer coding is required to establish the design optimization procedure and realize optimization algorithms. Its cons are obvious too. The user can have full control over the entire process of the design optimization and therefore, is able to make adjustments as he wishes.

It needs to be stated that some works in the core literature do not identify what technique they use to achieve the building energy efficient design optimization. Fig. 3 compares the number and

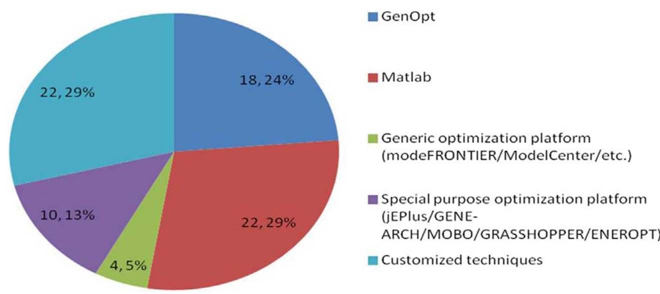

Fig. 3. The numbers and percentages of three categories of the building energy efficient design optimization technique (GenOpt and Matlab are counted separately).

percentage of each category of technique. Note that GenOpt and Matlab are counted separately because they are the two most often used optimization platforms.

2.4. Optimization objectives and optimized design variables

2.4.1. Optimization objectives

Since the subject of this review is on building energy efficient design optimization, the optimization objectives of all of the core literature are building energy related. However, they are in different forms. The optimization objectives can be explicitly on energy such as minimizing annual energy consumption [20,29,38,72,129,134]. The energy-related parameters being minimized can have slight variations while still explicitly on energy. For example, life cycle energy consumption, instead of annual energy consumption, is found in the core literature to be the optimization objective [95]. Besides the actual energy consumption, space condition load, i.e., heating and/or cooling load, is another optimization objective [69,79,99,109,131]. Although the space conditioning load is not equal to the actual energy consumption, they are closely related and describe the energy performance of a building in different ways.

Minimizing the energy consumption or space conditioning load of a building is obviously energy related objective. Other optimization objectives can be implicitly energy related such as minimizing CO2 emissions [68,70,75,85–87,92,96,120,133]. A typical way is to calculate or simulate building energy consumption first and then convert it to the amount of CO2 emitted. Other implicitly energy related optimization objectives include reducing energy cost [30,33,76,96] and life cycle cost [40,47,55,89,106,132]. Among the core literature, approximately 67% of them have explicitly energy related optimization objectives while the rest are implicitly energy related. Note that minimizing costs in different forms and reducing CO2 emissions are two commonly considered optimization objectives, accounting for approximately 52% and 14% of the core literature, respectively.

In addition to energy related optimization objectives, many reviewed works are multi-objective optimization studies. Therefore, the optimization objectives are diversified. Some examples are maximizing thermal comfort [65,81,83,136], minimizing discomfort hours [104,115], maximizing lighting quality [126,135], improving visual comfort [93], and zone mean air temperature [102].

2.4.2. Optimized design variables

To achieve energy efficient building design, many design variables need to be considered and optimized as demonstrated by the core literature. For the sake of this review, these design variables are categorized into 5 categories, namely opaque building envelope, transparent building envelope, shape and form, type of mechanical systems, and operation of mechanical systems.

The most common example of opaque building envelope variables is the overall thermal conductance (the U-value) of exterior walls [32,82,84,94,121] or its equivalents such as the thickness of insulation [55,58,103,106] or non-insulation wall components [65], the insulation type [73,83,87,89,119], the thermal resistance of exterior walls [97]. In addition to the thermal properties of external walls, the thermal properties of roofs and floors are also variables that can be optimized [135,136].

Design variables related to transparent building envelope include glazing, window size, window shading, etc. Some of these variables can take different but closely linked forms. Glazing types include single pane [134], double pane [76,124,134], and even expensive triple pane [76] with high performance. It is common that the glazing type is represented by the U-value of the glazing [29,42,58,72,136], which is the actually optimized variable anyway. Window size is another important design variable for transparent building envelope [16,20,42,48,84]. It is equivalent to the window-to-wall ratio when the size of the wall is a fixed number [29,76,85,86,124,133,135]. Window shading prevents solar radiation from transmitting into the building through the window and therefore, can effectively reduce the cooling load. Window shading can be fixed and non-adjustable overhang [105,114,126,132], adjustable blinds [126,127] or other types of shading device [53]. Glazing, window size or window-to-wall ratio, and shading are the most commonly optimized and transparent building envelope related variables that are found in the core literature. Other optimized variables include the solar heat gain coefficient (SHGC) of windows [131,132], glazing light transmission [132], and others.

The shape and form of buildings are of great interest to architects. In fact, they are the primary design variables that architects consider and study in the early design stage and throughout the entire design process. Hence, it is no coincidence that some works in the core literature attempt to optimize the shape and form of buildings to achieve energy efficiency. However, shape and form are different from other design considerations such as the thermal performance of external walls in that describing shape and form with one variable is difficult. To fully define the shape and form of a rectangular box building with simple interior space structure would typically require more than ten variables, let alone complex buildings such as large scale office buildings, shopping malls, museums, etc. When a non-linear complex shape is present, it is difficult to mathematically describe it, not to mention optimize it to satisfy the objective of being energy efficient. Therefore, the variables related to shape and form found in the core literature are relatively simple. Orientation, which can be quantified using the angle between the axis of the building floor plan and one of the four directions, is a common shape and form related design variable optimized [16,28,29,35–37,40,45–47,88,90,106,108,110,113,124,131,136]. If the building floor plan is rectangular, its aspect ratio, i.e., the ratio between the length and the width of the floor plan, is another commonly optimized shape and form related design variable [27,28,31,40,45–47,48,76,125,131].

Orientation and aspect ratio are the two most commonly optimized design variables related to shape and form for obvious reasons. They are easily quantifiable and thus, can be conveniently input into the energy simulation engine and the algorithm for optimization. They are also the most fundamental design variables to define the shape and form of a building. Since the aspect ratio only applies to rectangular shape floor plans, its application is somewhat limited when the architect desires more flexibility. Research works that attempt to explore more plan shapes are available. Bichiou and Krarti developed an energy simulation environment to optimally select both building envelope features and heating and air conditioning system design and operation settings [76]. Several different floor shapes are considered in the optimization simulation environment, namely rectangular, trapezoid, L-shape, U-shape, T-shape, cross-shape, and H-shape. Another study related to [76] can be found in [63]. Adamski analyzed the possibility of optimizing an abstract and symmetrical oval-shaped building with constant volume and height [52]. Caldas incorporated the shape grammar of Islamic patio house typology and generated new, alternative patio house designs with better energy performance while respecting the traditional rules captured from the analysis of existing houses [74]. Ullrich et al., inspired by the London City Hall designed by Norman Foster, presented an "Office Building" energy efficient design optimization example, in which the building floor takes the form of an ellipsoid and the principal axes ratio and five disc-scaling factors are design variables optimized [108]. Wang et al. presented a methodology to optimize building plan shapes represented by a multi-sided polygon [47]. Yi and Malkawi pointed out that most current research using optimization with building performance was restricted to simple geometry and that it considered the building form as a box, polygonal shape, or simple curvature, restricting its applicability and integration with the design process [60]. They introduced a new method to control building forms by defining hierarchical relationship between geometry points to allow the user to explore the building geometry without being restricted to a box or simple form. The optimized shapes and forms are quite complex in that their plan, elevation, and even the general shape all vary to different extents.

Since this review looks into the building energy efficient design optimization technique particularly from the perspective of architects, mechanical system related design variables are loosely grouped into two categories, namely the type of mechanical systems and the control of mechanical systems. The type of mechanical systems include heating and cooling source [33,48,68,76,84,90,91,94,101,103,121,134,137], pumps and fans [33,94,96], heating and cooling efficiency [94,96,134,135], heat recovery [31,55,68,91,94,101,103,137], heating and cooling distribution [101], photovoltaic system [31,84,91,94,96,98,101,107,113], solar thermal system [31,48,83,84,87,96,101], lighting [31,58,72,90,96,135], energy storage [31], etc. The control of mechanical systems includes heating and cooling setpoints [20,44,65,66,33,76,90,117,124,134], ventilation strategy [66,79,82,101,129,135], lighting control [31,58,82,90,94], etc. These design variables affect the energy efficient performance in different ways and with different agrees. They are typically the responsibility of mechanical engineers. Architects do not directly design these variables.

2.5. Energy simulation engines

As shown in Fig. 1, the energy simulation engine is a key component in the building energy efficient design optimization workflow. Its function is to calculate the energy consumption or other energy related parameters of the building being designed and optimized. The calculation results are then compared with the pre-defined design objectives. If the pre-defined design objectives are met, the design and optimization process will be terminated. Otherwise, the optimization algorithm will be called for to produce a new set of design variables and the process will be iterated. It is clear that without the energy simulation engine the design and optimization workflow shown in Fig. 1 cannot be implemented. In addition, the energy simulation engine determines, to a large extent, the overall efficiency of the design and optimization process. Since the energy simulation engine is called for many times in the workflow, its speed has a significant impact on the overall efficiency of the entire process. If the energy simulation engine is to perform a dynamic, detailed, and complex building energy calculation, the time needed to complete the design optimization process and locate the optimal design can be significant.

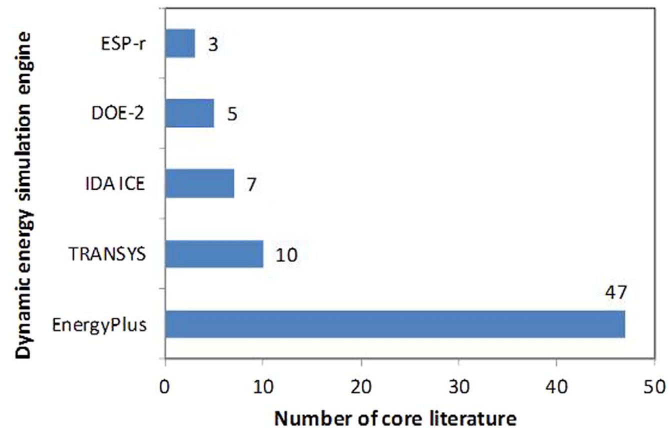

Fig. 4. The numbers and percentages of the core literature that use EnergyPlus, DOE-2, TRNSYS, ESP-r, and IDA ICE as the energy simulation engine.

On the contrary, if the energy simulation engine is a simplified model with a few straight forward equations, the calculation speed can be fairly rapid and the time needed to complete the design and optimization process can be relatively short.

Among 116 works in the core literature, EnergyPlus is by far the most commonly used energy simulation engine, accounting for 47 works or 40.5% of the core literature [16,20,39,42–44,50,56,60,64,67,69–71,72,75,81,84–86,88,89,92,93,100,102,104,105,110,113–115,117,118,120,122,124,125,129,130,132–136,138,139]. EnergyPlus is a representative of the category of detailed and dynamic energy simulation programs. Other energy simulation engines found in the core literature that falls into this category are DOE-2 [38,49,63,76,90], TRNSYS [48,65,73,83,99,107,109,123,131,139], ESP-r [57,77,126], and IDA ICE [55,61,66,68,78,82,91]. Fig. 4 compares the number of core literature that use these five dynamic energy simulation programs.

The main advantage of using detailed and dynamic energy simulation engines such as EnergyPlus is obvious, i.e., they are capable of simulating the energy consumption or other energy related parameters with accuracy and reliability. Another advantage is that most of these dynamic energy simulation programs have been developed for more than 10 years and tested extensively and applied on various projects. Therefore, the input and output functions of these programs are fairly complete. This trait is particularly important for energy efficient design optimization in that the energy simulation engine needs to be incorporated into the design optimization workflow as shown in Fig. 1, which means that the input and output modules of the energy simulation program need to be linked with other programs such as the optimization platform. Therefore, the user would find it convenient if the input and output functions of the energy simulation program are easy to find and decode.

Despite having the aforementioned advantages, detailed and dynamic energy simulation programs, when used in energy efficient design optimization, can cause long running time. This is probably the main reason some researchers attempt to utilize simplified energy simulation models to achieve energy efficient design optimization. In addition, a full-blown energy simulation may not be necessary, especially in the early design stage. ASHRAE (American Society of Heating, Refrigeration, and Air-conditioning Engineers) toolkit for building load calculation is an example of such simplified models [40,46,47]. Some works follow standard or code-recommended energy calculation methods and code them into the optimization workflow. Simons et al. coded the normative energy calculation approach defined by ISO (International Standardization Organization) 13,970 into an Microsoft Excel spreadsheet [101]. Shao et al. followed the German standard DIN V

18,599 and implemented the energy simulation module in Visual Basic for Microsoft Excel and used it to calculate various energy performance indicators beside annual operational energy consumption [119]. Han et al. adopted the BIN (or temperature frequency) method recommended by ASHRAE for its speed and convenience [112]. Evins et al. performed a multi-objective optimization for regulated carbon emissions versus capital and running costs using the heat balance model underlying the Standard Assessment Procedure of the UK [96]. It is stated that the model is reasonably comprehensive, but sufficiently simple (and hence quick to run) to allow extensive optimization. Gengembrea et. al. used a building thermal model called R5C1, which is a global normalized model in the French thermal regulation frame in order to assess the energy consumption of buildings [97]. Murray et al. coupled a static simulation modeling method (degree-days) outlined in CIBSE (Chartered Institution of Building Service Engineers) Guide TM41 with the genetic algorithms optimization technique and applied it to the retrofitting of existing buildings [121].

Non-standard, customized energy calculation models are also found in the core literature. These models vary significantly in complexity and completeness. It can be a whole building energy simulation program that estimates the annual energy performance of buildings, including daylighting, demand charges, life cycle costs, and floating temperatures in unconditioned zones [45] or a very basic model which can be described using several simplified equations [27,28,98,103]. The Admittance Procedure, which adopts the concept of thermal admittance to describe the thermal response of the building opaque components in dynamic conditions, is found to be used in two cases [99,128]. Advantages of these customized energy simulation models are that the energy simulation procedure can be fully comprehended and that the customer written simulation programs can be easily integrated into the design optimization workflow since all codes are available for manipulation. However, the accuracy and reliability of these customized energy simulation models will inevitably be asked. The question leads to a concern that using them may not be able to find the optimal design as accurately and effectively as using the standard dynamic energy simulation programs such as EnergyPlus. Our literature review does not find adequate research to address this concern, which hence remains to be a subject that warrants future study. Table 1 summarizes the advantages and disadvantages of the three types of energy simulation engines used in the building energy efficient design and optimization technique.

2.6. Optimization algorithms

The optimization algorithms, as shown in Fig. 1, is a critical part in the building energy efficient design and optimization workflow. It generates new designs, based on the predefined design objectives and the energy simulation results. Therefore, its performance is vital for the overall effectiveness and efficiency of the design optimization technique. Reviews that focus on the optimization algorithms in performance-based building design optimization are available [14].

From a perspective of architects, the optimization algorithm is probably the least familiar one among all components illustrated in Fig. 1. It reflects the inter-disciplinary nature of the field in that optimization algorithms are typically a research subject in computer science and mathematics. Their introduction into the field of architecture is relatively new. Furthermore, the classic curriculum or training of architects does not contain knowledge of optimization algorithms. Such knowledge can only be found on the frontier of architectural research [148] including the building energy efficient design optimization technique this review discusses.

The commonly used algorithms in building energy efficient design optimization can be grouped into three categories, namely evolutionary algorithms, derivative-free search algorithms, and hybrid algorithms [148]. Note that hybrid algorithms are not new algorithms. They are combinations of different algorithms, often evolutionary algorithms with derivative-free algorithms. A statistical analysis of the core literature shows that evolutionary algorithms are the most commonly used category of optimization algorithms, accounting for approximately 60%. The rest are derivative-free search algorithms such as Hooke-Jeeves direct search algorithm [42] and hybrid algorithms. In the category of evolutionary algorithms, genetic algorithm (GA) [20,33,38,48,51,56,58,60,62,64,66,69,72,74,75,84,105,107,108,116,121,134] or its variations such as non-dominant sorting genetic algorithm (NSGA) [67,73,77,82,85,92,103,117–119,124,131,133,136,137,139] are dominant. A general trend to shift from normal GA to NSGA is noted, probably because NSGA is more suitable to solve multi-objective optimization problems, which are common in architectural design. Particle swarm algorithm is another frequently used evolutionary algorithm [63,76,79,86,104,122].

Although most literature apply algorithms to building energy efficient design optimization without looking much into the algorithm itself, several studies shed light on how effective and efficient different algorithms are in finding the optimal design solution. Wetter and Wright compared Hooke-Jeeves direct search algorithm with genetic algorithm and concluded that the latter performs better than the former and that Hooke-Jeeves direct search algorithm can be trapped in local optimum [17]. Wetter and Wright compared the performance of eight algorithms, namely coordinate search algorithm, HJ (Hooke-Jeeves) algorithm, PSO (Particle Swarm Optimization) algorithm, PSO that searches on a mesh, hybrid PSO-HJ algorithm, simple GA, Simplex algorithm of Nelder and Mead, and Discrete Armijo gradient algorithm, for their performance in minimizing cost functions with different smoothness [18]. They found that the hybrid algorithm achieved the biggest cost reduction with a higher number of simulations and that the simple GA consistently got close to the best minimum. However, the performances of other algorithms were not stable. It is recommended that Simplex algorithm and Discrete Armijo gradient algorithm should be avoided if EnergyPlus is used

Table 1
Advantages and disadvantages of the three types of energy simulation engines used in the building energy efficient design and optimization technique.

Types	Examples	Advantages	Disadvantages
Dynamic and detailed energy simulation engines	EnergyPlus, DOE-2, TRNSYS, ESP-r, IDA ICE, etc.	High accuracy and reliability, complete input and output functions, convenient integration into the optimization workflow	Long running time
Simplified standard energy simulation models	ASHRAE toolkit for building load calculation, ISO normative building energy calculation approach, etc.	Fast running speed, suitable for the early design stage	Not very high (but often acceptable) accuracy and reliability
Customized non-standard energy calculation models	Admittance procedure, etc.	Fast running speed, full control of the energy calculation model	Difficult to evaluate accuracy and reliability, non-standard and thus not transferrable

to evaluate the cost function. Kämpf et al. compared the performance of two hybrid algorithms, PSO-HJ and CMAES/HDE (Covariance Matrix Adaption Evolution Strategy/Hybrid Differential Evolution), in optimizing five standard benchmark functions with different complexities [149]. They found that the CMAES/HDE outperformed the PSO-HJ in solving the benchmark functions with ten dimensions or less. However, when the number of dimensions was larger than 10, the PSO-HJ algorithm performed better. Wright and Ajlami examined the effect of starting conditions or control parameters on the robustness of the GA [20]. They concluded that there was no significant difference in solutions found between any of the parameter sets and that the GA was insensitive to the choice of the control parameters. Hamdy et al. tested the performance of three multi-objective algorithms (NSGA-II, aNSGA-II, pNSGA-II) on a building optimization problem and two benchmark test problems [91]. The aNSGA-II algorithm found high-quality solutions close to the true Pareto front with fewer evaluations and faster convergence. Elbeltagi et al. compared the performance of five evolutionary optimization algorithms, namely GA, memetic algorithm, PSO, ant-colony system, and shuffled frog leaping, in solving continuous and discrete benchmark functions [150]. They found that the behavior of each optimization algorithm in all test problems was consistent and that the PSO algorithm generally performed better than the others in terms of success rate and solution quality, while being second best in terms of processing time.

2.7. Application of the energy efficient design optimization technique on buildings

The ultimate objective of carrying out research on building energy efficient design optimization is to provide an innovative and more powerful means to achieve buildings with a better overall performance with a particular focus on energy. Therefore, it is imperative that the application of the technique on buildings is reviewed.

The first focal point of the review is to examine whether the energy efficient design optimization technique is applied to a real-world building or a simplified and fictitious building. It is believed that the finding coming out of this examination can indicate, to a reasonable degree, the maturity of the technique and its current status in design practice. Statistical analysis shows that among 116 works in the core literature, 32 of them apply the technique on real-world buildings, accounting for 27.6%, compared with 77 on simplified and fictitious buildings, accounting for 66.4%. The rest are 7 works that did not apply the technique on case buildings. Fig. 5 illustrates the composition of the core literature in terms of the different kinds of the case building. As Fig. 5 shows, the proportion of applying the energy efficient design optimization technique on real-world buildings is just over one quarter, a fairly low number indicating that the technique is relatively new and has not been widely adopted in building design practice. This finding is further supported by the data that almost 70% of the works reviewed apply the technique on simplified and fictitious buildings. Although valuable, these case studies cannot fully address the complex nature and challenges that designing a real-world building intrinsically has.

Despite that only a small percentage of literature reviewed use the energy efficient design optimization technique on real-world buildings, some of them are worth mentioning because they use relatively large scale and complex buildings to demonstrate the procedure, effectiveness, and capability of the technique. Jin and Overend applied a recently developed whole-life value based façade design and optimization tool on a real-world façade renovation project. The case building was constructed in 1945. It is a five-story steel-framed building with reinforced concrete floors, which holds part of the Department of Engineering, University of

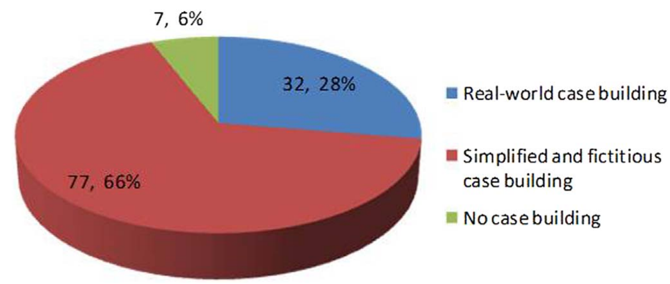

Fig. 5. Composition of the core literature in terms of the types of the case buildings.

Cambridge, the UK [85]. According to the figures included in [85], the building's floor area is close to 5000 m^2. Eisenhower et al. proposed a meta-model based building energy efficient design optimization methodology and applied it on the Atlantic Fleet Drill Hall (building 7230) at the Naval Station Great Lakes in Great Lakes, Illinois, the US. It is a two-storey facility with a gymnasium-like drill deck as well as a section primarily comprised of offices. The total area of the building is approximately 6430 m^2 [81]. Stojiljkovi et al. assessed greenhouse gas emissions in residential sector using the energy efficient design optimization technique. The case study is an urban residential settlement with multifamily buildings located in Niš, Serbia, with a total heated area of 27,045 m^2 [138].

In all case studies, residential buildings, office buildings, and educational buildings are the three most common types of buildings in terms of function, with 28, 27, and 7 cases, respectively. This finding is no surprising since residential and office buildings are probably the most commonly seen building types in general building stock. Other building types include retail [133], healthcare [44], industrial [103,123], hotel [84], religious [59], and sports [117].

Another revealing finding by analyzing the core literature is that among real-world buildings the majority of cases are renovation, 19 cases, rather than newly built, only 3 cases. The number of renovation projects is overwhelming for two possible reasons. First, the actual need for renovating existing buildings to improve the energy performance and achieve a low carbon society is high, especially in countries that have already gone through the urbanization stage and have a high percentage of existing building stock compared with newly built buildings. Secondly, for renovation projects the shape and form of the building are fixed. Therefore, the attention can be put on renovating building envelope and mechanical systems. This makes applying the application of the energy efficient design optimization technique somewhat easier.

3. Discussions

3.1. The overall state of the building energy efficient design optimization technique

Encouraged by the overall movement of green and sustainable buildings and assisted by the technological advancements such as energy simulation, building energy efficient design optimization is quickly becoming a new and promising technique to design buildings with higher energy efficiency and better overall performance. This trend is confirmed by a steady increase of the number of relevant literature, especially since 2011 (Fig. 2).

Building energy efficient design is intrinsically a multi-objective and multi-variable design task. The conventional trial-and-error design method or other methods relying on the designer's knowledge and experience can be inefficient or even ineffective when the building and the design task are complex. From a perspective of architects, the conventional architectural design method is an approach involving some basic design principles, mainly based on functions and forms. The driving force is the combination of the architect's rationality and sensibility [151]. Building energy efficient design is performance driven. In other words, the driving force for design generation and evolution should be quantifiable performance index, i.e., energy related performance parameters. Therefore, combining energy simulation with optimization algorithm is a natural means to deal with the challenges that the conventional design method cannot overcome, namely a rapid and accurate calculation of energy performance and a systematically guided search for the optimal solution in a large design space.

To achieve energy efficient design optimization for buildings, the first task is to develop a technique that can establish an automated workflow as shown in Fig. 1. This is one of the research areas that is fruitful. Various tools, software packages, and computer coding languages are used independently or together to realize the building energy efficient design optimization technique. Therefore, it is now possible for an architect to find such a technique that he feels comfortable with and use it to design an energy efficient building.

Besides the effort to develop the techniques, other research areas in building energy efficient design optimization are also explored with different depths. Studying the performance of algorithms is one of them. Some generally accepted findings are available such as the ability of evolution-based algorithms to find the optimum for non-linear problems and the effectiveness of combining evolution-based algorithms with direct search algorithms. Despite the progress, some key research issues regarding algorithms remain unresolved. For instance, building energy efficient design optimization problems have different natures such as linear versus non-linear, continuous versus discrete, etc. Evaluating a certain algorithm must take into account its performance on design optimization problems with different natures. The other important research task is to develop a system of performance indices to evaluate the effectiveness and efficiency of algorithms. These performance indices may include the ability to avoid being trapped in local minimum, the speed to find the near-optimum, robustness, stability, etc.

The other key component in Fig. 1 is the energy simulation engine. The building energy efficient design optimization technique is quite mature in this regard, thanks to the latest development of dynamic building energy simulation programs. EnergyPlus is the clear favorite for researchers. Other software packages such as TRNSYS, ESP-r, DOE-2, and IDA ICE are equally suitable to be integrated into the design optimization workflow as the energy simulation engine. It should be noted that being open-source is a major advantage because the workflow shown in Fig. 1 requires information exchange among the energy simulation engine, the optimization engine, and possibly other components.

3.2. What is missing for architects

Generally speaking, architects are not the inventor or developer of the building energy efficient design optimization technique, but the end-user. They do not and should not concern themselves with technical details of the design optimization approach. Aspects such as the overall capability, the user interface, post-processing, and integration with architectural modeling programs are what architects focus on and use to evaluate the effectiveness and efficiency of the building energy efficient design optimization technique.

Although the current state of building energy efficient design optimization, both as a design philosophy and technique, is encouraging, there are still missing pieces for architects. These missing pieces warrant future research. First and foremost, realizing building energy efficient design optimization requires software packages or skills that most architects are not familiar with. As discussed previously, generic optimization platforms such as Matlab, modeFrontier, GenOpt, etc. can be used to integrate energy simulation programs and establish the building energy efficient design optimization technique. However, all of these optimization platforms are not developed to address the special needs of architectural design. Therefore, their user interface and operating style are somewhat strange for architects. More importantly, they cannot be smoothly connected with the architectural modeling programs such as Google Sketchup. This is a significant challenge because architects rely on modeling programs to generate and modify the design, especially in the early design stage. To achieve design optimization, they now have to switch between the modeling environment and the optimization environment, which is inconvenient and susceptible to mistakes.

Another missing piece is that the design optimization technique is capable of dealing with design variables such as the thermal resistance of the wall system, the U-value of the windows, etc. However, when it comes to the shape and form of buildings, only very basic variables such as the aspect ratio of a rectangular shape floor plan can be successfully optimized. In reality, shape and form related design variables can be much more complex. As discussed previously, this limit is probably part of the reason why the majority of case buildings that the energy efficient design optimization technique is applied on are renovation rather than newly built because the shape and form are determined for renovation projects.

Post-processing capability in building energy efficient design optimization also limits the technique's usefulness in architectural design practice. The optimization results for single objective problems are easy to interpret. For multi-objective problems, the optimization results are often processed using methods such as the Pareto frontier methods. Although these methods are mathematically sound, it can be difficult to interpret them in an actual building design task.

3.3. Future work

Most, if not all, new technologies share the same pattern of development. They are first proposed as a new idea and developed to solve particular problems. Then they are put into use, whereby gaps between the technology and what is needed is identified. The technology is improved to address those gaps until it becomes mature. The building energy efficient design optimization technique follows the same pattern. There are still gaps that warrant future research work. The followings describe several important ones.

Develop more integrated design optimization software packages that can fit into the overall design workflow that architects are familiar with. A typical architectural design workflow starts from conceptual design, to detailed design, and to construction drawing design [69]. An integrated energy efficient design optimization software package should fit into this workflow with ease. One important requirement is for the software package to be able to communicate with commonly used architectural design programs such as Google Sketchup, AutoCAD, and Revit. The latest efforts made by DesignBuilder [152] and OpenStudio [153] align with this objective.

Conduct further research on optimization algorithms to determine which ones are the best for different energy efficient design optimization problems. Building energy efficient design optimization problems can vary in objectives and design variables. Because of this diversity, it is impossible to find one algorithm to fit all design optimization problems. As the literature review shows, the research in this area is relatively scarce.

Improve the post-processing capability of the current technique. Interpreting the design optimization results is as important as carrying out the process. A convenient, easy-to-understand, and graphical post-processing module is attractive to both architects and clients, who are typically not familiar with the mathematical details of the multi-objective optimization procedure.

4. Conclusions

Energy efficient design optimization is both a philosophy and a technique to assist architects and other professionals in designing buildings with higher energy efficiency and better overall performance. As the technique is maturing, a comprehensive and in-depth review from the perspective of architects is necessary and timely. A certain set of criteria are proposed to select from a large number of published papers and reports, yielding 116 works to form the core literature.

The general procedure of the building energy efficient design optimization technique is consistent in the core literature. It involves two critical driving forces, namely energy simulation engine and optimization algorithm engine (Fig. 1). In the optimization process, design objectives need to be defined by the designer. The rest should be highly automated.

The first paper presenting a design optimization study that meets all criteria was published in 1983, more than 30 years ago. Throughout the 1980s and 1990s, the research on building energy efficient design optimization was not very active. Since 2000, it has been steadily rising, especially in the past five years. The increased interest is caused by several reasons including the emphasis on building energy performance and the rapid development of building energy simulation technology.

Based on how design optimization is achieved, the building energy efficient design optimization techniques can be categorized into three groups, namely techniques integrating energy simulation programs into generic optimization platforms, techniques integrating energy simulation programs into special purpose optimization platforms, and customized techniques. A variety to software packages such as Matlab, ModelCenter, modeFRONTIER, GenOpt, jEPlus+EA, MOBO, ENEROPT, GENE_ARCH, Grasshopper, etc. are used, making building energy efficient design optimization a quite diversified field in terms of the means design optimization is achieved.

Although the design objectives of the core literature are all energy related, they can take different forms. Besides the design objectives that are explicitly on energy such as minimizing the annual energy consumption, implicit energy-related design objectives are also found such as minimizing CO2 emissions and reducing life cycle costs. The design variables can be divided into five categories, namely opaque building envelope, transparent building envelope, shape and form, type of mechanical systems, and operation of mechanical systems.

The most commonly used energy simulation engine in building energy efficient design optimization is EnergyPlus, accounting for 47 works or 40.5% of the core literature. Other dynamic energy simulation programs include DOE-2, TRNSYS, ESP-r, and IDA ICE. Simplified energy simulation models and non-standard energy calculation models are also found.

Evolutionary algorithms, derivative-free search algorithms, and hybrid algorithms are the three types of algorithms used in the building energy efficient design optimization technique, among which evolutionary algorithms, represented by the family of genetic algorithms, account for approximately 60%.

Examining the application of the energy efficient design optimization technique on buildings yields some revealing findings. Among 116 works in the core literature, 32 of them apply the technique on real-world buildings, accounting for 27.6%, compared with 77 on simplified and fictitious buildings, accounting for 66.4%. For the real-world buildings, the majority of cases are renovation. In terms of the type, residential buildings, office buildings, and educational buildings are the three most common ones.

The overall trend and development of building energy efficient design optimization are obviously encouraging. However, obstacles still exist. From the perspective of architects, some research subjects need to be further studied, such as developing design optimization software packages that better fit into the overall design workflow, determining which algorithms are the best for different energy efficient design optimization problems, and improving the post-processing capability of the current technique.

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