Decomposition Approaches for Building Design Optimization

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Abstract

Decomposition Approaches for Building Design Optimization

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Building performance simulation can be integrated with optimization to achieve high-performance building design objectives such as low carbon emission and cost-effectiveness by holistically considering design variables across different disciplines. However, the complexity of the design problem increases greatly with increasing dimensionality. In some cases, solving high-dimension problems is not technically feasible nor time-efficient. Decomposition is one way to reduce the complexity and dimensionality of optimization problems. However, the decomposed optimization might achieve local optimum. Therefore, deploying appropriate decomposition strategies to achieve global optimum is paramount. This study investigates the deployment of hierarchical and parallel decomposition for building design optimization problems to ensure identification of global optimum. The feasibility of combining sensitivity analysis and decomposition is also explored. At the end of this study, some recommendations are given to help select an appropriate approach in practice.

First, this thesis proposes a hierarchical decomposition. Hierarchical decomposition divides an optimization problem into several interconnected subproblems solved sequentially. The proposed approach is applied to the multi-objective optimization problem that minimizes buildings' operating costs and carbon emissions. The results show that the hierarchical decomposition approach can reduce the number of simulations while achieving global optimums.

Second, this thesis proposes a parallel decomposition. Parallel decomposition divides the original problem into several smaller subproblems to be solved separately, and potentially, concurrently. The proposed parallel decomposition approach is applied to solve the single-objective optimization problems of a benchmark function and a low-rise office building. The results show that the proposed approach finds the global optimum and takes less computation time than optimization without decomposition.

Third, this thesis explores the feasibility of combining sensitivity analysis with decomposition for dimensionality reduction. The efficiency and accuracy of different methods are compared through three case studies.

The proposed hierarchical and parallel decomposition approaches can be applied individually or combined into a hybrid decomposition approach. This thesis concludes with some recommendations to help choose a decomposition approach to solve building design optimization problems.

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Thank you, Claude, for the opportunity to work with you. The time spent working with you has given me much enlightenment. Thanks to Aditya, Ashleigh, Ata, Christine, Felipe, Francois, Nima, Vera, and all my friends in the research group. Your help and care made me feel warm.

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Chapter 1. Introduction

1.1 Building design optimization

Building design is rapidly transforming into an age of design automation where optimal design solutions can be identified from tens of thousands of computer-generated designs. The new capability opens up design opportunities for the architects and engineers but, at the same time, incurs high computational costs.

Building performance simulation software are used to simulate and predict future building performance during the design phase. Simulation coupled with optimization can help identify designs that achieve lowest energy consumption, operating carbon emissions and cost depending on the objective function. Some programs have integrated simulation with optimization, such as Building Energy Optimization (BEopt), Design Builder, or ESBO. In addition, some other simulation programs such as EnergyPlus and TRANSYS can be combined with the optimization platform such as GenOpt, Matlab, or ModeFRONTIER to perform the simulation-based optimization.

The design variables of building design optimization problems are mainly discrete, making these problems combinatorial optimization problems. An example is shown in Figure 1.1. In this example, four design combinations consist of two types of windows and two types of roofs. The two optimization objectives are to minimize operating costs and carbon emissions. The optimal solutions are highlighted in the figure referred to as Pareto designs, which can not be improved without degrading the other designs (Luc, 2008). The outputs can be plotted for decision-making when more variables are considered, as shown in Figure 1.2. The Pareto optimal solutions are the red points in this figure. The final decision is usually selected from the Paret front through multi-attribute decision-making (Li and Lee, 2018).

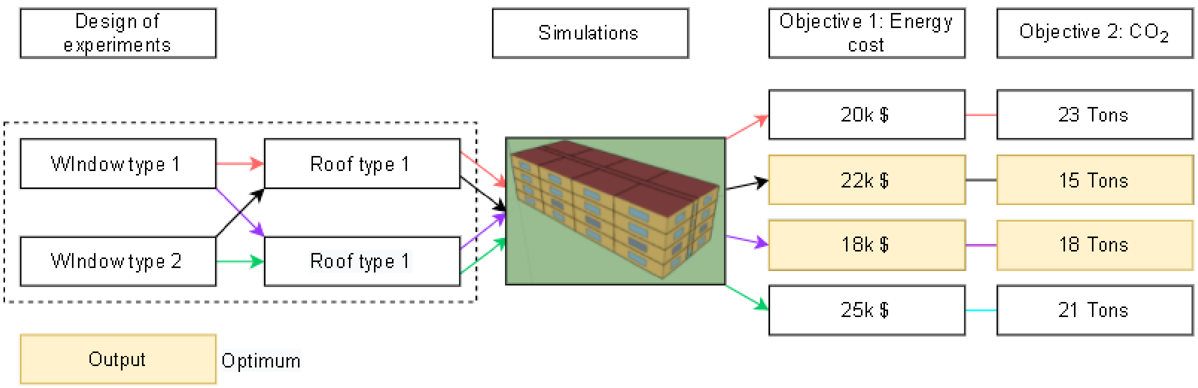


Figure 1.1 An example of building design optimization

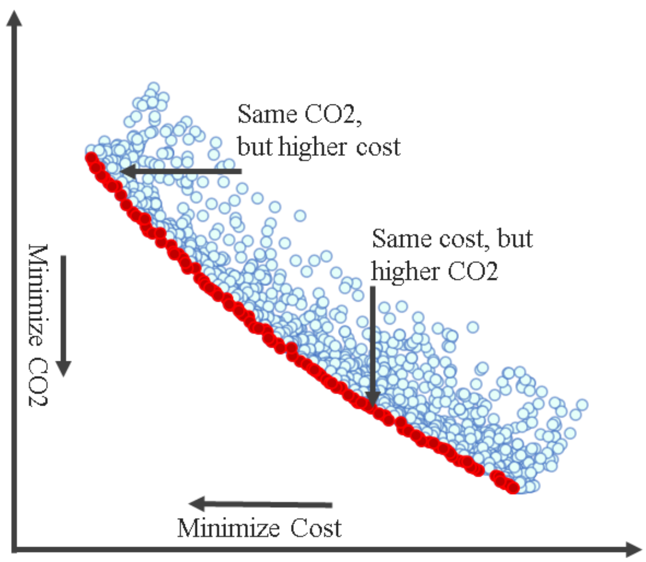


Figure 1.2 Illustration of Pareto front in optimization results

Genetic Algorithms are one of the most used methods to solve building design optimization problems (Nguyen et al., 2014). This type of algorithm uses randomized searching techniques derived from the evolutionary law of the biological world (the genetic mechanism of the survival of the fittest) (Someya & Yamamura, 2017). Genetic Algorithms do not require the objective functions to be derivative and continuous. Furthermore, it has inherent hidden parallelism and the ability of global optimization, and it uses the probabilistic optimization method, which can automatically guide the optimization adaptively adjust the search direction without determining rules (Caldas & Norford, 2002). These features match the requirements of building design optimization problems. However, the values chosen for the cross rate and mutation rate seriously affect the quality of the solution, and most of these values are currently selected by experience. Moreover, if the dimension of the optimization problem is high, the genetic algorithm converges to the local optimum prematurely.

With the development of optimization and simulation, different design methodologies have emerged to achieve higher performance, such as generative design, multidisciplinary integrated design, and robust design based on scenario exploration. Generative design refers to a process that utilizes an optimization algorithm with the simulation to automatically generate design results, which can help designers automate parts of the design process (Singh and Gu, 2012). The generative design encourages the architect and engineer to change from the traditional preliminary trial design and further explore the building performance. Another method using optimization and simulation is multidisciplinary integrated design (Gerber et al., 2014). Building is a complex system involving multiple disciplines to jointly complete the design of a project: architecture, structural, electrical, and mechanical engineering. Considering variables from different disciplines can explore higher building performance than the separated design process (Li and Lee, 2019). There are also studies using optimization and simulation for the robust design considering the uncertainty in scenario (Kotireddy et al., 2019) (Li et al., 2019). This type of uncertainty is referred to as deep uncertainty that the experts cannot agree on the probability distribution, or the probability distribution is not available (Marchau et al., 2019). Therefore, the optimization needs to be repeated for different scenarios to get a robust design (Li et al., 2021).

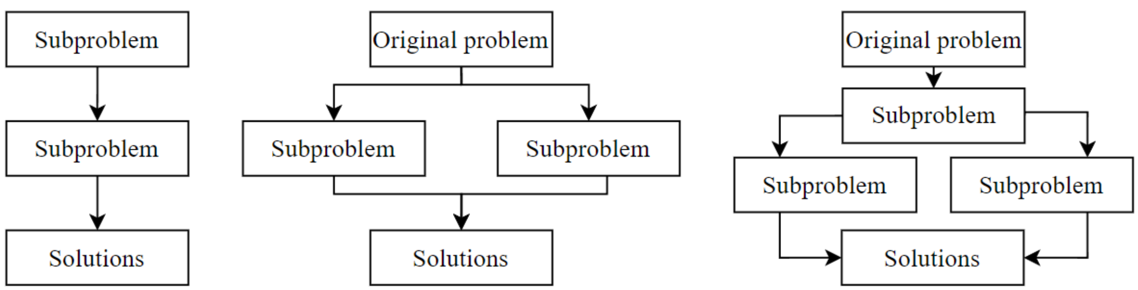
Although these applications of optimization and simulation can help building design achieve high performance, they also bring challenges. Since more variables are considered for optimization, the complexity of the problem increases, which leads to high-dimensional problems. In some cases, solving high-dimensional problems is neither technically feasible nor efficient. Therefore, dimensionality reduction strategies are required to greatly ease the optimization difficulty (Feng et al., 2019).

1.2 Problem decomposition

Decomposition is one way to deal with high-dimensional problems (Meselhi et al., 2022). Decomposition has been applied to problems such as structural design optimization, mechanical system optimization, and traffic system optimization. For example, Sobieszczanski et al. (1985) proposed a structural optimization by multi-level decomposition, separating the structural element optimization subproblems from the assembled structural optimization problem. Mínguez and Castillo (2009) applied decomposition on four types of reliability-based optimization problems in engineering works. Mesbah et al. (2011) proposed a methodology to optimize the mathematical model of transit priority using decomposition. In general, decomposition reported in the literature can be categorized into three types: product decomposition, process decomposition, and problem decomposition (Kusiak and Larson, 1995).

The product decomposition partitions a product based on physical components (Yoshimura et al., 2009). Product decomposition allows standardization, interchangeability, or a capture of the product structure. Geyer (2009) proposed a decomposition method by the component scheme and applied it to optimize a frame-based hall design. The process decomposition applies to problems involving the flow of elements or information, such as electrical networks or the design process itself (Kusiak and Wang, 1993).

The problem decomposition turns the original optimization problem into a vertical, horizontal, or hybrid structure depending on the relationship between the subproblems (Haftka and Gürdal, 2012). The vertical structure results from the hierarchical decomposition, which divides the problem into several levels, and each level has its own objectives and constraints, as shown in Figure 1.3 (A). The horizontal structure results from parallel decomposition, which divides the problem into several subproblems and optimizes them separately, as shown in Figure 1.3 (B). These two approaches can be combined as a hybrid one, as shown in Figure 1.3 (C).



(A) Hierarchical decomposition (B) Parallel decomposition (C) Hybrid decomposition

Figure 1.3 Different types of problem decomposition

Though problem decomposition can reduce dimensionality and save computation time of optimization problem, the optimization after decomposition might achieve local optimum (Floudas and Aggarwal, 1990). For example, the original problem is to minimize the objective function Q(X, Y) = X+Y, as shown in Figure 1.4. The hierarchical decomposition divides this problem into two levels, and the first-level optimization is to minimize the objective function P (X, Y) =X/Y. The optimal solution of the first-level optimization is X=1, Y=2. However, the optimal solution of the original problem is X=1, Y=1, which can achieve the global optimum Q = 2. This global optimal solution is excluded in the first-level optimization, which leads to the local optimum Q = 3. Another example is shown in Figure 1.5 to demonstrate when the parallel decomposition achieves the local optimum. When the two variables X and Y are separated for optimization, each variable

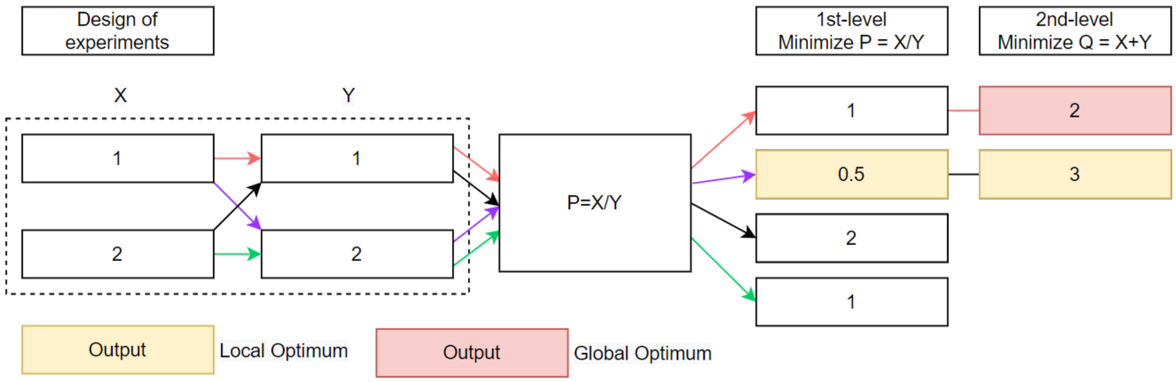


Figure 1.4 Hierarchical decomposition achieving local optimum

is optimized while the other is set as defaults. It is assumed that the default values of variables X and Y are -4 and 2. Therefore, the optimal solutions for the two subproblems are X = -4 and Y = 2, which leads to a local optimum P = -2. However, when the two variables are combined for optimization, the optimization can achieve the global optimum P = - 4 while X = 4 and Y = -1.

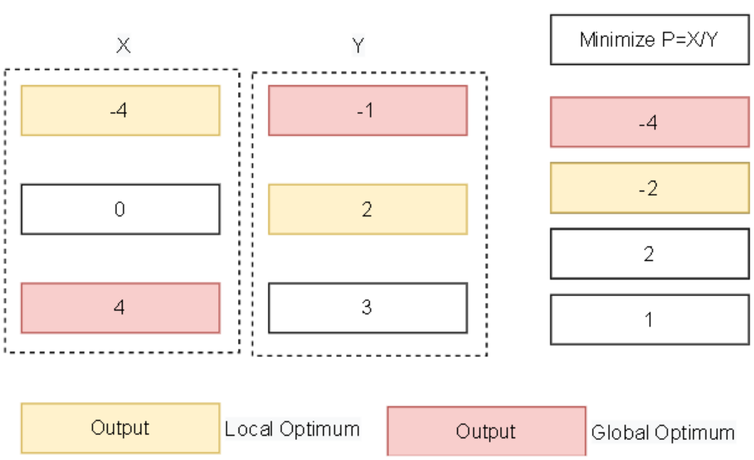


Figure 1.5 Parallel decomposition achieving local optimum

1.3 This work

This research proposes the hierarchical and parallel decomposition approaches for building design optimization problems, reducing the computation time while achieving global optimum.

Chapter 2 proposes the hierarchical decomposition, which divides the single-level optimization into multi-level optimization. In order to obtain the global optimum, the first-level optimization is required to keep the solutions of the original problem. It is proved in this study that this requirement is met if the original problem's objective functions are the linear sum of the first-level optimization's objective functions. Then, the proposed hierarchical decomposition is applied to the optimization problem minimizing the operating costs and carbon emissions. After decomposition, the first-level optimization minimizes energy consumption, while the second-level optimization minimizes operating costs and carbon emissions. A four-storey residential building is used as a case study to demonstrate the proposed approach.

Chapter 3 proposes the parallel decomposition, which divides the original problem into several subproblems and optimizes them separately. The parallel decomposition adopts the "divide-and-conquer" strategy, which focuses on the interaction between variables. The proposed parallel decomposition uses a dual-criteria variable grouping method to ensure the solutions of each subproblem are the same as the global optimal solutions. This approach can decompose the variables with strong interactions as long as the interactions do not impact the optimal solution of one variable. Regression-based sensitivity analysis and interaction plots are used to assess if the variables satisfy the criteria. A benchmark and low-rise office building are selected as case studies to demonstrate the proposed approach.

Chapter 4 evaluates the performance of the sensitivity analysis method used in Chapter 3 for both variable screening and grouping. The sensitivity analysis quantifies the interaction of variables for variable grouping in parallel decomposition. Another common use of sensitivity analysis for dimensionality reduction is to evaluate the main effect of variables and exclude unimportant variables. Three case studies are used to evaluate if the proposed sensitivity analysis method is capable of variable screening and grouping.

Chapter 5 summarizes this thesis and also gives some recommendations to help select an appropriate decomposition approach in practice.

The contributions of this thesis include:

- The relationships among subproblems in building design optimization problems are analyzed and classified. The classification supports informed decisions in identifying the appropriate hierarchical decomposition approach.

- A hierarchical decomposition approach is proposed to avoid the local optimal solutions while saving the computation time. The feasibility of the proposed approach is demonstrated by a building operating cost and carbon emission minimization problem.

- Introduce the concept of parallel processing in integrated building design.
- Propose suitable variable grouping criteria for building design optimization problems to separate variables with strong interactions.
- Propose a two-criteria parallel decomposition approach to reduce the computation cost while achieving global optimum.
- Suggest the solving sequence of the subproblems to increase the chance to achieve global optimum.

- Propose to use the regression-based sensitivity analysis with design resolution V for both variable screening and grouping to reduce the dimension of building design optimization problems.

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Chapter 2. A Hierarchical Decomposition Approach for Building Design Optimization

Hierarchical decomposition transfers single-level optimization into multi-level optimization. This chapter reviews different types of hierarchical decomposition approaches based on the relationship between the subproblems. A hierarchical decomposition approach is proposed to solve the optimization problem minimizing the operating costs and carbon emissions under different scenarios. A mid-rise residential building is used as a case study. The results show that the proposed approach can achieve the global optimum as the optimization without decomposition while taking less computation time.

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Nomenclature	
Symbol	**Description**
BIM	Building Information Modeling
DE	Design Explorer
ER_i	The emission factor of the ith energy source
$f_{cost}(X)$	The operating cost
$f_{emission}(X)$	The operating carbon emission

$f_{source(i)}(X)$	The energy consumption due to source type i
F(X)	The objective functions of the second-level optimization
G(X)	The objective functions of the second-level optimization
GA	Genetic Algorithm
$H_i(X)$	The objective functions of the first-level optimization
HOC	Hierarchical Overlapping Coordination
MOGA	Multi-Objective Genetic Algorithm
MPC	Model Predictive Control
$Price_i$	The unit price of the i^{th} energy resource
R^n	The n-tuples of real numbers
WWR	Window to wall ratio
$X= (x_1, x_2, \dots x_n)$	The design variable vector
x_n	The n^{th} design variable
X_R	The solutions of relaxation of the original problem

2.1 Introduction

2.1.1 Background

Building performance simulation and optimization tools enable building designers to search for the optimal solutions from an ocean of feasible designs, where the combinations of design variables are formed based on the defined set of constraints. However, the scale of the optimization problem becomes larger as the number of design variables increases in proportion to the number of possible energy-efficient measures implemented in the building design. For example, the search space of ten variables with ten levels per variable will compose 10^{10} = 10,000,000,000 simulations. The high-dimensional problem is often challenging to solve due to a large number of calculations. Hierarchical decomposition could reduce the scale of the problem by decomposing an optimization problem into two or more subproblems. After decomposition, each subproblem has its own objectives and constraints (Frigerio et al., 2018). Hierarchical decomposition can make use of the existing hierarchy of the model and has been applied to reduce the scale of different building design problems (Hamdy et al., 2013) (Ascione et al., 2016) (Ganjehlou et al., 2020). Depending on the relationships between the subproblems, different integration modes are used to combine partial solutions to obtain the final solution of the original problem (Chaieb et al., 2015).

2.1.2 Previous work

The basic relationships between two hierarchical subproblems in the building design problem can be classified into three types: (1) Sequential, (2) Coupled, and (3) Nested (Anandalingam and Friesz, 1992). They are summarized and represented in Figure 2.1.

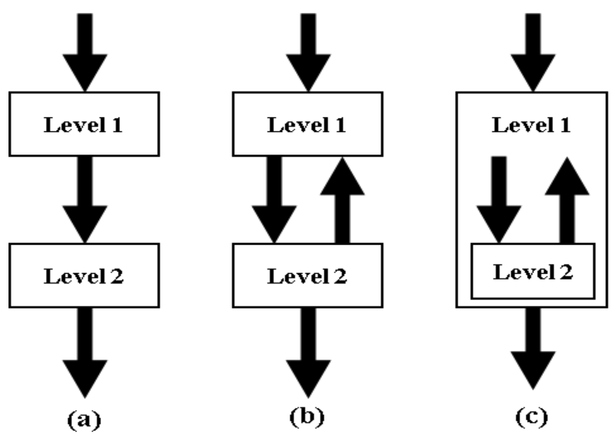


Figure 2.1 The basic hierarchical relationships between two subproblems

2.1.2.1 Sequential relationship

Figure 2.1 (a) shows the sequential relationship between the two subproblems with different variables and objectives. In this configuration, the obtained top level optimal designs impact the solutions on the lower level, but the lower level does not affect the results on the top level. The optimal solutions of the top-level subproblem are passed to the lower-level for the final results.

Hamdy et al. (2013) applied three stages of optimization to find the cost-optimal and Nearly Zero-Energy performance building solutions. The design variables included building envelope and heat-recovery units for the first stage, optimizing the present worth and space heating energy demand. In the second stage, heating and cooling systems were combined with the solutions obtained from the first stage, and their viability was assessed based on the primary energy consumption and the life cycle cost of the optimal combinations. In the last stage, thermal and photovoltaic solar energy systems were added as supplementary systems for heating and electricity production to improve financial and environmental viability of building envelope and HVAC system designs. The authors have concluded that their methodology has reduced the exploration effort and lead to more informative and transparent analysis. He et al. (2015) developed a method for two-level optimization of domestic building stock refurbishment. In the first level, the objective functions were the cost and energy consumption for an individual building while in the second level, those optimal designs were used to obtain the minimum cost and energy consumption for the building stock, including 759 houses. It was assumed that those houses were independent (without considering a community-shared heating system). Therefore, the results obtained from the second stage did not affect the first-level solutions. Ascione et al. (2017) proposed a multi-stage optimization framework to identify robust cost-optimal energy retrofit solutions and to assess their resilience to global warming. The objective functions were thermal energy demands for space heating and cooling in the first stage. The optimization was performed for four global warming scenarios, and four Pareto fronts were obtained accordingly. In the second stage, the objective functions were the global cost and primary energy consumption. Three macro-economic scenarios were considered. Finally, decision-making was performed to find robust retrofit designs considering the uncertainties in the environmental and economic scenarios.

As can be inferred from the review, sequential decomposition is applied to problems that can be solved in multiple stages in which the second stage variables do not impact the results of the first stage. The advantage of the sequential type of decomposition is that it can reduce the scale of the original problem into several smaller scale subproblems. Li and Wang (2019) reviewed the existing multi-stage design optimization methods optimizing the building envelope and energy system sequentially and concluded that these studies might not achieve global optimal solutions due to the interactions between the two subproblems. This issue can lead to the local optimal solutions of the original problem. Therefore, the sequential decomposition should be applied to studies with one-direction relationships.

2.1.2.2 Coupled relationship

In this configuration, the two subproblems are coupled, as shown in Figure 2.1 (b). Trcka (2008) introduced the strong and loose coupling in building systems and performed different co-simulation strategies for performance prediction of innovative integrated HVAC systems in buildings. In this approach, different aspects of a building can be coupled externally and solved while exchanging data during run-time bi-directionally. For instance, ESP-r and EnergyPlus can be used to solve building model(s) while TRNSYS solves the HVAC system model(s). Chen et al. (2020) proposed a cooperative distributive model predictive control (MPC) based on hierarchy decomposition. For this purpose, it was suggested that sub-systems with strong coupling should be grouped into the same sub-systems. In contrast, sub-systems with weak coupling can be separated and solved sequentially while considering the interactions. On the other hand, to minimize the communication burden between sub-systems, only intra-layer interactions were considered. Killian et al. (2014) introduced a hierarchical MPC concept for decoupled building heating control. The first subproblem was to optimize the user comfort, and the second subproblem was to minimize the costs of the building. Although this hierarchical MPC only found the local optima, the implementation effort was significantly reduced. Rysanek and Choudhary (2012) decoupled the whole-building simulation process into three sub-models to find the optimal low-carbon and low-energy building refurbishment options. The first sub-model only considered the occupant service demand including the internal loads technologies. The second building energy model estimated the end-use building energy demand. In the last sub-model, the energy supply system model estimated the primary energy consumption. In this approach, the results obtained from each model were used as inputs for the next sub-model. Tian et al. (2018) proposed a weak decoupling method for distributed energy systems optimization problem based on the graph and matrix theory. A combined cooling, heating, and power system consisting of a power generation unit, an absorption chiller, a storage tank, and a ground source heat pump were selected as a case study.

It can be inferred from the literature that the decomposition for subproblems with a coupled relationship mainly involves the co-simulation of multiple models. This is because the whole building design process usually uses separate optimization algorithms and simulation models (Rysanek and Choudhary, 2012). Although a global optimum is not guaranteed, decomposing the complex coupled sub-systems is very attractive, especially for building control applications and operation (Killian et al., 2014)

2.1.2.3 Nested relationship

If one subproblem is nested inside another subproblem, the outer level optimization's objectives and constraints depend not only on the external level variables but also on the optimal solutions of the inner level optimization, which is impacted by the outer level optimization. This configuration is shown in Figure 2.1 (c). Such optimization usually is referred to as bi-level optimization (Sinha et al., 2017). Wen and Hsu (1991), Vicente and Calamai (1994) , and Colson et al. (2008) have reviewed the algorithms and applications of bi-level optimization.

This method has been widely applied to building design problems with different objectives and characteristics. For instance, Barg et al. (2015) analyzed and compared the performance of three single-level optimization algorithms and one bi-level optimization algorithm considering the building envelope variables. The single-level optimization studies included two genetic algorithms and the gradient-based design explorer (DE) algorithm. The bi-level optimization used the DE on continuous variables such as shading elements and roof insulation. This inner loop was nested within the outer level, which evaluated the discrete variables of wall and window types using GA (Genetic Algorithm). The solution quality and computational efficiency were considered as performance metrics. The results showed that all the methods satisfied the efficiency metrics defined in this study. However, the bi-level method used in this study does not outperform the other methods due to the slow convergence of the DE and the number of iterations required for the outer GA loop.

Another common application of bi-level optimization is to solve simultaneous design and operation problems. For example, Evins (2016) used a single objective optimization of operational control nested within a multi-objective energy system optimization to minimize an energy center's capital costs and carbon emissions. The energy demands were pre-calculated using simulation. Moreover, Evins (2016) extended this bi-level optimization into three-level by replacing the pre-calculated energy demand with simulation optimization using EnergyPlus.

2.1.2.4 Other types of decomposition approaches

The previous sections summarize the common relationships and approaches to decompose the optimization problems. According to Engau (2007), there are other types of approaches that can be applied based on the coordination between the subproblems. In this type of approach, all subproblems are solved independently, and the solutions are coordinated in a master problem that achieves an overall optimal solution. Analytic target cascading is a multidisciplinary hierarchical optimization method that systematically distributes desired top-down performance targets to appropriate lower-level performance values (Choudhary et al., 2005). The characteristics of this method are: (1) target cascading, the parent system sets the target for the sub-system and passes the target to the sub-system; (2) each sub-system has an analysis module to calculate the corresponding sub-system; (3) it solves the problem of consistency between sub-systems by adjusting the deviation between sub-systems. In the collaborative stage, each sub-system is temporarily independently optimized. The optimization objective is to minimize the difference between the design optimization result of the sub-system and the target provided by the upper-level system optimization. The inconsistency of the optimization results of each sub-system design is coordinated by the upper-level system optimization (Kim et al., 2003). Choudhary et al. Choudhary et al. (2005) applied the analytic target cascading to perform the multi-level optimization for the thermal and HVAC design of a building. Hierarchical Overlapping Coordination (HOC) is another coordination-based hierarchical decomposition approach . This approach simultaneously uses two or more problem decomposition strategies, and each of them is associated with different partitions of the design variables and constraints. Thus, coordination is achieved by the exchange of information between results from different decompositions. However, this method's efficiency is very sensitive to the ranges of input variables and decomposition strategy (Park er al., 2001). Li and Wang (2019) proposed a coordinated multi-stage optimization to optimize the building envelope and energy system separately. The results showed that the coordinated multi-stage optimization achieved the global optimum while the uncoordinated one achieved the local optimum. However, the computation time of coordinated multi-stage optimization is 3-4 times of the uncoordinated multi-stage optimization. Therefore, there is a need to investigate a decomposition which can achieve global optimum efficiently.

This study focuses on building performance simulation-based optimization. The building energy simulation processes' workflow inherits a hierarchical structure from load to economic and environmental analyses, as shown in Figure 2.2. This workflow has a sequential structure since there is no data feedback between the steps (ASHRAE handbook, 2017). The outputs of each step can be selected as the optimization objectives for subproblems. Therefore, this study focuses on the sequential relationship decomposition.

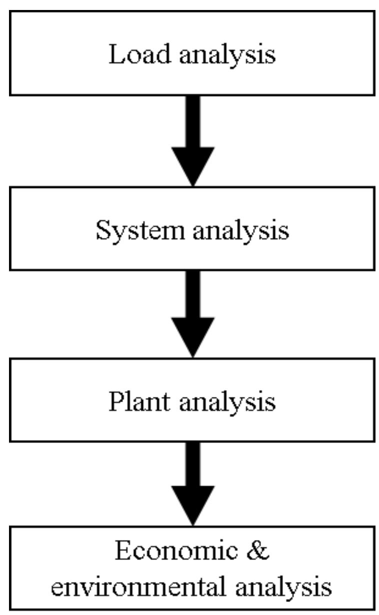


Figure 2.2 The hierarchy of building energy simulation program workflow (ASHRAE handbook, 2017)

Though hierarchical decomposition can reduce the scale of the optimization problem, this approach may result in local optimal solutions to the original optimization problem. This issue has received much attention in the studies of multi-level programming using mathematical approaches (Ho and Parpas, 2016) (Yue et al., 2019) (Sun et al., 2021). However, these approaches are not suitable for building engineering problems using simulation. Depending on the mathematical model of the problem, decomposition approaches often use matrix decomposition or calculus-based methods on objective functions and constraints to reduce the dimensionality (Conejo et al., 2006). Moreover, the outputs functions of the simulation program are usually implicit and unknown to the user (Shan and Wang, 2010). Furthermore, some design variables are discrete (e.g., types of windows), and the mathematic schemes are likely numerical rather than analytical (Kheiri, 2018). These features of the building design problem make the studies in mathematical optimization decomposition not applicable.

Other than the approaches mentioned above, relaxation-based decomposition methods can avoid the local optimal solutions (Noor-E-Alam and Doucette, 2012). In an example, Geoffrion (1971) explained the definition of relaxation. A relaxation of the minimization problem $z = min\langle f(x): x \in X \subseteq R^n \rangle$ leads to another minimization problem $z_R = min\langle f(x): x \in X_R \subseteq R^n \rangle$. The relaxation of a problem has an important property: $X \subseteq X_R$. This property means that the original problem's solutions are a subset of the relaxed problem's solutions (Geoffrion, 1971). In the relaxation-based decomposition, the first subproblem is suggested to be a relaxation of the original problem. This can be done by relaxing the objectives or the constraint of optimization. In such a case, the solutions of the first subproblem must include the solutions of the original problem. The second subproblem has the same objectives as the original problem, but the search space is reduced to the results of the first subproblem (Noor-E-Alam and Doucette, 2012).

2.1.3 This work

This research aims to propose a hierarchical decomposition approach that can reduce the computation time while avoiding the local optimal solutions of the original building design optimization problems. The major contributions of this paper are summarized as follows:

i. The relationships among subproblems in building design optimization problems are analyzed and classified. The classification supports informed decisions in identifying the appropriate decomposition approach.

ii. A hierarchical decomposition approach based on the problem relaxation for building design optimization is proposed. The first subproblem is the relaxation of the original problem, which can transfer the original solutions to the second subproblem. This decomposition can avoid the local optimal solutions while saving the computation time. The feasibility of the proposed approach is demonstrated by a building operating costs and carbon emissions minimization problem.

iii. It is identified in this study that the optimization problem minimizing the energy consumption is a relaxation of the optimization problem minimizing the operating costs and emissions.

Section 2.2 introduces the proposed hierarchical decomposition, which addresses the local optimal solution issue during the decomposition. Section 2.3outlines the case study and the implementation of the proposed decomposition approach. Next, section 2.4 discusses the results of optimizations with and without decomposition and the adjustments for the limitations. Finally, section 2.5 concludes this paper and outlines future work.

2.2 Methodology

A general format of the proposed decomposition approach is given in this section.

The original optimization problem is to minimize the objective functions $F(X)$ and $G(X)$ as shown below:

- Original optimization: Minimize $F(X)$ and $G(X)$.

Where X is the set of design variables. The optimization problem could be decomposed into two subproblems to be solved sequentially as below:

- First-level optimization: Minimize $H_1(X)$, $H_2(X)$, ..., $H_n(X)$.
- Second-level optimization: Minimize $F(X)$, $G(X)$.

The functions $H_1(X)$, $H_2(X)$, ..., $H_n(X)$ are used as the objective functions of the first-level optimization. The solution sets from first-level optimization form the search space of second-level optimization. The objective functions of the original optimization $F(X)$ and $G(X)$ become the second-level optimization's objective functions.

As proved in Appendix 2.B, if $F(X)$ and $G(X)$ are the linear sums of $H_i(X)$, such as $F(X) = \sum_{i=1}^{n} a_i \times H_i(X)$ and $G(X) = \sum_{i=1}^{n} b_i \times H_i(X)$, where a_i and b_i are constant coefficients, the first subproblem will be a relaxation of the original problem. Therefore, the results of the decomposed problem will be global optimal solutions of the original problem.

An example shown in Figure 2.3 is given to illustrate the issue of the local optimal solutions during decomposition. In an optimization problem with two variables, the original objective is to minimize one output Z. This optimization problem is decomposed into two subproblems. The first-level optimization has two objective functions, which are F1 and F2. The second-level optimization objective function is Z as the original problem.

If Z is represented as a linear sum of F1 and F2 such as Z1, the solutions of first-level optimization will include the global optimal solution, which is Z1=7. On the other hand, if the objective function is not the linear sum of F1 and F2, such as Z2, then the first-level optimization results in a local optimal solution, which is Z2=0. The global optimal solution Z2= -1.5 is eliminated after the first-level optimization.

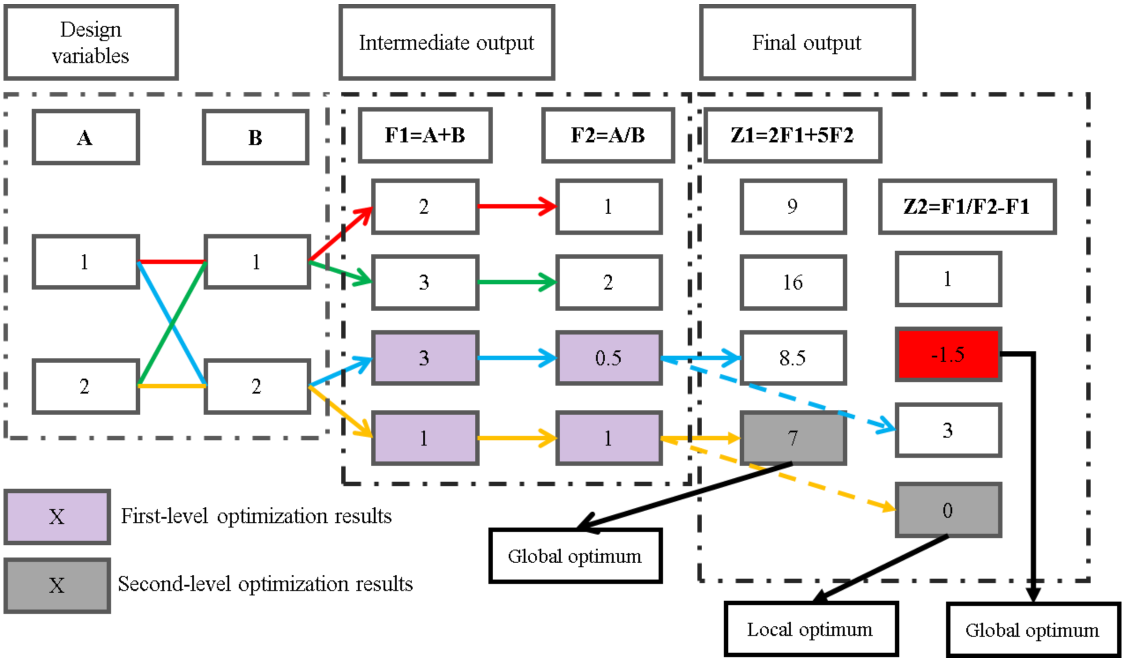


Figure 2.3 The illustration of the issue of the local optimal solutions during decomposition

This study applies the proposed decomposition approach to the optimization problem minimizing the building's operating costs and carbon emissions. This optimization problem considers different economic and environmental scenarios. In this paper, the energy price is assumed to be fixed-rate and applied to the annual energy consumption. The emission is the product of energy consumption and emission factors. The greenhouse gas intensity factor is used for electricity, and a conversion factor is used for natural gas emissions to convert energy consumption into carbon emission equivalent. The greenhouse gas intensity factor is the emission per unit of electricity and depends on the grid's energy source composition (Millia and Lewis, 2013). The conversion factor represents the amount of carbon equivalent when natural gas is burned (Harris et al., 2011). Equations (2.1) and (2.2) determine the operating cost and carbon emission, respectively.

$$f_{cost}(X) = \sum_{i=1}^{n} Price_i f_{source(i)}(X) \tag{2.1}$$

$$f_{emission}(X) = \sum_{i=1}^{n} ER_i f_{source(i)}(X) \tag{2.2}$$

Where the $f_{source(i)}(X)$ is the energy consumption due to source type i; X= (x_1, x_2, … x_n) is the design variable vector; x_n is the n^{th} design variable; $f_{cost}(X)$ is the operating cost; $f_{emission}(X)$ is the operating carbon emission; $Price_i$ is the unit price of the i^{th} energy resource; ER_i is the emission factor of the i-th energy resource. Therefore, other than a single-level optimization minimizing the cost and emission, another optimization minimizing the energy consumption is done before the original optimization.

When different energy price and emission factor scenarios are considered, the original optimization needs to be repeated for the different scenarios. However, after decomposition, the first-level energy consumption optimization is conducted only once, while the second-level cost and emission optimization is repeated. In this case, the second level can be solved easily since no simulation is involved. The relationship between the solutions of the two subproblems is illustrated in Figure 2.4: the solutions of cost and emission optimization under all scenarios are the subsets of solutions of energy consumptions optimization.

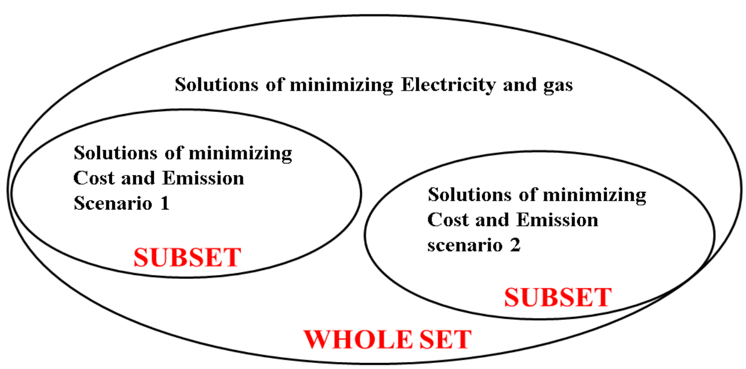


Figure 2.4 The relationship between the solutions of the first and second subproblems

2.3 Case study

2.3.1 Building model

A 4-story residential building shown in Figure 2.5 is selected to demonstrate the performance of the proposed decomposition strategy. The typical floor plan is shown in Figure 2.6. The total building footprint is 14.64 m x 15.84 m. The second to fourth floor consists of four apartment units. The two in the front have an area of 53.42 m^2, and the two in the back have an area of 48.45 m^2. The building's ground floor consists of two front units for retail and two back units for storage and maintenance applications.

This baseline building is simulated by EnergyPlus 8.9 using a weather file for Montreal, Canada. The envelope values are based on ASHRAE 90.1 (2013). The HVAC system consists of a gas boiler with 90% efficiency for heating and an air conditioning system with an Energy Efficiency Ratio (EER) of 10.24 for cooling. The thermal gains from lighting are assumed to be 8 W/m^2 for the apartment units, 7.1 W/m^2 for the corridor areas, and 16 W/m^2 for the retail areas. Electrical equipment is assumed to be 5.38 W/m^2. The lighting values come from ASHRAE 90.1 (2013). The electrical values are taken from the National Energy Code of Canada for Buildings (2015). Two occupants are considered for each unit, and all internal gains (lighting, occupancy, and equipment) are put on schedules. There are three schedules considered, which are apartment, corridor, and retail. For each of these categories, there is an equipment/lighting schedule and occupancy schedule. The design variables of optimization are the RSI values of the walls and the roof, the U-value of the windows, the building's orientation, and the Window to Wall Ratio (WWR) on the south wall of the building. Table 2.1 displays the variables along with their values used for optimization. For this study, three cost and carbon emission scenarios are assumed, as shown in Table 2.2. The operation cost includes the cost of electricity and natural gas in the ¢/kWh unit. The emission factor refers to the carbon emission ratios to electricity and natural gas in the $kgCO_2eq/kWh$ unit.

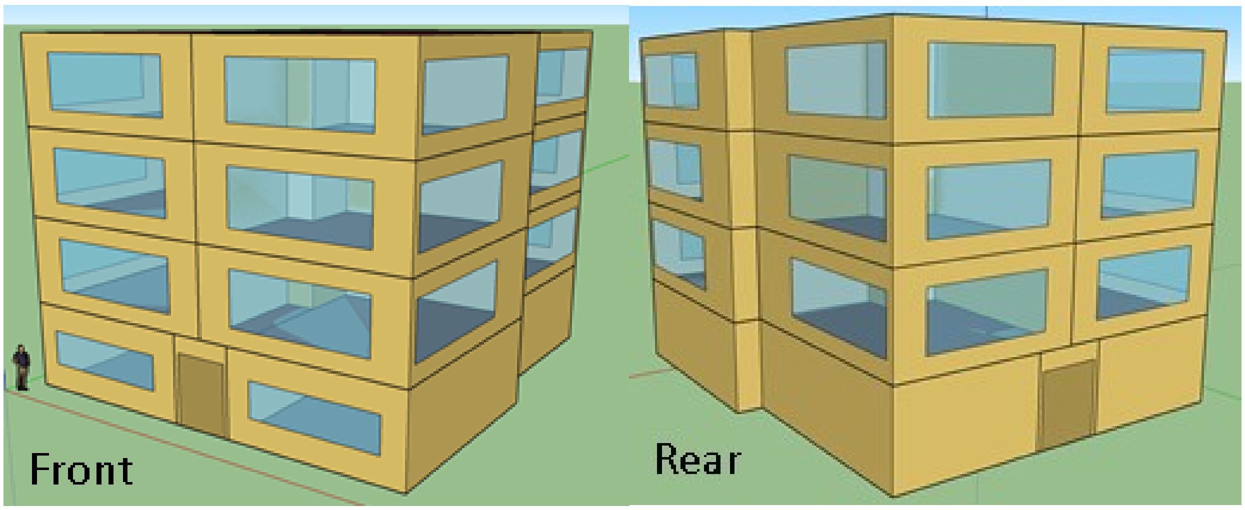


Figure 2.5 The front and rear view of the 4-story residential building

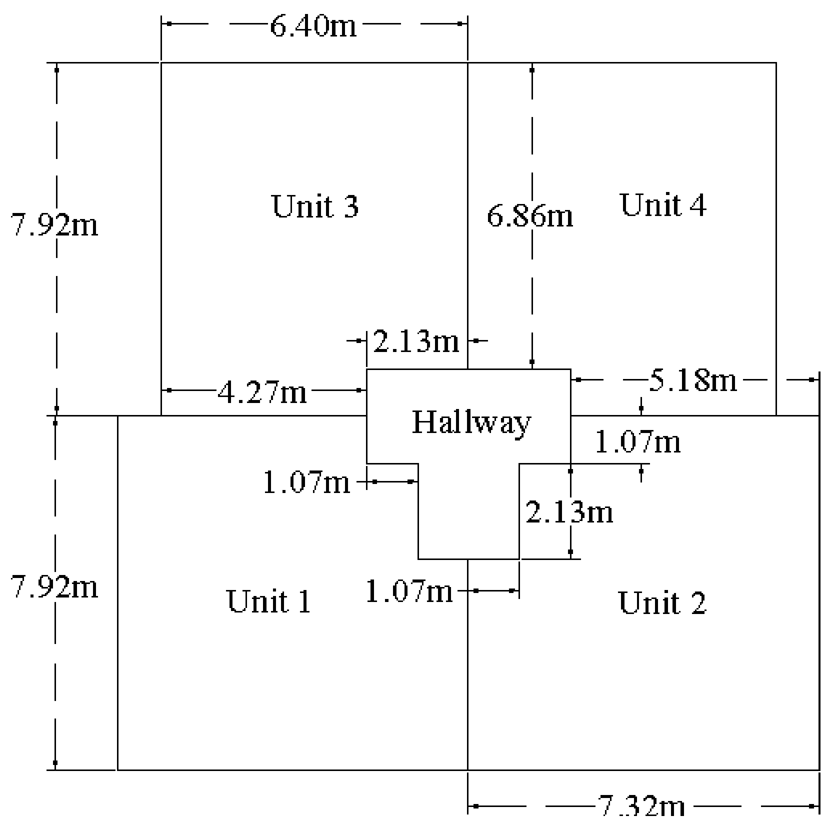


Figure 2.6 The typical floor plan of the 4-story residential building

Table 2.1 The design variables for optimization

Variable	Value
Building Orientation	(0° represents North, 45° represents Northeast, and 90º represents East)
RSI Value of Roof [m^2K/W]	(3, 4, 5)
RSI Value of Wall [m^2K/W]	(2.5, 3, 3.5, 4)
Window to wall ratio (South wall)	(10%, 13%, 16%, 19%, 22%)
U-Value Window [W/m^2k]	(1, 2, 3, 4)

Table 2.2 Cost and emission factors applied to the three scenarios

	Cost of Electricity	Cost of Natural Gas	Emission Factor of Electricity	Emission Factor of Natural Gas
Units	[$/kWh]	[$/kWh]	[kgCO_2eq/kWh]	[kgCO_2eq/kWh]
Scenario 1 (S1)	0.05	0.05	0.60	0.30
Scenario 2 (S2)	0.07	0.03	0.79	0.18
Scenario 3 (S3)	0.10	0.01	1.00	0.10

2.3.2 The hierarchical decomposition for the case study

The original optimization problem is to minimize the operating cost and carbon emission as shown below:

- Original optimization: Minimize Operating Costs and Carbon Emissions.

This optimization problem is decomposed into two subproblems solved sequentially as below:

- First level optimization: Minimize Annual Electricity Consumption and Annual Gas Consumption.
- Second level optimization: Minimize Operating Costs and Carbon Emissions.

The workflow of the original optimization problem is shown in Figure 2.7(a). After decomposition, the workflow is shown in Figure 2.7(b). The Multi-Objective Genetic Algorithm (MOGA) is chosen to generate the Pareto front for the original optimization in Figure 2.7(a) and the first-level optimization in Figure 2.7(b). The optimization platform ModeFRONTIER is selected to perform the MOGA. In this case, EnergyPlus is run from the command line module of ModeFRONTIER.

To set up this optimization, first, the range and levels of variables are defined. Next, the weather file, the idf file of the building model, and the batch file of Energyplus are imported as supporting files. Thirdly, the commands to run Energyplus are input in the Commend Line module of ModeFRONTIER. Then the design of experiment and optimization algorithm are set up. Finally, the template of the output file is imported, and the outputs to be optimized are defined. ModeFRONTIER is chosen because of its complete library of optimization algorithms, powerful pre-processing and post-processing functions, and visual programming tools. Furthermore, it provides seamless coupling with many third-party engineering programs, which can automate the simulation process.

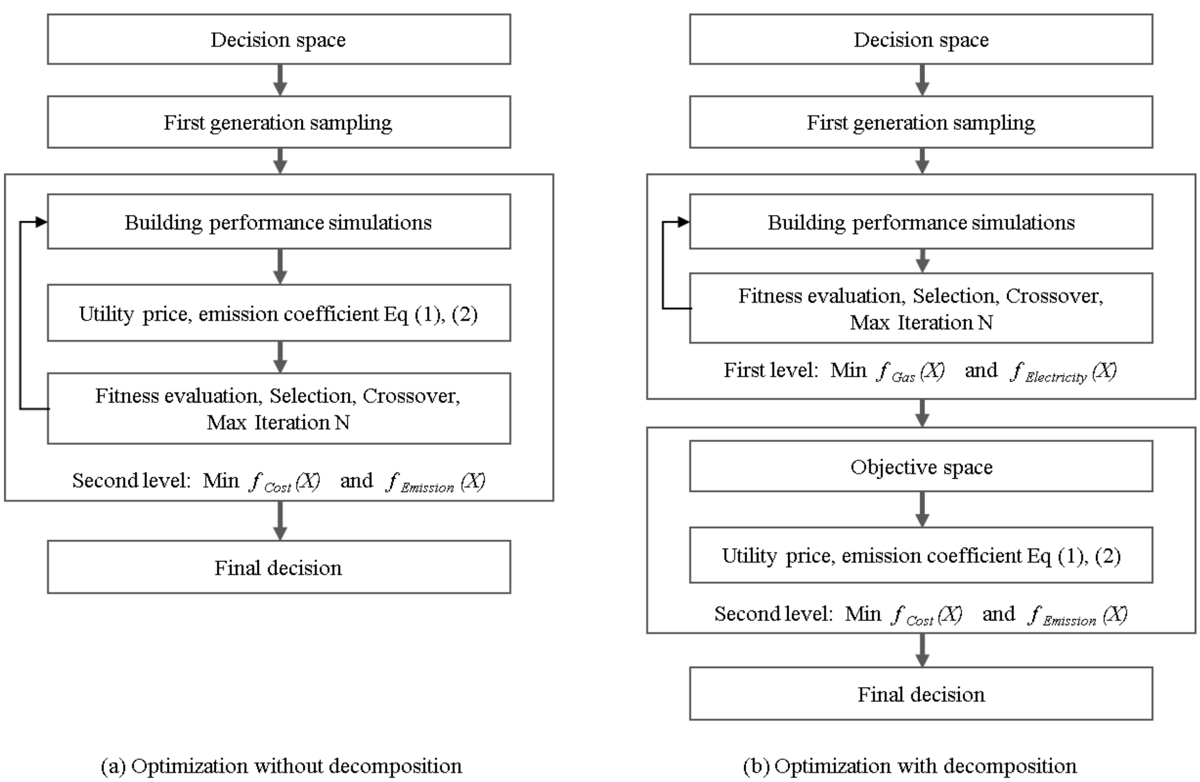


Figure 2.7 The workflow of optimizations (a) without and (b) with decomposition

For the second-level optimization, the operating costs and emissions of the solutions from the first-level optimization are calculated by Equations (2.1) and (2.2), respectively. Next, the optimal solutions can be identified by the algorithm developed by Messac et al. (2003). This algorithm compares the results of one design with the other, and the governed one is deleted. The pseudo-code of the algorithm is reprinted in Appendix 2.A for reference. The second-level optimization process is done in Excel in this study.

2.4 Results and discussion

The discussion of results has been divided into three subsections. First, in section 2.4.1, the calculation time of optimization with and without decomposition is discussed. Next, in section 2.4.2, the quality of optimization results with and without decomposition is presented. Then, in section 2.4.3, the results of optimization with decomposition are compared with the results of a full-factorial experiment to validate the effectiveness of the proposed method. Finally, in section 2.4.4, the limitation of the proposed approach is discussed.

2.4.1 Computation time comparison

For the optimization without decomposition, an initial search space of 30 configurations is first generated using Latin Hypercube Sampling (LHS) for each scenario optimization. As the optimization progresses through generations, MOGA will move to the more optimal search space. Deviation of the current search space from the previous one depends on the mutation setting, which must strike a balance between fast convergence and the consideration of all possibilities. The optimization is set to stop after 50 generations for each scenario.

For the optimization with decomposition, the initial search space of 30 configurations is generated with Latin Hypercube Sampling (LHS), and the optimization is set to stop after 50 generations for the first level energy consumption optimization. The optimal energy consumption results are processed using Equations (2.1) and (2.2) to get the operating cost and carbon s, respectively. The algorithm in Appendix 2.A is applied to the solutions of the first-level optimization to identify the Pareto front for the three scenarios.

The comparison of computation time between optimization with and without decomposition is shown in Table 2.3. For the optimization without decomposition, the simulation-based optimization is conducted three times for the three scenarios. It takes 123, 126 and 206 simulation runs to find optimal solutions for scenarios 1, 2 and 3, respectively. Each simulation takes 61 seconds. In total, the computation time is 7.84 hours. For the optimization with decomposition, the first-level optimization takes 285 simulation runs corresponding to 4.91 hours. For the second-level optimization, the optimal solutions are identified immediately for all three scenarios.

As a summary, it can be observed that the proposed decomposition approach can reduce the amount of calculation for optimization of different scenarios: For optimization without decomposition, the simulation-based optimization needs to be repeated under different scenarios. For optimization with decomposition, only the first-level optimization uses simulation. The second-level optimization involves simple data processing to generate the optimal solutions for different scenarios without running simulations.

Table 2.3 The computation time comparison between optimization with and without decomposition

Optimization without decomposition	Simulation runs	Computation time (Hours)	Optimization with decomposition	Simulation runs	Computation time (Hours)
Scenario 1	123	2.12	First level	285	4.91
Scenario 2	126	2.17	Second level (Scenario 1)	0	0
Scenario 3	206	3.55	Second level (Scenario 2)	0	0
Total	455	7.84	Second level (Scenario 3)	0	0
			Total	285	4.91

2.4.2 Quality of optimization results.

The objective space for the results of optimization without decomposition is shown in Figure 2.8. There are 6, 5, and 9 design solutions on the Pareto front for the three scenarios.

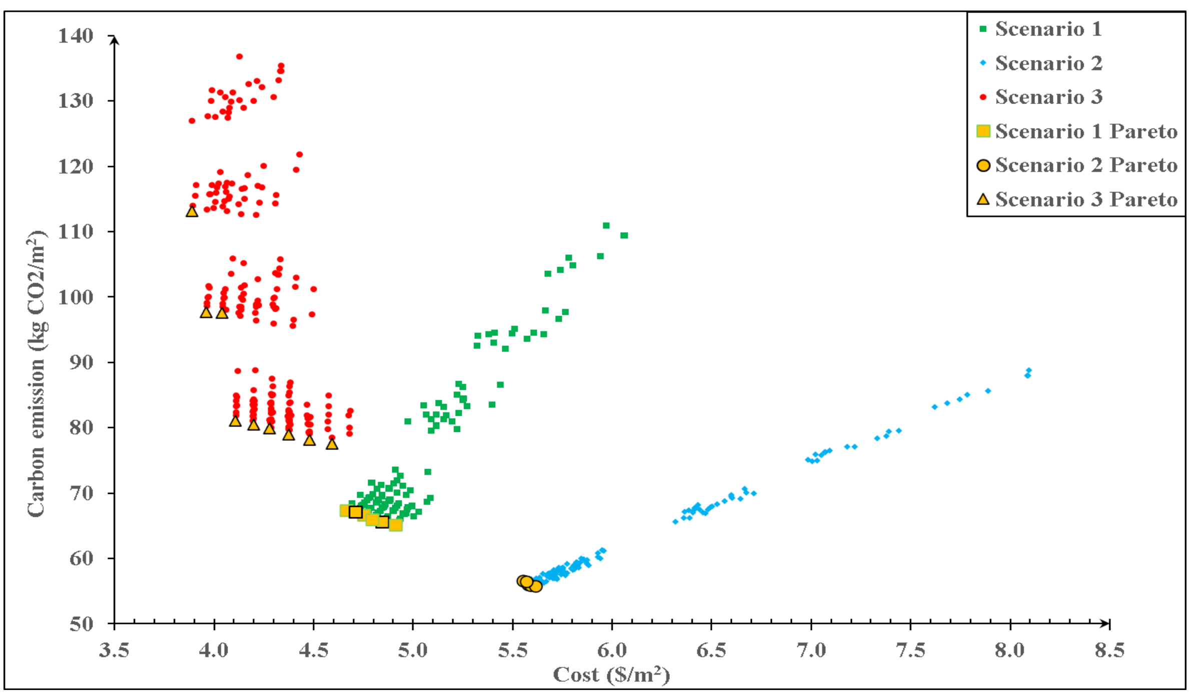


Figure 2.8 The objective space for optimization without decomposition

For the optimization results with decomposition, there are 50 optimal solutions on the Pareto front for the first-level optimization, as shown in Figure 2.9. The electricity and gas consumptions of these 50 solutions are used to calculate the carbon emissions and operating costs by Equation (2.1) and (2.2) for the three scenarios. The second-level optimization identifies the optimal solutions for each scenario, as shown in Figure 2.10. Same as the optimization results without decomposition, there are 6, 5, and 9 design solutions on the Pareto front for the three scenarios.

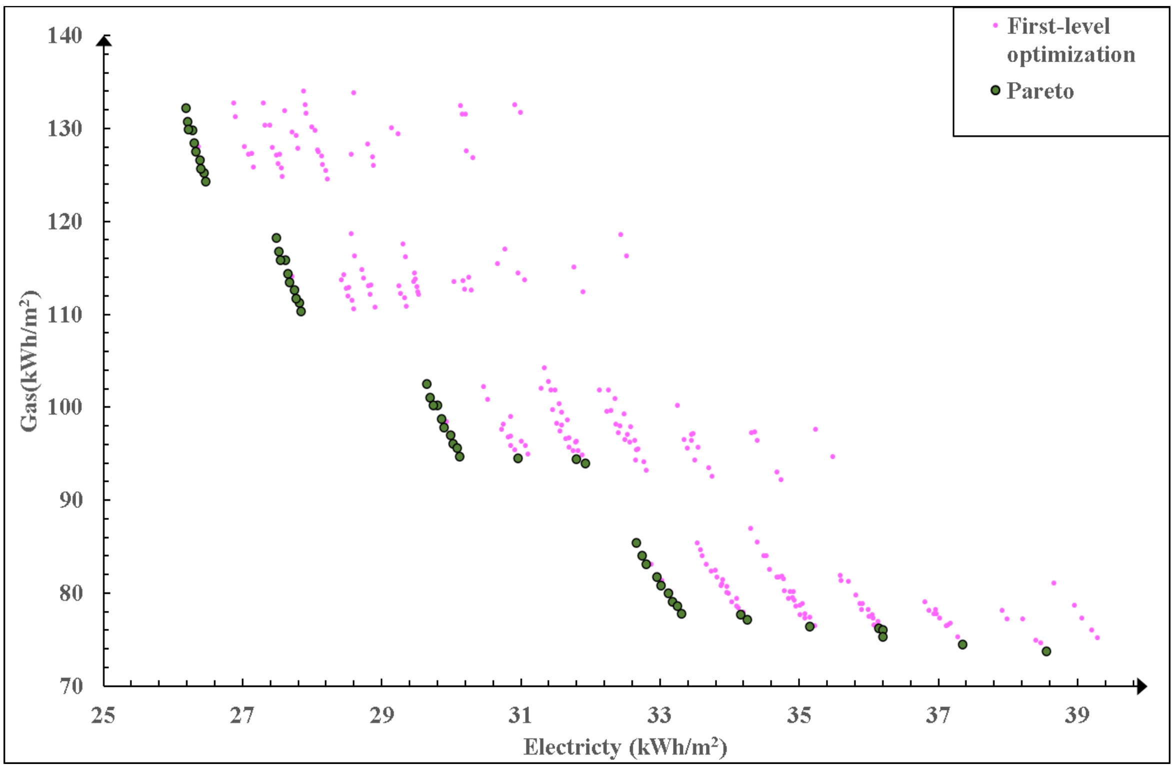


Figure 2.9 The objective space for the first-level optimization

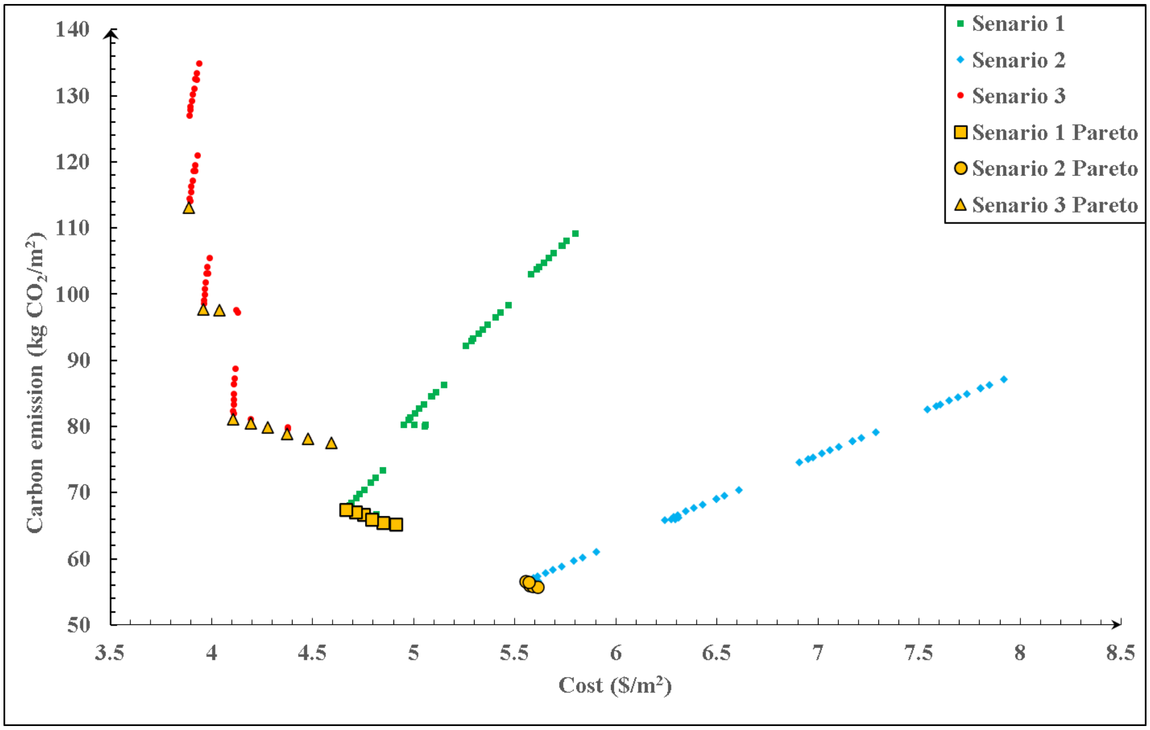


Figure 2.10 The objective space for the second-level optimization

To better compare the quality of results with and without decomposition, Table 2.4 shows the details of optimization results without decomposition. It can be found that the results of optimization with and without decomposition are the same.

Table 2.4 The comparison of the optimal solutions of optimization with and without decomposition

Optimal solution details for Scenario 1						
Design ID	Orientation (º)	RSI_roof (m^2·K/W)	RSI_wall (m^2·K/W)	U_{win} (W/m^2·K)	WWR (%)	Same for both approaches?
1	0	5	4	1	10%	Yes
2	90	5	4	1	13%	Yes
3	0	5	4	1	13%	Yes
4	90	5	4	1	16%	Yes
5	90	5	4	1	19%	Yes
6	90	5	4	1	22%	Yes
Optimal solution details for Scenario 2						
Design ID	Orientation (º)	RSI_roof (m^2·K/W)	RSI_wall (m^2·K/W)	U_{win} (W/m^2·K)	WWR (%)	Same for both approaches?

1	0	5	4	1	10%	Yes
2	0	5	4	1	13%	Yes
3	90	5	4	1	16%	Yes
4	90	5	4	1	19%	Yes
5	90	5	4	1	22%	Yes
Optimal solution details for Scenario 3						
Design ID	Orientation (º)	RSI_roof ($m^2 \cdot K/W$)	RSI_wall ($m^2 \cdot K/W$)	U_{win} ($W/m^2 \cdot K$)	WWR (%)	Same for both approaches?
1	0	5	4	1	10%	Yes
2	0	5	4	3	10%	Yes
3	0	5	4	2	10%	Yes
4	0	5	4	2	13%	Yes
5	0	5	4	1	13%	Yes
6	90	5	4	1	13%	Yes
7	90	5	4	1	16%	Yes
8	90	5	4	1	19%	Yes
9	90	5	4	1	22%	Yes

Remarks: Orientation is the building orientation, RSI_roof is the RSI value of the roof, RSI_wall is the RSI value of the wall, U_{win} is the window's U-Value, WWR is the window to wall ratio in the south facade.

This section demonstrates that the decomposed optimization can generate the same results as optimization without decomposition, using less computation.

2.4.3 The validation of the proposed approach

This section applies a full-factorial experiment to the three economic and environmental scenarios to validate optimization results with and without decomposition. As shown in Figure 2.11, the Pareto front results are identical between full-factorial experiment and the optimization results in Figures 2.8 and 2.10.

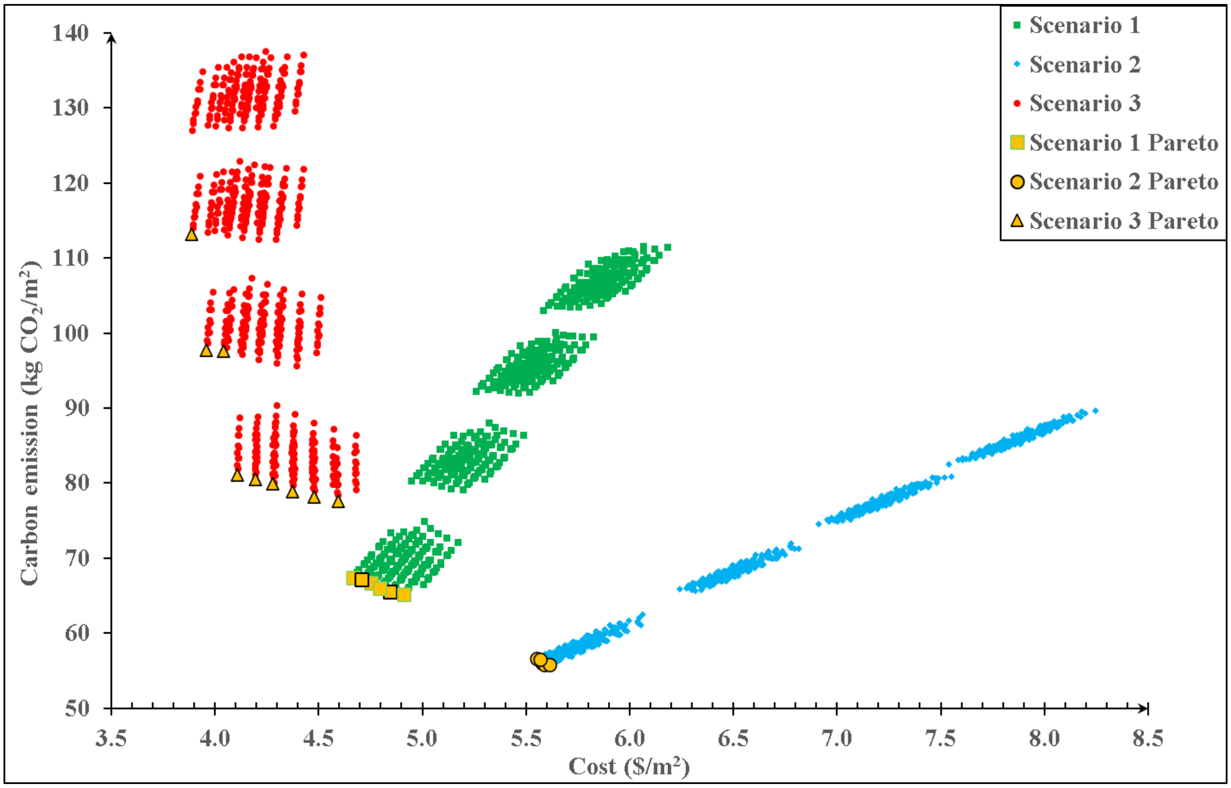


Figure 2.11 The full factorial experiments for the three scenarios.

2.4.4 Approach adjustment for limitations

The utility rate is assumed as an annual constant in this study. However, it can be flexible based on a time of use schedule. For example, the utility rate can be divided into three bands: off-peak, mid-peak, and on-peak. In such a case, the original operating costs and emissions optimization problem can be decomposed as below:

• First level optimization: Minimize Consumption(off-peak), Consumption(mid-peak), and Consumption(on-peak).

• Second level optimization: Minimize *Operating Costs* and *Carbon Emissions.*

However, when the utility rate structure is complex, the first-level energy consumption minimization will have many objectives. When the optimization objectives are more than four, the problem is referred to as a many-objective optimization (Fleming et al., 2005). Li et al. (2018) reviewed and compared the state-of-the-art approaches this type of optimization problem. One possible approach is to perform a full-factorial design experiment suggested by Lee et al. (2016). The authors applied a full-factorial design space exploration on the design of industrial halls compared with optimization. The case study demonstrated the benefits of using full-factorial design considering three objectives.

Therefore, other than applying the Genetic Algorithm for the first level optimization, the full-factorial design can be applied for the first subproblem if the objectives are more than four. As an illustration, the full-factorial experiment is applied to the case study model. Figure 2.12 shows the results of objective spaces obtained from the full-factorial experiment. The Pareto solutions obtained from the full-factorial experiment are the same as those obtained from the first-level optimization in Figure 2.9.

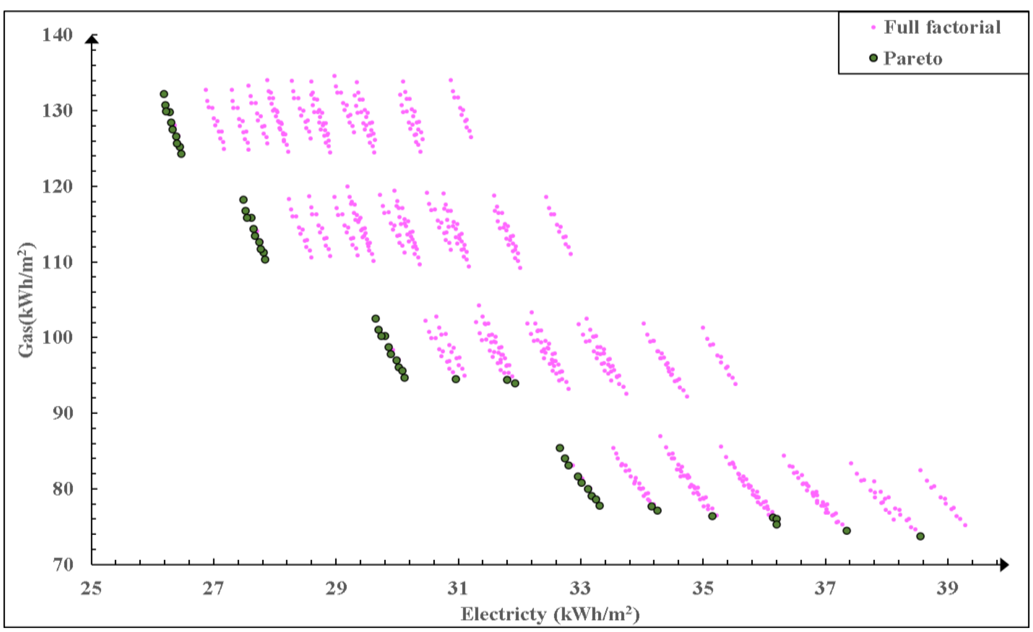


Figure 2.12 The objective spaces obtained from the full-factorial experiment for the first subproblem

2.5 Conclusion

This research proposes a hierarchical decomposition for building design optimization. The proposed decomposition transforms the original problem into several subproblems to be solved sequentially. The first subproblem is a relaxation of the original problem to ensure the global optimal solutions of the original problem. It is identified in this study that the optimization problem minimizing the energy consumption is a relaxation of the optimization problem minimizing the operating costs and emissions.

The building design optimization minimizing the operating costs and carbon emissions is used to demonstrate the approach. In the case study, the optimization with decomposition takes 285 simulations, while optimization without decomposition takes 455 simulation runs. The results are identical between these two approaches. When more cost and emission scenarios are considered, the proposed approach can avoid repeating simulation-based optimization.

There are some limitations using the proposed method, which can be investigated more in future research. This method is based on a fixed annual price, but it can also be adapted to accommodate a flexible price plan; if there are more objectives involved in the first-level optimization, the full-factorial experiment could be used to replace the optimization algorithm.

The essence of this proposed hierarchical decomposition is about problem relaxation. As future work, the proposed approach can be extended to consider the combination of building envelope and HVAC system design. Moreover, the life cycle cost and total carbon emission of the building, including the embodied energy of materials, can be investigated.

Appendix 2.A Pseudo-code for Pareto filter algorithm (Messac et al., 2003).

This algorithm identifies the Pareto solutions.

Step 1. Initialize

Initialize the algorithm indices and variables: i=0, j=0, k=1, and m=the number of generated solutions; m= f(m_k), u^i is generic i^{th} optimal objective.

Step 2. Set i=1+1; j=0.

Step 3. Eliminate non-global Pareto points by doing the following: j=j+1

If i = j go to the beginning of step 3

Else continue

If $u^i \neq u^j$ and $(u^i - u^j) \geq 0, \forall s$

Then u^j is not a global Pareto point.

Go to Step 4

Else if j = m

Then u^i is a global Pareto point

$p^k = u^i$

k=k+1

Go to Step 4

Else go to the beginning of step 3

Step 4. If i ≠ j, go to Step 2, else end.

Appendix 2.B The proof of relaxation using Proof by Contradiction.

Proof by Contradiction is used to prove that the optimization problem minimizing the energy consumption is a relaxation of the optimization problem minimizing the cost and emission. This statement can be described as that: if a design belongs to the Pareto front of cost and emissions optimization, it must belong to the Pareto front of the energy consumption optimization for any cost and emission scenario.

Proof by Contradiction is a method of proof that establishes the truth by assuming that the opposite proposition is true at first. The opposite proposition is proved false when contradiction is found. Therefore, the original proposition is automatically proven true. The process of applying the Proof by Contradiction method to prove the statement can be described in the following steps:

Step 1: The proposition is: If a design belongs to the Pareto front of cost and emissions optimization, it must belong to the Pareto front of the energy consumption optimization for any scenario of price and emission factor.

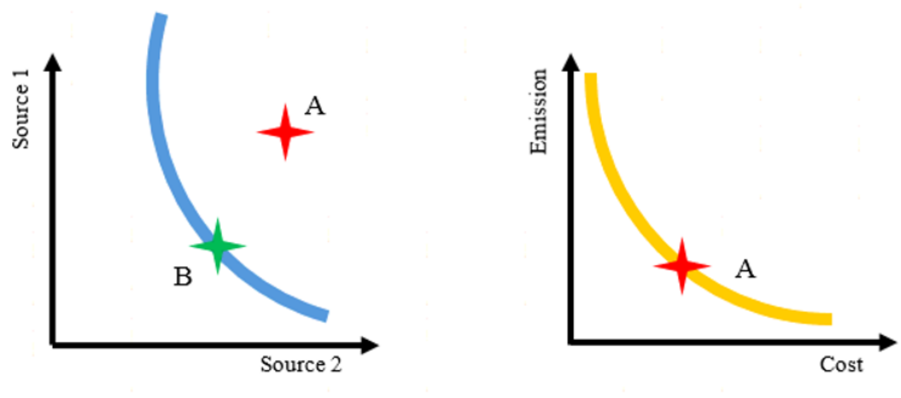
Step 2: Assume the opposite proposition is true: There exists one design (designated as design A) that belongs to the Pareto front of the cost and emissions optimization but not the Pareto front of the energy consumption optimization.

Step 3: Based on the assumption in Step 2, since this design A does not belong to the Pareto front of the energy consumption optimization, there must be one design (designated as design B) dominating design A, which means design B consumes less energy than A for every source.

Step 4: Step 3 infers that design B will also have less operating cost and emission than design A, which conflicts with the assumption that design B belongs to the Pareto front of the cost and emissions optimization.

Step 5: Since the opposite proposition leads to confliction, the original proposition is true: if one design belongs to the Pareto front of the cost and emission optimization, it must also belong to the Pareto front of the energy consumption.

Following the steps shown above, for the second step, it is assumed that one Design A belongs to the Pareto front of the cost and emission optimization in Figure 2.13 (b) but not the Pareto front of the energy consumption optimization Figure 2.13 (a).



(a) Pareto front of energy consumption (b) Pareto front of operating cost and emission

Figure 2.13 The illustration of step 2 and step 3

For the third step, since design A is not on the Pareto front of energy consumption, one design (designated as design B) must dominate A, as shown in Equation (2.3) and Figure 2.13 (a). There could be more than two types of energy sources; however, in Figure 2.13, only two energy sources are used to demonstrate the idea.

$$f_{source(i)}(B) < f_{source(i)}(A) \quad i = 1,2,3 \dots \tag{2.3}$$

For the fourth step, since the price and emission ratios are the same for all design alternatives, by Equation (2.3), it can be proved that the operating cost and carbon emissions of B dominate A for each type of energy source as shown in Equations (2.4) and (2.5).

$$Price_{source(i)} \cdot f_{source(i)}\,(B) < Price_{source(i)} \cdot f_{source(i)}\,(A) \tag{2.4}$$

$$ER_{source(i)} \cdot f_{source(i)}\,(B) < ER_{source(i)} \cdot f_{source(i)}\,(A) \tag{2.5}$$

Then by Equations (2.1), (2.4) and (2.5), it can be proved that for the total operational cost and carbon emission, design B dominates design A, as shown in Equation (2.6)

$$f_{cost}(B) < f_{cost}(A)\ and\ f_{emission}(B) < f_{emission}(A) \tag{2.6}$$

Since design B dominates A for operational cost and carbon emission, design A can does not belong to the Pareto front of cost and emission optimization. This conclusion is conflicting with the assumption in Step 2 that design A belongs to the Pareto front of cost and emission. This conflicting conclusion is shown in Figure 2.14. Therefore, this opposite proposition in Step 2 is false, which means the original proposition is 'True'. This statement can be extended in a general format as shown in methodology.

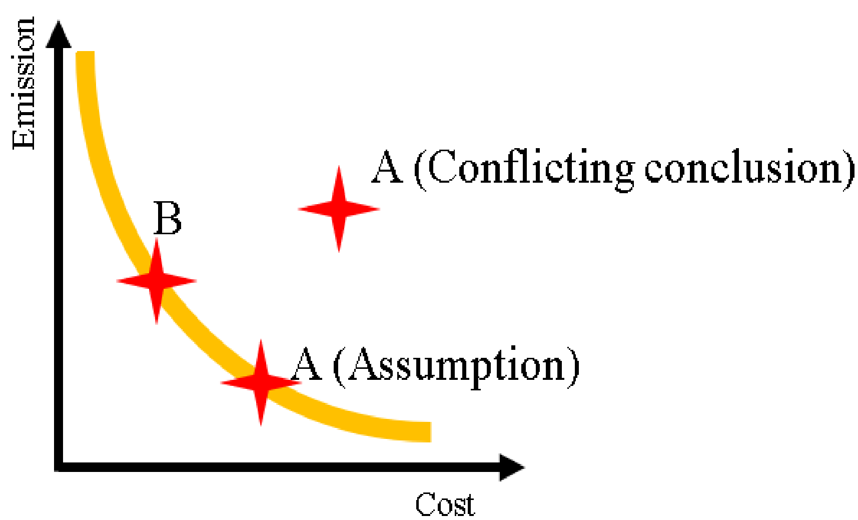


Figure 2.14 Illustration of confliction between assumption and conclusion

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Chapter 3. A Parallel Decomposition Approach for Building Design Optimization

Parallel decomposition divides the original problem into several subproblems. The first step of parallel decomposition is variable grouping, which divides variables into several groups for the subproblems. In this chapter, the variable grouping criteria are proposed to make sure the solutions of each subproblem are also the global solution of the original problem. Sensitivity analysis and interaction plots are used to assess if the variables meet the criteria. Two case studies are used to demonstrate the proposed approach. The results show that the proposed approach can achieve the global optimum as the optimization without decomposition while taking less computation time.

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Nomenclature	
Symbol	**Description**
$Depth_{OH}$	Overhang depth on east and west walls
DOE	Design of Experiments
FANOVA	Functional Analysis of Variance
GA	Genetic Algorithm

LHS	Latin Hypercube Sampling
R_{Wall}	RSI value of wall insulation
R_{Roof}	RSI value of roof insulation
SRC	Standard Regression Coefficient
U_{EW}	U value of windows on the east and west walls
U_{South}	U value of windows on the south wall
WWR_{East}	Window to Wall ratio of the east wall
WWR_{South}	Window to Wall ratio of the south wall
WWR_{West}	Window to Wall ratio of the west wall

3.1 Introduction

3.1.1 Background

Traditionally, buildings are designed using a linear design process, where elements are defined and developed in a series of isolated processes. As a result, architects, contractors, and engineers deal with each building element separately, missing the opportunity to achieve higher performance. On the other hand, energy and environmental issues are becoming increasingly prominent, and higher requirements are placed on building performance. Therefore, it is recommended to use integrated design methods in building design to achieve these goals (Robinson, 2020).

The integrated design requires the constructive cooperation of an interdisciplinary design team, including architects, engineers with different expertise, and other stakeholders from start to finish (Keeler and Vaidya, 2016). With the development of various simulation and optimization tools, integrated building design becomes technically feasible. However, this approach involves many design variables from different disciplines, which increases the dimensionality and complexity of the problem (Hong et al., 2014). Moreover, if the assumptions or constraints change, the optimization results will be invalid, and the whole design process must be repeated. When the cost of time and resources are too high for the professionals, the stakeholders will lose interest in integrated design and higher performance (Leoto and Lizarralde, 2019).

Problem decomposition that divides the original problem into smaller subproblems is one of the solutions to solve the large-scale complex problem (Kang et al., 2012). There are different types of problem decomposition. As shown in Figure 3.1 (A), the hierarchical decomposition divides the single-level optimization problem into several levels, and each level has its own objectives and constraints (Li et al., 2021). The parallel decomposition in Figure 3.1 (B) divides the problem into several subproblems and solves them separately (Yang et al., 2019).

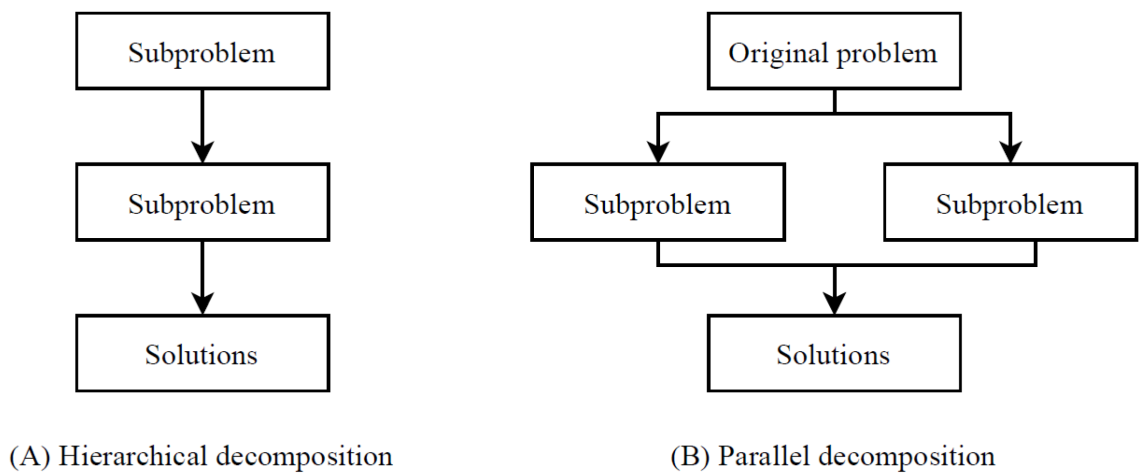


Figure 3.1 Two types of problem decomposition

Li et al. (2021) demonstrated the application and limitation of deploying hierarchical decomposition to building design. For problems without a hierarchy structure, parallel decomposition opens up opportunities that cannot be achieved with hierarchical decomposition. By Conducting the parallel decomposition, the subproblems can be solved on different machines separately (Zhang et al., 2019). This feature makes this approach very suitable for the current era of high-performance computers and cloud computing (Guo et al., 2017). Moreover, parallel decomposition provides a more efficient way to achieve the effect of integrated building design. The subproblems of a building design project can be assigned to small groups of architects, engineers, and consultants to be solved separately (Tsigkari et al., 2013). It reduces the communication time in integrated building design and increases the design process efficiency.

The general procedure applying parallel decomposition to a building design optimization problem is shown in Figure 3.2. In the first step, the variables are divided into several groups, and in the second step, the optimal solutions are found for each group. Each subproblem is independent and solved separately (Yang et al., 2016). The optimal solutions of subproblems are combined to obtain the final solutions (Boyd et al., 2008).

The key step of parallel decomposition is the variable grouping (Song et al., 2016). The variables can be grouped in different ways, but not all the variable grouping results lead to global optimum, which is the optimum of the original problem. Depending on the relationship between the variables, the variable grouping method can be based on the correlation or interaction (Hajikolaei et al., 2015). In this study, the building design variables considered are independent of each other. Therefore, this study focuses on the variable grouping methods based on the interaction between the variables.

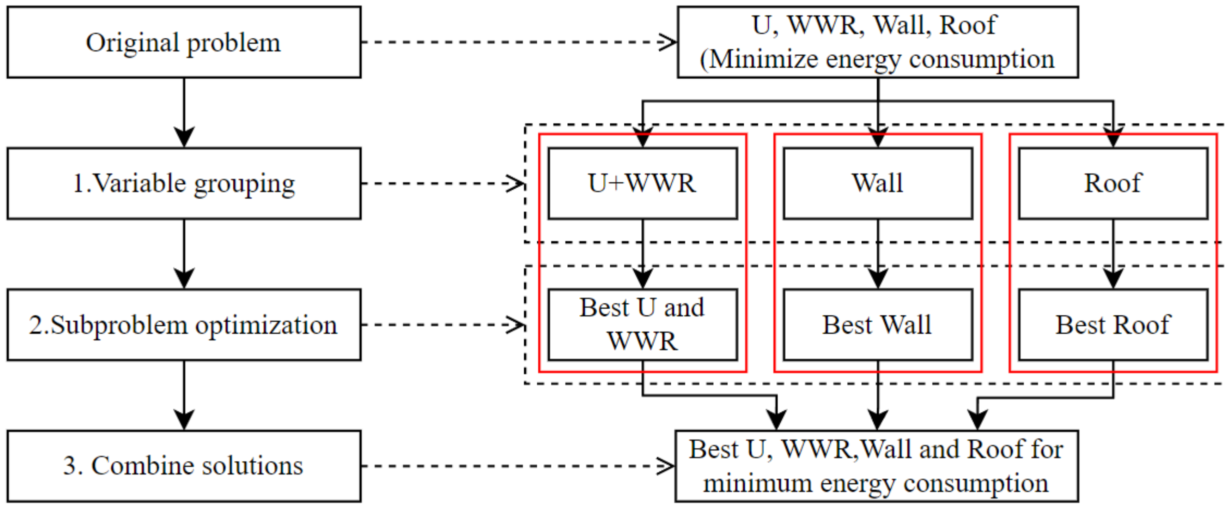


Figure 3.2. The general procedure of parallel decomposition

3.1.2 Previous work

There are two types of methods for variable grouping based on interaction: dynamic and static (Ma et al., 2018). The dynamic type of method regards the interaction between variables as a dynamic attribute and is executed during the evolution process of the optimization algorithm (Liu et al., 2020). The entire process remains intact since the variable grouping results change during optimization. In this way, the opportunity for parallel processing of integrated building design is missed. Therefore, the dynamic method is not considered in this study. The static method is usually performed before the optimization. Once the groups are determined, they remain unchanged during optimization. Therefore, the static method is investigated for the parallel decomposition in this study.

The existing variable grouping criterion of the static method focuses on whether there is an interaction. In general, this criterion is shown in Figure 3.3. First, some experiments are performed to evaluate the interaction between every two variables. If there are no interactions for two variables, the two variables are separated into different groups for optimization. Otherwise, the two are combined. All variables are divided into several groups after being assessed by this criterion. Theoretically, the decomposed optimization will achieve the global optimum of the original problem with this criterion. Because if there is no interaction between variables of different groups, the optimal solutions of the subproblems are independent of each other. As a result, the solutions are the same whether the subproblems are solved separately or combined.

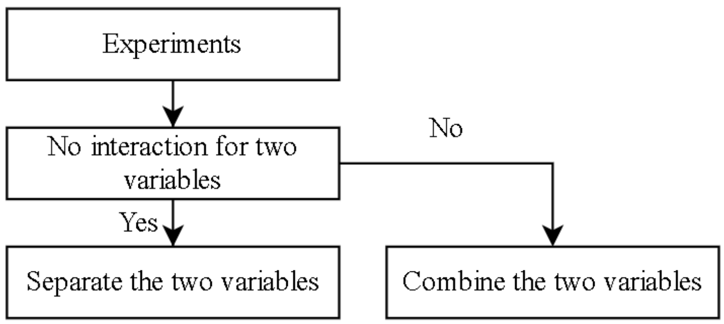


Figure 3.3. The existing criterion of variable grouping

Different studies have proposed methods to effectively assess variables for this criterion. They are applied by quantifying the different interaction indicators through a small number of experiments. If the indicator is smaller than a predefined threshold, it is assumed there is no interaction. The differential grouping method proposed by Chen et al. (2010) is one of the methods. This method performs four experiments for every two variables. The indicator is calculated by the performance difference of variables at different levels. Several researchers have studied this method, such as Sun et al. (2015), Omidvar et al. (2017) and Cao et al. (2020). There are also static methods that use sensitivity analysis to quantify the interaction for variable grouping. Ito and Dhaene (2013) proposed the interaction index derived from the Sobol method. This method screens the two-variables and three-variable interactions to decompose an optimization problem. Ivanov and Kuhnt (2014) used the Functional Analysis of Variance (FANOVA) graph to study the interactions of variables and used the information for the parallel decomposition on a sheet metal forming optimization problem.

Some issues exist when applying this existing criterion to building design optimization problems. Firstly, this criterion is mainly developed for the separable or partial separable problem (Liu et al., 2020). In this type of problem, the objective function can be expressed as an additive function, such as the function $f(x, y) = g(x) + q(y)$, where x and y are mutually exclusive variable sets (Jia et al., 2019). However, most building design variables interact, making building design optimization problems almost inseparable or can only be divided into a few subproblems. Therefore, this criterion is inefficient in reducing the dimensionality of building design optimization problems.

Secondly, the optimization results are unreliable for building design optimization problems using the existing criterion. The methods compare the interaction indicator with a threshold to determine if the interaction is small enough to be ignored. The impact of threshold on the optimization results is significant(Li et al., 2021). If the threshold is too small, all indicators are larger than the threshold, making the problem inseparable. On the other hand, if the threshold is too large, all indicators are smaller than the threshold, making all variables separated and leading to local optimum. The exact impact of the threshold on the optimization results is highly uncertain and varies from case to case, which makes the decomposed optimization results unreliable.

Thirdly, the sensitivity analysis methods, such as the Sobol method and the FANOVA, are time-consuming and unnecessary for building design optimization problems. These methods are variance-based methods that estimate both high and low-order interactions. Due to the sparsity-of-effects principle, a physical system is usually dominated by main effects and low-order interactions(George et al., 2005). Therefore, the main effect and the two-variable interactions are most likely to account for most of the contribution to the response variation. Most studies using sensitivity analysis in building design focus on the main and two-variable interactions such as Sanchez et al. (2014), Hsu (2015), Nguyen and Reiter (2015) and Yao et al. (2021). This study assumes that only two-variable interactions are considered in the variable grouping of the building design optimization problems.

3.1.3 Proposed work

Based on the issues mentioned in the previous section, this study proposes a new variable grouping criterion for building design optimization problems. Furthermore, this criterion is combined with the existing criterion as a dual-criteria variable grouping method for the parallel decomposition approach in this study. Two methods are proposed to assess each criterion effectively.

The proposed criterion is illustrated in Figure 3.4. For two variables, if the optimal solution of one variable is not impacted by another variable, they are separated. Otherwise, they are combined for optimization. As a result, after the grouping process, the optimal solutions of each group are not impacted by each other.

It can be proved that the proposed criterion will also achieve the global optimum of the original problem as the existing criterion. If the optimal solutions of one subproblem are not affected by other subproblems, the optimal solutions are the same whether the subproblem is solved individually or in combination with other subproblems. The latter ones are the global optimal solutions to the original problem. Therefore, the decomposed optimization should achieve the global optimum if the proposed criterion is effectively assessed.

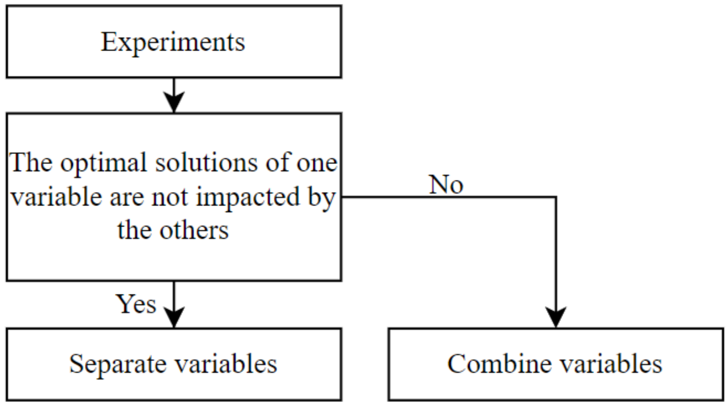


Figure 3.4. The proposed criterion

Compared with the existing criterion, the proposed criterion is more relaxed. The proposed criterion allows strong interactions between subproblems, as long as the interactions do not affect the subproblems' optimal solutions. Since the proposed criterion is qualitative, the threshold does not impact the optimization results. The comparison of the two criteria is summarized in Table 3.1. The proposed criterion is more adaptive for building design optimization problems than the existing criterion.

Table 3.1 The comparison between the existing criterion and the proposed criterion

	The existing criterion	The proposed criterion
Variable grouping criteria	No interaction between variables.	The optimal solutions of one variable are not impacted by the change of other variables.
Subproblem relationship	No interaction between subproblems.	The optimal solutions of each subproblem are not impacted by the others.
Sufficient to achieve global optimum	Yes	Yes

Allow strong interactions between subproblems	No	Yes
Impacted by threshold	Yes	No
Methods to assess if the variables satisfy the criterion	Differential grouping, Sobol, FANOVA. Regression-based SA (Proposed in this study)	Interaction plots (Proposed in this study)
Adaptability to building design optimization	Low	High

This research proposes a dual-criteria variable grouping method for parallel decomposition, as shown in Figure 3.5. The existing and proposed criteria are used as the first and second criteria, respectively. The second criterion assesses the variables that failed the first criterion. The first criterion is used to quantify the interactions between the variables. It reduces the number of investigations for the separability of variables in the second criterion.

Regression-based sensitivity analysis and interaction plots are proposed to evaluate whether the variables satisfy the first and second criteria, respectively. The proposed parallel decomposition is applied to solve the single-objective optimization problems in this study.

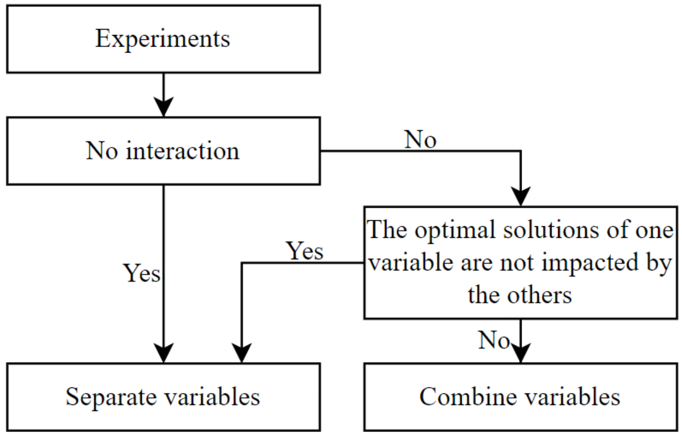


Figure 3.5. The dual-criteria variable grouping method

This study proposes the parallel decomposition approach that can reduce the computation cost while achieving global optimum. The contributions of this study are summarized as follows:

- Introduce the concept of parallel processing in integrated building design.
- Define the decomposition criteria that can achieve global optimum.
- Propose effective methods and indicators to judge whether the criteria are met.
- Provides evidence on the performance of this approach.

The remainder of this paper is organized as follows. Section 3.2 provides the development of the proposed parallel decomposition approach. Next, the proposed approach is applied to two case studies: a benchmark function and a low-rise office building described in Section 3.3. Next, the results of the case studies are summarized in Section 3.4. Then in Section 3.5, the assumptions and limitations of the proposed approach are discussed based on the case studies results. Finally, in Section 3.6, the conclusion and future work are highlighted.

3.2 Development of the parallel decomposition approach

In Section 3.2.1, the regression-based sensitivity analysis is proposed to assess if the variables satisfy the first criterion. Then, the interaction plots are proposed to assess if the variables satisfy the second criterion in Section 3.2.2. Finally, in Section 3.2.3, the parallel decomposition approach is proposed and implemented to solve the single-objective optimization problem based on Sections 3.2.1 and 3.2.2.

3.2.1 The characteristics of the studied building design optimization problems

This study focuses on the simulation-based optimization problems which integrate optimization techniques into building performance simulation. The simulation model is created based on fundamental physical principles and engineering practice. Simulation outputs such as energy consumption and carbon emissions are often used as optimization objectives. Since these objective functions are implicit, evolutionary algorithms such as genetic algorithms are often used for simulation-based optimization problems. Though the complexity caused by constraints and bounds of the optimization problems is important for decomposition, it is beyond the scope of this study. In this study, the objective function has no constraint, and the impact of variable bounds on decomposition is not discussed. The objective of the subproblems is the same as the original problem.

3.2.2 The method for the first variable grouping criterion

In the first criterion, the variable grouping depends on whether there is an interaction between variables, as shown in Figure 3.3. This study uses regression-based sensitivity analysis to quantify the two-variable interaction. The results are compared with a threshold to determine if the criterion is satisfied.

The regression-based sensitivity analysis uses the regression model in Equation (3.1) to evaluate the main and two-variable interactions (Heckert et al., 2002). The independent variable vector $X = (x_1, x_2 \ldots x_i)$ in this equation represents the design variables, and the dependent variable $y(x)$

represents the optimization objective such as energy consumption. This equation's coefficients b_i and b_{ij} evaluate the main effect and two-variable interactions, respectively. These coefficients can use quantitative sensitivity measures, such as the Standard Regression Coefficient (SRC) (Lee, 2014).

$$y(X) = b_0 + \sum_{i=1}^{k} b_i\, x_i + \sum_{j=1, j\neq i}^{k} \sum_{i=1, j\neq i}^{k} b_{ij}\, x_i x_j + \cdots \varepsilon \tag{3.1}$$

There are different Design of Experiments (DOE) methods for regression-based sensitivity analysis. The fractional factorial design is an efficient DOE method, which can control the number of experiments to achieve reliable low-order interactions results. The high-order effects are ignored by confounding with low-order effects (Heckert et al., 2002). This study uses the fractional factorial design as the DOE method for regression-based sensitivity analysis.

The fractional factorial design uses the concept of design resolution to control the number of experiments required to evaluate a certain level of interaction. Design resolutions III, IV, and V are commonly used in engineering research. The orders of interaction corresponding to these resolutions are listed in Table 3.2 (Heckert et al., 2002). The table shows that it is suitable to use resolution level V for this study because all the two-variable interactions are arranged to be investigated separately.

Table 3.2. The design resolution of fractional factorial design (Heckert et al., 2002)

Resolution level	Targeting effects
III	The main effect is not mixed with any other main effects but mixed with the two-variable interaction.
IV	Main effects are not mixed with any other main effects or two-variable interactions, but some two-variable interactions are mixed with other two-

	variable interactions, and main effects are mixed with three-variable interactions.
V	Main effects or two-variable interactions are not mixed with any other main effects or two-variable interactions, but two-factor interactions are mixed with three-variable interactions, and main effects are mixed with four-variable interactions.

As a summary, the first criterion is assessed using the regression-based sensitivity analysis method, as shown in Figure 3.6. The DOE of sensitivity analysis is the fractional factorial design. Then, SA generates the interaction indicators, and the indicators are compared with the threshold.

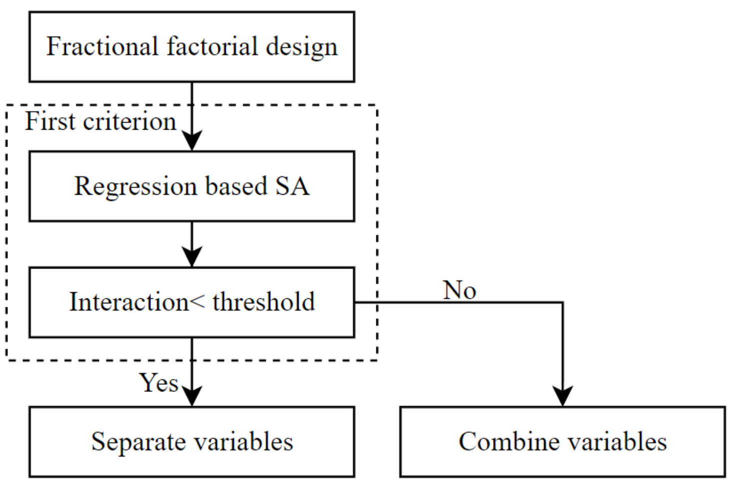


Figure 3.6. The method for the first variable grouping criterion

3.2.3 The method for the second variable grouping criterion

For the second criterion, the results of the fractional factorial design used in the first criterion can be used to assess this criterion, thereby avoiding additional experiments. Besides the interaction indicators in the previous section, the interaction plots are another analysis output of fractional factorial design. The interaction plots display the means of response for the levels of one variable on the horizontal axis and a separate line for each level of another variable. It shows how the response change of one variable depends on the value of the other variable (Heckert et al., 2002). For example, assuming there are five variables, the fractional factorial design generates 16 experiments for the five variables, according to the table in Heckert et al. (2002). Assuming one of the variables is roof insulation, and the other variable is foundation slab insulation. The response is the energy consumption of a building. Only the upper and lower boundaries of each variable are considered in the fractional factorial design. The responses of the 16 experiments are plotted to investigate the interaction between these two variables, as shown in Figure 3.7. The blue line links the mean energy consumption of maximum and minimum foundation slab insulation while roof insulation is at the lower bound. Similarly, the green line links the mean value while roof insulation is at the upper bound. This figure shows the impact of roof insulation on the performance of foundation slab insulation. The 16 experiments can be used to generate the interaction plots for each two of the five variables. These plots are used to assess if the second criterion is met.

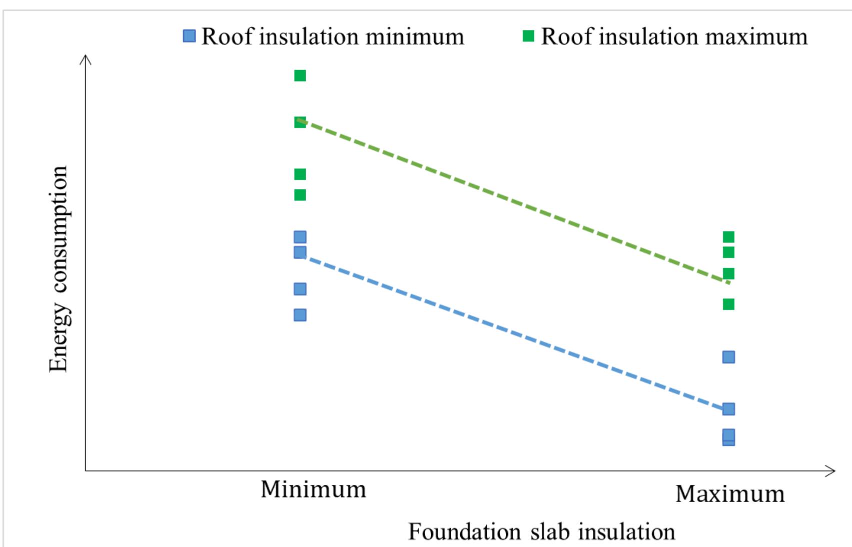


Figure 3.7. The example of the two-variable interaction plot

There are different types of two-variable interactions, as shown in Figure 3.8. The two dependent variables are designated as x and y. The upper and lower bounds of the two variables are designated as x2, y2 and x1, y1. If the two lines are parallel, it is assumed there is no interaction between two variables, as shown in Figure 3.8 (A). In this case, the two variables are separated for optimization. If the two lines are not parallel, the interaction effects can be categorized as synergetic or antagonistic (Lim et al., 2020).

If the interaction is synergetic, the performance of one variable is considered to be enhanced by the change of another variable. In such a case, it is assumed that the optimal level of one variable is not changed for different levels of another variable. For example, to minimize the response, the design with x_1 has a smaller response than the design with x_2 regardless of the value of y, as shown in Figure 3.8 (B). Therefore, x and y can be optimized separately.

If the interaction is antagonistic, the performance of one variable is considered to be weakened by the change of another variable, as shown in Figure 3.8 (C), (D) and (E). If the slope sign does not change, as shown in Figure 3.8 (C), it is assumed that the optimal solution of one variable remains the same regardless of the change of another variable. In such a case, the two variables are separated for optimization. If the slope sign changes, it is assumed that the optimal solution of one variable is impacted by the change of another variable, as shown in Figures 3.8 (D) and (E). In such a case, the two variables are combined for optimization.

If the interaction is a mixed effect, the performance of one variable will be weakened and then enhanced by the change of another variable, as shown in Figure 3.8 (F). Since the slope sign does not change, it is assumed that the optimal solution of one variable remains the same regardless of the change of another variable. Therefore, the two variables are separated in such a case.

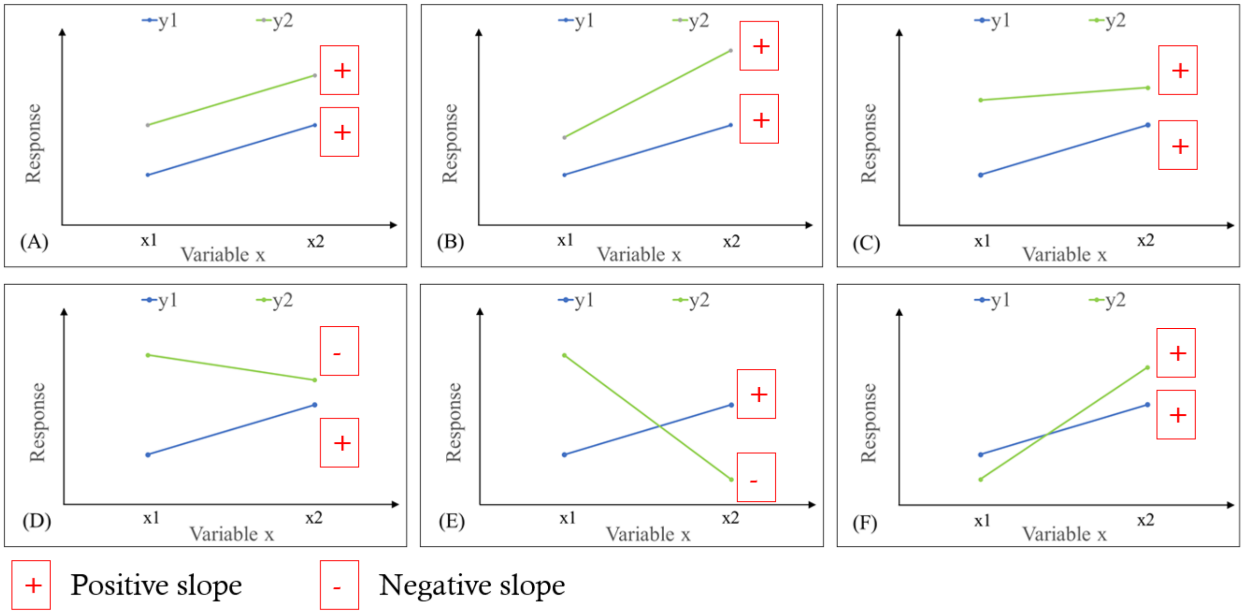


Figure 3.8. The interaction plots for different types of two-variable interactions

As a summary, the second criterion is assessed using the interaction plots as shown in Figure 3.9. If the slopes of the two lines in the interaction plots are the same, the two variables are separated for optimization. Otherwise, the two variables are combined. Interaction plots appear in pairs when the horizontal axis variable switch to the other. Therefore, the pairs of interaction plots for two variables should be examined when determining whether two variables can be separated.

These interaction plots are generated from the data of the fractional factorial design. The fractional factorial design is a fraction of full factorial design. Therefore, the interaction plots reflect the prediction other than the true two-variable interaction. However, the three-variable interactions and above are negligible due to the sparsity-of-effects principle. Therefore, the interaction plots should be sufficient to represent the two-variable interaction and assess if variables satisfy the criterion. The effectiveness of this method will be verified in the case study.

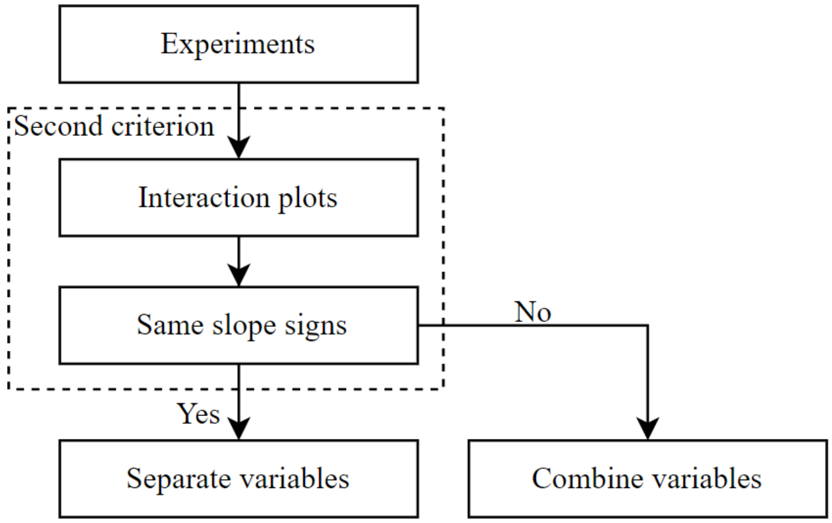


Figure 3.9. The method for the second variable grouping criterion

3.2.4 The proposed parallel decomposition approach

The two methods in Sections 3.2.1 and 3.2.2 are combined as the dual-criteria variable grouping method. As shown in Figure 3.10, first, the fractional factorial design is generated, and the resolution level is V. Then simulations are performed for the generated experiments, and the results are used to obtain the interaction indicators. All the interaction indicators are assessed if they are less than the threshold. If so, the two variables are separated. Otherwise, the pair of interaction plots are generated for the two variables using the results of fractional factorial design. If the slope signs of the two lines in each interaction plot are the same, the two variables are separated for optimization. Otherwise, they are combined.

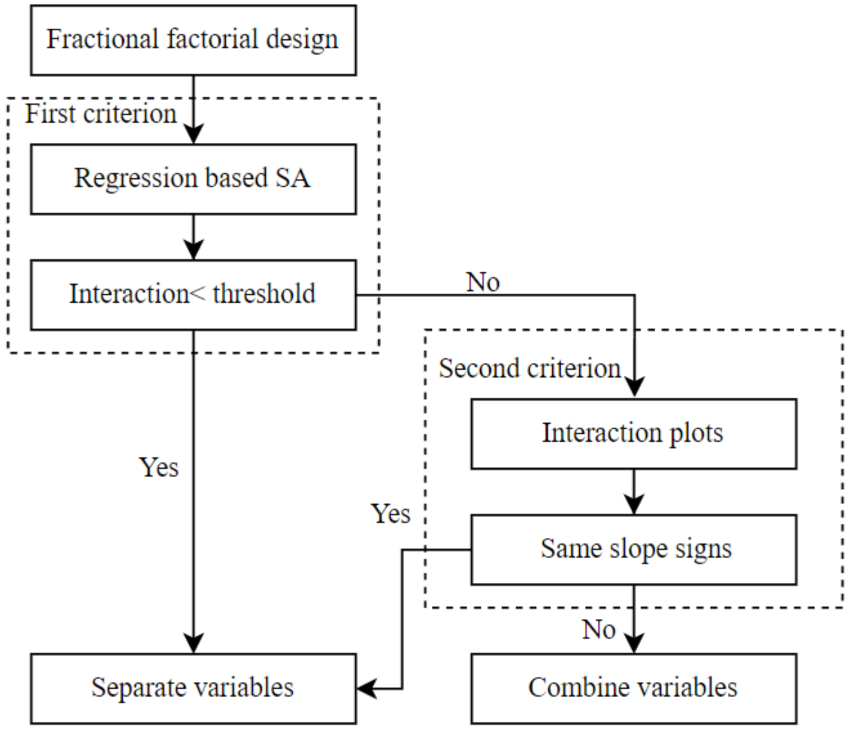


Figure 3.10. The dual-criteria variable grouping method

The dual-criteria variable grouping method is applied for the parallel decomposition of the single-objective optimization problems. This approach is divided into three steps, as shown in Figure 3.11:

Step 1: Divide the variables into several groups using the dual-criteria variable grouping method.

Step 2: Optimize each subproblem separately while the variables in other subproblems use the default values. The objective function of each subproblem is the same as the original problem, and the default values are chosen arbitrarily for each variable.

Step 3: The solutions of all subproblems are combined for the final result.

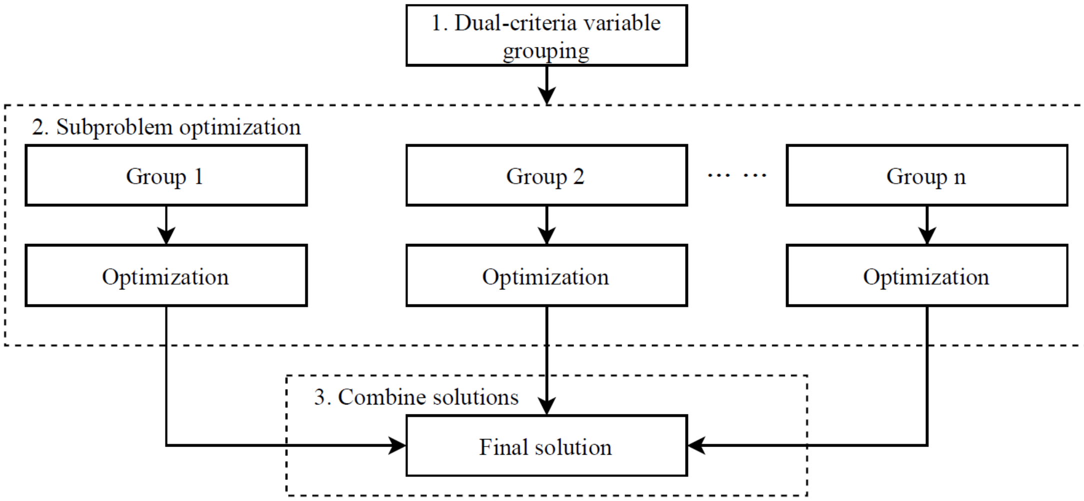


Figure 3.11. The proposed parallel decomposition for single-objective optimization problems

3.3 Case studies

Two case studies are used to demonstrate the application and performance of the proposed approach. The benchmark function is used as the first case study to validate the approach by comparing it with the results in other studies. The second case study presents a low-rise office building to demonstrate the details in applying the proposed approach in an integrated building design. The two case studies are introduced in Sections 3.3.1 and 3.3.2, respectively. MINITAB and ModeFRONTIER are used in this study to facilitate the proposed approach for the case studies. MINITAB generates the fractional factorial design, sensitivity analysis and interaction plots. ModeFRONTIER automates the function evaluation and simulation process, and it is also used to combine optimization with simulation. The building simulation is performed by EnergyPlus 9.0. The practical workflow is shown in appendix B for the reader to apply the proposed approach.

3.3.1 Benchmark function

In applied mathematics studies, many test functions are used to evaluate the performance of optimization algorithms. The Schwefel function is selected as the first case study to evaluate the performance of the proposed approach. The function is defined as in Equation (3.2).

$$f(X) = f(x_1, x_2, \dots x_n) = 418.9829n - \sum_{i=1}^{n} x_i \sin\left(\sqrt{|x_i|}\right) \tag{3.2}$$

Where $-500 \leq x_i \leq 500$. This function can be defined on n-dimensional space. Figure 3.12 shows the function response when there are only two variables. The x-axis is the first variable x_1, and the y-axis is the second variable x_2. The z-axis is the function response f(X). The colour scheme uses red for maximum value and blue for the minimum value. As the figure shows, this function contains many local optimums, making it hard to find the global optimum. This function is challenging for optimization algorithms because the algorithm easily converges to a local optimum.

In this study, the dimension is set to ten. Therefore, there are 10 variables. The global minimum of this function is close to 0 at X^*= [420.9687, …, 420.9687] (Ivanov and Kuhnt, 2014). Other studies have applied different methods to solve the 10-dimensional Schwefel function minimizing problem: Liang et al. (2006) conducted the comprehensive learning particle swarm optimizer; Awad et al. (2018) applied an improved differential evolution algorithm using the efficient adapted surrogate model. The results of these studies are compared with the results using the proposed approach. The Genetic Algorithm is also used in this study as a comparison. For the optimization using GA, the initial search space of 2000 experiments is generated using LHS, and the optimization is set to stop when the objective function of the best solution has the same value for two consecutive iterations.

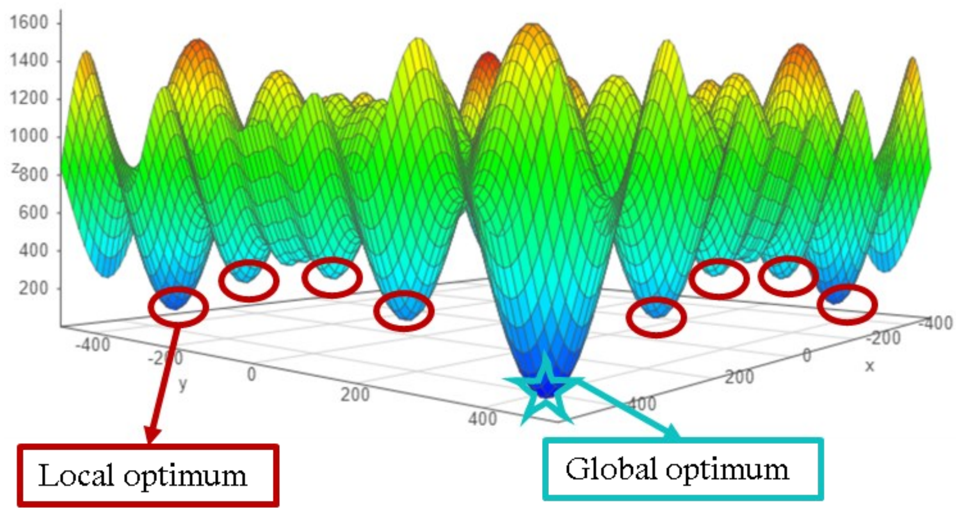


Figure 3.12. Local and global optimums in the two-dimensional Schwefel function

3.3.2 The small office building model

The second case study is a low-rise office building model developed based on the ASHRAE Standard 90.1 prototype building model using EnergyPlus, as shown in Figure 3.13. The model is simulated for an entire year using the weather file of Montreal, Canada. The building has four perimeter zones and one central core. The heating setpoint is 21 °C from 7:00 to 19:00, and the setback is 15 °C from 19:00 to 7:00. The cooling setpoint is 24 °C from 7:00 to 18:00, and the setback is 29 °C from 18:00 to 7:00. For each zone, the occupancy is assumed to be 16.6 m^2/person, the lighting load is 6.88 W/m^2, and the equipment load is 6.78 W/m^2. The building is a lightweight wood frame construction with insulated walls, roof, and concrete slab on grade.

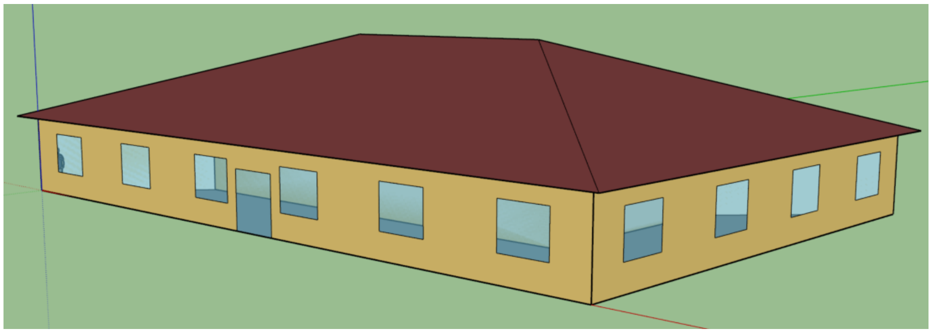


Figure 3.13. The low-rise office building model.

The single-objective optimization problem is to find the minimum annual energy consumption of the case study building. There are eight design variables, as shown in Table 3.3. This study considered both architectural and engineering variables to demonstrate the benefits of parallel decomposition for integrated building design. The first four variables are architectural design parameters, including the window-to-wall ratios at different facades and the overhang depth. The last four variables are the engineering parameters, including the RSI values of walls and the roof and the U-value of windows on different facades.

Table 3.3. The design variables for optimization

Architectural Variables					
Variable	Range	Interval	Unit	Levels	Default value
WWR_{East}	10% - 50%	10%		5	50%
WWR_{South}	10% - 50%	20%		3	50%
WWR_{West}	10% - 50%	20%		3	50%
$Depth_{OH}$	0.1 - 0.9	0.4	m	3	0.1
Engineering Variables					
Variable	Range	Interval	Unit	Levels	Default value
U_{EW}	1.0 - 3.0	1	$W/m^2.K$	3	3.0
U_{South}	1.0 - 3.0	1	$W/m^2.K$	3	3.0
R_{Wall}	3.0 - 7.0	2	$m^2.K/W$	3	3.0
R_{Roof}	4.6 - 8.6	2	$m^2.K/W$	3	4.6

3.4 Results

3.4.1 Benchmark function

3.4.1.1 Optimization results

The parallel decomposition approach divides the benchmark function optimization problem into ten subproblems. Each subproblem contains one variable, and the optimal solution for each subproblem is the same, which is $X_i = 420.9687$. Accordingly, the minimum value of *f(X)* is 1.272 $\times 10^{-4}$. The details of the results for each step are shown in Appendix A.

3.4.1.2 Comparison of optimal solution and computation time

The results show that the optimal solution $X_i = 420.9687$ found by the proposed approach is the same as other studies (Ivanov and Kuhnt, 2014).

To compare the computation time, the optimization convergence curve is plotted and compared with results using GA in Figure 3.14. The Y-axis is the best objective function value obtained during the optimization process, and the X-axis is the optimization history. The optimization with parallel decomposition takes 2411 runs in total. The subproblems are optimized simultaneously, and the history is not continuous. However, to compare the convergence efficiency with other methods, the convergence curve is shown for subproblems from X_1 to X_{10}. GA takes 88911 runs to find the optimal solution. The results from other studies are converted in the same scale and plotted in Figure 3.14. It can be seen from Figure 3.14 that the proposed approach converges to the optimal solution the fastest among the studied methods.

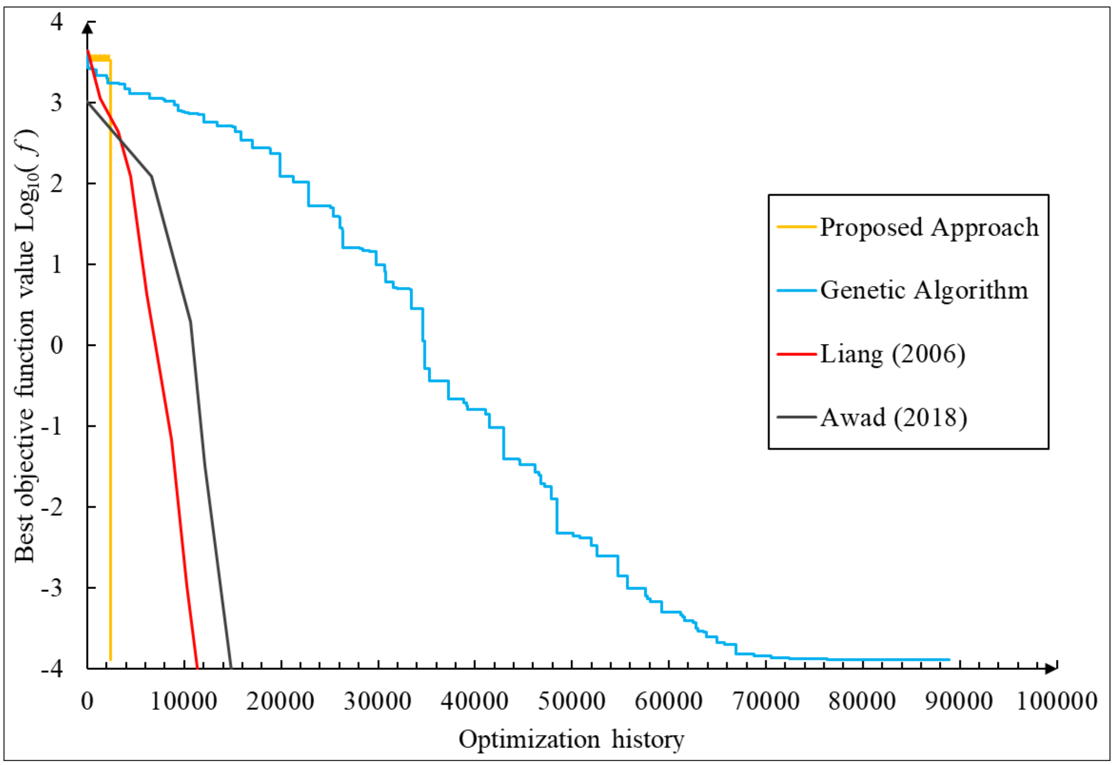


Figure 3.14. The convergence curves of different approaches

3.4.2 Parallel decomposition for the low-rise office building optimization.

3.4.2.1 Optimization results

For step 1, the fractional factorial design is first generated. For eight variables, 64 experiments are required considering design resolution V. The sensitivity analysis results are shown in Table 3.4 as a matrix. The diagonal numbers represent the main effects of each variable, and the other cells represent the interactions for every two variables. The threshold value is set to 0.005. The interaction cells with a value higher than the threshold are highlighted in Table 3.4. The interaction plots are generated for all these highlighted interactions. The sign of slope changes only between U_{South} and WWR_{South}, as shown in Figure 3.15. Therefore, these two variables are grouped and optimized together. In summary, the eight variables in this case study are divided into seven groups, as shown in Figure 3.16.

Table 3.4. The interaction indicator matrix for annual energy consumption.

	$Depth_{OH}$	R_{Roof}	U_{EW}	U_{South}	WWR_{East}	WWR_{South}	WWR_{West}	R_{Wall}
$Depth_{OH}$	0.0335	0.0018	0.004	0.0015	0.0166	0.0048	0.0189	0.0106
R_{Roof}	0.0018	0.46	0.0106	0.0111	0.0184	0.0252	0.0156	0.0033
U_{EW}	0.004	0.0106	0.4356	0.0101	0.1185	0.0224	0.1258	0.005
U_{South}	0.0015	0.0111	0.0101	0.2867	0.008	0.1451	0.007	0.007
WWR_{East}	0.0166	0.0184	0.1185	0.008	0.37	0.0206	0.0148	0.0259
WWR_{South}	0.0048	0.0252	0.0224	0.1451	0.0206	0.0475	0.0171	0.0382
WWR_{West}	0.0189	0.0156	0.1258	0.007	0.0148	0.0171	0.4743	0.0244
R_{Wall}	0.0106	0.0033	0.005	0.007	0.0259	0.0382	0.0244	0.2789

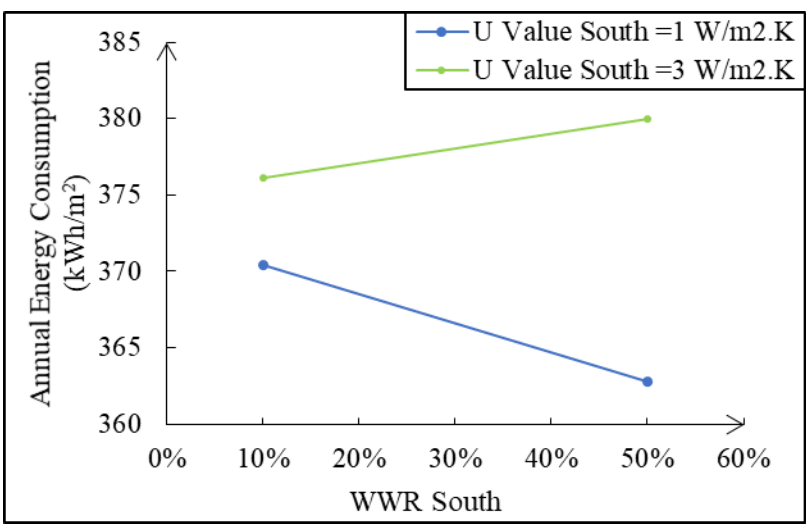


Figure 3.15. The interaction plot for WWR_{South} and U_{South}

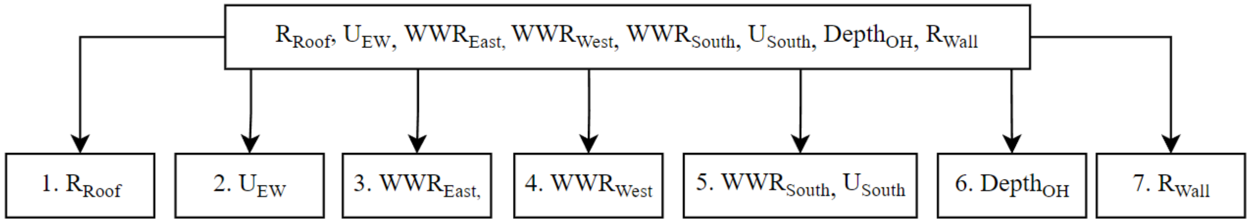


Figure 3.16. The results of variable grouping and generated subproblems

For step 2, all the subproblems are optimized separately. The variables that are not considered in one subproblem use the default value. The results are shown in Figure 3.17 (A)-(G). Because there is only one variable in most subproblems, all possible solutions are evaluated for each subproblem. For subproblem 5, for combinations of 3 levels of U_{South} and 5 levels of WWR_{South}, there are 15 experiments in total.

For step 3, the solutions of the subproblems are combined for the final solution. As a result, the proposed approach achieves the minimum energy consumption of 323.25 kWh/m^2.

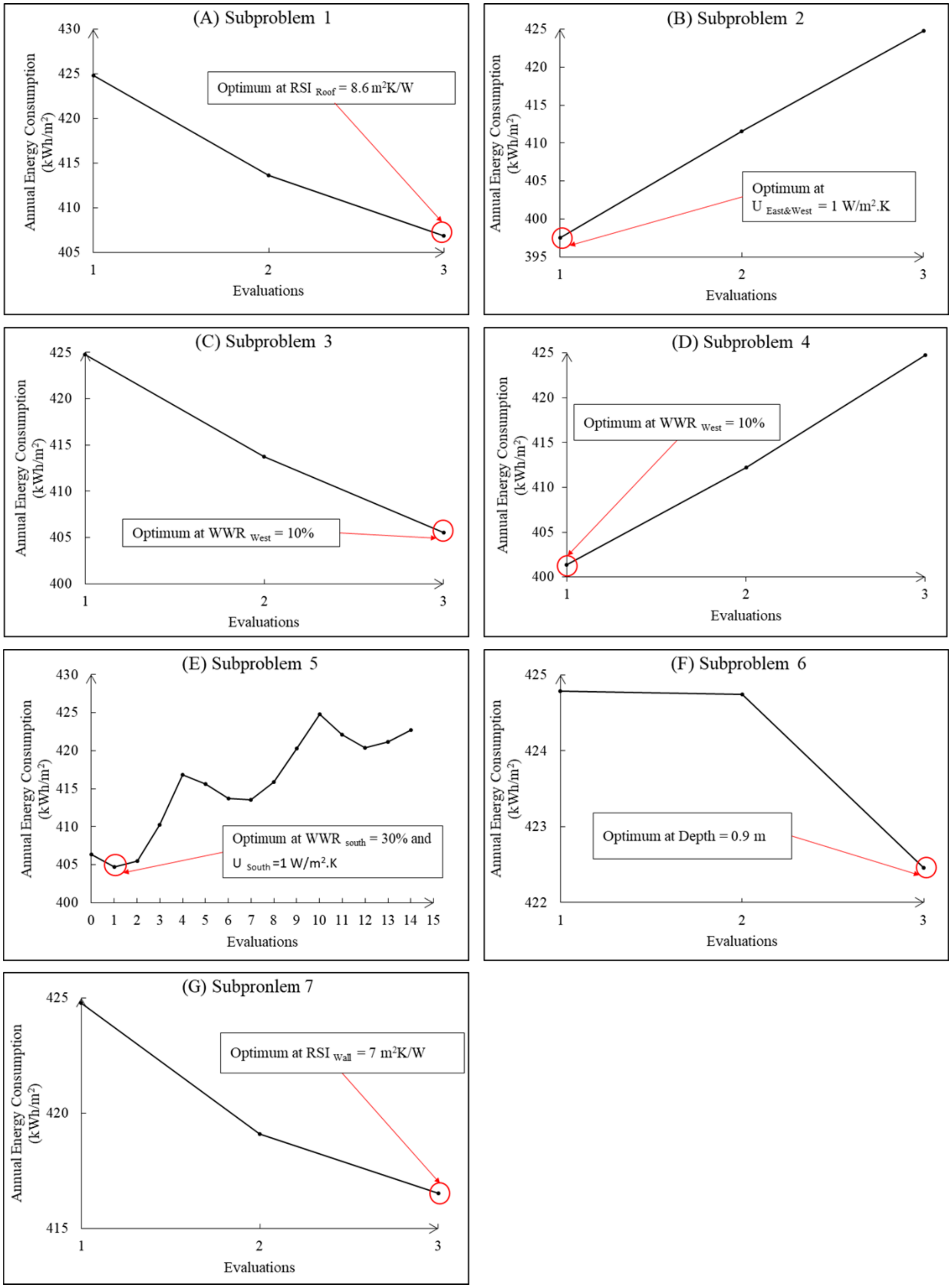


Figure 3.17. The subproblems optimization for the low-rise office building.

3.4.2.2 Comparison of optimal solution and computation time

To compare the optimal solution, the Genetic Algorithm and full factorial design are applied to optimize the building model. The optimal solutions of the proposed method, Genetic Algorithm and full factorial design, are shown in Table 3.5. It can be seen from the table that the optimal solutions are identical between these approaches.

Table 3.5. The optimal solutions comparison

Variable	Proposed method	Genetic Algorithm	Full factorial design	Unit
WWR_{East}	10%	10%	10%	
WWR_{South}	30%	30%	30%	
WWR_{West}	10%	10%	10%	
$Depth_{OH}$	0.9	0.9	0.9	m
U_{EW}	1	1	1	$W/m^2.K$
U_{south}	1	1	1	$W/m^2.K$
RSI_{Wall}	7	7	7	$m^2.K/W$
RSI_{Roof}	8.6	8.6	8.6	$m^2.K/W$

For the comparison of the computation time, the proposed approach is compared with optimization with GA. The initial search space of 50 experiments is generated using LHS. The optimization is set to stop when the objective function of the best solution has the same value during two consecutive iterations. The algorithm takes 213 runs, as shown in Figure 3.18.

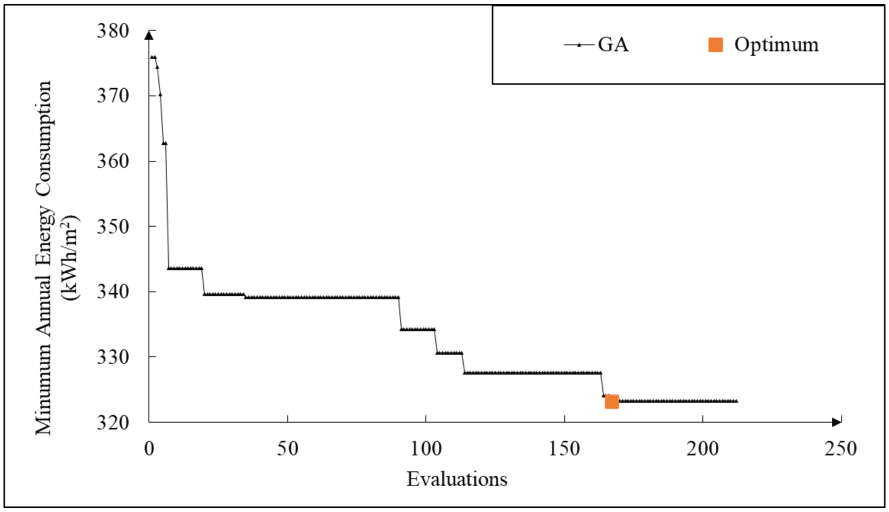


Figure 3.18. The optimization results without parallel decomposition

The comparison of computation cost is shown in Table 3.6. As it shows in the table, the optimization with parallel decomposition takes 98 runs, and the optimization without decomposition takes 213 runs.

Table 3.6. The computation cost for optimization with and without decomposition

Proposed approach	Simulation Runs	Comparison approach	Simulation Runs
Step 1. Variable grouping	64	GA	213
Step 2. Subproblem optimization	33		
Step 3. Combine solutions	1		
Total	98	Total	213

3.5 Discussion

3.5.1 The effectiveness of the methods to assess the criteria

Each subproblem is solved while the variables in other subproblems use the default values. As shown in Table 3.1, when applying the variable grouping criteria, as an outcome, the optimal solutions of each subproblem should stay the same regardless of the value of variables in other subproblems. Therefore, the choices of default values should not impact the optimal solutions of each subproblem. However, the sensitivity analysis and interaction plots might not be totally effective in achieving this result. The full factorial design is conducted to evaluate if each subproblem has the same results while the variables in other subproblems change.

For example, subproblem 7 in the second case study only has one variable, which is WWR_{West}. The optimal solution for this subproblem is WWR_{West} = 10%. It is solved while other variables use the default values in Table 3.3. The optimal solution is expected to be the same while the variables in other subproblems change. Therefore, this subproblem is solved for all possible scenarios of variable combinations in other subproblems. There are 3 levels × 3 levels × 3 levels × 3 levels × 3 levels × 3 levels × 5 levels = 3645 scenarios for subproblem 7 in total.

The results of subproblem 7 under different scenarios are shown in Figure 3.19. The X-axis is the three levels of WWR_{West}, and Y-axis is the optimization objective, the annual energy consumption. Each of the lines represents the results of subproblem 7 under one scenario. The slopes of these lines change very little, and the graph appears as strips of different colours. These lines are all monotonically increasing, implying that the smallest feasible value of WWR_{west} is optimal in every scenario. In such a case, the optimal level of WWR_{west} is always 10%, regardless of the level of other variables.

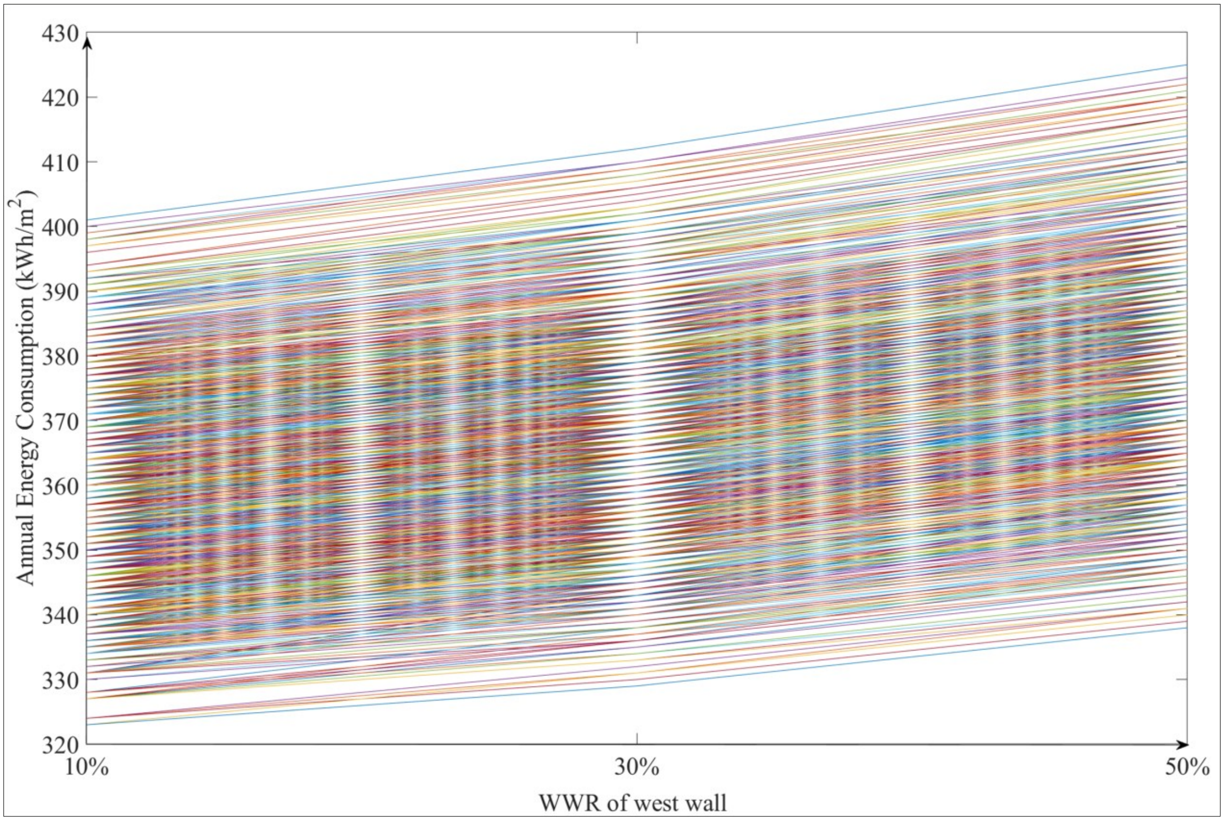


Figure 3.19. All scenarios of subproblem 7

The concordance rate is used to describe the effectiveness of the proposed methods. It is obtained by dividing the number of scenarios that have the same optimal solution as the global one with the number of total scenarios. It is defined as the percentage of a subproblem achieving the global optimum out of all scenarios.

For subproblem 7, the concordance rate is 100%. Table 3.7 shows the concordance rate for each subproblem. For subproblems 1, 2, 3, 4, 7, the concordance rate is 100%. That means the optimal solutions of these subproblems are not impacted by any other subproblems. The concordance rate is high for subproblem 6, which is 92%. For subproblem 5, the concordance rate of WWR_{South} and U_{South} of all scenarios are 54% and 100%, respectively. It can be seen that the proposed methods with SA and interaction plots are very effective in assessing the criteria.

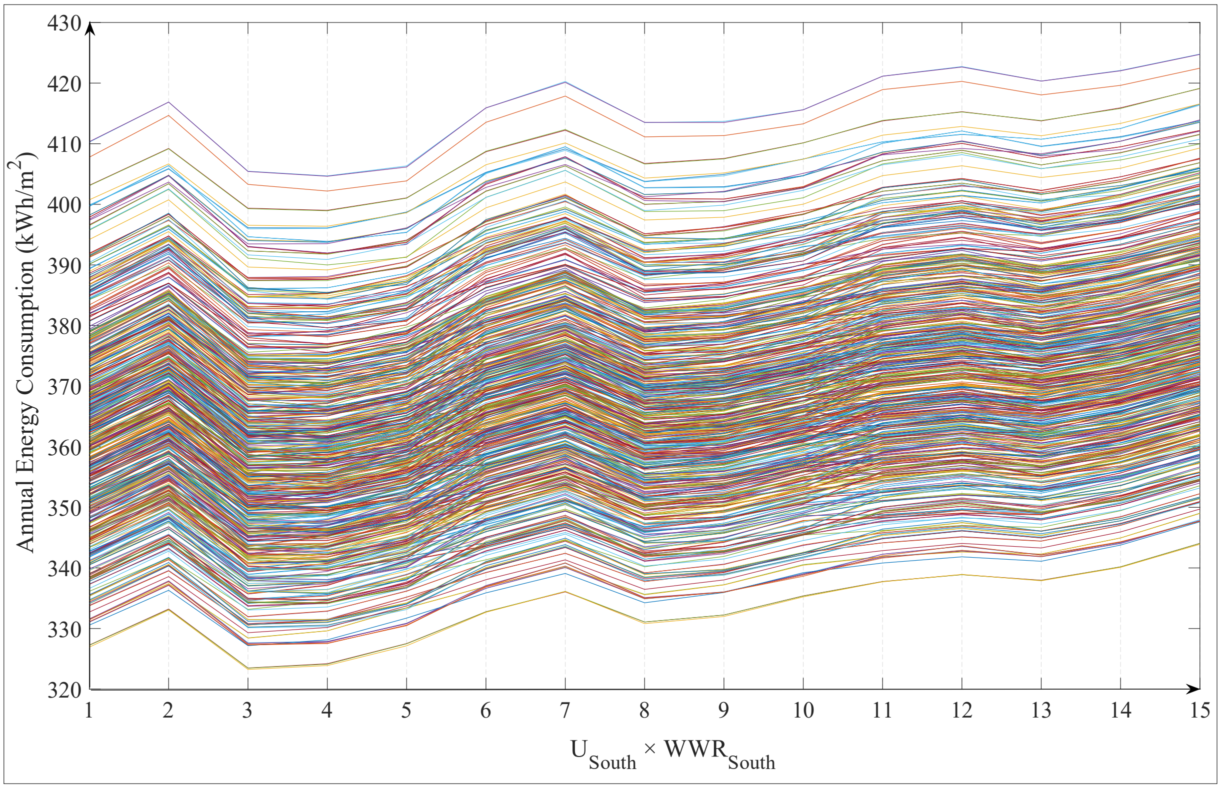
Table 3.7. Validation of variable grouping results.

Subproblem	Variable		Number of total scenarios	Number of scenarios that have the same solution as the global one	Concordance rate
1	R_{Roof}		3645	3645	100%
2	U_{EW}		3645	3645	100%
3	WWR_{East}		3645	3645	100%
4	WWR_{West}		3645	3645	100%
5	$WWR_{South} \times U_{South}$	WWR_{South}	729	729	100%
		U_{South}	729	391	54%
6	$Depth_{OH}$		3645	3341	92%
7	R_{Wall}		3645	3645	100%

3.5.2 The solving sequence of subproblems

In most cases, the optimal solutions of subproblems are not impacted when the default values of variables in other subproblems change, as shown in Table 3.7. However, there is still a chance the subproblem will achieve the local optimum other than the global optimum when the default values of variables change. This issue can be improved by arranging the order to solve the subproblems. It is suggested to optimize the subproblems from the one with the strongest main effect to the weakest main effect. As some of the subproblems are resolved, the influence of interaction is gradually reduced. Because the main effects usually dominate the response variation, the subproblems with strong main effects are less likely to be distracted by interaction.

For example, Figure 3.20 shows all scenarios for subproblem 5. For three levels of U_{South} and five levels of WWR_{South}, there are 15 levels in each scenario, and the full factorial experiments are plotted for 3 levels × 3 levels ×3 levels ×3 levels ×3 levels ×3 levels = 729 scenarios. The global optimum of subproblem 5 is at level 3. The response changes between levels 3 and 4 are small, and the lines are almost flat. Therefore, for 54% of the scenarios, the optimal level is level 3, and the rest is level 4.



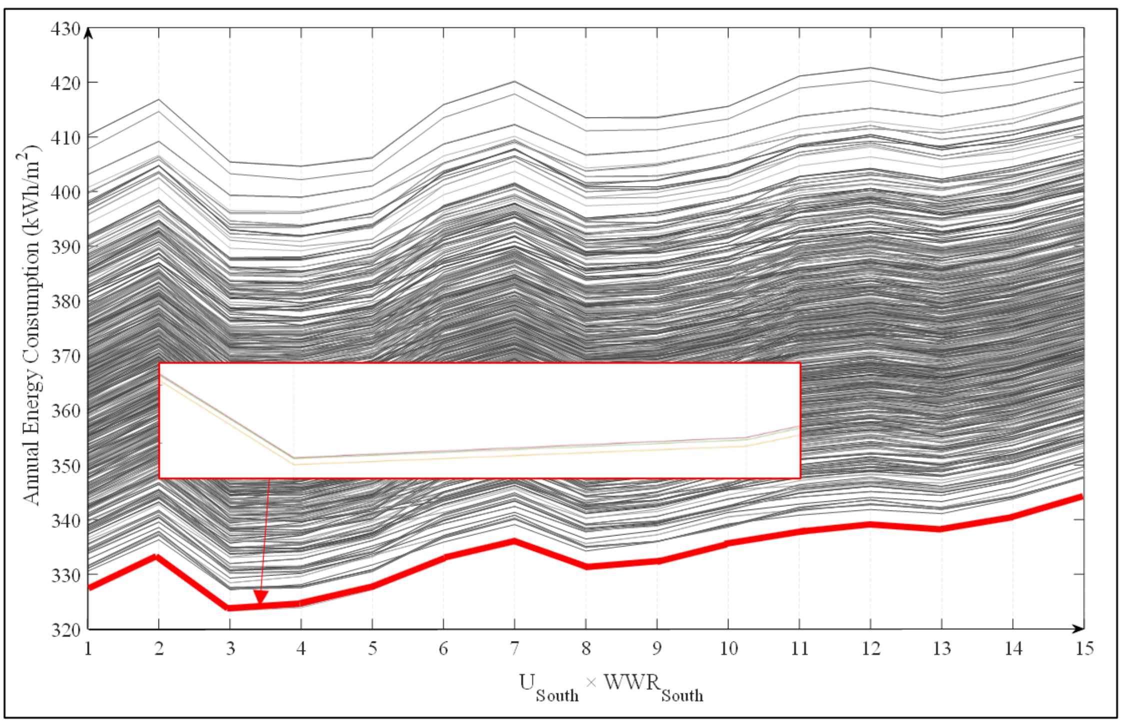
Level	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
U_{South}(W/m^2.K)	1	1	1	1	1	2	2	2	2	2	3	3	3	3	3
WWR_{South}	10%	20%	30%	40%	50%	10%	20%	30%	40%	50%	10%	20%	30%	40%	50%

Figure 3.20. All scenarios of subproblem 5

The main effects of variables from low to high can be found in Table 3.8, extracted from Table 3.4. As this table shows, the variables in subproblems 5 (WWR_{South}) and 6 ($Depth_{OH}$) have the weakest main effects. Therefore, the other six subproblems (1, 2, 3, 4, 7) are optimized first, and the results are used to solve subproblems 5 and 6. Since the concordance rates of these subproblems are 100%, these subproblems are guaranteed to achieve global solutions. As shown in Figure 3.21, when the other subproblems are solved, only three scenarios of subproblem 5 are left. In such a case, the concordance rates for subproblems 5 and 6 increase to 100% because level 3 is the optimal solution in all three scenarios.

Table 3.8. The main effect of variables

Subproblem	Variable	Main effect
6	$Depth_{OH}$	0.0335
5	WWR_{South}	0.0475
7	R_{Wall}	0.2789
5	U_{South}	0.2867
3	WWR_{East}	0.37
2	U_{EW}	0.4356
1	R_{Roof}	0.46
4	WWR_{West}	0.4743



Level	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
U_{South}(W/m^2.K)	1	1	1	1	1	2	2	2	2	2	3	3	3	3	3
WWR_{South}	10%	20%	30%	40%	50%	10%	20%	30%	40%	50%	10%	20%	30%	40%	50%

Figure 3.21. Three scenarios of subproblem 5

3.5.3 The sparsity-of-effects principle demonstration

The variable grouping criteria in this study focus on the two-variable interaction assuming the sparsity-of-effects principle is valid for building performance simulation. According to this principle, the responses are mostly contributed by the main effects and two-variable interactions. The high-order interactions, such as three-variable interactions, are negligible. The ANOVA is applied to the full factorial experiments results to demonstrate this principle. The contribution of main effects, two-variable and three-variable interactions to the variation in the response are 96.63%, 3.35% and 0.01%, respectively. It shows that the sparsity-of-effects principle is effective in this study.

3.5.4 The impact of threshold

In the second case study, the threshold is set to 0.005. As shown in Table 3.4, all variables interact, and most of the interactions are larger than the threshold. Therefore, the problem will be inseparable if the variables are only assessed with the first criterion. With the proposed criterion, only two variables are combined.

If the threshold increases from 0.005 to 0.5, the results with the first criterion changed from Table 3.4 to Table 3.9. However, with the dual-criteria variable grouping method, the variable grouping results are the same for both thresholds. In conclusion, the proposed approach can reduce threshold impact on the decomposition results, and the optimization results are reliable.

Table 3.9. The interaction matrix with a threshold value of 0.05

	$Depth_{OH}$	R_{Roof}	U_{EW}	U_{South}	WWR_{East}	WWR_{South}	WWR_{West}	R_{Wall}
$Depth_{OH}$	0.0335	0.0018	0.004	0.0015	0.0166	0.0048	0.0189	0.0106
R_{Roof}	0.0018	0.46	0.0106	0.0111	0.0184	0.0252	0.0156	0.0033
U_{EW}	0.004	0.0106	0.4356	0.0101	0.1185	0.0224	0.1258	0.005
U_{South}	0.0015	0.0111	0.0101	0.2867	0.008	0.1451	0.007	0.007
WWR_{East}	0.0166	0.0184	0.1185	0.008	0.37	0.0206	0.0148	0.0259
WWR_{South}	0.0048	0.0252	0.0224	0.1451	0.0206	0.0475	0.0171	0.0382
WWR_{West}	0.0189	0.0156	0.1258	0.007	0.0148	0.0171	0.4743	0.0244
R_{Wall}	0.0106	0.0033	0.005	0.007	0.0259	0.0382	0.0244	0.2789

3.6 Conclusion

Considering variables of different disciplines in an integrated building design drastically increases the dimensionality and complexity of building design optimization problems. Parallel decomposition can solve this problem by dividing the original problem into several smaller subproblems to be solved separately. This study proposes a parallel decomposition approach to facilitate the parallel processing for integrated building design. There are some advantages and limitations of this proposed approach.

The low-rise office case study shows that the proposed approach reduces more than half of the computation time than optimization without decomposition. Furthermore, most of the architectural design variables and engineering design variables are separated in this study. This result shows that exchanging information between different disciplines can be minimized when applying the proposed method to integrated design. Traditionally, the integrated design considers variables of different disciplines simultaneously. The proposed approach makes the integrated design more efficient by dividing it into several independent problems.

Each subproblem is solved while the variables in other subproblems use the default values. The discussion using full factorial design results shows that the choices of default values might impact the optimal solutions. This issue means the sensitivity analysis and interaction are not totally effective in assessing the criteria. This potential issue can be overcome by first optimizing the subproblem with the strongest main effect and using the results for subsequent subproblems with decreasingly weaker main effects.

This study focuses on the two-variable interaction between variables and assumes that the effects of higher-order interactions can be ignored according to the sparsity-of-effect principle. The results of the full factorial design demonstrate that this assumption is valid in the case studies. However, an extensive study of different building types and design variables shall be conducted to investigate the applicability of this principle in more complex building designs. In this study, a parallel decomposition approach is applied to solve single-objective optimization problems, and it can be extended to solve multi-objective building design optimization problems. Moreover, sensitivity analysis is used for variable grouping to assess the first criterion in this study. Sensitivity analysis can also be used to screen the variables to reduce the dimensionality of optimization problems. The two applications can be combined in future works.

Appendix 3.A Benchmark function optimization using parallel decomposition

128 experiments are generated for the first step for fractional factorial design level V in MINITAB. The sensitivity analysis results are shown in Table 3.10 in a matrix. The main effects of the variables are shown in the diagonal cells. The other cells show the interaction between every two variables. As the results show, there is no interaction between the variables. Therefore, there is no need to check the interaction plots. The optimization problem is decomposed into ten subproblems, and each subproblem only has one variable.

The ten subproblems are optimized separately using the Genetic Algorithm for the second step. For each subproblem optimization, an initial search space of ten experiments is generated using Latin Hypercube Sampling (LHS). Each optimization is set to stop when the objective function of the best solution has the same value during two consecutive days iterations. Since the solutions of the subproblems are the same, only the results of subproblem 1 are shown in Figure 3.22. It takes 241 runs for GA to find the global optimal solution for this subproblem.

Table 3.10. The interaction matrix for the Schwefel function

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
X_1	0.315	0	0	0	0	0	0	0	0	0
X_2	0	0.315	0	0	0	0	0	0	0	0
X_3	0	0	0.315	0	0	0	0	0	0	0
X_4	0	0	0	0.315	0	0	0	0	0	0
X_5	0	0	0	0	0.315	0	0	0	0	0
X_6	0	0	0	0	0	0.315	0	0	0	0
X_7	0	0	0	0	0	0	0.315	0	0	0
X_8	0	0	0	0	0	0	0	0.315	0	0
X_9	0	0	0	0	0	0	0	0	0.315	0
X_{10}	0	0	0	0	0	0	0	0	0	0.315

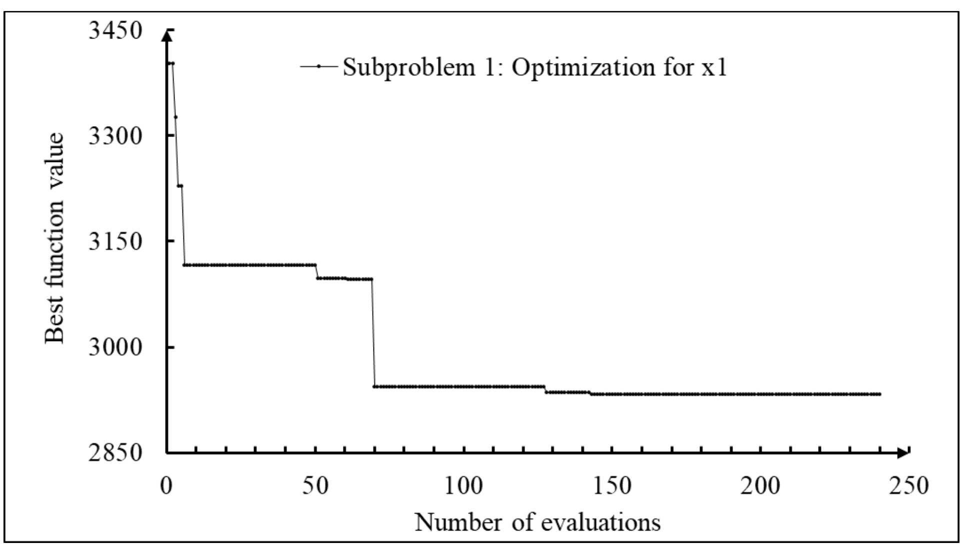


Figure 3.22. Subproblem 1 for benchmark function

Appendix 3.B. The practical workflow applying the proposed approach

The practical workflow in Figure 3.23 shows the steps for readers to apply the proposed approach. For the case study of the low-rise office building presented in this paper, MINITAB is used for steps 1.1, 1.3 and 1.5. ModeFRONTIER and EnergyPlus are used for steps 1.2, 2.1 and 3.1. Other optimization, simulation, and statistical programs can be used when applying the proposed approach.

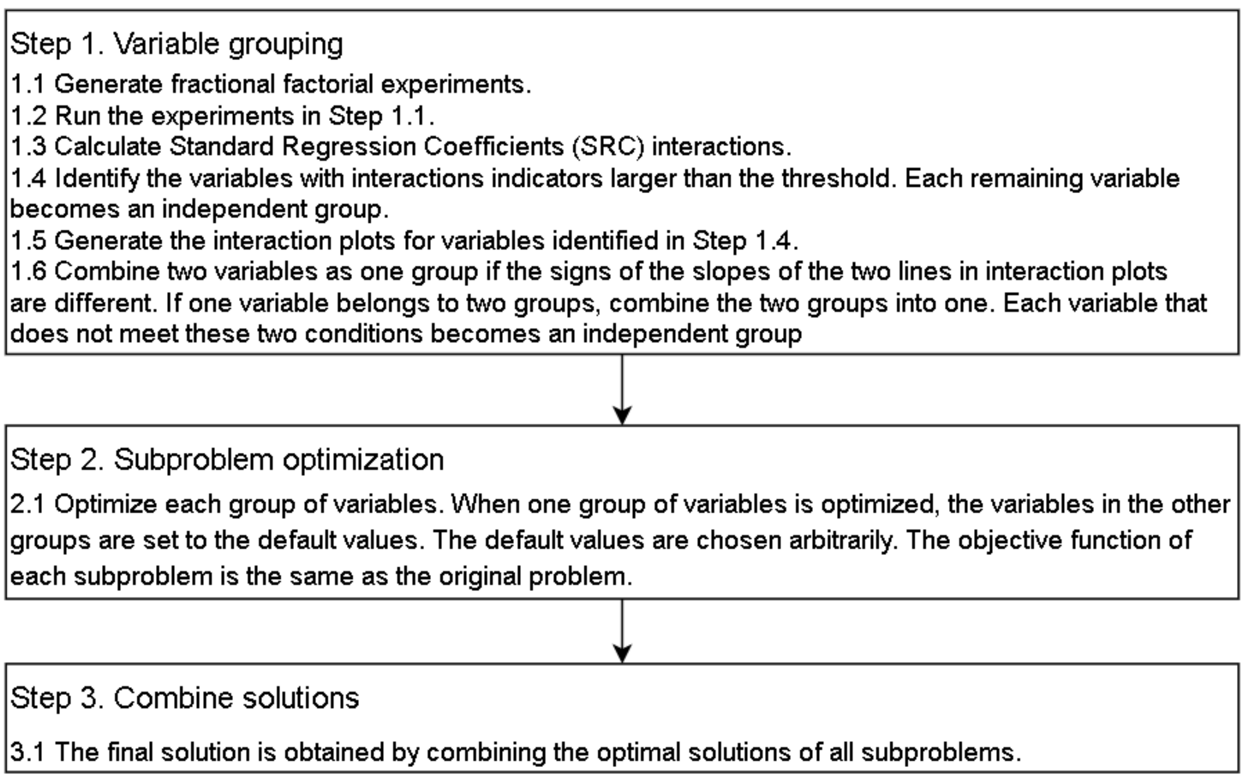


Figure 3.23. The practical workflow applying the proposed approach

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Chapter 4. Sensitivity Analysis for Dimension Reduction of Building Design Optimization

Regression-based sensitivity analysis using the two-level fractional factorial design is used for variable grouping in the parallel decomposition in the previous chapter. However, sensitivity analysis is more commonly used for variable screening. Both uses of sensitivity analysis can reduce the dimensionality of building design optimization problems. This chapter evaluates the performance of sensitivity analysis for variable screening and grouping through three case studies. The results show that the regression-based sensitivity analysis using the two-level fractional factorial design with resolution V is capable of both variable screening and grouping.

4.1 Introduction

Sensitivity analysis investigates how a model's input uncertainty affects output uncertainty. It has been applied to building performance simulations for different aims in different life cycle stages. Pang et al. (2020) summarized the applications of sensitivity analysis in building performance simulation studies and categorized them into five types: identification in design/operation, optimization in design/operation, and calibration in operation. This study focuses on the use of sensitivity analysis for optimization in design. For this purpose, sensitivity analysis is used for dimension reduction of building design optimization problems.

For dimension reduction, most studies use sensitivity analysis for the variable screening. After sensitivity analysis, the variables with small main effects are excluded from optimization (Pang et al. 2020). Besides variable screening, sensitivity analysis has also been used for variable grouping in the parallel decomposition of optimization problems in the other field. Parallel decomposition reduces the dimension of optimization problems by dividing the original problem into several subproblems (Yang et al., 2019). It is required that there is no interaction between the variables of different subproblems. Therefore, the subproblems can be optimized separately and achieve global optimum, as shown in Figure 4.1.

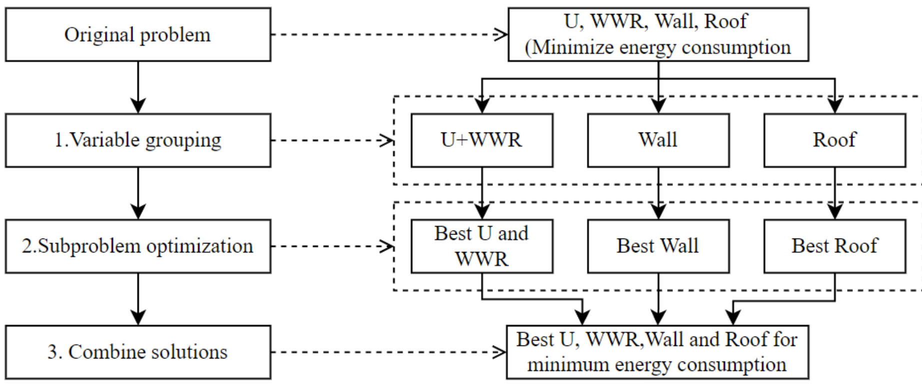


Figure 4.1 The concept of variable grouping for parallel decomposition

Sensitivity analysis is used to quantify the interactions of variables for the variable grouping of parallel decomposition. The variables with negligible interactions are separated for optimization, while those with strong interactions are grouped. Ito and Dhaene (2013) used the second and third-order interaction indices obtained by the Sobol method to decompose the optimization problem. Ivanov and Kuhnt (2014) applied Functional Analysis of Variance (FANOVA) to decompose the sheet metal forming optimization problem. However, there is a lack of study investigating this use of sensitivity analysis on building design optimization problems. To fully utilize sensitivity analysis for the dimension reduction of building design optimization problems, this study aims to identify a method capable of variable screening and grouping both.

For variable screening, sensitivity analysis is required to evaluate the main effects efficiently. For variable grouping, the sensitivity analysis is suggested to quantify the interactions to decompose building design optimization problems. According to the sparsity-of-effects principle, the high-order interactions are negligible because a physical system is usually dominated by main effects and low-order interactions such as two-variable interaction (Aiad and Lee, 2016). Therefore, a method needs to be identified to efficiently quantify the main effect andand two-variable interactions.

The studies about sensitivity analysis in building design for both main effects and two-variable interactions focused on convergence results (Nguyen and Reiter, 2015). However, as an optimization preprocessing, sensitivity analysis does not need to achieve ranking convergence and only needs to obtain the most important terms the same as the convergence results. For example, choosing five out of ten variables for optimization is acceptable as long as the top five variables are the same as the convergence results, without requiring each variable to achieve the correct ranking. Therefore, there is a need to identify a method to control the number of experiments to achieve acceptable results.

In conclusion, there are two issues to be addressed in this study:

1. Identify a sensitivity method that can efficiently quantify the main effects and two-variable interactions for variable screening and grouping.
2. Identify a Design of Experiment method for the sensitivity analysis method, which can control the number of experiments to achieve acceptable results.

The remainder of this paper is organized as follows. First, the two issues are addressed in sections 4.2 and 4.3, respectively. Then this study proposes the method for variable screening and grouping and the methodology to evaluate the performance in section 4.4. Next, three case studies are used to evaluate the performance of this method in sections 4.5 and 4.6. Finally, section 4.7 summarizes this research and proposes future work.

4.2 Sensitivity analysis for variable screening and variable grouping

In order to address the first issue, this section reviews different sensitivity analysis methods and discusses their feasibility for variable screening and grouping. The method's feasibility depends on the efficiency and amount of information provided by different methods. Since these two criteria are usually not met simultaneously, the pros and cons of different methods need to be discussed.

The process of sensitivity analysis using building performance simulation can be divided into three steps: generating designs, running the simulations, and calculating the sensitivity indicators (Tian, 2013). Depending on the type of indicator, sensitivity analysis can be divided into Morris, regression-based, and variance-based methods.

Morris first proposed the screening method in 1991 (Morris,1991). This method only changes one variable in each experiment while other variables remain unchanged. It evaluates the response change caused by the small change of the variable to obtain the elementary effect. The expectation and standard deviation of elementary effects determine the main effects and total interactions of variables. Initially, it could only qualify the total interactions, but some studies extended this method to qualify the two-variable interactions (Campolongo and Braddock, 1999). For example, Menberg et al. (2016) and Sanchez et al. (2014) applied the extended Morris method to investigate the main effects and two-variable interactions on building energy models.

The regression-based method uses a multivariate linear model to fit the complex building model as shown in Equation (4.1) (Suard et al., 2013), where y is the model response, x_i is the input variable, k is the number of variables, ε is the error term, and b_i is the coefficient of the regression model corresponding to x_i. These coefficients indicating the variable's sensitivity can be obtained by statistical measures such as Standard Regression Coefficient (SRC) (Lee, 2014).

$$y = b_0 + \sum_{i=1}^{k} b_i \, x_i + \varepsilon \tag{4.1}$$

The regression-based method can also quantify the two-variable interactions with the model shown in Equation (4.2) (Heckert et al., 2002).

$$y = b_0 + \sum_{i=1}^{k} b_i \, x_i + \sum_{i=1, j \neq i}^{k} b_{ij} \, x_i x_j + \cdots \varepsilon \tag{4.2}$$

The variance-based methods include the Sobol method (Sobol, 1993) and the FAST method (McRae et al., 1982). The Sobol method is suitable for nonlinear models and can quantify first and high-order sensitivity (Saltelli and Annoni, 2010). This method decomposes the total output variance into the sum of each variable's variance and the higher-order interaction terms. Thus, the sensitivity of variables is quantified by the contribution of the variance of each term. Compared with the Sobol method, the FAST method has a relatively low computation cost but is not suitable for discrete variables (Christopher Frey and Patil, 2002).

From the perspective of efficiency, the computing requirements from low to high are Morris, regression-based, and variance-based methods. The Morris method requires $r \times (k + 1)$ runs to evaluate interactions, where k is the number of input variables, and r is the number of trajectories ranging from 5 to 15 (Cropp and Braddock, 2002). The regression-based methods often use the Monte Carlo method for the design of experiment. Lomas and Eppel (1992) claimed that 60-80 experiments are enough for sensitivity analysis of building thermal model using the Monte Carlo method. Many studies have adopted this conclusion. However, this conclusion is developed for the total sensitivity indicator of all variables, which is the standard deviation of all outputs. It is stated in that study that the conclusion is not valid when applied to the individual variable's sensitivity. This statement is often overlooked, resulting in the abuse of this conclusion. Variance-based methods usually need more experiments than the other two types of methods. For example, the

Sobol method needs $N \times (D+2)$ for first-order sensitivity (Saltelli, 2002). For the second-order, $N \times (2D+2)$ is recommended, where D is the number of variables, and N is an order of hundreds or thousands (Herman and Usher, 2017). Nguyen and Reiter (2015) compared the Morris, regression-based, and variance-based methods on three benchmark functions and a building model. In the building model case study, the Morris, regression-based and variance-based methods required 70 runs, 140 to 700 runs and 3584 to 4374 runs to achieve convergent results, respectively.

From the perspective of information, the methods from less to more are Morris, regression-based, and variance-based methods. Morris method is qualitative, and the results cannot be interpreted physically. Therefore, it is mostly applied for qualitative variable screening. Nguyen and Reiter (2015) found that since the Morris method is based on random sampling, the small number of samplings might result in uneven distribution of variable levels. Therefore, the result of the Morris method is less reliable than the other methods. The regression-based and variance-based methods are both quantitative. The regression-based methods are very effective when applied to linear or monotonic models. Menberg et al. (2016) compared the main effects ranking of the building energy model obtained by the regression-based method and Sobol method. The results of the two methods are identical. The regression-based methods can provide the main effects and two-variable interactions as shown in Equations (4.1) and (4.2). However, the results may be unreliable when the sampling range is too narrow (Christopher Frey and Patil, 2002) or when the building model is highly nonlinear (Mara and Tarantola, 2008). The variance-based methods can quantify the main effects and all high-order interactions. It also performs well on nonlinear and non-monotonic models. Unlike the regression-based method, it works well when the sampling range is narrow.

Some conclusions can be drawn from the review above. First, the Morris method is the most efficient, but it cannot quantify the interactions. Therefore, it is only suitable for variable screening, not variable grouping. Secondly, the variance-based methods can provide comprehensive information on variables' main effects and interactions, but the computation cost is higher than other methods. Therefore, this type of method is not suitable for building design optimization problems preprocessing. Third, the regression-based methods are more efficient than the variance-based method and offer quantitative interaction information that the Morris method cannot offer. Though the regression-based method may perform poorly when the model is highly nonlinear, it is worth sacrificing accuracy for efficiency if the most important terms are similar to the correct result. In conclusion, the regression-based sensitivity analysis method is selected for the first issue.

4.3 Design of experiment method for sensitivity analysis

In conclusion of the previous section, this section aims to address the second issue: to find a design of experiment method that can control the number of experiments to obtain acceptable results. Different DOE methods have been used for regression-based sensitivity analysis. These methods can be divided into random sampling and factorial design.

The random sampling methods are related to aleatory uncertainty, which represents the randomness in nature (Tian et al., 2018). A probability distribution is used to describe this type of uncertainty. Latin Hypercube sampling is one of the random sampling methods. However, there is a lack of studies about the required sample size of Latin Hypercube sampling for the sensitivity analysis applied to the building performance simulation. Moreover, this study focuses on the uncertainty in the design phase. The uncertainty in the design phase is the epistemic uncertainty due to the lack of knowledge (Tian et al., 2018). Lavan (2019) addressed the concern about using probability to measure epistemic uncertainty. Therefore, the random sampling does not meet the criteria of this study, and the factorial design is considered as the design of experiment method for sensitivity analysis. In a factorial design, each variable is set as a factor with several levels, and each design is a combination of all factors at different levels. When the experiments cover all the possible combinations of the variable at all levels, it is called full factorial design. However, sensitivity analysis using full factorial design as optimization preprocessing is unnecessary since optimization is a subset of full factorial design.

Several special cases of factorial design are widely used to save computation time. Two-level factorial design is one of the methods (Heckert et al., 2002). Each variable uses the upper and lower boundaries in a two-level factorial design. It is beneficial in the early design phase when there are many factors. Since only two levels are considered for each factor, it is often assumed that the response is approximately linear over the range of the factor (Hinkelmann, 2012). This assumption coincides with the assumption of regression-based sensitivity analysis. However, some variables, such as the window-to-wall ratio, are related to energy consumption by a quadratic curve (Lee et al., 2016). The main effect and interactions obtained in this case might be less accurate, but it is worth sacrificing the accuracy for efficiency.

The fractional factorial design is another case that performs only a selected subset in a full factorial design. According to the Sparsity-of-effects principle, the fractional factorial design reduces the number of experiments by confounding high-order effects with low-order effects (Heckert et al., 2002). Different types of fractional factorial design have been applied for the sensitivity analysis of building performance simulation. Rahni et al. (1997) used regression analysis and Plackett and Burman designs on dynamic building energy simulation models. The Plackett and Burman design, one type of fractional factorial design, requires only k+1 simulation for k factors. However, this method can only be used for the main effect of the variable. The Taguchi method is another type of fractional factorial design. Yi et al. (2015) applied the Taguchi method with ANOVA to identify the significant building variables. Chlela et al. (2007) applied the Taguchi method with regression analysis as the sensitivity analysis for an office building's energy consumption.

The two-level fractional factorial design combines the features of fractional factorial design and two-level factorial design. Several studies have been applied it to the sensitivity analysis of building energy models. For example, Dhariwal and Benerjee (2017) applied this method for ANOVA as a sensitivity analysis for the building energy model. Langner et al. (2011) applied this method with factorial analysis to identify the critical design variables that affect the energy consumptions of commercial high-rise office buildings. de Lemos Martins et al. (2016) applied this method with a Simplified Radiosity Algorithm (RSA) as a sensitivity analysis for urban morphology factors regarding buildings' solar energy potential.

The two-level fractional factorial design is generated from a full factorial design by choosing the design resolution, which measures the degree of confounding. The high-order interactions are confounded with low-order effects. Design resolutions III to V are the most used resolution levels (Heckert et al., 2002). When the resolution is III, all the main effects are randomly confounded with all other interactions. When the resolution is IV, the main effects are confounded with three-variable interactions, and some of the two-variable interactions are confounded with each other. Finally, when the resolution is V, the main effects and two-variable interactions are distinguished but confounded with higher-order effects. The alias structure describes the details of confounding in the fractional factorial design.

Compared with the other method, the two-level fractional factorial design is very efficient, and it can control the number of experiments to achieve the targeting effect levels by choosing the design resolution. Furthermore, resolution IV and above is capable of variable screening using the main effects, and resolution V and above are capable of variable grouping using the two-variable interactions. Therefore, to meet the requirements of variable screening and grouping, this study proposes using the two-level fractional factorial design with resolution V as DOE for regression-based sensitivity analysis.

4.4 Methodology

This study proposes regression-based sensitivity analysis using the two-level fractional factorial design for variable screening and grouping. The proposed method is expected to meet these two requirements:

1. Control the number of experiments to achieve the target sensitivity level.
2. Obtain acceptable results rather than convergent results.

Three case studies are conducted to compare the proposed method with other SA methods to discuss if the two criteria are met. The sensitivity analysis results and the variable screening and grouping results are generated for each case study. Mara and Tarantola (2008) conducted a regression-based sensitivity analysis to a building energy model and defined parameters with a regression coefficient lower than 0.05 as non-significant. This study defines the threshold value for variable screening and grouping as 0.05 and performs variable screening and grouping separately, as shown in Figure 4.2. For variable screening, if the main effect is less than 0.05, the variable is excluded from optimization. Otherwise, the variable is considered for optimization. For variable screening, if the interaction indicator is larger than 0.05, the two variables are separated into two groups. Otherwise, the variables are combined for optimization. This process is repeated for every pair of variables, and two groups are merged if one variable belongs to two groups.

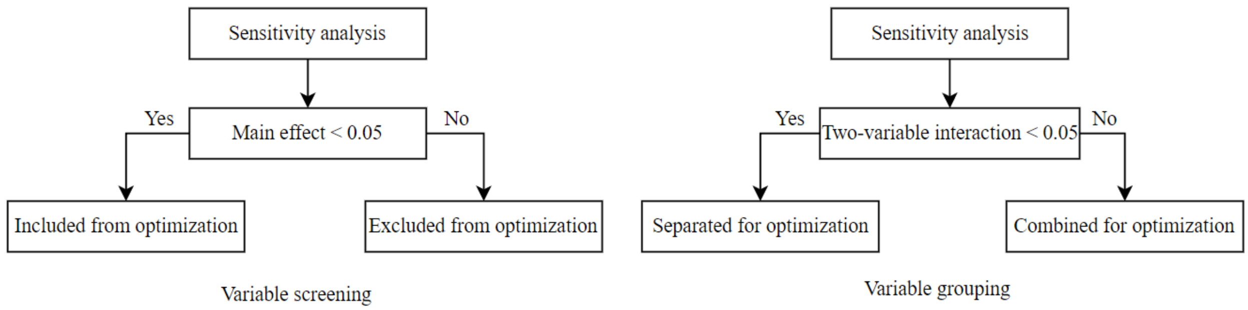


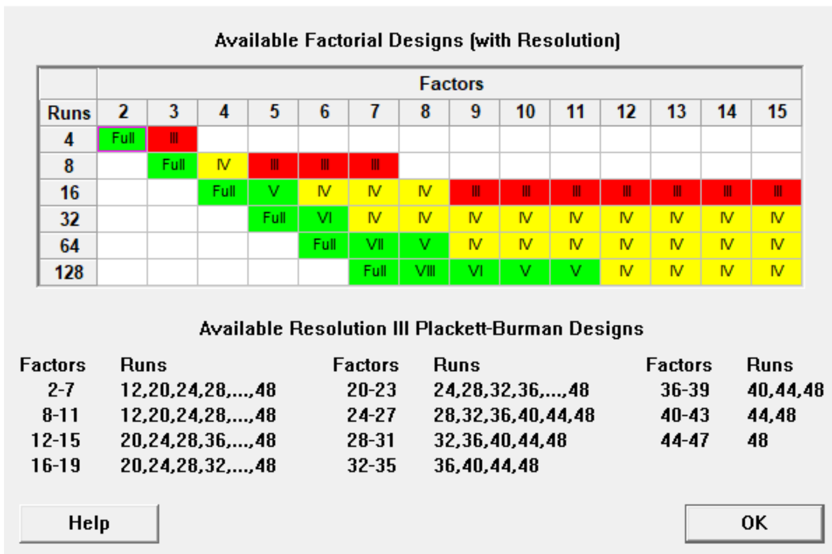
Figure 4.2 The criteria for variable screening and grouping

This method is first applied to a benchmark function from literature. This case study is to validate the performance of the proposed method by comparing the results obtained in this study with the ones in the literature. Then this method is applied to a low-rise office building with different design resolutions for the first requirement. It evaluates if the method can control the number of experiments to achieve the targeting levels. Finally, this method is applied to a mid-rise residential building for the second requirement. The results are compared with the results of the Sobol method to discuss its accuracy. The Sobol method is a variance-based method, which is more accurate than the proposed method. This case study evaluates if the proposed method can identify the most significant main effects and interactions rather than the exact ranking. The objectives of the three case studies are summarized in Table 4.1.

Table 4.1 The objectives of the three case studies

	Comparison group	**Research object**	**Objective**
Case 1	Fractional factorial design VS Latin Hypercube sampling	Main effects	Validation with results in another study
Case 2	Fractional factorial design with different resolutions	Main effects, two-variable interactions	Controllable?
Case 3	Regression-based SA VS Variance-based SA	Main effects, two-variable interactions	Accurate enough?

The fractional factorial design is generated using MINITAB. Figure 4.3 shows the table used in MINITAB defining the number of experiments needed to achieve different levels of design resolution. The experiments for the Sobol method are generated using MODEfrontier. The integration of EnergyPlus and Modefrontier facilitates the automated function calculation and simulation process. The generated designs are imported from MINITAB to MODEfrontier, and the output of the function and simulations are exported back from modeFRONTIER to MINITAB for sensitivity analysis.


Available Factorial Designs (with Resolution)

Runs	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	Factors													
4	Full	III												
8		Full	IV	III	III	III								
16			Full	V	IV	IV	IV	III	III	III	III	III	III	III
32				Full	VI	IV	IV	IV	IV	IV	IV	IV	IV	IV
64					Full	VII	V	IV	IV	IV	IV	IV	IV	IV
128						Full	VIII	VI	V	V	IV	IV	IV	IV

Available Resolution III Plackett-Burman Designs

Factors	Runs	Factors	Runs	Factors	Runs
2-7	12,20,24,28,....,48	20-23	24,28,32,36,....,48	36-39	40,44,48
8-11	12,20,24,28,....,48	24-27	28,32,36,40,44,48	40-43	44,48
12-15	20,24,28,36,....,48	28-31	32,36,40,44,48	44-47	48
16-19	20,24,28,32,....,48	32-35	36,40,44,48		

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Figure 4.3 Table of resolution levels for fractional factorial design in MINITAB

4.5 Case studies

4.5.1 Test function

A linear test function is selected as the first case study to validate the proposed method with the results from Nguyen and Reiter (2015). The equation is shown in equation (4.3), in which $x_i \in U\,(0,1)$ and $c_i = (i-11)^2$ for $I = 1, 2, \ldots, n$.

$$f(x) = \sum_{i=1}^{n} c_i \left(x_i - \frac{1}{2}\right) \tag{4.3}$$

The results from Nguyen and Reiter (2015) used Latin Hypercube sampling for the regression-based sensitivity analysis. The correct order of variables' main effects from high to low is $x_1, x_2, x_3, x_4, x_5 \ldots x_n$. This function can be defined on n-dimensional space, and in this study, the dimension n is defined as six. Since this is an additive function, there is no interaction between the variables. Therefore, only the main effect is quantified. The SA with different resolution levels is applied to show the impact of different resolution levels on the main effect results. The fractional factorial design is conducted for three resolutions: 8 runs for resolution III, 16 and 32 runs for resolution IV, and 64 runs for resolution V.

4.5.2 The small office building

The second case study selects a small office building model based on the phototype building developed by Pacific Northwest National Laboratory (PNNL), as shown in Figure 4.4. This case study evaluates if the method can control the number of experiments to achieve the targeting levels. The location is assumed at Montreal, Canada. The model is built using EnergyPlus. The performance indicator is the annual energy consumption. There are four parameters zoom and one core zoom. The idea load air system is assigned to each zoom meeting heating and cooling loads. There are ten variables for the sensitivity analysis, as shown in Table 4.2. The regression-based sensitivity analysis is performed to assess the main effects and two-variable interactions of variables on the annual energy consumption using resolution from level III to V. The two-level full factorial design is conducted to validate the results.

Table 4.2 Design variable for the small office building

Designation	Variable	Value

A	Orientation (Degree)	[0, 10, 20, 30, 40, 50]
B	Window to wall ratio	[40%, 43%, 46%, 50%, 53%, 56%, 60%]
C	Roof insulation thermal resistance (m^2-K/W)	[4, 4.5, 5, 5.5, 6]
D	Floor slab thickness (m)	[0.15, 0.17, 0.19, 0.21, 0.23, 0.25]
E	Foundation insulation thermal resistance (m^2-K/W)	[4, 4.5, 5, 5.5, 6]
F	Wall insulation thermal resistance (m^2-K/W)	[3, 3.5, 4, 4.5, 5]
G	Heating setpoint (° C)	[20.5, 20.75, 21, 21.25, 21.5]
H	Cooling setpoint (° C)	[23.5, 23.75, 24, 24.25, 24.5]
J	Solar heat gain coefficient	[0.27, 0.18, 0.13]
K	Roof construction type	[Asphalt shingles, Metal roof]

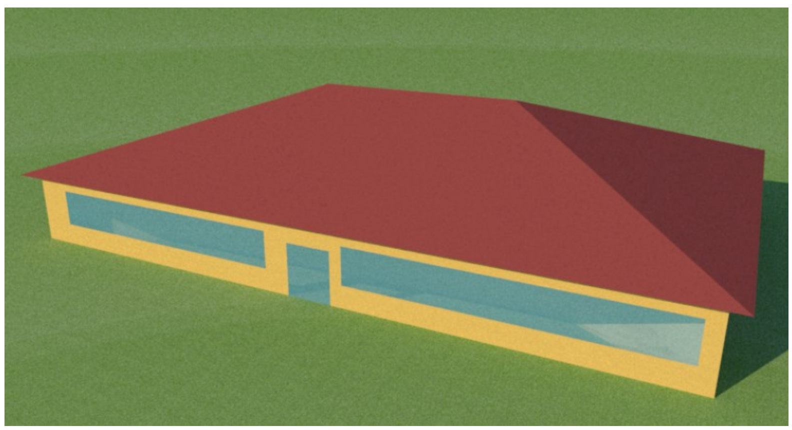

Figure 4.4 The small office building model

The fractional factorial designs for different resolution levels are generated: III (16runs), IV (32runs), IV (64 runs), V (128 runs), and two-level full factorial (1024 runs). The alias structures for each resolution level except full factorial are shown in Tables 4.3 to 4.6. Due to the limited space, interactions higher than two-variable are not shown in these tables. For resolution III (Table 4.3), all the main effects are confounded with the two-variable interactions. For resolution IV (Tables 4.4 and 4.5), the main effects are partially confounded with some two-variable interactions, and some two-variable interactions are confounded with each other. These tables indicate that resolution levels III and IV are effective for the main effects when the two-variable interactions are negligible. For resolution V, all the main effects are not confounded with the two-variable interactions, and all the two-variable interactions are not confounded with other two-variable interactions, as shown in Table 4.6. In this case, it can thoroughly quantify all main effects and the two-variable interactions.

Table 4.3 Alias structure for resolution III (16 runs)

Alias	Alias Structure	Alias	Alias Structure	Alias	Alias Structure	Alias	Alias Structure
1	A + BK + FJ	5	E + CK + DJ	9	J + AF + BG + CH + DE	13	AE + BC + DF + GH
2	B + AK + GJ	6	F + AJ + GK	10	K + AB + CE + DH + FG	14	AG + BF + CD + EH
3	C + EK + HJ	7	G + BJ + FK	11	AC + BE + DG + FH	15	AH + BD + CF + EG
4	D + EJ + HK	8	H + CJ + DK	12	AD + BH + CG + EF		

Table 4.4 Alias structure for resolution IV (32 runs)

Alias	Alias Structure	Alias	Alias Structure	Alias	Alias Structure	Alias	Alias Structure
1	A	14	AE	27	CE	40	EJ
2	B	15	AF	28	CF	41	EK
3	C	16	AG + BH	29	CG	42	FG
4	D	17	AH + BG	30	CH	43	FH
5	E	18	AJ	31	CJ + DK	44	FJ
6	F	19	AK	32	CK + DJ	45	FK
7	G	20	BC	33	DE	46	GJ
8	H	21	BD	34	DF	47	GK
9	J	22	BE	35	DG	48	HJ
10	K	23	BF	36	DH	49	HK
11	AB + GH	24	BJ	37	EF		
12	AC	25	BK	38	EG		
13	AD	26	CD + JK	39	EH		

Table 4.5 Alias structure for resolution IV (64 runs)

Alias	Alias Structure	Alias	Alias Structure	Alias	Alias Structure	Alias	Alias Structure
1	A	14	AE	27	CE	40	EJ
2	B	15	AF	28	CF	41	EK
3	C	16	AG + BH	29	CG	42	FG
4	D	17	AH + BG	30	CH	43	FH
5	E	18	AJ	31	CJ + DK	44	FJ
6	F	19	AK	32	CK + DJ	45	FK

7	G	20	BC	33	DE	46	GJ
8	H	21	BD	34	DF	47	GK
9	J	22	BE	35	DG	48	HJ
10	K	23	BF	36	DH	49	HK
11	AB + GH	24	BJ	37	EF		
12	AC	25	BK	38	EG		
13	AD	26	CD + JK	39	EH		

Table 4.6 Alias structure for resolution V (128 runs)

Alias	Alias Structure	Alias	Alias Structure	Alias	Alias Structure	Alias	Alias Structure
1	A	15	AF	29	CE	43	EH
2	B	16	AG	30	CF	44	EJ
3	C	17	AH	31	CG	45	EK
4	D	18	AJ	32	CH	46	FG
5	E	19	AK	33	CJ	47	FH
6	F	20	BC	34	CK	48	FJ
7	G	21	BD	35	DE	49	FK
8	H	22	BE	36	DF	50	GH
9	J	23	BF	37	DG	51	GJ
10	K	24	BG	38	DH	52	GK
11	AB	25	BH	39	DJ	53	HJ
12	AC	26	BJ	40	DK	54	HK
13	AD	27	BK	41	EF	55	JK
14	AE	28	CD	42	EG		

4.5.3 The mid-rise apartment building

The third case study selects a mid-rise residential building model based on the phototype building developed by Pacific Northwest National Laboratory (PNNL), as shown in Figure 4.5. This case study evaluates if the proposed method can obtain acceptable results rather than convergent results. The location is assumed at Montreal, Canada. It is a four-story apartment building with 31 apartments plus offices. The performance indicator is the annual energy consumption. There are seven design variables shown in Table 4.7. This case study compares the ranking of main effects and two-variable interactions obtained by the proposed method with the Sobol method. The Sobol method is a variance-based method that quantifies all high-order interactions. For variable screening and grouping, the sensitivity analysis results do not need to converge, but the significant terms are expected to be the same as the results of the variance-based method or full factorial. This study assesses whether the main effects and interactions, which accounted for 95% of the overall variance, were the same between the Sobol method and the proposed method.

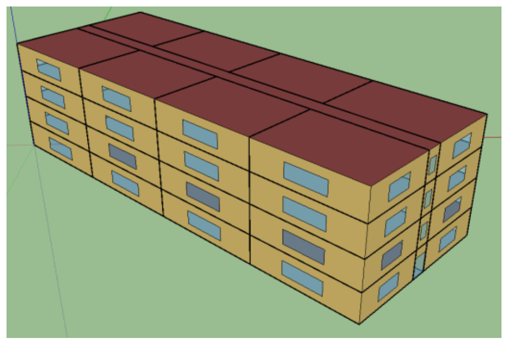

Figure 4.5 The mid-rise apartment building for case study

Table 4.7 The design variables of the mid-rise apartment for sensitivity analysis

Variable	Value
Floor slab thickness (m)	0.1, 0.125, 0.15, 0.175, 0.2
Foundation slab thickness (m)	0.1, 0.125, 0.15, 0.175, 0.2
Orientation (Degree)	0, 22.5, 45, 57.5, 67.5, 90
Roof Insulation thickness (m)	0.2, 0.225, 0.25, 0.275, 0.3
Solar heat gain coefficient	0.3, 0.345, 0.39, 0.435, 0.48
Wall Insulation thickness (m)	0.2, 0.225, 0.25, 0.275, 0.3
WWR (Window height) (m)	0.5, 0.625, 0.75, 0.875, 1

4.6 Results and discussion

4.6.1 Test function

The correct order of variables' sensitivity from high to low is $x_1, x_2, x_3, x_4, x_5, x_6$ (Nguyen and Reiter, 2015). The results are shown in Figure 4.6. It can be observed that the results are stable from resolution III (8 runs) to resolution V (64 runs). In the study of Nguyen and Reiter (2015), the Latin hypercube achieved stable results after 140 runs. Since this case study is not a building model, the variable screening and grouping criteria in Figure 4.2 do not apply to this case study. Therefore, only the sensitivity analysis results are discussed.

The sensitivity analysis results are the same between the proposed method in Figure 4.6 and the ones in Figure 4.7 from Nguyen and Reiter (2015). This case study validates the effectiveness of the proposed method. Furthermore, the results show that the fractional factorial design is more efficient than LHC in estimating the main effects, and the resolution level above III is sufficient to estimate the main effect if the interactions do not exist.

The results show that the fractional factorial design is more efficient than the Latin Hypercube for the main effects of variables. Latin Hypercube uses large numbers of experiments to reflect the characters of uncertainty. When the number of samples is too small, the results of LHC are difficult to converge. For fractional factorial design, when the response of variable is linear or monotonic, the variable boundaries relate to the response boundary, making the results converge with fewer experiments.

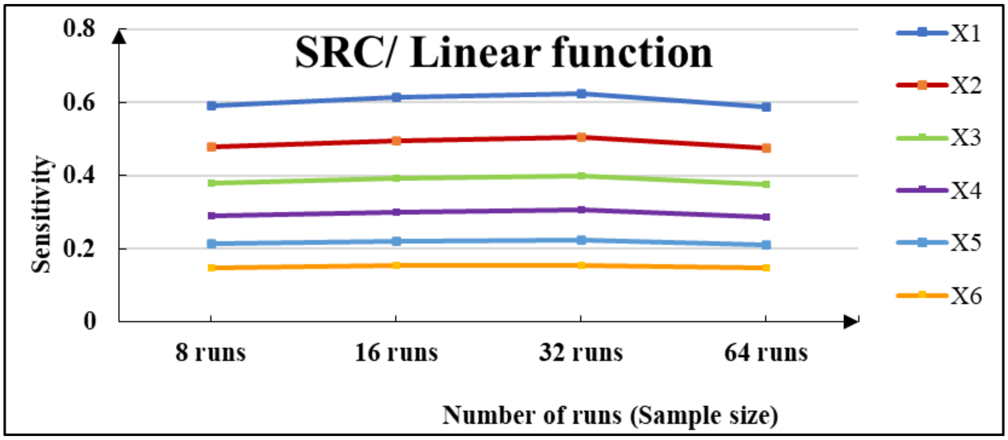

Figure 4.6 Results of test function sensitivity for different resolution levels.

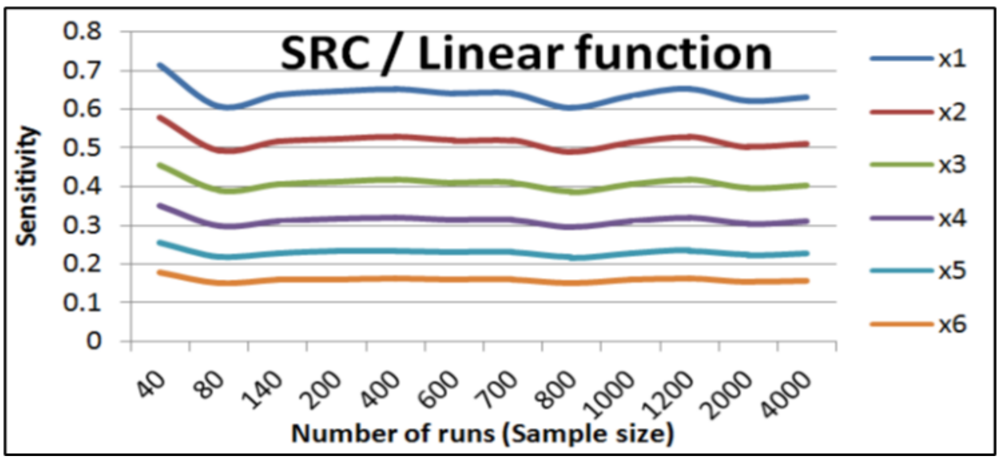

Figure 4.7 Results of test function sensitivity in Nguyen and Reiter (2015)

4.6.2 The small office building

4.6.2.1 Main effects

The fractional factorial designs for different resolution levels are generated: III (16runs), IV (32runs), IV (64 runs), V (128 runs), and two-level full factorial (1024 runs). Figure 4.8 shows the main effect results with different resolution levels, and Table 4.8 shows the difference of results compared with the full factorial design results in percentage.

It can be seen from Figure 4.8 that the value of the main effect converges at level IV, but the ranking does not change from level III to full factorial design. It can be seen from Table 4.8 that there is a certain difference between the main effect value of level III and full factorial, such as roof type. The main effect of roof construction type (K) in resolution III is 64.72% more than the full factorial design. This difference is because the main effect of roof type is very little but confounded with many other interaction terms for level III. Even so, it does not affect the overall ranking of the main effect of all variables. From this case, it can be concluded that fractional factorial design with resolution level III is adequate for the main effect, and it can be used for the variable screening for building design optimization.

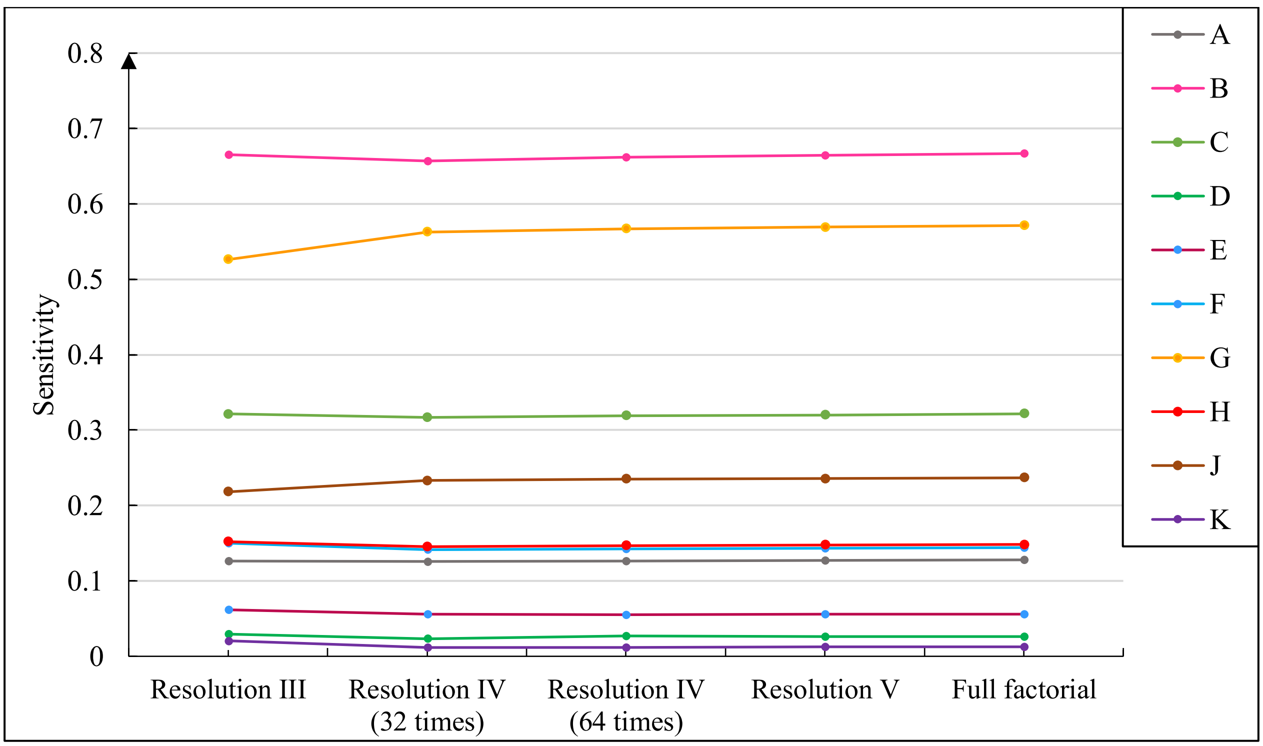

Figure 4.8 The main effect for sensitivity analysis with different resolutions

Table 4.8 Main effects of different resolutions compared with full factorial design

Factors	Resolution III	Resolution IV	Resolution IV	Resolution V

	(16 runs)	(32 runs)	(64 runs)	(128 runs)
A	1.52%	1.66%	1.02%	0.35%
B	0.26%	1.48%	0.73%	0.34%
C	0.03%	1.48%	0.67%	0.42%
D	11.08%	12.45%	1.04%	0.08%
E	10.01%	0.05%	1.59%	0.86%
F	4.31%	1.67%	0.70%	0.19%
G	7.90%	1.50%	0.75%	0.37%
H	2.59%	1.85%	0.79%	0.36%
J	7.85%	1.62%	0.59%	0.39%
K	64.72%	6.66%	2.72%	0.92%

4.6.2.2 Two-variable interactions

There are 45 two-variable interactions in total. Table 4.9 shows the two-variable interactions from resolution level III to two-level full factorial design. It is shown in the table that the two-variable interaction results of resolution III are very different from the other results. The results except level III are shown in Figure 4.9. The results converge to the results of two-level full factorial design as the resolutions increase, and the results of resolution V are almost the same as the two-level full factorial design. Spearman's Rank Correlation Coefficient (SRCC) is calculated for vectors of each resolution and full factorial to evaluate how similar the results of each resolution and full factorial design are. The SRCC from resolution III to V are 0.679, 0.824, 0.897, and 0.986.

It can be concluded from the results that the resolution level III is not capable of evaluating the two-variable interactions; resolution level IV can evaluate the two-variable interaction at the expense of some accuracy; the results of two-variable of resolution level V is almost the same as the results of full factorial design. Above all, this case study validates that the design resolution of fractional factorial design can control the number of experiments to achieve the claimed resolutions. Moreover, resolution V is recommended to be used for the estimation of two-variable interactions for the variable grouping.

Table 4.9 Two-variable interaction sensitivity for different resolutions

Interactions	Resolution III (16 runs)	Resolution IV (32 runs)	Resolution IV (64 runs)	Resolution V (128 runs)	Full factorial (1024 runs)
AB	0.029	0.009	0.011	0.011	0.011
AC	0.002	0.003	0.002	0.002	0.002
AF	0.526	0.002	0.001	0.000	0.000
AJ	0.011	0.036	0.037	0.037	0.037
AK	0.022	0.008	0.002	0.000	0.000
CB	0.021	0.006	0.007	0.007	0.006
CF	0.152	0.001	0.003	0.000	0.000
CJ	0.012	0.013	0.013	0.013	0.013
CK	0.665	0.001	0.002	0.001	0.001
DA	0.665	0.013	0.001	0.001	0.001
DB	0.126	0.016	0.003	0.001	0.001
DC	0.022	0.036	0.001	0.001	0.000
DF	0.218	0.001	0.019	0.000	0.000
DG	0.011	0.002	0.025	0.001	0.001
DJ	0.150	0.003	0.003	0.004	0.003
DK	0.002	0.002	0.005	0.000	0.000
EA	0.012	0.001	0.002	0.002	0.002
EB	0.152	0.004	0.004	0.004	0.004
EC	0.011	0.002	0.002	0.001	0.002
ED	0.011	0.006	0.001	0.003	0.002
EF	0.021	0.003	0.001	0.001	0.001
EH	0.022	0.007	0.005	0.005	0.005
EJ	0.002	0.001	0.002	0.001	0.001
EK	0.150	0.009	0.017	0.000	0.000
FB	0.011	0.024	0.025	0.026	0.026
GA	0.150	0.001	0.000	0.000	0.000
GB	0.218	0.018	0.019	0.018	0.018
GC	0.011	0.008	0.008	0.009	0.008
GF	0.126	0.009	0.003	0.004	0.004
GJ	0.665	0.002	0.003	0.003	0.003
GK	0.012	0.003	0.002	0.002	0.001
HA	0.011	0.006	0.000	0.000	0.000
HB	0.062	0.003	0.007	0.007	0.007
HC	0.150	0.009	0.002	0.002	0.002
HD	0.012	0.046	0.001	0.001	0.000
HE	0.665	0.024	0.001	0.001	0.001
HF	0.321	0.004	0.001	0.000	0.000
HG	0.002	0.005	0.005	0.005	0.005
HJ	0.022	0.016	0.017	0.017	0.017
HK	0.011	0.018	0.002	0.000	0.000
JB	0.526	0.046	0.046	0.046	0.046
JF	0.029	0.006	0.008	0.007	0.007
KB	0.321	0.005	0.000	0.000	0.000
KF	0.062	0.007	0.001	0.000	0.000
KJ	0.011	0.002	0.001	0.000	0.000

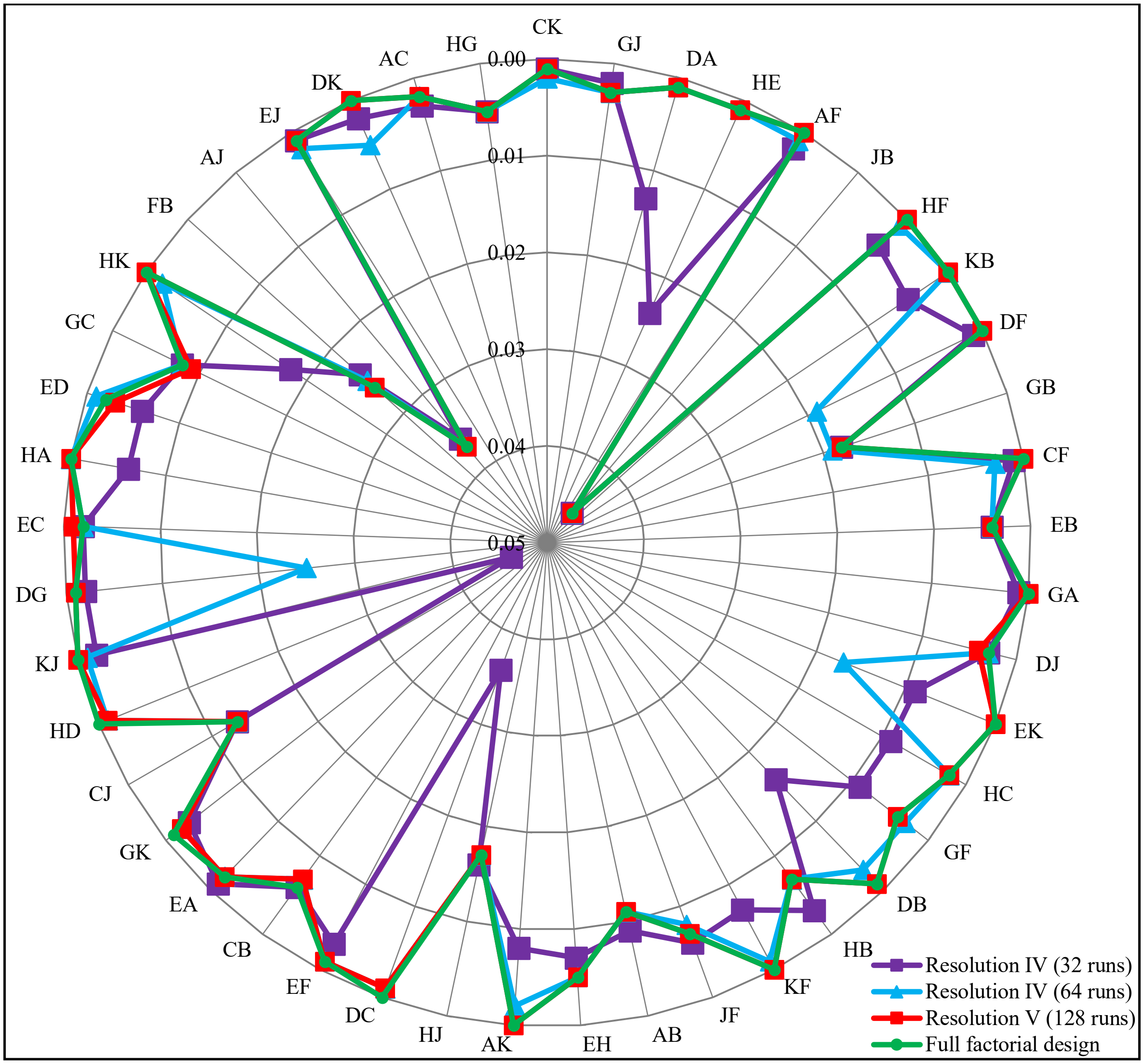

Figure 4.9 The two-variable interactions for different resolutions

4.6.2.3 Variable screening and grouping results

The variable screening and grouping criteria in Figure 4.2 are applied to the results of main effects and two-variable interactions in the previous sections. For variable screening, the results are the same for all resolutions: the floor slab thickness (K) and roof construction type (D) are excluded from optimization. For variable screening, 19 two-variable interactions in level III are larger than the threshold, making the optimization problem inseparable. The results of level IV to full factorial design are all less than the threshold, and the original optimization problem is divided into ten subproblems.

4.6.3 The mid-rise apartment building

The design resolution of fractional factorial design used in this case study is V. The regression-based method takes 64 runs for the seven variables, while the Sobol method takes 900 runs. The results of the main effect and two-variable interaction are compared. Since the sensitivity indicators used by these two methods are not the same, it is not possible to directly compare the value of indicators. Therefore, the rankings of the two variables are compared.

4.6.3.1 Main effects

The rankings of the main effect for the two methods are compared in Table 4.10. It can be seen from the results that the rankings using the regression-based method are the same as the results using the Sobol method.

Table 4.10 The rankings of the main effects for the regression-based method and the Sobol method

Variable	Ranking	
	Regression	Sobol
WWR	1	1
SHGC	2	2
Wall insulation	3	3
Roof insulation	4	4
Orientation	5	5
Floor slab thickness	6	6
Foundation slab thickness	7	7

4.6.3.2 Two-variable interactions

The rankings of the two-variable interaction for the two methods are shown in Figure 4.10. As the table shows, the regression-based method results differ from the Sobol method results for the two-variable interactions. Based on Sobol method analysis results, Table 4.11 lists the effects contributing 95% of the total variation, including the main effects and two-variable interactions. It can be observed from the table that 11 effects contribute to the 95% variation for the Sobol method. The top 11 ranked effects of the regression method are the same as the ones of the Sobol method with slightly different rankings. The results show that the regression-based method does not achieve the same ranking results as the Sobol method, but the four important interactions are the same between the two methods. Therefore, it is appropriate to use regression-based sensitivity analysis for variable grouping.

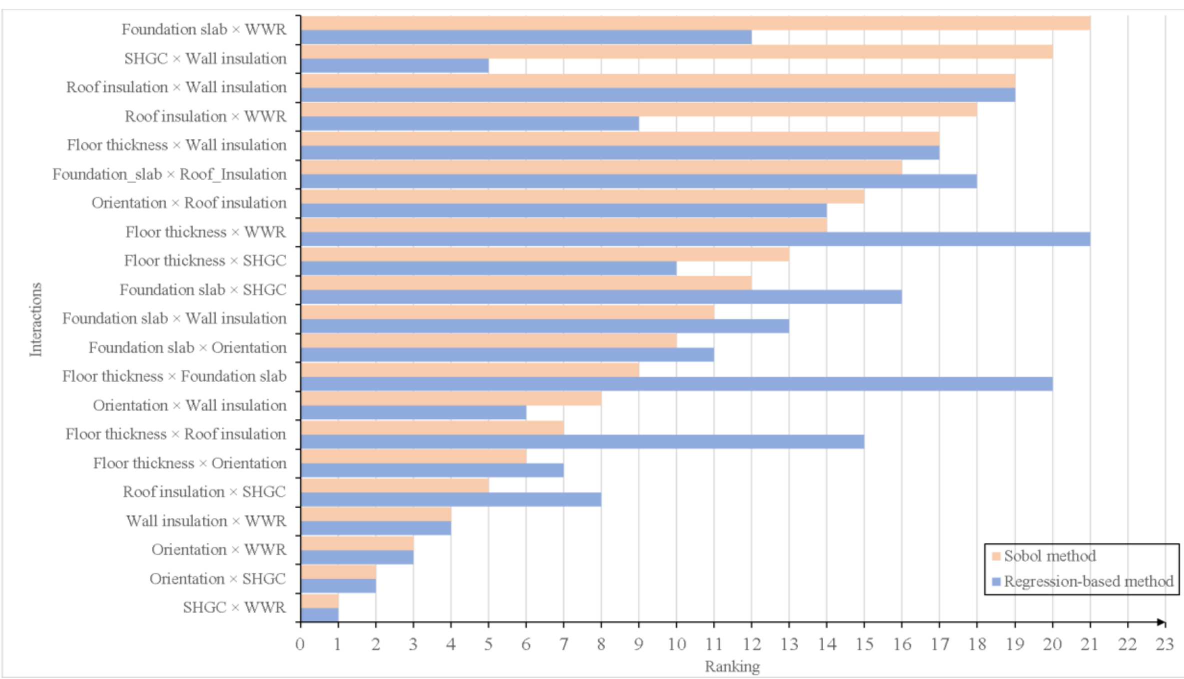

Figure 4.10 The rankings of interaction between the proposed method and the Sobol method

Table 4.11 The ranking comparison within 95% of the cumulative contribution rate

Factors	Sobol ranking	Regression ranking
WWR	1	1
SHGC	2	2
Wall insulation	3	3
Roof insulation	4	4
Orientation	5	5
Floor slab thickness	6	9
SHGC × WWR	7	6
Orientation × SHGC	8	7
Orientation × WWR	9	8
Wall insulation × WWR	10	11
Foundation slab thickness	11	10

4.6.3.3 Variable screening and grouping results

The variable screening and grouping criteria in Figure 4.2 are applied to the results of main effects and two-variable interactions. For variable screening, the floor slab thickness and foundation slab thickness are excluded from the optimization for the regression-based method. Since the Sobol method uses different indicators, the threshold in the criteria does not apply to the results of the Sobol method. However, if selecting six out of seven variables is required, the variable screening results will be the same for the two methods.

For variable grouping, only the interaction of window to wall ratio and solar heat gain coefficient obtained by regression-based method is larger than the threshold. Therefore, the optimization problem with seven variables is divided into six subproblems, as shown in Figure 4.11. The subproblems have only one variable except for the subproblem optimizing the window to wall ratio and solar heat gain coefficient. For the Sobol method, the variable grouping results will be the same as the results of the regression-based method if it is asked to group the variables with the strongest interactions.

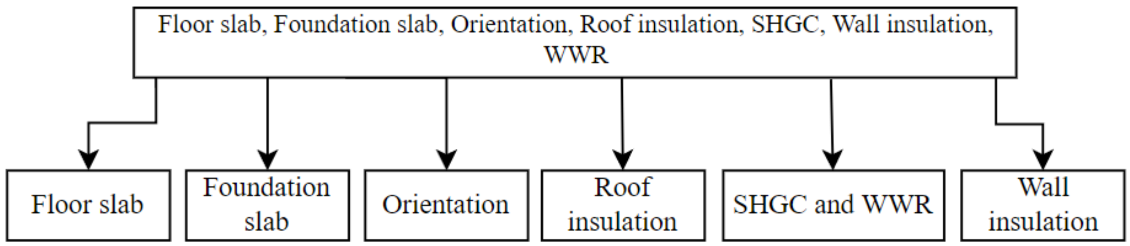

Figure 4.11 Results of variable grouping

4.7 Conclusion

This research investigates the feasibility of sensitivity analysis for variable screening and grouping. The variable screening uses the main effects, and the variable grouping uses the two-variable interactions. For these purposes, the sensitivity analysis method is required to achieve acceptable results with a controllable number of experiments. This study proposes to apply the regression-based sensitivity analysis using the two-level fractional factorial design. Three case studies are used to discuss the performance of this method using the results of sensitivity analysis and variable screening and grouping. The results of the second case study show that if only variable screening is performed, resolution IV is recommended, and if both variable screening and grouping are performed, resolution V is recommended. The results of the third case study show that the proposed method can achieve the same variable screening and grouping results as the results using the Sobol method. However, this method might perform poorly if the variables have significant nonlinear performance. In such a case, the mixed-level factorial design can be used. The variables with nonlinear performance can be assigned with three levels, and the monotonic variables are assigned with two levels. Moreover, the results of variable screening and grouping are discussed separately. A dimension reduction methodology for building design optimization problems using variable screening and grouping simultaneously could be developed. These studies could be done in the future.

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Chapter 5. Conclusions

This study proposes two decomposition approaches for building design optimization problems to save computation time while achieving the original problem's global optimum. In addition, the feasibility of combining variable screening and parallel decomposition for dimensionality reduction is discussed.

The hierarchical decomposition divides the optimization problems into multiple levels. In order to achieve the global optimum, first-level optimization is required to keep the solutions to the original problem. This study proves that if the objective functions of the first-level optimization are the linear sum of the objective functions of the original problem, the first-level optimization will retain the solutions of the original problem. The proposed approach is applied to solve the optimization problem minimizing the operating costs and carbon emissions under different energy price and emissions scenarios. After decomposition, the first-level optimization minimizes the energy consumption while the second-level optimization minimizes the operating costs and carbon emissions under different energy price and emission scenarios. The case study results show that the proposed approaches reduce the computation time and achieve the global optimum of the original problem. The energy prices are assumed as annually constant in this study. However, the energy prices could be flexible other than annually constant. This study provides adjustments according to the change of this assumption.

The parallel decomposition applies the “divide-and-conquer" strategy, dividing the original problem into several subproblems. In order to achieve global optimum, a dual-criteria variable grouping method is developed. The criteria require one variable to be separated from the other variables for optimization if its optimal solution stays the same regardless of the value of the other variables. The criteria are assessed using sensitivity analysis and interaction plots. After decomposition, each subproblem is solved while the variables in other subproblems are set as default values. The case study shows that the sensitivity analysis and interaction plots are not totally effective in assessing the criteria. Therefore, the subproblem might miss the global optimal solution when the default value of the variables in other subproblems change. The performance of the proposed method can be improved by first optimizing the subproblem with the strongest main effect and using the results for subsequent subproblems with decreasingly weaker main effects. Two case studies are applied to demonstrate the proposed approaches, and the results show that the proposed approaches reduce the computation time and achieve the global optimum of the original problem.

The regression-based sensitivity analysis using the fractional factorial design quantifies the interaction for the variable grouping in Chapter 3. This study discussed the potential to use this method for variable screening and grouping. The performance of this method on sensitivity analysis, variable screening and grouping is investigated through case studies. It is found that this method can achieve acceptable results with a controllable number of experiments. Therefore, the parallel decomposition developed in Chapter 3 can be combined with the variable screening to further reduce the dimensions of building design optimization problems.

The two decomposition approaches proposed in this study can be used individually or combined as a hybrid decomposition. An example of hybrid decomposition is shown in Figure 5.1. In this example, the original problem is to minimize the building's operating costs and carbon emissions. After hierarchical decomposition, it is divided into two levels. The first-level optimization minimizes energy consumption, and the second-level optimization minimizes operating costs and carbon emissions. The parallel decomposition decomposes the first-level optimization into several subproblems. In the future, a case study can be done to demonstrate the benefits of using the hybrid decomposition approach.

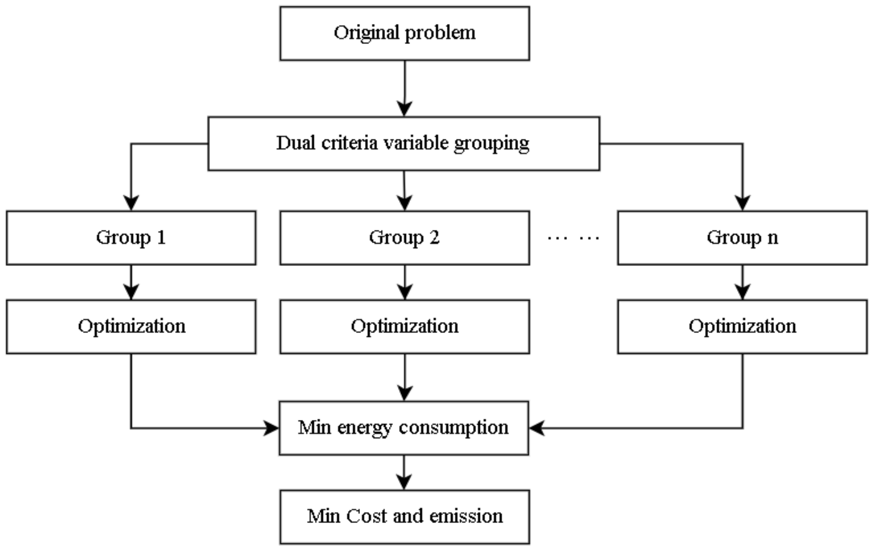

Figure 5.1 Hybrid decomposition combining the hierarchical and parallel decomposition

The following recommendations are provided to help users to select a decomposition approach. There are three scenarios as shown in Figure 5.2:

Option 1: When one problem has a hierarchy structure, and the objectives of this problem are the linear sum of another problem's objective functions, it is recommended to apply the hierarchical decomposition.

Option 2: When the computation cost is still high after the hierarchical decomposition, applying the parallel decomposition to the first-level optimization as a hybrid decomposition is recommended.

Option 3: It is recommended to only apply parallel decomposition when the hierarchical decomposition conditions in option 1 are not met.

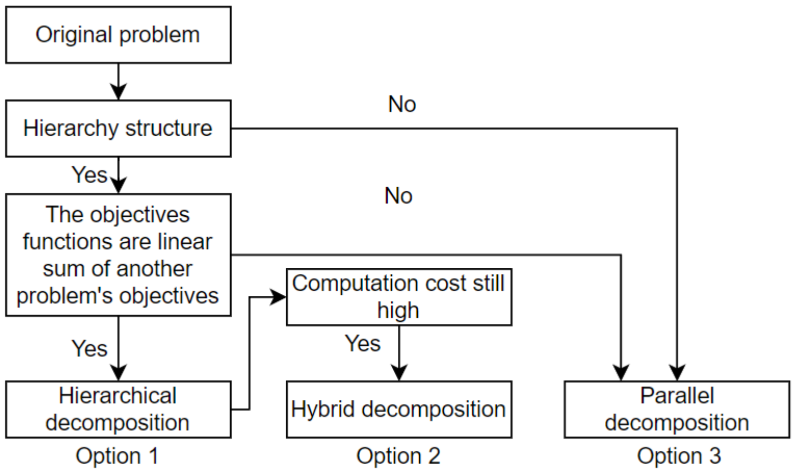

Figure 5.2 Recommendations for selecting a decomposition approach

Publication Contributions

This thesis is based on scientific papers written to meet the Ph.D. project objectives set during the research to advance scientific and industrial goals. Most of the details of this study are comprised of the papers below, and therefore the submitted manuscript should be aimed only as a summary of the overall research. This study is the outcome of my research as a Ph.D. student at the Department of Building, Civil, and Environmental Engineering, Concordia University, Montreal, Canada, and has resulted in three journal papers and two conference papers listed below:

Journal papers:

1. Li, Yin, Nima Bonyadi, Ashleigh Papakyriakou, and Bruno Lee. "A hierarchical decomposition approach for multi-level building design optimization." Journal of Building Engineering 44 (2021): 103272.
2. Li, Yin, Nima Bonyadi, and Bruno Lee. "A parallel decomposition approach for building design optimization." Journal of Building Engineering. Under review

Conference paper:

1. Li, Yin, and Bruno Lee. "Applying multi-attribute decision making to identify robust multi-objective design solutions in building design application." In Proceedings of 2018 eSIM conference, Montreal, QC, Canada
2. Yin, L., & Lee, B. (2019, June). Simulation-based building performance comparison between CLT-concrete hybrid, CLT, and reinforced concrete structures in Canada. In Proceedings of the 2019 CSCE Annual Conference, Laval, QC, Canada