BIM-BASED MULTI-OBJECTIVE OPTIMISATION FOR SUSTAINABLE BUILDING DESIGN

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ABSTRACT

The ever-increasing attention towards environmental sustainability in the building industry drives the development and adoption of energy-efficient buildings. Passive design strategies have been widely investigated, such as the building's orientation and the material selection of both the transparent and opaque envelope components. This method involves a vast domain of design variables, which makes the design process complicated and error prone. Furthermore, enhancing the energy performance of a building might impose economic burdens, necessitating a trade-off between energy-efficient practices and cost. This paper proposes a novel methodology to integrate building information modelling (BIM) with energy simulation and optimisation engines to provide designers with a building's energy plan at the early design stage. The model developed in this paper can reduce the complexity of the optimisation process and design errors by creating an automated workflow and lowering manual inputs. A multi-objective optimisation was carried out using the non-dominated sorting genetic algorithm-II to achieve a balance between two conflicting objectives, namely minimising energy consumption and the life cycle cost of the building. Design variables considered include building orientation, various materials for external walls, roof, floor, window-to-wall ratio, and shading types. The effectiveness and feasibility of the proposed model were validated using a case study building located in Sydney, Australia. Following the evaluation of numerous design possibilities, the energy plan was demonstrated by utilising results derived from Pareto front solutions. The findings of this study serve to aid decision-makers in identifying optimal design solutions based on their respective priorities, thereby facilitating the delivery of a sustainable building design.

Keywords: BIM, energy-efficiency, life cycle cost, sustainable design, multi-objective optimisation.

1 INTRODUCTION

Sustainable development has become a significant focus across academia, industry, and society due to its fundamental objective of meeting present needs while ensuring the ability of future generations to meet their own requirements [1]. In this context, addressing the energy consumption by industrial activities is of paramount importance in promoting sustainability and mitigating the adverse effects of global warming and climate change [2]. The building sector, in particular, stands out as the largest contributor to energy consumption and carbon emissions around the world [3]. As a result, policymakers are implementing regulations with the objective of promoting the adoption of energy-efficient building practices within the construction industry. This approach seeks to expedite the progression towards a more sustainable future.

To address these concerns, it is important to explore a range of active and passive design strategies that aim to minimise the energy demand of buildings while adhering to sustainability principles. By making changes to key design parameters such as the building's shape, orientation, window-to-wall ratio (WWR), and thermal properties of various elements, it is possible to reduce energy consumption in buildings [4]. However, determining the most effective design solution to enhance buildings' energy performance can be challenging due to the presence of multiple objectives that often have conflicting interests.

The attainment of a building design that achieves high energy performance has the potential to increase investment costs significantly, primarily due to the integration of new

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technologies or materials with higher thermal resistance [5]. However, it is important to recognise that an energy-efficient building can effectively alleviate the overall financial burden by reducing the energy requirements for meeting thermal comfort during the building's operational phase [6].

To effectively mitigate energy consumption in buildings, it is imperative to comprehensively assess the key factors that govern the thermal performance of a building, as these factors have a direct impact on energy usage [7]. Several crucial considerations play a significant role in determining energy consumption, including local climate conditions, building layout and shape, and the characteristics of the building envelope. The building envelope holds significant importance during the design process as it serves as a protective barrier surrounding the building's interior and has a substantial influence on its response to external climate conditions [8]. Several factors are closely linked to the thermal performance of the building envelope. These include the building's orientation and shape, the level of insulation in opaque components, the configuration of windows and walls, and the thermal properties of window and shading materials [8], [9].

When assessing the energy efficiency of buildings, it is important to consider factors other than energy consumption as well. Factors such as financial aspects are needed to be considered, as they play a significant role in decision-making processes regarding the construction of new buildings or retrofitting existing ones to achieve sustainable designs [10]. Nevertheless, the task becomes increasingly complex when the objective is to simultaneously maintain the economic feasibility of the design while reducing energy usage [11].

Cheng et al. employed a multi-objective genetic algorithm (MOGA) as a computational tool to determine the optimal material selection for enhancing energy efficiency, enhancing comfort levels, and minimising environmental impacts [12]. Ciardiello et al. highlighted the potential for significant performance enhancements during the initial design stage. To address this, they employed a two-phase optimisation technique. They used a non-dominated genetic algorithm II (NSGA-II) to explore optimal building geometry designs in the initial phase. In the second phase, they examined optimised design configurations of the building envelope and active strategies using findings from the Pareto frontier. The results indicated that the first phase led to substantial energy savings compared to the second phase [13]. Harlequin, a comprehensive framework provided by Ascione et al. [14], featured a multi-phase and multi-objective design optimisation technique. With the aim of improving the sustainability of an office building in Italy, the study covered a wide range of design factors, including the building envelope, geometry, thermostat setpoints, and active strategies. The research initially conducted energy simulations using EnergyPlus, followed by data analysis and multi-objective optimization employing the NSGA-II algorithm implemented in MATLAB [14].

For a sustainable building design, various parameters must be taken into account, leading to challenges in terms of complexity, time requirements, and the potential for errors. The majority of previous studies focused on improving the energy performance of specific case studies, with comparatively less attention given to the design process itself. However, achieving this goal presents challenges as it involves various design parameters and conflicting objectives. To address these complexities, building information modelling (BIM) can be utilised as a decision support system, seamlessly integrating the design process with optimisation techniques. By increasing the level of automation, BIM aids designers in implementing various design schemes to achieve specific outcomes aligned with their priorities. By enhancing automation, BIM supports designers in executing alternative design schemes to accomplish specific outcomes based on their priorities [7], [15].

Efforts are needed to establish systematic methodologies for designing sustainable buildings that simplify the design process and encourage early implementation of energy-efficient practices. Previous studies have shown the complexity and time-consuming nature of sustainable design, which is due to requiring the substitution of numerous parameters and conducting simulations to evaluate the impacts of design choices. However, the integration between BIM and optimisation models has been limited, hindering comprehensive integration.

To address these gaps, this research proposes a systematic BIM-based multi-objective optimisation model that considers energy, and cost to provide stakeholders with a range of design possibilities. The model extracts the initial design from the BIM model, analyses the impacts of design variables on objective functions, and employs a NSGA-II for optimisation. The outcome of the Pareto front solutions provides a range of design alternatives, enabling decision-makers to choose the most suitable solution based on their specific requirements. Finally, the selected design is incorporated into the BIM model to finalise the design process.

2 METHODOLOGY

The developed model presents a novel strategy with the objective of integrating the sustainable design process into the BIM environment. The primary goal of this integration is to mitigate the time and complexity associated with sustainable design, thereby facilitating the development of energy-efficient and cost-effective designs during the early stages of the design process. A scheme of the proposed model can be seen in Fig. 1.

2.1 Model conception

The proposed framework encompasses three platforms, each assigned specific tasks that contribute to the overall objective. The subsequent section elaborates on the functionalities and roles of these platforms in detail.

2.1.1 BIM

The BIM model is a central component developed using a BIM authoring tool. It enables seamless information flow among the three platforms during the optimisation process. The main functions of the BIM platform are storing the initial building design, exporting relevant data for optimisation, and importing the optimised design back into the BIM model. Then, using revised geometry and component characteristics, the BIM model is modified in accordance with the chosen optimal design.

2.1.2 Data collection

To streamline the optimisation process, a comprehensive database is constructed to encompass a wide range of design alternatives featuring different material options and their respective properties. This database serves as a valuable resource, providing essential information for evaluating and comparing various design choices. The materials within the database are organised into two distinct categories: opaque components and transparent components of the building envelope. Each category includes specific properties crucial for energy performance assessment, such as thermal resistance, specific heat, density, and U-value. In each iteration of the optimisation process, a design configuration is selected within the third platform. The simulation engine then generates the final result, considering the chosen design configuration and its associated properties.

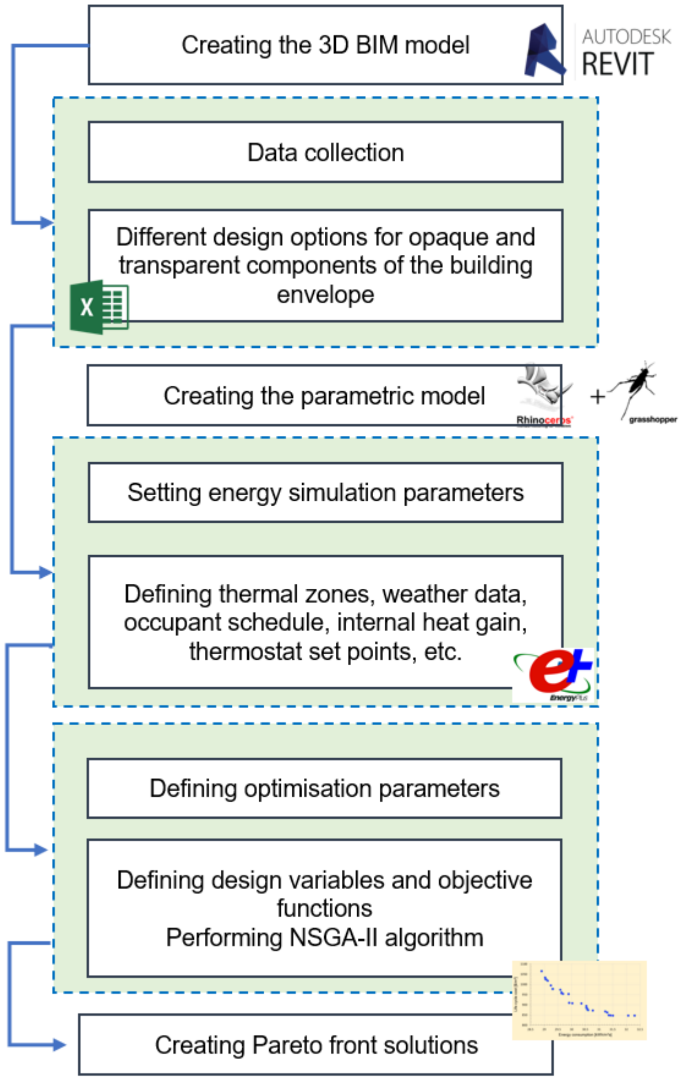

Figure 1: Scheme of the proposed framework.

2.1.3 Parametric modelling

The BIM-derived 3D model is transferred to the third platform for energy simulation. Parametric modelling enables designers to evaluate building performance across different design scenarios effortlessly. By manipulating parameters, such as window size, multiple design options can be quickly generated. The building is divided into thermal zones based on occupancy, and each zone is assigned energy simulation parameters. The simulation engine considers factors like building orientation, weather data, and internal loads to estimate energy consumption and cost. These simulations are integrated into a multi-objective optimisation process, where designs are systematically evaluated. Results are stored for further analysis, leading to an energy plan aligned with optimal design schemes.

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2.2 Optimisation parameters

2.2.1 Objective functions

The proposed model employs multi-objective optimisation to optimise the trade-off between energy consumption and life cycle cost according to eqns (1) and (2):

$$f_1(x_1, x_2, \dots, x_n) = \text{Minimise energy consumption,} \tag{1}$$

$$f_2(x_1, x_2, \dots, x_n) = \text{Minimise life cycle cost,} \tag{2}$$

where x is a combination of various building elements and n is the total available material options for each building element.

The operational energy consumption of a building includes the energy needed for heating, cooling, lighting, and electrical appliances. Electrical appliances are not considered as design variables and are assumed to remain fixed during the building energy simulation, which subsequently contributes to the building's heat gain, which impacts the thermal loads in each zone.

The life cycle cost analysis conducted in this study comprehensively encompasses both immediate expenses, such as construction material costs, and long-term expenditures, including the energy costs incurred throughout the building's entire lifespan. To account for the time value of money, interest and inflation rates are factored in using a specified discount rate. It should be mentioned that this study assumes that no material replacements take place during the operational phase of the building. Consequently, costs associated with maintenance and replacement are not considered within the analysis.

2.2.2 Design parameters

The design parameters examined in this study are crucial for thermal comfort and operational energy consumption. These variables consist of 21 parameters (including building components and their properties), categorised into three groups: opaque and transparent elements of the building envelope, and building geometry according to Fig. 2. Opaque variables involve external walls, roofs, floors, and related components. Transparent variables include window type, shading system, and shading position. Building geometry variables comprise building orientation and WWR. The building shape is predetermined and not a decision variable for the optimisation.

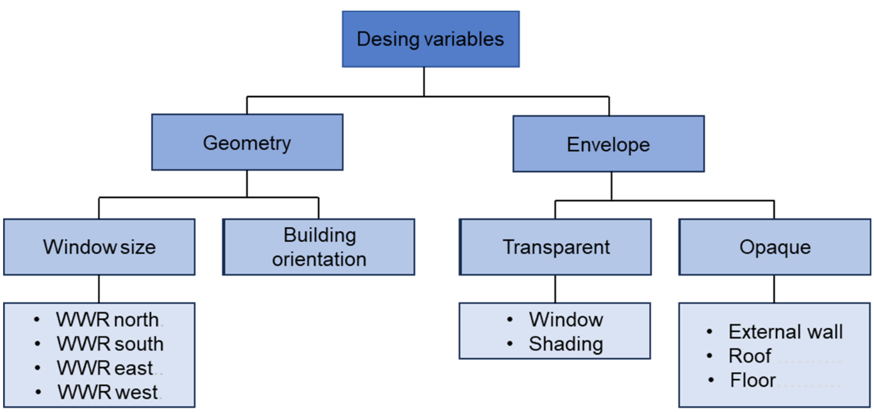

Figure 2: The design variables for the optimisation process.

2.2.3 Optimisation method

The optimisation algorithm aims to find the best solution based on defined objective functions. The choice of algorithm type relies on the particular problem being addressed. Prior research has emphasised that the inclusion of discrete variables may introduce specific obstacles, such as inconsistencies in energy simulation outputs, which can impact the outcomes of design iterations [16]. To address this, population-based algorithms like genetic algorithms (GA) are suitable. The NSGA-II is used in this study, known for its effectiveness in building optimisation. The optimisation process begins with population initialisation, followed by selection, crossover, and mutation operators to generate offspring. The parent and offspring populations are combined, and individuals for the next generation are selected based on dominance and other criteria. These steps are repeated iteratively until the termination criteria are met. The algorithm ultimately generates a collection of optimal solutions referred to as the Pareto front. In this set, any improvement in one objective function would result in a degradation of at least one other objective function.

2.3 Model development

The developed model aims to attain an energy plan for buildings by effectively balancing energy and comfort performance alongside cost considerations. In order to achieve this, a set of specialised tools is utilised within the model. Autodesk Revit 2022 serves as the main building design software, accompanied by Dynamo as a valuable component enabling automated data exchange. Microsoft Excel is employed for efficient data management, ensuring seamless communication among the software, the parametric model, and the database. Grasshopper, integrated within Rhinoceros, provides robust parametric control over the building design. Energy simulation is carried out utilising the EnergyPlus engine, facilitated by the Grasshopper plugins Honeybee and Ladybug for comprehensive setup for energy simulation and retrieval of weather data. The optimisation process is executed within the Grasshopper platform, and NSGA-II algorithm is employed to identify optimal solutions, ultimately leading to the generation of a Pareto frontier.

3 CASE STUDY

A case study is utilised to validate the applicability of the proposed model. The chosen case study pertains to a residential building situated in Sydney, Australia, encompassing a total floor area of 182 m^2. Visual representation of the building's 3D BIM model, created using Autodesk Revit, is displayed in Fig. 3. Within this model, there exist a total of nine distinct thermal zones, six of which are subject to conditioning, while the remaining three remain unconditioned.

The weather data required for conducting the energy simulation in Sydney is sourced from the EnergyPlus weather database, ensuring accurate representation of the local climatic conditions. The thermostat setpoints for heating and cooling operations are established at 19°C and 26°C, respectively. Additional parameters and settings employed for the energy analysis are outlined in Table 1. Likewise, Table 2 provides details concerning the thermal characteristics of the building's envelope, that are used as design variables.

In accordance with the preceding section, the life cycle cost analysis of the building encompasses two primary components: material cost and electricity cost. The material cost, which is dependent on the design variables, is calculated using data from the Australian building handbook. The electricity cost is considered at 28.7 cents per kilowatt hour. Moreover, to ascertain the present value of the electricity cost throughout the building's lifespan, a discount rate of 3.1% is applied, aligning with conventional financial practices.

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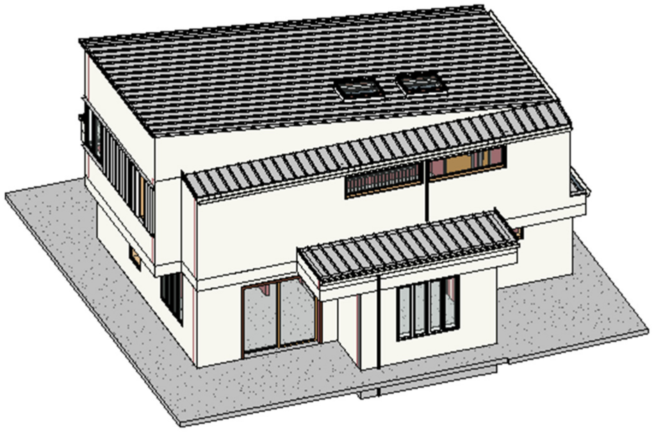

Figure 3: The 3D BIM model of the case study.

Table 1: Parameters configuration for the energy simulation.

Parameters	Values
Lifespan of the building	40 years
Thermostat set point for heating	19°C
Thermostat set point for cooling	26°C
Internal heat gain from occupants	110 W
Lighting load	2.8 W/m2
Infiltration rate	0.8 ACH

Table 2: Characterisation of the design variables.

Design variables	Description		Range of variability
Insulation	EPS, wool, XPs, polyisocyanurate	Thickness	0.05–0.15 (m)
Wall cladding	Brick, timber, fibreboard	Thickness	0.0045–0.07 (m)
Wall core	Concrete, concrete aerated, brick veneer, timber	Thickness	0.05–0.21 (m)
Roof	Terracotta tiles, aluminium sheets, steel zincalume ribbed	Thickness	0.00042–0.008 (m)
Floor	Concrete slab, timber	Thickness	0.15–0.3 (m)
Window material	Clear float glass 3, Clear float glass 6, Double glazing 2 side float Argon filled 4	U-value	2.52–5.8 (W/m^2.k)
Shading	Material properties	Reflectance Transmittance Emissivity	0.2, 0.5, 0.8 0.1, 0.4, 0.7 0.1, 0.4, 0.8
Window size	Window-to-wall ratio	°	10%, 20%, 30%, 40%, 50%, 60%, 70%
Building orientation	Degree to north	°	0, 45. −45, 90

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4 RESULTS AND DISCUSSION

The outcomes of multi-objective optimisation derived from the application of the proposed model are visually presented in Fig. 4. The scatter plot illustrates different design scenarios, where each point represents a unique combination of genes (design variables) and its corresponding outcome in terms of the building's life cycle cost and total energy consumption. Notably, the red point illustrated within the scatter plot represents the Pareto front solution, which embodies the optimal set of solutions among all other options generated during the optimisation process. This Pareto front solution serves as a representation of the trade-offs between cost and energy consumption for the building.

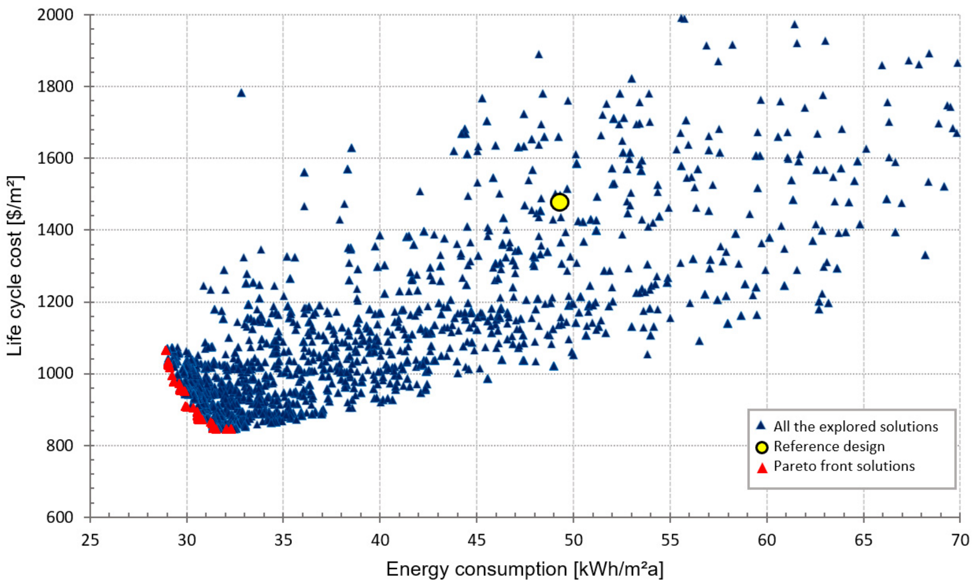

Figure 4: The result of multi-objective optimisation.

The NSGA-II algorithm offers significant advantages in this scenario. Given the presence of 21 design variables or genes, the search space becomes incredibly large (around 1.1e20), making it infeasible to explore all possible combinations. However, the genetic algorithm efficiently narrows down the search by selecting and refining the design variables that lead to better results while disregarding less-promising scenarios. The optimisation process in this study involved 4,500 iterations, resulting in the examination of 4,500 different design scenarios. This approach allows for a comprehensive analysis of diverse possibilities within a manageable timeframe, overcoming the computational challenges posed by the extensive search space.

Fig. 4 demonstrates that the life cycle cost ranges from \$845.5 to \$2000/m^2, whereas the energy consumption varies between 28.9 to 70 kWh/m^2 per annum. Fig. 5 presents the investment cost versus the electricity cost. Notably, the left side of the graph exhibits a horizontal distribution, indicating a consistent electricity cost of approximately \$200/m^2, while the corresponding investment cost fluctuates within the range of \$620 to \$890/m^2. This indicates that applying different passive design can reduce the building investment cost while maintaining the energy performance of the building at a good level. This observation emphasises the importance of careful considerations during the early stages of building design, when it is possible to achieve high energy performance while simultaneously ensuring cost-effectiveness.

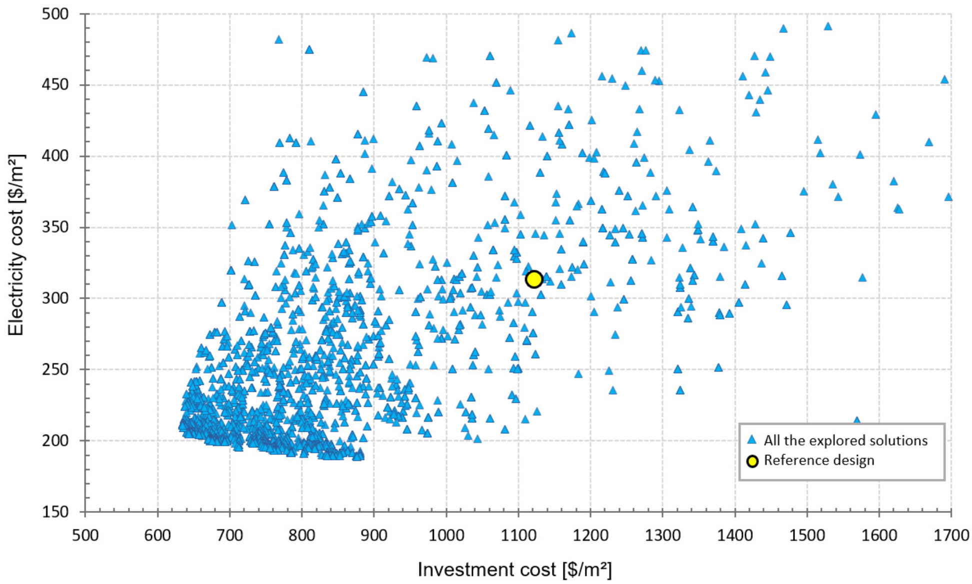

Figure 5: The result of multi-objective optimisation for investment cost versus electricity cost.

Fig. 6 exclusively presents a summary focused on the Pareto front solutions that effectively minimise both energy consumption and life cycle costs. The analysis reveals notable improvements in both life cycle cost and energy consumption when comparing the reference design to the Pareto-optimal solutions. The minimum life cycle cost achieved is $845.5/m^2, representing a significant 42.5% improvement over the reference design. Similarly, focusing on the design that minimises energy consumption according to the Pareto front, an annual energy reduction of 41.3% can be achieved. This substantial reduction in energy usage amounts to saving 520,992 MJ of energy over the lifetime of the selected case study, thereby contributing to a significant reduction in carbon emissions as well.

To identify the most optimal building characteristics, it is recommended to select the design scheme located along a diagonal line from the middle of the graph within the Pareto front. This design scheme represents a balance between energy efficiency and cost-effectiveness. The design variables associated with this scheme, along with other design variables that represent the most energy-efficient and cost-effective designs, are presented in Table 3. It is important to note that these results have been carefully selected from the Pareto frontier, which encompasses a range of viable design options. Stakeholders can prioritise their preferences and requirements when choosing alternative design schemes that align with sustainability objectives. For example, if there are constraints related to the initial investment budget, it may be necessary to exclude design schemes that exceed the allocated budget from the scatter plot. This selective approach allows stakeholders to focus on design alternatives that are both sustainable and financially viable, facilitating decision-making during the design process.

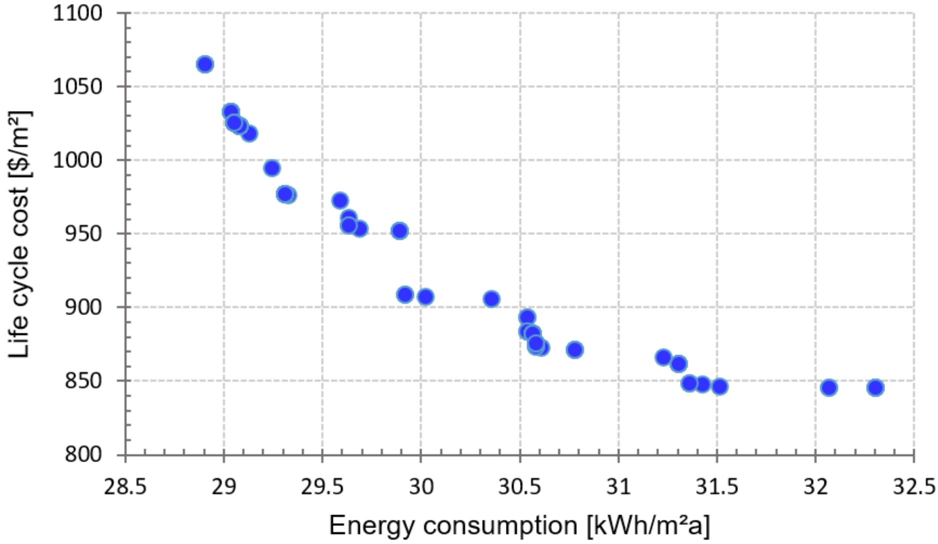

Figure 6: Pareto front results.

Table 3: Characterisation of optimised design scheme.

Parameter	Thickness (t, m)	Conductivity (k, W/m.K)	Density (ρ, kg/m^3)
Roof			
Cladding	0.001	15	7,800
Insulation	0.15	0.022	40
Floor			
Core	0.2	0.76	1,400
Insulation	0.18	0.038	23
Wall			
Cladding	0.015	0.3	750
Core	0.11	1	2,000
Insulation	0.15	0.022	40
Window			
WWR	Bed 1 = 20%, Bed 2 west = 20% , Bed 2 north = 40%, Bed 3 north = 20%, Bed 3 west = 30%, Bed 4 = 40% , Living room 1 south = 50%, Living room 1 west = 30%, Living room 2 north = 40%, Living room 2 north = 30%		
Material	Double glazing 2 side float 6 mm SHGC = 0.703, VT = 0.7 U-value = 2.56 (W/m².K)		
Building orientation			
Degree to north	0°		
Shading	Reflectance = 0.2, Transmittance = 0.1, Emissivity = 0.1		

5 CONCLUSIONS

This paper presents a novel methodology that integrates BIM with energy simulation and optimisation engines to facilitate the early-stage energy planning of buildings to achieve a sustainable design. The proposed model effectively addresses the complexity and potential errors associated with the optimisation process by automating workflows and reducing manual inputs. By utilising a multi-objective optimisation approach using the NSGA-II algorithm, the study achieves a trade-off between minimising energy consumption and the life cycle cost of the building. The model considers various design variables, including building orientation, materials for external walls, roof, floor, WWR, and shading types, to identify optimal design solutions. The effectiveness of the proposed model is validated through a case study of a residential building located in Sydney, Australia. The results demonstrated substantial improvements over the reference design, with a 42.5% reduction in life cycle cost and 41.3% reduction for annual energy consumption. The results obtained from the proposed model can support decision-makers in selecting optimal design schemes based on their priorities.

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