PROCEEDINGS OF ECOS 2023 - THE 36TH INTERNATIONAL CONFERENCE ON
EFFICIENCY, COST, OPTIMIZATION, SIMULATION AND ENVIRONMENTAL IMPACT OF ENERGY SYSTEMS
25-30 JUNE, 2023, LAS PALMAS DE GRAN CANARIA, SPAIN

Trade-off between embodied and operational carbon emissions of residential buildings in early design stage

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Abstract:

Buildings are responsible for a significant portion of the global energy use and carbon emissions. There is great potential to reduce a building's environmental impact in the early stages of design. Over the past decade, there has been a concerted effort to create energy-efficient and net-zero buildings by reducing operating energy. However, additional materials and new applications are needed to reduce energy demand. This may result in an increase in embodied carbon, which is the carbon emitted during the materials and construction phase. Since there is a trade-off between embodied and operational environmental environment, it is important to consider both in the design process. However, there is a lack of research that addresses this issue. To help with this challenge, a multi-objective optimization model that combines machine learning, building information modelling, and life cycle assessment has been developed. This model can help in making design decisions that balance embodied and operational carbon emissions. An actual building project has been used to verify the model developed. The findings reveal that early design stage has the potential to save 32.5% emissions for mid-rise buildings in hot summer and cold winter climate zone in China. Moreover, window-to-wall ratio and number of floors largely affecting the trade-off between embodied and operational impacts. The findings of this study can provide low-carbon and energy-efficient design solutions for residential buildings in the early stages of design.

Keywords:

Embodied carbon; Operational carbon; Optimization; Building design.

Nomenclature:

Abbreviations

LCA	-	Life cycle assessment	SVM	-	Support vector machine
BIM	-	Building information modelling	LSSVM	-	Least squares linear machine
HVAC	-	Heating, Ventilation, and Air Conditioning	NSGA-II	-	Non-dominated genetic algorithm II
WWR	-	Window-to-wall ratio	TOPSIS	-	Technique for order preference by similarity to an ideal solution

Symbols

μ	-	Average	R^2	-	Coefficient of determination
Z	-	Standard deviation	a_{i1}	-	low bounds of the i^{th} design variable
$\hat{y}_i$	-	Predicted value by the LSSVM model	a_{i2}	-	up bounds of the i^{th} design variable
$\bar{y}_i$	-	Arithmetic mean of y_i	x_i	-	Input variable
n	-	Number of training examples	x	-	Output variable
∂_i	-	Lagrange multipliers	C	-	Penalty parameter
b	-	Bias term	CO_2-eq	-	Carbon dioxide equivalents

1. Introduction

https://doi.org/10.52202/069564-0271

A significant share of the global negative environmental effects (e.g., use of resources and environmental consequences of releases) are caused by the building sector. The International Energy Agency stated that in 2020, the construction industry accounted for 36% of world energy consumption and 37% of carbon dioxide emissions [1]. The environmental impacts of a building over its life cycle can be divided into embodied environmental impacts and operational environmental impacts. Operational impacts are caused by energy usage during building operation, whereas embodied impacts are connected to the raw material extraction, construction, end-of-life treatments, recycling, and final disposal [2]. The embodied impacts are significant and occasionally equal operational environmental impact levels [3]. It is therefore a pressing need to simultaneously minimize embodied and operational environmental impacts for creating environmentally preferred buildings. However, there is a reciprocal relationship between the embodied and operational environmental impacts. This relationship can be attributed to additional materials and new applications and systems are required to reduce the resources consumption and energy demands during building operational stages [4]. The extra materials and equipment may lead to a decrease of impacts due to operational energy use while increasing embodied environmental impacts. As a result, buildings with energy-efficient measures may cause more total environmental impacts [4,5]. Therefore, it is of great importance to focus on the trade-off between embodied and operational environmental impacts whilst lowering the total environmental impacts.

The environmental impacts of a building over its life cycle are largely influenced by the decisions made during the early stages of design [6]. Creating an eco-friendly building design in the early design practice presents a significant opportunity to lower the total environmental impact of a building and find the optimal trade-off between embodied and operational impacts. However, the early design of a building involves making decisions on numerous design variables, such as floor height, floor area, building shape, building orientation, window-to-wall ratio (WWR), and number of floors. Accordingly, thousands of design alternatives can be generated by varying these design variables. It becomes a significant challenge to determine the most appropriate design that reduces the total environmental impact of a building and achieves an optimal trade-off between embodied and operational impacts. The complexity of building design constraints and the large number of design options make it difficult to find out the optimal design solution.

Life cycle assessment (LCA) is a powerful tool to quantify the environmental impacts of a building over its lifetime [7,8]. On the other hand, building information modelling (BIM) digitally represents the physical and functional characteristics of a facility and related information of the building project [9]. BIM model includes all the necessary information for the assessment of embodied environmental impacts and the simulation of energy demand [10]. BIM applications in the environmental impact assessment of a building enable to improve assessment quality [11]. Moreover, the integration between BIM and LCA has been widely accepted and proven effective for assessing the embodied environmental impact assessment. However, the complexity of assessment process using BIM-LCA integration approaches makes it impractical to identify the optimal design solutions that balance embodied and operational impacts. The repetitive procedures and processes involved in the combined use of BIM and LCA make it challenging to determine the optimal design solutions.

Multi-objective optimization methods allow for different trade-offs between conflicted objectives and have been widely used in the construction industry in a variety of practical topics and contexts. These include, for example, designing building facades [12], selecting building shape [13], and choosing building components or materials such as type of glazing [14] and window type [15]. Multi-objective optimization methods have also been employed to balance the embodied and operational energy in buildings [4]. In the context of building design, multi-objective optimization methods addressed with the parametric design issues [16]. Additionally, multi-objective optimization methods have been applied to address environmental impact topics such as bridge maintenance [17], energy and investment costs management [18], and green building rating systems [19]. For a more comprehensive overview of multi-objective optimization methods applied in the construction industry, see the review articles by Guo and Zhang [20]. The optimization methods have also been used to address other issues such as prefabrication, supply chain, work safety and risk management.

Above discussion reveals that despite the significance, there has been limited focus on the use of multi-objective optimization methods to find the optimal design solutions in linking embodied and operational environmental impacts in early design practice. To address the research gap, this study aims to develop a multi-objective optimization model by using a combination of multi-objective optimization methods and BIM-LCA integration programs to identify optimal solutions that balance the embodied and operational impacts of a building during early design practice. The findings can provide designers with more comprehensive and in-depth understanding on the potentials to save carbon emissions and the relationships between embodied and operational impacts.

2. Research methodology

https://doi.org/10.52202/069564-0271

To fulfil the research aim, this research developed a multi-objective optimization model based on a BIM-LCA integration approach and a meta-based multi-objective optimization method. There are three modules in this developed model: 1) embodied and operational impacts evaluated by a BIM-LCA integration approach, 2) environmental impact prediction based on a machine learning method, and 3) multi-objective optimization of embodied and operational impacts.

2.1. Environmental impact assessment based on integration between BIM and LCA

The first module involves conducting the environmental impact assessment of a building over its life cycle, following a standard process for life cycle assessment outlined in ISO 14040 framework. This process consists of four phases: 1) goal and scope definition, 2) life cycle inventory analysis, 3) life cycle assessment analysis, and 4) life cycle interpretation [21]. In this study, the environmental impact assessment of a building starts with creating a BIM model of the design solutions selected. The goal and scope definition phase includes assumption about the system boundary of life cycle assessment and the building's lifespan. The system boundary in this study includes the product stages (A1-A3), the use stages (B2-B6), and the end-of-life stages (C2-C4), while environmental impacts produced in construction phase (A4) are excluded due to their small proportion of the total environmental impacts [6]. During the life cycle inventory analysis and life cycle assessment phases, the environmental impacts are assessed. Tally is used to assess the embodied impacts by manually matching BIM objects to the building components in Tally. If identical building components cannot be found, similar ones would be used. Moreover, Tally is also used to assess the operational environmental impacts by importing the amount of energy consumption which is simulated by Green Building Studio. Specifically, the physical parameters and thermal properties of the building components, derived from Autodesk Revit database of building components and the common practice in local building projects, are incorporated into the BIM mode to ensure the accuracy of energy simulation. Then, BIM model is transferred into an energy analysis model. Energy analysis parameters are determined such as the operational time of a building, the way of Heating, Ventilation, and Air Conditioning (HAVC) operation. Then, the energy analysis model is imported into Green Building Studio for energy simulation. Green Building Studio is a flexible cloud-based service that uses the DOE2 simulation engine and allows to run building performance simulations to optimize energy efficiency in the design process. In addition, the climate files of the building are set in the performance simulation process. The simulation results are manually input into Tally to assess the operational impacts. In life cycle interpretation phase, the environmental impacts of a building over its life cycle are expressed by environmental impact indicators based on the TRACI 2.1 characterization method [22]. TRACI 2.1 method covers ten different environmental impact indicators by default, such as the global warming potential, non-renewable energy consumption, ozone potential and others. For our calculation, this study considers global warming potential (expressed in the amount of carbon dioxide equivalents (CO_2-eq) to indicate the total environmental impacts of the building.

2.2. Environmental impact prediction by machine learning method

Support vector machine (SVM) developed by Vapnik and Cortes [23], is a machine learning technique based on the statistical learning theory. This technique can solve nonlinear problems very well and is suitable for small sample sizes studies [24]. Least squares linear machine (LSSVM) was developed based on SVM by using a least squares linear system as a loss function to transform the inequality constraints of the optimization problem into equality constraints, thus yielding better performance than an SVM. A training and design of an LSSVM model is an iterative algorithm, and it basically involves four steps: (1) define the problem as the classification or the regression problem, (2) pre-process the input data, (3) determine the model parameters, and (4) validate the model obtained [25]. This study attempts to learn the input-output relationship from the training data, where the inputs are n-dimensional vectors, and the outputs are continuous values. The details about developing the LSSVM model are presented as follows:

The raw data was randomly divided into 80% training data and 20% test data. Given that the units, value domains, physical meanings of independent variables in raw dataset vary substantially, z-score normalisation was performed on raw data to eliminate the influence of different eigenvalue dimensions on the prediction accuracy by applying Equation (1)

$$x' = \frac{x-\mu}{z} \tag{1}$$

Where x denotes the raw data, μ is the average of the sample data, and z represents the standard deviation of the sample data. The processed data follows the standard normal distribution. The average value and the variance of the processed data are 0 and 1 respectively.

The Gaussian kernel function has excellent anti-interference ability [24]. Therefore, Gaussian kernel function Equation (2) was adopted for the prediction model in this study.

$$k(x_i, x) = e^{-\frac{\|x_i - x\|^2}{2\sigma^2}} \tag{2}$$

 https://doi.org/10.52202/069564-0271

Where x_i is the input variable, x is the output variable, and σ^2 is the variance of the Gaussian kernel.

Penalty parameter C controls the trade-off between generalization capacity (wide margin width) and the empirical error of the prediction model. Large C leads to small number of misclassifications and consequently to the smaller margin (good generalization capacity) and vice versa [25]. The selection of penalty parameter C and variance σ^2 greatly affects the prediction error of the model. Normally, the parameters were determined by a trial-and-error process.

Cross validation is often used to optimize the selected values of model parameters (i.e., C and σ^2 in this study) in a refined scale. The process is also called tuning, which is generally empirical, with various values for the parameters systematically evaluated, and the combination of values that generate the highest overall accuracy is assumed to be optimal [26]. K-fold cross-validation method was adopted to search for the optimal combination of C and σ^2. Specifically, the sample data is divided into K sample subsets, where one sample data is selected for testing and the other (K-1) samples are used for training. The cross-validation is repeated K times to obtain the optimal parameter values. Accordingly, the LSSVM model can be obtained by using the optimal C and sigma for training.

To the end, the prediction accuracy of the LSSVM model is measured by coefficient of determination (R^2) in this study, which are defined as Equation (3). The higher the R^2, and the less difference between two sets of data.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{3}$$

Where y_i is the assessment value of i^{th} training example by BIM-LCA integration approaches, $\hat{y}_i$ is the predicted value by the LSSVM model, $\bar{y}_i$ is the arithmetic mean of y_i, and n is the number of training examples passed to LSSVM model.

2.3. Multi-objective optimization based on NSGA-II algorithm

The third module is the multi-objective optimization that deals with the optimization problem related to the environmental impacts of a building.

For this study, the LSSVM-trained model is adopted as the objective functions in the multi-objective optimization process. The relationships between design variables and embodied and operational environmental impacts of buildings are presented as Equation (4):

$$lssvm(x_1, x_2, \dots, x_n) = \sum_{i=1}^{n}(\partial_i - \partial_i^{*})\, e^{-\frac{\|x_i - x\|^2}{2\sigma^2}} + b \tag{4}$$

Where $x_1, x_2, \dots, x_n$ are the design variables. ∂_i and ∂_i^* are Lagrange multipliers, b is the bias term, x_i is the input variable, and x is the output variable (i.e., embodied or operational impacts in this study).

Then, the objectives in each design stage are expressed as follows:

$$\begin{cases} \min f_{embodied}(\, lssvm(x_1, x_2, \dots, x_n)) \\ \min f_{operational}(\, lssvm(x_1, x_2, \dots, x_n)) \end{cases} \tag{5}$$

Where $x_1, x_2, \dots, x_n$ are the design variables in early design stage, $f_{embodied}(lssvm(x_1, x_2, \dots, x_n))$ is the embodied environmental impacts of a building, and $f_{operational}(lssvm(x_1, x_2, \dots, x_n))$ is the operational environmental impacts of a building in early design stage.

Constraints on the objective functions are used to ensure the generated solutions reasonable and feasible. The value ranges of design variables according to the design codes, standards and rules were set as the constraints of the objective functions. The constraints on the design variables can be expressed in inequation (6):

$$a_{i1} \le x_i \le a_{i2} \tag{6}$$

Where x_i denotes the i^{th} design variables in each design stage, while a_{i1} and a_{i2} are the low and up bounds, respectively of the i^{th} design variable.

The non-dominated genetic algorithm II (NSGA-II), developed by Deb [27] was adopted to solve the multi-objective optimization problems in this study. The NSGA-II genetic algorithm can be coupled easily with a backbox model and can handle a set of solutions simultaneously allowing to obtain several pareto frontiers in a single run. The optimization model was used to select the optimum building alternatives with minimum embodied and operational environmental impacts. After obtaining the pareto optimal solution set, the technique for order preference by similarity to an ideal solution (TOPSIS), a multi-criteria decision-making approach was employed to the determine the optimal trade-off point. The TOPSIS method figures out the positive-ideal option in which the maximum gain from each of the objectives is taken and the negative-ideal option in which the maximum loss from each of the objectives is taken. Towards the end, the option that is closest to the positive-ideal solution and farthest away from the negative-ideal solution is selected by the TOPSIS method.

3. Case study

The proposed model was verified by using a mid-rise residential building (refer to a residential building between 4 and 8 floors). The purpose of the case study is to identify the optimal design solutions that balance the trade-off between embodied and operational impacts at early design stage. The case selected for this study was adapted from an actual residential apartment built in Chongqing, China. This project is located in a hot summer and cold winter climate zone, which was built in accordance with the Design Code for Residential Buildings [28]. The long sides of the building are facing north and south. The project is an 8-story, reinforced concrete frame building, and the floor height is 2.8m. The construction methods and building elements from the second floor to the seventh floor are the same. Each floor of the building has a single family which owns four bedrooms, a kitchen, a living room, a storeroom, a balcony and two bathrooms. The building has a total above-basement floor area of 1297.12 m^2 with a life expectancy of 50 years. The building project is a typical example of an apartment building in Chongqing, China representing common building materials and construction techniques for walls, floors, and other building components. Figure 1shows the sketches and 3D model of the building.

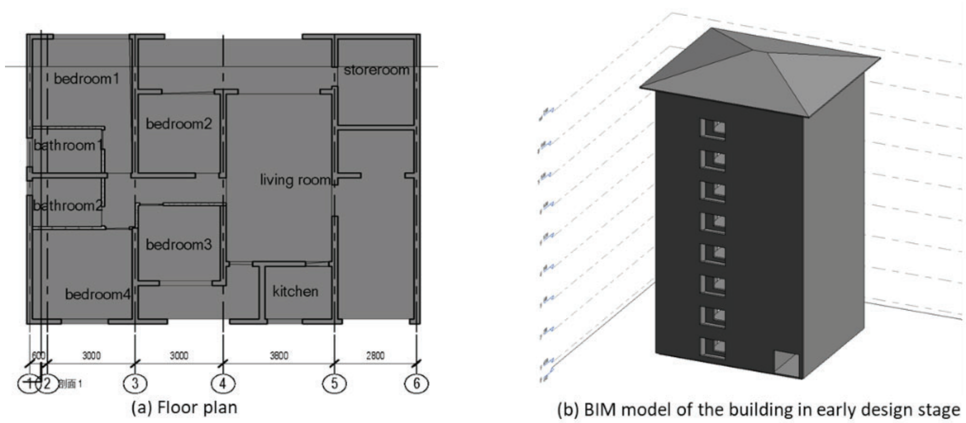

Figure. 1. Sketches and 3D model of the building in early design stage.

There are four design variables affecting the environmental impacts of a building in early design practice [29]. The design variables include: (1) floor height, (2) building orientation, (3) window-to-wall ratio (WWR) and (4) number of floors in early design stage. The variables can be continuous or discrete, and the values or value ranges are determined by national building design and construction standards, regulations and codes [30,31]. The values of the design variables in early design stages are shown in Table 1.

Table 1. Characteristics of design variables for the building in early design stage.

Design variables	Value/value domain	Variable types	Number of options
Floor height	[2.4m, 2.8m]	Continuous	0.1m uniform step (5 options)
Building orientation	[15°, 75°]	Continuous	10° uniform step (7 options)
Window-to-wall ratio	[0.1, 0.5]	Continuous	0.05 uniform step (9 options)
Number of floors	4, 5, 6, 7, 8	Discrete	5 options

4 Results and Discussion

Having examined the design variables and values, possible design alternatives in each design stage are generated by varying design variables. Orthogonal experiment was then conducted to obtain the design samples. In this study, there are 4 design variables and 9 levels in early design stage. Accordingly, 65 design samples were obtained. In referring to the life-cycle environmental impact assessment, BIM models of the design samples were created in Revit. They were then imported into Green Building Studio and Tally for the life-cycle carbon emissions through the BIM-LCA integration approach. The building operating schedule, HVAC system, and outdoor air information are out of the scope of this research, and therefore the building service system is assumed to satisfy the ideal conditions for heating and cooling. As a result, the amount of embodied and operational impacts, expressed by kg CO2eq/m2 for design samples are presented in Figure 2.

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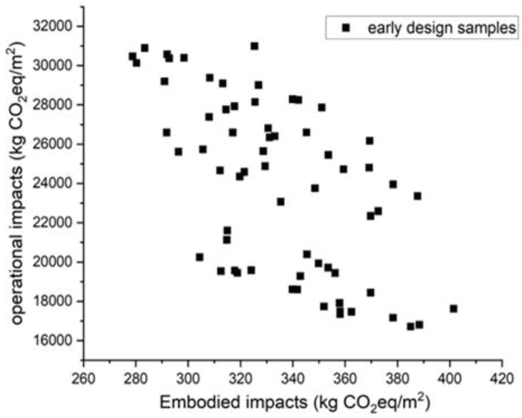

Figure. 2. Environmental impacts of early design alternatives.

As shown in Figure 2, the operational environmental impacts account for a large portion of the life-cycle environmental impacts (over 90% in each design stage). Having obtained the environmental impact assessment results of design samples at each design stage, the MATLAB has been used to train and develop the LSSVM model for predicting the embodied and operational impacts of a building over its design process. 80% of the sample cases (52 cases for early design stage) were used to train the LSSVM model. All inputs and outputs were normalized according to Equation (1). The training results for embodied and operational impact assessment of three design stages are shown in the left of Figure 3. The goodness-of-fit R^2 is 0.97997 for embodied impact assessment and 0.90934 for operational impact in early design stage. They were found very close to 1 for the output studied, thus demonstrating a very good correlation between outputs and target values.

Subsequently, the developed LSSVM model was validated with 13 cases, the rest 20% sample cases. The results of the LSSVM prediction on the testing set are basically consist with the assessment result, as shown in the right of Figure 3. The goodness-of-fit R^2 is 0.9068 and 0.91751 for embodied and operational impact prediction in early design stages, which shows a high prediction accuracy. Therefore, the relationship between design variables and environmental impact established by LSSVM model enables to be used as the objective function of the multi-objective optimization.

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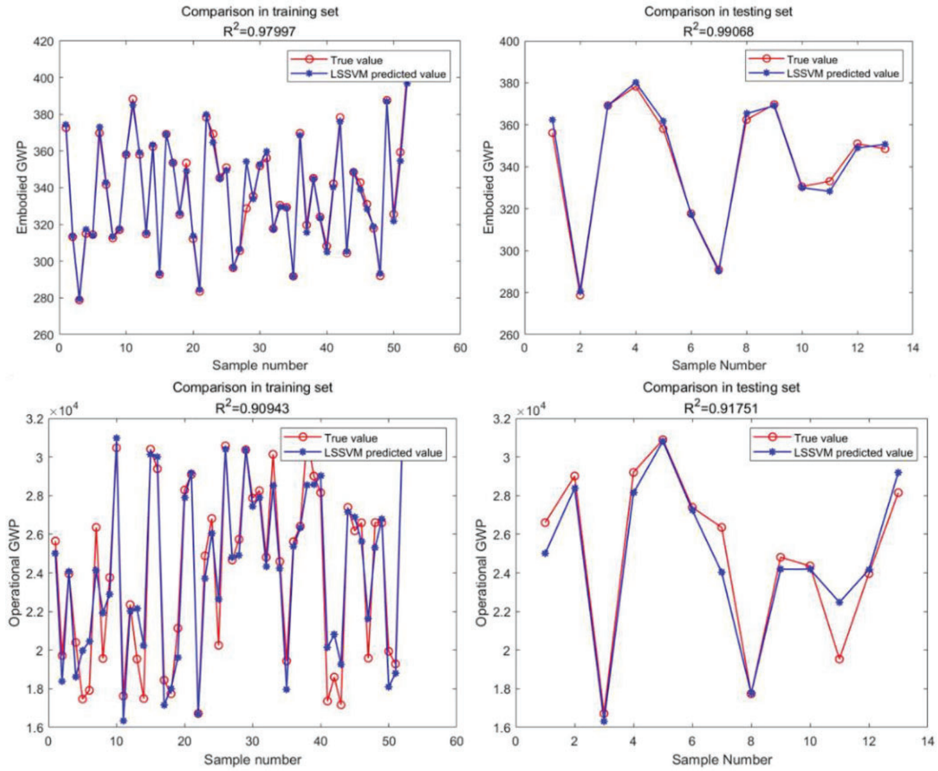

Figure. 3. Environmental impact prediction model.

The combination of LSSVM models and NSGA-II was conducted in Matlab environment to explore the optimal design solution in each design stage. The initial population was set as 100 due for 200 generations based on recommendation. A high mutation rate and a large population size were chosen to avoid getting stuck in local optima. The progress of the objectives was always supervised during the optimization, and if no major improvement could be observed, the algorithm was stopped.

The optimal design solutions are elaborated according to the following optimization cases: (1) Single-objective optimizations for total life-cycle environmental impacts; and (2) A multi-objective optimization considering the operational and the embodied environmental impacts with equal weights. The optimal design solutions are illustrated in Figure 4 and Table 2.

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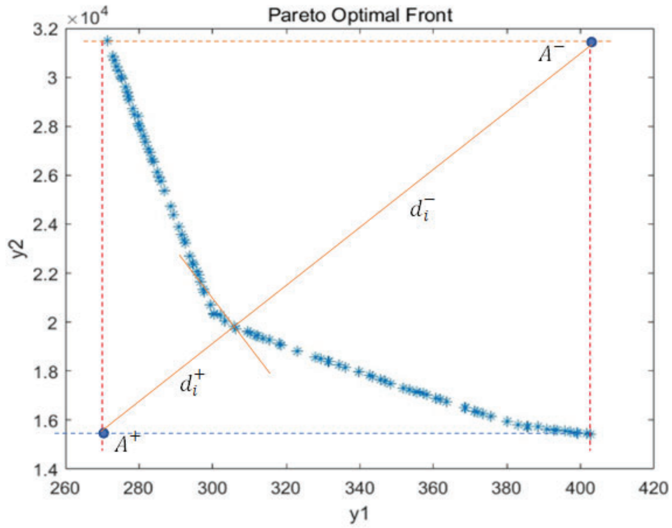

Figure. 4. Pareto optimal front in early design stages.

Table 2. Optimization design solutions.

	Floor height(m)	Orientation (°)	WWR	Number of floors	Embodied impacts	Operational impacts	Total impacts
Original design	2.8	0°	0.25	8	335.38	23070.34	23405.72
Design solution with minimum total environmental impacts	2.8	15°	0.1	4	402.6102	15403	15805.61
Design solution with trade-off between embodied and operational impacts	2.8	15°	0.4	8	322.9659	18831	19153.97

The Pareto frontier in early design stage is illustrated in Figure 4. It indicates that there is a trade-off between embodied and operational environmental impacts in early design stage. As embodied impacts (denoted as y1 in Figure 4) increase, the operational impacts (denoted as y2 in Figure 4) decrease. In referring to the single objective optimization for total life-cycle environmental impacts, the minimum total impact (15805.61 kg CO_2eq/m^2) is obtained in the design option where there are 4 number of floors with floor height of 2.8 m, the WWR is 0.1, and the orientation of building is 15° south to west, as shown in Table 2. The total CO_2eq generated by the optimal design equals to 67.5% of that from the original building design. In other words, it is possible to reduce 32.5% of the environmental impacts for the original design by varying the design parameters in early design practice. The difference between the optimal design solution and the original one lies in the building orientation (15° vs. 0°), WWR (0.1 vs. 0.25) and number of floors (4 vs. 8).

In referring to the trade-off between embodied and operational impacts, the TOPSIS analysis results reveal that the trade-off design solution is the case (number of floors: 8, floor height: 2.8m, orientation: 15° south to west, and WWR: 0.1). The total environmental impact is 19153.97 kg CO_2eq/m^2, which consists of an embodied impact of 322.97 kg CO_2eq/m^2 and an operational impact of 18831 kg CO_2eq/m^2. The operational impact of trade-off design increases by 8.8% while the embodied impact decreases by 25.8%, compared with the original design. Since the trade-off solution intends to simultaneously minimize the embodied and operational impacts of the original design, its total environmental impacts are larger than "the minimum total impacts" (15805.61 kg CO_2eq/m^2). Interestingly, the difference between the "trade-off solution" and the "solution with minimum total impacts" only lies in the design values of "WWR" and "number of floors" (The floor height and orientation of the building keep constant). This indicates that WWR and number of floors seem to have a strong influence on the trade-off between embodied and operational impacts of a building.

5 Conclusion

This research developed a multi-objective optimization model based on the combined use of BIM-LCA integration approaches, machine learning method and NSGA-II algorithm to find out the balance between embodied and operational impacts of a building in its early design practice. The man conclusion based on the case study are as follows: 1) early design stage has the potential to save 32.5% emissions for mid-rise buildings in hot summer and cold winter climate zone in China. 2) window-to-wall ratio and number of floors largely affecting the trade-off between embodied and operational impacts. Further research needs to investigate other design stages throughout the entire design process. Moreover, future research can also explore other building types in different climate zones.

Acknowledgements

The authors wish to acknowledge the financial support from the Australian Research Council (ARC), Australian Government (No: DP190100559, DP200100057, IH200100010) and the financial support from Sustainable Development Goals Project Allowance Grant in Western Sydney University.

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