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Developing a multi-objective optimization model for improving building's environmental performance over the whole design process

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A B S T R A C T

This study is built upon two previous articles which focus on identifying the key design variables affecting the life-cycle environmental impacts in each design stage of the building design process. This research aims to investigate the trade-offs between embodied and operational impacts and explore potential reduction in the total environmental impacts of a building by varying the identified design variables in each stage of the design process. A multi-objective optimization model based on BIM and LCA integration has been developed to find out the design solution with the optimal trade-offs between the embodied and operational impacts and the option with the minimal environmental impacts. Applying the proposed model to a mid-rise residential building, the results showed that the design process has the potential to lower the environmental impacts of the building by approximately 47.6 %. Moreover, the potential for reducing carbon emissions is greater in the early design stages, with the potential to lower emissions by up to 32.5 %, compared to the lower emission reduction potential of approximately 7.5 % in the detailed and construction design stages. Furthermore, solutions aimed at addressing the trade-off between embodied and operational impacts were identified in each design stage. The study provides an insight into the understanding of how building design can be optimized to mitigate environmental impacts.

1. Introduction

1.1. Background

Building sector accounts for 36 % of global energy use and 37 % of carbon dioxide emissions [1]. Reducing environmental impacts (e.g., use of resources and environmental consequences of releases) of buildings is a pressing need. Over their life cycle, environmental impacts of buildings can be split into embodied environmental impacts and operational environmental impacts [2]. Embodied impacts are related to raw material acquisition, construction, end-of-life treatment, recycling and final disposal, while operational impacts are caused by energy use in the building during its operation [3]. The embodied and operational environmental impacts are equally important [2,4]. Therefore, it is crucial to simultaneously minimize embodied and operational environmental impacts for reducing total environmental impacts of buildings.

However, there is a reciprocal relationship between the embodied and operational environmental impacts. For example, to reduce the consumption of resources and energy during building operational stages, additional materials and new applications are required, such as the adoption of alternative thermal insulating materials [5]. The use of such additional materials may contribute to a reduction in energy use during building operation, while increasing environmental impacts are incurred during the construction process [5,6]. Therefore, it is of great importance to focus on the trade-offs between embodied and operational environmental impacts, with the ultimate goal of minimizing the total environmental impact.

Nearly 70 % of the life-cycle environmental impacts of a building are determined by the decisions made in design processes [7,8]. There is a great potential to lower environmental impacts of a building during its design process by varying design variables. Researchers and practitioners have recognized the importance of varying the building design in minimizing the environmental impacts. For example, a couple of design variables, such as number of floors, window-to-wall ratios, glazing type and insulation type have been investigated to lower the life-cycle environmental impact [9–11] Despite helpful in understanding the influence of design variables in the mitigation of environmental impacts, these studies have focused on limited design variables or have

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investigated multiple design variables that should not coexist simultaneously. In a real design process, the design variables are chosen sequentially. The already fixed design variables are separated from those to be determined in later design stages. The interaction between design variables that should not coexist simultaneously can negatively affect the results of the environmental impact assessment. Therefore, it is important to sequentially investigate all possible design variables at each design stage with regards to environmental impact reductions.

This study is built on two previous articles in which a general building design process is divided into three stages, namely early design stages, detailed design stages and construction design stages [12,13]. Moreover, previous studies reveal that 14 variables have great effects on the environmental impacts of the building throughout its design process [13]. 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; (1) thermal insulating material for external walls, (2) external wall structure, (3) thermal insulating material for internal walls, (4) internal wall structure, (5) thermal insulating material for floors, and (6) type of window frame and glazing in detailed design stage; and (1) finishing material for external wall, (2) finishing material for internal wall, (3) finishing material for floor, and (4) type of roof tiles in construction design stage.

Having gained an understanding of the key design variables at each design stage, two crucial questions that arise are: *1) how to figure out the optimal design solutions of the embodied versus operational environmental impacts trade-off at each design stage?* And 2) *to what extent could life-cycle environmental impacts be lowered throughout the whole building design process?*

1.2. Literature review on methods

To achieve design solutions that have minimum negative environmental impacts, the environmental performance of design options must be known. Life cycle assessment (LCA) is a powerful tool to quantify the environmental impacts of a building over its lifetime [14,15]. 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 [16]. A BIM model includes all the necessary information for the assessment of embodied environmental impacts and the modelling of energy simulation [10]. BIM applications in the environmental impact assessment of a building can improve assessment quality [17,18]. Numerous programs for integrating BIM and LCA tools have been developed over the past decade such as Tally and oneClickLCA [19]. These programs can quickly show the embodied environmental impacts of an individual design solution, allowing for picking the most environmentally friendly design in a limited number of design options. However, the developed BIM-LCA integration models or commercial programs cannot show the environmental impacts of a building at the operational stage. Moreover, assessing the environmental impact of a building by BIM and LCA integration approaches is a complex task. It is not practically feasible to assess the environmental impacts of thousands of design options and find out the optimal option by repetitively using the procedures and processes of BIM and LCA integration approaches.

The trade-off between embodied and operational impacts is a multiple-objective optimization problem as two conflicted objectives (embodied versus operational impacts) need to be optimized simultaneously. Multi-objective optimization methods, such as the pareto method and the scalarization method, allow to find the optimal solutions to a problem with several contradictory objectives [20]. The Pareto method is commonly used in the situation where the desired solutions and performance indicators are separate, while the scalarization method involves incorporating a scalar function into the objective function and enables to generate a single solution. The multi-objective optimization of environmental impacts of a building is a typical nonlinear problem for which there is no single best solution that can simultaneously minimize the embodied and operational impact of a building [6]. Therefore, the Pareto method appears to be appropriate for solving the problem related to the optimal design solutions of the embodied versus operational environmental impacts trade-off in this study.

Moreover, a proper objective function is a prerequisite for the accurate and efficient performance of the multi-objective optimization. Mathematical function is often used as the objective function [21]. However, in cases where the relationship between input variables and output variables are complex and cannot be expressed by specific mathematical functions, an implicit function, called surrogate-model can be built to express the relationships by using machine learning technologies. For example, artificial neural network (ANN) was used to build a surrogate model to define the relationship between design variables and thermal comfort and total energy consumption [22]. In another study, support vector machine (SVM) was used to establish the surrogate models for heating, cooling and lighting energy use [23]. Additionally, a comparative review was conducted on the use of SVM and ANN techniques, as the most frequently employed techniques, for forecasting energy demands in buildings [24]. The machine learning techniques were compared in terms of their accuracy and robustness in estimating and predicting the energy production and consumption in the building sector. The study emphasised that SVM was more robust when compared with ANN-based methods in the building energy demand sector.

Furthermore, multi-objective optimization methods have been widely used in the construction industry in a variety of practical topics and contexts. These include, for example, the design of building facades [25], the selection of building shape [26], and the selection of building components or materials such as type of glazing [27] and window type [28]. Multi-objective optimization methods were also adopted to balance the embodied and operational energy in buildings [5]. In the context of building design, the parametric design issues were addressed by an iterative process for multi-objective optimization [29]. Within the environmental impact topics, multi-objective optimization methods have been applied, for example, in bridge maintenance [30], energy and investment costs management [31], and green building rating systems [32]. For a review of multi-objective methods applied in the construction industry, see the review articles by Guo and Zhang [33]. Other examples include prefabrication, supply chain, work safety and risk management.

Above discussion on the methods reveals two limitations: (1) BIM and LCA integration approaches cannot show the operational environmental impacts of a building and fail to identify the optimal solution from thousands of design alternatives; and (2) Despite wide use of multiple-objective optimization methods in the construction industry, there has been limited focus on desirable design solutions in linking embodied and operational environmental impacts at each design stage throughout the whole building design process. Moreover, above discussion also shows that SVM appears to be a robust machine learning algorithm in the building sector.

The purpose of this study is to answer the aforementioned questions and address the limitations. To address the issues, this study develops a multi-objective optimization model. This proposed model incorporates the advantages of BIM-LCA integration approaches in assessing environmental impacts, and the pareto method to handle the relationship between embodied and operational impacts of a building throughout the entire design process. The novelty of this research is: 1) The potentials to reduce environmental impacts in building design is examined at each design stage in a sequential manner; 2) A joint workflow for assessing the life-cycle environmental impacts is established based on integrating BIM and LCA; 3) A model combining the developed joint workflow and multi-objective optimization method is developed to optimize the life-cycle environmental performance of a building; 4) The design solution of a building is continuously optimized throughout the entire design process from the perspective of minimal life-cycle environmental impacts and trade-off between embodied and operational impacts. Despite

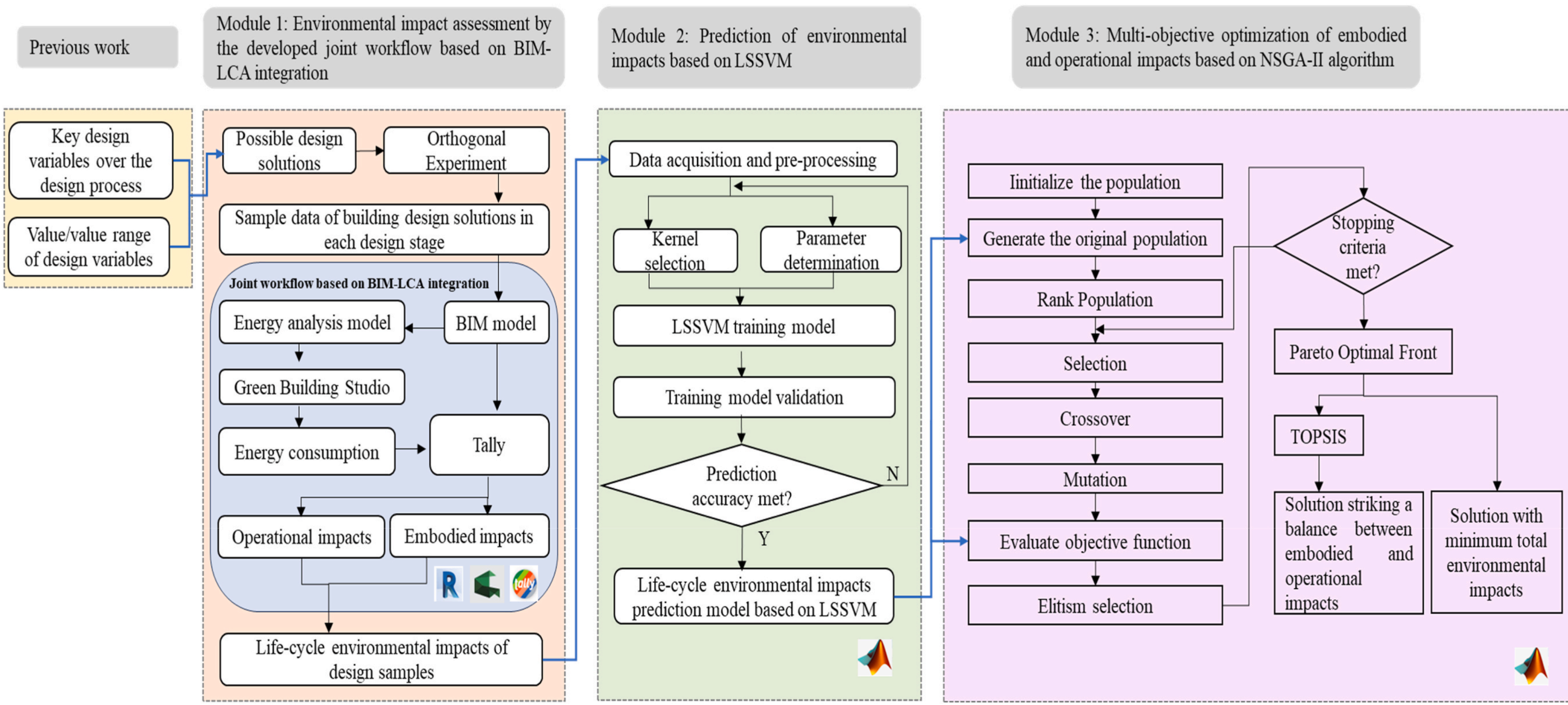


Fig. 1. Framework of the proposed multi-objective optimization model.

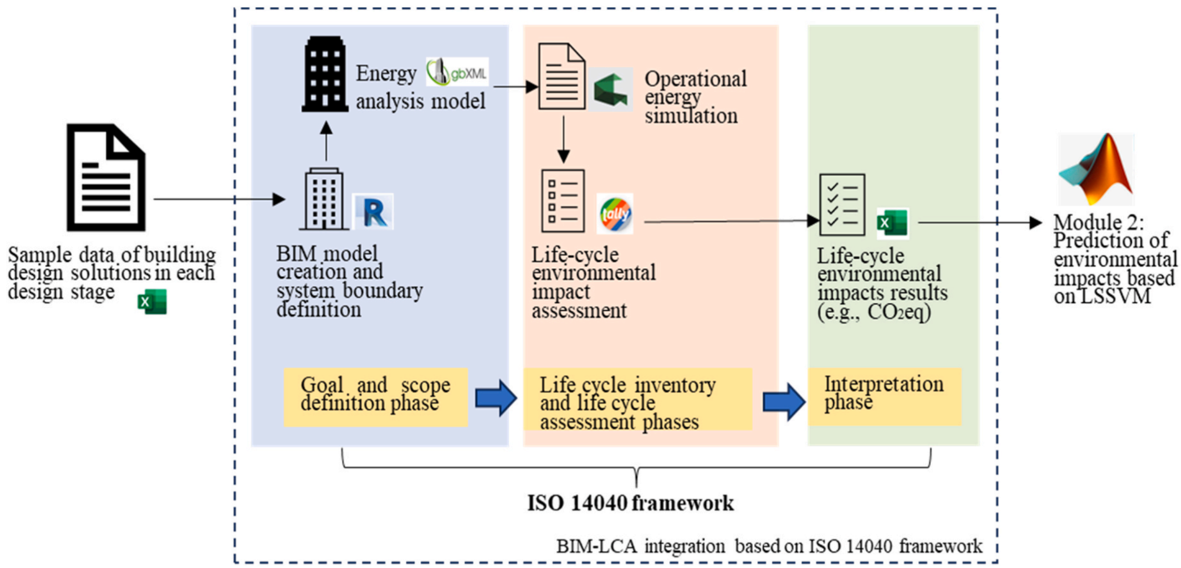


Fig. 2. Workflow for life-cycle environmental impact assessment based on the integration between BIM and LCA.

the scope of this study focusing on the environmental performance of a building, the developed model can be extended to other optimization objectives of building design.

The rest of this article is organized as follows. In Section 2, the multi-objective optimization model based on BIM and LCA integration is proposed and explained. The proposed model is applied in an actual case in Section 3. Findings and discussions are presented in Section 4 and 5, respectively, which is followed by the conclusions in Section 6.

2. Multi-objective optimization model based on BIM-LCA integration

The aim of this research is to identify the optimal design solutions at each design stage with minimum environmental impacts of a building and solve the trade-off problem between embodied and operational environmental impacts throughout its design process. To fulfill the aim, a multi-objective optimization model is proposed. The framework of the proposed model is depicted in Fig. 1.

As can be seen, the proposed model is divided into three main modules namely, life-cycle environmental impact assessment of design solutions by the developed joint workflow based on BIM-LCA integration, prediction of embodied and operational impacts based on LSSVM, and multi-objective optimization based on NSGA-II algorithm. The procedures in each module are described in detail in the following sub-sections.

2.1. Environmental impact assessment of design samples

The first module is to conduct life-cycle environmental impact assessment of design samples by using a joint workflow based on the integration between BIM and LCA. This sub-section initially elaborates the developed joint workflow and then assesses the life-cycle environmental impacts of the design samples by using the joint workflow.

2.1.1. A joint workflow for assessing life-cycle environmental impacts

The joint workflow for assessing the life-cycle environmental impacts of a building is developed by following the life cycle assessment rules in International Organization for Standardization (ISO) 14040-ISO 14044 standards. The set of ISO standards have created a general methodological framework to support LCA implementation. In addition to the ISO 14040 standards, there are standards specifically targeting building sector, such as ISO 21930, EN 15978, EN15804 and others (European Committee for Standardization, 2011; ISO 21930, 2017). ISO 21930 and EN 15804 focus on providing the rules, specifications, and requirements to develop an environmental product declaration (EPD) for construction products and services, construction elements and integrated technical systems used in any type of construction works. However, these standards do not directly present a framework for LCA implementation, and the quantified environmental data in environmental declaration is predetermined based on ISO 14040 and ISO 14044. Furthermore, very few BIM-LCA integration studies have been executed according to these standards. On this point, although ISO 14040 standard series provides a general systematic framework for conducting an LCA, the application of the ISO 14040 framework has been well received in previous BIM-LCA integration studies [34–36]. Therefore, the basic framework for LCA in ISO 14040 and ISO 14044 is adopted in this study. The framework includes four phases: 1) goal and scope definition, 2) life cycle inventory analysis, 3) life cycle assessment analysis, and 4) life cycle interpretation [37]. The workflow is shown in Fig. 2, where the embodied and operational impacts are jointly assessed in Tally within BIM environments.

In goal and scope definition phase, the system boundary of life cycle assessment and the lifespan of the building are assumed. EN 15978:2011 (Sustainability of construction works. Assessment of the environmental performance of buildings. Calculation method) defines the system boundary that applies at the building level. This standard divides the life-cycle stages of a building into four stages, namely product stage (A1-A3), construction process stage (A4-A5), use stage (B1–B7), and end-of-life stage (C1–C4). In this study, system boundary includes the product stages (A1-A3), the use stage (B2–B6), and the end-of-life stages (C2–C4). Environmental impacts produced in construction phase (A4) are excluded because they account for a small proportion of the total environmental impacts [4].

In life cycle inventory analysis and life cycle assessment phases, the life-cycle environmental impacts of the design solution are assessed in Tally, as shown in Fig. 2. To assess the embodied impacts, a built-in LCA database in Tally that combines material attributes, assembly details and architectural specifications with environmental impact data was utilized. LCA modelling was conducted in Gabi 8.5 using GaBi 2018 database and in accordance with GaBi databases and modelling principles. BIM objects were matched to building components in Tally. Similar building component were substituted if an identical building component could not be found in Tally. On the other hand, the analysis of operational energy demand is conducted in Green Building Studio (GBS).

Initially, the physical and thermal characteristics of building materials and components, such as the density and the thermal conductivity, are collected from literature and BIM databases. These characteristics are then integrated with BIM objects. Subsequently, an energy analysis model is created based on the BIM model. The energy analysis model is exported as a gbXML file, which is uploaded to GBS for energy simulation using the DOE2 simulation engine. It should be noted that the transfer process from the BIM model to the gbXML file may result in the loss of certain building components and materials due to the poor compatibility. To address this issue, the Spider gbXML Viewer is employed to visualize the energy analysis model. By identifying the missing components in the Spider gbXML Viewer, the BIM model is amended accordingly to improve the effectiveness of the energy analysis model. Finally, the simulation results were imported into Tally to calculate operational environmental impacts. Through this approach, the life-cycle environmental impacts of the building are assessed in Tally, and the results are imported into Excel for further analysis.

In life cycle interpretation phase, the environmental impacts of a building are expressed by environmental impact indicators based on the TRACI 2.1 characterization method [38]. 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 (CO2-eq)) to indicate the total environmental impacts of the building.

2.1.2. Life-cycle environmental impact assessment of design solutions

All Possible design solutions in each design stage could be generated by varying the identified design variables in corresponding design stage. Then, the Allpairs software is utilized to design the orthogonal experiment for obtaining the samples of building design solutions in each design stage. The sample size for observations depends on the value ranges/values of design variables of each design stage. The design samples collected are then conducted life-cycle environmental impacts by BIM-LCA integration approaches.

The embodied and operational environmental impacts of design samples in each design stage are assessed by the developed joint workflow as shown in Fig. 2. The values of design variables are varied in design samples, modifications to the building model are necessary to accommodate diverse design solutions. Accordingly, the life-cycle environmental impacts could be assessed by iteratively implementing the workflow, yielding unit outcomes. Ultimately, the study combines the building design samples in each design stage with their corresponding assessment results to generate a building performance dataset. The dataset is used for subsequent prediction and optimization sessions.

2.2. LSSVM-trained model

This sub-section attempts to learn the relationship between the design variables and embodied/operational environmental impacts at each design stage based on the building performance dataset generated. The process of training and design of a LSSVM model is an iterative algorithm, and it involves three steps: (1) pre-process the input data, (2) determine the model parameters, and (3) validate the model obtained [39]. The training process is conducted in MATLAB environment, which are presented as follows:

The raw dataset in each design stage (i.e., each design solution and environmental impact) was randomly divided into 80 % training data and 20 % test data. 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.

Four parameters should be determined for using LSSVM, namely the kernel function, the penalty parameter C, the shape parameter of kernel function, and cross-validation method. The Gaussian kernel function has the advantage of being a radial basis kernel function and has excellent anti-interference ability [21]. Moreover, Gaussian kernel function has been widely adopted for the assessment and prediction of building performance (e.g., building energy demands, and building lighting) [23]. Therefore, Gaussian kernel function Equation (2) is adopted for the prediction model in this study.

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

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

The penalty parameter C and variance σ^2 greatly affect the prediction error of the model. The parameters are determined by a trial-and-error process. Moreover, 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. K-fold cross-validation method is adopted to search for the optimal combination of C and σ^2 in this study as this method requires less processing time [40]. 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.

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

Where y_i is the assessment value of i^{th} training example by BIM-LCA integration approaches, $\widehat{y}_i$ is the predicted value by the LSSVM model, $\overline{y}_i$ 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 trade-off problem between embodied and operational impacts and the optimization problem related to total environmental impacts of a building during its design process. There are three critical aspects for successfully employing multi-objective optimization to solve problems, namely building objective functions and constraints, obtaining Pareto front, and making final decision from the Pareto front [33].

2.3.1. Objective functions and constraints

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/operational environmental impacts of a building in each design stage are presented as Equation (4):

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

Where $x_1, x_2, \ldots, x_n$ 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:

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

Where $x_1, x_2, \ldots, x_n$ are the design variables in various design stages,

Table 1
Design scheme of base building in three design stages.

Design stage	Building components					
	External walls (thickness: mm)	Internal walls (thickness: mm)	Floor (thickness: mm)	Roof (thickness: mm)	Door (thickness: mm)	Windows (thickness: mm)
Early design stage	Cast-in-place concrete (200)	Perforate brick (190)	Cast-in-place concrete (100)	Cast-in-place concrete (100)	None	None
Detailed design stage	Cement mortar (5) Mineral wool boar (40) Cement mortar (7) Cast-in-place concrete (200) Cement mortar (7)	Cement mortar (5) EPS board (40) Cement mortar (7) Perforate brick (190) Cement mortar (7)	Cement mortar (20) EPS board (15) Cement mortar (20) Cast-in-place concrete (100)	Polyurethane waterproof coating (2) Cement mortar (20) XPS board (25) Cast-in-place concrete (100)	Wood door	Aluminum window frame with monolithic glazing
Construction design stage	Facing stone (30) Cement mortar (5) Mineral wool boar (40) Cement mortar (7) Cast-in-place concrete (200) Cement mortar (7)	Acrylic latex (5) Cement mortar (5) EPS board (40) Cement mortar (7) Perforate brick (190) Cement mortar (7) Acrylic latex (5)	Wood plank (12) Cement mortar (20) EPS board (15) Cement mortar (20) Cast-in-place concrete (100)	Concrete tile Polyurethane waterproof coating (2) Cement mortar (20) XPS board (25) Cast-in-place concrete (100)	Wood door	Aluminum window frame with monolithic glazing

$f_{embodied}(lssvm(x_1, x_2, \ldots, x_n))$ is the embodied environmental impacts of a building in each design stage, and $f_{operational}(lssvm(x_1, x_2, \ldots, x_n))$ is the operational environmental impacts of a building in each design stage.

Constraints on the objective functions are used to ensure the generated solutions reasonable and feasible. For this study, 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):

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

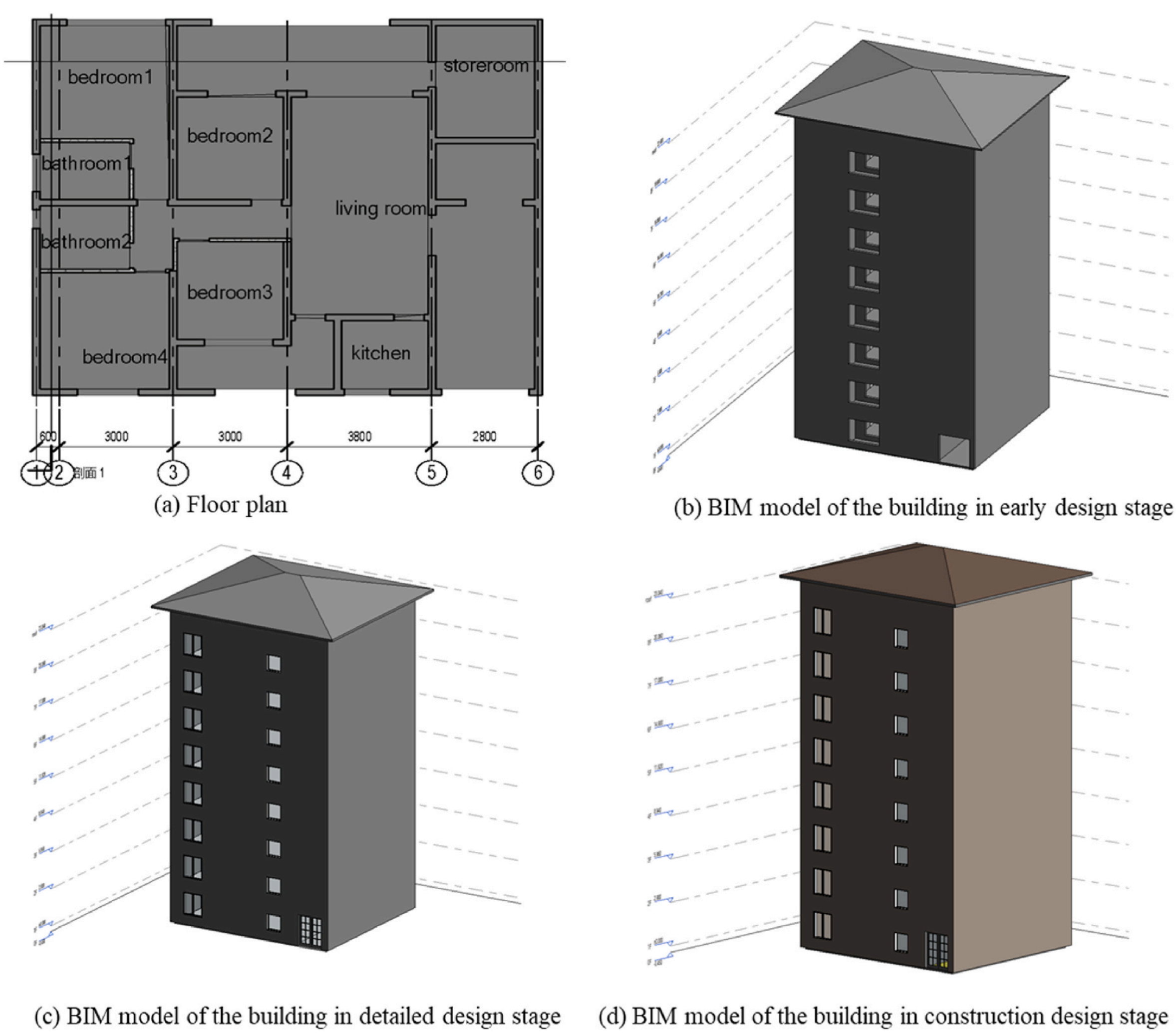


Fig. 3. Floor plan and 3D model of the building.

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.

2.3.2. Optimal design solutions

The non-dominated genetic algorithm (NGSA-II) II, developed by Deb et al. [41] is adopted to determine the Pareto front 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 algorithm was used to select the optimum building alternatives with minimum embodied and operational environmental impacts by referring to the process shown in Fig. 1.

(1). The optimization process begins with setting up certain parameters of the NSGA-II algorithm, such as the number of generations, population size, mutation rate, and crossover rate.
(2). In the second generation, the parent and offspring populations are combined, and a fast non-dominated sorting is conducted. Additionally, the distance between individuals is calculated to determine the degree of crowding. A new population is then established based on the non-dominated relationship and crowding distance between individuals.
(3). A new offspring population is produced by using three genetic mechanisms mentioned above.
(4). The second and third steps are repeated until the maximum number of offspring generations has been reached, at which point a set of Pareto optimal solutions is generated.

Having obtained the pareto optimal solutions, decision-making rules are required to determine the final optimal solution. For this study, the technique for order preference by similarity to an ideal solution (TOPSIS) was employed to the determine the optimal trade-off point of embodied and operational impacts. The TOPSIS method figures out the positive-ideal option (A^+) in which the maximum gain from each of the objectives is taken and the negative-ideal option (A^-) in which the maximum loss from each of the objectives is taken [42]. The option that is closest to the positive-ideal solution and farthest away from the negative-ideal solution is selected.

3. Application to a case study

The applicability of the proposed model was verified by using a medium-low rise residential building (defined as residential buildings between 4 and 8 floors). The aim of the case study is to find out the design solution The case selected was adapted from an actual mid-rise residential apartment built in Chongqing, China. This project is located in a hot summer and cold winter climatic zone and its design complies with the Design Code for Residential Buildings [43]. 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 2.8 m. 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 50-year life expectancy. The building project is a generic apartment building example in Chongqing. The geometrical parameters and the types and features of the building components and materials presented are commonly used in the Chinese construction sector and they are collected from national building design and construction standards, regulations and codes [44]. A general description of the materials and building components is shown in Table 1. Sketches and 3D model of the building are shown in Fig. 3.

Table 2
Design variables for the building in early design stage.

Key design variables	Value/value range	Variable types	Number of options
Floor height	[2.4 m, 2.8 m]	Continuous	0.1 m 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

By implementing the developed model in each design stage, the building design is optimized in sequence in each design stage throughout the design process. The design variables are determined in sequence in each design stage, therefore the design solutions for each design stage should be determined separately.

The results of three modules at each design stage is presented in the following sub-sections.

4.1. Environmental impact assessment

The value ranges or values of the key design variables affecting the environmental impacts in early, detailed and construction design stages are shown in Table 2, Table 3, and Table 4, respectively. Notably, other variables that were not selected for each stage were keep consistent with values in the original design as they have less important influence on the optimization of environmental performance of a building according to findings in previous work [13].

All possible design alternatives in each design stage are generated by varying design variables. An orthogonal experiment was executed to generate the design samples in each design stage required for this study. This process yielded a total of 65 design samples for early design stages, 93 design samples for detailed design stages, and 40 design samples for the construction design stage. Utilizing the workflow for life-cycle environmental impact assessment, the embodied and operational environmental impacts of each design sample in three design stages were assessed. The building operating schedule, HVAC (Heating, Ventilation and Air conditioning) system, and outdoor air information were out of the scope of this research, and therefore the building service system was assumed to satisfy the ideal conditions for heating and cooling. The amount of embodied and operational impacts, expressed by kg CO_2eq/m^2 for design samples were presented in Fig. 4.

As shown in Fig. 4, the operational environmental impacts accounted for a large portion (over 90 %) of the life-cycle environmental impacts of a building throughout all design stages. Moreover, as building design evolves, the embodied impact increased due to the consumption of additional building components and materials that are closely related to embodied impact. For example, placeholders may exist for windows, but the actual windows are not included during the early design stage. It is only in the detailed design stage that the windows will be installed. However, the operational impact of a building during the detailed and construction design stages was lower than in the early design stage. This may be attributed to the use of thermal insulating materials that save energy consumption during these stages.

4.2. Environmental impact prediction based on LSSVM

The LSSVM model was trained on 80 % of the sample cases, comprising of 52, 74 and 32 cases for early, detailed and construction design stage, respectively. The trained LSSVM model was validated by the rest 20 % sample cases. The results of the LSSVM prediction on the testing set were basically consist with the environmental results assessed in early design stages, detailed design stages and the construction design

Table 3
Building component types and properties in detailed design stage.

Building component	Design variables	Value	Thickness of building components/ materials (unit: mm)	Number of options
External wall	Type of thermal insulating material	Expanded polystyrene (EPS) board	15, 30, 40, 50, 60, 70, 80, 90	32
		Extruded polystyrene (XPS) board	25, 40, 50, 65, 70, 80	
		Polyurethane (PUR) board	20, 30, 40, 50, 60, 65	
		Open cell spray-applied polyurethane (PU) foam	10, 20, 30, 40, 50, 60	
		Mineral wool board	40, 50, 60, 70, 80, 90	
	Type of external wall structure	Reinforced Concrete built in situ	200	7
		Concrete hollow block	190	
		Lime-sand brick	240	
		Perforated brick	190,240	
		Aerated concrete block	200,250	
Internal wall	Type of thermal insulating	EPS board	30, 40, 55	8
		EPS thermal insulation mortar	15, 25, 40, 75, 100	
	Type of internal wall structure	Reinforced Concrete built in situ	200	6
		Concrete hollow block	190	
		Lime-sand brick	240	
		Perforated brick	190 , 240	
		Light aggregate concrete hollow block	190	
Floor	Type of thermal insulating	EPS board	15	5
		XPS board	20	
		High strength perlite board	30	
		Emulsified bitumen perlite board	30	
		Composite silicate board	20	
Window	Type of window frame	Aluminium window frame	–	12
		Steel window frame	–	
		Wooden window frames	–	
		Plastic window frame	–	
	Type of glazing	Monolithic glazing	–	
		Double pane glazing	–	
		Triple-pane glazing	–	

stage, as shown in Figs. 5–7, respectively.

As shown in Figs. 5 and 6, ad 7, the goodness-of-fit R^2 for predicting embodied and operational impact in early design stage were high, at 0.9068 and 0.91751, respectively. The R^2 for detailed design stages were at 0.80798 and 0.81783 for embodied and operational impact prediction, respectively. For construction design stage, the accuracy rate for predicting embodied and operational impact is approximately 85 %. In general, the developed LSSVM models developed in this study demonstrated good performance for environmental impact prediction. Therefore, the relationship between design variables and environmental impact established by LSSVM model could be used as the objective function of the multi-objective optimization.

Table 4
Design variables for the building in construction stage.

Design variables	Value	Thickness of building materials (unit: mm)	Number of options
Finishing material for external wall	Paint	5	5
	Facing stone	30	
	Ceramic mosaic tile	5	
	Rigid sheet (e.g., PVC rigid sheet)	15	
	Facing stone (e.g., granite stone slab)	30	
Finishing material for internal wall	Paint	5	8
	Dry-mixed Gypsum plaster	10	
	Acrylic latex	5	
	Wallpaper	3	
	Facing brick or glazed brick	7	
	Plywood	5	
	Rigid sheet (e.g., PVC rigid sheet)	10	
	Thin facing stone (e.g., marble slab)	12	
Type of flooring	Brick flooring (e.g., glazed brick flooring)	10	7
	Prefabricated terrazzo flooring	25	
	Ceramic floor tiles	5	
	Facing stone	20	
	Carpet	10	
	Vinyl flooring	3	
	Wood plank	12	
Type of roof tiles	Ceramic tile	10	5
	Cast glass tile	10	
	Concrete tile	10	
	Terracotta tile	10	
	Stone tile	10	

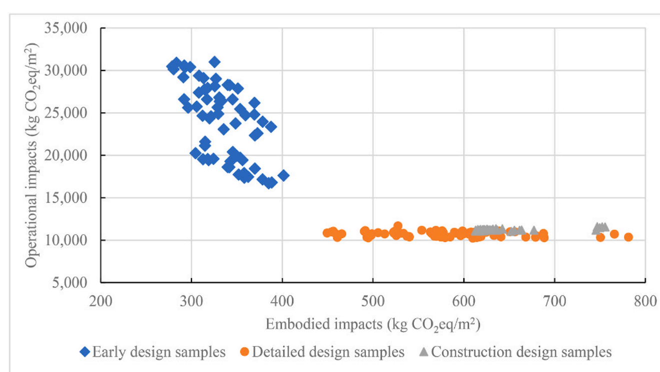


Fig. 4. Environmental impacts of design samples.

4.3. Optimal design solutions

The combination of LSSVM models and NSGA-II was conducted in Matlab environment to explore the optimal design solution in each design stage. The population size was set at 40 and the number of maximum generations was due for 200, within which the optimization was found to be able to get converged. The final results of the optimization process for three design stages were presented in Fig. 8. $y1$ indicates the embodied carbon emissions (kg CO_2eq/m2) while $y2$ denotes

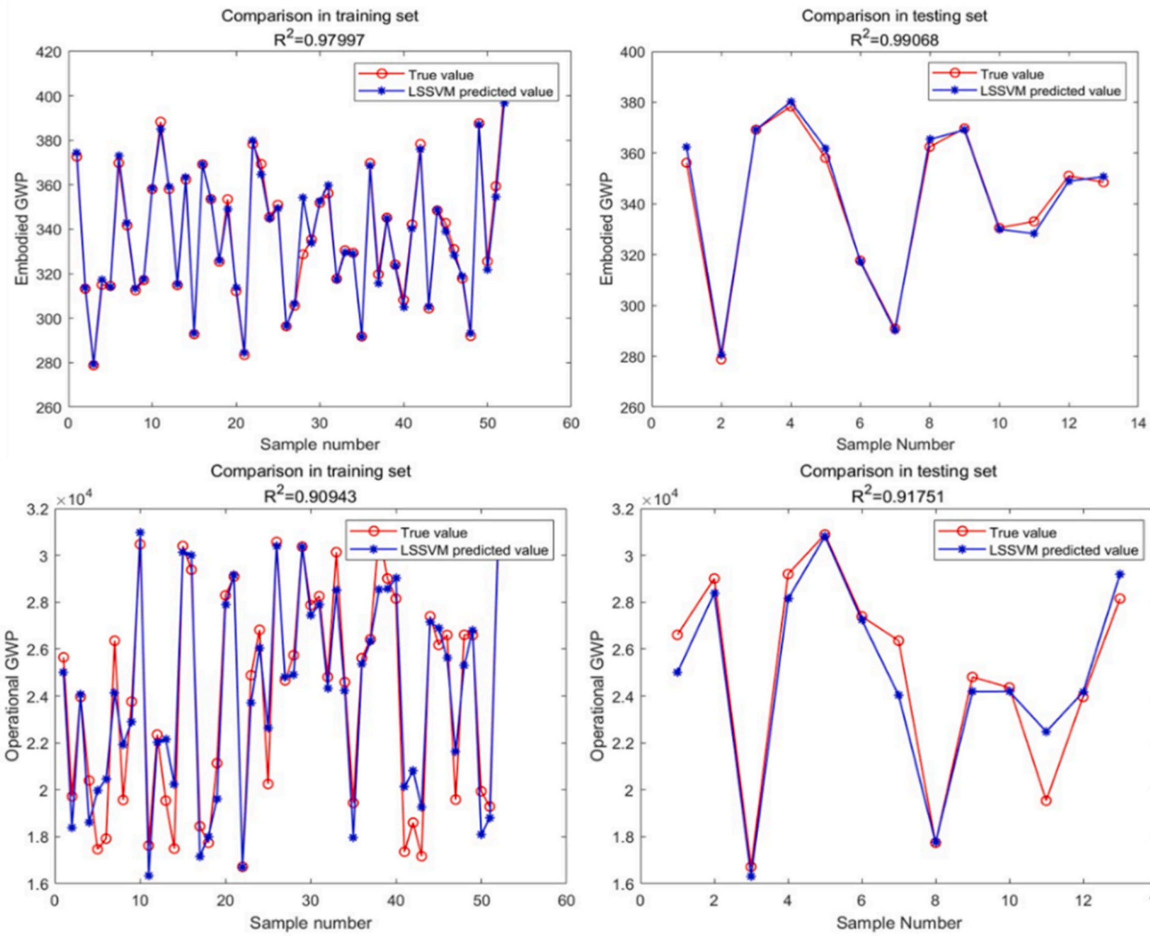


Fig. 5. Prediction model in early design stages.

the operational carbon emissions (kg CO_2eq/m2).

The optimal design solutions in each design stage were elaborated separately in two optimization cases to answer the two questions examined in this study:

Case 1. A multi-objective optimization considering the operational and the embodied environmental impacts with equal weights (To address Q1)

Case 2. Single-objective optimization for the minimum total environmental impacts of a building over its life cycle in the context of the trade-off between embodied and operational impacts (To address Q2)

4.3.1. *Optimal results in early design stages*

Answer to Q1 in early design stages: The Pareto frontier in early design stage was illustrated in Fig. 8 (a). The TOPSIS analysis results revealed that the trade-off design solution was the case (number of floors: 8, floor height: 2.8 m, orientation: 15° from N–S towards the NE-SW orientation, and WWR: 0.1), as shown in Table 5. The total environmental impact was 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 increased by 8.8 % while the embodied impact decreased by 25.8 %, compared with the original design.

Answer to Q2 in early design stages: As shown in Table 5, the minimum total impact (15805.61 kg CO_2eq/m^2) was 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 5. It consists of an embodied impact of 402.61 kg CO_2eq/m^2 and an operational impact of 15403 kg CO_2eq/m^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). Moreover, despite an increase of 20 % of the embodied impact, the optimal design solution contributes to a decrease of 33 % operational impacts compared to the original design.

Interestingly, the difference between the "optimal 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 conflicted influence on the embodied and operational impacts of a building.

4.3.2. *Optimal results in detailed design stages*

Answer to Q1 in detailed design stages: The Pareto frontier solutions in detailed design stage was shown in Fig. 8 (b). The TOPSIS analysis results revealed that the optimal trade-off detailed design of embodied versus operational impacts occurred in the case where external walls were built with concrete hollow block (thickness: 190 mm) and XPS board (thickness: 50 mm) for thermal insulation; internal walls are created by concrete hollow block (thickness: 190 mm) with EPS board (thickness: 55 mm) for thermal insulation; floors are covered by PUR board (thickness: 20 mm); and steel windows with monolithic glazing are installed. The total environmental impact was 11180.69 kg CO_2eq/m^2 which consists of an embodied impact of 427.33 kg CO_2eq/m^2 and an

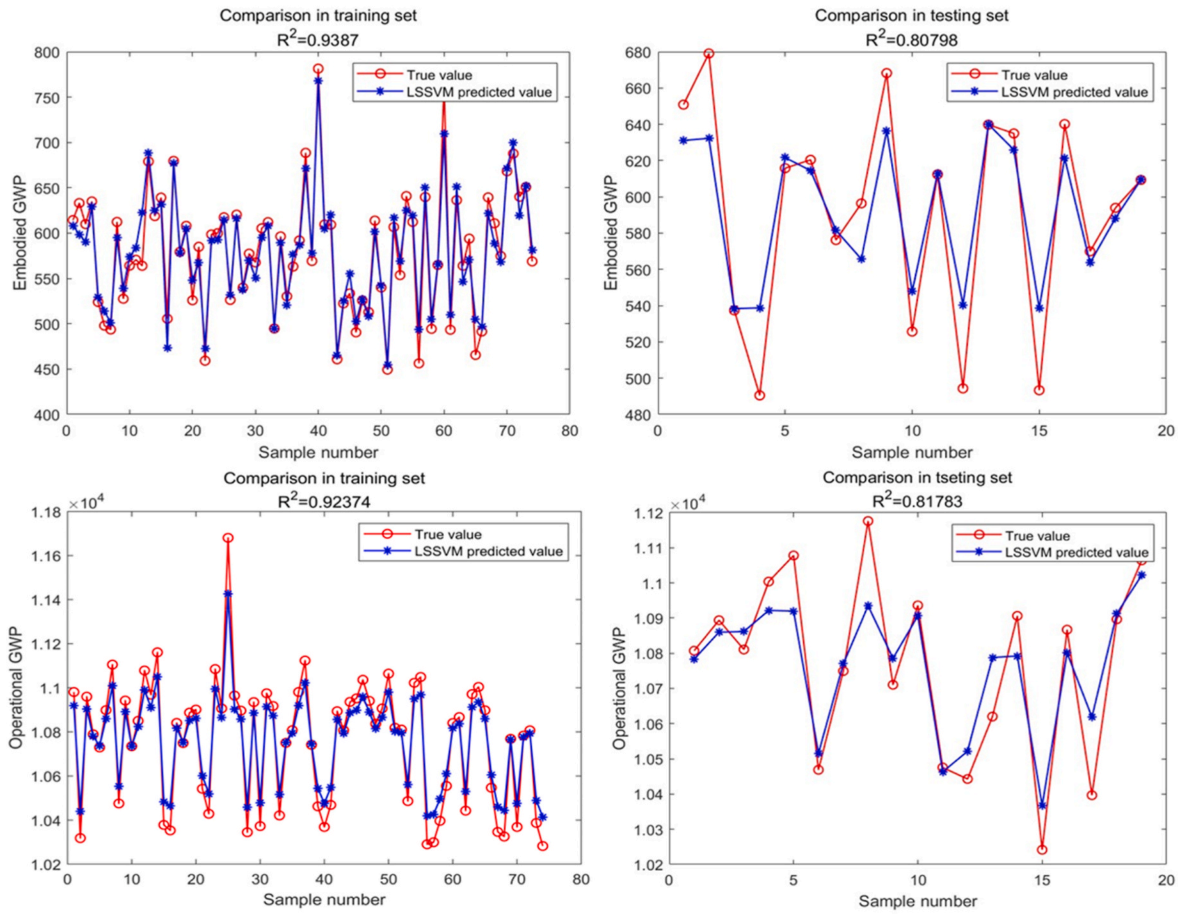


Fig. 6. Prediction model in detailed design stages.

operational impact of 10753.37 kg CO_2eq/m^2. Despite a slight decrease in the total environmental impacts compared to the original design, the trade-off design solution largely lowered the embodied impact (26 %) of the original design. Moreover, there was also a slight reduction in operational impact, at 3 %, for the trade-off design solution. The results indicate that the embodied and operational environmental impacts can be lowered simultaneously if appropriate types and thickness of building components and materials are chosen.

Answer to Q2 in detailed design stages: The design solution that prioritizes the minimum total environmental impacts (10806.21 kg CO_2eq/m^2) was the option with external walls of reinforced concrete built in situ (thermal type: PUR board), internal walls of concrete hollow block (thermal type: EPS board 30 mm), PUR board for the thermal insulation of floors, and aluminium windows with triple-pane glazing, as shown in Table 5. The optimal detailed design reduced 874.99 kg CO_2eq/m^2 compared to the original detailed design. In other words, 7.5 % of the total impacts can be lowered by varying the thickness and specification of building materials and components. The difference between the optimal design solution and the original one lies in the thermal insulating materials of external walls (PUR board vs. Mineral wool board), composition of internal walls (concrete hollow block with 30 mm EPS board vs. perforated brick with 40 mm EPS board), thermal insulating materials of floors (20 mm XPS board vs. 15 mm EPS board) and the glazing type for windows (triple-pane vs. monolithic glazing).

Another finding is that the structure and thermal insulating materials for internal walls and floors remained unchanged between the design with minimum total environmental impacts and the trade-off design solution. The variation of both design solutions lied in the compositions of external walls and the types of window frame and glazing. This suggests the trade-off between the embodied and operational impacts might be largely affected by the design of the external system of a building.

4.3.3. *Optimal results in the construction design stage*

Answer to Q1 in the construction design stage: Fig. 8 (c) illustrates the Pareto frontier solutions in the construction design stage. The TOPSIS analysis results revealed that the optimal trade-off construction design was the option where external walls were finished with painting; internal walls were finished with glazed bricks; floors were covered by bricks; and cast glass title were installed, as shown in Table 5. Its total environmental impact was 11423.8 kg CO_2eq/m^2 which consists of an embodied impact of 572.93 kg CO_2eq/m^2 and an operational impact of 110850.8 kg CO_2eq/m^2. There was a relatively great reduction in embodied impact (24 %) in the trade-off design solution compared to the original one.

Answer to Q2 in the construction design stage: The optimal construction design that has the minimum total environmental impacts (11378.9 kg CO_2eq/m^2) was finished with painting for external walls, rigid sheet for internal walls, brick for floors, and cast glass title for roof cladding, as shown in Table 5. The optimal construction design reduced 941.81 kg CO_2eq/m^2 compared to the original construction design, which indicate 7.6 % of the total impacts were eliminated by varying the specification of the finishing of building components. The difference between the optimal design solution and the original one lied in the finishing materials for external walls (paint vs. facing stone), finishing for internal walls (rigid sheet vs. acrylic latex) and flooring (bricks vs. wood). Moreover, the embodied and operational impacts were simultaneously decreased in referring to the optimal construction design.

Another finding is that only the finishing materials for internal walls varied between the trade-off design and the optimal design with minimum total impacts. This suggests that finishing type of internal walls

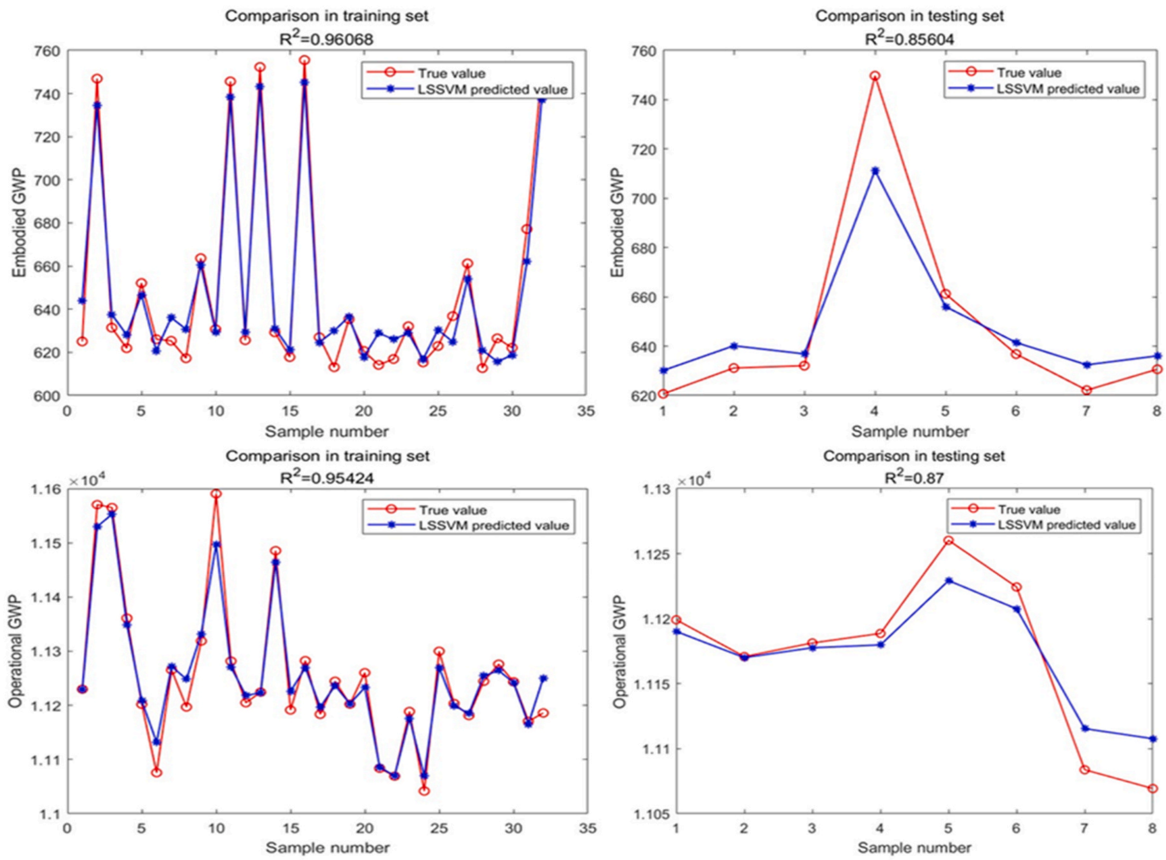


Fig. 7. Prediction model in construction design stages.

might largely affect the trade-off between embodied and operational impacts of building design in construction design stage.

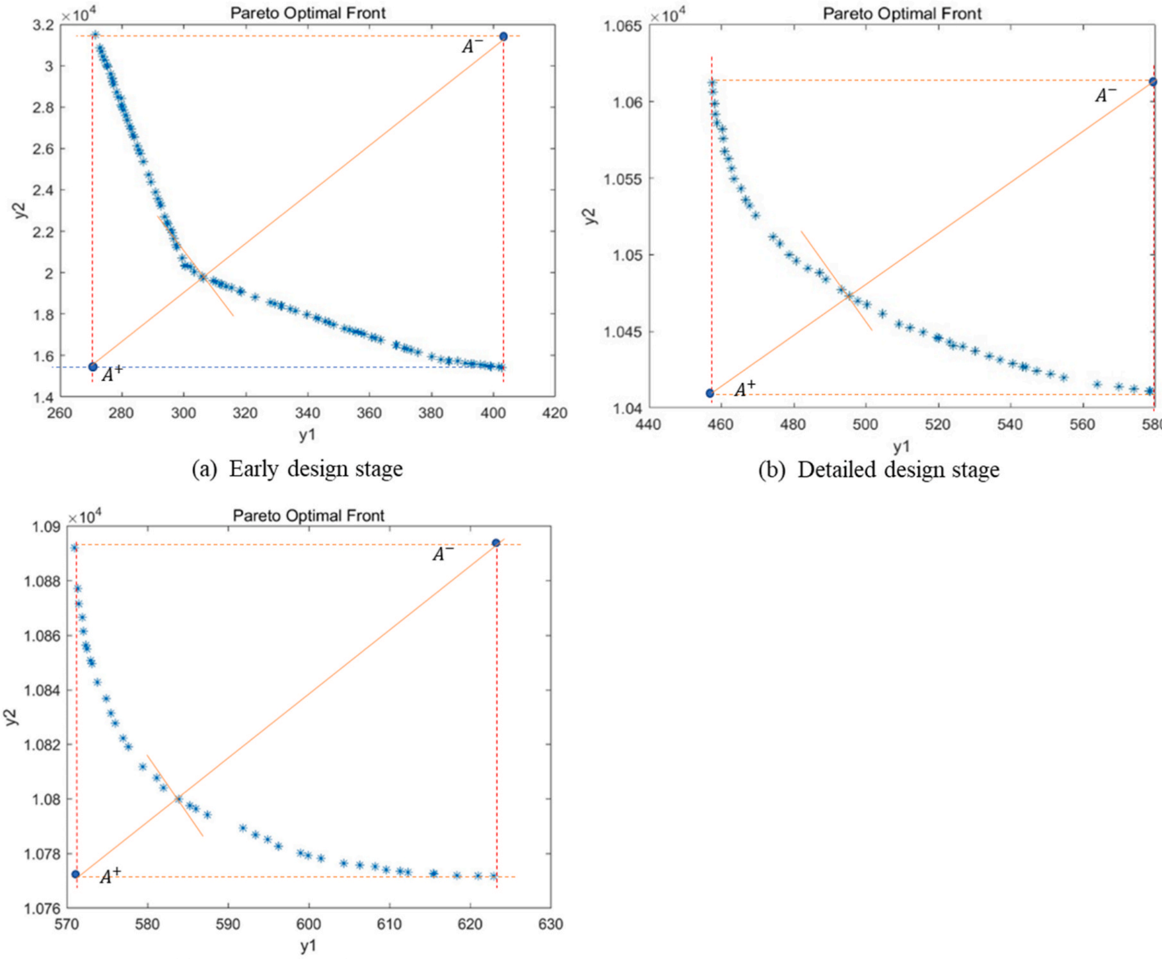
5. Discussion

The discussion is presented in two parts according to 1) the results for case study throughout the entire design process and 2) the effectiveness and efficiency of the model developed in this study. Discussion on the case study is explained in terms of the potentials to lower environmental impacts and the trade-off between embodied and operational impacts.

5.1. Potentials to reduce environmental impacts

The optimal design solutions identified indicate that there is a great potential to reduce the environmental impacts of the building sector by varying the design parameters throughout the entire design process. As demonstrated in the case study, it is possible to lower approximately 47.6 % of the total carbon emissions for the original design if the design solutions with the minimum total environmental impacts in each design stage are adopted. The case selected in this study is a typical mid-rise residential apartment in the hot summer and cold winter climatic zone in China. Similar buildings are expected to be constructed and operated to improve the housing. For instance,378,951,900 m^2 floor space of residential buildings were under construction in Chongqing in 2021 and mid-rise residential buildings accounted for about 28 % of the total areas (about 106,106,532 m^2) [45]. In this case, a maximum of 51 million tons of CO_2-eq may be reduced for building sector by optimizing the design of buildings. Furthermore, from the perspective of the entire design process, the earlier the design stage, the greater the potential for emission reduction. Early design stage can reduce 32.5 % of the total carbon emissions, while detailed and construction design practice together can lower about 16.1 % of the carbon emissions.

Although the optimal design solutions vary in different climatic conditions where the building is located, WWR, building orientation, and number of floors were also observed to have great influence on environmental emissions of an early building design in other climatic zones. For example, WWR was found being a dominated factor affecting the operational energy, energy efficiency and material quantities in the climatic zones of mixed humid and warm marine [46]. Moreover, researchers observed that a properly oriented building in City of Hertfordshire (climatic condition: temperate maritime climate)saved a large amount of energy throughout its life cycle [47], contributing to a marked saving in operational emissions. The influence of number of floors with other building geometric parameters on building LCA was examined and found that a mid-rise building with 4–7 storeys is the optimal [10]. The finding coincides with the 4 storeys identified in this study. With reference to the influence of the properties of building components and materials, a study on low-rise building revealed that incorporates triple-glazed yields the optimum low environmental impacts [25]. This conclusion is also true a high-rise building [48]. When combined with the finding in this study, adoption of triple-glazed windows may eliminate a considerable environmental impact for a building. Insulation materials have been considered a critical way to reduce the emissions related to energy consumption due to heating and cooling [49]. Increasing the insulation thickness of walls was suggested as a way of reducing environmental emissions of a high-rise residential building [50]. However, for the mid-rise residential building in this study, increasing insulation thickness of walls does not necessarily lead to reduction in environmental emissions and the composition of the insulation materials of walls matters as well. The finishing materials also make great contribution to reducing environmental impacts of a building. Interior finishing was found to be closely connected with moderating the thermal environment of a building [51]. In other words,



(a) Early design stage (b) Detailed design stage (c) Construction design stage

Fig. 8. Pareto Optimal Front in three design stages.

interior finishing may affect the energy demand for building operation and the operational environmental impacts accordingly.

5.2. Trade-off between embodied and operational impact

The results and analysis of the trade-off solutions show that a significant reduction in embodied impacts can be achieved by sacrificing only a little in the operational impacts. For instance, 25.8 % of the embodied impacts can be saved whilst increasing 8.8 % of the operational impacts by varying early design values. The results suggest that a building in which the embodied impacts reach the magnitude of operational impacts, such as a green building, may save more embodied environmental impacts than the operational environmental impacts.

The number of floors is identified to affect the trade-off embodied and operational impacts of a building. With increasing building height, the floor areas also increase, and it is generally observed that the environmental impacts per square meter of floor area tend to decrease. However, Foraboschi et al. [52]) observed an exponential growth in embodied energy with the increase in the number of storeys. A higher building requires a strong structure to resist the wind load and hence consumes more energy-intensive materials (such as steel), the manufacture of which generate great carbon emissions [53]. In addition, an increase in building height could increase heat loss and therefore consumes greater energy, which leads to more operational carbon emissions [53]. Moreover, WWR is identified to have a conflicting influence on embodied and operational impacts in early design practice. The reasons are probably that reducing WWR could decrease the amount of heat gained through the building envelope and hence reduce cooling energy use [54]. However, a smaller WWR increases areas of walls and materials required for creating walls, which in turn would lead to more embodied carbon emissions [12]. Apart from the WWR, the composition of external walls such as the insulation of walls and window type are identified as being closely linked with the trade-off design solutions [5].

5.3. Effectiveness and efficiency of the model

Regarding the effectiveness of the developed model, this study shows that a mid-rise residential building can eliminate 47.6 % of its total impacts. The finding is comparable with a multi-objective optimization study, which concluded that 52.7 % of the impacts of a mid-rise building can be saved by optimizing the building design [55]. Although the prediction accuracies of developed model in detailed and construction design stages are relatively low due to the incompatibility between BIM model and Green Building Studio, the potentials to reduce environmental impact in these two design stages are not great. The potential to significantly lower total environmental impacts of a building depends on early design stage where the prediction accuracy is high. Therefore, the developed model is effective for optimizing the environmental performance of a building from the perspective of its entire design process. On the other hand, the time consumed to identify optimal design solutions by combining LSSVM and NSGA-II was about a few seconds. This is much quicker than the traditional environmental impact assessment approaches. The time required to calculate the quantities of building material, assess the embodied impacts, and simulate the operational

Table 5
Optimization design solutions throughout the design process.

		Floor height	Orientation	WWR	Number of floors	External wall structure	External wall thermal	Internal wall structure	Internal wall thermal insulating	Floor thermal insulating	Window frame and glazing	External wall finishing	Internal wall finishing	Floor finishing	Roof cladding	Embodied impacts	Operational impacts	Total impacts
Early Design	Original design	2.8	0°	0.25	8	–	–	–	–	–	–	–	–	–	–	335.38	23070.34	23405.72
	Minimum total environmental impacts	2.8	15°	0.1	4	–	–	–	–	–	–	–	–	–	–	402.6102	15403	15805.6102
	Embodied vs. operational impacts	2.8	15°	0.4	8	–	–	–	–	–	–	–	–	–	–	322.9659	18831	19153.9659
Detailed Design	Original design	2.8	0°	0.25	8	Reinforced Concrete built in situ 200	Mineral wool board 40	Perforated brick 190	EPS board 40	EPS board 15	Aluminium window frame with monolithic glazing	–	–	–	–	576.2014	11105.00112	11681.20252
	Minimum total environmental impacts	2.8	15°	0.1	8	Reinforced Concrete built in situ 200	PUR board 65	Concrete hollow block 190	EPS board 30	XPS board 20	Aluminium window frame with Triple-pane glazing	–	–	–	–	477.6299	10328.58	10806.2099
	Embodied vs operational impacts	2.8	15°	0.1	8	Concrete hollow block 190	XPS board 50	Concrete hollow block 190	EPS board 55	XPS board 20	Steel window frame Monolithic glazing	–	–	–	–	427.3254	10753.37	11180.6954
Construction Design	Original design	2.8	0°	0.25	8	Reinforced Concrete built in situ 200	Mineral wool board 40	Perforated brick 190	EPS board 40	EPS board 15	Aluminium window frame with monolithic glazing	Facing stone 30	Acrylic latex 5	Wood plank 12	Ceramic tile 10	755.546	11565.15	12320.69
	Minimum total environmental impacts	2.8	0°	0.25	8	Reinforced Concrete built in situ 200	Mineral wool board 40	Perforated brick 190	EPS board 40	EPS board 15	Aluminium window frame with monolithic glazing	Paint 5	Rigid sheet 10	Brick flooring 10	Cast glass tile 10	596.23	10782.7	11378.9
	Embodied vs operational impacts	2.8	0°	0.25	8	Reinforced Concrete built in situ 200	Mineral wool board 40	Perforated brick 190	EPS board 40	EPS board 15	Aluminium window frame with monolithic glazing	Paint 5	Glazed brick 7	Brick, flooring 10	Cast glass tile 10	572.933	10850.8	11423.8

energy consumption for a design option would be aa few minutes and even longer [56]. The proposed model improves the computing speed significantly when it comes to predicting and assessing the environmental impacts. Implementing this model could thus make it more practical to solve more complex building optimization problems.

6. Conclusion

This research examined optimal design solutions with the trade-offs between embodied and operational impacts and explored the potential for reducing environmental impacts of a building in each design stage of the building design process in a sequent manner. A machine learning based multi-objective optimization model, incorporating with a joint workflow based on the BIM-LCA integration approach was developed to address the issues. A case study was conducted to implement the developed model. Main findings in this research are concluded as follows:

(1) a LSSVM-NSGA–II–based multi-objective optimization model coupling with BIM-LCA integration approach was developed and validated for the optimization of building design.
(2) 47.5 % of the total CO_2eq for a mid-rise building in hot summer and cold winter climatic zone in China can be saved by optimizing the building design throughout its design process.
(3) The earlier the design stage, the larger potential to reduce the carbon emissions. Early design stage can save 37.5 %, while detailed design and construction design can save 7.5 % and 7.6 % carbon emissions respectively.
(4) WWR, building orientation, and number of floors contribute to the minimum environmental emissions in early design practice. The optimal design solutions in detailed design stage are closely related to the thermal insulating materials of external walls, composition of internal walls, thermal insulating materials of floors and the glazing type for window. Finishing for walls and flooring may contribute to the optimal construction design solutions.
(5) The early design solutions with the trade-off between embodied and operational can be found by varying the WWR and number of floors. The design of external system including the compositions of external walls and the types of window frame and glazing may contribute to achieving the trade-off solutions in detailed design stage. The trade-off solution in construction design stage can be achieved by selecting appropriate finishing materials of internal walls.

This research results reveal in this study are valuable to both researchers and practitioners. First, this research developed a multi-objective optimization model for striking a balance between embodied and operational impacts and lowering the total environmental impacts of a building. The developed model is an improvement on previous models that primarily focused on the balance between embodied and operational energy performance [6,57]. Moreover, this research provides a good example of how embodied and operational impacts can be balanced when creating design solutions to lower the environmental emissions of a building. The research also provides a theoretical basis for the pursuit of better environmental performance in building design. Besides, despite the scope of this study focusing on the environmental performance of a building, the developed model can be extended to other optimization objectives of building design. In terms of practical implications, the research provides a powerful tool for assessing the environmental impacts of a building over its life cycle. Furthermore, using the developed multi-objective optimization model contributes to lowering the environmental impacts of a building and to achieving global energy saving and a reduction in environmental emissions.

Nevertheless, it is appreciated that this study solely focuses on the optimization of architecture design, while structure design is not considered. In addition, a limitation of the approach is that the LCA data for certain building components in Tally is insufficient, leading to the adoption of LCA data from substituted components for those specific components. An alternative to this limitation is to utilize an editable database in the manual approach, which would allow for the inclusion and updating of LCA data for all building components. However, the manual assessment approach can be time-consuming and prone to human errors.

This framework and the methodology can be further extended to the optimization of structural components with regards to environmental impact reduction. Also, it is possible to explore an automated BIM-LCA integration approach which allows for updating LCA database and automatically assessing the life-cycle environmental impacts of a building. Furthermore, future research could assess optimal design solutions in different climatic zones, attempting to compare and analyse the influence of varying climatic conditions on the optimal design solutions of buildings.

CRediT authorship contribution statement

Yijun Zhou: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft, Writing – review & editing. **Vivian WY. Tam:** Conceptualization, Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing. **Khoa N. Le:** Writing – review & editing, Conceptualization, Formal analysis, Funding acquisition, Supervision, Validation, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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