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A graph-based decision-support method for early-stage building transformation layout design through spatial suitability evaluation

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ABSTRACT

Building transformation is common and critical in urban regeneration, especially when buildings become functionally obsolete or abandoned. Conflicts usually arise between the new intended function and the existing spaces, making it essential to evaluate their compatibility during the early design phase to avoid resources wastage and decision failures. Traditionally, architects rely on trial-and-error drafting to match function programs with existing spatial layouts, while existing research has limited considerations for reconcile the transformation targets and existing conditions systematically in the early design stage. This study proposes a systematic decision-support method for evaluating spatial suitability in early-stage building transformation layout design. The method integrates graph topology, data-driven spatial analysis, and human-machine-integrated techniques, comprehensively considering existing building characteristics, design regulations and constraints, user requirements, design flexibility and sustainability to address the potential conflicts between transformation goals and existing conditions. It was validated through a practical industrial building transformation project in China. The results demonstrate that the proposed approach facilitates alternative layout generation and spatial suitability evaluation in transformation design, enhancing the design efficiency and reducing decision-making risks in the early stage. The novelty of the study lies in a high-dimensional graph-based spatial representation framework, human-machine integration for adaptive layout generation and suitability assessment, and a graph-matching evaluation system incorporating feature vectors, similarity measure and space syntax techniques. This method contributes to offering architects and stakeholders an efficient and practical tool for evaluating function-space compatibility in early-stage building transformation design.

1. Introduction

Building transformation is a process to adapts vacant, obsolete, or abandoned buildings whose functions are outdated or unsatisfied with users, for new functions and different purposes [1,2]. It is considered as a sustainable alternative to prolong the building lifespan instead of demolition and new construction [3]. Nowadays, it emerged both in academic and practical fields for quantities of existing building stock that are obsolete, abandoned, or functional outdated. The typical building transformation types include from industrial

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to commercial, cultural and sports, from commercial to residential, from office to commercial and in turn, from residential to educational, and so on [4–6]. In China, after nearly 40-year of rapid urbanization, the building stock has reached 69.6 billion square meters by 2020, with 20 % being non-residential buildings [7], resulting in a significant number of aging, vacant, or obsolete buildings to be renovated or transformed to meet new functional and sustainability demands. In 2021, the Chinese government first explicitly emphasizes urban regeneration in the national Five-Year Plan. Municipalities across China have also published relevant regulations and policies to encourage transformation of existing vacant and abandoned buildings for new sustainable uses. Table 1 lists relative policies, regulations and guidelines that have been issued in China over recent years to support building transformation.

Despite the rising demands for building transformation, it still faces critical challenges in practical applications: (1) conflicts may rise between the new function program with the building's characteristics such as physical dimensions, spatial layout and structure system when converting to the new building use; (2) transformation design should comply with the updated building codes and regulations; (3) despite the design constraints, the new function program should not only satisfy users' requirements, but also consider economic, social and environmental feasibility and sustainability; (4) building transformation may face more uncertainty for higher risk of return on investment, the probability of cost and time overrun, and unknown conditions of existing buildings [8–10]. To address such challenges, researchers have pointed out the necessity of detailed condition analysis and suitability evaluation during architectural programming at the early design stage for building transformation and renovation [11,12]. Such pre-evaluation process can facilitate decision-making for important design strategies such as building function program, spatial organization and structure intervention, reducing the discrepancy between the client's goals and building potentials [13,14]. Besides, the designer's design decisions at the early design stage have a greater impact on design performance at a relatively smaller cost of design alteration than at post design stage [15]. Following the clients' demands and directly dive into design without study on the compatibility of existing spatial layout and design conditions has a high risk of design alternation and failure afterwards [16]. Conversely, full consideration of the compatibility of existing building spaces and new intended functions during the pre-design phase can facilitate the implementation of transformation strategy, increase consistency among different stakeholders, and enhance design efficiency from the perspective of full life cycle. Therefore, this research advocates for a comprehensive analysis and evaluation method, to validate the functional feasibility and spatial suitability, assisting decision-making during the early design phase.

In practice, architects usually rely on trial-and-error method based on multiple drawings and manual experience to tackle this problem. However, human cognitive limitations in processing high-dimensional information could result in much time-consuming and decision-making challenges ensuring design quality in the early design stage [17]. For example, architects may overlook certain data

Table 1
Policies and guidelines for building transformation in China.

Year	Level	Department	Document	Contents related to building transformation
2018–09	National	Ministry of Housing and Urban-Rural Development	Notice by the Ministry of Housing and Urban-Rural Development on Further promoting the Preservation, Utilization, and Renovation of Urban Existing Buildings	Adhere to the principles of maximizing use and functional transformation.
2021–03	Municipal	Standing Committee of Shenzhen Municipal People's Congress	Regulations of the Shenzhen Special Economic Zone on Urban Renewal	Comprehensive urban regeneration has seven categories including building functional transformation
2021–08	Municipal	People's government of Beijing Municipality	Action Plan for Beijing Municipality Urban Renewal (2021–2025)	Encourage mixed-use for inefficient commercial buildings; encourage obsolete industrial buildings to be added regional education, medical care, culture and sports and other public service functions
2021–08	Municipal	Standing Committee of Shanghai Municipal People's Congress	Regulations of Shanghai Municipality on Urban Regeneration	Encourage functional improvement and transformation compatible with land use
2021–10	Municipal	Beijing Municipal Commission of Planning and Natural Resources	Guidelines on Initiating the Renovation of Obsolete Industrial Buildings	Encouraging functional transformation or adaptive reuse of aging and obsolete industrial buildings
2023–03	Municipal	People's government of Beijing Municipality	Regulations of Beijing Municipality on Urban Renewal	Encourage aging industrial buildings to be reused for public service and high-tech industries; encourage inefficient commercial and office buildings to be added cultural, sports, education, medical, social welfare and other functions
2023–08	National	The State Council	Guiding Opinions on Planning and Building Affordable Housing	Encourage transform vacant commercial and office buildings to dormitory-type affordable rental housing
2023–12	Municipal	Beijing Municipal Commission of Planning and Natural Resources	Notice of Beijing Municipal Commission of Planning and Natural Resources on Issuing the "Guiding Opinions on Mixed Use of Construction Land in Beijing (Trial Implementation)"	Encourage functional conversion and formulate rules for management and conversion scale ratio control for commercial, cultural, educational, medical, social welfare and industrial buildings
2024–05	National	Ministry of Natural Resources	Notice of the General Office of the Ministry of Natural Resources on further strengthening planning and land policies to support the renovation and renewal of old residential communities	Encourage functional conversion of existing building spaces and of idle state-owned assets for community public services

dimensions or spend lots of time managing and interpreting large sets of spatial data; they can only process each dimension of spatial data individually and information for each spatial unit separately. Besides, determination on appropriate positions for new function units is usually based on experience and manually design adjustments, resulting in risks of conflicts among various space units and functions units and repetitive experiments to assess each unit one by one, lacking global adaptability. Previous studies have identified two kinds of methods to alleviate this, including criteria-based decision analysis and graph-based spatial analysis methods. Criteria-based decision analysis methods usually identifies several function alternatives, provides a multiple criterial system for stakeholders and experts to evaluate, then ranks and selects optimal functions applying multi-criteria decision analysis (MCDA) or multi-criteria decision making (MCDM) techniques [18,19]. Graph-based spatial analysis method uses graph topology to transform the key information in spatial layout and function program into abstract forms such as adjacency matrices, feature vectors and graphs for calculation. Such methods often employ computer-aided, human-machine-integrated and data-driven techniques to generate, evaluate or optimize layout design [20,21].

These two types of methods, however, have certain limitations. (1) Criteria-based decision analysis methods lack consideration for spatial layout design, such as important geometric information and topologic relationships between building spaces, which may reduce the practicality and effectiveness of the method [22,23]. Besides, consideration of function adjacency and continuity is crucial in spatial layout design, while it was not prioritized in quantitative evaluation which focus on rank and select the optimal major function [24]. (2) Graph-based spatial analysis methods focus on layout optimization from the perspectives of mathematics and computer science. Therefore, the generated solutions often lack comprehensive consideration for practical indicators such as structure limitation, local building codes and regulations, functional continuity [20]. It may underestimate the complexity of the underlying logic of traditional architectural design that is more than an abstract mathematical problem. (3) Both of these two methods lack consideration and efficient techniques for exploring the spatial potential for transformation, which may limit the further design flexibility.

This research aims to develop a systematic decision-support approach for evaluating spatial suitability in building transformation layout design. The objectives are to provide a robust framework that enables high-dimensional spatial data storing, processing and presenting, and comprehensive evaluation for function-space compatibility, leveraging both human expertise knowledge and computational tools to ensure both design efficiency and practicality, with less reliance on architects' experience and manual trial-and-error methods. The proposed approach integrates graph topology and computer-aided spatial analysis to matching the new intended function program with existing building spaces, considering building characteristics, design regulations and constraints, user requirements, design flexibility and sustainability. This facilitates layout transformation design during the early stage for converting to new building uses, to address the function-space compatibility challenges in reality. The main innovation of this study lies in the development of a graph-based structure for spatial data storage, analysis, and mining, which considers various spatial features, functional adjacency, and spatial connectivity for more robust transformation analysis. By employing a human-machine-integrated approach, the proposed method enhances the efficiency of generating alternative transformation layouts incorporating both human-defined design criteria and topological adaptability. Additionally, through graph matching and similarity measures, the study provides a comprehensive evaluation of layout transformations, moving beyond single-space verification to an efficient, holistic assessment of spatial compatibility. The study is expected to make contributions to the field of architectural programming and design of building transformation, demonstrating how data-driven and human-machine-integrated approaches can enhance the design efficiency and reducing decision-making risks in the early stage.

The remainder of this study is organized as follows: section 2 provides a literature review for two types of relative methods used for suitability evaluation and spatial layout design in building transformation, and addresses research gaps. Section 3 introduces the detailed framework of the proposed method, including analysis of spatial potential, similarity evaluation for individual spaces, and suitability assessment for spatial organization. This approach is then applied to a case study of industrial building transformation in section 4. Finally, section 5 illustrates the discussions and limitations of the proposed approach, while section 6 presents the main conclusions and recommendations of the research.

2. Literature review

2.1. Criteria-based decision analysis

Criteria-based decision analysis method usually provides conceptual frameworks for assessing the reuse potential and selecting the best function for existing building. During developments of these frameworks, several function alternatives are first defined based on several main principles [14]. It then constructs an evaluation criteria index from economic, environmental, social, technical, and sometimes architectural consideration. After that, it usually involves experts or stakeholders to rank alternatives based on the criteria system applying multi-criteria decision analysis tools to rank and select the optimal options for the building [25]. Therefore, previous studies of criteria-based decision analysis focus on three main aspects: principles selected for alternatives, criteria system establishment, and decision analysis tool selection.

For the principles defining function alternatives, it usually includes compatibility, economic and technical feasibility, and externality. For example, Wang and Zeng screened for a short list of reuse proposals based on site locations, building conditions, economy and maintenance [18]. Giuliani et al. identified 5 constraints for proposing the reuse program, including technical and economic feasibility, reversibility, structural, functional and aesthetic compatibility, interest of the community, and compliance with urban regulations and building codes [24]. Ribera et al. listed physical and technical feasibility, urbanistic permit, financial sustainability, and economic externality as principles to provide potential uses [19].

When it comes to the criteria system, previous studies have structured different sets of criteria to evaluate function alternatives based on values of economic, environmental, social, architectural and cultural. Most of indicators in such criteria systems focus on economic, environmental and social benefits, such as community involvement, living quality for social aspects [19,23]; market demand, externality for economic aspects [18,24]; sustainability, environmental externality for environmental aspects [26]. However, less consideration has been provided for compatibility and potential conflicts between new functions and existing spaces. Table 2 summarizes all the relative criteria for such consideration that assesses the matching performance of function options with existing building spaces.

For decision analysis tools, researchers have used various MCDM (multiple-criteria decision making) and MCDA (multiple-criteria decision analysis) methods to assess the function options, involving stakeholders or experts via Delphi scoring method or questionnaires. Spina uses Analytic Hierarchy Process (AHP) method to select building use alternatives and validate the financial feasibility via discounted cash flow analysis [22]. Wang and Zeng combine Analytic Network Process (ANP) model with Fuzzy Delphi method to select reuse strategies for historic buildings [18]. Bottero et al. employ Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE) to evaluate reuse alternatives for abandoned industrial buildings [27]. Oppio et al. applied multicriteria-spatial decision support systems (MC-SDSS) by integrating integrates multi-criteria analysis tools with geographic information system to analyze the potential reuse opportunities [32]. Ferretti et al. employ Multi-Attribute Value Theory (MAVT) approach to choose appropriate historic industrial buildings for reuse planning [33].

One of the main limitations of criteria-based decision analysis methods is the reliance on predefined criteria that might not fully capture the nuances of complex spatial relationships in a building transformation project. For example, it cannot fully consider all the features of each space unit and their topological relationships to adapt to functional adjacency. It might also struggle to adapt to changing priorities in function allocation or space utility. Besides, this kind of approaches can only identify the optimal function or the combination of several functions for the existing building. It cannot verify the feasibility of a complete function program for the existing layout and structure, lacking the flexibility to incorporate mixed uses, new needs of stakeholders, or unexpected spatial constraints that arise during renovation.

2.2. Graph-based spatial analysis

Graphs indicates a set of objects and the relationships among them. A graph consists of two basic elements – vertices (points) and edges (lines connect the points) [34]. Vertices are typically depicted as circles or dots, while edges are shown as lines or curves joining these points, as shown in Fig. 1. Since the early 1970s, architects have utilized graph theory to analyze spatial layout design at both interior and urban scales [35,36], especially for architectural programming during the early design phase [37]. Generally, there are non-computerized and computerized graph analysis methods.

Non-computerized graph analysis method relies on traditional empirical design with the help of diagram tools. For building transformation, previous studies have tried to use architectural diagram or matrix to assess the suitability between new functions and existing buildings. For example, Pyburn uses room-characteristic matrix to assess matching suitability between existing building features and potential uses for each room [13]. Giuliani et al. use architectural diagrams for qualitative evaluation on floors, openings, volumes, façade based on four qualitative variables including feasibility, reversibility, compatibility, and social interest [24]. Such diagram analysis methods facilitate visualization for selecting the optimal function, but they rely on manual data analysis, and have challenges for reproducing and generating multiple solutions with high design efficiency.

Computerized graph analysis method is commonly used in spatial analysis for two kinds of application. The first one is for spatial configuration cognition and classification. For example, Chen et al. analyze building patterns by capturing spatial similarity between topological graphs [38]; Ferrando et al. identify typological and functional characteristics of building plan layouts to classify religious buildings based on graph theory [39]; Harding and Derix utilize spectral graph theory to recognize spatial pattern and to generate reconfigurable exhibition plan layouts [40]. In these researches, graphs can abstractly present structural features of building spaces. The second application for graph theory in architectural spatial analysis is spatial layout generation. Here, graphs can not only present spatial layouts, but also function programs. For example, Merrell et al. have used graphs as bubble diagrams to represent function programs and spatial characteristics for residential building layouts generation [41]. Each individual space or room is considered a function and space unit, with the entire building comprising a collection of these units, so graphs can not only represent the function of individual spaces within buildings, but also the functional relationships among them.

Furthermore, two computer-aided spatial analysis instruments that based on graph topology theory have been applied in spatial analysis and layout planning problems: graph matching and space syntax.

Graph matching, or graph similarity scoring, intends to deal with graph isomorphism problem, which involves finding a

Table 2
Assessment criteria for matching transformation functions with existing buildings.

Indicators	Description	Relative studies
Physical dimensions	Width, length, depth, height, floor area, size, volume	[13,27,28–30]
Spatial organization	Layout, connectivity, adjacency, accessibility	[23,27,28–31]
Structure	Structure system and elements	[13,23,24,28,30,31]
Building codes	Complication with updating codes and standards	[18,19,23,24,29]
Materials	Envelope, interior spaces, cladding	[24,28,29]
Floors	Number of building floors, vertical position of individual spaces	[28,30]
Degree of intervention	Demolition, deconstruction, addition, installation	[19,22,24,31]

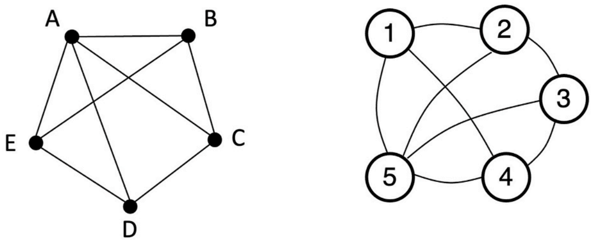


Fig. 1. Graph diagrams.

correspondence between the vertices (nodes) and edges of two graphs that preserves the graph's structure [42]. The suitability evaluation of function program and existing spaces involves measuring the similarity between two graphs: one representing the new intended function program and the other depicting the existing spatial layout. The graph matching process typically consists of two levels: node matching and edge matching.

- Node matching: this level measures similarity of pairs of nodes from two graphs based on certain criteria, such as node attributes or structural features [43]. Common methods to score the node similarity is to use similarity measure [44,45] to measure the distance between nodes. In this way, a single space or function with a set of characteristics can be represented as a feature vector [46,47]. This vector represents an object with multiple features that each forms a dimension of the vector. The vector's length and direction representing the object's overall features. Therefore, any function or space unit can be abstracted into a feature vector with multiple attributes, representing architectural characteristics such as floor area, length, width, and height, for further comparison and evaluation. Common methods of similarity measure include Euclidean distance, Manhattan distance, Cosine similarity, Pearson Correlation Coefficient, and Jaccard Similarity [48,49], to deal with different situation.
- Edge matching: Edge similarity reflects structural relationships (i.e., connections) between nodes, with indicators such as edge attributes and connectivity. Methods in edge matching includes graph isomorphism testing and subgraph matching. Graph isomorphism precisely tests one-to-one correspondence between the vertices and edges of two graphs, helpful for graphs required to be matched perfectly. Subgraph matching identifies the largest or most significant subgraph that can be matched between the two graphs, which is particularly useful when dealing with large and complex graphs [50]. Other studies also use mathematical calculation methods such as Graph Edit Distance and Fréchet Inception Distance to evaluate the graph similarity from a global perspective [51,52]. However, the searching process of these approaches may have conflicts with logic of architectural design, and lack consideration for practical architectural indicators.

Space syntax is another computerized spatial analysis approach to quantitatively analyze spatial configurations and organization based on topology theory. It helps conceive spatial arrangements of accessibility, space influence, social interactions, cultural and economic behaviors [53,54]. Space syntax has been applied broadly in urban issues, but also in architectural theory. It can facilitate studying on the way spatial units link to each other in buildings [55], or assessing the improvement result in renovation projects from spaces, traffic, social and economic aspects [56]. In space syntax, connectivity and integration are two crucial indicators to evaluate the relative positions and relationships of the target space in the whole floor plan. Connectivity indicates the number of spaces that the target space connects to, or the number of lines that the target axis intersects with [53]. A space unit with high connectivity has many adjacent space units, suggesting it is well-linked in its local environment, but does not necessarily indicate its overall position in the layout system. Integration, the other index, is a normalized measure of the distance from an origin space to all other spaces within a spatial layout, indicating how close the origin space is to every other spaces [53]. Space units with high integration values have high global accessibility, meaning they are more easily reached or connected to other spaces within the system. Space syntax provides a deeper understanding of the structural relationships between nodes. It can reveal patterns that traditional edge matching methods might overlook, such as the centrality of nodes, the integration of different spaces, and the overall connectivity of the layout. For example, Derix and Jagannath have applied space syntax approach for spatial classification, reducing layouts with multiple spatial data to a unified prototype graphs that are easier to compare; it also facilitates identifying functional and spatial similarities among individual spaces for function allocation based on the suitability of spatial attributes [57].

Graph-based spatial analysis methods can be limited by its dependency on accurate input data and its inability to account for non-spatial factors that influence design decisions, such as structure system, building codes, material constraints, lighting needs, or user behavior. In practical cases, like historical buildings where conservation regulations and historic values play critical roles, this method may overlook important design nuances that are not easily represented as graph nodes or edges. The advantages of addressing mathematical and topological problems of such approaches can also leads to overlooking the complex and underlying logic of spatial layout design, generating oversimplified layouts that cannot be applied in real cases.

2.3. Research gaps

Prior studies have implemented effective methods for identifying appropriate functions and exploring spatial layout design in building transformation projects. However, these methods still have limitations and some research gaps are summarized as follows.

(1) Complexity of spatial data storage and representation: traditional layout analysis methods often struggle to effectively process high-dimensional spatial data, particularly in cases where spatial relationships and functional adjacencies are critical. Criteria-based decision analysis methods have relatively comprehensive study on assessment criteria for matching transformation functions with existing spaces, but they might lack consideration for quantitative architectural and technical constraints, such as geometric layout information and topologic relationship between individual building spaces. Graph-based spatial analysis may overlook practical indicators that are crucial to the complexity and underlying logic of spatial layout design.
(2) Need of human-machine integration: previous studies identify limitations in design efficiency when relying solely on manual adjustments and in design practicality when relying on fully automated transformations. There is a need for a hybrid approach to leverage both human expertise knowledge and computational tools to ensure both design efficiency and practicality. This kind approach is expected to reduce cognitive and calculative load on architects, allowing them to focus on making strategic design decisions.
(3) Lack of a robust evaluation framework: the literature also revealed that many existing evaluation frameworks focus on individual space suitability rather than evaluating an entire layout's compatibility and thus requiring extensive manual verification. There is a need to assess global layout compatibility for transformation, based on exploration of spatial potential and enough alternatives though form-changing.

Therefore, existing research gaps call for a systematic and holistic method to tackle the complexity of spatial layout design in building transformation. This approach is expected to enable a more comprehensive representation and analysis of high-dimensional spatial data and spatial relationships. It can balance human-defined design requirements with computational topological transformation. Additionally, the method should tackle the challenge of overall spatial compatibility evaluation, which is essential for ensuring the practicality and adaptability of transformed layouts.

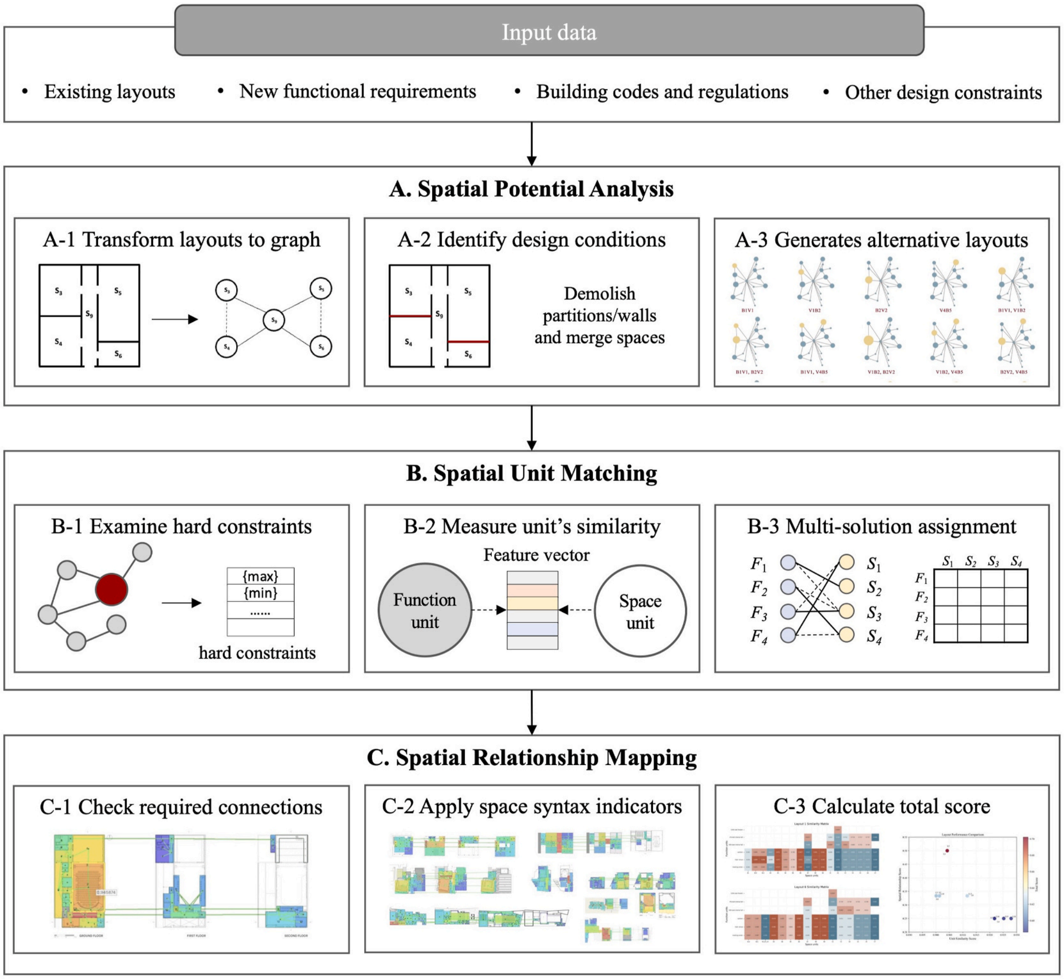


Fig. 2. Suitability evaluation model in building function transformation.

3. Methodology

This study proposes a methodology for evaluating feasibility of converting spatial layouts to new function programs in building transformation. As illustrated in Fig. 2, the framework consists of three sequential steps.

(1) Spatial potential analysis: use human-machine-integrated approach to analyze existing spatial characteristics and generate alternative layouts based on topology transformation. We first transform the existing floor plan layout into a graph with attributes of space units and connectivity relations understandable by computer language; then identify potential walls or partitions that can be demolished or added under design conditions; finally, generate alternative layout graphs incorporating new attributes of space units and function relations by computer programming.
(2) Spatial unit matching: assess unit or nodes in graph applying feature vector and similarity measure to search for suitable alternatives of major function transformation. The hard constraints of target functions are examined for each space unit in the layouts, and overlapping indicators are identified to facilitate similarity measurement. Second, a normalized Euclidean distance metric is employed to compute the similarity between each space unit and its corresponding target function unit, assessed on a pairwise basis. Finally, the Hungarian algorithm is applied for multi-solution assignment, enabling the identification of potential optimal assignments for space units across the alternative layouts.
(3) Spatial relationship mapping: assess the spatial organization of assignments derived from the similarity scoring to ensure appropriate function-to-space relationships We first measure the alignment with required connections between functions for potential space unit assignment; then Compare key spatial properties including integration and connectivity based on space syntax theory with a reference database of similar building types; finally, combine the connection relationship score and spatial syntax score into a single total score, reflecting the overall spatial organization quality of the layouts.

3.1. Spatial potential analysis based on topology transformation

Building transformation usually involve deconstruction, expansion, addition and modifications that change the spatial topology of existing buildings. The spatial topology, on the one hand, represents the spatial configuration and organization, and thus corresponds to the spatial layout. On the other hand, the topology should be consistent with the function composition and adjacency relationship in that space. Therefore, in order to validate the feasibility of transferring the existing spatial layout to the new function program, it is necessary to first explore the potential of spatial configuration before evaluating the compatibility between them. Spatial potential here refers to modification of walls, partitions, or even floors, which not only affect the connectivity and adjacency of spaces, but also change the size and area of each space unit, resulting in a transformation of spatial topology.

The approach here first use computer programming to analyze existing spatial characteristics and generate alternative layouts with data storage of each individual space's multi-dimensional attributes. This process aims to provide potential layout options for suitability evaluation of layouts and programs, which consists of three steps:1) transform the existing floor plan layout into a graph with attributes of space units and connectivity relations understandable by computer language; 2) identify potential walls or partitions that can be demolished or added under design conditions; 3) generate alternative layout graphs incorporating new attributes and function relations by computer programming.

Step 1 - structure a graph G_0 for the existing floor plan: input the number of space units as nodes S_1, S_2 … … S_n in the graph with the attributes of floor area, width, length, and height. Programmers can also add qualitative features such as structure and color to the attributes; then input edges according to the space unit connections. After setting these parameters, the existing floor plan has been drawn as the graph G_0 in the Python 3.0 computer language. Fig. 3 gives an example of graph representation. There are four rooms of S_3, S_4, S_5, S_6, with floor area of 24, 24, 36 and 12 m^2, and a corridor S_9 that connects the four rooms with 18 m^2.
Step 2 – remove potential walls and partitions: first, identify p partitions that are eligible for demolition. Using a computational approach, the program will exhaustively generate all potential demolition scenarios: starting with each single partition (e.g., E_1, E_2, …, E_p), then proceeding to all possible combinations, such as any two partitions at a time, up to the complete removal of all p partitions. This iterative approach ensures all potential demolition configurations are considered, which are $(2^p\text{-}1)$ combinations in

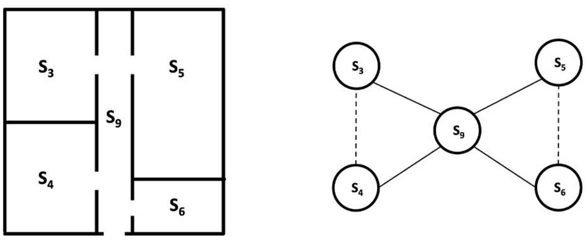


Fig. 3. Floor plan layout and graph of the example.

total. In the example shown as Fig. 4, there are two partitions that can be demolished, three schemes thus can be generated including demolishing E_1 linking S3 and S4, E_2 linking S5 and S4, and E_1 and E_2.

Step 3 – generate new potential plan layouts: after deleting the edges in the graph, adjacent space units will merge into a bigger space unit, which in the graph two nodes will be merged into one node and their attributes will be added together to represent the feature of the new room. The topology of the new layouts is shown as well. The attributes of each space unit in each new graph are also generated into a table for presentation (Table 3) and later evaluation. It should be clarified that if the number of partitions is relatively large, programmers can identify the potential new layout without consideration of functions and input the data of space list.

Although the spatial analysis of potential topological transformation is applicable for the buildings with walls and partitions inside, this approach can also be used in open-space building renovation projects such as industrial reuse projects with factory cluster which are common in China. In that circumstance, the outdoor open space among factories can also be considered as a space unit, while the boundaries of outdoor and indoor spaces can be seen as the partitions. Programmers should first identify the boundaries of potential outdoor open space and the existing buildings, and then input the corresponding data to be analyzed, considering the site as a plan layout.

3.2. Spatial unit matching based on similarity measure

Units represents a single function in the functional relationship graph, or a single room in the spatial topologic graph. Matching these units is the first step in suitability evaluation from the perspective of individuals or nodes. Each individual space or function unit can be abstracted into a feature vector to quantitatively represent the unit characteristics. The unit similarity measure process consists of three steps: 1) check hard constraints of target functions for each space unit in each alternative layout and identify overlapping indicators for similarity measure; 2) apply Normalized Euclidean Distance measure similarity between space units and the target function unit by pairs; 3) utilize Hungarian algorithm for multi-solution assignment to find potential best assignments for space units in each alternative layout.

Based on criteria-based decision analysis researches presented in section 2.1, we summarized key characteristics for the individual space in building layout for transformation which can be classified into seven categories: physical dimensions, spatial organization, structure, building codes, materials, floors and degree of intervention. The most common spatial feature is the physical dimensions such as width, length, depth, height, floor area, size and volume. Existing space units have specific values for these features, while the target function unit may not have these detailed data, and demands for translating the requirements into spatial language with quantitative data. For example, the floor area can be estimated by multiplying the number of users by the unit area per person, which can be obtained from the clients, practical experience, design guides, building codes or previous cases. The other significant feature is related to spatial organization, including layout, connectivity, adjacency and accessibility. Structure feature is significant for some specific building types, such as storage room or libraries, which require higher strength than normal.

Compliance with building codes is demanding in building transformation, and some of the codes and regulations can be abstracted to quantitative or discrete features. For instance, orientation is important for spaces like classrooms or patients' wards, which must face specific directions according to building codes (e.g., south-facing in China). Material is also a discrete feature that includes various kinds of tags for individual spaces. The floor feature indicates the vertical position, number of stories of a space unit. The vertical position feature relates to other issues such as the degree of privacy, fire codes and accessibility. For example, office spaces can be positioned on higher floors for greater privacy. The degree of intervention relates to economic, environmental and social sustainability,

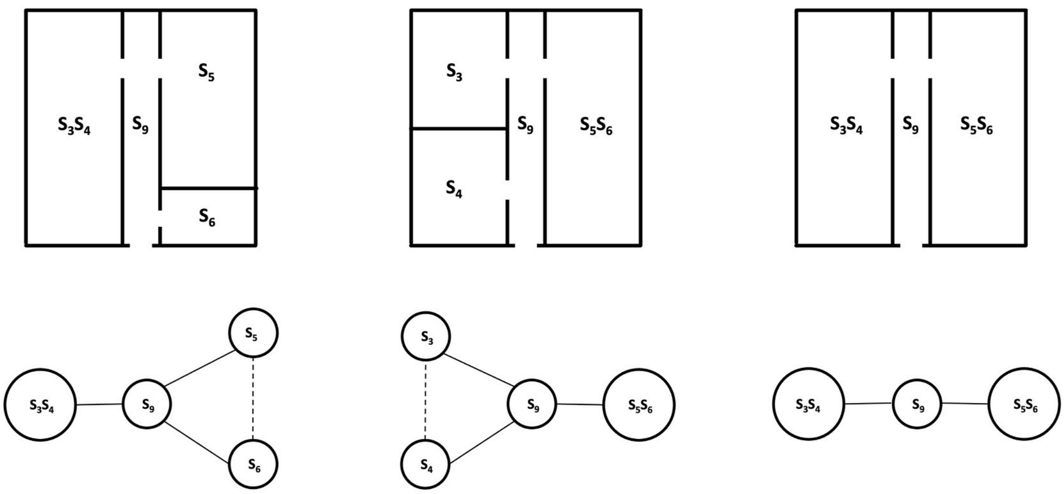


Fig. 4. Floor plan layout and graphs after modifying partitions.

Table 3
Space data of transformed potential layouts.

Layout	Space No	Area (m^2)	Length (m)	Width (m)	Height (m)	L/W
Graph 1	S3S4	48	12	4	3.2	3
	S5	36	9	4	3.2	2.25
	S6	12	4	3	3.2	1.33
	S9	18	12	1.5	3.2	8
Graph 2	S3	24	6	4	3.2	1.5
	S4	24	6	4	3.2	1.5
	S5S6	48	12	4	3.2	3
	S9	18	12	1.5	3.2	8
Graph 3	S3S4	48	12	4	3.2	3
	S5S6	48	12	4	3.2	3
	S9	18	12	1.5	3.2	8

which can be estimated and quantified by construction volume and consumption of building materials. These are the basic features of a function and space unit for compatibility assessment. Since the feature vector can have multiple dimensions, quantitative or qualitative features can be added or eliminated according to specific project situations.

During the matching process of functional units to spatial units, certain essential requirements, known as hard constraints, must be satisfied for a spatial unit to be considered. Examples of such constraints include a minimum ceiling height or a specific floor area. Spatial units that fail to meet these mandatory conditions are excluded from further consideration. Only those that fulfill all hard constraints proceed to the next stage, where they are evaluated against additional, flexible criteria, or soft constraints, such as dimensional similarity, adjacency, or accessibility.

Among all the similarity measure, Euclidean distance shows high sensitivity to scales and measurement of absolute difference. When evaluating the similarity between function and space units, it is important to identify a space closely matches the absolute area and size of the required function, rather than just the proportions of length and width. Therefore, we use Euclidean Distance in this research to evaluate nodes similarity between function units' requirements and existing spaces' features. It is noticed that all the vectors can only be compared and calculated using Euclidean distance method only if they have the same number of dimensions. Table 4 shows some of the basic features of space and function units and their overlapping dimensions for comparison using Euclidean distance method. The "overlapping feature" represents attributes shared by both function units and space units, enabling a quantitative assessment of similarity between the two. By incorporating this feature into the Euclidean distance calculation, we can effectively measure how closely each function unit aligns with the spatial characteristics of available space units.

For a single function unit F_i and space unit S_k, each with m feature dimensions, the similarity score is calculated as the Euclidean distance between the two feature vectors in m-dimensional space. However, because each feature dimension has distinct magnitudes and units of measurement, and some dimensions may have extreme values, scaling each variable is essential to ensure balanced contributions across features. To account for these variations, we choose to normalize the variables to the range of [0, 1] before applying the Euclidean distance as equation Eq. (1). We obtain the normalized equation to calculate Euclidean distance of a function unit F_i and a space unit S_k with m dimensions as Eq. (2) shows and the corresponding similarity score as shown in Eq. (3).

$$x' = \frac{x - min(x)}{\max(x) - \min(x)} \tag{1}$$

$$D_{ik} = \sqrt{\sum_{j=1}^{m} \left(\frac{F_{ij} - S_{kj}}{s_j}\right)^2} \tag{2}$$

Table 4
Some basic features of function and space unit.

No	Feature of space	No	Feature of function	No	Overlapping feature	Scale
1	gross floor area (GFA)	1	number of users/equipment			
		2	m^2/person or m^2/equipment			
		3	floor area	1	floor area	quantitative
2	length(l)					
3	width(w)					
4	dimension of l/w	4	dimension of l/w	2	dimension of l/w	quantitative
5	story height (h)	5	minimum story height (h)	3	story height	quantitative
6	ceiling height (h)	6	minimum ceiling height (h)			
7	dimension of l/h	7	dimension of l/h	4	dimension of l/w	quantitative
8	link to the outside	8	requirement of link to the outside	5	link to the outside	qualitative
9	vertical position	9	preference to the floor	6	floor/story	quantitative
10	structure	10	bearing capacity	7	structure strength	qualitative
11	orientation	11	orientation requirement	8	orientation preference	qualitative
12	… …	12	… …	9	… …	… …

$$Similarity\_score_{ik} = 1/(1 + D_{ik}) \tag{3}$$

For each alternative layout, all space units meeting the hard constraints can be evaluated against the function units. We then apply Hungarian algorithm to derive multiple globally optimal space-function assignment schemes for each layout, ensuring that every function is assigned to the most suitable space while maximizing the overall similarity score. The Hungarian algorithm, also known as the Kuhn-Munkres algorithm, is an efficient combinatorial optimization method for solving assignment problems [58,59]. It ensures an optimal pairing between two sets, such as functional units and spatial units, by minimizing or maximizing a predefined cost function. The algorithm begins by constructing a cost matrix representing the assignment problem and iteratively adjusts weights and matches between elements to find the optimal solution. Through its systematic approach, the Hungarian algorithm guarantees globally optimal assignments, making it widely applicable in diverse fields requiring resource allocation or pairing optimization. In this research, it begins by determining the globally optimal solution to obtain the first assignment scheme. Second, it iteratively evaluates candidates against predefined criteria to acquire sub-optimal solutions based on several parameters, including maximum similarity threshold, minimum score, limit number of solutions, a diversity requirement of different assignments per solution, and maximum iterations to ensure computational efficiency. During the search, a candidate solution is accepted if it meets the minimum score, remains within the similarity threshold, and differs sufficiently from existing solutions. The process terminates once the maximum number of solutions or iterations is reached or if no viable solution can be found. This approach ensures both solution quality and diversity via difference checks, and avoids excessive computation. By incorporating flexible parameter settings, this method mitigates the limitations of focusing solely on similarity and allows for discovering alternative spatial arrangements that may lead to more rational organizational structures and a comprehensive evaluation of results.

3.3. Spatial relationship mapping based on space syntax

The spatial organization of generated layouts is evaluated through a scoring system that integrates functional-space assignments derived from the similarity scoring and optimization process using the Hungarian algorithm. The evaluation consists of two main components, connection relationships and spatial syntax indicators. This scoring system balances global spatial relationships with specific functional connection requirements, providing a comprehensive evaluation of spatial organization quality.

The connection relationship score assesses the satisfaction of connection requirements between function units. Three specific connection types are set for each pair of units based on the path length calculated in layout graph, which are direct, adjacent and distant connections. Direct connection indicates that two functional units are directly connected through doors or open walls, without any intermediate spaces or barriers, such as kitchen and dining area in a residential layout. Adjacent relationship represents a near connection where the two space units are separated by one intermediate unit, such as a hallway, corridor, or transitional space. For instance, an office room adjacent to a lounge area ensures accessibility and proximity while maintaining a degree of privacy. Distant connection denotes a spatial relationship where the function units are separated by multiple intermediate spaces, indicating limit interaction or accessibility. If the actual connection strength meets or exceeds the required strength, the pair receives a full score of 1.0; otherwise, the score is assigned proportionally based on the ratio of actual to required strength as shown in Eq. (4). The final connection relationship score is the average of all connection requirement scores.

The spatial syntax score evaluates the compliance of functional spaces with integration and connectivity requirements. The functional composition of a building is typically determined by its type, with similar building types presenting comparable spatial organization and functional relationships. For buildings of the same type, the connections and adjacencies between primary functional units are expected to follow consistent patterns, reflecting shared design principles and usage requirements. For example, the performance hall as the major function of a theater has relatively fixed auxiliary functions, the corresponding adjacency and connection relationships. If the performance hall in a theater is positioned far from circulation paths or lacks adjacency to essential support areas, this could disrupt spatial flow and reduce functional effectiveness. Such risks are evaluated in terms of their impact on user movement, interaction, and accessibility within the spatial layout. This kind of problem occurs less in new construction projects since the function adjacency and relationships are programmed in the design brief from the beginning. While in renovation projects, the existing spaces have fixed spatial organization and adjacency relations, which limits the new function layout to be inserted. As mentioned in Section 2.2, connectivity and integration are two crucial indicators to evaluate the relative positions and relationships of the target space unit within the spatial layout from local and global perspectives. Here we use these two indicators to evaluate the suitability of the function units' positions in alternative spatial layouts. For function units with specified space syntax parameters, the integration value and connectivity of potential space units to match with the function are calculated. Space units meeting the required ranges for these metrics receive a score of 1.0. The final syntax score is computed as the average score across all syntax requirements as shown in Eq. (5). The total spatial organization score is calculated as shown in Eq. (6).

$$Connection\_score_i = \begin{cases} 1.0, \text{if actual strength} \geq \text{required strength} \\ \dfrac{\text{Actual strength}}{\text{Required strength}}, \text{otherwise} \end{cases} \tag{4}$$

$$Syntax\_score_j = \begin{cases} 1.0, \text{if integraion[HH\} and connectivity meets requirements} \\ \text{Average of individual scores, if some requirements are met} \end{cases} \tag{5}$$

$$Total\_score_{spatial\_relationship} = 0.5\frac{\sum_{i=1}^{n_{conn}} Connetion\_score_i}{n_{conn}} + 0.5\frac{\sum_{j=1}^{n_{syntax}} Syntax\_score_j}{n_{syntax}} \tag{6}$$

The integration and connectivity features of functions can be obtained from database analysis from similar building types. This research takes performance building type as an example for case collection and analysis. We analyze the topological characteristics of 20 performance building cases in the space syntax tool - DepthmapX software. These 20 cases are selected from a worldwide-know architecture website- Archdaily.com, which all have the performance hall, with floor area around 2000–5000 m^2 and with 1–4 floors. As shown in Fig. 5 for the case “Politeama Theatre”, the connectivity of the performance hall on the ground floor is 3, indicating connection with 3 other rooms; the normalized integration value is 0.9565, which ranks third in the whole layout, just behind the lobby and the corridor, indicating that the performance hall has relatively highest global accessibility and prominence among the function units in the floor layout plans, so it is more easily reached from other areas or connected to other spaces within the system. Table 5 shows the database of all the 20 cases. In most of the 20 cases, the performance hall always has the highest integration value among all the functional spaces, ranging from 0.7 to 1, ranking behind circulation spaces such as lobby, foyer, corridor, storage and stair space, which means it prominence in global accessibility among all the function units within the spatial layout. And the connectivity value of the performance hall usually ranges from 3 to 6 in the database, indicating that the performance hall is often required to link at least 3 space units such as dressing room, rehearsal room, foyer, stair and corridor.

4. Case study

Pingyao Film Palace (Fig. 6) is a reuse project of Pingyao Diesel Engine Factory built in the last 70s, located in Pingyao, Shanxi Province, China, with less characterized by a less harsh industrial aesthetic features compared to typical industrial sites. The project with total floor area of 11000 m^2 is now used as the venues of Pingyao Crouching Tiger Hidden Dragon International Film Festival, also as a theater for the public at ordinary times (Fig. 7). The project has contributed to the diversification of tourist groups and local socio-economic sustainability in the UNESCO World Heritage Site of Pingyao city, improving residents’ quality of life by adding new large public spaces and facilities for cultural activities.

The Pingyao Film Palace project is a completed transformation project that was specifically designed to meet the requirements of international film festivals. The determined function program and strict limitations due to its location in a historic district are the primary consideration in this case. These challenges made the suitability evaluation of function program and existing spaces a critical concern. In the pre-design phase, the architects should ensure that the spatial layout could accommodate various functions necessary for the film festival while adhering to the historic constraints. This process involved identifying suitable spaces for major functions, such as a theater and cinema halls. The architects used a trial-and-error approach based on numerous sketches to explore layout possibilities iteratively, to ensure the design met both functional and regulatory criteria. This research utilizes the suitability evaluation model to enhance this process, which enables a more systematic screening of potential spatial configurations by quantitatively assessing the compatibility of various spaces with the required functions. This method provides a set of viable options for consideration in the early stage, facilitating the decision-making and reducing the reliance on manual sketching alone.

4.1. Target function program

The Pingyao Diesel Engine Factory consists of 14 separate existing buildings on site, 11 of which can be transformed to serve the international film festival (Fig. 8). Key functional requirements include a 1500-seat theater, a 200-to-500-seat cinema hall, the main venue for the film festival, four small cinema halls, a meeting center and a canteen. Additional functions include news office, office, VIP

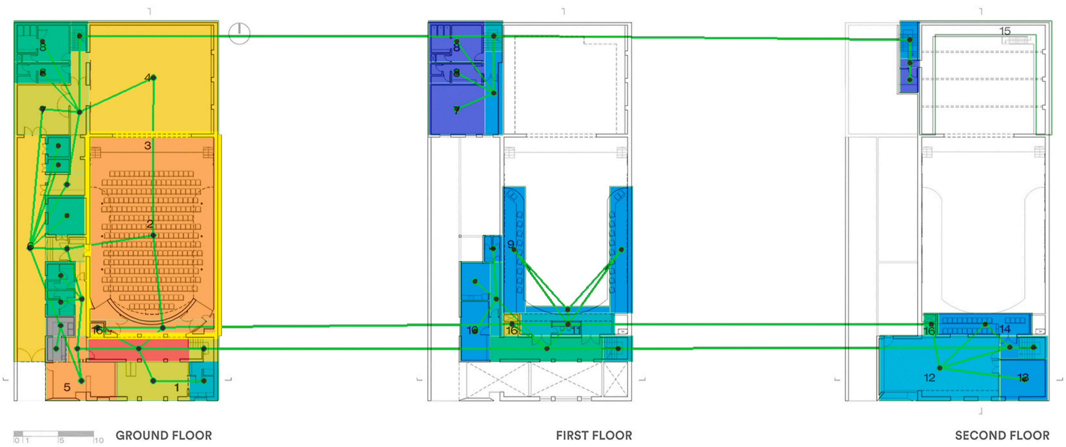


Fig. 5. Integration analysis of the primary function in the example in Space syntax software.

Table 5
Space syntax values for the performance function unit of 20 similar cases.

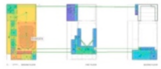
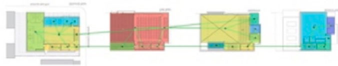
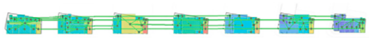
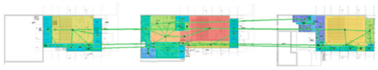
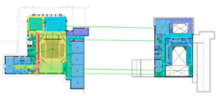
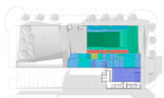
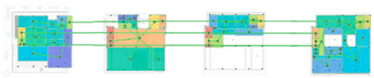
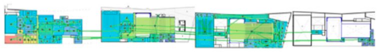
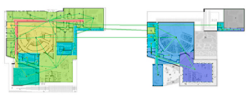
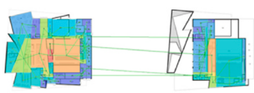
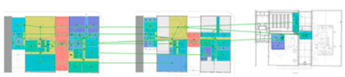
No.	Project	Connectivity	Normalized integration value	Integration value ranks behind	Convex map
1	Politeama Theatre	3	0.9656	lobby, corridor	
2	Théâtre de Quat'sous	4	0.9615	stair, lift	
3	Hattiloo Theatre	5	0.7540	corridor	
4	360 Paris Music Factory	5	0.6040	stair, lift, corridor	
5	Odsherred Theatre	3	0.9210	lobby	
6	Peter Hall Performing Arts Centre	4	0.6628	stair, corridor	
7	Renovation of the Oscense Theatre	6	1.0000	none	
8	Blue Barn Theatre & Boxcar 10	4	0.4390	lobby, corridor	
9	The You Art Centre	1	0.8757	lobby, corridor	
10	Theatre 95	6	0.9234	corridor	
11	Theater Jacques Carrat	4	0.8045	stair, corridor	
12	Writers Theatre Opens New Theatre Center	5	0.8391	stair, corridor	
13	Polyvalent Theater	5	0.9565	open hall as corridor	
14	Multicultural Centre in Isbergues	5	0.9495	stair, lobby	
15	Young Centre for the Performing Arts	3	0.8524	corridor, lobby	

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Table 5 (*continued*)

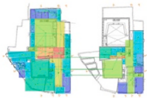
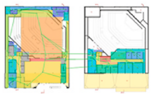
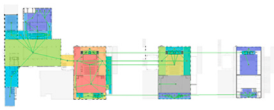
No.	Project	Connectivity	Normalized integration value	Integration value ranks behind	Convex map
16	Neushoorn	5	0.8215	corridor, stair	
17	Everyman Theatre	6	0.9114	corridor, stair	
18	House of Music and Theater	3	0.5380	corridor, stair, foyer	
19	Freight & Salvage Coffeehouse	4	0.9555	corridor, stair, foyer	
20	Theatre de Kampanje	4	1.0000	none	

Fig. 6. Aerial view of Pingyao Film Palace (Source from Architectural Design and Research Institute of Tsinghua University).

Fig. 7. Master plan of Pingyao Film Palace.

rooms, exhibition and other auxiliary spaces. Table 6 shows the target requirement features of key functions based on design regulations, practical experience and client's demands. For each function unit, the requirements include hard constraints and soft constraints. As illustrated in section 3.2, hard constraints are mandatory conditions for space units before similarity evaluation, such as minimum floor area and minimum ceiling height (net height). Soft constraints refer to conditions or preferences that are not mandatory but are considered desirable to achieve optimal or improved outcomes. In this case, the theater and cinema halls mainly consider the floor area according to user capacity and the area per capital; it also requires appropriate ratio for viewing experience, and width and net height for different kinds of screens such as standard screen, widescreen, and IMAX screen. For the main venue, meeting center and canteen, requirements focus on the floor area and net height, with no demands on specific length, width or aspect ratio.

In addition to dimensional features, we also identified required spatial relationships between these function units according to utilization, operation and management (Table 7). The 1500-seat theater, the 500-seat cinema hall and four small cinema halls are all preferred to closely related to the Main venue. The 500-seat cinema hall and four small cinema halls are better to be connected directly for visitors moving conveniently among different cinema halls. The main venue should connect to the entrance directly for the opening ceremony of the film festival. In addition to connection requirements, we also identified topological relationships in the layout for primary functions, with the help of the database mentioned in section 3.3. The 1500-seat theater and main venue are most important function units in this case. These two types of function units usually possess relatively highest integration and connection values in such building type. Therefore, we also identify the range of these space syntax indicators for the two functions for spatial organization evaluation.

4.2. Spatial potential analysis

Before evaluation, the initial step involves exploring the topological potential of the site and organizing spatial data for subsequent analysis. The topological transformation follows the three steps introduced in section 3.1: 1) organize existing spatial data to structure a graph G_0 for the original layout; 2) identify removable walls and partitions for spatial transformation; 3) generate alternative spatial layout graphs with data lists of new space units. In this case, vacant outdoor spaces between existing buildings can be utilized for expansion, complying with the fire code of maintaining a 6-m setback from the existing buildings' boundaries. Therefore, we first input the feature data list of eleven existing buildings and six eligible vacant outdoor spaces into the programming procedure. These spaces are represented as nodes within a graph, with edges linking adjacent spaces (Fig. 9). Each space unit is input as a node with seven feature attributes for data analysis.

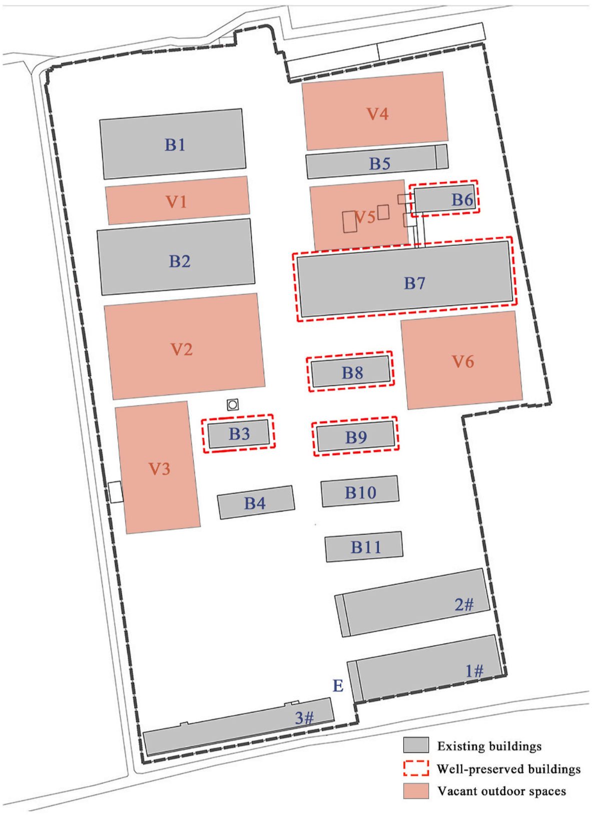


Fig. 8. Existing building spaces and vacant outdoor spaces.

Table 6
Target requirements and hard constraints of key functions.

No	Functions	Area (m^2)	Length (m)	Width (m)	L/W	Net height (m)	Hard constraints
1	1500-seat theater	3750	75	50	1.5	15	Min_area = 2250, Min_width = 35, Min_height = 11
2	500-seat cinema hall	1500	45	30	1.5	12	Min_area = 750, Min_width = 15, Min_height = 8
3	Main venue	500	–	–	2	6	Min_height = 4
4	4*small cinema hall	2800	12	–	1.5	7	Min_area = 1500, Min_height = 7
5	Meeting center	400	–	–	2	6	Min_height = 4
6	Canteen	400	–	–	2	6	Min_height = 4

Table 7
Connection requirements of key functions.

Function 1	Function 2	Required connections	Target syntax requirements
1500-seat theater	Main venue	Adjacent	–
500-seat cinema hall	Main venue	Adjacent	–
4*small cinema hall	Main venue	Adjacent	–
500-seat cinema hall	4*small cinema hall	Direct	–
1500-seat theater	–	–	Integration: 0.7–1; Min_Connectivity: 3
Main venue	–	–	Integration: 0.7–1; Min_Connectivity: 3

- *Length* (m) and *width* (m): sizes of the longer and shorter sides of the space unit.
- *Area* (m^2): the floor area of the space unit, reflecting the space capacity.
- *Length/width (L/W)*: the aspect ratio of the space unit reflecting the building type and functions.
- *Foundation* (m): the ground level of the space units.
- *Original height* (m): the roof elevation level of the existing building.
- *Net height* (m): the ceiling height of the existing building; for the vacant outdoor space, the attribute is the distance between the 8-m height restriction with the ground level.

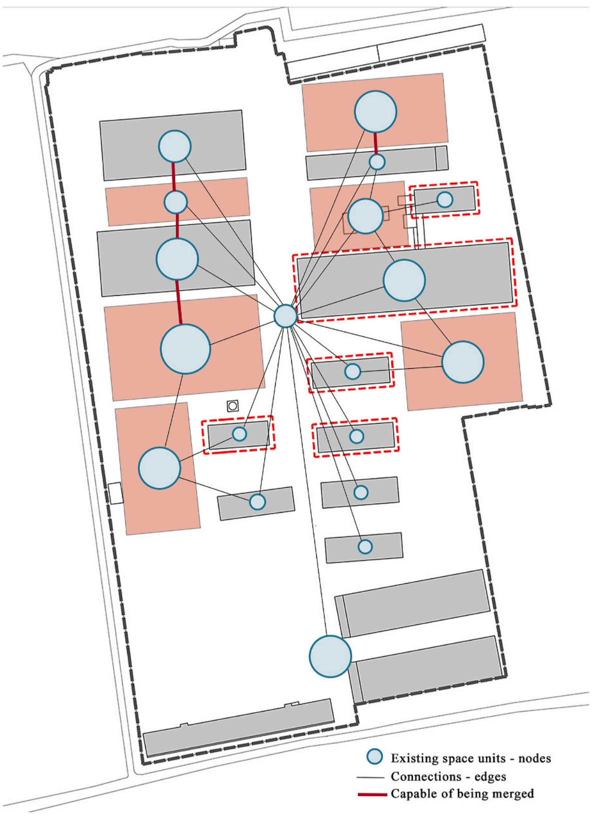


Fig. 9. Topological graph of existing space units.

In the Pingyao historic district, new construction is restricted to a maximum height of 8 m. For existing buildings, the structural elements and roofs are to be preserved, ensuring no changes to their original height. For outdoor vacant spaces, the feasible construction height is determined by subtracting the foundation elevation from the maximum allowable height of 8 m.

In addition to feature attributes of space units, the data list also records the connection relationships between each two of them. This data list helps to describe the original graph for the existing spatial layout. Second, we identify walls and partitions that are eligible for demolishment. There are three primary reasons for identifying the connections for resolution in space merging in this case study. First, buildings with historic or architectural values on the site should be preserved and cannot undergo demolition. To ensure their original form and integrity are maintained, the merging process excludes these buildings and any configurations that might affect them. Second, this study operates under the predefined assumption that all space units remain in rectangular shapes after merging to simplify topological transformations. For two space units to be eligible for merging, they must have approximately the same width or length to form a new rectangular shape. Third, the identified connections prioritize those with the highest potential for successful transformation based on compatibility with functional and spatial needs, as well as compliance with regulatory and design constraints. As shown in Fig. 9, five existing buildings with high historic values are prioritized for preservation. Among the rest of space units, considering the adjacency and integrity, 4 connections are identified to be resolved for space merging and expanding, which are connections between B1-V1, V1-B2, B2-V2 and V4-B5. This strategy allows for the reconfiguration of the layout to better accommodate new functional requirements of the film festival, such as large theaters and other key facilities. By inputting the four connections eligible to be removed, the computer programming automatically generates 15 alternative spatial layout graphs based on combinations of different walls and partitions as shown in Fig. 10. Each graph is recorded with a spatial data list of new nodes and edges to be evaluated in the next step.

4.3. Spatial unit matching

According to Table 7, space units in each alternative layouts is first evaluated against predefined hard constraints. If the spatial unit fails to meet any of these constraints, it is excluded from further consideration. For spatial units that satisfy all hard constraints, a further evaluation is performed using soft constraints. Here, three target features are identified as recommended indicators to evaluate the similarity between space units and function units.

- *Target area* (m^2): the recommended floor area of the function unit, considering clients' goals and good user experience.
- *Target length/width (L/W)*: the appropriate aspect ratio of the function unit for high-quality utilization.
- *Target net height* (m): the recommended ceiling height of the function unit.

After normalizing the variables, we apply Eqs. (2) and (3) to calculate the Euclidean distance between each pair of units. For each alternative layout, all space units that satisfy hard constraints are evaluated to each function unit. The similarity scores constitute a similarity matrix for each layout. Fig. 11 shows similarity matrices of three alternative layouts, which are the original layout, the one merging B1 and V1 units, and the one merging B1, V1 and B2 units. Blank units indicate the space unit fails to meet these mandatory

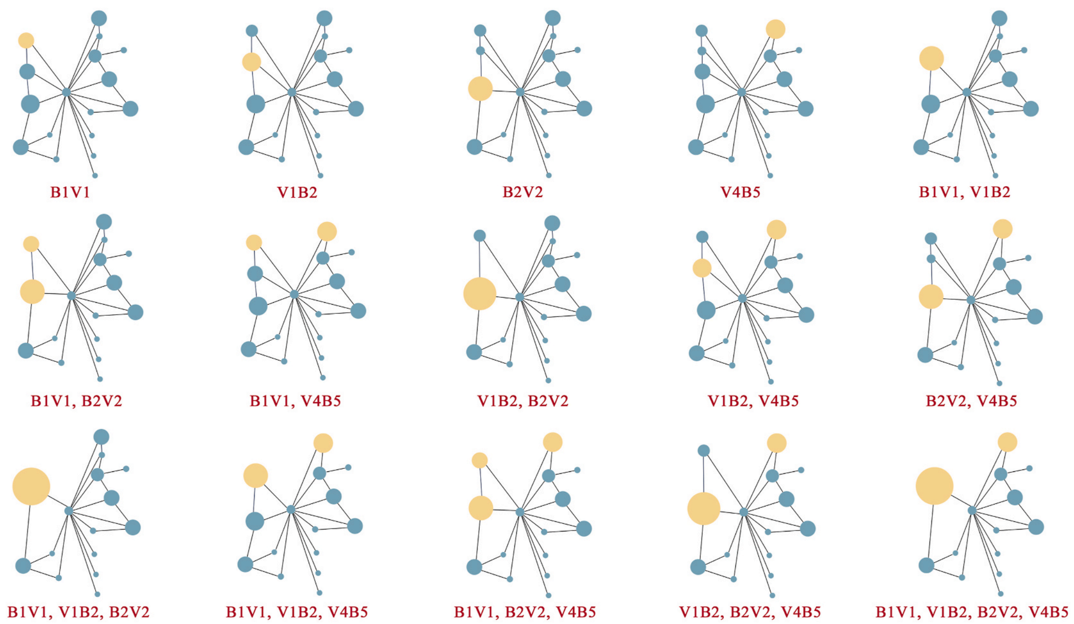


Fig. 10. Alternative spatial layouts for transformation evaluation.

conditions and is excluded from further consideration. The matrices show potential optimal space unit for each function unit based on target indicators. For example, only space unit V2 can satisfy the hard constraints of the 1500-seat theater in both three alternative layouts.

Based on the similarity matrices for alternative layouts, we then apply Hungarian algorithm to identify multiple globally optimal space-function assignment schemes for each layout, ensuring that each function is matched to a suitable space while optimizing overall similarity scores. As mentioned in Section 3.2, we set key parameters for the algorithm first to ensure solution quality and diversity: the maximum similarity threshold with 0.05 difference from the best score, the minimum score set as 0.7, the limit number of solutions as three, and at least two different assignments per solution, with maximum of ten iterations to ensure computational efficiency. Each alternative layout then will generate no more than three spatial assignments for target function units based on global similarity scores, which are evaluated on spatial relationship in the next step.

4.4. Spatial relationship mapping

As mentioned in section 3.3, we evaluate the spatial relationships of potential assignments to alternative layouts based on connection requirements and spatial syntax indicators. According to Table 7, there are four required connections and two target syntax

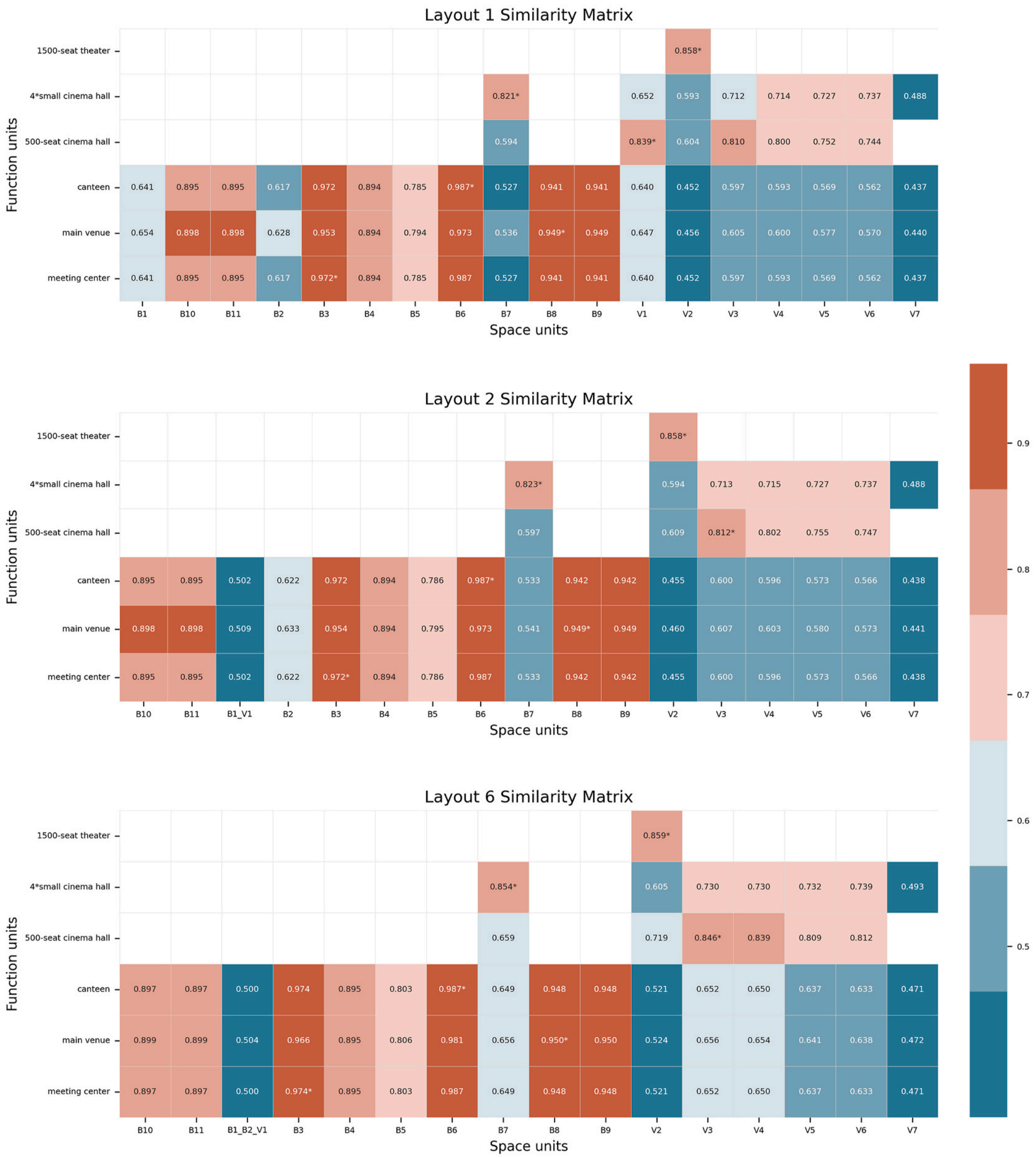


Fig. 11. Similarity matrices of three alternative layouts.

requirements for function units. For connection scoring, we set parameters for the three types of connections: Direct (path length = 1, score = 1.0), Adjacent (path length = 2, score = 0.6), and Distant (path length >2, score = 0.0). If the actual connection strength meets or exceeds the required strength, the pair receives a full score of 1.0; otherwise, the score is assigned proportionally based on the ratio of actual to required strength. The final connection relationship score is the average of all connection requirement scores.

For space syntax scoring, the requirements focus on the connectivity and integration value of the 1500-seat theater and the main venue, which are primary functions in this case. We calculated the two indicators for potential space units for these two functions in each alternative layout. If the integration value and connectivity fall within the required range, then a score of 1.0 will be assigned to the space unit. The final syntax score is the average score across all syntax requirements. As mentioned in Section 3.3, we have prepared a database of 20 performance building cases to study the spatial characteristics of primary function units in such building type. The function unit of the performance hall is expected to have highest integration values except for that of circulation spaces, with relatively highest global accessibility and prominence among the function units in the floor layout plans. And it usually with link with 3–6 spaces such as dressing room, rehearsal room, foyer, stair and corridor, with the connectivity value ranging from 3 to 6 in the database. Therefore, the space unit of performance hall in this case study is expected to align with this topological rule.

Fig. 12 shows the integration analysis results. Spaces in red color have higher integration values than those in dark blue color. Then central corridor in red color has the highest integration value, while the space unit of B1 building in dark blue on the northern edge of the site has the lowest integration value. Except for the main circulation spaces, the space unit with relatively highest integration value is B7, V2, and B8, representing higher accessibility, longer duration of stay, and bigger possibility of going through, which facilitates to attract people to come from other spaces and to stay here for longer time. Apart from analyzing the integration of each space unit considered in the whole site, we could also apply common analysis of road axis to compare the accessibility of roads in front of each space to deduce the accessibility of the potential function unit. Fig. 13 shows the axis map analysis of the site. Each line is the longest axis in the space of roads. Same as the visualization in the convex map, lines in red color have higher integration values than those in dark blue color. The central north-south road which connects most space units has highest integration value than any other paths, serving as the main road of the site. The other west-east path in the center of the site with relatively high integration value shows the accessibility of space units along the road, such as unit V2, B3, B8, B9 and V6, which can be appropriate alternatives for primary functions.

Fig. 14 visualizes the final results of suitability evaluation on all the alternative layouts in the case of Pingyao film palace. The original layout (L1) and the layout merging V4 and B5 space units (L5) are the optimal layouts for the target function program. The function assignment is as follows: V2 for the 1500-seat theater, B8 for the main venue, B7 for the 4*small cinema hall, B3 and B6 for the

Fig. 12. Integration analysis of convex map of space units.

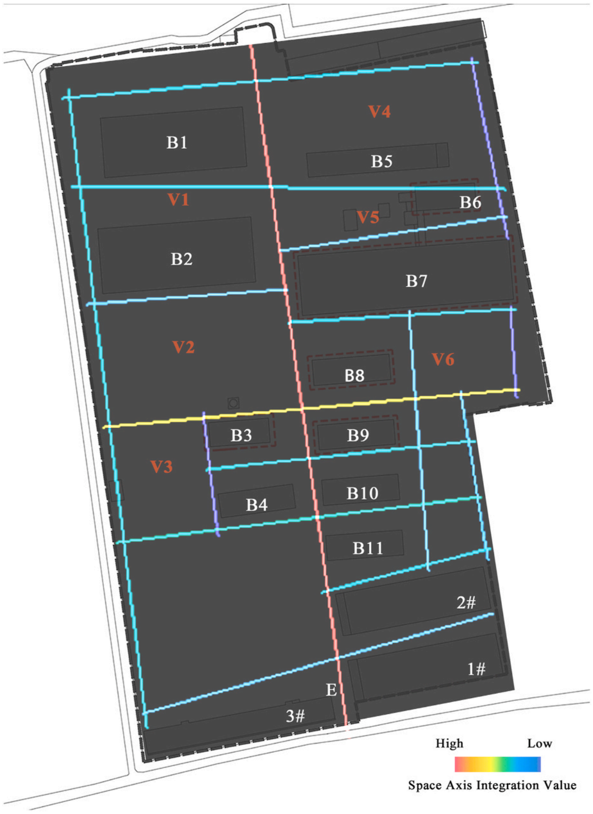


Fig. 13. Integration analysis of axis map of roads on site.

meeting center and the canteen, and V6 for the 500-seat cinema hall. The final choice for the primary functions is the same as the one chosen by the architects and in the final project (Fig. 15). The results from the suitability evaluation model are consistent with those obtained through the traditional sketch-based trial-and-error method, validating the effectiveness of the computer-aided approach, and demonstrating how this model can enhance efficiency as well as ensure feasibility and practicality in the design process, particularly in complex projects with stringent requirements.

The renovation design prioritized historic preservation, adhering closely to the original factory campus layout. The careful programming and feasibility study during the pre-design phase allowed the design development and construction process to be completed within just ten months and at a low cost. Due to the successful design strategy, it was awarded 2020 UNESCO Asia-Pacific Awards for Cultural Heritage Conservation Awards for Merit, 2016–2018 WA China Architecture Awards Urban Contribution Award for Best Work, and many other architectural awards. Following the international film festival, the buildings are operated as a film culture plaza and cinema open to the public. This transformation, from an old factory to a modern international film venue, demonstrates that factories that have ceased their original functions can be revitalized to play new roles in the cultural industry.

5. Discussion

Based on the above results, we find that the proposed systematic decision-support approach for evaluating spatial suitability in building transformation layout design can facilitate effectively early-stage decision-making on feasibility of function program and spatial compatibility in complex transformation projects like the Pingyao Diesel Engine Factory. By traditional trial-and-error methods, architects manually explore numerous layout configuration, which require a few days to a week with limited number of alternatives. They typically use design intuition and past experience when assessing space compatibility and adjusting layouts for complex structures by repetitive experiments. Additionally, architects rely heavily on memory or constant reference to documents to track the characteristics, spatial relationships, and design constraints of existing spaces. This process can be mentally exertive, particularly for large or complex layouts with numerous unique spaces and requirements. This process leads to cognitive overload when dealing high-dimensional spatial data and spatial constraints, where multiple spatial relationships must be balanced simultaneously. In Pingyao Diesel Engine Factory case study, architects only proposed four alternative layouts for positioning the primary functions, and uses quantities of sketches to test different spatial arrangements to determine which layout best accommodates the new functions while respecting the structural and regulatory constraints.

In contrast, the proposed approach can achieve high efficiency and ensure practicality when exploring spatial potential of the

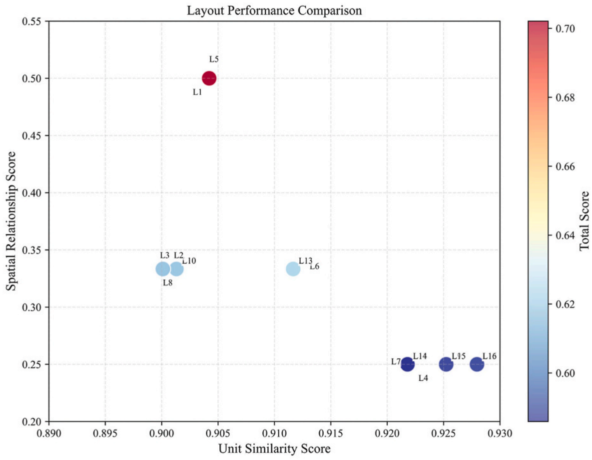


Fig. 14. Final result of suitability evaluation.

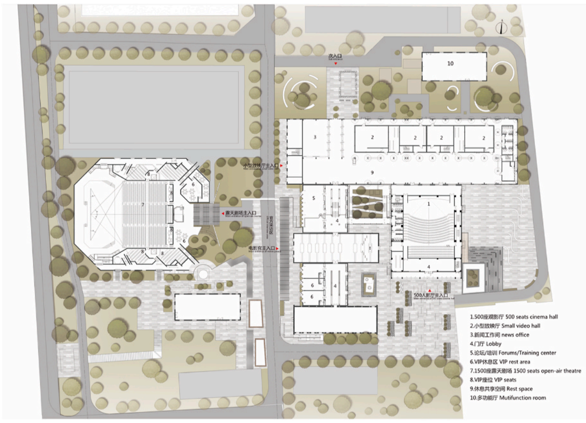


Fig. 15. Ground floor plan of Pingyao Film Palace (from Architectural Design and Research Institute of Tsinghua University).

existing building layout and selecting the optimal building space for the primary function. Applying human-machine-integrated topological transformation, it improves the spatial analysis process by generating multiple alternative layout graphs in seconds, with a dataset of new attributes for distinct rooms and spatial configuration. Through spatial unit matching and spatial relationship mapping, the function accommodation process comprehensively considers various aspects such as building characteristics, design regulations and constraints, users' requirements, design flexibility and sustainability, incorporating advantages of criteria-based decision analysis and graph-based spatial analysis methods. The proposed method alleviates this burden by systematically storing, analyzing, and presenting spatial data, allowing architects to focus on strategic design decisions rather than memorizing or frequently cross-referencing details. This reduction in cognitive load not only streamlines the design process but also minimizes the risk of human error in tracking design requirements across multiple spaces. Additionally, this approach provides stakeholders and architects with a data-driven technique for spatial analysis in the early stage, addressing specific challenges commonly encountered in complex situations such as historic districts by allowing architects to identify constraints and requirements as dimensions within feature vectors, which can then be assigned weights based on their importance to the transformation design. In the Pingyao case study, for instance, there were multiple crucial constraints, including height restrictions, minimal intervention policies, fire code compliance, façade preservation, and limited allowable structural alterations. By applying this method, each of these constraints was input quantitatively or qualitatively as separate dimensions in the feature vectors. These vectors were then evaluated through similarity measures, allowing the system to assess and match each space unit to suitable functions based on these varied requirements. The method's flexibility in adding new dimensions and adjusting weights is particularly beneficial for managing the complex preservation and adaptation requirements typical of historic contexts. This adaptability not only streamlines the evaluation process but also ensures that each constraint is respected, enhancing the precision and reliability of architectural programming and decision-making in such sensitive settings. This method also has a degree of flexibility and adaptability for different types of architectural projects, since the process integrates the interaction between computer programming and human experience.

This article also has limitations to be addressed or improved in the future research. First, in the first step to explore the potential of existing layouts, this article considers the removal of partitions and walls, and possibility to connect the indoor or outdoor spaces, but not including the addition of walls, the removal or addition of floors, or other spatial transformation strategies. Future researches can incorporate a broader range of transformation strategies for horizontal and vertical extension, or separation in computer programming through parametric design simulations, where form-changing rules such as floor additions, extensions, and selective demolitions are dynamically adjustable. Another limitation is the criteria index for evaluating the suitability of both units (nodes) and relationship (edges) in the graph. The complexity and uniqueness of certain architectural features can make it difficult to model them accurately. Future improvements in the evaluation criteria can expand for a flexible range of quantitative and qualitative dimensions through establishing a comprehensive assessment index for indicator selection, ensuring a more nuanced and extensive assessment of spatial suitability. Last, although the assessment approach for spatial relationship mapping in layout graphs based on space syntax provides valuable insights into the centrality and accessibility of key spaces, it does not account for the full range of interactions between all nodes and edges within the graph. Future research could refine the spatial relationship mapping process by integrating more advanced graph-theoretic algorithms or machine learning techniques to capture complex adjacency and connectivity requirements more accurately.

6. Conclusion

In order to assist architects in effectively managing complex information and efficiently obtaining feasible layouts during the early design phase, this article provides a systematic decision-support method for evaluating spatial suitability in building transformation. By integrating graph topology and computer-aided spatial analysis techniques, the proposed approach addresses critical challenges of function-space compatibility, comprehensively considering existing building characteristics, design regulations and constraints, user requirements, design flexibility and sustainability goals. The results of case study demonstrate the practical advantages of the proposed method in the early-stage decision-making of spatial suitability evaluation for complex functional requirements, existing conditions and design regulations, particularly under the constraints of historical preservation and limited site flexibility. This approach can reduce the cognitive load on architects, enhance design efficiency while ensure practicality compared to traditional trial-and-error method.

The key novelties of this research include.

(1) Graph-based spatial representation: unlike previous studies that often focus on individual spatial features, our methodology incorporates a high-dimensional graph representation of spatial layouts. This structure captures not only space types and dimensions but also adjacency and connectivity information, enabling more detailed spatial data storage, analysis, and mining.
(2) Human-machine integration for design efficiency: this approach integrates human-defined design criteria with computer-aided topological transformations, a combination not fully addressed in current literature. By allowing design conditions set by experts to guide the computer-aided generation of layout alternatives, we ensure both practical applicability and flexibility. This integration leverages both human expertise knowledge and computational tools, reducing the reliance on manual trial-and-error methods, thus significantly improving design efficiency.
(3) Comprehensive graph matching for evaluation: existing research primarily evaluates spatial transformations at the individual unit level, often requiring extensive manual verification. In contrast, our methodology incorporates a graph-matching-based evaluation system that assesses overall spatial compatibility through a two-level framework—node and edge matching—-which uses feature vectors, similarity measures, and space syntax techniques to assess layout compatibility as a whole. This approach enables the evaluation of multiple layout alternatives at once, streamlining the process, enhancing research efficiency, and ensuring the practicality and coherence of transformed layouts.

The main theoretical contributions of this study lie in establishing a systematic framework that integrates graph topology, data-driven spatial analysis and human-machine-integrated techniques and incorporating them into evaluation and design of building transformation layouts. These contributions offer essential theoretical support and guidance for early-stage architectural programming and spatial layout design in building transformation. Furthermore, for building design practice, this method allows architects to evaluate the spatial compatibility for the new function program in advance, to identify potential conflicts and make informed adjustments and optimization in design, reducing the reliance on traditional trial-and-error methods. It can also facilitate feasibility study for stakeholders to making rational decisions on function conversion and site selection, reducing risks of discrepancy between ambitious goals and existing building conditions.

We believe that future research can broaden the scope of spatial form-changing mechanism in the computer program to include additional layout transformations, such as floor additions, horizontal extensions, and separations. Additionally, enhancing the evaluation criteria to better model specific architectural features by integrating quantitative and qualitative dimensions will provide a more holistic assessment of function-space suitability. Finally, exploring advanced graph matching algorithms to capture complex architectural relationships will further strengthen this approach, enabling it to better address more intricate spatial challenges in building transformation projects.

CRediT authorship contribution statement

Yetong Huang: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Weimin Zhuang:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Funding acquisition. **Fang Zheng:** Writing –

review & editing, Visualization, Supervision, Funding acquisition.

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.

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Data availability

Data will be made available on request.

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A human-machine integrated optimization method for long walkway space

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School of Architecture, Tsinghua University, Beijing, China

ABSTRACT

With the development of cities, the design of long walkway spaces have exposed a series of issues. These spaces suffer from layout inefficiencies due to the complex interaction of multiple factors, affecting walking experiences. Optimization schemes for such spaces typically involve the calculation and evaluation of various influencing factors, necessitating comprehensive and systematic judgment. In recent years, the advancement of computer technology has made it possible to utilize genetic algorithms for multi-objective optimization of spatial layouts. Through human-machine collaboration based on genetic algorithms and expert judgment, diverse schemes can be generated more quickly and the optimal solution can be effectively selected. This article aims to explore how to use generative technology combined with expert judgment in a human-machine collaboration approach to address the multi-objective optimization of long walkway spaces. Research results indicate that this process can enhance the efficiency and quality of optimizing layouts for long walkway spaces. After further refinement through manual comparison, the rationality of the results is improved, achieving optimization effects based on the previous layouts. In the future, this method can be promoted to other areas and application scenarios within urban design and planning, demonstrating significant potential for development.

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Long walkway space; walking experience assessment; genetic algorithm; generative design; human-machine collaboration

1. Introduction

With the rapid development of cities, the planning and design of long walkway spaces have exposed a series of urgent issues alongside the provision of convenience for residents' travel within urban spatial systems. Long walkway spaces refer to large spaces with relatively fixed external boundaries and structures, characterized by flexible internal functional groupings and arrangements that form lengthy pedestrian pathways. Representative examples of such spaces include station areas, exhibition halls, urban parks and more. Due to the complex interaction of multiple factors during spatial layout, inadequate design considerations often result in irrational space arrangements and poor walking experiences, leading to inconvenience for urban residents. Optimization schemes for such spaces typically involve the calculation and evaluation of various influencing factors, necessitating comprehensive and systematic judgment.

In recent years, the progress of computer technology has made its application in spatial optimization design feasible. The generative design method can quickly and flexibly generate a variety of solutions, enhancing design efficiency and garnering increasing attention from designers. Due to the complexity of architectural problems, current research still focuses on explorations of generative techniques for two-dimensional spatial layouts. Genetic algorithms, as rule-based generative techniques, simulate natural selection for multi-objective optimization, thus offering advantages in addressing architectural problems with multiple influencing factors and high complexity. By selecting reasonable evaluation criteria, the human-machine collaboration workflow based on genetic algorithms and expert judgment can generate diverse schemes more quickly and effectively select the optimal solution. This method has the potential for application in the multi-objective optimization generation of long walkway spaces.

This article aims to explore how to use generative technology combined with expert judgment in a human-machine collaboration approach to address the multi-objective optimization problems of long walkway spaces. We first provide an overview of the research progress on generative design of architectural plans and spatial layouts, and after comprehensive evaluation, selects genetic algorithms as the technical approach for optimizing the generation of long walkway spaces. Based on a summary of existing research, the aim is to integrate existing methods to optimize the layout of long walkway spaces with the goal of enhancing pedestrian's walking experience. By

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introducing an evaluation system for walking experience as the optimization target for genetic algorithms, a complete system for factor assessment, algorithm generation, and comparison verification is established, thus creating a feedback loop from walking experience assessment to genetic algorithm generation. The paper also explores how to conduct human-machine collaborative interactive design within this framework to enhance the rationality of results.

The remaining structure of this paper is as follows: the second section reviews relevant research progress. The third section proposes the research approach of this paper and constructs the framework of the "Genetic Algorithm – Walking Experience" method. The fourth section constructs the factors influencing walking experience and the evaluation system. The fifth section builds the generation program, conducting genetic algorithm and plan generation based on the multi-objectives influencing walking experience and then carrying out experimental tests in three scenarios – station area, exhibition space and urban park, specifically demonstrating the process of human-machine collaboration. The sixth section summarizes and analyzes the generated results, reflecting on the optimization potential of the experiments and providing an outlook for future research.

2. Review of relevant research

2.1. Overview of generative design

With the development of computer technology, generative technology has gradually been applied across various fields. Generative design refers to the process of automatically generating and iterating design solutions with the assistance of computer technology, making it more efficient and flexible compared to traditional design methods (Lobo et al. 2021). Depending on the generation method, generative design can be divided into rule-based generative design and AI-based generative design. The former primarily uses algorithms and programs to gradually generate designs through rule settings, while the latter employs artificial intelligence and machine learning to generate designs by mimicking and learning through neural networks. Designers should choose the appropriate generative technology based on the specific characteristics of the problem at hand. Scholars have proposed a framework for the process of generative design, combining existing generative technologies with design principles, exploring how humans and machines can better collaborate to enhance design efficiency and quality. Chew et al. (2024) summarized four steps of generative design: 1) Design goals; 2) Employ algorithm; 3) Evaluate various options and adjust parameters; 4) Further evaluation and manufacturing by the designer. This emphasizes the profound impact and potential applications of generative design in the built environment sector. In fields such as product design (McKnight 2017) and industrial design (Gradišar, Dolenc, and Klinc 2024), scholars have begun to apply the aforementioned generative design processes and have achieved preliminary results.

However, the field of architecture still lacks the integration and application of generative design, with many efforts in the exploratory phase of generative technology. The spatial layout optimization problem addressed in this article falls within the proposal stage of architectural design, requiring the generation of numerous potential design directions in a short time based on design goals, followed by the selection and refinement of the best options. Due to its efficiency and flexibility, generative technology is gradually being applied to the study of architectural plans and spatial layouts.

2.2. Research on the generative design technology of architectural layouts

Rule-based spatial layout generation utilizes specific algorithms and program design to generate diverse schemes in a short time. For example, Michalek, Choudhary, and Papalambros (2002) considered factors such as energy consumption and transportation, using quadratic programming models to generate architectural layout plans. Guo and Li (2014) created a plan evolution model based on given objectives and rule algorithms, studying the results of plot division generated under game optimization. Zhang and Li (2020) provided automated program algorithms for architectural layout and road generation in residential area planning based on multi-agent systems, Voronoi partitioning, and Dijkstra pathfinding algorithms. They also abstracted and refined the translation rules for commercial buildings, utilizing a morphological coding strategy to divide shop layouts in shopping mall floor plans based on specific rules (Zhang and Li 2022). These rule-based generative methods enhance design efficiency while expanding design possibilities. However, the formulation of rules carries a level of subjectivity from the designers, and if the rules are not established properly, it may result in suboptimal generation outcomes.

Based on the imitation and generation ability of deep learning neural networks for images, some studies have attempted architectural plan and spatial layout generative design. Huang and Zheng (2018) achieved the design generation of apartment floor plans by learning architectural floor plans with room labels through the Pix2pixHD network. Nauata et al. (2020) used bubble diagrams representing the adjacency relationships of different rooms as input constraint conditions to train House-GAN, enabling it to learn to generate a variety of residential layouts under these bubble diagram constraints. Zheng and Ren

(2020) developed a tool capable of learning and predicting vectorized data for generating architectural floor plans, reducing accuracy loss caused by pixelated image data. Liu et al. (2021) constructed a campus layout sample dataset based on the preferences of specific architects, trained generative adversarial networks to automatically generate campus layout floor plans with boundary conditions and traffic networks as inputs. However, machine learning often relies on a large number of training samples, and the generation effect needs improvement. Therefore, for situations with fewer samples or difficult-to-obtain samples, rule-based generation is often more efficient and effective compared to AI-based generation.

2.3. Genetic algorithm for spatial layout optimization

The utilization of genetic algorithms belongs to the category of rule-based generative design methods. Genetic algorithms are multi-objective optimization algorithms that simulate the process of natural selection. By simulating genetic operations such as crossover and mutation, they select two or more fitness objectives as evaluation criteria to measure the rationality of results and search for the optimal solution within the candidate solution space.

The adaptability of genetic algorithms to complex problems enables their application in spatial layout optimization problems affected by multiple factors, and relevant research has made certain progress. In cases with certain generation rules and evaluation objectives, and limited sample sizes, multi-objective optimization based on genetic algorithms often has advantages over machine learning. For instance, Laignel et al. (2020) proposed an automatic method for residential floor plan generation, which integrates mutation, crossover, and selection of final units through genetic algorithms after functional layout and circulation design. Lv, Wang, and Grzywinski (2020) combined nonlinear optimization models with genetic algorithms to design a program for generating tenant space layouts in shopping malls. Kumalasari et al. (2023) focused on the concept of a "walkable city," using greenery rate and functional convenience as fitness objectives to generate multiple block layout schemes for walkable neighborhoods using genetic algorithms. Boyukliyski et al. (2022) comprehensively considered building area (GFA) and per capita green area, and realized multi-objective optimization and multi-scheme comparison of spatial layouts in urban design based on genetic algorithms.

2.4. Limitation of previous research

In summary, generative design has made progress in optimizing architectural plans and spatial layouts. But due to the complexity of architectural design and the diversity of influencing factors, generative design of spatial layouts also faces some challenges and problems. Generally, it is difficult to directly generate a highly reasonable result through computers, and manual inspection and optimization are still required. When and how designers intervene, how to form a good interaction and combination with computer programs to enhance the rationality of solutions are all issues worthy of consideration. Existing studies have constructed the methodology of generative design; however, it tends to be relatively macro and abstract, lacking specificity and not having been practically applied in the fields of architecture and urban planning. In the context of architectural design scenarios, the process of determining, evaluating, and utilizing influencing factors to generate schemes remains relatively isolated in existing research and practice, lacking a systematic generative design system. The interaction and collaboration between influencing factors and algorithmic procedures, combined with human judgment to generate more reasonable solutions, are still worth exploring. This paper, focusing on the characteristics of the field of architecture and addressing the specific issues related to the multi-objective optimization of long walkway spaces, aims to integrate existing methods, establish a complete system from pedestrian experience evaluation to genetic algorithm generation, and explore how to conduct human-machine collaborative interactive design within it to enhance the rationality of results. In the future, this method can be extended to application scenarios in urban design, spatial planning, and other areas of architecture, demonstrating significant potential for development.

3. Methodology: multi-objective optimization for walking experience with genetic algorithm

3.1. Method framework

This paper selects long walkway spaces as the research subject, aiming to enhance the walking experience for pedestrians as the optimization goal for spatial layouts. Leveraging the Rhino-Grasshopper platform, the program is developed to generate interior layout schemes for such complex spaces using genetic algorithms. The framework (Figure 1) primarily consists of two parts: establishing a walking experience assessment system and conducting multi-scheme comparison through genetic algorithms, with both parts interacting to form a feedback loop.

The core of the walking experience assessment system lies in the construction of influencing factors. Factors affecting the walking experience serve as fitness objectives for the genetic algorithm, measuring the quality of generated results. Drawing on existing research and expert interviews, this paper selects convenience, safety, and experience as three dimensions, each with six specific indicators as influencing factors for the walking experience.

The genetic algorithm generation process consists of four steps, including generation program construction, genetic algorithm calculation, multi-scheme comparison, and classification of plans with scheme refinement. Leveraging Grasshopper for program construction and using the Wallacei plugin for genetic algorithm execution, the paper employs various data statistical methods and clustering algorithms for scheme classification and comparison, followed by further refinement in specific application scenarios.

In this methodological framework, the collaboration between human and machine is crucial for enhancing the rationality of the results. The establishment of the assessment system requires human judgment to determine the main influencing factors as indicators for evaluating walking experience and as optimization targets for the genetic algorithm. After the computer generates results using the genetic algorithm, designers need to analyze these results, combining professional judgment to select outstanding outcomes for further adjustment and refinement. The modified schemes will return to the assessment system for scoring, and designers will decide based on the specific situation whether to proceed with another round of iterative optimization by the computer. This realizes a feedback loop of "genetic algorithm – walking experience," ultimately yielding the optimal solution. This represents a collaborative working process of "human-machine-human."

3.2. Walking experience assessment

This paper summarizes research on walking experience, combining expert interviews and surveys, finding that convenience, safety, and experience are the three most frequently mentioned factors influencing walking experience (D'Orso and Migliore 2019). Convenience is at the core of transportation modes, and modes of travel that are efficient are more likely to be accepted by people (Schlossberg and Brown 2004). With the development of transportation, in addition to focusing on speed and efficiency, people also have higher demands for the safety of space and the experience of walking (D'Alessandro, Appolloni, and Capasso 2016; Ellis *et al*. 2015). How to layout functional spaces along long walkway spaces to achieve optimal results has become a focal point. Therefore, this paper selects convenience, safety, and experience as three dimensions and sets up six indicators as influencing factors for the walking experience assessment of long walkway spaces. Specifically, as shown in the table below (Table 1).

Since the framework constructed in this article is flexible, the influencing factors are not fixed and can be adjusted based on different circumstances to accommodate various target requirements, thus creating personalized assessment and optimization schemes. Taking into account multiple factors such as technology and data collection, this study uses the six influencing factors above as examples to demonstrate the construction process of the "genetic algorithm – walking experience" feedback loop and the working process of human-machine collaboration, thereby validating the feasibility of this methodological framework.

Once the influencing factors for walking experience are determined, the study constructs an assessment system covering the six factors mentioned above using Grasshopper program (Figure 2). This system will serve as the fitness objective for the genetic algorithm, preparing it for the input genetic algorithm program module.

The specific construction process involves two steps:

(1) Incorporating planar information: Selecting a planar space for long walkway routes and

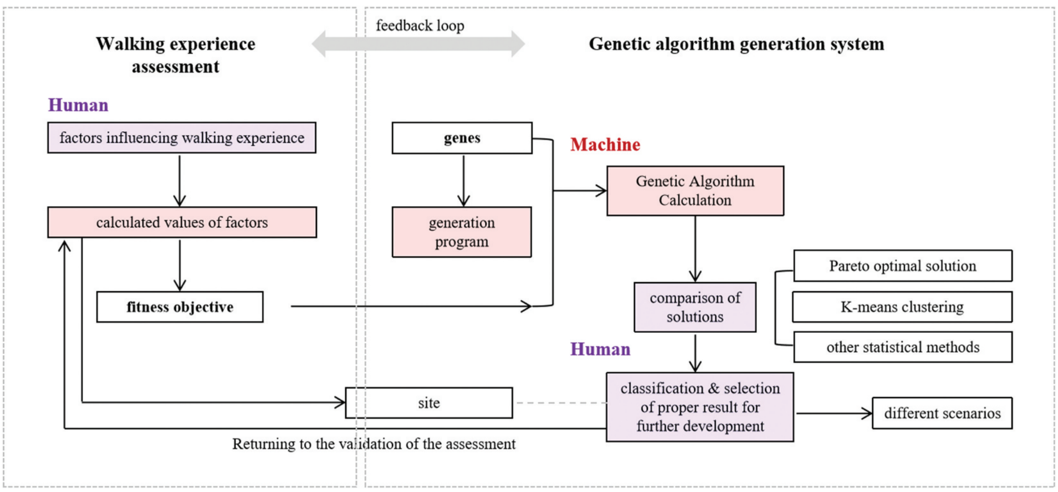


Figure 1. Method Framework.

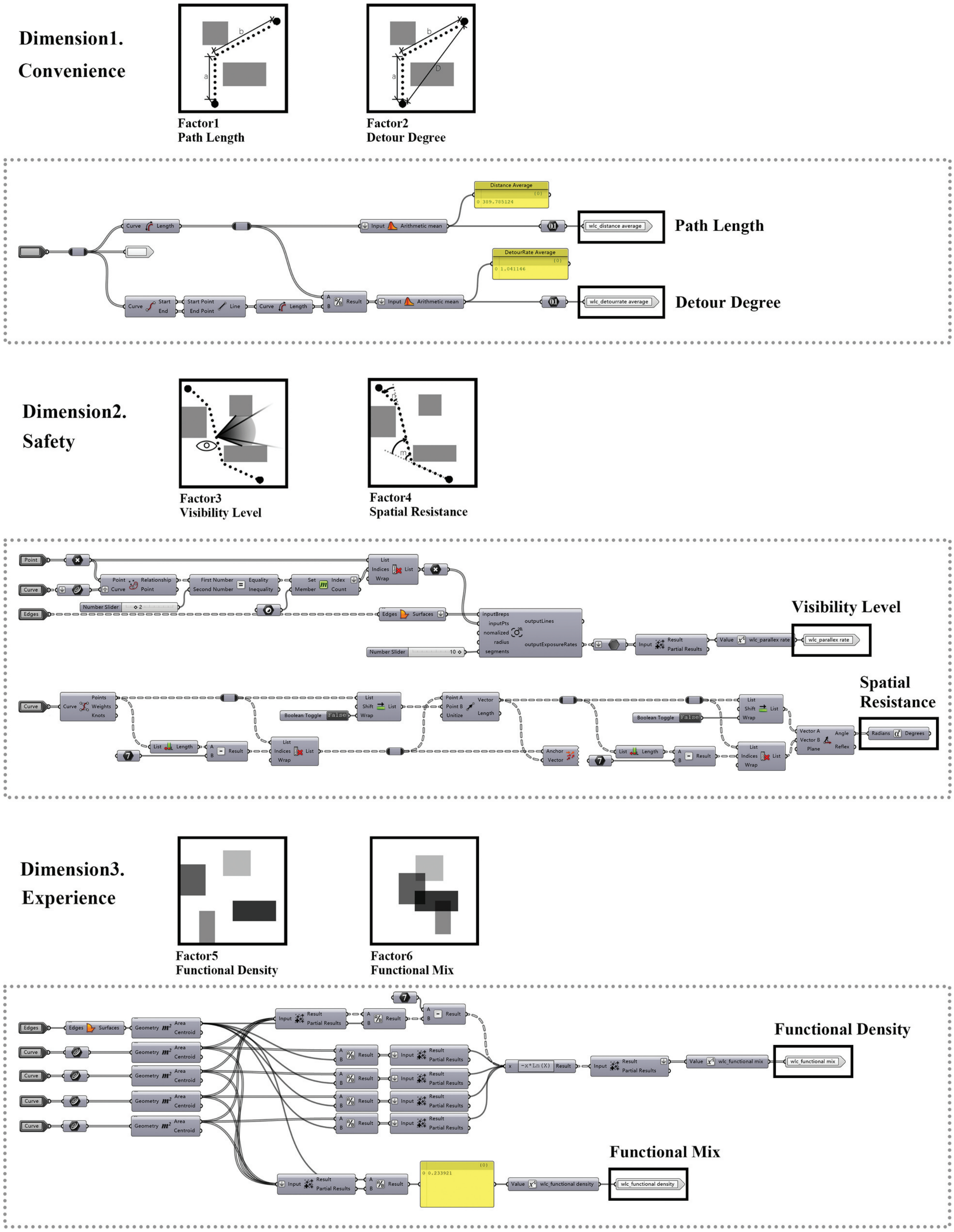


Figure 2. Using grasshopper to build a walking experience assessment system.

simplifying it accordingly. Retain the planar outline, entrances and exits (start and end points of walkways), and boundaries of functional blocks. Depending on the actual situation, integrate and classify the functional types of blocks.

(2) Generating all walking routes based on the simplified plane and calculating the numerical values of the six influencing factors using the corresponding program. These values will serve as the fitness objectives for the genetic algorithm.

Table 1. Factors influencing walking experience.

Dimension	Influencing Factors	Meaning of influencing factors
Convenience	Path Length	Path length from entrance (start point of walkway) to exit (endpoint of walkway)
	Detour Degree	Ratio of walkway length to straight-line distance from entrance to exit
Safety	Visibility Level	visibility level $= (N \times \log_2 \frac{3}{N} - N + 1)/(4TD - 4N + 4)$ Using the concept of integration in spatial syntax as a measure (where TD represents topological depth, N represents the number of nodes calculated), namely the likelihood of seeing the boundaries of various functional blocks on the walkway.
	Spatial Resistance	Sum of turning angles at all nodes on the walkway
Experience	Functional density	Ratio of sum of areas of all functional blocks to total plan area
	Functional mix	$\text{mix} = -\sum_{i}^{m} Pi \times \ln pi$; where "mix' represents functional mix, 'm' represents the number of functional blocks, and 'pi' represents the ratio of the number of certain type of functional block 'i" to the total number of functional blocks

3.3. Genetic algorithm generation system

The generation system is built upon Rhino-grasshopper with Wallacei plug-in constructing genetic algorithm (Figure 4). The process can be divided into the following five steps:

(1) Gridding: According to the scale size of the selected optimization target, the optimized plane is subdivided into suitable scale grid points, and the total number of grid points is limited to facilitate the subsequent calculation process.
(2) Generation of point sets: The random factor (defined here as random factor 1/Gene1) in the Genetic Algorithm plug-in is used to assign a value to each grid point, where 0 represents an empty point and 1 represents a real point, where non-empty grid points represent the location of functional areas, and empty space points represent walking areas. Through the existing functional blocks and walking area size control of the number of hollow grid points, to ensure that the optimization of the functional area before and after the area remains stable.
(3) Clustering: Using the principle of similar cellular automata (Figure 3), for the existing grid points for several approximate iterations, eliminating the more independent scattering points, the program fills in some of the vacancies within the point set, so that the iteration of the collection of real points to form a group, close to the reality of the plane of the layout logic.
(4) Functional classification: Through the k-means clustering algorithm, we try to analyze and sort out each independent functional block, and seek convex envelope for it to form the basic outline of the plane functional block, and give different functional attributes to different blocks through the random factor of Wallacei plug-in (here defined as random factor 2/Gene2).
(5) Genetic Algorithm Calculation: Through the built-in algorithmic logic of Wallacei plug-in, we input the existing plane contour and the functional area contour for calculation, and each individual transforms the two random factors and calculates the corresponding evaluation index. Through the genetic algorithm to the excellent individual characteristics of genetic, and constantly through random changes to produce new individual characteristics, and ultimately in the preset number of iterations after the calculation, to obtain in the adaptability of the target conditions of the Pareto optimal solution set.

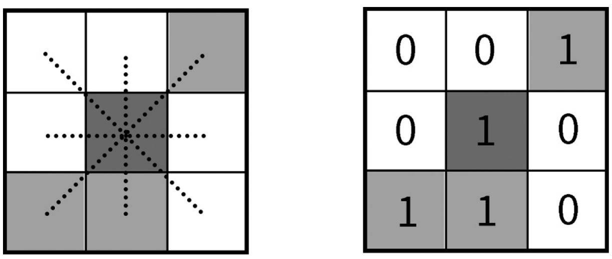


Figure 3. The principle of similar cellular automata: after randomly selected points generate functional lattice, the cellular automata is used for iteration, and the selected points are assigned a value of 1 and 0. Find 8 points around each point, assigning 0 to that point if there are more than 3 ones and 1 to that point if there are more than 2.

3.4. Statistical methods and comparison of solutions

On the basis of the Pareto optimal solution set obtained by the genetic algorithm, different statistical graphs (the standard deviation graph, mean value trend line graph, diamond graph, etc.) can be obtained from the analysis of Wallacei data, so as to judge the degree of optimization of each objective, and to compare it with the influence factors of the walking experience, so as to facilitate the manual comparison and determination of deepening solutions.

The following are the specific steps:

(1) Assess the optimization status of each indicator based on the standard deviation graph and the mean value trend line graph (Figure 5a). In the standard deviation graph on the left side,

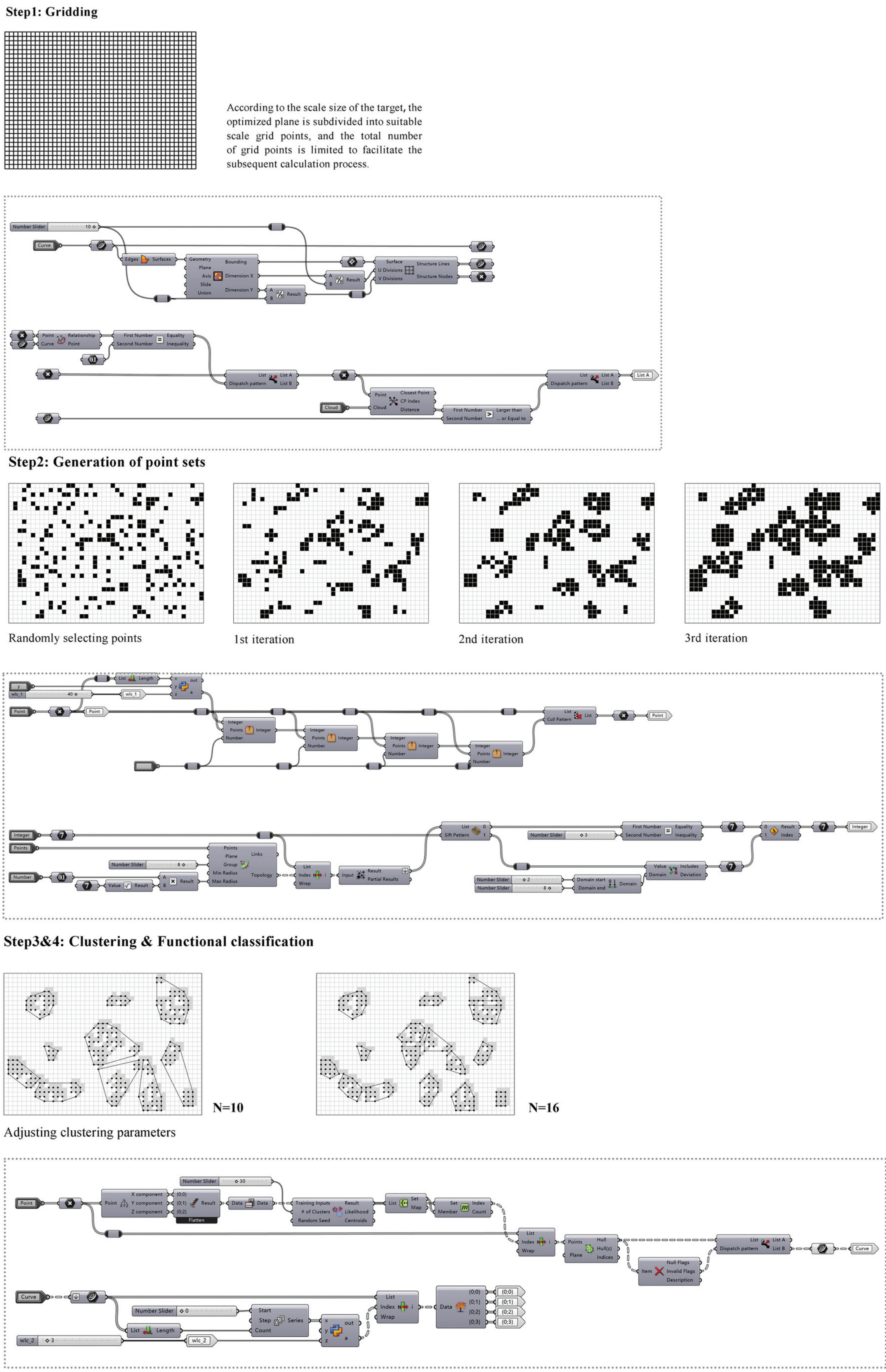


Figure 4. Generate system program construction and effect demonstration.

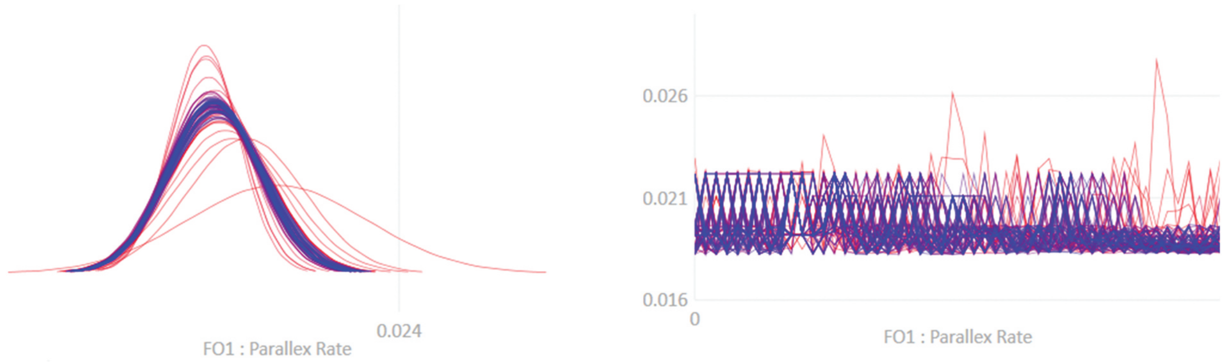


Figure 5a. The final iteration results are represented in blue. In the standard deviation graph, it is evident that the kurtosis of the curve has decreased, indicating that the optimization results have become more concentrated and stable; the curve exhibits a high left skew, suggesting a significant degree of optimization. In the mean value trend line graph, the degree of fluctuation of the indicators has reduced, showing a stable trend. This indicates that comprehensive optimization has been achieved.

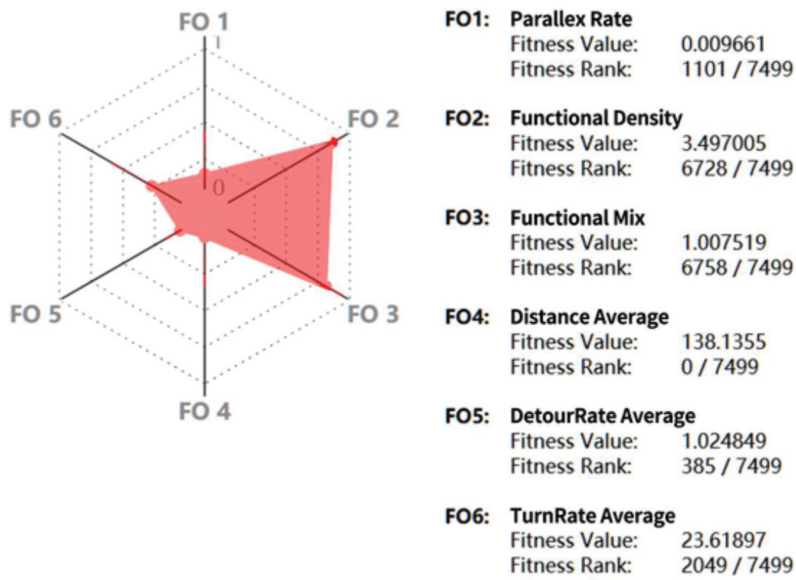


Figure 5b. Diamond graph: In this graph, indicators 2 and 3 (experiential indicators) are particularly prominent, while the optimization levels of the other four indicators are relatively low. This indicates that functional density and functional mix are the primary factors for optimization, highlighting the characteristic of the layout as having “high experiential quality.”.

a smaller kurtosis of the curve indicates that the data has become more concentrated and stable during the optimization process of the genetic algorithm. The skewness of the curve represents the extent of optimization of the indicators compared to the original conditions. Similarly, in the average trend line chart on the right side, the degree of fluctuation of indicator values corresponds to the kurtosis of the standard deviation chart, and the magnitude of the values corresponds to the skewness. Therefore, in an ideal state of optimization, when all indicators show a left-skewed trend with decreasing kurtosis, it indicates that the genetic algorithm has achieved comprehensive optimization.

(2) By performing a cluster analysis of the indicators and referencing the diamond graph (Figure 5b), the generated results can be classified. The diamond graph reflects the magnitude of each indicator’s value, making it clear and intuitive to observe the characteristics of each indicator in the layout. Additionally, the explanatory text on the right side of the diamond chart includes the ranking of each indicator within all the results, which can assist in assessing the optimization status of the indicators.

(3) The designer assesses the factors that have a greater impact based on the architectural characteristics and selects the optimal solution according to the optimization characteristics of each category of indicators.

(4) At the same time, we organized over 10 individuals with training in architecture to provide scores, and the final refined result was determined based on a comprehensive evaluation.We will provide a detailed demonstration of the above steps in Section 4.

4. Application of the proposed methodology

In this part, three types of representative long walking flow spaces (station space, exhibition space, urban park) are selected to experiment the mutual feedback process of "genetic algorithm – walking experience", and demonstrate the application of the method and the workflow of human-machine collaboration in actual scenarios.

4.1. Station space – an example of a large transport station

A railway station is located in the inner city of a key city in the north of China, and is one of the most important railway transport hubs in the city, which was officially opened for operation at the end of the 20th century. Due to the complexity of the built environment and the scarcity of public space in the inner city, the passenger flow pressure on the railway station has far exceeded its design threshold after nearly 30 years of operation. Due to its early construction, the design factors such as the span of the waiting room and the spacing of the load-bearing columns were limited by the technical conditions at that time, and the station space inside the station was relatively crowded, which significantly reduced the capacity of this large station and the travelling efficiency of the passengers.

Considering the above factors, under the premise that the location of this large transport station is extremely important, the reconstruction of its internal station space is a more suitable optimization target for this procedure than direct reconstruction, which can better guarantee the traffic convenience and economic benefits. Based on the analysis of the existing plane of the waiting room, we extracted four internal station space attributes, namely, commercial, catering, service and others, and inputted the existing plane of the second-floor waiting hall as the object of optimization, and carried out the genetic algorithm operation for 150 generations (the sample capacity of each generation is controlled as 50), with a total of 7,500 sub generations of individuals.

The preliminary results generated by the genetic algorithm are illustrated in the following figures. Figure 6 displays the current layout pattern of the large train station. Due to the concentration of ticket gates on the two long sides of the rectangular plan, the waiting area and commercial spaces in the center are compressed, leading to noticeable congestion. We assess the optimization results using the standard deviation trend line chart (Figure 7), and the specific evaluation method is detailed in Section 3.4. In the actual calculation results for this scenario, four indicators – visibility level, functional density, functional mix, and path length – show significant optimization compared to the baseline layout. In contrast, the improvements in detour degree and spatial resistance are relatively minor.

By conducting a clustering analysis of all offspring, the general optimization directions of the genetic algorithm can be categorized into three types: functionality, convenience, and balance. The indicator values of the layout results for the three categories are shown in Table 2. Some layouts stand out particularly in experiential indicators, but the optimization levels of the other four indicators are relatively low, classifying them as "functionality" type layouts. Conversely, another set of layouts has prominent values in the other four indicators while slightly lagging in functional indicators, defining them as "convenience" type layouts. Additionally, there are still a few layouts that achieve varying degrees of optimization across all six indicators, attempting to

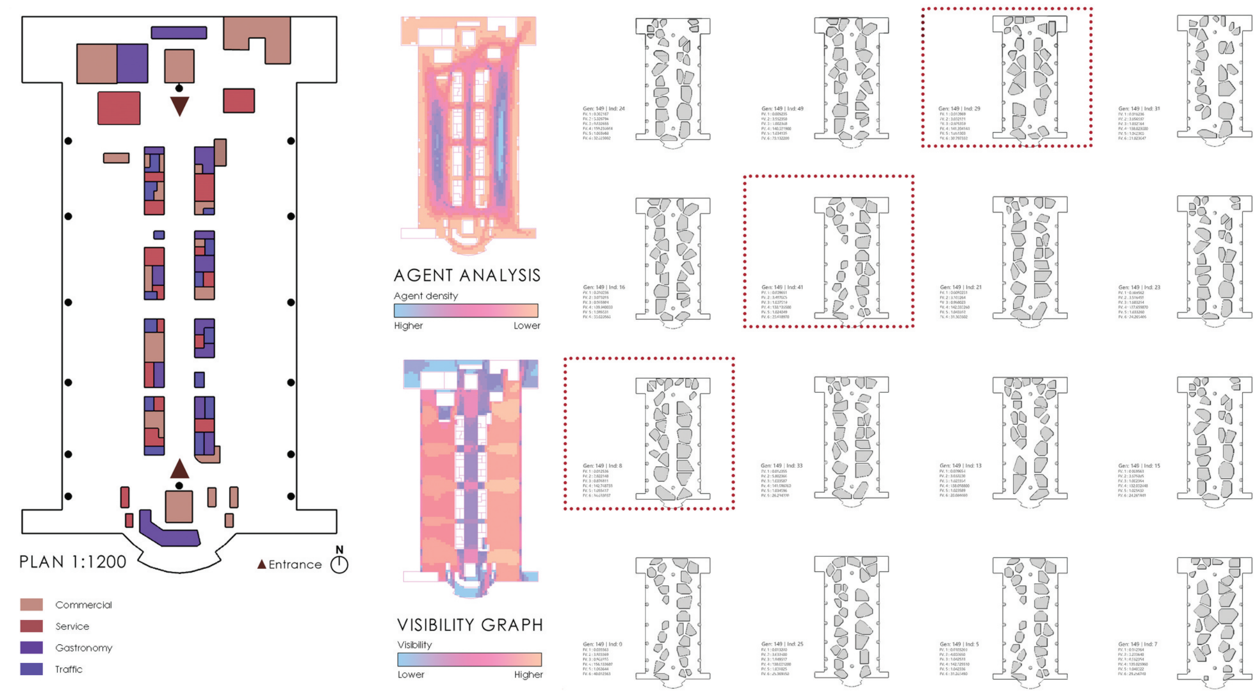


Figure 6. The current situation of a large transport station and the results of the last generation of the genetic algorithm.

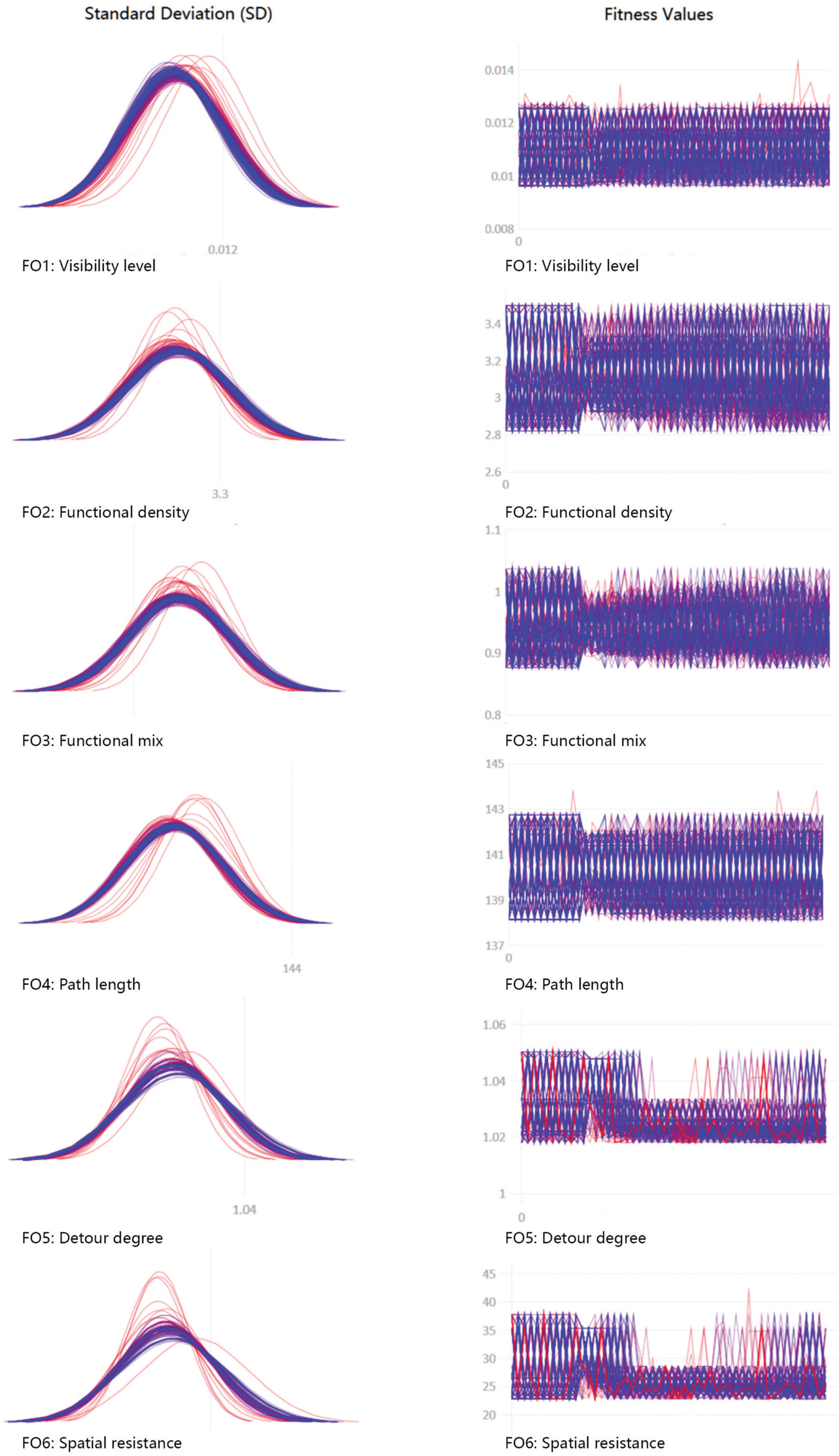


Figure 7. Standard deviation graph and standard deviation trend line graph of genetic algorithm.

balance all aspects, which are defined as "balance" type layouts. The representative layouts of the three types are shown in Figure 8.

Based on this analytical principle, we select three different types of preliminary optimized layouts and organize over 10 professionals trained in architecture

Table 2. Indicator values of the layout results (station space).

	Counts	Mean of factors					
Type		Visibility Level	Functional density	Functional mix	Path length	Detour Degree	Spatial Resistance
Functionality	16	0.009	3.498	1.007	138.136	1.025	23.618
Experience	26	0.012	2.922	0.876	142.478	1.055	34.633
Balance	8	0.01	3.032	0.925	141.394	1.051	30.796
Total	50	0.01072	3.12392	0.92576	140.91512	1.04476	30.49428

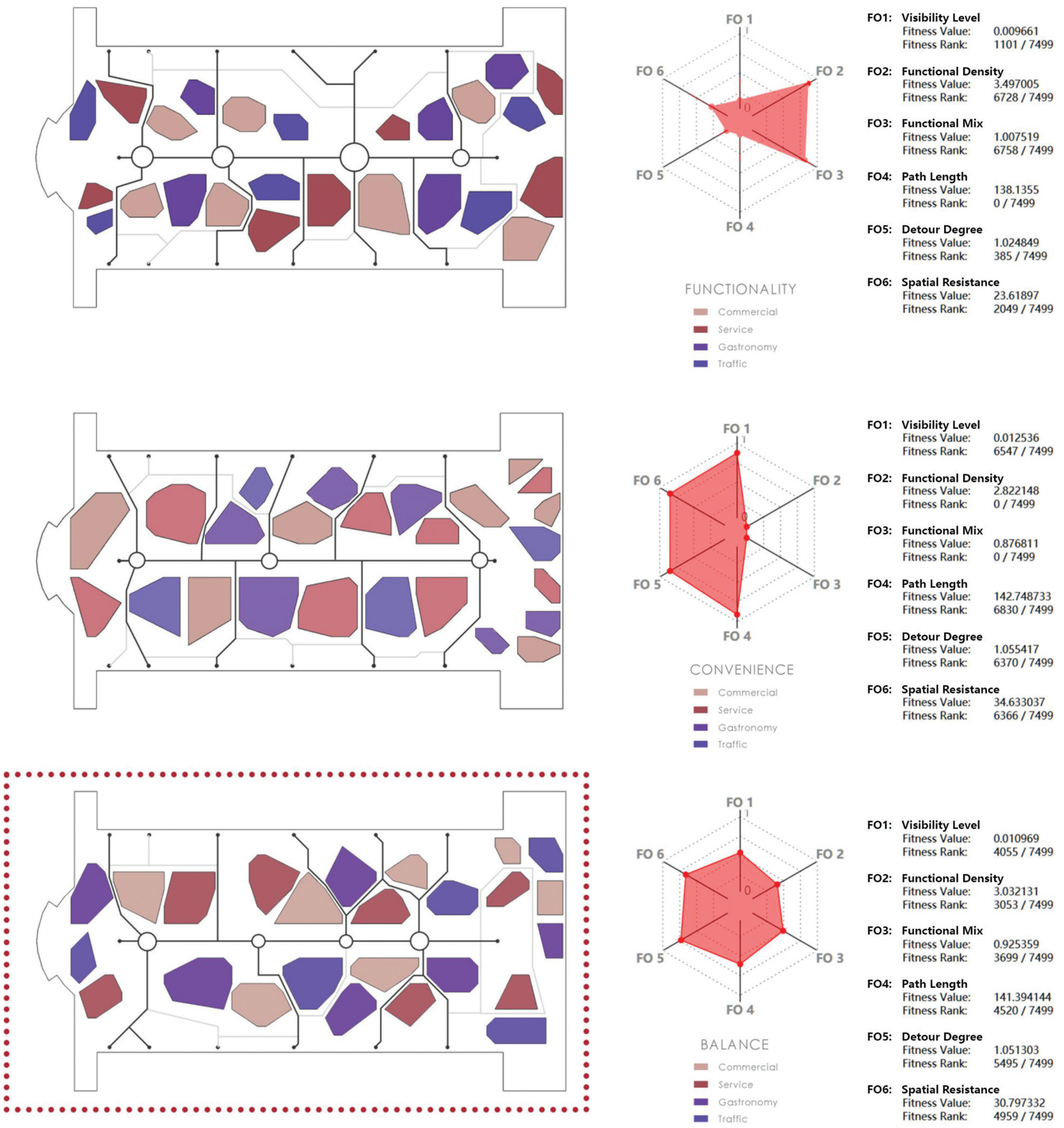
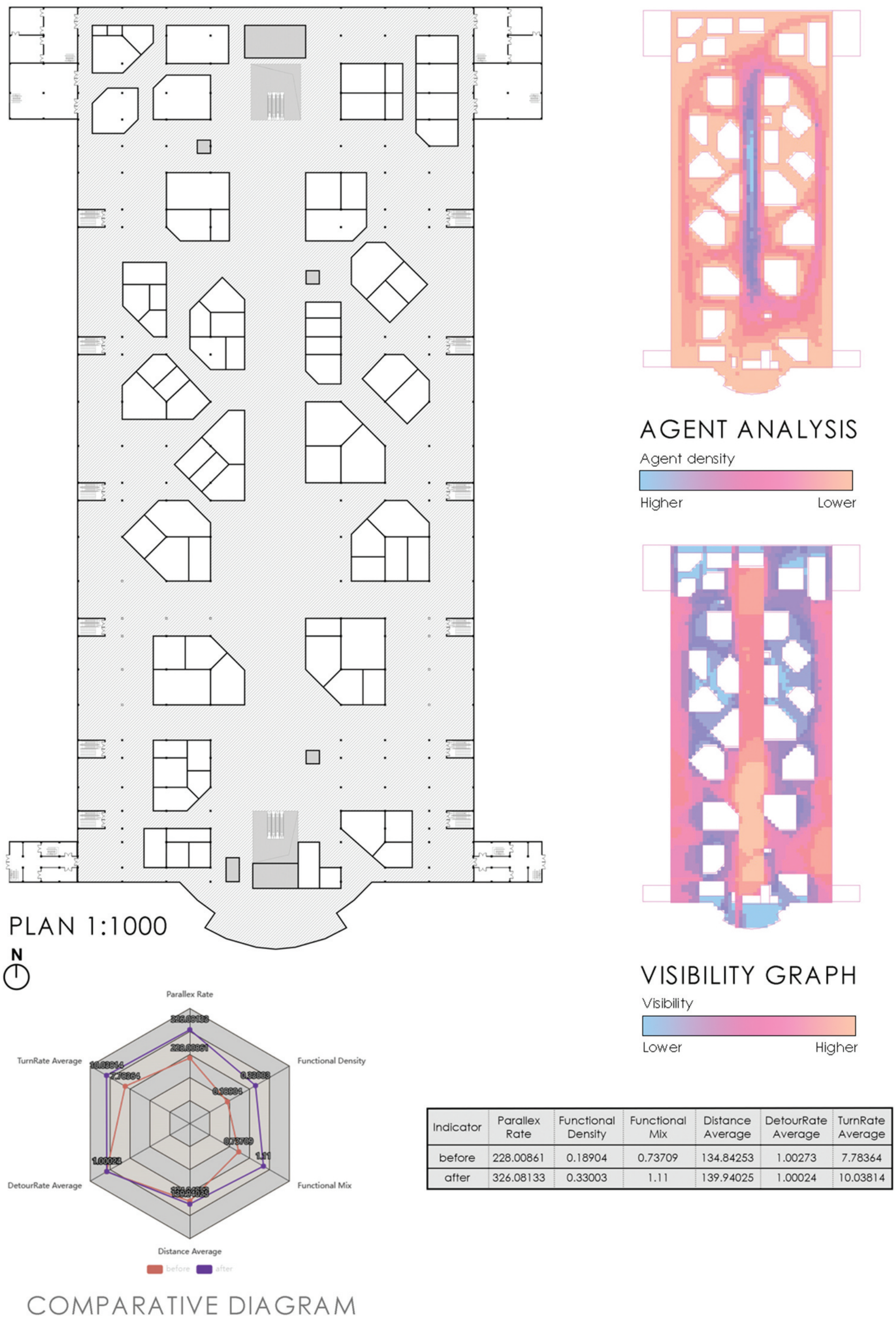


Figure 8. Manual screening of good samples from a large transport station.

to score them in order to comprehensively decide on the scheme for further refinement. Considering the current trends in transportation building design in China, various train stations feature vast waiting hall scales, but passengers are no longer satisfied with merely having seating for rest. A rich array of retail and entertainment activities has become essential in transportation architecture. Thus, after comprehensive scoring, we ultimately select the "balance" type layout for optimization.

We further deepen the obtained Pareto optimal solution and get the final optimized plane after manual comparison processing. After selecting the "balance" type layout for further refinement, we take into account the actual functional needs of the station. We reserve and slightly adjust the queue space in front of the ticket gates. Within the station, we incorporate service, commercial, dining, and other functional areas according to the functional classifications generated by the genetic algorithm. This is done while ensuring that the walking space and flow lines remain unaffected, ultimately enhancing the travel experience for passengers. The final outcome is a balanced type station optimization layout (Figure 9), achieved through human-machine collaboration.

Comparing and analyzing it with the original station space, the following conclusions can be obtained. Based on the core characteristics of the station space, pedestrians generally come in from a small number of entrances and disperse to a large number of scattered ticket gates, so the newly built station space generally has a large span to carry the queue of people gathered at the ticket gates. However, due to the limitation of the span of the transport station itself, the space for the queue of pedestrians gathering at the station is not sufficient. From the simulation images, it can be seen that the original plan of station compresses the normal indoor space as much as possible to provide space



Indicator	Parallex Rate	Functional Density	Functional Mix	Distance Average	DetourRate Average	TurnRate Average
before	228.00861	0.18904	0.73709	134.84253	1.00273	7.78364
after	326.08133	0.33003	1.11	139.94025	1.00024	10.03814

Figure 9. Artificial deepening plan result of a large transport station.

for pedestrians to walk, but congestion still occurs in the middle of the station. On the contrary, the genetic algorithm provides a "fishbone" shaped treatment, which is widely used as a layout, to rotate and tilt the pedestrian space, which provides a larger gathering space for pedestrians and at the same time alleviates the situation where the commercial space is drastically squeezed. By comparing the specific indexes before and after optimization, the "fishbone" layout significantly increases the richness and safety in the relevant indexes of the transport station, and the commercial and catering space has a larger and more flexible spatial arrangement mode; meanwhile, the pedestrians entering from the north and south sides can go to the ticket gates more directly through the slanting corridor to gather. The original congregation of travellers was concentrated at the queue spaces in front of various security checkpoints; however, after optimization, this has shifted to the central commercial area. This effectively alleviates the significant issue of queue interference with normal walking flow lines at different ticket gates within the station.

4.2. Exhibition space – an example of a large museum

A large museum is one of the important museum buildings in China, which was renovated and expanded at the beginning of this century and officially opened more than 10 years ago. The large museum has a great architectural scale and size, and the building area is far more than the general museum exhibition building. For this type of building, the layout and furnishings of the exhibition halls are important factors affecting the pedestrian viewing experience. Classifying and arranging different exhibition areas in a super-scaled exhibition hall is an important part of museum design. We will take the north-east corner exhibition hall of this large museum as an example and test the optimization using a genetic algorithm program.

Based on the existing display status and floor plan of this exhibition hall, we classify the exhibition areas into four categories: closed exhibition rooms, high display cabinets and walls, low booths and open exhibits. Basically retaining the original exhibition hall of the main exhibition flow areas and core entrances and exits, 120 generations (each generation of sample capacity control for 50), a total of 6000 children of individuals of the genetic algorithm procedure operation to obtain the following results.

The preliminary results are illustrated in the following figures, with Figure 10 showing the current layout pattern of the large museum exhibition hall. As a museum exhibition hall, allowing visitors to fully experience a leisurely walking tour is a core design principle. However, in this oversized exhibition hall, the entrance is overly spacious and empty, resulting in a certain degree of foot traffic congestion. Analyzing the standard deviation trend line chart and the average value trend line chart (Figure 11), we observe that in this application environment, the functional mix and functional density indicators show little potential for further optimization, while the optimization trend of the visibility indicator is most pronounced.

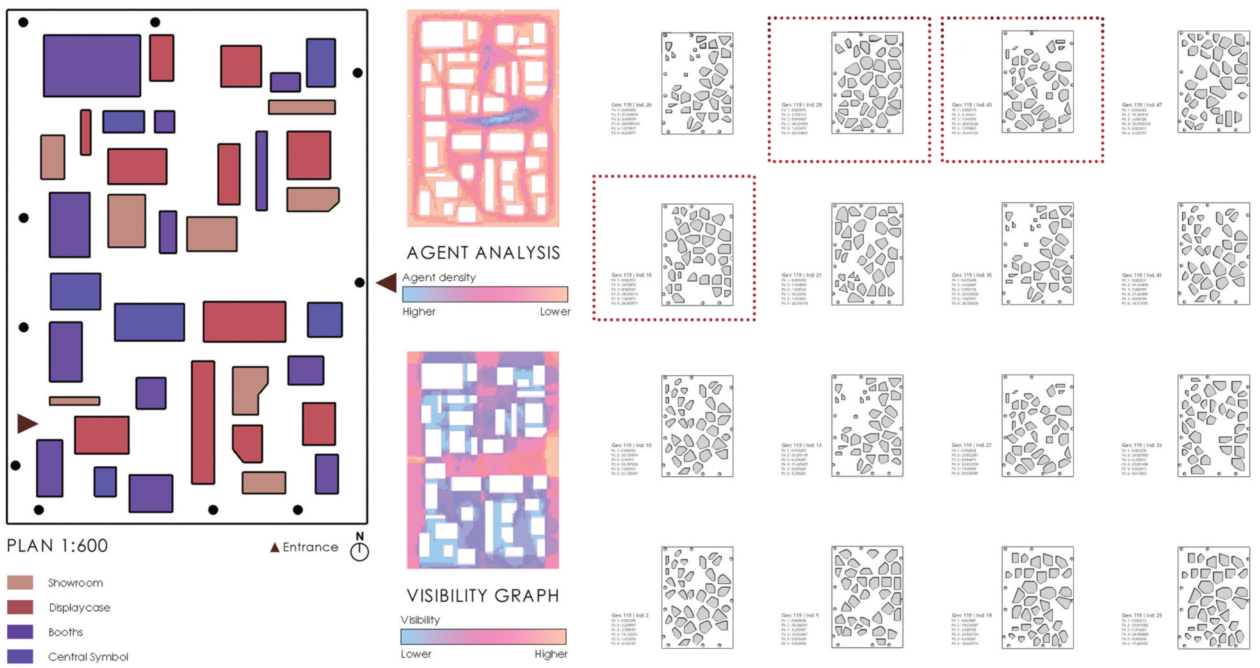


Figure 10. The current situation of a hall of a large museum and the results of the last generation of the genetic algorithm.

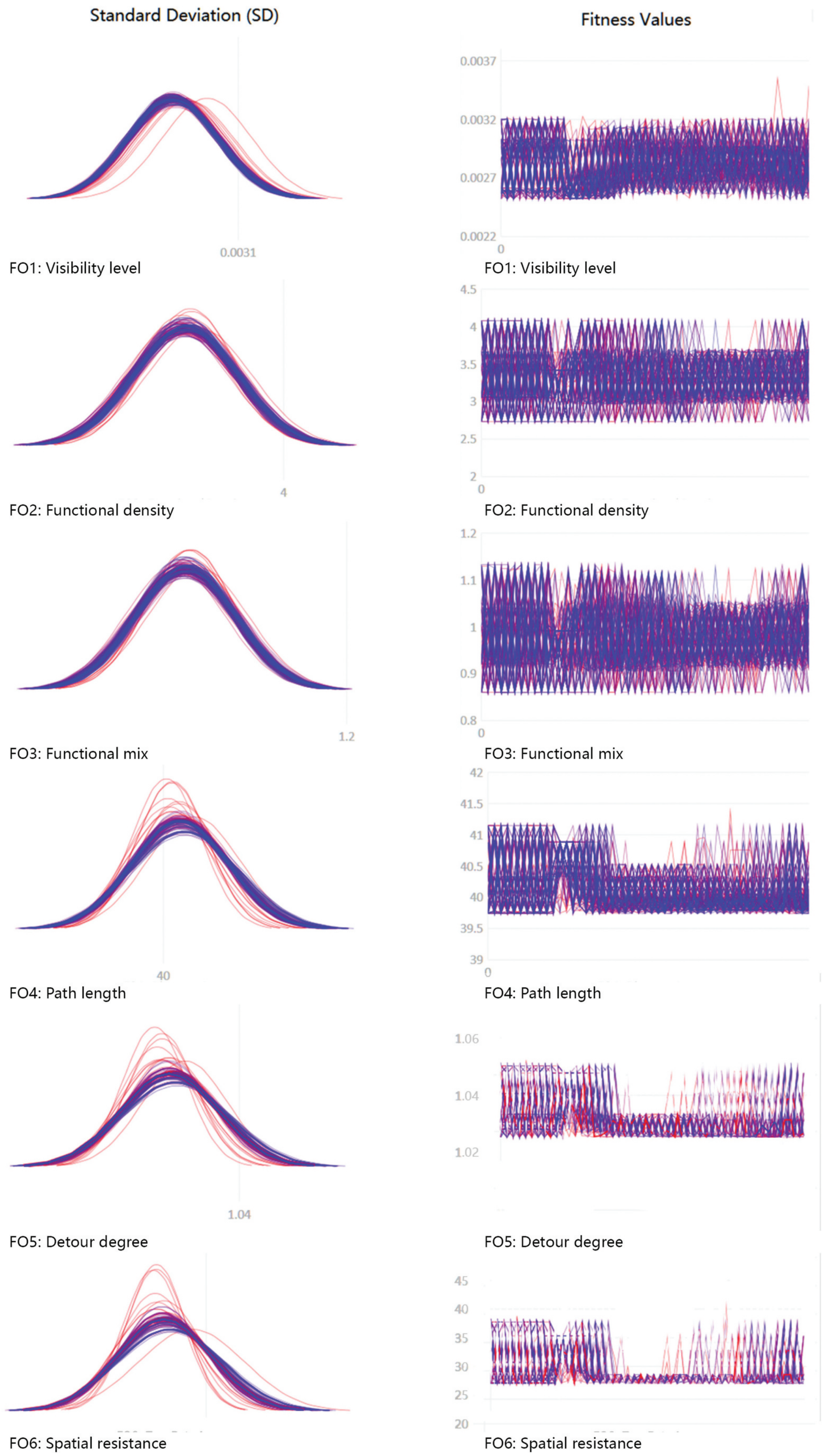


Figure 11. Standard deviation graph and standard deviation trend line graph of genetic algorithm.

Table 3. Indicator values of the layout results (exhibition space).

	Counts	Mean of factors					
Type		Visibility Level	Functional density	Functional mix	Path length	Detour Degree	Spatial Resistance
Functionality	23	0.002	3.693	1.044	39.873	1.019	25.411
Experience	15	0.004	2.734	0.862	40.331	1.033	26.518
Balance	12	0.003	3.071	0.929	39.968	1.023	26.561
Total	50	0.00284	3.25602	0.9618	40.0332	1.02416	26.0191

Upon conducting an indicators analysis of all offspring, we classify the computational layout results into three categories based on the functional experiential needs of the museum and the degree of optimization of functional indicators: functionality, convenience, and balance. The indicator values of the layout results for the three categories are shown in Table 3. Some layouts further optimize functional-related indicators while the other indicators remain largely unchanged, defining them as "functionality" type layouts. Another set of layouts maintains the existing levels of functional indicators while making appropriate improvements to the other four indicators, defining them as "balance" type layouts. A small number of layouts reduce the levels of functional indicators but significantly enhance the convenience and safety of the layouts, categorizing them as "convenience" type layouts. The representative layouts of the three types are shown in Figure 12.

Based on this analysis principle, we select three different types of preliminary optimized layouts and similarly organize over 10 trained architectural professionals to score them to comprehensively determine which scheme to further refine. Considering the actual design requirements of the museum, the integration of exhibition areas aimed at reducing walking distances clearly does not align with functional needs. Meanwhile, the exhibition hall space, after further enhancing the experiential aspects, becomes overly fragmented and homogeneous, leading to chaotic flow lines. We ultimately choose the "balance" type layout for optimization, taking into account both functional needs and scoring recommendations.

The plan obtained after manual comparison and optimization is quite different from the original exhibition layout. The museum is a place where exhibition visits are the core, so in the process, we gave up the plan for optimizing the layout for the factor of convenience, and chose richness as the core reference index instead. In the exhibition hall layout, we incorporate different types of exhibition spaces according to the functional classifications generated by the genetic algorithm. By utilizing exhibition walls, exhibition rooms, display stands, and other different exhibition languages, we achieve a thorough organization of the internal circulation of the large exhibition hall. Ultimately, this leads to the development of a balanced type museum optimization layout, completed through human-machine collaboration.

In the optimized layout (Figure 13), it can be seen that the program calculates a number of core open spaces for people to gather inside the exhibition hall based on the locations of pedestrian entrances and exits, further optimizing the cross-layout of the exhibition area to strengthen the richness and the sense of pedestrian experience while ensuring safety. In terms of the design layout of the exhibition space, the procedure can effectively help find suitable open space nodes and effectively improve the pedestrian walking tour rhythm. Further, in the case where the exhibition building is fixed, the exhibition party can use the optimization method to quickly carry out the exhibition layout and replacement by controlling the type of exhibition area and the size of the area, so as to meet the design needs of the personalized exhibition space.

4.3. *Urban parks – an example of an urban park*

A natural landscape park is located in the core city of an important northern city, developed and expanded around the 1970s with a natural landscape as its core, and gradually constructed into an existing key city park. The park covers an area of more than 100 hectares and is divided into cherry blossom area, wetland area, leisure and sports area, and cultural exhibition area, and has a long history of garden construction with the construction of some public service facilities and landscaping in the park. In recent years, the number of visitors to the urban park has been increasing year by year, and the original park infrastructure and recreational route layout can no longer match the existing flow of people. The design of urban parks is an important topic in architectural landscape design, and we try to use genetic algorithm model for optimization in the plan layout of large-scale landscape parks.

In the urban park, the pedestrian walking path has a large openness and randomness, we choose a part of the island in the city park with clear and independent entrances and exits as the optimization object. According to the established functional zoning of the urban park, the internal area of the park is divided into four attributes: landscape, business, leisure, and service, and the genetic algorithm procedure is performed for 100 generations

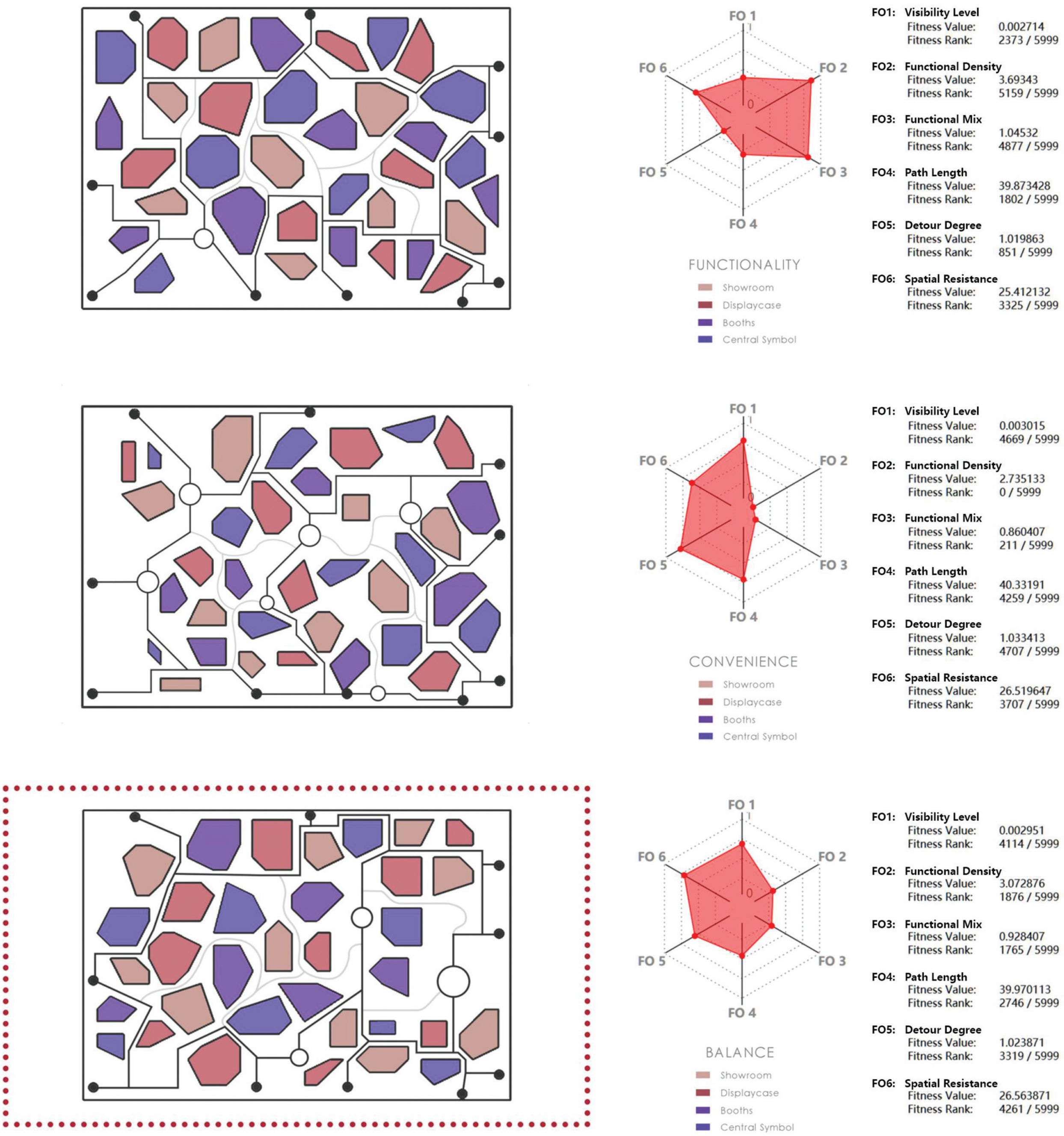
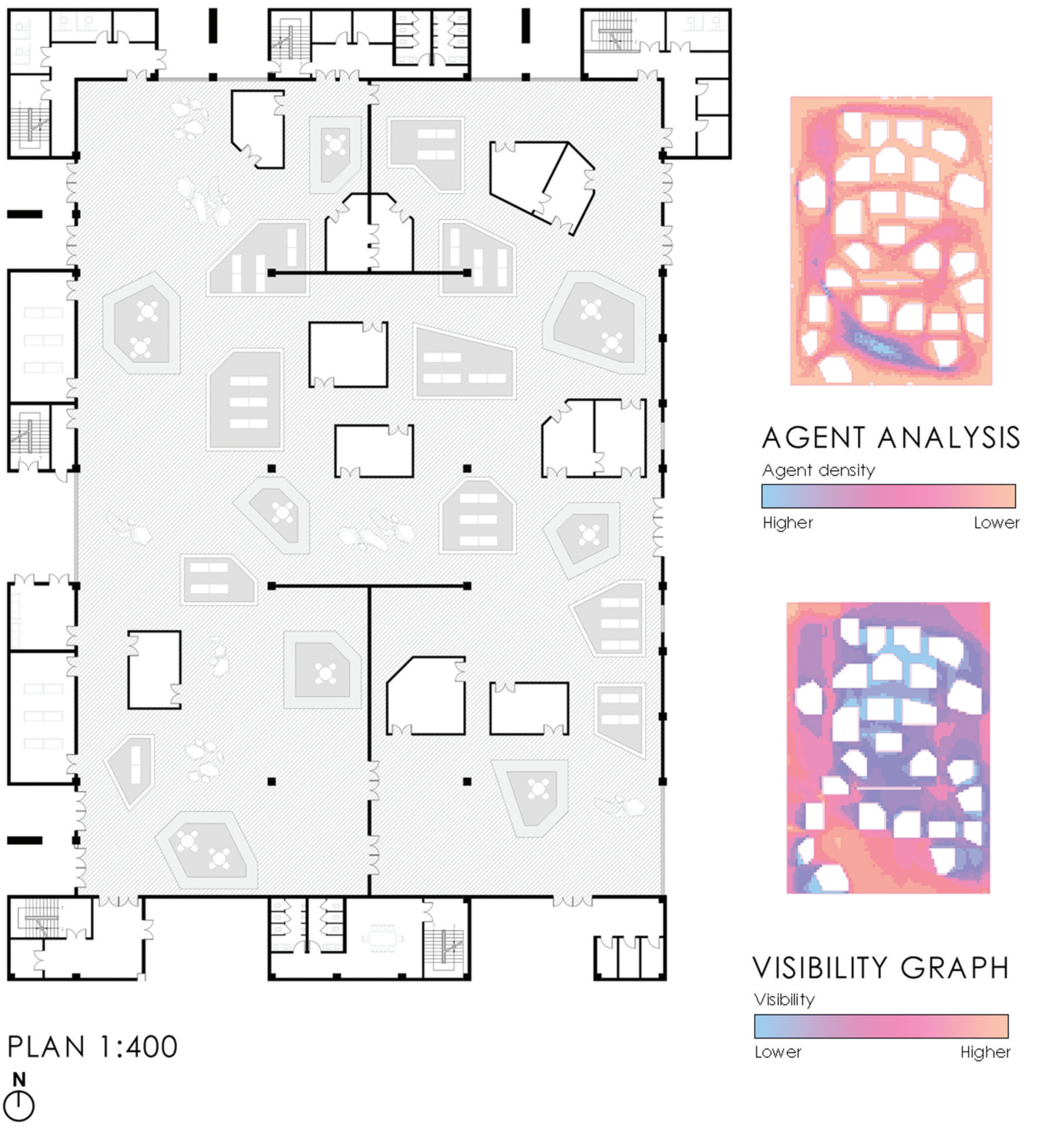
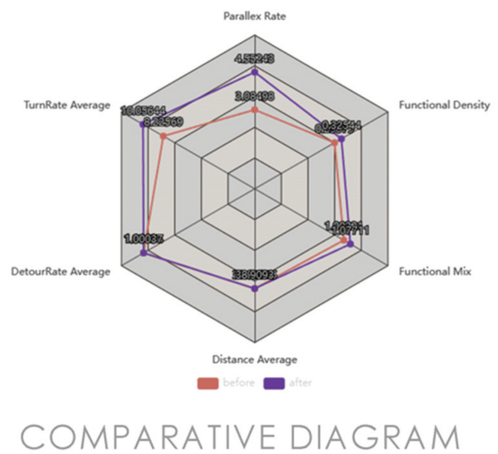


Figure 12. Manual screening of good samples from a large museum.

(the sample capacity of each generation is controlled to be 50), with a total of 6,000 offspring individuals to obtain the following results.

The preliminary results are illustrated in the following figures, with Figure 14 showing the current construction status of the main island in the urban park. This park has a long history and boasts excellent landscape resources. Currently, various functional buildings are concentrated on the island, creating open spaces that form clear nodes of pedestrian congregation. Analyzing the standard deviation trend line chart and the average value trend line chart (Figure 15), we find that in this application environment, the genetic algorithm has made significant optimizations in the indicators of functional density, functional mix, and visibility level, while the improvements in path length, detour degree, and spatial resistance are relatively minor. Considering the park's role as a scenic leisure area, providing a rich and rhythmic slow walking experience is a more appropriate design requirement, thus validating the reasonableness of this optimization result.





Indicator	Parallex Rate	Functional Density	Functional Mix	Distance Average	DetourRate Average	TurnRate Average
before	3.08498	0.29979	1.00321	38.94975	1.00134	8.22569
after	4.55243	0.32544	1.07711	38.90930	1.00037	10.05644

Figure 13. Artificial deepening plan result of a large museum.

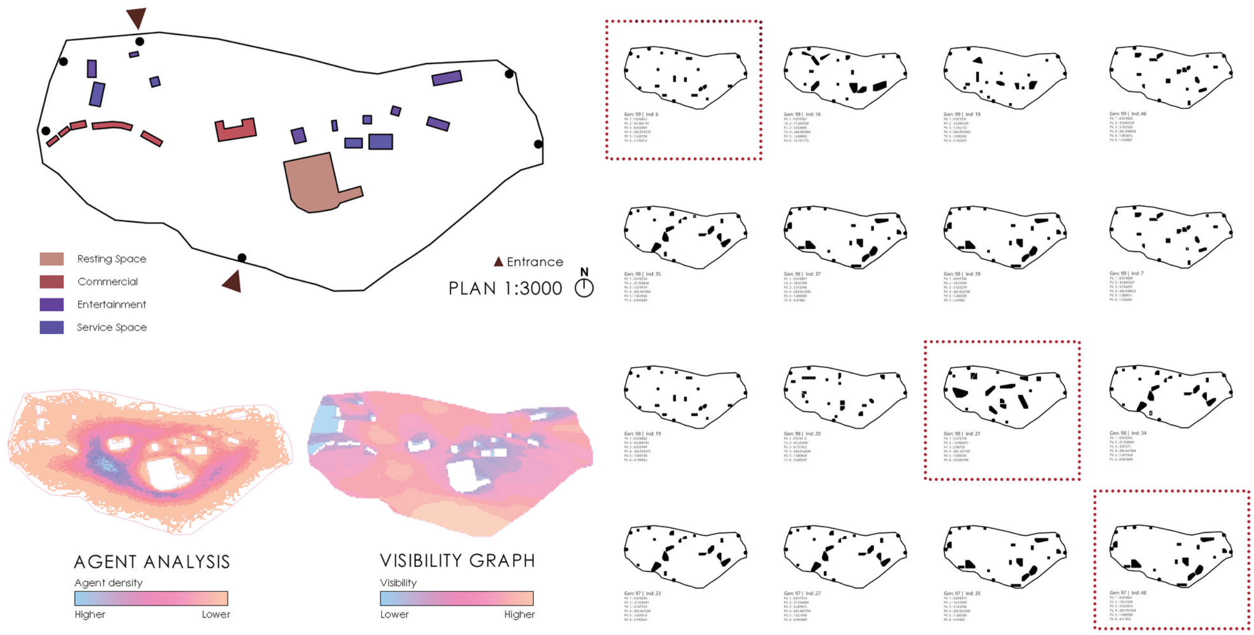


Figure 14. The current situation of a hall of an urban park and the results of the last generation of the genetic algorithm.

By conducting an indicators analysis of all offspring, we can categorize the general optimization directions of the genetic algorithm into three types: experience, convenience and balance. The indicator values of the layout results for the three categories are shown in Table 4. Similar to the optimization results of the station, some layouts particularly excel in experiential indicators, while the optimization of the other four indicators is limited, defining these as "experience" type layouts. In contrast, another set of layouts exhibits prominent values in the other four indicators, categorizing them as "convenience" type layouts. There are also layouts where all six indicators have been optimized to varying degrees, defining them as "balance" type layouts. The representative layouts of the three types are shown in Figure 16.

Based on this analytical principle, we selected three different types of preliminary optimized layouts and similarly organized over 10 trained architectural professionals to score them in order to comprehensively decide on which scheme to proceed with for further refinement. Given the actual design requirements of the park, the design results need to ensure that the public facilities within the park have a high degree of accessibility and convenience, while also offering the surrounding landscape paths a rich rhythm and flow. Taking into account the comprehensive functional needs and scoring recommendations, we ultimately choose the "balance" type layout for optimization.

he "balance" type layout combines the characteristics of the other two layout types. At the concentrated entry and exit points, it exhibits the features of an "convenience" layout, while the majority of the area retains the "experience" qualities typical of urban landscapes. By incorporating various community service functions based on the existing park spatial layout, the algorithmically optimized layout effectively integrates the richness of traditional garden walking experiences with the openness of social plazas, resulting in a "balance" type urban park optimization layout achieved through human-machine collaboration (Figure 17).

lthough the other two alternative layouts were not selected as the final designs for further development, designers can still gain insights from them through critical reflection and assessment. The "experience" type layout features larger functional zones that act as obstacles within the park, similar to boulders that impact walking flow. This effectively enhances the walking experience and comfort during leisurely strolls but significantly reduces accessibility. In contrast, the "convenience" type layout divides various spaces too small to avoid interfering with the park's walking paths, failing to achieve a normal functional arrangement. However, both alternative layout types showcase important design concepts from landscape architecture, such as landscape corridors, axial alignment, and the techniques of "changing scenes with movement". Therefore, when optimizing the design, it is essential to consider the characteristics of these two alternative layouts. This approach will allow for a more comprehensive human-machine collaboration in the design of walking spaces at a larger scale.

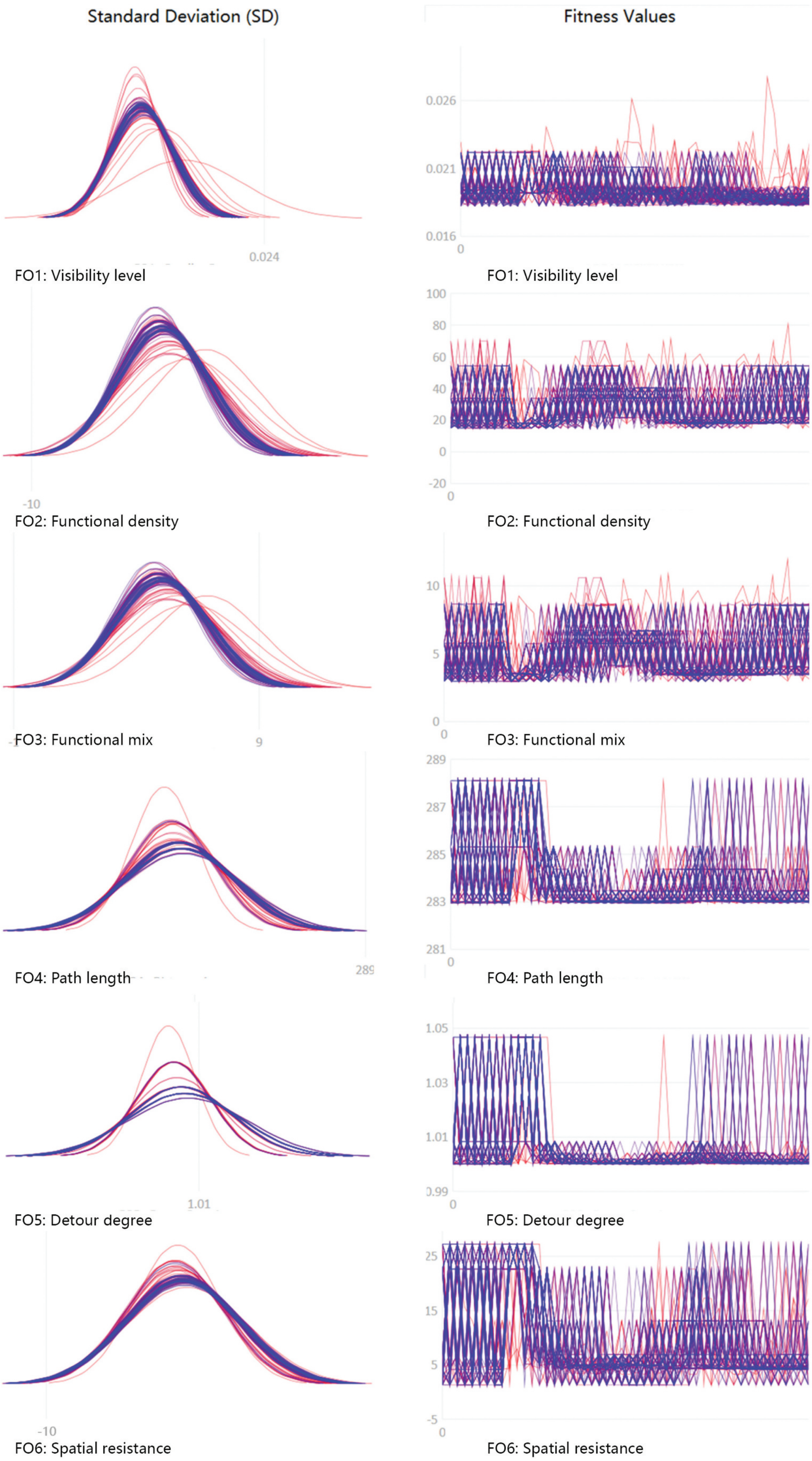


Figure 15. Standard deviation graph and standard deviation trend line graph of genetic algorithm.

Table 4. Indicator values of the layout results (urban park).

	Counts	Mean of factors					
Type		Visibility Level	Functional density	Functional mix	Path length	Detour Degree	Spatial Resistance
Functionality	15	0.018	54.269	8.667	283.019	1.001	4.196
Experience	14	0.021	14.992	2.968	285.309	1.008	12.483
Balance	11	0.019	18.521	3.568	284.008	1.002	6.645
Total	50	0.01546	24.55308	4.2161	151.3075	0.80298	6.21594

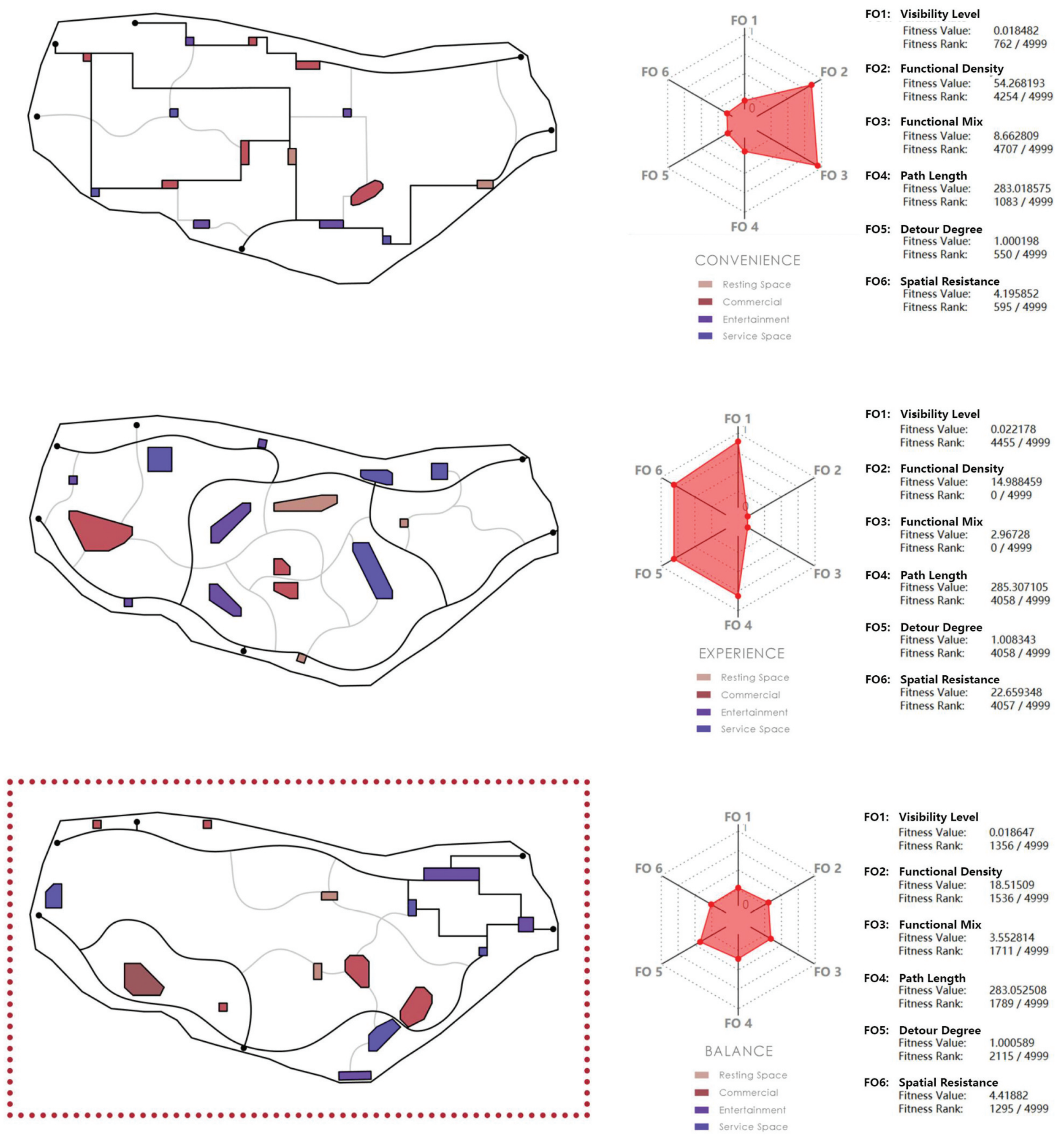


Figure 16. Manual screening of good samples from an urban park.

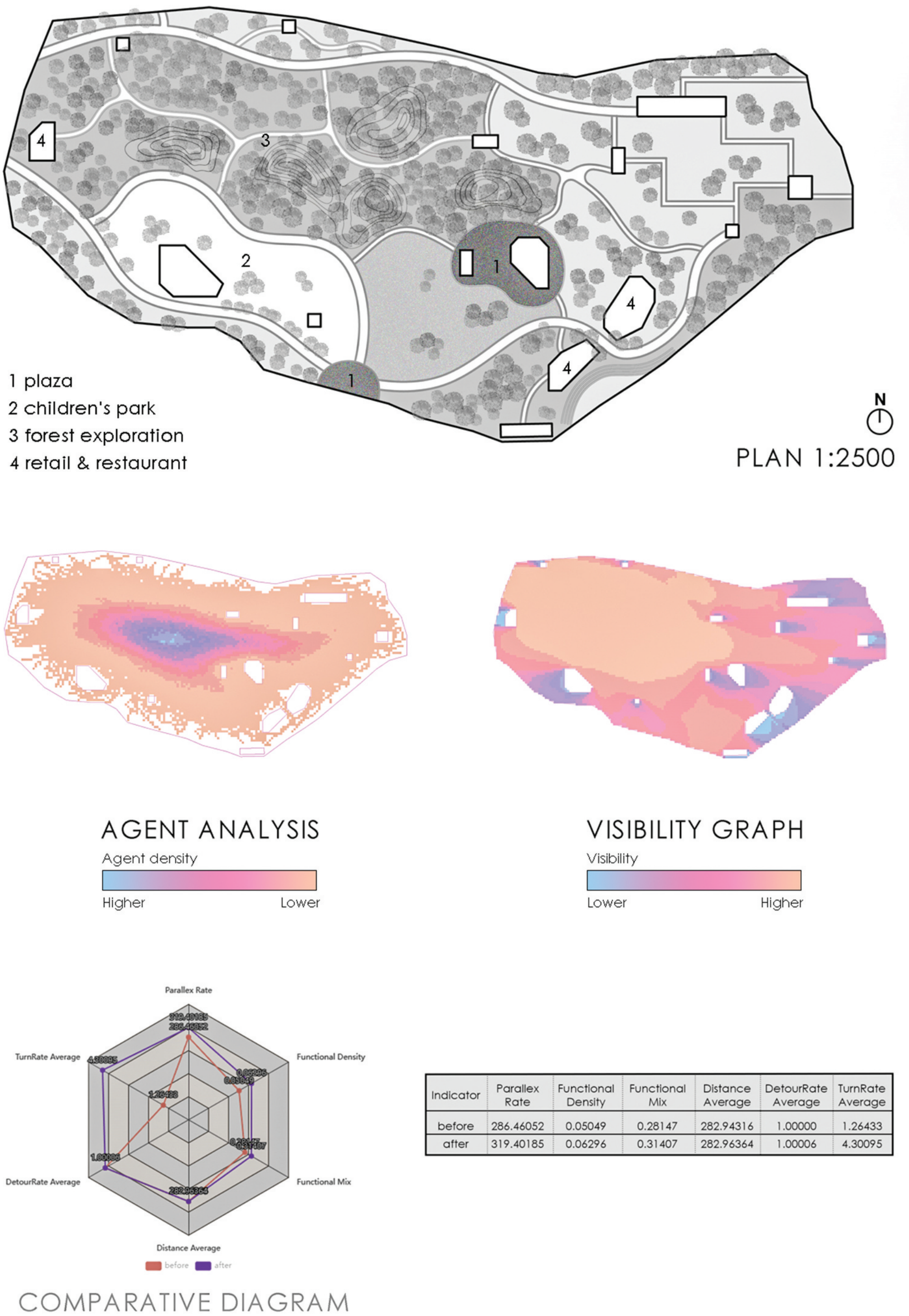


Figure 17. Artificial deepening plan result of an urban park.

Table 5. Results of three different spaces.

		Convenience		Safety		Experience	
Type		Path length	Detour degree	Visibility level	Spatial resistance	Functional density	Functional mix
station	before	138.84	1.00273	228.01	7.78	0.19	0.74
	after	139.94	1.00024	326.05	10.04	0.33	1.11
exhibition	before	38.95	1.00134	3.08	8.23	0.30	1.00
	after	38.91	1.00037	4.55	10.06	0.33	1.01
urban park	before	282.94	1.00000	286.46	1.26	0.06	0.28
	after	282.96	1.00006	319.40	4.30	0.06	0.31

5. Conclusion

5.1. Results and findings

This study focuses on the layout design and optimization of long walkway space in urban areas. With the combination of generative design techniques and the aim of improving walking experience, a complete system integrating factor assessment, algorithm generation, and comparison verification is established, namely a feedback loop between “genetic algorithms” and “pedestrian experience”. The reliability of the aforementioned process is tested through the application of three actual scenarios: station space, exhibition space, and urban parks. Furthermore, the study explores how to conduct interactive design involving human-machine collaboration within these scenarios.

In the three experimental scenarios, the plans generated and optimized through the genetic algorithm and manual selection demonstrate significant improvements over the previous layouts (Table 5). For the preliminary layout generated by the genetic algorithm, there has been an improvement compared to the original layout, with a majority of areas being reasonable and some exhibiting excellent results. However, the preliminary optimized layout generated by the algorithm also has some common issues: 1. The distances between various functional zones are too small, which does not meet the requirements for pedestrian evacuation; 2. The arrangement of functions is relatively dispersed and random, lacking an overall spatial division layout awareness; 3. Some functional blocks have shapes with sharp angles, which are inconvenient for spatial use.

Therefore, the subsequent manual screening and adjustments are particularly important. Considering the comprehensive functional requirements and scoring recommendations, we have chosen the “balance” type layout for further development in all three types of spaces:

(1) Station space: The layout is designed to simultaneously meet the characteristics of efficiency, convenience, and rich experiences. The optimized “fishbone” layout alleviates the issue of ticket queue interference with normal walking flows, and the leisure spaces allow for more flexible arrangements. However, there is a concern regarding the excessive number of dining and commercial spaces, which compresses the areas available for pedestrian dispersal.

(2) Exhibition space: While ensuring convenience and safety, this layout prioritizes the experiential aspect as a more significant indicator. The optimized layout not only maintains safety but also further enhances the layout of exhibition areas through an improved cross-design, strengthening both diversity and the walking experience for visitors. However, the shapes of the exhibition areas have become overly complex and varied, which may hinder efficient and economical modular exhibition setups.

(3) Urban park: The design ensures public facility accessibility and convenience while incorporating an abundance of rich landscapes. The optimized layout features characteristics of both convenience and experiential types, effectively integrating the richness of traditional garden walking experiences with the openness of public squares. Nonetheless, there are issues related to overly large landscape areas and a lack of diversity in vegetation.

When comparing the three types of spaces horizontally, we can see that the values of various indicators and their optimization statuses differ based on the scale of each space. Due to the different spatial scales, the urban park has the largest scale, and relative to the station space and exhibition space, the distance indicators before and after optimization are the highest. The exhibition space is characterized by its richness; among the three types of spaces, it has the highest functional density and functional mix both before and after optimization. Additionally, due to its relatively smaller scale, visibility level is the lowest among the three. Although all three spaces have seen improvements in their indicators after optimization, the degree of improvement for each indicator varies depending on the spatial type: for the station space, the functional indicators show more prominent increases, indicating the necessity and possibility of enhancing passenger experience while ensuring convenience and safety. In the exhibition space, the safety indicators have improved significantly, suggesting that despite the variety of functional spaces available, considerations such as visibility level and spatial resistance are still essential for creating a safer viewing environment. Conversely, the urban park exhibits a unique characteristic: the increase in detour degree after optimization suggests that convenience is not the primary consideration in park design. Instead, the winding paths and diverse walking experiences have become the focal points of design.

Overall, these outcomes align with professional insights from architects and corroborate the practical experiences of designers, lending credibility to the findings. In summary, the research results indicate that the plans generated through genetic algorithms and refined by designers offer a more targeted and scientific approach to optimizing design objectives. Comparing the scores provided by the system to those of the generated results shows significant enhancements across all indicators, illustrating a level of balance. Each phase involves the division of labor and collaboration between humans and machines, ultimately achieving a collaborative optimization of long walkway spaces with multiple objectives. This approach contrasts with traditional subjective design by architects or completely "black box" machine design, demonstrating a synergistic combination of both. While the machine enhances design efficiency and scientific rigor, designers can also leverage their subjective creativity to select and refine outcomes, thereby providing greater human controllability.

5.2. Reflection and future perspective

Reviewing the process of this study, there is still more room for subsequent improvement. In terms of program construction, there is potential for further optimization of the algorithms. On one hand, regarding the establishment of the walking experience evaluation framework, we have extracted and utilized a relatively abstract simulation framework for walking flows, and we have idealized pedestrian behaviors such as detours and stays. In the future, it would be beneficial to integrate more advanced simulation technologies to create simulations of walking flows that more accurately reflect real-world conditions.

On the other hand, the design scope considered in this study is limited to a two-dimensional plane, uniformly excluding the influence of height in three-dimensional space on the experimental results. In the actual architectural design process, for the station space and exhibition space, the height of the internal body of the building may affect the visibility and diversions rate of the system; and in urban parks, the vertical design involving vegetation and landscape topography will also interfere with the convenience of the pedestrian system factor. In future research, three-dimensional generation could be considered to enhance the richness of the indicators, making the generated schemes more detailed and specific.

For the human-machine collaboration workflow, although this study has achieved a "human-machine-human" division of labor, there are still some limitations. Firstly, when designers determine the influencing factors of walking experience, relying on literature research and expert interviews introduces a degree of subjectivity. In the future, machine assistance could be incorporated, utilizing big data statistics to enrich and refine the evaluation system, allowing for more precise quantification of each influencing factor. Secondly, there may be instances where the functionality generated by the computer through genetic algorithms is unreasonable or deviates from the objectives, necessitating real-time attention and adjustments from designers during the generation process. Enhancing the mutual cooperation between humans and machines is crucial, particularly for optimizing the "feedback" process between the evaluation system and the genetic algorithm. This study only achieved a single feedback loop from machine to human selection; future research could incorporate multiple rounds of iterative feedback adjustments. During the generation process, parameters for the fitness value could be adjusted in real-time based on the results generated by the computer, further refining different types of layout and spatial functions according to design objectives. This would make the program more adaptable to various real-life scenarios, achieving a customized and efficient architectural generative design process. Thirdly, due to limitations in technology and time, this study was confined to experiments in three specific scenarios. In the future, for different types and scales of spaces, designers could conduct multi-scenario experiments, combining statistical analyses of multi-source data from computers to establish parameter values for user reference, thereby forming a complete database to enhance general applicability.

In summary, this research attempts to introduce an evaluation system for walking experience as an optimization target for algorithms, building a connecting bridge between previously independent research fields based on various generative design and genetic algorithm studies. Using the multi-objective optimization of long walkway spaces as an example, it references existing generative design processes and explores human-machine collaborative design methods in the fields of architecture and urban planning. This framework effectively enhances the optimization design efficiency and quality of long walkway spaces, holding significant implications for high-density urban planning and spatial renewal. It establishes a human-machine collaborative workflow model that spans from the construction of influencing factors to genetic algorithm generation, followed by designer participation in selection, system evaluation feedback, and continuous iterative design refinement. This approach has the potential to be expanded to larger-scale spatial designs and applied in urban design and planning practices.

Disclosure statement

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ARTICLES FOR FACULTY MEMBERS

MULTI-OBJECTIVE OPTIMIZATION ALGORITHM FOR AUTONOMOUS SPATIAL LAYOUT DESIGN

An improved multi-objective optimization and decision-making method on construction sites layout of prefabricated buildings / Yao, G., Li, R., & Yang, Y.

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Article

An Improved Multi-Objective Optimization and Decision-Making Method on Construction Sites Layout of Prefabricated Buildings

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Abstract: Construction site layout planning (CSLP) that considers multi-objective optimization problems is essential to achieving sustainable construction. Previous CSLP optimization methods have applied to traditional cast-in-place buildings, and they lack the application for sustainable prefabricated buildings. Furthermore, commonly used heuristic algorithms still have room for improvement regarding the search range and computational efficiency of optimal solution acquisition. Therefore, this study proposes an improved multi-objective optimization and decision-making method for layout planning on the construction sites of prefabricated buildings (CSPB). Firstly, the construction site and temporary facilities are expressed mathematically. Then, relevant constraints are determined according to the principles of CSLP. Ten factors affecting the layout planning on the CSPB are identified and incorporated into the method of layout planning on the CSPB in different ways. Based on the elitist non-dominated sorting genetic algorithm (NSGA-II), an improved multiple population constraint NSGA-II (MPC-NSGA-II) is proposed. This introduces the multi-population strategy and immigration operator to expand the search range of the algorithm and improve its computational efficiency. Combined with the entropy weight and technique for order preference by similarity to an ideal solution (TOPSIS), improved multi-objective optimization and decision for the CSLP model is developed on the CSPB. Practical cases verify the effectiveness and superiority of the algorithm and model. It is found that the proposed MPC-NSGA-II can solve the drawbacks of the premature and low computational efficiency of NSGA-II for multi-constrained and multi-objective optimization problems. In the layout planning on the CSPB, the MPC-NSGA-II algorithm can improve the quality of the optimal solution and reduce the solution time by 75%.

Keywords: sustainable construction; construction site of prefabricated buildings; multi-objective layout and optimization; MPC-NSGA-II algorithm

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1. Introduction

With increasing attention to environmental protection and sustainability, the construction industry is becoming aware of its role in environmental protection and sustainability [1]. The new intelligent construction technology is a vital instrument for achieving energy management, environmental protection and safety, and improving the sustainability of buildings [2]. Prefabricated buildings are an important component of sustainable construction, and they are typically space-constrained projects. Prefabricated buildings require adequate resources for various materials, equipment, and temporary facilities for the extensive prefabrication operations on the CSPB [3,4]. Among these resources, hoisting equipment and prefabricated components occupy a large space on the CSPB [5]. Unreasonable layout planning of CSPB can cause conflict in the workspace, increase the distance of material transportation, and increase the workload of mechanical equipment. Furthermore, a cluttered layout of CSPB can increase the safety uncertainties on the construction site [6,7].

Relevant scholars have explored the CSPL problem of traditional cast-in-place buildings [8–11]. Currently, the CSPL optimization methods are mainly divided into mathematical programming [12,13] and heuristic algorithms [14–16]. The mathematical programming method mainly uses integer programming [17], linear programming [18], nonlinear programming [19], dynamic programming [20], and other mathematical methods [21] to produce a single-objective or multi-objective optimization function of the exact solution to provide a reasonable scheme of CSPL. However, its computational complexity is large, its solution time is long, and it is only suitable for solving small-scale problems, often making it impractical for engineering purposes [18,19]. Heuristic algorithms emphasize solving combinatorial optimization problems based on empirical rules. At this stage, heuristic algorithms usually focus on simulating natural selection and the natural evolution of organisms, such as genetic algorithms [22,23], particle swarm algorithms [24], and ant colony algorithms [25]. Heuristic algorithms are used to find the suboptimal solution of a problem or its optimal solution with a certain probability. Their good generality, stability, and fast convergence make them more commonly used in engineering [22,25]. Genetic algorithms have global search capabilities and can quickly solve complex non-linear problems. However, their programming implementation can be complex, and they have a slower search speed, which can tend to fall into prematureness [22]. The non-dominated sorting genetic algorithm (NSGA) proposes a non-dominated ranking criterion based on the classical genetic algorithm. The NSGA algorithm has shown significant advantages in solving multi-objective optimization problems. However, there are also complications, including great computational effort, lack of optimal individual retention schemes, and difficulty determining shared parameters [26]. The NSGA-II algorithm introduces improvements such as fast non-dominated sorting, crowding degree, and elite strategy based on the NSGA algorithm, which can be used without setting any parameters and reduces computational complexity. However, the NSGA-II algorithm tends to be premature in multi-constrained, multi-objective optimization problems, making it challenging to obtain the entire Pareto front surface and thus losing part of the optimal solution [27–29].

The heuristic algorithm commonly used in CSPL needs further improvement and optimization. For the characteristics of CSPB, a more reasonable and improved CSPL method is needed to achieve sustainable building construction [30,31]. The authors propose an improved multi-objective optimization and decision-making method in Section 2. Firstly, the construction site and temporary facilities are expressed mathematically, then three constraints are identified. Furthermore, ten factors affecting the layout planning on the CSPB are identified and incorporated into the method of layout planning on the CSPB in different ways. The MPC-NSGA-II algorithm applicable to layout planning on the CSPB is proposed. Furthermore, the solutions output from the MPC-NSGA-II algorithm is evaluated and selected by combining the entropy weight-TOPSIS method. In Section 3, a multi-objective optimization and decision model for layout planning of CSPB is proposed through practical engineering cases. The parameters required for calculating the improved algorithm are determined. The improved algorithm and the model for layout planning on the CSPB are validated using MATLAB 2020b software in Section 4. Meanwhile, the MPC-NSGA-II algorithm is compared with the NSGA-II algorithm in the layout planning on the CSPB. Finally, the conclusions of this study are drawn.

2. The Improved Multi-Objective Optimization and Decision-Making Method

2.1. Construction Site and Temporary Facilities Analysis

Many factors, including site area, structure type, duration, and transportation conditions, influence the CSPL. Necessary assumptions about the construction site and temporary facilities need to be made to facilitate the construction of a multi-objective optimization and decision model for the layout planning on the CSPB. Currently, the common assumption methods used on construction sites include location distribution, continuous space, and raster methods. The common assumptions for temporary facilities on construction sites include the ignoring facility size method, the actual shape method, and the approximate geometric shape method (AGSM). Different expressions of the construction site and temporary facilities can affect the process of searching for the optimal solution of the model.

After arranging and combining the construction site assumptions and construction site temporary facilities assumptions, all optional combinations are shown in Figure 1.

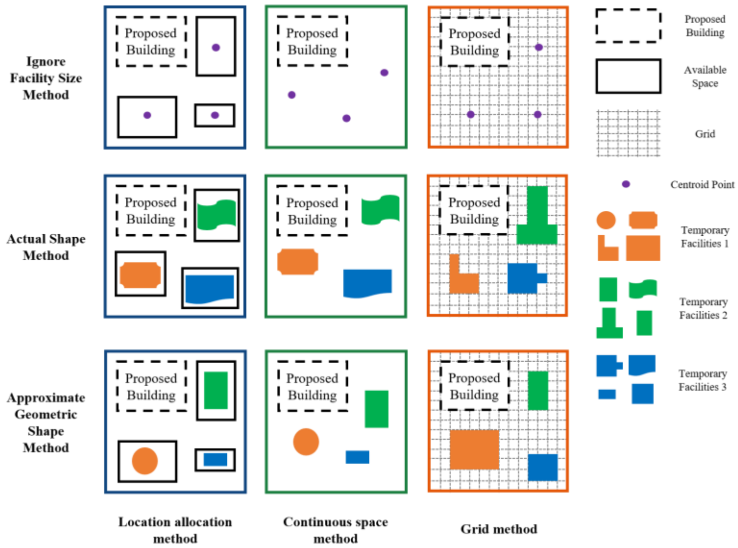

Figure 1. Construction site assumptions and construction site temporary facilities assumptions combination arrangement diagram.

The location assignment method has a simple calculation process. However, its way of determining the predetermined location in advance leads to the limitation of the model [32]. The continuous space method is closest to the actual site space, but its calculation process is complex and requires much time [33]. The raster method considers the advantages of the location assignment and continuous space methods. It balances the computational complexity and the accuracy of the optimization results [34]. Furthermore, the raster method is more flexible, thus, applicable to different construction sites. Representing temporary facilities by shape center point in the ignoring facility size method can simplify the calculation but is different from the actual situation [10]. In the actual shape method, the horizontal projection of the actual shape of the construction site facilities represents the temporary facilities closest to the actual site space [35]. However, it has more constraints on the construction function and is more difficult to calculate. Considering the influence of the facility shape on the search results and the complexity of the calculation, the basic geometry of the temporary facility represented by the AGSM can envelop the actual edge of the facility [31]. Therefore, the construction site of the model is assumed by the grid method, and the AGSM represents the temporary facilities.

Considering other influencing factors, the prerequisite assumptions of the improved multi-objective optimization and decision-making method include: (1) The construction site space is divided by the grid method, and the AGSM represents the construction site's temporary facilities; (2) It is flat and even inside the construction site; (3) The southwest corner of the construction site is considered the origin of the arrangement for later calculations; (4) The location of the fixtures is predetermined and will not be changed; (5) The model uses the centroid position of the field facilities to represent the real position of the temporary facilities; (6) The model assumes that the shape and dimensions of the site facilities remain unchanged throughout the project construction period.

2.2. Constraints Analysis

2.2.1. Site Boundary Constraints

The site boundary constraint means that temporary facilities must be placed within the red line boundary of the construction site regardless of any construction phase of the project. Furthermore, it should be ensured that the temporary facilities boundary of the construction site is kept at a sufficient safety distance from the construction fence.

Assume that the coordinates of the form center of the temporary facilities to be arranged at the construction site are (x_i, y_i). The length in the x-direction is l_i. The length in the y-direction is h_i. The red line horizontal coordinate range of the construction site is $a_1 \sim a_2$. The range of vertical coordinates is $b_1 \sim b_2$. Therefore, the coordinates of the temporary facility i should meet Equation (1).

$$\left\{ \begin{array}{l} y_i - \frac{h_i}{2} - b_1 - \varphi \geq 0 \\ y_i + \frac{h_i}{2} - b_2 + \varphi \leq 0 \\ x_i - \frac{l_i}{2} - a_1 - \varphi \geq 0 \\ x_i + \frac{l_i}{2} - a_2 + \varphi \leq 0 \end{array} \right\} \tag{1}$$

where φ is the safety distance between the consideration of temporary facilities and the construction fence. In the actual CSPB, the value of φ is usually taken as 3.0 m.

2.2.2. Facility Coverage Constraints

The facility coverage constraint means that there should be no coverage conflicts between individual construction facilities. Facility coverage constraints need to be satisfied to avoid spatial conflicts. With construction facility i and construction facility j, the required fire distance between the two facilities is W_{ij}. The facility coverage constraint stipulates that at least one of the criteria in Equation (2) should be met.

$$\left\{ \begin{array}{l} \left| x_i - x_j \right| - \frac{l_i + l_j}{2} \geq W_{ij} \\ \left| y_i - y_j \right| - \frac{h_i + h_j}{2} \geq W_{ij} \end{array} \right\} \tag{2}$$

2.2.3. Tower Crane Coverage Constraints

The tower crane boom needs to cover all temporary production facilities as far as possible. It can safety the fixed tower crane layout principles while avoiding the secondary handling of components and raw materials in the field as far as possible.

Assume that the site coordinates of the fixed tower crane are (x_t, y_t) and the boom length of the tower crane is R_t. The temporary construction site facilities and the tower crane should be met by Equation (3).

$$\sqrt{(x_t - x_c)^2 + (y_t - y_c)^2} \leq R_t \tag{3}$$

Temporary living spaces and office facilities should be as far from the tower crane's coverage as possible to protect staff safety.

2.3. Optimization Factor Ranking Analysis

A multi-objective optimization problem is one in which multiple objectives need to be achieved in each scenario. However, there is generally a conflict between objectives, and the optimization of one objective is at the cost of the deterioration of other objectives, so it is not easy to have a unique optimal solution. Therefore, the determination of optimization objectives must be based on the importance of the influencing factors.

Before determining the optimization objectives of the model, various factors affecting the layout of temporary facilities on CSPB need to be clarified. Through literature analysis, 16 influencing factors with high frequencies in relevant construction site temporary facilities arrangement studies were initially summarized.

An expert scoring method distributed questionnaires to industry experts and relevant practitioners. Based on their opinions, the importance of 16 influencing factors in determining the arrangement scheme of temporary facilities on CSPB was analyzed. The sources and composition of the experts are shown in Table 1. The contents of the questionnaire are in the Supplementary Materials.

Table 1. Number and source of experts.

Institution	Number of People	Percentage
Construction enterprise	16	48.5%
College and universities	8	24.2%
Design institute	9	27.3%
Total	33	100%

The reliability analysis of this questionnaire was performed using Cronbach's alpha coefficient method. The reliability coefficient value of 0.858 was obtained using SPSS 26 software analysis [36]. Therefore, the data obtained from this expert scoring is stable and reliable. The results of the questionnaire analysis are shown in Figure 2.

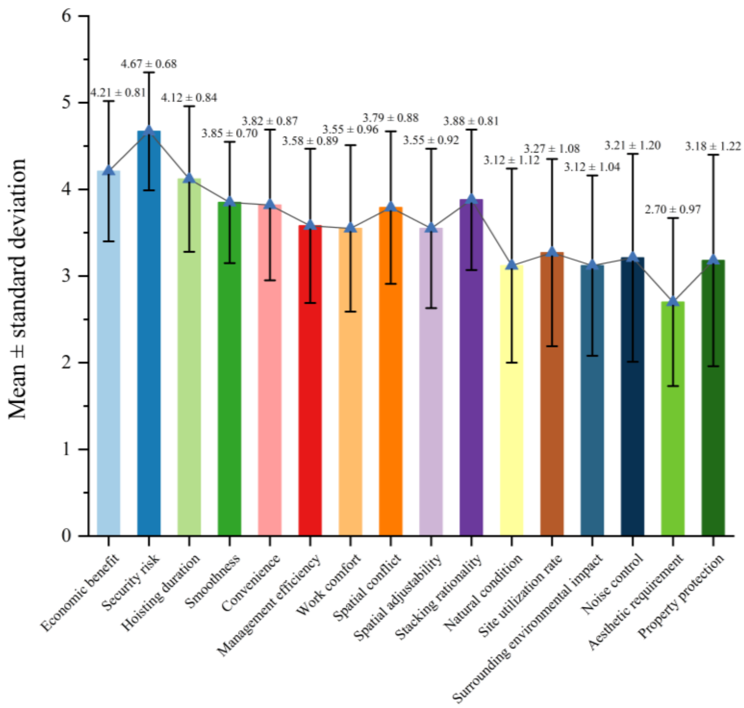

Figure 2. Statistical results of expert scores.

From Figure 2, we can see that the standard deviation of the five factors of "Natural condition", "Site utilization rate", "Surrounding environmental impact", "Noise control", and "Property protection" is greater than 1. It means that the expert's opinions are inconsistent, so they are excluded. The average score for "Aesthetic requirements" was only 2.70. According to the scoring rules, an average score of less than 3 is not a significant factor, so this factor was removed. A total of 10 influencing factors were finally included in the model consideration. In descending order of average score, they are: "Security risk", "Economic benefit", "Hoisting duration", "Stacking rationality", "Smoothness", "Convenience", "Spatial conflict", "Management efficiency", "Spatial adjustability", and "Work comfort". Among them, the three influencing factors, "Security risk", "Economic benefit", and "Hoisting duration", have an average score greater than 4. Therefore, these three influencing factors should be focused on the temporary facility layout of CSPB. The prefabricated component combination "stacking reasonableness" is taken as the input constraint of the model to ensure the proper stacking of prefabricated components. Two influencing factors, "space conflict" and "working comfort", are considered in the constraints. The rest of the factors are incorporated into the decision factors.

The top three influencing factors are taken as the optimization objectives. The objective functions are minimizing security risks, maximizing economic benefits, and minimizing hoisting durations.

2.4. Objective Functions Determination

2.4.1. Security Risk Function

Construction facilities can be divided into risk source facilities prone to security risks and vulnerable facilities that need protection. The construction security risk value can be quantified by analyzing the interaction process of the two types of facilities. Assuming that the hazard transfer value of the facility is H, and the vulnerability of the facility is V. Then the security risk interaction value R can be obtained from Equation (4).

$$R = H \times V \tag{4}$$

where H is the hazard transfer matrix and the individual element values represent the magnitude of the hazard transfer values.

The diagonal elements in H are the hazard levels between construction site facilities, which could be calculated from Equation (5).

$$H = \begin{bmatrix} h_{11} & & \\ & \ddots & \\ & & h_{nn} \end{bmatrix} \tag{5}$$

The hazard generated by the source decays with distance, and the remaining elements in H can be determined according to the law of risk decay from Figure 3 and Equation (6).

$$h_{ij} = \max\left\{ \begin{array}{c} h_{ii} + \frac{dH}{dd} \times d_{ij} \times \rho \\ 0 \end{array} \right. \tag{6}$$

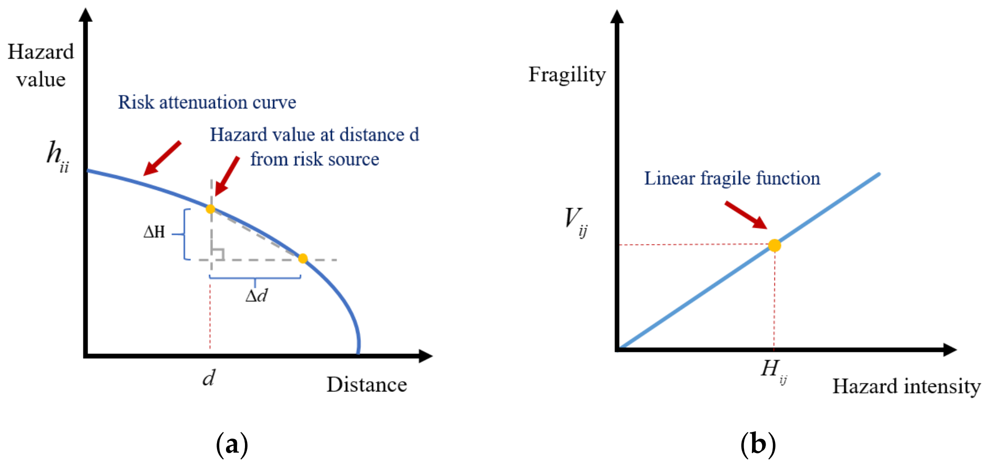

Figure 3. Risk attenuation curve and Linear fragile function (**a**) Risk attenuation curve; (**b**) Linear fragile function.

When $i = j$, $\rho = 0$, when $i \neq j$, $\rho = 1$, d_{ij} is the Euclidean distance. The relevant research suggests that the slope of the risk attenuation curve takes the value of 0.01 at the construction site [37].

The hazard transfer matrix is normalized in Equation (7).

$$h_{ij}{}^{*} = \frac{h_{ij}}{\max[h_{ii}]} \tag{7}$$

It is assumed that the hazards do not occur simultaneously. Therefore, the total risk of the construction site is the accumulation of the risks arising from each object. The objective function of security risk is set to minimize the potential security risk. The objective function of security risk can be deduced in Equation (8):

$$F_1 = \min \sum_{i=1}^{n} \sum_{j=1}^{n} R_{ij} = \min\{\boldsymbol{H}^* \boldsymbol{V}^*\} \tag{8}$$

$\boldsymbol{H}^*$ in the equation is the normalized hazard transfer matrix and $\boldsymbol{V}^*$ is the normalized fragility matrix.

2.4.2. Economic Benefit Function

The economy is one of the critical concerns of decision-makers in engineering project management. Some researchers have shown that the temporary facilities on the CSPL significantly impact the transportation costs of components and raw materials within the construction site. A reasonable scheme of CSPL can significantly reduce the related costs [38]. In addition, the location of temporary facilities may change during different stages of the project. This results in the cost of changes to the temporary facilities due to dismantling, relocation, and installation. The second objective function F_2 is to minimize the sum of the above two costs to maximize the economic benefits of the resulting construction site temporary facilities layout solution. The mathematical expression for F_2 is Equation (9).

$$F_2 = \min\left\{ \sum_{i=1}^{n} \sum_{j=1}^{i} C_{ij} d_{ij} + \sum_{k=1}^{n} \sum_{t=1}^{T} \left(C_{Dk} + C_k d_k^{(t-1,t)} + C_{Bk} \right) z_{kt} \right\} \tag{9}$$

Where C_{ij} is the transportation cost per unit distance between construction facility i and construction facility j; d_{ij} is the distance between construction facility i and construction facility j; C_{Dk} is the cost of dismantling temporary facilities k; C_k is the unit distance movement cost of temporary facility k; $d_k^{(t,t+1)}$ is the spatial distance between temporary facility k in stage 1 and stage 2; C_{Bk} is the cost of installation required for the rearrangement of temporary facilities k; z_{kt} is the value for judging the change of location of temporary facility k. When a change occurs, z_{kt} takes the value of 1, otherwise, it takes the value of 0. The value of C_{Dk}, C_k, and C_{Bk} need to be determined in accordance with the relevant standards, combined with the actual project works to determine the value of parameters.

2.4.3. Hoisting Duration Function

Prefabricated components are significant in number and individual weight, and installation machines are used frequently on the CSPB. The hoisting objective function is to make the shortest hoisting duration for prefabricated components through a reasonable layout of temporary facilities on the CSPB.

The hoisting process of a single prefabricated component contains six operations: tying, hoisting, alignment, temporary fixing, alignment, and final fixing [5]. The hoisting action can be divided into horizontal motion (horizontal tangential motion, horizontal radial running) and vertical motion. Therefore, the hoisting duration of a single prefabricated component can be divided into two parts: horizontal movement duration and vertical movement duration.

Assume that the fixed tower crane position is (x_t, y_t), supply point position is (x_s, y_s, z_s), demand point position is (x_d, y_d, z_d), and hoisting reserved safety operation height is h. The hoisting schematic diagram is shown in Figure 4.

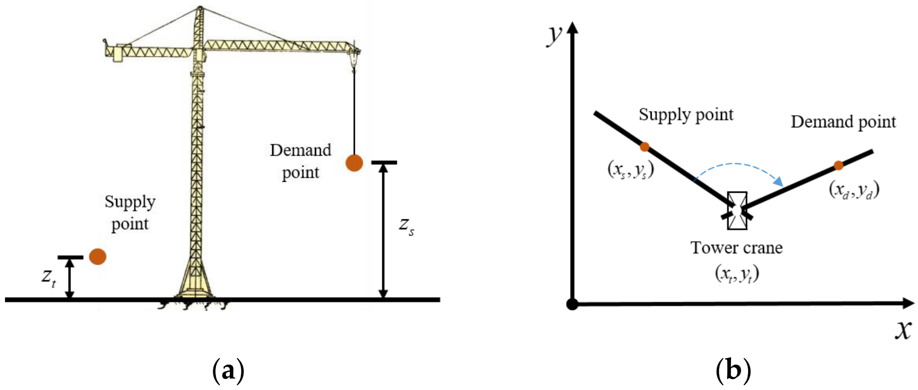

Figure 4. Schematic diagram of tower crane hoisting. (**a**) Tower crane hoisting front view; (**b**) Tower crane hoisting overhead view.

The hook horizontal movement duration can be divided into three types, including radial travel duration, tangential travel duration, and horizontal movement duration, and the calculation methods are shown in Equations (10)–(12), respectively.

$$T_r = \frac{\left|\sqrt{x_d^2 + y_d^2} - \sqrt{x_s^2 + y_s^2}\right|}{V_r} \tag{10}$$

$$T_a = \frac{\left|\tan^{-1}\left(\frac{y_d - y_t}{x_d - x_t}\right) - \tan^{-1}\left(\frac{y_s - y_t}{x_s - x_t}\right)\right|}{V_a} \tag{11}$$

$$T_h = \max\{T_r, T_a\} + \lambda \min\{T_r, T_a\} \tag{12}$$

The λ in Equation (12) considers the operator's ability to move the hook in the radial and tangential directions simultaneously. That is, considering the degree of overlap between the radial and tangential movements, λ takes a value between 0 and 1.

1. The hook vertical movement duration calculation method is given in Equation (13).

$$T_v = \frac{2(|z_d - z_s| + h)}{V_v} \tag{13}$$

2. Furthermore, the total hook travel duration can be calculated from Equation (14).

$$T_t = \mu(\max\{T_h, T_v\} + \eta \min\{T_h, T_v\}) \times Q \tag{14}$$

The μ parameter indicates the uncontrollable conditions of the construction site, such as extreme weather and obstructions to the view, and the value of μ is 0.1. The smaller the value of μ, the more favorable the site is for hoisting; the η parameter is the ability of the operator to move the hook in both horizontal and vertical directions, and the value of Q is the number of prefabricated components to be hoisted.

The hoisting duration objective function of F_3 can be expressed as Equation (15):

$$F_3 = \min[\mu(\max\{T_h, T_v\} + \eta \min\{T_h, T_v\})] \tag{15}$$

The objective function of the multi-objective optimization problem of temporary facilities arrangement on the CSPB can be expressed as F, and it is shown in Equation (16). The constraints of CSPB can be summarized in Equation (17).

$$F = \left\{ \begin{array}{l} F_1 = \min\{\boldsymbol{H}^*\boldsymbol{V}^*\} \\ F_2 = \min\left\{ \sum\limits_{i=1}^{n} \sum\limits_{j=1}^{i} C_{ij}d_{ij} + \sum\limits_{k=1}^{n} \sum\limits_{t=1}^{T} \left(C_{Dk} + C_k d_k^{(t-1,t)} + C_{Bk} \right) z_{kt} \right\} \\ F_3 = \min[\mu(\max\{T_h, T_v\} + \eta \min\{T_h, T_v\})] \end{array} \right\} \tag{16}$$

$$s.t. = \left\{ \begin{array}{l} y_i - \frac{h_i}{2} - b_1 - \varphi \geq 0 \\ y_i + \frac{h_i}{2} - b_2 + \varphi \leq 0 \\ x_i - \frac{l_i}{2} - a_1 - \varphi \geq 0 \\ x_i + \frac{l_i}{2} - a_2 + \varphi \leq 0 \\ |x_i - x_j| - \frac{l_i + l_j}{2} \geq W_{ij} \\ |y_i - y_j| - \frac{h_i + h_j}{2} \geq W_{ij} \\ \sqrt{(x_t - x_c)^2 + (y_t - y_c)^2} \leq R_t \end{array} \right. \tag{17}$$

2.5. MPC-NSGA-II Optimization Algorithm

Premature maturity is a highly likely phenomenon in multi-constraint and multi-objective optimization problems. In this case, the applicability of the NSGA-II algorithm is low [39]. Therefore, this study proposes a multi-objective optimization algorithm based on the NSGA-II algorithm with the constraint domination method to improve the initialization population and crowding distance in the NSGA-II algorithm. It proposes that the MPC-NSGA-II algorithm applies to the layout planning on the CSPB. The specific optimization elements of the improved MPC-NSGA-II algorithm are: (1) Adopting the Multi-population Strategy to expand the search range of the algorithm while achieving elite retention and thus avoiding premature maturity; (2) Reducing the interference of subjectively determined parameters through the constrained dominance method; (3) Introducing Harmonic distance to determine the congestion degree.

2.5.1. Multi-Population Strategy

Multi-population strategy is practiced by introducing three populations, the immigration operator and non-dominated sorting. The introduced populations are POP-a, POP-b, and POP-c. The POP-a population has a low variation probability and is responsible for searching for local optimal solutions. The POP-b population has a high variation probability and is responsible for searching for optimal global solutions. The POP-c population is an elite population responsible for recording the optimal solutions appearing in POP-a and POP-b populations. The formation process of the elite population POP-c is shown in Figure 5. The advantage of introducing this strategy is that by setting populations with different parameters, the global and local search capabilities of the algorithm are taken into account, thus expanding the search range. The elite population control algorithm process avoids the premature problem in the NSGA-II algorithm.

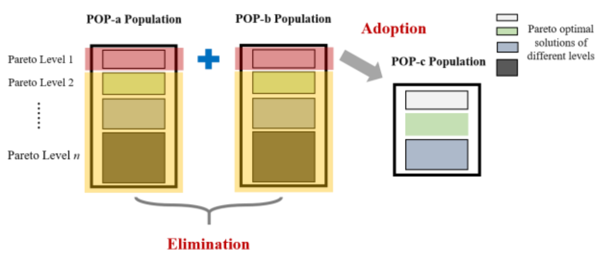

Figure 5. Elite population formation process.

The immigration operator is a procedural operator that periodically introduces the optimal solution in a population to other populations during the algorithm iteration, which works as shown in Figure 6. The optimal solutions in the two populations are replaced by the relatively inferior solutions of the other populations through the migration operator. On one hand, it realizes the synergistic exchange between the two populations of POP-a and POP-b to promote co-evolution. On the other hand, this exchange operation speeds up the elimination of inferior individual solutions and drives the convergence of the algorithm.

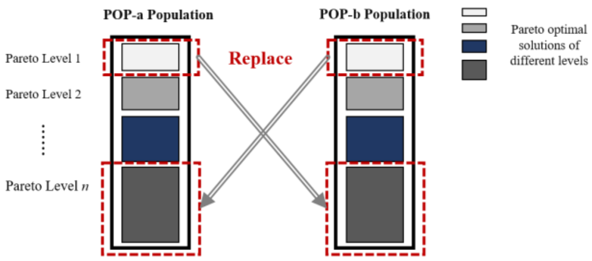

Figure 6. Working principle of the immigration operator.

The relatively inferior solutions within the set are removed by non-dominated sorting. It is possible to maintain optimal individuals without losing them and elite populations without crossover and mutation.

2.5.2. Constraint Domination Methods

Currently, the multi-constraint optimization problem is mainly solved by the following four methods [40]: (1) Considering feasible solution methods; (2) Penalty functions; (3) Random ordering methods; (4) Constraint domination methods. The constraint domination method avoids the artificial parameter interference present in the previous three methods while dealing with the constraints; hence, the method has been applied in this research.

Compared with the crowding distance in the NSGA-II algorithm, the Harmonic distance can better reflect the crowding level between individuals and is a more effective method. The crowding distance is introduced and given in Equation (18).

$$d_i = \frac{N-1}{\frac{1}{d_{i,1}} + \frac{1}{d_{i,2}} + \cdots + \frac{1}{d_{i,j}} + \cdots + \frac{1}{d_{i,N}}}, \quad i \neq j \tag{18}$$

where N is the population size and d_{ij} denotes the spatial Euclidean distance between individual X_i and individual X_j. The flow chart of the improved MPC-NSGA-II algorithm is shown in Figure 7.

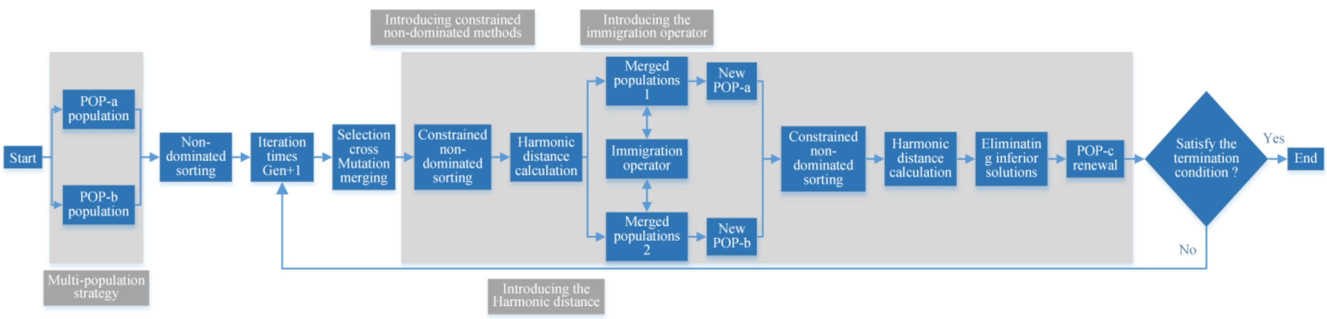

Figure 7. Algorithm flow chart of MPC-NSGA-II.

2.6. Entropy Weight-TOPSIS Decision-Making Method

After the MPC-NSGA-II optimization algorithm is used to output multiple construction site temporary facilities layout optimization schemes, the schemes are selected by a comprehensive evaluation and decision-making method by combining other influencing factors. To minimize the influence of human factors on the results, the entropy weight-TOPSIS integrated decision-making method is used to evaluate the output optimization solutions to obtain the best solution.

The entropy weight method determines the weight of indicators based on the amount of information reflected by the data of each indicator. Compared with subjective weighting methods (expert scoring, hierarchical analysis, etc.), the entropy weight method can reflect the importance of each index more objectively and accurately [41].

In an evaluation system with m options to be evaluated and n evaluation indicators, the weight ω_i of the i evaluation indicator is defined in Equation (19).

$$\omega_i = \frac{1-\Phi_i}{n-\sum\limits_{i=1}^{n}\Phi_i} \tag{19}$$

where the entropy value of the i evaluation indicator Φ_i is defined in Equation (20).

$$\Phi_i = -\frac{1}{\ln m}\sum_{j=1}^{m} Co_{ij}\ln Co_{ij} \tag{20}$$

where ω_i is the entropy weight coefficient, Φ_i is the entropy value of the first i evaluation index, and n represents that there are n evaluation indexes.

A larger ω_i means that the greater the amount of information represented by the indicator, the greater the effect on the comprehensive evaluation the greater the effect.

TOPSIS, also known as the "ideal solution method", is based on calculating the distance between the evaluation object and the optimal and inferior solutions. The basic principle of the TOPSIS method is to calculate the distance between the evaluation object and the optimal solution and the worst solution as the primary basis for evaluating the merits of the solution [42]. The ideal proximity C^* is calculated in this research from Equation (21).

$$C^* = \frac{S_i^-}{S_i^+ + S_i^-}, i = 1, 2, \ldots, m \tag{21}$$

where S^+ is the distance scale from the target to the ideal solution and S^- is the distance scale from the target to the anti-ideal solution. After calculating C^*, each solution is ranked according to the size of C^*. The larger C^* means the better scheme, and the best scheme is selected.

3. Engineering Analysis

3.1. Engineering Situations

The project has two teaching buildings with three floors. The length of the building is 40 m, the width is 20 m, the story height is 3.9 m, and the total height is 17.05 m. The building belongs to a Class A public building, with a total construction area of 4478 m^2. The BIM model of the building is shown in Figure 8.

The prefabricated components in the project are composite slabs and prefabricated stairway sections. The construction site layout size is 105 × 100 m. There is a 5.0 m wide proposed permanent circular road within the site. According to the principle of construction road layout, it will be used as a construction road. There are two entrances to the CSPB communication with the outside world. The main entrance is located on the south side of the site, and the secondary entrance is located on the east side of the site. According to the principle of fixed tower crane selection, the QTZ5010 was used on-site for hoisting work. The initial construction site of the project is shown in Figure 9.

Figure 8. BIM model of the building.

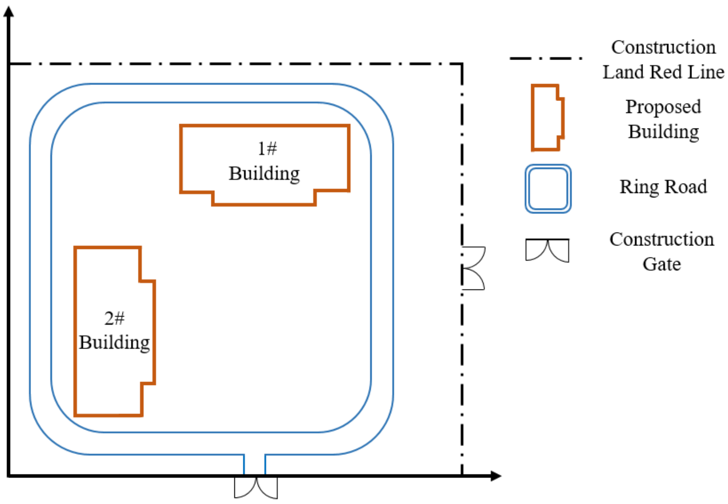

Figure 9. Initial construction site of the project.

3.2. Technical Analysis Route

The multi-objective optimization and decision-making model structure of temporary facilities arrangement on the CSPB is shown in Figure 10.

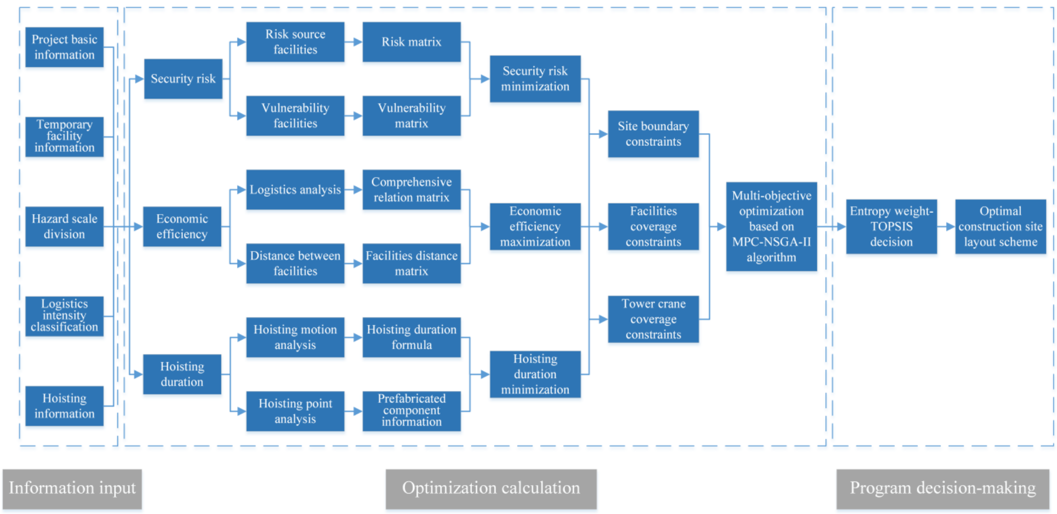

Figure 10. Multi-objective optimization and decision-making model structure of temporary facilities arrangement on the CSPB.

The MPC-NSGA-II multi-objective optimization algorithm consists of three main parts: initializing the populations, loop iteration, and loop termination.

Take the southwest corner of the site as the origin of the coordinate system of the whole construction site based on the basic information of the construction site. Divide the grid size (usually square grid) according to the actual situation and determine the coordinate information of fixed facilities. From Section 2.1, the model has too many constraints. If the initial population is randomly generated, it will increase the difficulty of searching for feasible solutions. Constraints must be checked and passed before a valid initial population is obtained. Therefore, the entire Pareto front surface can be obtained so that the solutions generated by the initialized population are all in the feasible domain.

The population evolves continuously in a loop iteration, so the iterative result gradually approximates the actual Pareto front surface. The loop iteration process of the model consists of three key components: population selection, crossover, mutation operations, immigration operator updates, and elite population updates.

The selection, crossover, and mutation of populations give the algorithm a powerful spatial search capability.

The selection is the operational process of transmitting good genes to the next generation by selecting high-quality individuals in the parent population. The binary tournament selection method places randomly selected individuals into the mating pool.

The crossover is performed by exchanging chromosomal information of two individuals in the mating pool, forming a new individual. Assume that the parents are X_i and X_j, respectively, and a single point of crossover is used between them to achieve the update of genetic information. The process is shown in Figure 11.

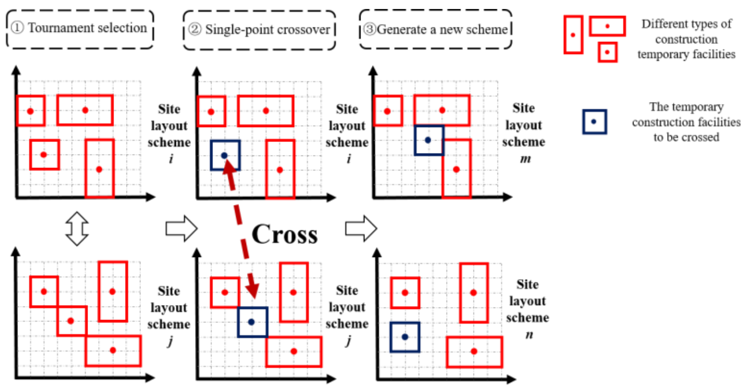

Figure 11. Schematic diagram of population crossing.

The mutation is a mutation of genetic information somewhere in a chromosome that results in the formation of a new individual. Due to the constraint relationship between individual facilities in a feasible temporary facility layout scheme, classical variation can easily lead to the generation of infeasible solutions. Therefore, the model does not use the classical variation approach. A new arrangement scheme is generated when the chromosome satisfies the mutation condition.

The model is terminated by the number of generations in which the optimal number of individuals remains constant with the maximum number of iterations. In other words, the model is stopped when the number of generations in which the optimal number of individuals in the elite population POP-c remains constant, reaches a preset value or when the maximum number of iterations is set.

3.3. Parameter Determination

The parameters to be determined are site and fixed facility parameters, temporary facilities parameters, hazard scale division parameters, logistics intensity classification situation, and hoisting parameters information parts.

3.3.1. Site and Fixed Facility Parameters

The southwest corner of the project construction site is taken as the origin of the coordinate axis, the AGSM is used to simplify the teaching building into a 40 × 20 m rectangular block, and the circular road within the site is regarded as a combination of four rectangular blocks to obtain the fixed facility coordinates. The length of the tower crane tail end of QTZ5010 is 12.72 m. According to the tower crane arrangement method, the proposed tower crane was arranged at (50, 50). Table 2 provides the relevant location information of the fixed facilities.

Table 2. Dimensions and coordinates of fixed facilities.

Number	Facility Name	Coordinates	Size (Unit: m)
B1	1 # Teaching building	(60, 75)	40 × 20
B2	2 # Teaching building	(25, 35)	40 × 20
O1	Tower crane	(50, 50)	2 × 2
O2	Construction Road 1	(47.5, 7.5)	75 × 5
O3	Construction Road 2	(7.5, 45)	5 × 90
O4	Construction Road 3	(47.5, 92.5)	75 × 5
O5	Construction Road 4	(87.5, 45)	5 × 90
O6	South gate	(55, 0)	——
O7	East gate	(105, 50)	——

The simplified initial construction layout is shown in Figure 12.

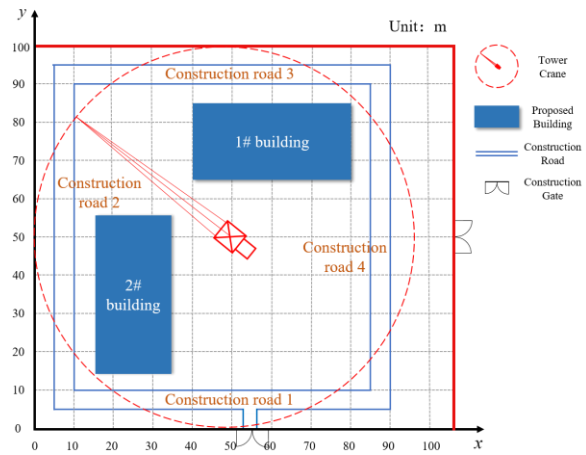

Figure 12. Simplified initial construction layout drawing.

According to the simplified preliminary construction layout plan, combined with the actual situation on-site, the coordinate range of the available sites for other temporary facilities is divided.

3.3.2. Temporary Facility Parameters

The prefabricated component yard is the key consideration in the temporary facilities layout on CSPB. Therefore, it is necessary to determine the area of the prefabricated components yard and its size first. The two buildings in the project have the same structure. A total of 76 prefabricated laminated panels are required for this floor, with a total of 2 types of sizes, of which 54 are required for DBS-67-3318 and 18 are required for DBS-67-4218. The prefabricated stairs are selected from SAT-39-25, and 2 stairs are required for each floor, with 4 stair sections.

The dimensions of all prefabricated components are summarized in Table 3.

Table 3. Summary of parameters of prefabricated components on the second floor.

Name	Size (mm)	Number per Layer
DBS-67-3318	3120 × 1800	54
DBS-67-4218	4020 × 1800	18
SAT-39-25	3660 × 1180	4

According to the construction plan and site conditions, a layer of prefabricated components needs to be reserved at the construction site. Therefore, 10 stacks of DBS-67-3318 precast laminated panels, 3 stacks of DBS-67-4218 precast laminated panels, and 1 stack of precast stairs were calculated. Considering the prefabricated components stacking requirements and the construction site space, the prefabricated laminated panels and stairs are placed in one yard.

The schematic diagram of the temporary storage of prefabricated components is based on the prefabricated component stacking requirements, as shown in Figure 13. The figure shows that the interval distance between prefabricated component stacks is 1 m, as reserved space for operation.

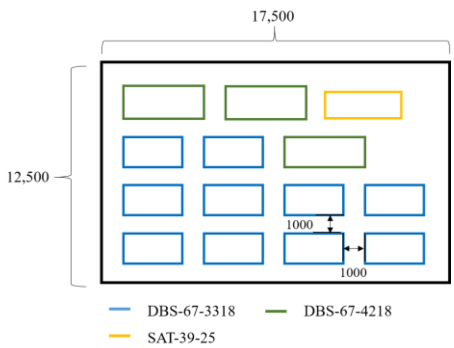

Figure 13. The layout of prefabricated components on the construction site.

In addition, seven temporary production facilities and two temporary living facilities were selected according to the actual situation on-site, and the information related to the temporary facilities is summarized in Table 4.

Table 4. Temporary facilities information.

Facilities Number	Facility Name	Size (Unit: m × m)	Facilities Properties
F1	Precast component yard	17.5 × 12.5	Non-fixation
F2	Steel processing shed	15 × 4	Non-fixation
F3	Steelyard	15 × 4	Non-fixation
F4	Woodworking processing shed	5 × 10	Non-fixation
F5	Woodworking yard	4 × 10	Non-fixation
F6	Construction waste yard	10 × 5	Non-fixation
F7	Small warehouse	8 × 5	Non-fixation
F8	Dormitories	5 × 30	Non-fixation
F9	Office building	4 × 30	Non-fixation

3.3.3. Hazard Scale Parameters

The hazard scales of each facility need to be divided in advance to calculate the objective function. Related research [37] generated the criteria for dividing the hazard scales of construction facilities in his research. The hazard scales of the facilities in this project are shown in Table 5.

Table 5. Hazard scale division of temporary facilities.

Temporary Facility	B1	B2	O1	F1	F2	F3	F4	F5	F6	F7	F8	F9
Hazard scale	2	2	4	3	3	3	3	3	2	4	1	1

3.3.4. Logistics Intensity Classification

We must grade the logistics intensity between the construction facilities before determining the objective function. According to the information on the engineering budget of the Ministry of Commerce for the project, the logistics intensity grading between construction facilities is shown in Figure 14.

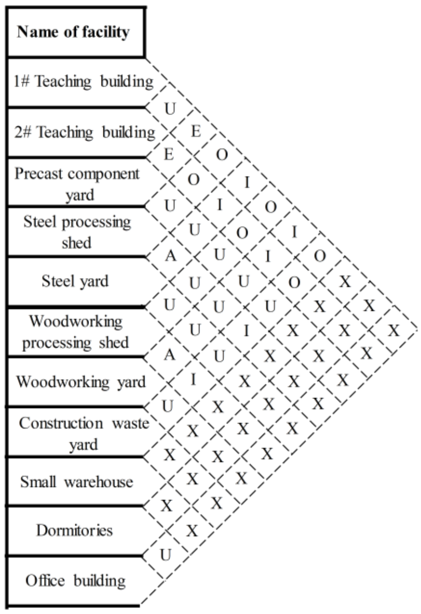

Figure 14. Logistics intensity classification.

Related research generated quantitative values of logistic intensity levels using the fuzzy set theory [28], proving the suggested values' validity by using practical projects [43]. Therefore, these suggested values are used in this case: A is 7776, E is 1296, I is 216, O is 36, U is 6, and X is 1. This project is the main structure construction phase, and the temporary facilities do not change their location during the construction period of 0.

3.3.5. Hoisting Information Parameters

The construction and installation machinery used in this project is the QTZ5010 tower crane. To ensure smooth installation work, the tower crane is used to hoist at four times the rate. Hook hoisting and radial and rotation speeds are 0.6 m/min, 20 m/min, and 0.5 rad/min, respectively. The prefabricated components of the proposed building are arranged symmetrically from left to right. Considering the flowing construction, the whole building is divided into two construction sections, and each section is considered as a whole, as shown in Figure 15. The center of the prefabricated staircase is used as the hoisting point, and the location of the prefabricated staircase demand point can be obtained. Because of many prefabricated laminated panels, the centers of the two construction sections are used as the demand point coordinates of the prefabricated laminated panels to consider the calculation volume and accuracy.

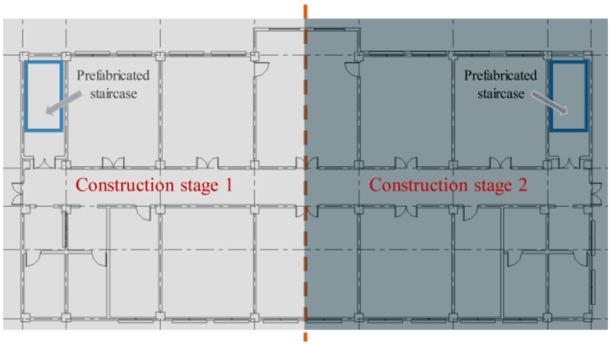

Figure 15. Division of construction section.

4. Results and Discussion

The computer hardware configuration for this validation simulation experiment is Intel (R) Core (TM) i5-13600KF CPU @ 5.10GHz, 32.0G of RAM, and a 64-bit operating system. The model was run in MATLAB 2020b. The input parameters were assigned to the MPC-NSGA-II optimization algorithm. The POP-a, POP-b, and POP-c population sizes were set to 150, the crossover rate was 0.9, the mutation rate was set to 0.05 and 0.7, respectively, and the maximum number of iterations was 200. A total of 23 optimal feasible solutions were generated from the model runs, and the results are shown in Figure 16 and Table 6.

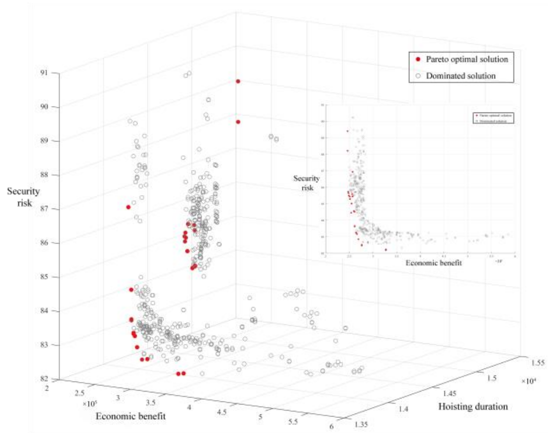

Figure 16. MPC-NSGA-II model iteration results.

Table 6. The fitness value of the Pareto optimal solution set.

Serial Number	Economic Benefit	Security Risk	Hoisting Duration	Serial Number	Economic Benefit	Security Risk	Hoisting Duration
1	269,245	82.85	13,824.48	13	261,066	84.52	13,824.48
2	266,083	83.18	13,824.48	14	276,176	82.51	13,824.48
3	253,839	84.46	14,574.44	15	276,145	82.47	13,884.65
4	251,443	85.29	14,509.67	16	246,257	89.40	15,152.66
5	250,740	85.44	14,509.67	17	246,332	88.21	15,152.66
6	248,977	85.50	14,639.03	18	259,524	84.56	14,556.61
7	254,804	85.02	14,509.67	19	259,534	84.54	14,556.61
8	247,711	85.74	14,574.44	20	264,183	83.24	13,824.48
9	256,963	86.94	13,824.48	21	264,178	83.26	13,824.48
10	255,990	85.59	14,477.65	22	261,232	83.63	13,824.48
11	248,274	85.65	14,639.03	23	261,231	83.66	13,824.48
12	256,693	85.45	14,477.65				

To provide a more precise illustration of the decision part of the model, four Pareto optimal solution schemes with significant layout differences were selected from the above optimization results for comparison. The simple arrangement of the four schemes is shown in Figure 17. The parameters are shown in Table 7.

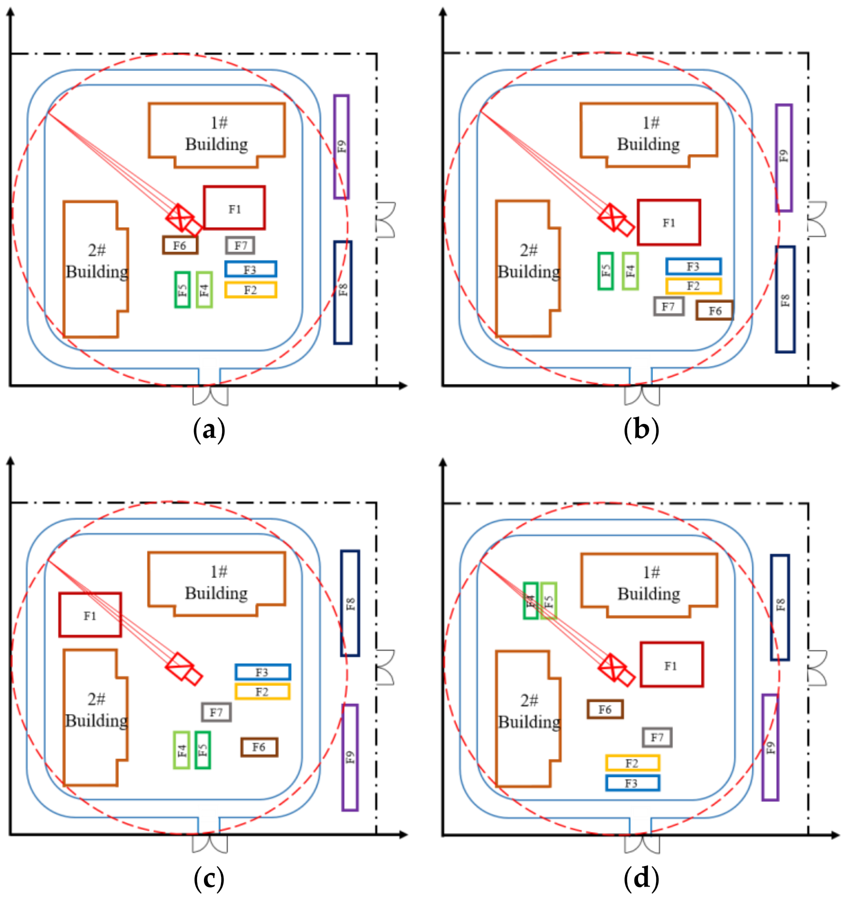

Figure 17. Schematic diagram of four Pareto optimal solution layout schemes. (**a**) Scheme 1; (**b**) Scheme 2; (**c**) Scheme 5; (**d**) Scheme 9.

Table 7. Four Pareto optimal solution layout schemes.

Scheme	Coordinate	F1	F2	F3	F4	F5	F6	F7	F8	F9
1	x	65	70	70	56	51	49	67	97	97
	y	52	28	34	28	28	41	41	27	70
2	x	65	72	72	54	47	78	65	98	98
	y	52	34	39	38	38	27	28	30	70
5	x	24	73	73	50	56	72	60	98	98
	y	68	46	51	29	29	30	40	71	27
9	x	65	54	54	30	25	46	61	99	97
	y	52	25	20	72	72	41	33	70	30

To choose the best solution, a comprehensive evaluation is proposed using the entropy weight-TOPSIS method. There are four evaluation attributes to be considered: "Smoothness", "Convenience", "Management efficiency", and "Spatial adjustability".

The project manager performs the fuzzy evaluation of the four judging factors of each program. First, the set of judging index factors U_f is established in Equation (22).

$$U_f = \{\text{Smoothness}, \text{Convenience}, \text{Management efficiency}, \text{Spatial adjustability}\} \quad (22)$$

The evaluation level V_e is established in Equation (23).

$$V_e = \{V_1, V_2, V_3, V_4, V_5\} = \{\text{Excellent}, \text{Good}, \text{Fair}, \text{Pass}, \text{Poor}\} \tag{23}$$

$V_1 \sim V_5$ correspond to 5, 4, 3, 2, and 1 scores, respectively. The initial decision matrix is obtained by combining the fuzzy evaluation results of the three project managers and then normalizing the decisionalization matrix.

The ideal and anti-ideal solutions are in Equations (24) and (25)

$$C^+ = \begin{bmatrix} 0.1344 & 0.3334 & 0.1090 & 0.0705 \end{bmatrix} \tag{24}$$

$$C^- = \begin{bmatrix} 0.0768 & 0.1192 & 0.0672 & 0.0434 \end{bmatrix} \tag{25}$$

Finally, the ideal proximity C^* is calculated, and the results are listed in Table 8.

Table 8. Entropy weight-TOPSIS evaluation calculation results.

Evaluation Object	Ideal Solution Distance	Anti-Ideal Solution Distance	Ideal Proximity C^*	Ranking
Scheme 1	0.1836	0.0471	0.2043	3
Scheme 2	0.2263	0.0107	0.0453	4
Scheme 5	0.0098	0.2250	0.9583	1
Scheme 9	0.0478	0.1829	0.7927	2

According to the evaluation results, scheme 5 is the best temporary facilities layout scheme on CSPB. To visually check whether the output best scheme is reasonable, a 3D temporary facilities layout model was established in BIMMAKE 2022, and the results are shown in Figure 18.

Figure 18. The layout of prefabricated components on the construction site.

To verify the superiority of the MPC-NSGA-II algorithm, the classical NSGA-II algorithm in the field of multi-objective optimization is used as a control experiment. The optimization results of the MPC-NSGA-II algorithm are compared with those of the NSGA-II algorithm in multiple dimensions. To eliminate the influence of chance factors as much as possible, the simulation tests were run 10 times, and the best optimization results were selected for comparison. The test parameters of the NSGA-II algorithm in the test were set as follows: population size N was 300, crossover probability was 0.8, variation probability was 0.1, and the maximum number of iterations was 200 generations.

The test results in Figure 19 show that for this case, the MPC-NSGA-II optimization algorithm is more computationally efficient, the number of Pareto optimal solutions obtained is higher, and the quality is higher. In terms of computational time, the NSGA-II algorithm takes 1702.0 s on average, while the MPC-NSGA-II algorithm takes 421.0 s on average, and its computational time is only 25% of that of the NSGA-II algorithm. In terms of computational results, the number of optimal solutions obtained by the NSGA-II algorithm is 9, and the number of optimal solutions obtained by the MPC-NSGA-II algorithm is 23. In terms of computational quality, the optimal solutions obtained by the MPC-NSGA-II algorithm dominate the optimal solutions obtained by the NSGA-II algorithm. Therefore, the MPC-NSGA-II optimization algorithm obtains more and better solutions with higher computational efficiency.

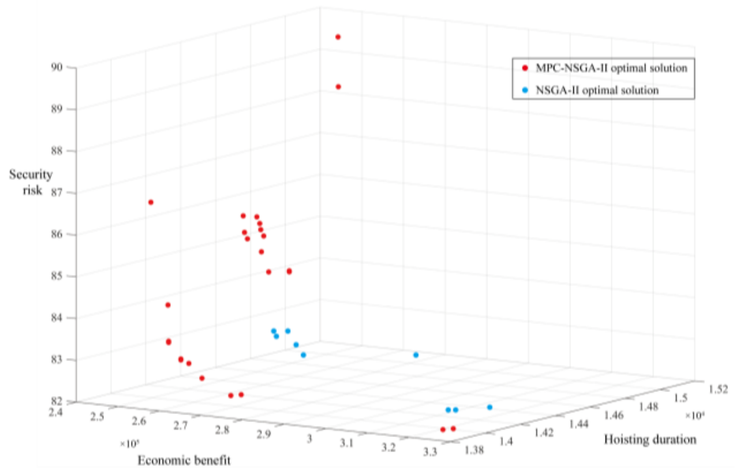

Figure 19. Comparison of results of two algorithms.

5. Conclusions

This study proposes that the MPC-NSGA-II algorithm applies to multi-constraint and multi-objective optimization problems based on the basis and general principles of layout on the CSPB. The main results of this study are as follows.

(1) The construction site and temporary facilities assumptions for the CSPB were determined by literature analysis. It is found that the grid method assumption of the construction site and the AGSM for temporary facilities are more suitable for CSPB analysis. With a large workload of hoisting work on the CSPB, the tower crane coverage constraint, site boundary constraint, and facility coverage constraint should be taken as constraints on the CSPB. Influencing factors of temporary facilities layout on the CSPB were screened out by literature analysis. The expert scoring method ranked the degree of importance of the influencing factors. Ten factors to be included in the model were finally identified and incorporated into the method of layout planning on the CSPB in different ways.

(2) The multi-objective optimization functions of CSPB were determined, and the quantitative formulas were proposed. Combined with the characteristics of CSPB, the Security risk function was quantified by the hazard interaction matrix and the vulnerability interaction matrix; the Economic benefits function was quantified by the systematic layout planning method; the Hoisting duration function was quantified by decomposing the hoisting process and calculating the horizontal and vertical running time respectively.

(3) The MPC-NSGA-II algorithm for multi-constraint and multi-objective optimization problems was proposed. It effectively improved the NSGA-II algorithm with disadvantages such as premature maturity and computational inefficiency. By introducing multiple swarm strategies, the global search and local search capabilities of the algorithm were taken into account, thus expanding the search range. Meanwhile, introducing elite populations avoided the loss of optimal solutions and improved the stability of the optimal solution set. The migration operator promoted collaborative communication among populations, sped up the elimination of inferior individual solutions, and improved the computational efficiency of the algorithm. Adopting the constraint domination method reduced the interference of the considered parameters. Harmonic distance improved the distribution of feasible solutions and sets and increased the efficiency of the algorithm.

(4) The multi-objective optimization and decision-making model of temporary facilities arrangement on the CSPB was established. The MPC-NSGA-II algorithm combined the entropy weight-TOPSIS decision-making method to output the best temporary facility arrangement scheme based on a practical case. The BIMMAKE 2022 established a visualized 3D construction site temporary facilities layout to verify the rationality of the best scheme and the theoretical model.

(5) The practical case verified the superiority of the MPC-NSGA-II algorithm and the theoretical model. The results of the MPC-NSGA-II and NSGA-II algorithms were compared in multiple dimensions. It was found that the MPC-NSGA-II algorithm has 3 times higher computational efficiency, 1.6 times higher number of optimal solutions, and higher quality of optimal solutions.

(6) There are also areas for improvement in this study. Only stationary tower cranes on the CSPB were considered. Mobile cranes also take on the critical role of transporting components in practical applications. Subsequent studies could consider the impact of each type of transport machinery working in concert with the temporary facility of the CSPL. Meanwhile, only one case was used in this study for validation analysis, and different cases should be used in future studies to demonstrate the model's generalizability.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su15076279/s1, Expert Consultation Form.

Author Contributions: Conceptualization, G.Y. and Y.Y.; methodology, G.Y.; software, R.L.; validation, G.Y., Y.Y. and R.L.; formal analysis, Y.Y.; investigation, R.L.; resources, G.Y.; data curation, R.L.; writing—original draft preparation, R.L. and Y.Y.; writing—review and editing, G.Y., Y.Y. and R.L.; visualization, R.L.; supervision, G.Y.; project administration, G.Y. and R L.; funding acquisition, G.Y. and Y.Y. All authors have read and agreed to the published version of the manuscript.

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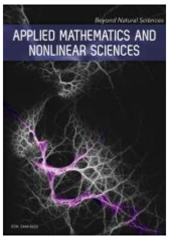

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Application of Genetic Algorithm to the Traditional Layout and Spatial Optimization Design of Suzhou Gardens

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Abstract

The optimization of the spatial layout of the garden is the key to the garden design. This paper draws on the smooth organization of the dynamic line and the reasonable arrangement of the area of the Suzhou Garden and designs an optimization algorithm based on the genetic algorithm for the layout of the garden. The two optimization objectives of "function" and "dynamic line" are proposed, and genetic algorithm optimization of garden layout is carried out by defining spatial connectivity and accessibility fitness function, integer crossover, and gene exchange. Case analysis shows that the optimization time of the genetic algorithm is much lower than that of the stochastic optimization algorithm; the average connection value and depth value are 1.925 and 0.737, respectively, and the investigation score is close to the professional design scheme. It shows that the application of genetic algorithms to optimize the garden layout has the advantages of being less time-consuming, having a reasonable spatial layout, and being highly professional.

Keywords: Genetic algorithm; Garden layout; Spatial optimization; Arithmetic example analysis.
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1 Introduction

Suzhou space layout and design are very important and worthy of reference - repair hidden or strengthen the main axis of the garden, adjust the layout of the line of sight spatial flow, so as to achieve the need to borrow the scenery or obstacles [1]. Adjustment of spatial flow, on the one hand, on the other hand, can be contrasted, set off, and transformed to make the landscape of the garden soft, open, and close to maximize the presentation of the beauty of the garden [2]. At the same time, the flow line generated by the tour in which the time dimension so that the three-dimensional space has become a living four-dimensional space, you can appreciate the time-space changes in the interest of understanding the natural symbiosis of all things “Road” [3-4]. Genetic algorithm has a significant position in garden planning and design, its role depends on its characteristics. The interactivity, immersion, imagination and multisensory nature of genetic algorithms are reflected in the auxiliary design of landscape planning and strengthening the expression of the program [5-6]. The application of genetic algorithms in landscape design makes the spatial experience of the designer more intuitive and interactive and provides new ideas for the design of the designer’s program design, which makes the program design more reasonable and perfect [7-8]. In the presentation of the project, the audience can experience the designer’s design intention in person through multi-angle and real-time interaction. The application of the genetic algorithm in the traditional layout and spatial optimization design of Suzhou Gardens is of great significance for the overall control of the construction site, the reasonable arrangement of the progress, the scientific guidance of the whole process of construction, to ensure the safety of the project, and to reduce the waste of resources, etc. [9-11]. Genetic algorithm has a broad application prospect in garden planning and design.

Literature [12] studied the design of an interactive landscape digital reconstruction system based on particle swarm algorithm, realized the reconstruction of the garden through GIS technology, and proposed the use of digital technology and particle swarm algorithm to solve the limitations of the current garden and meet the needs of the times. Literature [13] proposes an active model based on operator optimization genetics, realizes a new Chinese landscape cognitive model, provides guidance for the landscape-style space design of the new Chinese style, and verifies the practicability and effectiveness of the model. Literature [14] constructed a landscape pattern spatial optimization model based on a particle swarm optimization algorithm, which is driven by innovative design, using particle position to simulate layout spatial optimization of the landscape and improve the comprehensive benefits of integrating economy, ecology, and ecological environment. Literature [15] proposes taxing algorithms to make comprehensive judgments on the impact of noise on the environment, which can realize the integration of urban planning and architecture, better spatial planning, and expand the development potential of space. Literature [16] designed a new optimization method for landscape sculpture space structure. Compared with the algorithm commonly used nowadays, the optimization method of the improved particle algorithm has a short processing time, the vegetation area and the harmony between the sculpture and garden are significantly improved, and the application effect is better. Literature [17] based on the optimization method of natural evolution and genetics, through the simulation of the biological evolutionary process, research on the evolutionary law of natural species, the reasonable planning and combination of functional areas in the garden, reflecting the algorithm has good algorithmic performance and optimization efficiency.

This paper analyzes the unique dynamic line design of Suzhou Garden and takes this as the focus to optimize the spatial layout of the garden. Through the analysis, the focus of garden space optimization is determined as “functional space allocation” and “reasonable organization of the dynamic line”, and then the optimization algorithm of Suzhou Garden is designed according to the basic principles of genetic algorithm. The optimized landscape areas and tourist flow were identified and coded, and the adaptive function was established based on spatial connectivity and accessibility. The integer crossover method is used for the crossover iteration of the garden optimization scheme, and intraindividual gene swapping is used for the mutation operation of the iteration process. Finally, the complete process of optimizing the garden's spatial layout is summarized, and arithmetic examples are analyzed in terms of the algorithm's computing time and optimization effect.

2 Design of movement lines in Suzhou Gardens

The line of motion is the route for people to flow in the space, which determines their feeling of the space form and their understanding of the level of space order. Under the premise of meeting basic functional needs, setting up the dynamic line is also an important way to shape the psychological space.
There are two main ways to set up the dynamic line in Suzhou Garden: one is to set it up according to the mountain, and the other is to set it up around the water. But no matter how to set up, its principle is "through", two is "zigzag", three is "interesting", and four is "secluded".

First of all, "through" is the requirement that there should be no dead ends, there should be a sequence of links between the various space forms, and there is a rhythm to avoid the appearance of walking the "wrong way". Secondly, "zigzag" is to increase the visitors in the space of the retention time, the full flavor of the garden in the ingenious design, so that appreciators and designers to produce more resonance. Third, "interesting" is to have changes, such as the path in Suzhou Garden by the corridor, bridge, platform, halls, caves, rocky islets, and paths, which also has a change in the height of the ups and downs of the changes in the two sides of the clamping material changes in the texture of the ground pavement changes. These factors have increased the psychological stimulation of visitors, effectively improving their aesthetic fatigue. Bridge on the Water presents a variety of styles, such as the Humble Administrator's Garden small flying rainbow of the corridor bridge, stay in the Garden of the Water Valley of the stone bridge, the Humble Administrator's Garden Xiangzhou wooden railing bridge, the Humble Administrator's Garden in the Lotus Wind four-sided Pavilion and the far between the Hall of the fragrance of the curve of the bridge, and so on. Suzhou Garden's road surface changes are even richer, with numerous masonry and rubble paving patterns. Fourth, "quiet", the path in the Suzhou Garden is not a spacious road; paths on both sides of the charming scenery make people forget to go back. Or the waterfront lotus fragrance, or the ancient vine accompanied by, or the sparse plum slanting, or the quiet of the small windows, or along the ladder and up, into which the heart is refreshed and happy.

3 Application of genetic algorithms to optimize the layout design of Suzhou gardens

The dynamic line design is an important foundation of garden space design, and all aspects of space are inseparable. However, the contemporary landscape garden space design process pays more attention to the functional design and ignores the dynamic line design. The landscape garden space moving line is a complex moving line. Many contemporary landscape garden spaces appear purely to pursue the harmony of the formal composition. The ultimate result is to produce chaotic moving line organization, chaotic functional layout and other issues.

In this paper, the focus of landscape garden space optimization is summarized as follows: (1) the distribution of functional space. The correct logic connects each functional space to ensure the strongest accessibility and connectivity of the overall space. (2) the rationality of the organization of the dynamic line after the completion of the functional sub-layout should also be in accordance with the smooth, flowing characteristics of the Suzhou Garden dynamic line to generate space to ensure that the overall space has the strongest connectivity and accessibility.

3.1 Fundamentals of Genetic Algorithms

Suzhou garden space requires space with the strongest accessibility and the closest connection between spaces, and a multi-objective genetic algorithm facilitates the intelligent optimization of the generated plan layout, so this paper adopts a genetic algorithm to optimize the spatial layout of the garden.

3.1.1 Concept of Genetic Algorithms

Genetic algorithms (GA) are artificial intelligence algorithms for adaptive optimization, which simulate the process of continuously generating individuals and reproducing populations adapted to natural conditions through heredity and mutation. In essence, a genetic algorithm is an intelligent, globally parallel search method that automatically gathers data from the search space and adjusts the search process to find an optimal solution [18].

3.1.2 Flow of the genetic algorithm

The basic working principle of genetic algorithm is to map the problem variables onto chromosomes, create populations with appropriate coding procedures, change the information on the chromosomes through genetic operations such as crossover, selection, mutation, etc., and iterate to obtain an optimized population that ultimately satisfies the optimization conditions. The main process of a genetic algorithm is as follows:

1) Population coding

   The process of encoding involves mapping the feasible solution of a problem to be optimized from the actual solution space to the genetic space, while decoding involves the opposite process. At present, the commonly used encoding methods mainly include binary encoding, integer encoding, Gray code encoding, and so on.

2) Population initialization

   The initial population creation is the primary objective of the genetic algorithm and the most significant matter. Chromosomes form individuals. Individuals form populations. Each chromosome corresponds to a solution to a problem, and the number of individuals in a population indicates the size of the population. At the start of the program, the genetic toolbox randomly generates individuals to form an initialized population, and this initialized population is then iteratively operated to achieve the global optimal solution [19]. Selecting the appropriate initial population can improve the operation efficiency of the algorithm. The initial population in the genetic algorithm is randomly generated, mainly by the following methods: (1) According to the specific practical problem, determine the feasible domain of the solution and then create the initial population. (2) Determine the size of the population, select the best individuals to join the initial population, and repeat the operation until the number of initial population requirements are met.

3) Adaptation function

   Fitness is used to evaluate the goodness of a solution or an individual, and the function that represents fitness is called the fitness function. The fitness function is usually transformed from the objective function of the problem to the fitness function, which must be non-negative and processed non-negatively. There are three main ways to convert the general objective function $f(x)$ to the fitness function $Fit(f(x))$ [20].

The direct conversion method changes the sign of the original objective function to realize the conversion according to solving the problem:

$$Fit(f(x))=\begin{cases} f(x) \textit{ when the objective function} \\ \textit{is a } \max \textit{imisation problem} \\ -f(x) \textit{ when the objective function} \\ \textit{is a } \min \textit{imisation problem} \end{cases} \tag{1}$$

The direct transformation method is easy to implement and simple to operate, but non-negative treatment of the objective function.

The linear transformation method is an improvement of the direct transformation method that ensures the nonnegativity of the fitness function. When the objective function of the solution is to solve the minimization problem, the following transformation is performed:

$$Fit(f(x))=\begin{cases} C_{\max}-f(x) & f(x)<C_{\max} \\ 0 & Other \end{cases} \tag{2}$$

Where $C_{\max}$ is a sufficiently large value and (the maximum estimate of $f(x)$) is generally slightly larger than the $f(x)$ maximum.

When the objective function to be solved is a maximization problem, the following transformation is performed:

$$Fit(f(x))=\begin{cases} F(x)+C_{\min} & f(x)>C_{\min} \\ 0 & Other \end{cases} \tag{3}$$

Where $C_{\min}$ is the minimum estimate of the value of the $f(x)$ function.

Inverse method. When the objective function to be solved is a minimization problem, the following transformation can be done:

$$Fit(f(x))=\frac{1}{1+C+f(x)} C\geq 0, C+f(x)\geq 0 \tag{4}$$

When the objective function to be solved is a maximization problem, the following transformation can be done:

$$Fit(f(x))=\frac{1}{1+C-f(x)} C\geq 0, C-f(x)\geq 0 \tag{5}$$

Where C is an estimate of the $f(x)$ bound.

4) Selection

The selection operation is the process of choosing individuals based on their fitness value to produce a new population. Generally, the higher the fitness score, the higher the probability that an individual will be selected. Commonly used selection methods include roulette selection, best-retention selection, linear sorting selection, and elite selection strategies.

5) Crossover

Crossover operations first pair individuals in a population, and then each pair of chromosomes exchange genetic information with each other. Common crossover methods include single-point crossover, two-point crossover, and multipoint crossover [21].

6) Mutation

Mutation is the genetic modification of genes located on an individual's chromosome with a specific probability of producing a new individual. Mutation operators are used mainly to improve the local search ability of genetic algorithms, maintain population diversity, and prevent premature maturation. Commonly used variation operations are basic positional variation, uniform variation, binary variation, Gaussian variation, and so on. [22].

7) Termination conditions

A genetic algorithm has the property of convergence, but in the actual operation, the algorithm can not carry out unlimited iterations, so practical applications must set the convergence condition. When the convergence condition is satisfied, the iteration operation stops. At present, there are mainly given a maximum number of evolutionary generations based on the total number of individual evaluations and stay in the optimal search for the solution of the maximum number of steps and other convergence of the guidelines.

3.2 Design of Optimization Algorithm for Suzhou Garden

The spatial layout optimization problem is a longer-scale optimization problem with an iteration cycle. In order to improve the efficiency of optimization, reduce the computational amount of the optimization problem, and get more accurate superior results, the algorithm is specifically designed as follows:

1) Data selection

Select the landscape blocks that need to be optimized for t iteration and the tourist flow of each block.

2) Individual coding

Individual coding using integer coding, each individual indicates that the iteration needs to optimize all the landscape blocks. For example, in t this iteration needs to optimize the landscape blocks coded as $[10531812]$, which means that starting from the 10th landscape area, in turn through all the landscape blocks.

3) Adaptation value

The adaptation degree function is defined as follows:

Objective 1: The landscape area space has the highest number of connections with other spaces:

$$Coverage:\max\left(\sum_{i=1}^{m}x_i\sum_{j=1}^{n}a_{ij}p_j\right) \tag{6}$$

i for the number of current and pending gardens, j for the number of landscape areas, and p_j for the number of connections to other landscape areas for each landscape area. a_{ij} is the decision variable for the allocation of functional landscape facilities i and demand points j.

Objective 2: Accessibility is best:

$$TravelDis:\min\left(\sum_{i=1}^{m}x_i\sum_{j=1}^{n}a_{ij}d_j\right) \tag{7}$$

Equation (7) describes the accessibility best, i.e., the minimum objective function of the total walking distance of all visitors to the neighboring landscape blocks. d_{ij} is the temporal distance between demand point j and landscape area i, which is obtained through the OD Cost Matrix module in the network analysis function of ArcGIS 10.2 software.

4) Crossover operation

The crossover operation adopts the integer crossover method, randomly initializing the crossover position on the basis of selecting the crossover individual and then realizing the crossover by interchanging the gene values, assuming that the crossover gene positions are randomly selected as Position 3 and Position 5, and the operation method is as follows:

$$\begin{matrix} Individual-[94213761085] \\ Extreme\ value-[92163741085] \end{matrix} \xrightarrow{Crossover} New\ Individuals-[94163761085] \tag{8}$$

The new individuals generated are adjusted if there are duplicate locations, and adjustments are made by replacing duplicate included landscape areas with landscape areas not included in the individual, as follows:

$$[94163761085]\xrightarrow{Adjustment}[94213761085] \tag{9}$$

5) Mutation operation

The mutation method adopts the way of gene swapping within the individual, firstly, randomly select the two mutation positions of the individual and then swap the mutation positions to realize the mutation operation, assuming that the individual mutation positions are position 2 and position 4, and the mutation operation is shown as follows:

$$[94213761085]\xrightarrow{Mutation}[91243761085] \tag{10}$$

The algorithm optimization process of the spatial layout optimization algorithm of the landscape area based on the genetic algorithm is shown in Figure 1. As can be seen from Figure 1, the algorithm can be mainly divided into three steps. The first step, according to the i th search for the number and location of landscape blocks to be optimized, is the initialization of the genetic algorithm parameters. In the second step, the genetic algorithm is used to optimize the spatial layout of landscape blocks. The third step is to output the spatial layout optimization results.

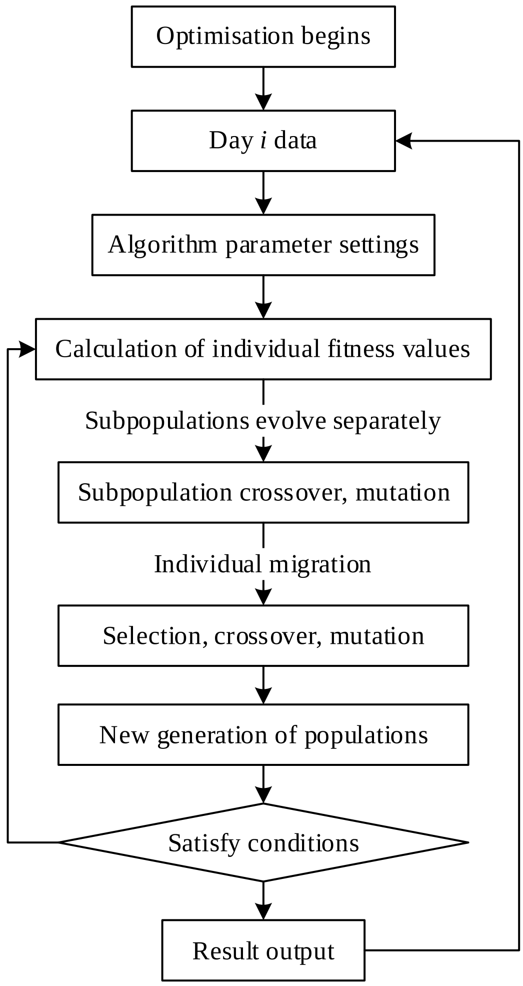


Figure 1. Optimization process of garden space layout algorithm

4 Analysis of examples

4.1 Comparison of algorithmic computation time

To verify the feasibility of genetic algorithms applied to garden layout optimization, this paper compares them with stochastic optimization methods. For this purpose, we implemented a non-parallel version of the simulated annealing algorithm from the work of Merrell et al. We first add garden spaces of the same size to the defined region of the layout as the initial layout. One of the following operations is then performed iteratively during the optimization process:(1) Swap the positions of any two landscape blocks. (2) Move any wall. We evaluate the quality of the generated layout by calculating the energy E' of the current result. If energy E' is less than the energy E of the previous layout, then we accept the generated layout as the current layout, otherwise, we accept the generated layout with probability $\exp(-E'-E)/t$, where t is the temperature. We gradually decrease the temperature t in each iteration. The algorithm terminates when E is less than a threshold.

Fig. 2 shows the performance comparison between the simulated annealing method and the genetic algorithm at different complexities. Complexity here is defined as the sum of the number of landscape blocks and the number of design constraints. The stochastic optimization method's running time increases significantly when it becomes more complex, while the genetic algorithm's running time grows slowly. When the sum of the number of landscape blocks and the number of design constraints is 55, the stochastic optimization method takes 10.3 times longer than the genetic algorithm, and the stochastic optimization method takes nearly 300 seconds. Even so, the stochastic optimization method has not found a feasible solution that satisfies all the constraints. The stochastic optimization method has left unfilled areas in the layout, and some spaces are too small for effective landscaping.

Therefore, it can be seen that the genetic algorithm shows good computational performance in the optimization process of garden space and layout design, which also indirectly verifies the feasibility of using a genetic algorithm for the optimization of garden space layout in this paper.

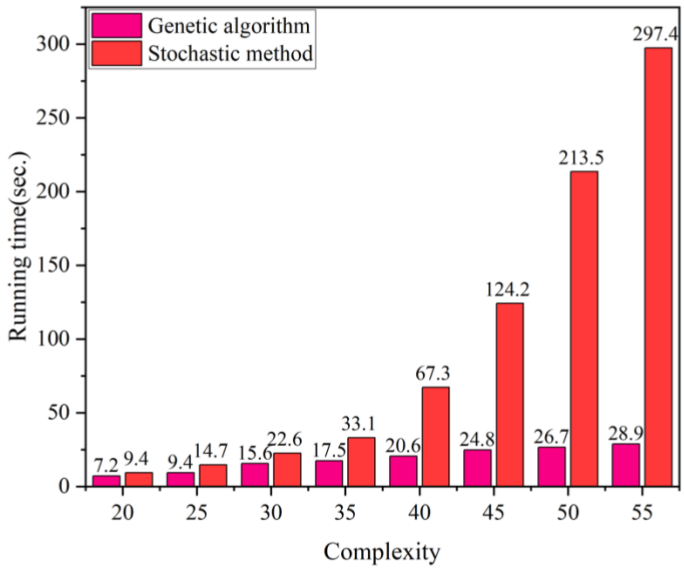


Figure 2. Comparison of simulated annealing method and genetic algorithm

4.2 Analysis of the optimization effect of garden layout

4.2.1 Comparison of Layout Optimization Results

The optimization algorithm constructed in the previous section provides a variety of optimization schemes, from which the most effective one is selected to compare with the two optimization schemes provided by the stochastic optimization method. In this paper, we use "connection value" and "depth value" to quantify the "spatial connection" and "accessibility" of the garden, respectively. The "connection value" and "depth value" are used to quantify the "spatial connection" and "accessibility" of the garden, respectively. The "connection value" represents the number of times a node is connected to other spaces. The higher the "connection value" of a space, the higher the degree of connection between the space and other nodes in the space, and the stronger the public nature of the space. The "depth value" represents the difficulty of reaching the space. The higher the depth value, the worse the accessibility of the space. In order to ensure that the accessibility of the space is the strongest and each functional space is closely connected, it is necessary to ensure that the connection value in the space is the largest and the depth value is the smallest. A Grasshopper-based spatial syntax plug-in is used to calculate these two indicators for different schemes. The comparison of the effects of the three optimization schemes is shown in Table 1.

Comparison found that the average connection value and depth value of several landscape categories selected from the reference gardens are 1.272 and 1.486, respectively; the average connection value and depth value of Scheme 1 are 1.362 and 1.367, respectively; the average connection value and depth value of Scheme 2 are 1.165 and 1.151, respectively; whereas the average connection value of the scheme in this paper is 1.925 and the average depth value is 0.737. It can be seen that, in general, the optimization scheme after genetic algorithm optimization better meets the optimization objective of "maximum connection value and minimum depth value", indicating that each landscape or functional area spatial optimization scheme is more satisfying. 0.737, it can be seen that, in general, the optimization scheme of garden space optimized by genetic algorithm better meets the optimization objective of "maximum connection value and minimum depth value", which indicates that the spatial connection of various landscapes or functional areas is close and highly accessible.

Finally, the reference scheme for optimization of garden space layout after genetic algorithm optimization can be summarized as follows: 18,048.6 square meters of water area, 5,998.3 square meters of pavilion area, 6,775.3 square meters of rockery area, 7,762.3 square meters of corridor area, and 727.8 square meters of public toilet area.

Table 1. Comparison of the three optimization schemes

	Landscape/functional area	Block area (m^2)	Total garden area (m^2)	Area ratio (%)	Connection value	Depth value
The status of the garden	Waterbody	18133.9	41343.6	43.86%	2.087	0.930
	Pavilion	4701.3	41343.6	11.37%	0.402	1.204
	Rockery	5807.55	41343.6	14.05%	1.353	2.009
	Corridors	7251.15	41343.6	17.54%	1.104	0.755
	Toilet	637.7	41343.6	1.54%	1.414	2.533
Random optimization plan one	Waterbody	14576.7	41343.6	35.26%	1.563	1.59
	Pavilion	6155.9	41343.6	14.89%	1.571	1.571
	Rockery	6594.3	41343.6	15.95%	1.427	1.147
	Corridors	7407.8	41343.6	17.92%	1.384	0.657
	Toilet	487.6	41343.6	1.18%	0.864	1.871
Random optimization plan two	Waterbody	16557.6	41343.6	40.05%	1.871	1.381
	Pavilion	4664.8	41343.6	11.28%	0.471	1.854
	Rockery	5222.1	41343.6	12.63%	1.174	1.387
	Corridors	6983.1	41343.6	16.89%	0.871	0.547
	Toilet	884.8	41343.6	2.14%	1.438	0.587
Genetic algorithm plan	Waterbody	18048.6	41343.6	41.24%	2.012	0.971
	Pavilion	5998.3	41343.6	13.54%	1.857	0.874
	Rockery	6775.3	41343.6	13.97%	1.654	0.711
	Corridors	7762.3	41343.6	18.78%	2.843	0.457
	Toilet	727.8	41343.6	1.76%	1.258	0.674

4.2.2 Comparison of user satisfaction

We compare the optimized method in this paper with other methods and manual design solutions through user research.

1) Comparison method

The current mainstream methods are used to compare the methods in this paper. A scenario generation network can be used to locate landscape blocks, which is called ISSNet. Given the location of landscape blocks, the distribution of walls can be determined by the optimization method based on MIQP, which is called MIQP. Then we form a total of four groups of comparison objects by combining the methods in these two works. The first group of comparison objects is to use the method of ISSNet to locate the position of landscape blocks, and then use the method of MIQP to locate the position of walls, which is recorded as ISSNet+MIQP. The second group of comparison objects uses the method of genetic algorithm to locate the position of landscape blocks and then uses the method of MIQP to locate the position of walls, which is recorded as GA+MIQP. The third group of comparison objects is to use the method of ISSNet to locate the position of landscape blocks, and then use the method of MIQP to locate the position of walls, which is recorded as GA+MIQP. ISSNet method to locate the position of landscape blocks, and then use the genetic algorithm to locate the position of the wall, noted as ISSNet+GA. The fourth group of comparison objects is compared with the results of the designer's design, which is noted as human. We conducted user research on each of these four comparison groups.

2) User Research

Similar to user research in past work, we asked users to perform a mandatory comparison selection for a pair of floor plan layouts with identical boundaries. In each comparison task, experimental participants were required to select the layout plan they considered more reasonable. We randomly choose a sample of user research from the generated results based on experimental fairness considerations. In each comparison task, the order in which the layout plans were placed was randomized. Four questionnaires were created for each of the four comparison groups. Each questionnaire consisted of 30 forced-choice comparison questions, and for every 15 questions, we designed one question as a "warning test" containing a clearly irrational layout plan.

For each user study, the number of participants in the experiment was 84, 82, 87, and 101, respectively. The participants were divided into two categories: general users and designers specializing in landscape architecture. If a participant failed to achieve 100% accuracy in the vigilance test, their experimental data was not included. The statistics related to the participants in the user study are shown in Table 2. For each participant, we recorded the number of choices they had to utilize the method of this paper to generate the garden layout plan, denoted as N.

Where the number of participants who passed the vigilance test is denoted as "#part", the mean age and its standard deviation are a_{avg} and a_{dev} respectively, the number of participants who are engaged in the profession of landscape design is denoted as "#prof", the mean and standard deviation of the number of years of the designer's career are denoted as y_{avg} and y_{dev} (years), and the mean and standard deviation of the time taken to complete the questionnaire were recorded as t_{avg} and t_{dev} (minutes).

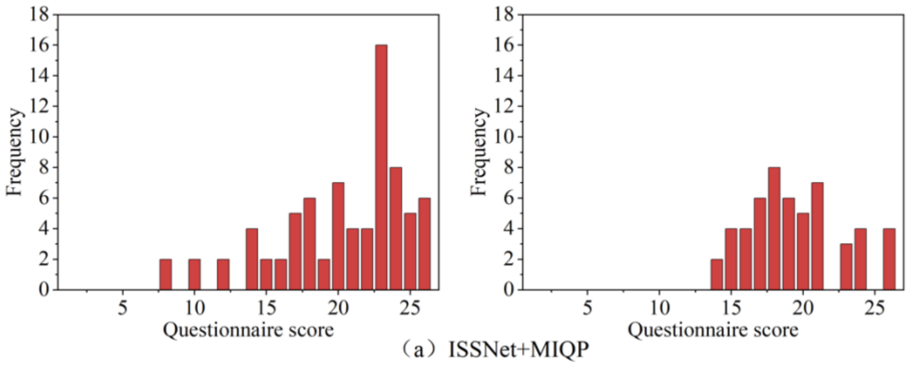
Table 2. Statistics of the subjects

Competitor	#part	Age range	a_{avg} / a_{dev}	Male, female	#prof	y_{avg} / y_{dev}	t_{avg} / t_{dev}
ISSNet+MIQP	70	[18,51]	58.4/3.69	42,28	26	3.46/1.98	3.44/2.46
GA+MIQP	61	[19,48]	23.47/5.11	37,24	27	2.72/1.46	1.97/1.06
ISSNet+GA	63	[18,50]	24.72/5.77	41,22	30	3.71/2.65	2.33/1.67
Human	76	[21,52]	27.38/5.75	46,30	34	3.95/2.3	3.46/2.6

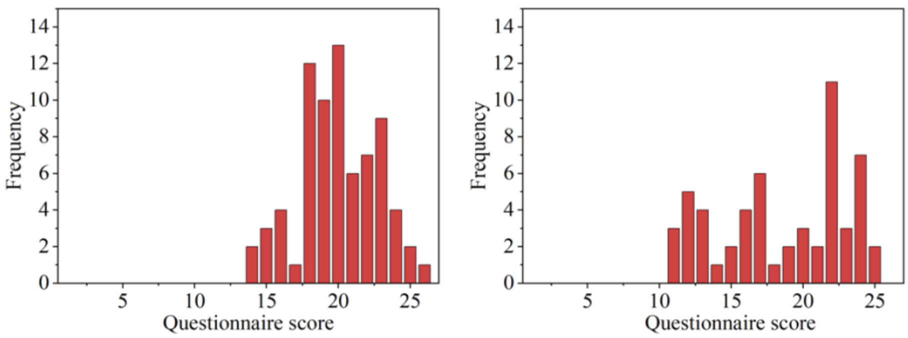
3) Comparison results

Figure 3 shows the results of the user research. The distribution of N is recorded in the figure, and each row represents the comparison results of ISSNet+MIQP, GA+MIQP, ISSNet+GA, and Human, respectively, where the left column represents the distribution of N for the different algorithmic solutions, and the right column represents the distribution of scores for the manual algorithmic design solution. If a participant receives about 12 points on the questionnaire (out of a total of 24 non-vigilante test questions), this is an indication that the two comparison methods are comparable. The distribution in Figure 3 shows that our method is comparable to the comparison of humans and outperforms the other three comparisons.

It is also noted that the average score of an average user is lower than that of a designer. For example, in the comparison result with Humans, the average score of regular users is 14.78, while the average score of designers is 12.73. We believe that designers tend to prioritize the details of the layout plan, such as orientation and dimensions, while regular users typically judge the rationality of the layout design based on their personal preferences. And our method may not be able to explore these details thoroughly. Participants who are involved in the design profession preferred manually designed layout floor plans over ordinary users.



（a）ISSNet+MIQP



（b）GA+MIQP

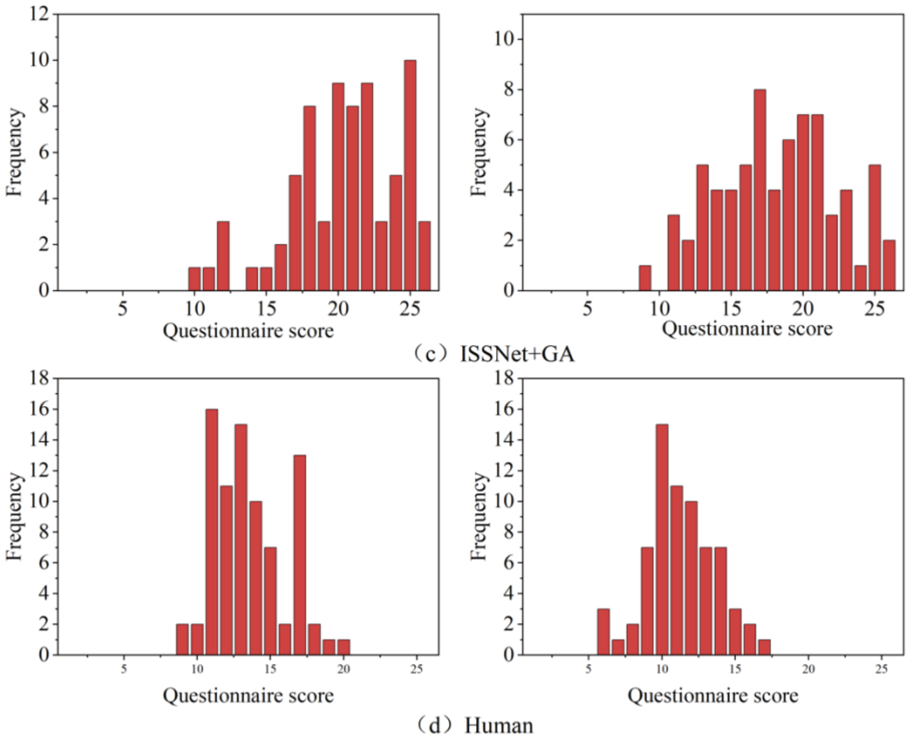


Figure 3. User research results

5 Conclusion

Comparing the performance of the genetic algorithm selected in this paper with that of the stochastic optimization method in the process of spatial layout optimization, it is found that the operation time of the genetic algorithm is always less than that of the stochastic optimization method, and the rising trend is slow. When the sum of the number of landscape blocks and the number of design constraints reaches 55, the optimization time of the genetic algorithm is only one-tenth of that of the stochastic optimization algorithm, and the optimization time is 28.9 seconds. According to the two indexes of connection value and depth value, the optimization scheme derived from this paper's method outperforms the comparison scheme, with an average connection value of 1.925 and an average depth value of 0.737. In addition, according to the questionnaire survey, the distribution of evaluation scores of this optimization scheme is closer to that of the professional design scheme, which proves that this scheme possesses the design professionalism of landscape design. In summary, the method of applying genetic algorithms to optimize the spatial layout of the Suzhou garden proposed in this paper has feasibility and effectiveness.

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ARTICLES FOR FACULTY MEMBERS

MULTI-OBJECTIVE OPTIMIZATION ALGORITHM FOR AUTONOMOUS SPATIAL LAYOUT DESIGN

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RESEARCH ARTICLE

A review on simulation based multi-objective optimization of space layout design parameters on building energy performance

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Abstract

Improving the energy performance of buildings is crucial for environmental protection, energy savings, and a better living environment. The growing emphasis on sustainable building practices has led to an increased focus on optimizing space layout design parameters to enhance building energy performance. This review explores the application of simulation-based multi-objective optimization techniques in the context of studying the impact of space layout design on building energy efficiency. The integration of advanced simulation tools with optimization algorithms allows for a comprehensive analysis of multiple conflicting objectives like energy performance, user comfort as well as cost factor. The review begins by outlining the key parameters influencing building energy performance, including spatial configurations, orientation, and space perimeter variables. Subsequently, it delves into the various simulation tools employed to model the complex interactions between these parameters and their effects on energy performance. The integration of energy simulation software is highlighted as a crucial step towards achieving accurate and realistic assessments. In summary, this review delivers a comprehensive overview of the state-of-the-art methods in simulation-based multi-objective optimization for studying space layout design parameters and their impact on building energy performance, offering insights for researchers, practitioners, and policymakers in the field of sustainable architecture. There is a requirement for a comprehensive multi-objective framework for complex structures in the investigation of building energy performance giving more focus on reducing the cooling load and optimization of space layout along with envelope parameters.

Keywords Architectural Space layout · Energy Performance · Optimization algorithms · Cost factor

Abbreviations

ANN	Artificial Neural Network
AAPPD	Annual Average Predicted Percentage Dissatisfied
AC	Acoustics Comfort
ACL	Annual Cooling Load
AEC	Annual Energy Consumption
AED	Annual Energy Demand
AEOCO	Annual Energy Operating Costs
ALL	Annual Lighting Load
aNSGA-II	Active Archive Non-Dominated Sorting Genetic Algorithm II
ASED	Annual Specific Energy Demand
ATL	Annual Thermal Load
CD	Cooling Demand
CL	Cooling Load
CO_2	Carbon Dioxide
DA	Daylighting, Autonomy
DB	DesignBuilder
DGI	Discomfort Glare Index
DI	Daylight Illuminance
DL	Daylighting
EC	Energy Consumption
ECO	Energy Cost
ED	Energy Demand
EE	Energy Efficiency
EP	Energy Performance
ES	Energy Saving
EUI	Energy Use Intensity (EUI)
EWSOA	Enhanced Water Strider Optimization Algorithm
GA	Genetic Algorithm
GCO	Global Cost
GHG	Greenhouse Gas Emissions

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HD	Heating Demand
HL	Heating Load
HVAC	Heating, Ventilation and Air conditioning
ICO	Investment Cost
LCA	Life Cycle Assessment
LCC	Life Cycle Cost
LL	Lighting Load
MLRGA	Multi-Linear Regression Genetic Algorithm
MO	Multi-objective Optimization
MOABC	Multi-objective artificial bee colony
MODE	Multi-Objective Differential Evolution
MOGA	Multi-Objective Genetic Algorithm
MOPSO	Multi-Objective Particle Swarm Optimization
NSGA-II	Non-dominated Sorting Genetic Algorithm II
OT	Operative Temperature
PE	Polluting Emissions
PMV	Predicted Mean Vote
PPD	Predicted Percentage of Dissatisfaction
PSO	Particle Swarm Optimization
SC	Solar Surface Coefficient
SHGC	Solar Heat Gain Coefficient
SOGA	Self-Organizing Genetic Algorithm
SR	Solar Radiation
TCO	Total Cost
TEC	Total Energy Consumption
TED	Total Energy Demand
TC	Thermal Comfort
TL	Thermal Load
TPMVD	Total Percentage of Cumulative Time with Discomfort
UDI	Useful Daylight Illuminance
VC	VISUAL COMFORT
VP	Visual Performance
VT	Visible Transmittance
WWR	Window-To-Wall Ratio

1 Introduction

The energy usage of built structures accounts for a substantial share of worldwide energy demand. The built sector is responsible for 30% of final total global energy consumption (EC) and 26% of total energy sector emissions [1]. Although the overall final energy utilization of the global building sector remained steady in 2020 compared to prior years, CO_2 (Carbon Dioxide) emissions from building projects increased by nearly 28% of total global energy-related CO_2 emissions [2]. Building and infrastructure construction contribute significantly to global warming because of the high participation of equipment and material consumption [3]. Making thoughtful, executive-level decisions on energy efficiency is one of the most important strategies to reduce the amount of energy used in buildings. Furthermore, implementing building energy efficacy measures is a significant strategy for reducing greenhouse gas emissions, that contributes to climate change mitigation and worldwide public health improvement [4]. An energy performance (EP) upgradation should lower the annual energy usage expenses based on the building's primary energy sources and annual CO_2 emissions in the environment [5]. In this context, research aimed at enhancing building EP has stimulated the concern of several researchers from around the world [3]. The optimization approach appears to be crucial in the battle to overcome these challenges. In the area of optimization, which is related to applied mathematics and computer science, models and algorithms are employed to address challenging problems. Optimization is the process of selecting the ideal combination of different solutions when the specified constraints are met [6]. For optimization to take place, constraints, decision variables as well as objective functions are required [7]. Using optimization to reduce building resource and energy needs will have a significant influence on resource management and related energy expenses. Optimization can be defined in terms of a single objective function, whereas multi-objective optimization can also contain two or three objective functions. Optimization objectives can be expressed explicitly, such as by reducing the annual energy needed for comfort, heating, cooling, ventilation as well as daylighting in buildings, or they can be expressed implicitly, such as by reducing CO_2 emissions or the price of energy-generating equipment [8]. It is easy to compare the values of each solution's objective function in a single-objective optimization problem, but in a multi-objective optimization (MO) problem, a solution's utility is determined by how well it excels with alternative solutions [9]. A single objective function is insufficient to explain a situation where many goals must be achieved simultaneously, necessitating the use of multi-criteria approaches [4].

MO can be used to balance many building design requirements, including optimum comfort, least amount of energy used, and least number of resources used. Considering that complicated optimization problems involving integrated building design include multiple independent variables and goals. Building performance optimization is always best understood as a MO problem, for which the exchange of the many objectives is the appropriate course of action.[10].The optimization algorithm chosen is determined by the problem that needs to be solved [11]. It takes time to investigate all of the possibilities to create an effective design [12]. Given that complex optimization issues with integrated building design involve several independent variables and objectives, non-gradient-based techniques are employed to resolve complex discontinuous objective functions. The main objectives of building energy design, as stated by the objective functions, are to reduce energy consumption, costs, and discomfort. Numerous ideal solutions are put up to satisfy the demands of different public and private stakeholders [13]. In real-world building design concerns, including low EC and optimum thermal comfort or minimal EC and construction cost, building designers commonly have to reconcile conflicting design aims. MO is therefore frequently more appropriate than the single-objective approach. Building engineers use their knowledge, experience, and inventiveness to solve problems in the field; these qualities are hard, if not impossible, to translate into automated optimization systems [14]. Building design innovation aimed at improving energy efficiency, cutting CO2 emissions, and lowering life cycle cost (LCC)s has received a lot of attention in many countries in the name of sustainable development. Energy efficiency is crucial for energy-intensive constructions. While identifying the best options without considering all feasible combinations of retrofit interventions, the employment of a multi-objective optimization algorithm in combination with a building simulation can enable the exploration of all practical alternatives [9].

Building systems, building design, building management, and building geometry/orientation are the key areas of optimization for prior building energy performance optimization research. There are many reviews focused on the algorithms, softwares in multi objective optimization for total building energy performance, whereas focused building design and geometry/orientation influences on energy performance analysis through multi objective optimization research are negligible. This review paper focused on the building design especially, space layout related variables along with geometry and orientation and their influence on energy performance, cost, comfort and environmental impact through multi objective optimization strategy. Determining the arrangement of spaces is among the most crucial elements of architectural design. According to Tiantian Du, space layout design variables include function distribution, space volume/shape, interior division, and interior openness [15]. A building space layout refers to the arrangement and positioning of various elements within a structure, such as walls, rooms, corridors, doors, windows, and other architectural features. It's a critical aspect of architectural and interior design that involves planning how the space within a building will be organized to fulfil functional, aesthetic, and practical requirements. The previous study has shown that room layouts, as well as thermal, visual, and acoustical comfort, have a significant influence on energy use for cooling, heating, lighting, as well as ventilation. Changing space layout variables like an envelope, window details, zoning of spaces, etc. proved reductions in the annual final EC in various studies [15]. Optimization of numerous design management approaches such as building space load, occupancy, lighting, and Heating, ventilation, and air conditioning (HVAC) becomes unavoidable for a successful spatial layout on EP [16]. In order to save a substantial amount of time and money when evaluating architectural space layout elements like building orientation, overhang details, shading, window size, glazing, and wall material attributes on building EC, Delgarm, Navid, et al. evaluated the effects of specific architectural features of a standard room on electrical EC in four different climates of Iran [4]. Zhang et al. suggested a modelling-simulation optimization method for constructing free-form buildings using space efficiency and shape coefficient as geometric constraints to maximize solar radiation gain [17]. The process of selecting the best design from a wide range of space layout design options while verifying the energy performance requirements is known as building energy optimization [18]. Building energy performance optimization is a common example of a multi-objective issue. Designers usually address conflicting spatial design considerations simultaneously, such as consumption of energy, thermal comfort, building expense, and so forth [11]. When dealing with MO problems that have multiple contradictory objectives, the common approach is to combine the objectives into a scalar function and solve the resulting single-objective optimization problem [19]. In MO issues, there are two or more competing optimization goals, which means that achieving one goal would compromise the achievement of another [20].

MO can consider multiple factors of performance and has a wide range of applications in the field of building design. Because all variables are considered, 2–3 objectives are typically chosen to optimize the building design. The four main types of objective functions that are typically used in building performance research are energy use, cost, environmental impact and comfort. The efficacy and efficiency of different optimization methods depend on how well they function [21]. Because there are numerous potential solutions for any optimization problem, both the selection of the algorithm and the adjusting of the algorithm parameters may require repeated tries and errors [10]. The algorithms utilized in the multi-objective optimization frameworks includes Non-dominated Sorting Genetic Algorithm II (NSGA-II), Multi-Objective Particle Swarm Optimization (MOPSO), Multi-Objective Genetic Algorithm (MOGA), and Multi-Objective Differential Evolution (MODE). From this review we are able to identify the effective multi objective optimization algorithms in the study of space layout variables on energy performance. This article comparing various frameworks on MO connected to space layout variables on building energy performance. Investigating and contrasting various simulation-based optimization variables and methodologies in the field of building energy performance in relation to space layout parameters, as well as comprehending and analyzing the behaviors of various optimization algorithms in order to solve building performance design issues, are the primary goals of the review [11]. This research paper also aims to identify the interaction between space layout design variables and related functional objectives in the process of the MO method as well as the developments regard to this topic through the review of previous works of literature.

2 Methodology

Depending on the objective and level of execution, many review approaches, such as systematic, semi-systematic, integrative, etc., may be used. A semi-systematic literature review could be an effective strategy when it is impossible to read every article that might be pertinent to the subject at hand [22]. This type of study can be useful for determining the shared issues within a specific research area or methodology [23]. Among the potential contributions are the capacity to map a field of study, summarize the body of knowledge, and provide an agenda for upcoming research on a particular topic [22]. This review study has been conducted on simulation-based MO, building EP, and the cost-effectiveness of space layout and related variables. The search criteria are based on aforesaid topic-related keywords in the Scopus database. The main searched keywords are "multi-objective optimization", "Simulation-based optimization", "Energy performance of the building" and "Architectural space layout". Research published from 2016 to 2023 is considered for the review to investigate the recent trends in the field of MO framework in the study of space layout on building EP. Only journal publications focusing on simulation-based multi-objective optimization framework to examine the effects of space layout-related variables on EP were analysed where conference proceedings, review papers and book chapters were excluded. In this review, as a large volume of candidate papers came out of the initial survey, subsequently, papers got filtered in the areas of access (open), subject type (energy and engineering), year (2016–2023), research type (journals), publication status (final), language (English). Based on the titles and abstract reading some papers discarded by the author for the full paper reading criteria. The final phase was applied to screen the selected works based on fulfilment of various criteria which included the proposed optimization approach on energy, comfort as well as cost performance and the variables should be directly related to space layout along with space boundary, space character. The references of the extra relevant documents are included if they match the selection criteria or to elaborate some information. There is total 46 papers were selected after the full paper review. Ultimately, the following data was taken out of each of the chosen works: the publishing date, the kind of building, the location of the building, the climate, the optimization goals, the parameters of the space layout, the simulation tools, and the optimization tools, as indicated in Table 1 [24]. This study has highlighted new findings in the body of literature and offered possible directions for further investigation.

3 Analysis and discussion

3.1 General details

The optimization problem, the multi-objective optimization strategy, software and algorithms, variables and targeted objectives, the example used to evaluate a model, and the comparison with alternative approaches were all covered in 46 papers that were chosen between 2016 and 2023 [63]. The publication trend from the reviewed articles is shown in Fig. 1.

The majority of the reviewed research was concerned with building optimization, residential buildings accounted for 46% of the case studies examined, while offices made up 22% of the building typology. (Fig. 2). Building optimization frequently involves climate-based modelling, therefore determining the goals and required results of the optimization process can be greatly influenced by the building's location and its climate zone. Asia was the site of a sizable number of investigations, with China being the primary location. According to Fig. 3, the majority of the sites mentioned in the evaluated literature in this survey study, approximately 46% were in China, while Iran coming in second with 24%. It's important to note that research was done on multiple climate zones in the Asian continent.

In this review, researchers tried to optimize multiple functional objectives broadly categorised as energy performance, comfort/environmental and management factors through MO method which appears to be a robust and effective tool to obtain optimal solutions in lesser time with conflicting objective functions using efficient algorithms. The many EP objectives include minimizing EC, energy demand, total building energy load, heating and cooling loads, and maximizing savings. The building design variables segregated as space layout parameters, envelope (space boundary) parameters, functional (space character) parameters which includes services. Variables related to envelope are further divided to design aspects, material property and construction detailing.

3.2 Functional objectives and design variables in multi-objective optimization

The envelop parameters are much studied variable on energy, comfort and cost analysis factor. Tables 2 & 3. shows the studied functional objectives and types of space layout variables through MO framework in reviewed articles.

Table 1 The details of multi-objective optimization framework on energy performance of the building

Author	Year	Location	Case Study	Simulation Model	Climate	Optimization Algorithm	Simulation /optimization engine/tool, Softwares	Objective Function	Design Variables
[25]	2016	IRAN-Tehran, Kerman, Bandar	Office building	Test room	Temperate, warm-dry, warm-humid and cold	MOABC (Multi-objective artificial bee colony), MOPSO	EnergyPlus, jEPlus	EP, PPD (Predicted Percentage of Dissatisfaction), indoor TC	Rotation of the room, window dimensions, cooling/heating setpoint temperatures, wall and glazing material properties
[4]	2016	Iran	Office building	Case study model	Cold, mild, warm-dry, & warm humid	NSGA-II	MATLAB /EnergyPlus	ACL (Annual Cooling Load) ALL (Annual Lighting Load), ED (Energy Demand)	Building orientation, window size, overhang specifications
[26]	2016	Spain-Madrid	Residential building	Actual layout	Other	Harmony Search algorithm	EnergyPlus	ACL, ALL, ED	Shading devices
[27]	2016	Iran	Multi-story building	Single thermal zone test case model	Cold, mild, warm–dry, warm–humid	MOPSO	EnergyPlus	Comfort, ED, TDC, LDC, impact on summer comfort	Building orientation, shading/overhang specifications, window size, wall and glazing material properties
[28]	2016	Italy- Naples	Hospital	Reference /Block model	Mediterranean	Bi/Tri-objective genetic algorithm	MATLAB/EnergyPlus/DB(DesignBuilder)	AEC (Annual Energy Consumption), HL (Heating Load), CL, LL (Lighting Load)	Geometry/shape, envelope details
[29]	2017	Italy-Naples	Residential building	Case/Reference building model	Mediterranean	Mono/Bi-objective genetic algorithm	MATLAB/EnergyPlus	TDC, Cost, operating cost for conditioning of space	Building envelope's thermal characteristics, HVAC
[30]	2017	Italy	Office building	Reference model	Mediterranean	MOGA	MATLAB/EnergyPlus/DB	Global cost savings, EC, discomfort hours, polluting emissions	Envelop parameters
[31]	2017	Argentine Littoral region	Residential building	Typical house	_____	NSGA-II	Energy Plus/Python	Heating/cooling degree-hours ED, HD (Heating Demand), CD (Cooling Demand)	Roof, external/internal wall types, solar orientation, solar absorptance, shading details
[32]	2017	Ankara, Turkey	Other-Library	Computer model	Other	SOGA (Self Organizing Genetic Algorithm), MOGA	EnergyPlus/Open Studio	Building space, layout, EC, DL (Daylighting)	Design constraints / weights, initial building form
[33]	2017	China-Harbin	Residential building	Reference Building	cold	Multi objective evolutionary algorithm	EnergyPlus/Grasshopper, Radiance, and Daysim	DA (Daylighting Autonomy), UDI (Useful Daylight Illuminance), EUI (Energy Use Intensity), TCO (Total Cost)	Building width, roof height, south/ north WWR (Window-To-Wall Ratio), window height, Building orientation
[11]	2017	China, Nanjing	Residential building	Base case model	Hot summers & cold winters	NSGA-II, MOPSO, MOGA, MODE	MATLAB/EnergyPlus	Total Percentage of Cumulative Time with Discomfort (TPMVD), LCC, CO_2,	Conductivity, thermal absorbance, visible absorbance, WWR, azimuth

Table 1 (continued)

Author	Year	Location	Case Study	Simulation Model	Climate	Optimization Algorithm	Simulation /optimization engine/tool, Softwares	Objective Function	Design Variables
[34]	2018	China -Wuhan	Other -two-star green building	Base case model	Hot summer-Cold winter	ANNGA, MLRGA (Multi-Linear Regression Genetic Algorithm)	EnergyPlus/DB	Annual thermal load (ATL), total number of discomfort degree hours	Different concrete /insulation thickness, absorbance of solar radiation for each exterior wall/roof, WWR for each façade
[35])	2018	25 different places	Residential building	Base case model	25- different climates	NSGA-II	TRNSYS	CD, HD, LCC	External walls, thermal transmittance of roof, ground & glazing, WWR, glazing type
[13]	2019	Italy-Milan	Office building	Case study model	Mediterranean, with mild winters, hot, dry summers	GA	MATLAB/EnergyPlus	EC, GCO (Global Cost), CO_2	Building Geometry, Envelope
[36]	2019	Italy	Residential building	Base model	Mediterranean climate	GA	MATLAB/EnergyPlus	EP, economic benefits, Thermal Comfort (TC)	Window type, building orientation, Set point temperatures, radiative properties of plasters, thermo-physical properties of envelope elements
[37])	2019	Iran-Tehran	Office building	Typical space layout	Hot, arid,	MO	EnergyPlus/ GRASS HOPER, Ladybug Archsim	CD, HD, thermal discomfort time, Operative Temperature (OT)	Shading, building orientation, insulation, internal thermal mass & glass type
[38]	2019	China-Nanjing	Other	Hypothetical room model	Hot summers and cold winters	NSGA-II	MATLAB/EnergyPlus	TEC (Total Energy Consumption), indoor thermal environment, VP (Visual Performance)	WWR, Building orientation, outer glass, filling gas, inner glass of a double-paned window
[39]	2019	China	Other -Tourist centre	Case study	Hot summers & cold winters	NSGA-II	EnergyPlus/Open Studio	Annual Energy Demand (AED), Annual Average Predicted Percentage Dissatisfied (AAPPD)	Window types, shape of the eaves, thermal properties of opaque walls and roofs, thermostat set points
[40]	2019	Canada-Montreal	Institutional building	Case study	——	NSGA-II	EnergyPlus/DB	EC, LCC, LCA (Life Cycle Assessment)	Roof, fenestration, external walls, shading
[41]	2020	USA -Houston, Texas	Residential building	Reference model	Hot humid climate	Ray-tracing algorithm	EnergyPlus/ RADIANCE, Rhino Grasshopper	CL, DL performance during summer season	Geometric configurations of envelopes
[42]	2020	North Argentina	Residential building	Case study	Other	NSGA-II	Python (DEAP)/EnergyPlus	EE (Energy Efficiency), TC	Roof / external & internal wall types, solar orientation, solar absorptance, size/ type of windows, dimension of external window shadings

Table 1 (continued)

Author	Year	Location	Case Study	Simulation Model	Climate	Optimization Algorithm	Simulation /optimization engine/tool, Softwares	Objective Function	Design Variables
[5]	2020	European Countries	Residential building	Case study model	Arid, warm temperate, snow, polar	MOGA, aNSGA-II	Python/EnergyPlus/Open Studio	AED, Construction & Investment Cost (ICO), Annual Energy Operating Costs (AEOCO), Green-house Gas Emissions (GHG)	Climate, costs of primary energy sources & carbon intensity
[6]	2020	other	Other	Case study model	Mediterranean climate	aNSGA-II	Python/EnergyPlus/Open Studio	TED (Total Energy Demand), HD, CD	Geometry, passive & active Strategies
[43]	2020	ROME	Residential building	Case study model	Mediterranean climate	aNSGA-II, NSGA-II	Python/EnergyPlus	ICO, ECO (Energy Cost), ED, CO_2 emis-sions	Insulation thickness, windows type
[44]	2020	Iran	Office building	Case study	Cold semi-arid, Mediterranean, Cold desert, Hot semi-arid, Humid continental Hot desert	NSGA-II	Python/EnergyPlus	AEC, PPD, DGI (Dis-comfort Glare Index)	Window orientation, shading control strategy & set points, shading location, dimensions, angle, material
[45]	2020	China	Office building	Base case model	Severe cold, cold, hot summer, cold winter, hot summer & warm winter climate	NSGA-II	DB with jEplus + EA	HL, CL, LL, discomfort hours,	Building orientation, window configura-tion, shading system, window materials, installation angle and depth of overhangs
[46]	2020	Iran	Reference office room			Hypervolume-based evolutionary algo-rithm (HypE)	Octopus (A Grasshopper plugin)	LL, DL, view to the outside	Window width and height, window sill and head height
[47]	2021	Iran	Residential building	Base case model	Hot and dry	Enhanced Water Strider Optimization Algo-rithm (EWSOA)	EnergyPlus,	TC, GHG	Insulations for outer wall, roof, floor, airtightness
[48]	2021	Serbia	Residential building	Physical model	Cold	NSGA-II	EnergyPlus/DB	HD, CD, minimum number of discomfort hours	WWR, glazing type, facade wall details, window/facade shading arrangement
[49]	2021	India -Delhi	Other	Case study	Composite climate	NSGA-II	MATLAB	TC, VC (Visual Com-fort), AC (Acoustics Comfort)	Total floor area, storey height, the total number of stories, envelope parameters
[50]	2021	China -Nanjing	School	Case study	Subtropical monsoon climate	ANN (Artificial Neural Network), NSGA-II, MOPSO	Python/EnergyPlus	DL, TC, ES (Energy Saving), economy	Thermal conductivity/ solar absorptivity/thick-ness/ material density/ specific heat of the wall, WWR, U-Value, Solar Heat Gain Coef-ficient (SHGC), Visible Transmittance (VT) of an external window

Table 1 (continued)

Author	Year	Location	Case Study	Simulation Model	Climate	Optimization Algorithm	Simulation /optimization engine/tool, Softwares	Objective Function	Design Variables
[51]	2021	Turkey-Osmaniye & Erzurum	Residential building	Reference model	Mediterranean climate	NSGA-II	MATLAB/EnergyPlus/ Open Studio	LCC, low-capacity thermal equipment	Building orientation, external wall material, thermal mass, insulation thickness, glazing types, WWR
[52]	2021	China	School -Primary & Secondary	Simulation model	Sub-Tropical climate	NSGA-II ANN	Python/EnergyPlus	TC, DL, EC	Thermal conductivity/ solar absorptivity / thickness/material density/specific heat of wall, WWR, U-Value, SHGC, VT, height, overhanging depth of exterior window, orientation, cooling setpoint, heating setpoint, air tightness grade
[53]	2021	Jordan	Residential building	Computer model	Cold climate	GA	EnergyPlus/DB	TEC, CD, HD	Site orientation, WWR, types of shading, glazing, window blind infiltration rate, type, flat roof construction, external wall construction, natural ventilation rate, type, window shading control schedule, partition construction
[17]	2021	China, Shenyang,	Other-Exhibition Hall	Reference model	Cold climate	MOGA	Octopus/Grasshopper plug-in,	SR (Solar Radiation), SC (Solar Surface Coefficient0, Space Efficiency	Core space, envelope
[54]	2021	China-Hanzhong	Residential Building	Baseline model	Hot summer & cold winter zone	NSGA-II	EnergyPlus/IDA-IEC, TRNSYS	TEC, IICO	Building orientation, dimensions of south & north windows, wall & roof thickness, insulation material type, window type (U-values & SHGC) & Shading Parameters

Table 1 (continued)

Author	Year	Location	Case Study	Simulation Model	Climate	Optimization Algorithm	Simulation /optimization engine/tool, Softwares	Objective Function	Design Variables
[52]	2021	Southern China	Primary and secondary school classrooms		Subtropical monsoon climate	ANN, NSGA-II	EnergyPlus software	TC, EC, DL	Thermal conductivity/ solar absorptivity/ thickness/ material density/ specific heat of the wall, WWR, U-value /SHGC/VT of the external window, the height and depth of the overhanging, orientation, cooling/ heating setpoint, air tightness grade
[55]	2021	Morocco	Typical house	Simulation model	tropical climate	NSGA-II, MOPSO and MOGA	TRNSYS	ATED, HD, CD, discomfort degree-hours,	Thermal transmission coefficient of external walls/ roof/windows, thermal resistance of floor, solar factor of the glazing
[56]	2021	China-Guangzhou	School	Simulation model	Hot & humid climate	ANN, NSGA-II	Python/EnergyPlus/Rhino Grasshopper, Radiance	TC, VC, TEC	Building orientation, geometry, envelop parameters -windows, shading devices, wall
[57]	2022	Indonesia -Jakarta	Residential Building	Base case model	Continental Temperate, dry-cold, dry-hot, tropical	NSGA-II	Python/TRNSYS	TL (Thermal load), ICO	Building orientation. insulation level of envelope, window detailing for passive cooling, WWR, shading fraction, radiation-based shading control,
[58]	2022	China-Sanya	Office building	Simulation model	Tropical	MOGA	OpenStudio	CL, UDI, PMV (Predicted Mean Vote)	WWR, window height, and louvers
[59]	2022	China	Residential building	Prototypical models	Cold	SPEA-2 algorithm	Rhino-Grasshopper	DL, HL, CL, TC	Northward, westward and southward WWR are 0.10, 0.11, 0.12, transmittance
[60]	2022	Birmingham, UK, Jakarta, Indonesia, Sydney, Australia	Office	Hypothetical room model	Different climates	(HypE)- Hypervolume-based evolutionary algorithm	Octopus (a Grasshopper plugin)	UDI, EC	Orientation/rotation of louvers
[7]	2022	China-Harbin, Beijing, Shanghai, Shenzhen and Kunming	Residential building	Typical layout	Severe Cold, Cold, Hot Summer & Cold Winter, Hot Summer & Warm Winter, Temperate	NSGA-II, ANN	Grasshopper /Honeybee and Ladybug	TED, HD, CD, DI (Daylight Illuminance)	Floor height, total building width, WWR
[61]	2023	Iran -Tehran	Office building	Middle-floor office room	Hot and dry	NSGA-II	Grasshopper plugin Wallacei 2.6	TEC, TC, VC	WWR, multi-slat shading depth, angle/distance to the wall, orientation
[62]	2023	Passo Fundo, southern Brazil	Multifamily social housing buildings	Warm temperate climate	Cold region	NSGA-II	python/EnergyPlus	CD, HD	Building orientation/ shape

Many researchers optimized two to five or more five independent variables in more than 70% of studies. There are more than 60 different functional objectives are accounted for in the MO method from the reviewed articles. Several functional objectives are of maximum 7 numbers and a minimum 2 numbers are considered in the reviewed articles. Annual cooling load, heating demand,and annual energy load were studied in more than 10 articles each whereas EC, DL, thermal comfortglobal cost, and investment costs are cited in more than 5 articles each.

Building envelope characteristics as a space perimeter are one of the factors that significantly affect a building's performance, along with space layout variables including how much energy is used for heating, cooling, lighting, and ventilation as well as for environmental factors like thermal comfort, visual and acoustical comfort along with cost factor [64].

The building geometry and orientation along with physical aspects of the building envelope and window details were optimized simultaneously to achieve the optimization of functional objectives (Fig. 4). Building space layout variables like orientation, geometries, number of stories, room configurations, along with space perimeter variables like wall. roof, window and shading configurations, material characteristics as well as functional requirements of the space have been optimised to enhance energy performance parameters like heating, cooling, lighting EC, and comfort parameters and also to discover the mutually beneficial relationship between them via optimization procedures using selected algorithms [13, 51, 54]. Along with energy performance and comfort parameter the cost management which includes LCC, material cost, global cost, and investment cost are also the main functional objectives in many MO research. Lin, Y et al. chose to optimize 19 continuous design variables, with the target functions being thermal load and annual discomfort degree hours. These variables included different concrete and insulation thicknesses, solar radiation absorbance for each exterior wall and roof, and window-to-wall ratios for each façade [34].

Ascione et al. considered 16 design variables relating to set point temperatures, plaster radiative characteristics, thermo-physical properties of envelope materials, window type, and building orientation of a residential building located in four different climate zones in Italy for a MO to minimize primary EC, energy-related global cost, and discomfort hours [13]. It has been observed that a major portion of an office building's net EC is related to window heat loss and cooling requirements caused by solar radiation, while also reducing lighting EC. Because solar radiation via windows has different impacts on building EC and comfort in the winter and summer, window design is a complex multi-objective challenge[45]. Building position, window, and shading configuration settings, including window materials, installation angle, and depth of overhangs, have all been considered to minimize heating, cooling, lighting EC, and discomfort hours, as well as to discover the mutually beneficial relationship between them via ha optimization procedures using selected algorithms[13, 45, 51, 54]. The annual EC expenses are based on the building's primary energy sources and annual carbon dioxide emissions in the atmosphere [5]. In this context, research aimed at enhancing building EP has stimulated the interest of several researchers from around the world [3]. In general, along with space layout variables the perimeter parameters like window and shading design along with wall construction detailing affect the building energy performance and indoor environmental quality (IEQ) for occupant comfort as well as cost factor [61]. The window, wall and shading material properties which includes U-value, transmittance values, insulation along with their design, orientation, placement with different incremental values are highly optimised to achieve desired energy performance, comfort level and cost management, which also have an impact in reducing environmental emissions.

3.3 Multi-objective optimization algorithms and simulation tools

Optimization approaches for building design are developing as a captivating tool for constructing energy-efficient buildings that meet a variety of goals [26]. Because there are various optimization alternatives accessible for each of the architectural design layout characteristics of the building, and there are many viable design solutions. The search for the ideal design combination is a demanding endeavour that becomes significantly more difficult when many performance criteria must be met. A building simulation optimization strategy is used to find the optimal combination of energy-efficient design elements. It does this by combining building energy simulation models with optimization algorithms to find the ideal parameters for structures that meet a specific set of desired goals. An optimization procedure for a building simulation consists mostly of two elements: building energy models and optimization algorithms. The optimization algorithm looks throughout the architectural space for a design solution that, when combined with the selected set of envelope parameters, will best meet the specified objectives. In contrast, building energy models assess the design solutions' fitness by analysing how the building will behave during its operational phase [49].

The energy simulation model EnergyPlus, DOE-2, TRNSYS, IDA-ICE, and Radiance software are widely applied simulation engines and software packages for optimizing building EP in the review articles. DB, Rhino Grasshopper, and open studio are just a few of the software packages available for building modelling and simulation and also acted as

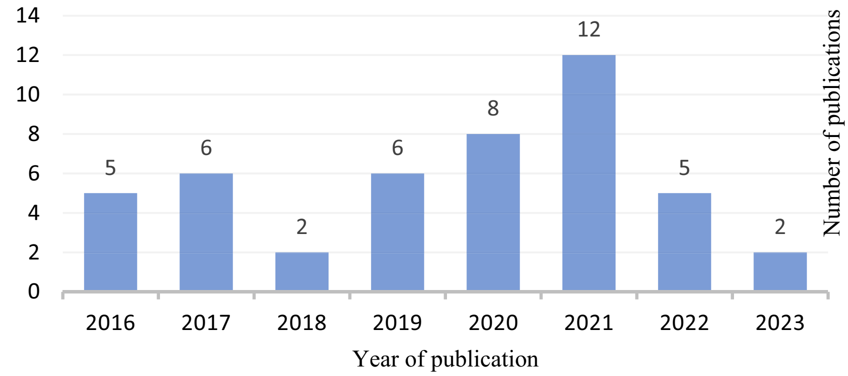


Fig. 1 Year wise publication trends from reviewed articles

a graphical interface to the EnergyPlus simulation engine. These building simulation softwares helps to generate the energy simulation model based on the optimization targets and variables that have been defined in the studies. The review shows that MATLAB was explored to perform optimization analyses together with TRNSYS, and EnergyPlus software, in 30 studies. MATLAB is the most widely used platform for optimization. It is followed by mathematical optimization, GenOpt, JEPlus, BeOpt, mode FRONTIER, ENEROPT, etc. From the review, more than 10 researchers investigated to conclude that the EnergyPlus SE coupled with the optimization tool MATLAB implied in most algorithms like GA, NSGA-II [4, 11, 38, 42, 51], MOGA [11, 17, 30] MOPSO [11], MODE [11] to optimize the energy and cost-efficient related objective to get the effective results from MO technique. Python and MATLAB were the most used programming languages for developing optimization methods**.**

About 8 researchers used the EnergyPlus simulation engine in conjunction with DB as a visualization tool in this investigation. DB performs far better than other software when it comes to defining building geometry, segmenting thermal zones, and defining pertinent thermophysical property parameters for the building envelope, internal gains, shading overhangs system, lighting management, and HVAC system [45]. Open studio in another software prominently coupled with EnergyPlus which is an open software and comparatively found to be less reliable than DB. Since there is a limitation in the model development of a building in DB software, the rhino Grass hopper gained more popularity among the reviewed articles from past 5 years because of its parametric approach and design flexibility. The highest studies with 8 numbers utilized Rhino Grasshopper and related plugins as optimization software to analyse the energy performance, comfort and cost factors.

The top 4 MO algorithms from the literatures are analysed further to identify their efficiency on functional objectives of energy performance, environmental performance and cost analysis factor. In most of the articles energy performance objectives are studied using NSGA-II and aNSGA-II algorithms where as MOPSO and MOGA used to analyse the environmental performance factors like comfort, emissions etc. (Fig. 5).

According to Jing Zhao et al., the jEplus + EA linked NSGA-II algorithm is a powerful tool for architecture and engineering optimization. Unlike Matlab and Rhinoceros Grasshopper, jEplus + EA does not require designers to create sophisticated optimization engine programs, construct

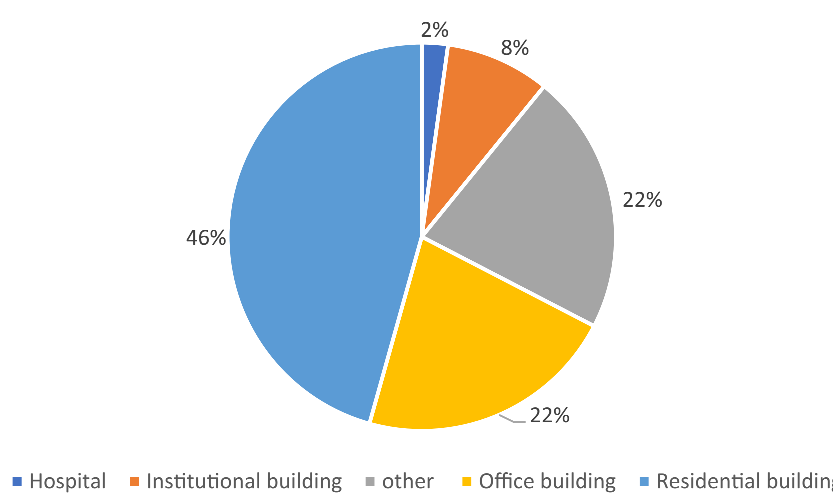


Fig. 2 Building typology publication trends from reviewed articles

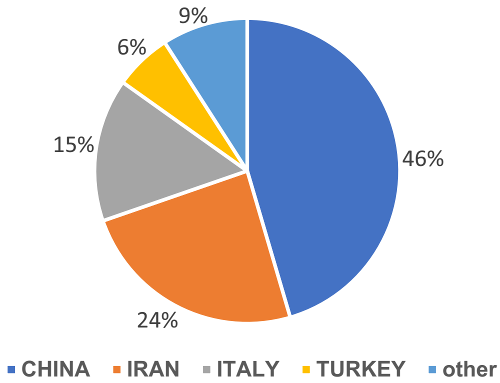


Fig. 3 Location wise publication trends from reviewed articles

complicated mathematical expressions of objectives, or make intricate connections, which is a significant advantage for non-programming designers. Binghui Si et al. used a surrogate model created by the ANN in conjunction with the multi-objective algorithm NSGA-II to increase energy efficiency and indoor thermal comfort in a newly constructed building. To choose the best algorithm for the optimization problem, the performances of four commonly used MO algorithms, namely, NSGA-II, MOPSO were compared using the research performance criteria. The results showed that the effectiveness of NSGA-II is best in all performance aspects, followed by MOPSO, whereas ES and MOGA are not competitive, with MOGA appearing to be sensitive to the parameters of the research [39].

Ascione, F. et al. proposed a multi-stage MO that combined MATLAB with EnergyPlus to consider the HVAC system and thermal characteristics the envelope parameter of a multi-zone residential building in a Mediterranean-climate of Italy. They used mono-objective GA and bi-objective GA to identify the cost-optimal building thermal design in the presence of an enhanced simulation-based model predictive control (MPC) strategy for space heating and cooling operations [29]. He also presented CASA, a multi-stage framework for cost-optimal analysis using MO and artificial neural networks, for the rigorous assessment of cost-optimal energy retrofit in another research [30]. Dino & Üçoluk offered a design to handle building performance challenges while also considering design decisions such as building shape, spatial layout, orientation, and envelope articulation. Genetic optimization is used in two stages by the optimization application Multi-objective Architectural Design Explorer (MADE). In order to maximize the energy and DL performance of the structures, MADE first uses a single objective GA to produce building layouts that meet formal, topological, and placement requirements. Next, it uses a MOGA to calculate the opening sizes of the generated layout or layouts [32]. Ascione, F et al. proposed Harlequin, a three-phase structure related to the implementation of a GA, smart exhaustive sampling, and finding the optimal design solutions to optimize design variables like building geometry, systems and envelope details while considering different energy, comfort, economic, and environmental performance indicators[29]. Delgarm et al. proposed a novel multi-criteria optimization using NSGA-II with the architectural design parameters and their corresponding objective functions, which demonstrated that even though the annual lighting energy demand of an office building increases by 1.0% to 4.8%, the annual cooling load decreases from 55.8% to 22.7%, and the total energy demand decreases 76.4% to 42.2% when compared to the baseline model in the cold climate [4]. Khoroshiltseva et al. used an m-EDO technique that combined Harmony search and Pareto-based procedures to design shading devices with an appropriate shape area of 7.84 m^2, reducing overheating of building space by roughly 20.19% and EC rate [26]. We can find that NSGA-II is the most used algorithm from the maximum

Table 2 Building performance factors and associated functional objectives in reviewed articles

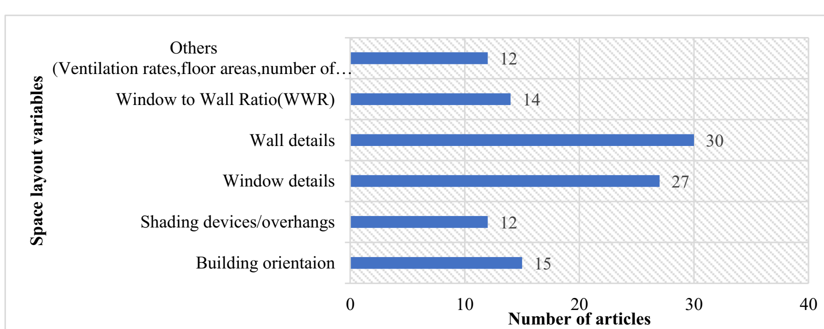
Building performance factors	Functional objectives	Authors
Energy performance	AED, AEC, HL, LL, ATL, CD, CL, EC, ECO, ED, EE, EP, ES, EUI, HD, HL, LL, TEC, TED	[5–7, 13, 17, 25–62]
Comfort environmental performance	AC, AAPPD, CO_2, DI, DL, DA, GHG, ITC, ITE, OT, PMV, PPD, SR, SSC, TC, TDC, TL, UDI, VC, VP, Comfort, Cooling degree-hours, OT, Space efficiency performance during summer season, DGI, Discomfort hours, ED impact on summer comfort, Heating degree-hours, Impact on summer comfort, Lightning discomfort, Minimum number of discomfort hours, Polluting emissions, Thermal discomfort time, Total number of discomfort degree hours, TPMVD over a whole year	[5, 7, 11, 13, 25–27, 29–34, 36–39, 41–45, 47–50, 52–62]
Cost factor	GC, IIC, IC, LCA, LCC, TCO, ECO, AEOCO, Economy, GCO savings, Operating cost for conditioning of space, Construction & installation costs	[5, 6, 13, 29–31, 33, 34, 36, 43, 50–52, 57]

Table 3 Building design variables identified in reviewed articles

Building design variables		Authors
Space layout parameters	Climate, building orientation, building geometry, total floor area, building width, floor height, number of stories, core space, room rotation	[4–7, 13, 17, 25, 27, 28, 32, 33, 36–38, 45, 49, 51, 53, 54, 56, 57, 60–62]
Envelope (Space perimeter) parameters		
Design aspects	Geometric configurations of envelopes. Shading devices -installation angle, depth, dimensions, location, system, shape, control, louvers, Windows -types, WWR, size (height, width), orientation, roof types, external/internal wall types	[4–7, 11, 13, 17, 25–28, 30, 31, 33–45, 47–49, 51–54, 56–59]
Material property	Absorbance of solar radiation for each exterior roof/wall, external wall, shading material, Insulation of envelope, type of insulation, Insulations for floor/roof/outer wall, internal thermal mass, radiative properties of plasters, thermal mass, Thermal properties of roofs/opaque walls, thermal transmittance of roof, thermo-physical properties of envelope, SHGC, VT of exterior window, Wall Material Density, Wall Solar Absorptivity, Wall Specific Heat, Wall Thermal Conductivity, U-Value -wall, window transmittance, window glazing, window materials, window blind infiltration rate, external wall type, glazing material properties, glazing type, internal wall types, overhang specifications, wall/Roof thickness	[5, 7, 11, 13, 17, 25, 27, 29–31, 34–40, 42–45, 48–54, 57, 59]
Construction detailing	External wall types, flat roof construction, glazing material properties, glazing types, overhang specifications, partition construction, thickness of wall, roof, different concrete thicknesses	[4, 5, 7, 17, 27–31, 36, 37, 39, 40, 45, 48, 49, 51–54, 56, 57]
Functional (space character) parameters	Active Strategies, air tightness grade, Carbon intensity, cooling /heating setpoint, HVAC, natural ventilation rate, passive Strategies, thermostat set points	[5–7, 25, 29, 39, 43–45]

number of researchers implementing it along with EnergyPlus and TRYNIS in the framework of MO to investigate the energy, comfort and cost performance of the building towards efficiency leading to more sustainable design [35, 42, 57]. MOGA is the second-highest-used algorithm in the reviewed articles. Ascione et al., in much of their research on MO for EP and cost-optimal analysis coupled the optimization tool MATLAB with the EnergyPlus SE and in a couple of research used DB software as a visualization tool for the study building model [28–30]. There are 4 number of researches highlighted the intervention of Artificial neural network with optimization algorithm NSGA -II to reduce the consumption time of MO to optimize energy demand cost factor along with environmental factors like GHG emission, DL, and CO_2 emission by researchers. When faced with an energy-efficient design optimization problem, the algorithm

Fig. 4 Major space layout variables considered in the review articles



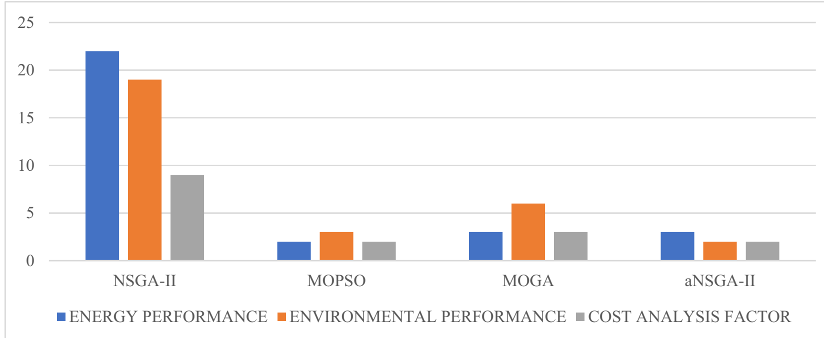


Fig. 5 Analysis of MO algorithms on functional objectives

should be carefully chosen depending on the nature of the problem and the most important performance indicators. The appropriate multi-objective algorithms can be chosen based on their performance characteristics, which include validity, speed, coverage, and locality. European countries in 2020 used the advanced algorithm aNSGA-II in MO along with NSGA-II and MOGA to mainly on energy performance and cost management along with environmental emissions[5, 6, 43]. By using aNSGA-II, it was possible to significantly reduce the computational time and identify the multi-objective optimal solution. This solution was able to maintain an almost 60% lower investment cost compared to other criterion-optimal solutions while reducing annual energy demand by 49.2%, annual energy costs by 48.8%, and annual CO_2 emissions by 45.2% [43].

4 Conclusions

The MO method has seen significant growth in the construction industry over the last 5–6 years. From the review we can observe that there is negligible multi objective optimization research done considering only the space layout design on energy performance study. Most of the studies focused on space perimeter variables in the study of optimization on performance of the buildings. along with space layout variables from the review, wall construction details with 65%, window details with 59%, shading details with 28% and window to all ratios with 22% are investigated. Window design and detailing appears to be complex and significant optimisation task in contribution to building energy performance, DL and occupant comfort especially in buildings like offices, institutions as well as residences. WWR optimization plays a major role in enhancing energy performance and user comfort in any buildings along with cost effective strategies as per the researchers. The building orientation also played another important variable in the building energy optimization process with 31% of reviewed studies. Based on a study of the optimization targets, 3 separate categories could be identified, with the majority of the examined research focusing on energy-related objectives as opposed to cost analysis factors and environmental performances. Material characteristics as well as properties to be optimised along with spatial configuration or design to get effective energy performance, occupant comfort in the building along with cost effectiveness. The cooling load was found to be a main functional objective in many reviewed articles which is addressed by considering perimeter parameters as effective variables in the MO framework. The thermal comfort were the next highest studied functional objectives through MO method. NSGA-II identified the most popular algorithms among 50% of researchers, of which 85% are used in conjunction with EnergyPlus in the MO framework to study the energy, environmental and cost performance due to its good quality solutions and diversity preserving mechanism, which give users more flexibility to estimate their preferences with diverse objectives and variables. To handle computational obstacles as well as raise energy-related issues to building design, an integrated strategy for optimizing both spatial layout and building performance is important. There has been a lot of work done on building algorithms and software to improve the art of establishing energy-efficient designs that contribute to sustainable architecture. The architects and designers can contribute significantly in optimization to minimize building EC and cost in their design in adaption to local restrictions, usage needs, investment scale, etc. Since most of the studies focused on residential, office and educational buildings, there should be greater research into complex structures like hospitals, which have a wide range of functional requirements as well as occupant comfort levels including specialized design aims. Very few studies have examined hospital design typologies in terms of simulation-based multi-objective optimization, considering comfort, cost, and spatial arrangement in relation to energy performance. For healthcare buildings, good energy planning and management based on the principles of energy efficiency and cost-effectiveness is required, without neglecting functional needs or architectural flexibility. There is a need for an effective multi-objective framework to improve the EP of healthcare facilities, which currently consume more energy than other building typologies.

Author contributions Harshalatha -Wrote main manuscript text, Conceptualization, Analysis and Writing—original draft preparation.

Shantharam Patil—Resources, overall supervision, Writing—Review and editing the manuscript.

Pradeep G Kini—Resources, Supervision- Review and editing the manuscript.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

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Comparative Analysis of Rank and Roulette Wheel Selection Strategies in Genetic Algorithms for Spatial Layout Optimization

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***Abstract*—Autonomous urban planning, facility layout design, and interior design are critical and meticulous tasks that require the optimization of space arrangement. One of the main purposes of space arrangement is to achieve high space utilization with a non-complex arrangement for emergency assistance, particularly to enhance pedestrian safety in panic situations. This study explores the optimization of spatial layouts by employing Genetic Algorithms (GA) due to their robust search capabilities. However, spatial layout size limitations may affect the search capability and significantly impact space arrangement and utilization. Hence, this study presents a comparative study of two GA selection operator methods: Rank Selection (RS) and Roulette Wheel Selection (RWS) for determining the effectiveness in optimizing spatial layout arrangements and space utilization. The results demonstrated significant improvements in crowd flow management, with the RWS method showing the highest fitness value despite slower convergence compared to RS. The study highlighted the impact of different methods on the convergence of the multi-objective fitness value based on space elements such as overlapping and standard walkway distances. While both selection methods proved to be effective in optimizing space utilization, the RWS method demonstrated greater computational efficiency while still adhering to standard layout designs. This efficiency helps to ensure smoother evacuation and ease of movement during emergency situations.**

***Keywords*—Genetic algorithm; optimization; spatial layout arrangement; space utilization; urban planning; facility layout design; rank selection; roulette wheel selection**

I. Introduction

Pedestrian safety is a critical aspect of urban planning, especially in emergency scenarios. A surging pattern of fatalities due to entrapment incidents in recent years has led to the increased demand for safer building designs and effective emergency protocols. In response, numerous studies have been carried out to uncover the impactful spatial features that significantly influence the pedestrians' movement during the evacuation process. The previous studies have proposed an enhanced spatial layout design that aimed at reducing casualties and improving overall safety [1-6].

Spatial layout arrangement involves the organization and positioning of elements within a given space, serving as a crucial aspect of spatial layout design. This design practice is essential in the planning and construction phases of housing development, ensuring efficient use of space and optimal functionality. The design will outline the blueprint of the layout by assisting in the arrangement of the assigned elements for reaching the suitable order, sorting, grouping, alignment, function, and scale to the layout size. In later times, the spatial layout was designed by employing the manual design method and focusing on the standard design procedure and being influenced by the local demographic structure's culture and current trend [7][8]. However, with the advancement of computer intelligence systems, spatial layout design application tools have been introduced for autonomous spatial layout design [9-11].

The demand for autonomous space arrangements has surged significantly, driven by the need for multi-objective functions in design. However, due to some limitations on the complex computation of the various parameters, the autonomous spatial layout arrangement generated a non-fitness design and constructed a less scalable and less functional floor plan [12]. Traditional autonomous layout designs often fall short in managing crowd movements during panic situations. Ineffective layouts have resulted in numerous entrapment incidents during emergencies [13]. Research by [13] has highlighted the significant impact of optimizing interior resources' allocation and occupancy within the layout. Hence, arrangement and allocation optimality are the new approaches to ensure the traffic flow and the safety of the pedestrians in the layout. This approach can improve the overall quality of life and the environment rather than focusing solely on the layout structure, and functionality.

However, previous research has shown that optimizing layout utilization can lead to several issues, including overlapping objects, low space occupancy, and non-standard layout design [14-23]. Hence, it is necessary for the computer-aided layout design to exploit a suitable optimization method for constructing the high occupancy elements' layout while adapting the architecture building design policy in constructing the space arrangement. This study addresses this gap by proposing an optimized spatial layout that leverages advanced algorithms to enhance safety and efficiency.

The study begins by introducing the optimization method, Genetic Algorithm (GA) as a suitable approach for computing multi-objective functions, and followed by a methodology section, discussing the GA framework, the selection process, and the rank selection techniques adopted in this study. Next, the results section presents the findings, and the conclusion summarizes the key outcomes and suggests directions for future research.

II. Genetic Algorithm

In [24], the authors show that the optimization with multi-objective functions can be inspired by the principles and inspiration of biological evolution. Numerous studies have been proposed in layout design optimization using bio-inspired algorithms for applications such as optimal job scheduling, structural design, cost minimization, flow control, and space occupancy. For example, research by [25] explored the use of Genetic Algorithm (GA), Differential Evolution (DE), Artificial Bee Colony (ABC), Charge Search System (CSS), and Particle Swarm Optimization (PSO) algorithms to optimize robot workcell layout in manufacturing systems, focusing on optimizing layout area and robot operation time. Meanwhile, research by [26] proposed optimal design solutions for planar trusses in structural roof articulations using Elitism-Based Genetic Algorithm (EBGA), Ant Colony Optimization (ACO), Artificial Honey Bee Optimization (AHBO), and PSO, with an emphasis on minimizing truss weight. Research by [27] explored the optimization of construction layout arrangements to reduce transportation costs, comparing the performance of PSO, ABC, and Symbiotic Organisms Search (SOS) algorithms. Additionally, research by [28] applied a GA to garden landscape design, aiming to adhere to the fundamental principles of landscape and urban design while meeting people's needs, showing improvements over traditional methods. Research by [13] utilized GA for resource allocation to enhance spatial layout design, and research by [29] employed GA to optimize land use for sustainable land resource management. These studies highlight that only a small number of works focus on indoor design and spatial element arrangement, despite the growing use of bio-inspired algorithms in layout optimization. Building on this foundation, the focus of this study is to evaluate and compare the effectiveness of GA, PSO, ACO, and ABC specifically for optimizing spatial layout arrangements in the context of urban planning and design.

One of the suitable bio-inspired algorithms is Genetic Algorithm (GA). GA is the adaptation of the natural evolution process inspired by Charles Darwin's theory of genetic evolution for the survival of the fittest genes. Genetic evolution is based on the genetic structure, and the natural selection operation carried out for the genes' transformation and modification for the next generation [30] [31]. The principles of Darwinian natural selection are based on heredity, variation, and selection. In selecting a GA for optimizing spatial layout arrangements, its flexibility and adaptability make it a compelling choice. GA is particularly effective for complex problems with large solution spaces. The ability to perform global searches and avoid local optima makes GA well-suited for layout optimization, where multiple variables and constraints must be balanced. Additionally, GA can be easily modified and combined with other techniques to enhance its performance and tailor it to specific problem domains, such as spatial layout optimization. This adaptability, combined with their proven success in various domains, makes GA a suitable and powerful method for optimizing spatial layout arrangements, ensuring efficient use of space while meeting design criteria.

GA has three operators: 1) Selection, 2) Crossover, and 3) Mutation. These operators will converge the genes to find the best fitness function to generate the fittest final offspring. The GA process will begin with the initialization of the random production of N number of chromosomes, with each chromosome containing an array of gene bits. The objective function will be assigned for determining the fitness values of the chromosomes. There are many types of selection schemes that can be used for discriminating the fittest values and the lowest values of the spatial layout design solutions; 1) Rank Selection (RS), 2) Roulette Wheel Selection (RWS), 3) Tournament Selection (TS), 4) Stochastic Universal Sampling (SUS), and many more.

The RWS is the proportionate fitness selection that represents the circular wheel that is divided based on the probability of the fitness value from the whole values and represented in the circle's degree value (the ratio of individual fitness value and the total fitness of overall individuals in the population). The fittest individual will have a bigger degree region in the circle and have a greater chance of being selected during the spinning process. Hence, the probability of being the fittest individual is high. A fixed point will be generated randomly to represent the real roulette wheel spinning. The fitness values selected by the fixed point will be selected as the parents. The RWS is also implemented in SUS. However, in SUS selection, there are multiple fixed points marked as the random stochastic selection, and the parents can be obtained in a single spin. This setup will be able to encourage the highly fit parents to be selected at once.

RS ranks individuals based on fitness values and applies a roulette-wheel-like method for parent selection, where each individual has an equal share (same probability) of being selected as the parents. The selection sometimes will make poor selections of parents who have a possibility of selecting the least fit solutions for reconstructing the fitter individuals. TS is the selection strategy that selects the k-number of solutions from the whole available solutions and comparing the fitness values among them. The fittest candidates among the k-individuals will be passed on to the next-gen. The probability of the selection is based on the candidate's likelihood in the tournament group. The tournament size will be able to affect the selection process as the less fit solution will have a low possibility of being selected in the large tournament group as it must compete with the stronger candidate with a high fitness solution. Based on the type of selection schemes, RS and RWS have been selected to be compared as one of the selected selection methods in comparing the spatial layout designs to find the higher fitness parents for the recombination and diversification of the offspring. This selection scheme has been selected due to its ability to contribute to the high convergence rate, as the fittest parents are able to construct better offspring with fitter fitness values.

TS and SUS selection methods are also able to give a high possibility of convergence rate. However, the random selection for the first step of the methods will contribute towards the divergence of the parents and will have a high possibility of not being able to construct the offspring that have the best inheritance from the parents. Whereas both RS and RWS are able to create a great balance between convergency and divergence of the offspring construction as there will be a high possibility of the selection approach to select the fittest parents, and there are also chances of selecting less fit parents but with low possibility. Therefore, this research focuses on utilizing RS and RWS for the parent selection phase in GA.

In light of the research problem, the goal is to transform spatial layouts into safer, more navigable spaces during emergencies. In contrast to existing studies that focus solely on layout efficiency or cost-based metrics, this study offers a novel comparative analysis of GA selection strategies using RS and RWS for managing the integration of multi-objective functions that include crowd flow safety and layout efficiency. The aim is to achieve autonomous high occupancy space arrangements that comply with spatial design standards and improve pedestrian movement flow, particularly during evacuation processes.

III. Methodology

Genetic Algorithms (GA) are powerful optimization tools inspired by the process of natural selection. In the context of constructing a spatial layout, GA facilitates the generation of optimized solutions through iterative processes. This research study focuses on comparing two selection methods; Roulette Wheel Selection (RWS) and Rank Selection (RS). Both methods are evaluated using a consistent approach involving uniform crossover and bit flip mutation to ensure a fair comparison.

A. Genetic Algorithm (GA) Framework

The three fundamental phases need to be highlighted for constructing a spatial layout based on GA's design; 1) the selection phase, 2) the crossover phase, and 3) the mutation phase. Fig. 1 shows the fundamentals of genetic evolution processing for optimizing genetic fitness.

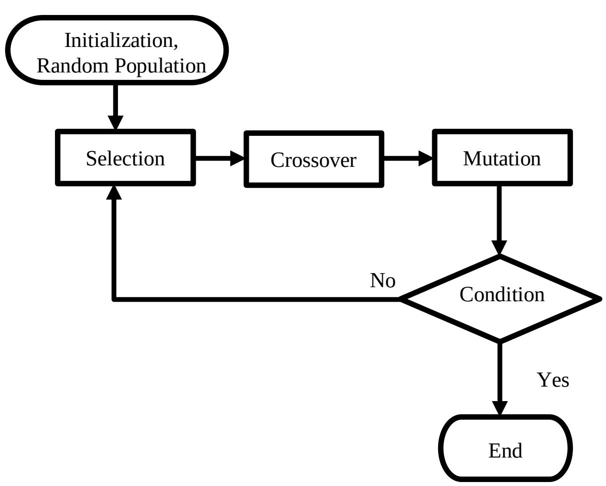


Fig. 1. Fundamental genetic evolution process

The optimized spatial layout arrangement is constructed based on the adaptation of the binary GA as shown in Fig. 2.

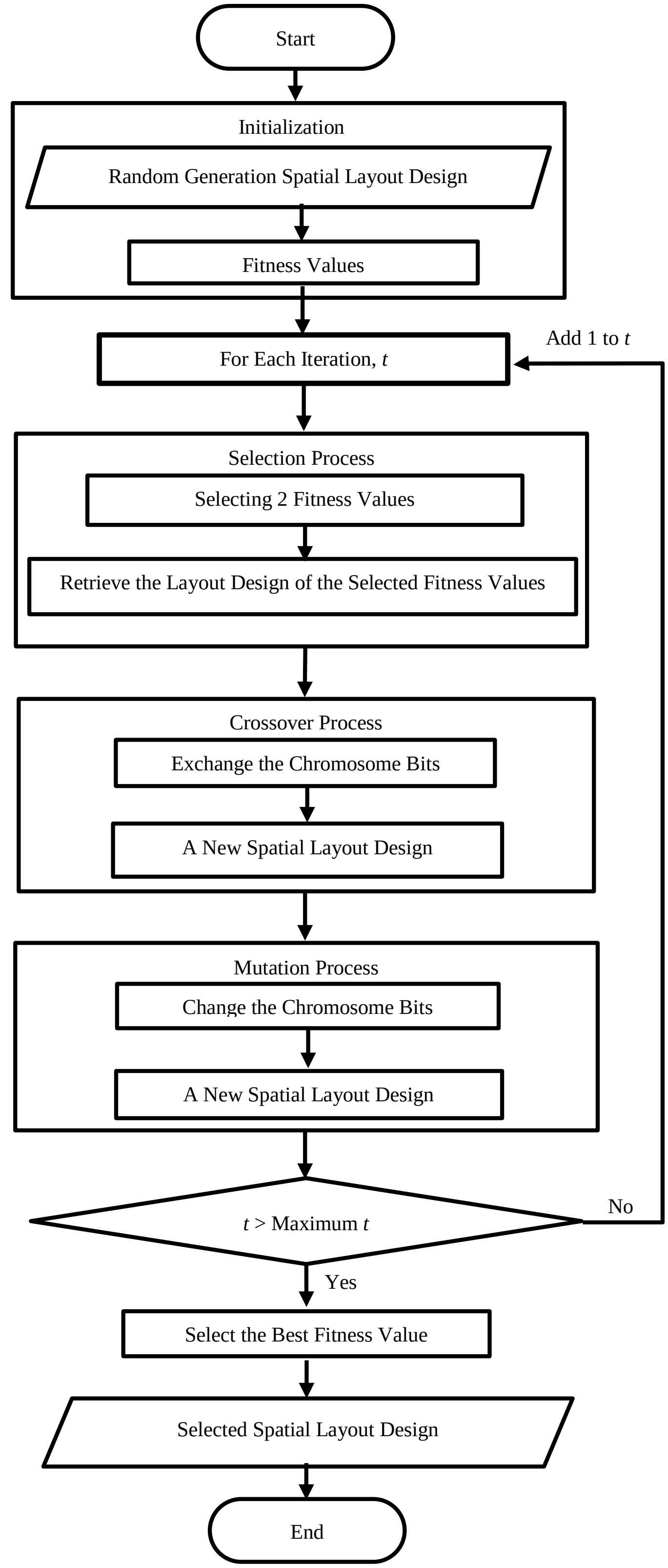


Fig. 2. Adaptation framework on GA in constructing an optimal spatial layout.

Pseudocode 1 GA Based Spatial Layout Construction Optimization

Load training samples
begin
Step 1:
  Generate the initial layout population z_i, i = 1 ... SN
  Evaluate the fitness (f_i) of the population
  Initialize iteration cycle = 1 ... SN
Step 2:
  set cycle to 1
  repeat
    //Selection Phase
    Apply greedy selection for f_i of i, $i(h_1)$ and $i(h_2)$
    //Crossover Phase
    Exchange the chromosome genes of $i(h_1)$ and $i(h_2)$
    //Mutation Phase
    Change the chromosome genes of $i(h_1)$ and $i(h_2)$
    Calculate the offspring's fitness f_i, $h_1(f_i)$ and $h_2(f_i)$
    Search for least fit individuals, $i(g_1)$ and $i(g_2)$
    //New generations
    Replace spatial layout g_1 and g_2 with h_1 and h_2
    cycle = cycle + 1
  until cycle = SN
Step 3:
  Memorize the best solutions z_i
  Output the best spatial layout found
end

Based on the framework in Fig. 2, Pseudocode 1 is developed to show the fundamentals for spatial layout design optimization based on GA, adapted from the algorithms overview by McCall [32]. Based on Pseudocode 1, the GA parameters must be initialized by setting the population size, SN to 50. Each individual in the population, z_i is generated with a unique spatial layout design, which includes 300 obstacles. The six obstacles are combined into one large obstacle representing the furniture. Each of the population fitness values f_i will be calculated based on the objective function: 1) overlapping of the elements generated as static obstacles, and 2) distance 1.2 m from doors and walls to meet the standard of interior design.

The number of furniture elements left in the layout after the overlapping process and exist within the layout that has a 1.2 m distance range from doors and walls has been calculated as the total fitness value of the layout. The iteration cycle has been initialized, and in this research, the iteration is set to 100. When entering the iteration cycle, the process will be entering into three phases: 1) selection phase, 2) crossover phase, and 3) mutation phase. A solution acceptance rule is implemented to ensure that the elements do not exceed the allocated space within the layout. Based on this rule, the number of furniture elements must not exceed the initial 300 loaded obstacles, even after 100 iteration cycles. This constraint ensures that the layout remains within the grid limits and complies with interior design standards, particularly by preserving sufficient walking space for pedestrians to access exit points.

B. Selection Process

The selection process in GA determines which individuals from the current population will be the parents to the next generation. This process mimics natural selection in choosing the fittest individuals based on performance or fitness scores. The primary goal is to ensure that high-quality traits are preserved and propagated, thereby improving the overall solution quality over successive generations. Every method available for selection operation has a unique approach to balancing exploration and exploitation within the search space.

1) Roulette Wheel Selection (RWS). The RS method is implemented to find the parents for the further recombination and restoration process of the offspring. This discrimination phase offers selective pressure that applies greedy selection based on the fitness proportionate selection approach as a method in guiding the evolution of spatial layout design. The fitness value fi has been determined from each of the solutions z_i of population i. The roulette slot size probability will be computed based on Eq. (1):

$$p_i = \frac{f_i}{\sum_{i=1}^{SN} f_i} \qquad (1)$$

where, the p_i is the probability of each of the fitness values fi from the whole fitness values in the population i and SN is the maximum number of populations, i. The cumulative probability, q_i, for each chromosome is calculated based on Eq. (2):

$$q_i = \sum_{i=1}^{SN} p_i \qquad (2)$$

here, p_i is the probability of each of the fitness values, and the cumulative probability has been calculated for each of the population i until reaching the maximum number of the population, SN. The fixed point of the roulette wheel can be constructed based on the random number generation r, where $r \in (0, 1)$. The parents are selected based on the condition; if $r < q_1$, then the first solution, z_1 is chosen as the parent. Otherwise, if $r > q_1$, the algorithm searches for another solution z_i such that $q_{i-1} < r \leq q_i$ and selects it as the parent. The steps have been repeated for two times for each iteration cycle to find the two parents' spatial layout to be recombined and explored for the fittest offspring.

2) Rank Selection (RS). RS method is implemented to identify parents for further recombination and restoration processes in generating offspring. Unlike the RWS method, which relies on fitness proportionate selection, RS imposes selective pressure by ranking individuals based on their fitness and then selecting parents according to their rank, rather than their absolute fitness values. This approach ensures that even individuals with lower fitness have a chance of being selected, thus maintaining diversity within the population.

In RS, each individual solution z_i in the population is assigned a rank r_i, with the fittest individual receiving the highest rank. The selection probability for each individual is then determined based on its rank, not its fitness value. The probability of selecting an individual is calculated using a rank-based probability distribution, where higher-ranked individuals have a greater chance of being selected as parents. This can be represented by Eq. (3):

$$p_i = \frac{2x(SN - r_i + 1)}{SN \times (SN+1)} \quad (3)$$

where, p_i is the probability of selecting the individual with rank r_i, and SN is the maximum number of individuals in the population. This rank-based probability distribution ensures a more uniform selection pressure compared to fitness-proportionate methods to avoid cases where a single individual with a much higher fitness dominates the selection process. The cumulative probability q_i for each individual is calculated based on Eq. (2), as the formula is similar. However, compared to RWS, the p_i is the probability of each of the ranks, and the cumulative probability has been calculated for each of the populations i until reaching the maximum number of the population, SN.

Similar to RWS, the fixed point of the roulette wheel can be constructed based on the random number generation r, where $r \in (0, 1)$. The parents can be selected by the condition; if $r < q_1$, then the first solution, z_1 has been selected as the parent. However, if $r > q_1$, then the other search has been made on the other individual solution z_1 such that $q_{i-1} < r \leq q_i$. The steps have been repeated for two times for each iteration cycle to find the two parents' spatial layout to be recombined and explored for the fittest offspring.

RS offers a more stable selection process by mitigating the effects of disproportionately high fitness values that can dominate the selection in methods like RWS. This method ensures a balance between exploration and exploitation by allowing less fit individuals a chance to contribute to the next generation, thus enhancing the evolutionary search for optimal spatial layout arrangements.

C. Uniform Crossover

In this research, the uniform crossover has been selected, and the selected parents have been recombined with the crossover phase. Both parents' allele genes have been recombined to construct better spatial layout offspring that are able to produce fit fitness values. The uniform recombination process has examined the genes in the parents separately and recombines each of the genes based on the coin flip method. The flip coin method has randomly made the decision based on 50-50 probabilities [0,1]. If the toss is "0", the gene for both parents has been maintained, whereas if the toss resulted in "1", the gene has been exchanged between the parents. The offspring constructed from the recombination method has been explored to prevent premature convergence to the local optimal solution and diversify the genetic population via the mutation phase approach.

D. Bit Flip Mutation

The mutation phase has amended the offspring solutions to construct new solutions. In this research, the random resetting mutation has been used by selecting each of the obstacles based on the bit flip mutation function, in which the probability of the obstacles' gene selection has been set to a 0.01 mutation rate. Each of the genes of the offspring has been examined, and a random number has been generated to check the mutation rate condition. Based on the rules set, when the random number < 0.01, the mutation has occurred, and the gene bit has been flipped, whereas when the random number >= 0.01, the bit of the offspring has remained the same. The obstacles that are assigned with the random number < 0.01 have been assigned to a randomly chosen gene in the spatial layout grid.

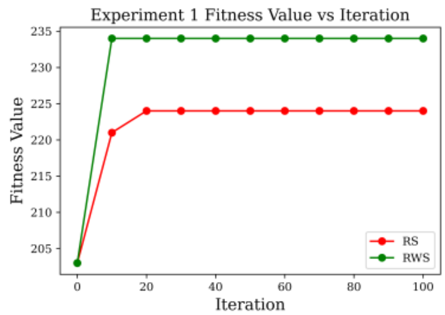
This method is suitable for spatial layout arrangement as the solutions will still provide the 50 large orders of obstacles. The fitness value of the offspring has been determined, and the value has been compared with the fitness values of the current population, f_i. The offspring constructed has been passed to the next iteration cycle as a member of the population and replaces the least fit solutions. The final population i with spatial layout solution z_i after 100 iterations have been compared, and the fittest solution will be selected to represent the selected result for the GA approach in designing an optimal spatial layout.

IV. Results

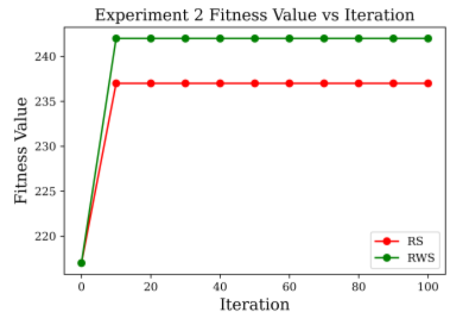
This research compared the Rank Selection (RS) and Roulette Wheel Selection (RWS) methods for constructing GA-based spatial layout arrangements. To ensure unbiased results, ten experiments were conducted, each with 100 iterations. Fig. 3 presents the graphical results of these experiments, illustrating the fitness value for every iteration of each selection method.

Based on the overall result in Fig. 3, both RS and RWS show the characteristic of GA algorithm results with premature convergence. These results align with the study's focus on optimizing spatial layout arrangements and space utilization, which are critical for applications like autonomous urban planning, facility layout design, and interior design. Given the emphasis on high space utilization and non-complex arrangements for emergency assistance, the selection of GA operators is crucial, especially in scenarios with limited spatial layout size.

Based on the observation, the highest fitness value for both selection methods shows different values throughout the ten experiments. Based on the graphs in Fig. 3, RS outperformed RWS in 20% of the experiments by optimizing the population fitness value, especially in Experiment 6 and 10. In Experiment 6, RS achieved a fitness value of 230.0 by iteration 40, whereas RWS plateaued at a maximum fitness value of 226.0, beginning as early as iteration 10. Similarly, in Experiment 10, RS reached a fitness value of 236.0 by iteration 40, while RWS plateaued at 232.0 from iteration 50 onwards. These results highlight the potential of RS for achieving faster convergence in certain scenarios.



(a) Experiment 1



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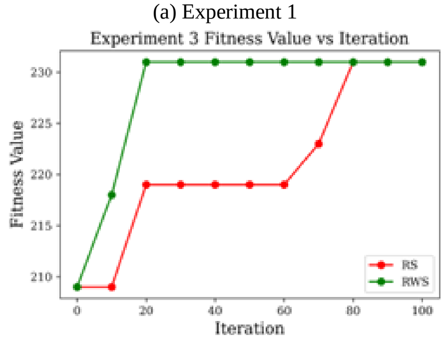
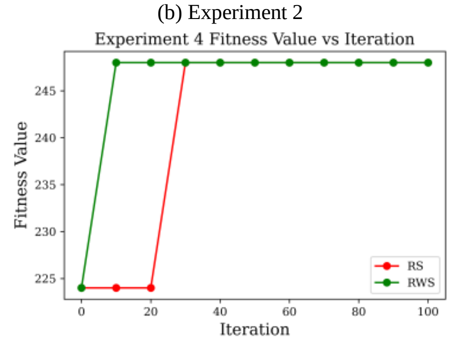


(c) Experiment 3



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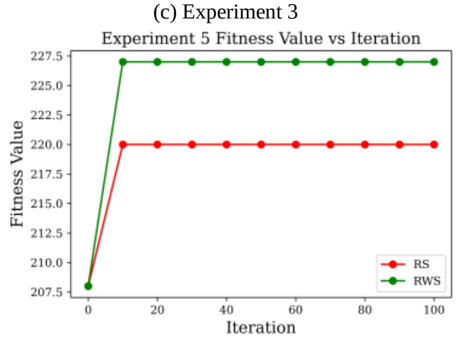
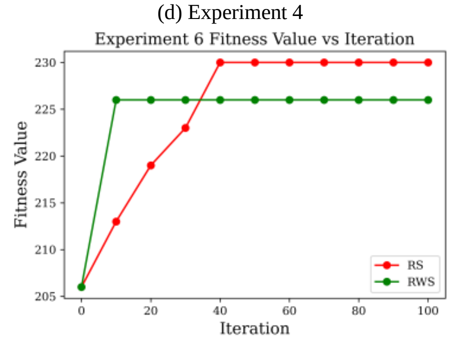


(e) Experiment 5



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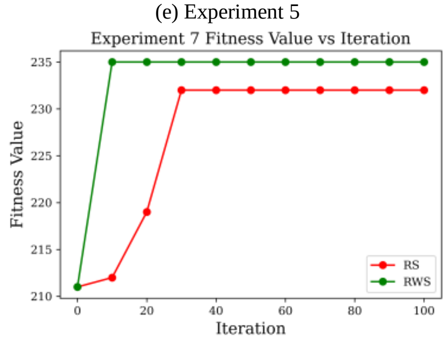
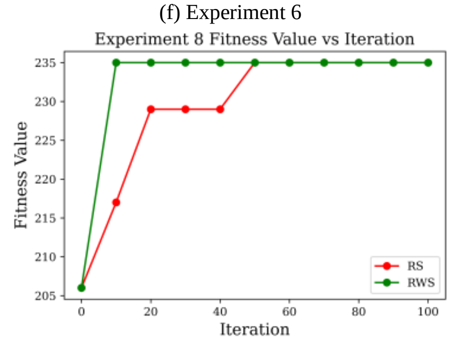
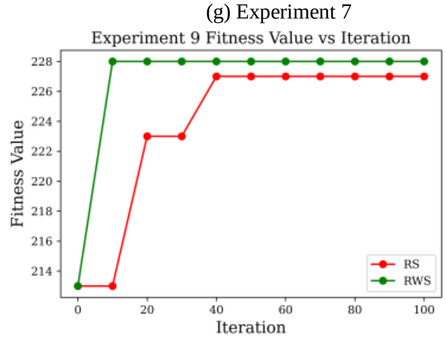


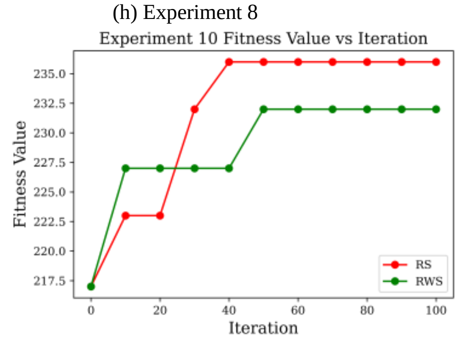
(g) Experiment 7



(h) Experiment 8



(i) Experiment 9



(j) Experiment 10.

Fig. 3. Graph comparison of Rank Selection (RS) and Roulette Wheel Selection (RWS) fitness value of over 100 iterations.

In 30% of the experiments, both RS and RWS exhibited comparable performance, achieving similar fitness values at different iterations. Based on the observations, the maximum fitness value for Experiment 3 reached 231.0 at iteration 80 using RS but was achieved earlier by RWS at iteration 20. The maximum fitness for Experiment 4 reached 249.0 at iteration 30 by RS but achieved earlier by RWS at iteration 10. In addition, the maximum fitness value for Experiment 8 reached 235.0 at iteration 50 by RS while RWS reached it earlier at iteration 10. These results indicate an overlapping convergence behavior, likely due to the limitation of layout size in accommodating all layout elements.

Furthermore, in 50% of the experiments, the RWS selection method outperformed the RS in terms of final fitness value. RWS shows better optimization compared to RS due to the offspring selection strategy that is based on the relative fitness of individuals. This proportional selection approach groups individuals by fitness level, increasing the likelihood that higher-fitness individuals are selected as parents, thereby generating stronger offspring. Compared to RWS, the selection in RS is also able to generate higher fitness values. However, due to the selection of the top 2 highest-fitness parents in RS caused the offspring generated to be too fit and unable to replace the lowest value of population members. Hence, resulting in the slow convergence speed compared to RWS. Although RWS is generally associated with slower convergence, its use of a solution acceptance rule (i.e., constraints related to layout capacity) allows it to increase fitness values earlier in the experiment, often resulting in the highest fitness value by iteration 100. Additionally, the RS selection method is computationally expensive due to the population sorting based on the fitness value compared to the RWS selection method. Fig. 4 shows the graph comparison between the processing time (milliseconds) in every experiment for the RS and RWS-based GA approach spatial layout design arrangement.

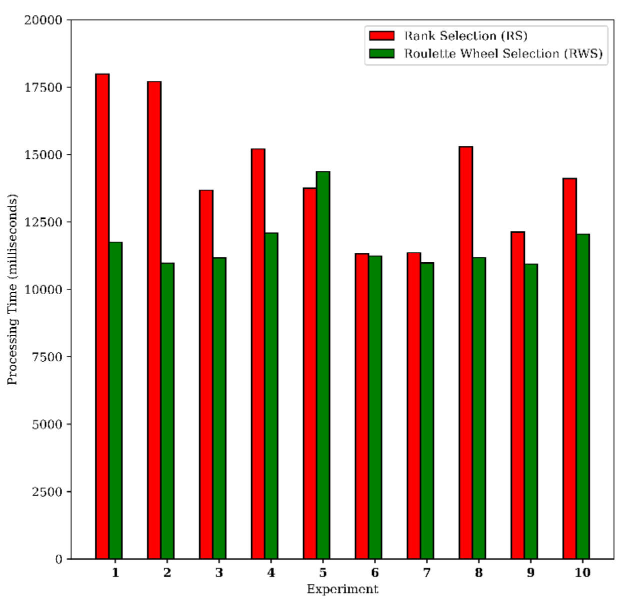


Fig. 4. Graph comparison between the processing time of Rank Selection (RS) and Roulette Wheel Selection (RWS) for 10 experiments.

Based on Fig. 4, the graph of processing time shows that RS consistently takes extra processing time compared to RWS in most experiments, with the exception of Experiment 5 as the 10% outlier, where RS recorded 13752 ms compared to 14369 ms for RWS. This result indicates that RS is generally slower in this context. In Experiments 1, 2, 3, 4, 6, 7, 8, 9, and 10, RWS shows significantly faster processing time, with 90% of the experiments showing the improvement of processing time percentage. Table I summarizes the percentage improvement of RWS over RS.

TABLE I. PROCESSING TIME COMPARISON WITH PERCENTAGE OF RWS IMPROVEMENT COMPARED TO RS

Experiment	RS Time (ms)	RWS Time (ms)	Faster Method	RWS over RS (%)
1	17991	11747	RWS	34.69
2	17708	10974	RWS	38.02
3	13681	11168	RWS	18.37
4	15209	12088	RWS	20.54
5	13752	14369	RS	-4.49
6	11320	11236	RWS	0.74
7	11359	10986	RWS	3.28
8	15292	11178	RWS	26.89
9	12130	10941	RWS	9.80
10	14110	12047	RWS	14.62

Based on Table I, among the 90% of experiments where RWS demonstrated superior performance, the results show the improvement ranging from modest gains, such as 0.74% in Experiment 6, to substantial differences exceeding 38% in Experiment 2. The most significant time reductions were observed in Experiments 1 and 2, where RWS reduced computation time by 34.69% and 38.02%, respectively, compared to RS. This substantial difference in the efficiency of these two methods is potentially due to the computation cost in population sorting based on fitness value that is required in the RS algorithm, which increases the computation complexity. RWS, by contrast, is more computationally efficient and enables faster spatial layout optimization.

Compared to the other experiments, in Experiment 5, RS was slightly faster by 4.49%, which is an exception to the trend observed from the whole experiment. This anomaly suggests that under certain conditions, particularly where early convergence occurs or solution acceptance thresholds align more favorably, RS may offer computational advantages. However, this case appears to be an outlier rather than a consistent pattern. The outlier also reflects the unbiased nature of the experimental setup, which was intentionally designed to allow either method to succeed under appropriate conditions.

Based on Fig. 4 the solution acceptance rule acts as a limiting factor for space utilization optimization, and RWS demonstrates a better balance between the fitness value optimization and processing time that making it a more practical choice for the selection process in the future GA approach for optimizing the autonomous spatial layout arrangement design and space utilization in autonomous urban planning.

V. CONCLUSION

This study aimed to evaluate the effectiveness of two Genetic Algorithm (GA) selection methods: Rank Selection (RS) and Roulette Wheel Selection (RWS) in optimizing spatial layout arrangements to improve space utilization and emergency responsiveness. Through this research, it was shown that RWS was able to outperform RS by consistently achieving higher fitness values and demonstrating greater computational efficiency. This was due to its proportional selection mechanism, which enhances the likelihood of selecting fitter individuals and accelerates convergence while maintaining layout standards for emergency situations. While RS occasionally showed better performance in specific instances, its approach often led to slower convergence and increased computational demands. The requirement for population sorting based on fitness in RS contributed to its higher computational cost. Overall, RWS proved to be the more effective method for optimizing spatial designs, meeting the study's objective of identifying the most efficient GA operator for enhancing spatial layout arrangements and space utilization in autonomous urban planning. The future research direction of this study is to explore hybrid selection methods in GA that combine the selection mechanisms and features of RS and RWS to further enhance the optimization of spatial layout arrangements in urban planning. Additional studies can be carried out to investigate the application of RWS in different urban planning scenarios to validate its effectiveness in improving space utilization and emergency responsiveness across diverse environments.

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ARTICLES FOR FACULTY MEMBERS

MULTI-OBJECTIVE OPTIMIZATION ALGORITHM FOR AUTONOMOUS SPATIAL LAYOUT DESIGN

Multi-objective optimization analysis of construction management site layout based on improved genetic algorithm / Yin, H.
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Multi-objective optimization analysis of construction management site layout based on improved genetic algorithm

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A R T I C L E I N F O

Keywords:
Construction management
Site layout
Multi objective optimization
Genetic algorithm
Ant colony

A B S T R A C T

In construction management, the rationality of on-site layout is crucial for project progress, cost, and safety. In order to improve the rationality of on-site layout, a multi-objective optimization model combining ant colony algorithm and Pareto optimal solution was constructed based on genetic algorithm, and this model was applied to practical engineering cases. The results show that in terms of computational time, the genetic algorithm takes an average of 1702.0 s, while the improved algorithm takes an average of 421.0 s, which is 1281s less and 85.9% more than before the improvement. The performance of the improved algorithm is the best, and the optimal solution can be obtained through multiple iterations. The improved algorithm has improved the efficiency of on-site layout optimization, and possesses practical application value for the layout of construction management sites. It offers a certain reference for the reasonable setting of construction management sites.

1. Introduction

Recently, as the boost of China's economy, the construction industry is an essential pillar industry of China's economic advancement, and industry advancement has prompted construction enterprises to self transform. The on-site layout (OSL) is an essential part of the construction, and project management may take consideration into the OSL. However, in the entire project construction management, there is not enough emphasis, and on-site management personnel often plan the OSL on the ground of their own experience, without a scientific management system [1]. The Genetic Algorithm (GA) is a computational model that simulates the natural selection and genetic mechanisms of Darwin's biological evolution theory, as well as a method of searching for optimal solutions (OSO) through simulating the natural evolution [2]. Ant colony algorithm (ACA) is a probabilistic algorithm utilized for finding optimal paths, inspired by the behavior of ants discovering paths while searching for food [3]. Therefore, the multi-objective optimization (MOO) model combining the global search capability of GA and the local search algorithm of ACA, as well as the Pareto optimal solution, is applied to the field of construction project management. The aim of the study is to be able to explore the solution space more comprehensively and maintain a balance between multiple objectives. The core achievements of this study are reflected in the efficiency of using GA to search for global optimal solutions and the accuracy of ACA in searching for local optimal solutions. The proposed model can explore the solution space more deeply and comprehensively for dealing with multi variable and multi constraint problems in construction project management, improving the possibility of finding the optimal solution. The proposed model applies Pareto optimal solutions, effectively achieving a balance between multiple project management objectives such as cost, time, and quality, and optimizing the overall performance of project management. The main contribution of this study is to improve the overall management efficiency and success rate of projects. The proposed model is integrated into a wider range of project management systems, providing managers with real-time, data-driven decision support. This study provides a new approach to using hybrid optimization techniques to solve complex engineering problems, and future research can explore more algorithm fusion and application scenarios based on this foundation. The research mainly includes four parts. The first part is a summary of research on the layout of construction management sites. The second part introduces the MOO of construction management site layout (SL) using improved GA. The first section is about the construction of a layout model for the construction management site. The second section focuses on MOO of construction management SL using Pareto ant colony GA. The third part is the analysis of MOO results for the layout of construction management sites using improved GA. The first section introduces the parameter settings of ACA and GA. The second section is the optimization analysis of the improved algorithm. The fourth part is the conclusion of MOO analysis of construction management SL using improved GA.

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2. Related works

The scientific and reasonable layout of the construction management SL is helpful for improving construction efficiency and systematic management. Many experts have conducted relevant research in this regard. Ning et al. utilized a hybrid GA ant colony MOO model for planning the construction SL to reduce noise pollution to workers, addressing the transportation costs and potential safety risks caused by the interaction between on-site facilities. The results indicate that the model is effective and feasible [4]. Xue and other professionals use improved biogeographical optimization algorithms to schedule the production of prefabricated components, which facilitates the formulation of more scientific and reasonable production plans, reduces costs, and improves the efficiency of the entire prefabricated building project. The results indicate that the model has a certain effect [5]. To collect and process all data used for SL modeling using systematic methods, Le's team has built a multi-objective dynamic temporary construction SL design framework to save costs and ensure preferences for temporary facility relationships. The results indicate that the model has practicality [6]. Lee analyzes the construction plan of modular projects through building information models to address the issue of on-site construction planning, and completes the application analysis of efficiency and necessity. The results indicate that this method has good effectiveness [7]. Scholars such as Schwabe, to complete the layout planning task of construction sites, combined the business rule management system of industry foundation classes and open source rule engine Drools to assist managers in decision-making tasks. The results indicate that this method can safely achieve planning tasks [8]. Li and other researchers proposed a dynamic visualization platform that combines GA and low rank matrix for dynamic planning of building component storage areas, which can automatically identify vacant locations on site in real-time. The results show that the construction efficiency of this method has been improved by 19.4%, and the processing cost has been reduced by 21.9% [9].

Improved machine algorithms have wide applications in various aspects. A large number of scholars have conducted relevant research and achieved good results. For addressing the high economic costs in the closed-loop logistics network of fresh food, scholars such as Huo Q have built a relevant logistics network model on the ground of GA. The results show that the MOO satisfaction of the model reaches 92%, which has a certain effect [10]. Chen designed an improved GA based green cold chain logistics location and path optimization method to address the distribution efficiency and cost issues of cold chain logistics, effectively reducing carbon emissions and costs during the cold chain distribution process, and accelerating convergence speed. The results indicate that this method is feasible [11]. To enhance the efficiency of urban green economy, professionals such as Liu T have proposed a model for urban green economy planning that combines machine learning and GA for simulation analysis, and measures inputs and expected outputs. The results indicate that the model is effective [12]. Ala 's team designed long-term and short-term memory and particle swarm optimization to improve efficiency and security for the classification accuracy of patient medical data. Various indicators and benchmarks were determined, and the results showed that the accuracy of this method was 92% [13]. In order to reduce the cost of warehouse systems, Attari et al. built an automatic reverse storage mathematical model to improve profits, optimize latency, and total costs. The results showed that the algorithm has good performance [14]. Ala et al. designed an intelligent trading system with Markov logic network to improve operational efficiency for efficient retail supply management, and the results showed the feasibility of the system [15].

In summary, there have been many good results in the layout of construction management sites and the improvement of GA, but there is still relatively little research combining the two. In order to improve construction efficiency and implement system management, the global search capability of GA and the local search algorithm of ACA were combined with the multi-objective processing strategy of Pareto optimal solution to construct an optimization model for the construction site layout plan. Taking the renovation project of the teaching building as an example, verify the model.

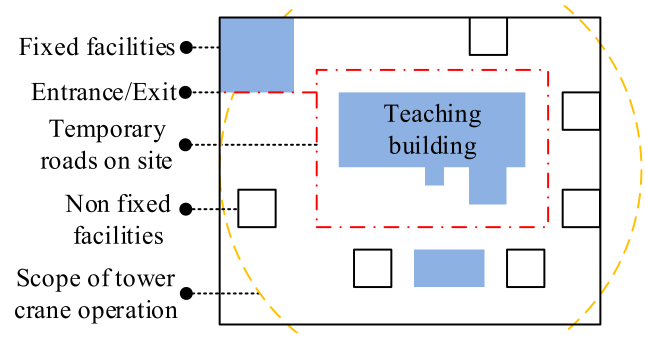


Fig. 1. Layout plan of construction site.

3. Multi-objective optimization of construction management site layout on the ground of improved genetic algorithm

To improve the rationality of OSL and optimize project management safety, cost, and environmental objectives, a GA is used to establish a construction SL model, thereby establishing an optimization objective function for cost. At the same time, Pareto ant colony GA is used to establish a MOO model for construction management SL, which optimizes the cost objective mathematical function of the SL.

3.1. Building a layout model for construction management sites

To achieve the integration, coordination, and integration of the entire project construction, the purpose of the construction SL of the building project is to assist the entire project construction and integrate various parts such as management personnel, materials, facilities, etc. The MOO of construction management SL is aimed at the aspect of layout. Firstly, the cost optimization algorithm is used to obtain the plan for SL. Secondly, it further strengthens the collaborative work of various processes through management methods, which can achieve multiple goals of optimal cost, good safety, and minimal construction impact on the environment. Before solving this problem, it is assumed that the total area required for all facilities is the same, that is, any facility can be placed in any vacant space, and any vacant site can accommodate the facilities to be arranged. Secondly, it is assumed that the mechanical and facility projects have already been clarified. The location of the final fixed facilities has been determined in advance [16]. The layout plan of the construction site is shown in Fig. 1.

In Fig. 1, the construction task lasts for 10 months, and the flat area of the construction site is rectangular, with dimensions of 100 m long and 80 m wide. The teaching building covers an area of 682.8m^2, with a total construction area of 3099.0m^2. The building has five floors above ground and a height of 20.950 m from the outdoor ground to the roof surface. Reinforced concrete frame structure with seismic fortification intensity of 8°. The QTZ80 (TC5610) tower crane was selected for the project to facilitate lifting, with a working radius of 55 m. The construction site roads are set up in the inner area of the building's peripheral facilities to facilitate on-site transportation and save transportation distance. Due to the numerous materials, machinery, and complex facilities involved in the construction site, especially the large size of some project sites, the management area will be divided to distinguish which are needed at the current stage of the site and which are not needed at the site. Secondly, it searches for various locations on the site plane and organizes, registers, and cleans up any unnecessary items on site. And the construction site plane design management zoning is shown in Fig. 2.

In Fig. 2, there are eight parts: material stacking area, machinery

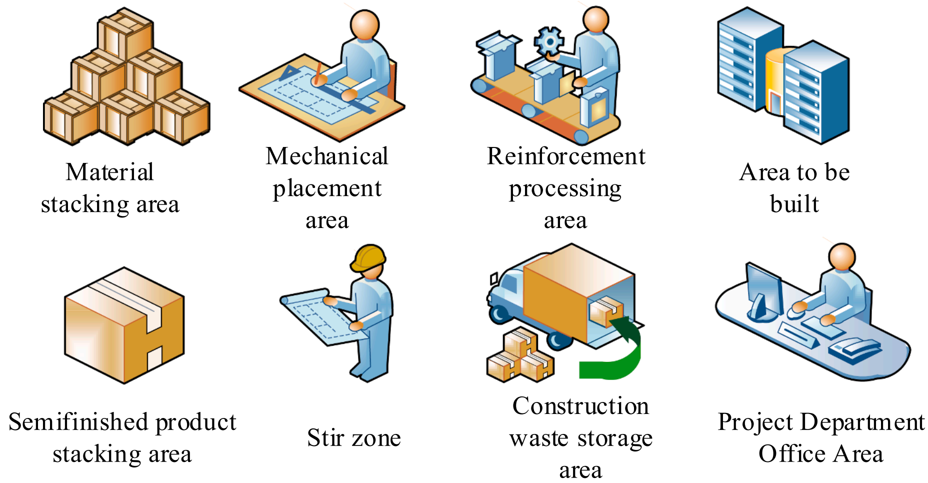


Fig. 2. Construction site graphic design management zoning.

placement area, including tower cranes, material elevators, steel processing area, building area to be constructed, semi-finished product stacking area, construction waste stacking area, mixing area, and project department office area. There are many elements that influence the layout of the construction site, and the three major elements of a construction project are time, quality, and cost. So the construction management SL can be optimized from these three aspects. When studying the layout of construction management sites, it is difficult to quantify the construction quality, which limits the direct indicators that can be used for mathematical modeling. The study chose transportation time and cost, which are relatively easy to measure and calculate, as the main quantitative indicators. The objective function is defined as considering both transportation time and cost simultaneously. That is, the established construction SL model only considers its transportation time and cost. Transportation time refers to the time for personnel movement and the transportation of building materials, depending on the means of transportation and distance. Its transportation time is set to, as expressed in Eq. (1).

$$T = \sum_{j=1}^{n}\sum_{i=1}^{n}\frac{t_{ij}d_{ij}}{v_{ij}} + \sum_{j=1}^{n}\sum_{i=1}^{n}\frac{f_{ij}d_{ij}}{u_{ij}} \tag{1}$$

In Eq. (1), n serves as the quantity of facilities. t_{ij} serves as the transportation frequency. d_{ij} serves as the transportation distance between two facilities. v_{ij} serves as the speed of the selected transportation method between two facilities. f_{ij} is the frequency of personnel turnover. u_{ij} is the walking speed of a person. The design cost is C, the cost includes two aspects: material transportation cost and construction cost of temporary facilities. The cost calculation expression for the flow of engineering materials between facilities and facility layout on the construction site is shown in Eq. (2).

$$C = \sum_{i=1}^{n}\sum_{j=1}^{n}\left[d_{ij}\sum_{k=1}^{n}\left(p_{ijk}q_{ijk}\right)\right] + \sum_{i=1}^{n}t_{ij}(x_i, y_i) \tag{2}$$

In Eq. (2), p_{ijk} is the transportation price per unit quantity of materials. q_{ijk} is the transportation quantity of materials between two facilities. $t_{ij}(x_i, y_i)$ is the cost required to establish a temporary facility at a certain location. The objective function for optimizing the construction SL is the synthesis of these two indicators. Due to the different dimensions of these two indicators, it is necessary to dimensionalize them and assign them appropriate weights to obtain the comprehensive objective function. It uses the min max standardization method to dimensionalize, and the function expression is shown in Eq. (3).

$$y_i = \frac{x_i - \min x_i}{\max x_i - \min x_i} \tag{3}$$

In Eq. (3), $\max x_i$ and $\min x_i$are the maximum and minimum values that can be obtained from the numerical value x_i. From this, the dimensionless values of cost and transportation time can be obtained separately. In terms of weight allocation between the two objectives, this study determines the specific values of the weights of the transportation distance and cost sub objectives using expert scoring method, as shown in Eq. (4).

$$S = \min(\omega_1 T^* + \omega_2 C^*) \tag{4}$$

In Eq. (4), ω_1 and ω_2 are the weights of transportation distance and cost, respectively. Where T^* is the minimum total time cost after optimization, as shown in Eq. (5).

$$T^* = \min\sum_{j=1}^{n}\sum_{i=1}^{\min}\frac{t_{ij}d_{ij}}{v_{ij}} + \sum_{j=1}^{n}\sum_{i=1}^{\min}\frac{f_{ij}d_{ij}}{u_{ij}} \tag{5}$$

C^* is the minimum total cost after optimization, as shown in Eq. (6).

$$C^* = \min\sum_{i=1}^{n}\sum_{j=1}^{\min}\left[d_{ij}\sum_{k=1}^{\min}\left(p_{ijk}q_{ijk}\right)\right] + \sum_{i=1}^{\min}t_{ij}(x_i, y_i) \tag{6}$$

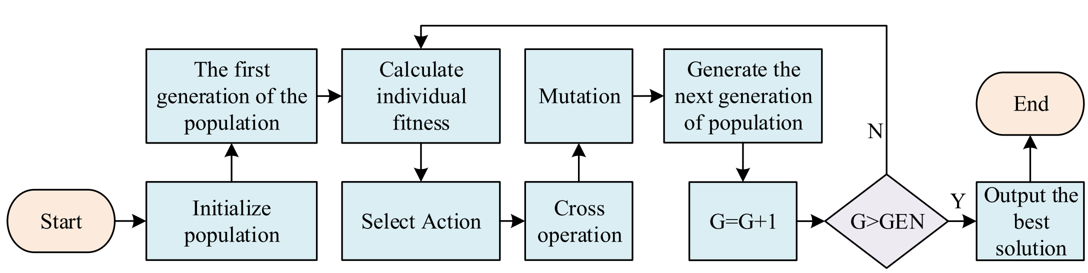


Fig. 3. Flow of genetic algorithm.

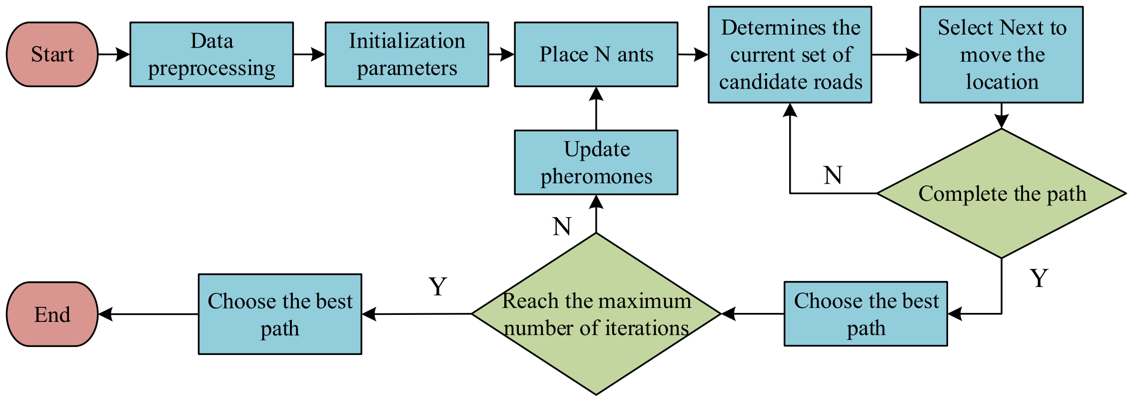


Fig. 4. ACO algorithm flow.

3.2. Multi-objective optimization of construction management SL based on improved genetic algorithm

After constructing a construction management SL model, the construction management SL can be seen as a secondary allocation problem. GA is a self-learning heuristic optimization algorithm. It randomly generates a set of initial solutions, calculates the fitness function values of each initial solution, and uses them as a criterion to judge the quality of the solution. Then, through genetic operations, the OSO is selected and passed on to the next generation [17]. The quality of the next generation solution is affected by the quality of the previous generation solution. The process is showcased in Fig. 3.

In Fig. 3, the GA algorithm through special methods and operations transforms the problem-solving process into a process resembling the crossover and mutation of chromosome genes in biological evolution. The design of the construction SL adopts a proportion selection operator. The content of its selection operator is that the probability of genetic operation on a single selection in the population is proportional to its fitness function value [18]. This study sets population size N, population $P = \{a_1, a_2, ..., a_n\}$.One individual $a_j \in P$ is randomly selected with an adaptation value of $f(a_j)$, and the probability value of each individual in the next generation population, as shown in Eq. (7).

$$P(a_j) = \frac{f(a_j)}{\sum_{i=1}^{n} f(a_j)}, a_j = a_1, a_2, ..., a_n \tag{7}$$

Each iteration generates a random number between [0,1] as a pointer to lock the selected individual. The above formula indicates that the larger the fitness function value of an individual, the higher the probability of being selected and retained. On the contrary, the probability of being selected and retained is smaller. The retained individuals can pair up and then cross again. F_{a_i} serves as the fitness of individual a_i, and the probability of individual a_i being chosen and passed through genetic manipulation to the next generation population is shown in Eq. (8).

$$P_{a_i} = F_{a_i} \Big/ \sum_{a_i=1}^{n} F_{a_i} \tag{8}$$

ACO performs the best in solving secondary allocation problems. Its outstanding features include positive feedback, parallelism, and self catalysis, as well as strong robustness, excellent distributed design, and easy integration with other algorithms. However, its most prominent shortcomings are long search time and easy to fall into local optima [8]. The ACO algorithm process is shown in Fig. 4.

In Fig. 4, the ACO algorithm first preprocesses the data, then initializes parameters to prevent N ants. Then, the algorithm determines the current candidate road set for each ant and selects the next moving position on the ground of probability. If the path is not completed, redefine the road set. If the path is completed, the best path is selected, and the best path is selected when the maximum quantity of iterations is achieved. If the maximum quantity of iterations is not achieved, update the pheromone and reposition the ants. It determines the heuristic information of the problem on the ground of its characteristics, and the heuristic information of different problems varies. Therefore, ACA can more effectively solve various problems. For the quadratic allocation problem, the heuristic information$n_{ij}(t)$ can be expressed as Eq. (9).

$$n_{ij}(t) = \frac{1}{e_{ij}(t)} \tag{9}$$

In Eq. (7), f_i is the sum of flows between facility i and other facilities. d_j is the sum of the distances between position j and other positions. $p_{ij}^k(t)$ represents the probability of state transition of ant k from point t to point j at time i, as shown in Eq. (10).

$$p_{ij}^k(t) = \frac{[\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}(t)]^\beta}{\sum_{l \in N_i^k} [\tau_{il}(t)]^\alpha \cdot [\eta_{il}(t)]^\beta} \tag{10}$$

In Eq. (10), $\tau_{ij}(t)$ serves as the pheromone information at iteration t. $\eta_{ij}(t)$ serves as the heuristic information between facility i and location j. α and β represent the relative influence parameters of pheromones and heuristic information, respectively. N_k^i is a selectable location near the i point. After all ants complete a task, the pheromones generated by each ant on the path should be updated. In addition to being influenced by passing ants, the pheromones on the path will also evaporate over time. Update the expression of pheromone calculation, as shown in Eq. (11).

$$\tau_{ij}(t+1) = \rho \cdot \tau_{ij}(t) + \Delta\tau_{ij}^{best} \tag{11}$$

In Eq. (11), $\rho(0 < \rho < 1)$ is the residual factor of pheromone information. $\Delta\tau_{ij}^{best}$ is the increment of pheromones. τ_{ij}^{best} is solved as shown in Eq. (12).

$$\tau_{ij}^{best} = \begin{cases} \dfrac{1}{F_{\phi^{best}}} \\ 0 \end{cases} \tag{12}$$

In Eq. (12), ϕ^{best} is the OSO retrieved in this iteration. $F_{\phi^{best}}$ is the objective function solved as ϕ^{best}. The MOO problem is written as the following mathematical model, as shown in Eq. (13).

$$\min f(X) = (f_1(X), f_2(X), ..., f_n(X)) \tag{13}$$

In Eq. (13), $f(X)$ represents all objective functions that need to be considered, with the goal of achieving the minimum value. The relevant conditions are showcased in Eq. (14).

$$s.t. g_i(X) \leq 0 \tag{14}$$

The range of decision variables is shown in Eq. (15).

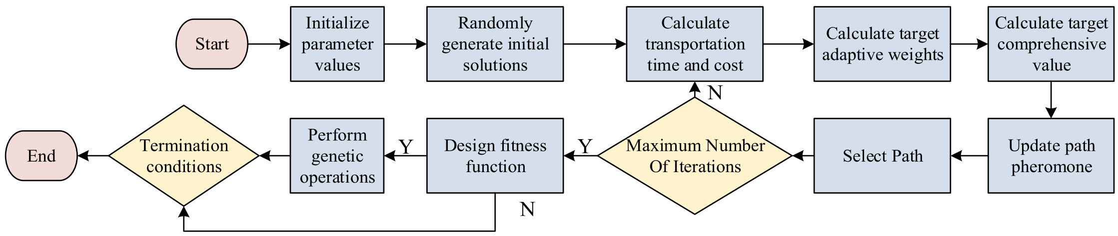
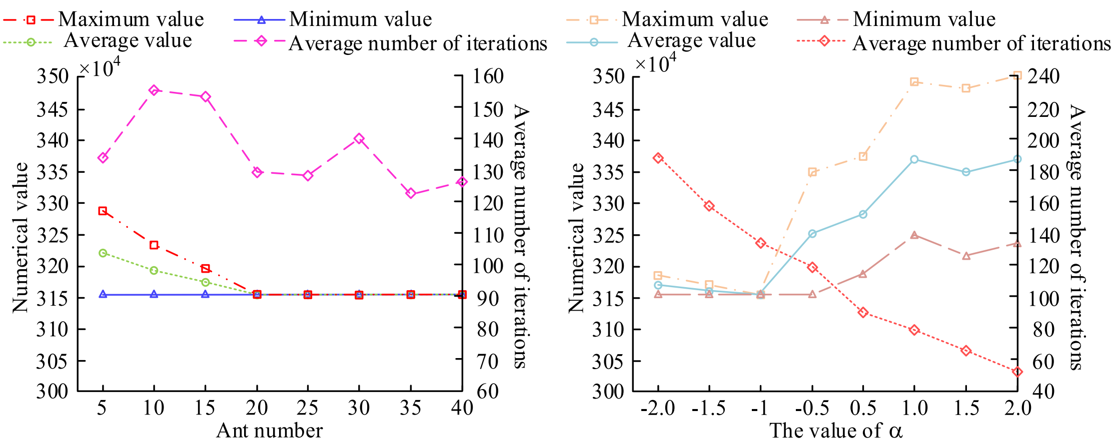


Fig. 5. Process for improving algorithms.



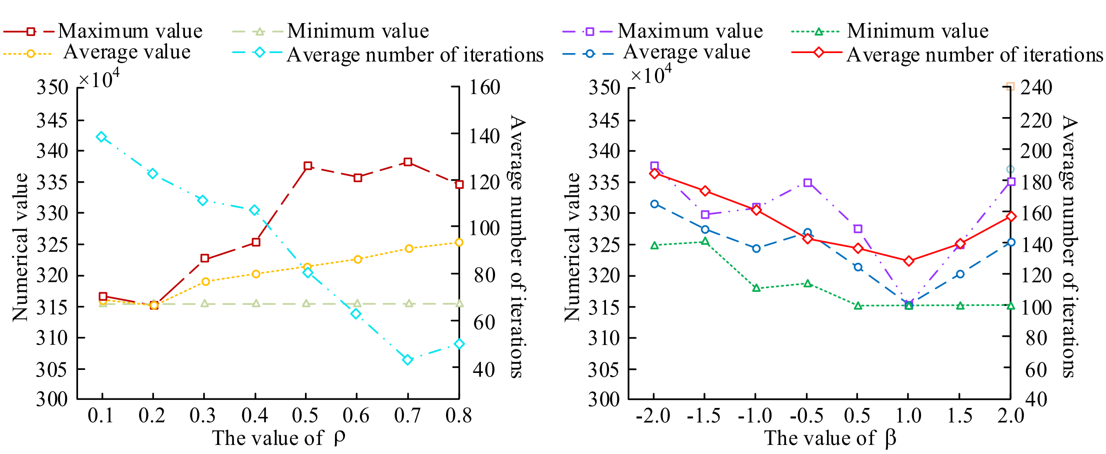
(a) The Influence of Different Ant Numbers on Algorithm Results (b) The influence of different pheromone influencing parameters on algorithm results

Fig. 6. Solution of the algorithm with different parameter values.

$$X = (x_1, x_2, \ldots, x_m)^T \tag{15}$$

For enhancing the initial solutions, thereby enhancing the quality of offspring solutions, and improving the operational efficiency and performance of GA, the optimal initial solution is found through ACO. Then, through the powerful search function of GA, it can be further optimized to design an algorithm that combines the two algorithms, improving the efficiency and performance of solving quadratic allocation problems [19]. This study transforms MOO problems into single objective problems, and then searches for the OSO through single objective optimization methods. Then it solves the MOO problem of building construction management SL, setting two goals first, cost and safety. Afterwards, the study synthesized these two objectives into a single objective and optimized it using Pareto ant colony GA. The process of improving the algorithm is shown in Fig. 5.

In Fig. 5, the initialization parameter values are randomly generated to generate initial solutions, calculate cost and transportation time, calculate target adaptive weights, calculate target comprehensive values, and update path pheromones. Then it selects the path for each ant and determines whether it is the maximum number of iterations. If it matches, design a fitness function, perform genetic operations, and finally output the Pareto solution set.



(a) The influence of different pheromone residual factors on algorithm solving (b) The Influence of Different Heuristic Information on Parameters on Algorithm Solving

Fig. 7. Solution of the algorithm when two parameters have different values.

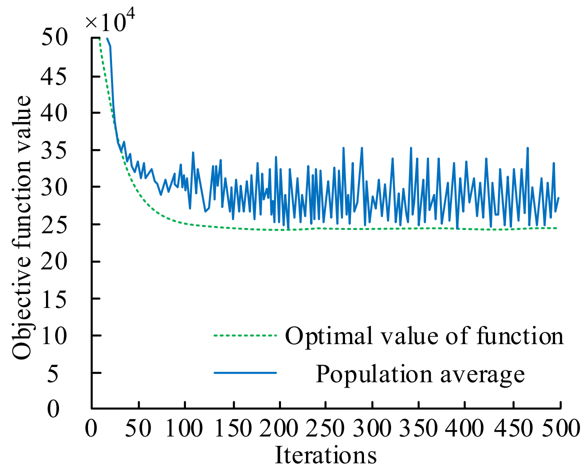


Fig. 8. MATLAB operation function values.

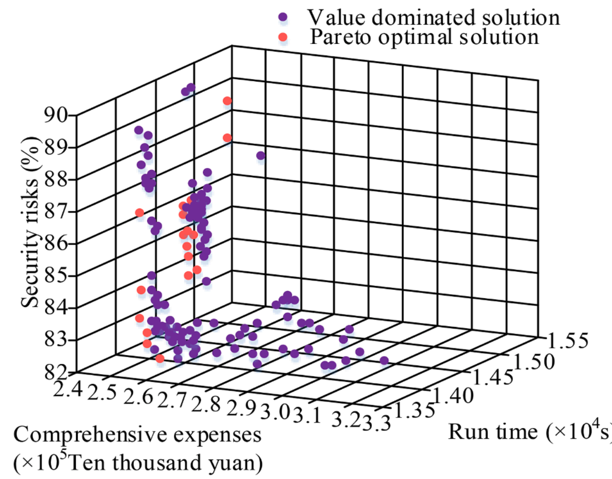


Fig. 9. Improved model iteration results.

4. MEthods/experimental: analysis of multi-objective optimization results for OSL of construction management using improved genetic algorithm

This study introduces the parameter setting of ACA and GA, as well as the optimization analysis of improved algorithms.

4.1. Parameter setting of ant colony algorithm as well as GA

The parameters of ACA include the number of ants, pheromone influence parameter α, heuristic information influence parameter β, and pheromone residual factor ρ. To achieve optimal search results and keep other parameters unchanged, the influence of different ant numbers and pheromone influence parameters α on the algorithm solution was studied. The relevant results is showcased in Fig. 6.

In Fig. 6(a), when the quantity of ants is 20 or more, the OSO for each running problem is 3,153,023, and the average number of iterations at this time is 130. When the number of ants is 20–40, the maximum, minimum, and average values remain consistent. This indicates that increasing the number of ants to a certain extent can improve the algorithm's global optimization ability and stability. In Fig. 6(b), the average number of iterations decreases as α increases. This indicates that the convergence speed accelerates with the increase of α. The numerical changes in the mean and minimum values indicate that the speed of convergence is not necessarily related to whether the OSO can be found. The acceleration of convergence speed greatly increases the likelihood of the algorithm falling into local optima. At $\alpha = -1$, the algorithm performs best and can find the OSO multiple times. It maintains other parameters unchanged and studies the impact of different pheromone residual factors ρ and different heuristic information influence parameters β on algorithm solving. The relevant results is showcased in Fig. 7.

In Fig. 7(a), the convergence rate accelerates with the increase of ρ. But the average value of the comprehensive objective function increases with the growth of ρ, and the OSO cannot be found. This indicates that an increase in ρ can cause the algorithm to fall into local optima. The algorithm performs best when $\rho = 0.2$, and can obtain the OSO through multiple iterations. In Fig. 7(b), the heuristic information affects the stability of the algorithm when the parameter β is 1. At this time, the average, maximum, and minimum values are all the same results, and iteration can also obtain the best solution. After determining the assignment of parameters, the study inputs each parameter value into the algorithm. Due to the randomness of a single run, it cannot guarantee that all Pareto solutions can be obtained. Therefore, the program is run multiple times to ensure that all Pareto solutions can be output.

4.2. Optimization analysis of improved algorithms

The study used software MATLAB for calculations and verified that the computer hardware configuration for the simulation experiment was Intel (R) Core (TM) i7–7700 CPU @ 3.60 GHz, 16.0GB of memory, and a 64 bit operating system. Firstly, it determines the parameter values of the GA. The initial population size is set to 100, with a crossover probability of 0.4, a mutation probability of 0.05, and an iteration count of 500. The results are shown in Fig. 8.

In Fig. 8, the optimal value of the model function is 25.35×10^4. On the ground of this optimization, the corresponding solution can be obtained by placing the facilities in the corresponding positions in sequence. The objective function value of the population average rapidly decreases before 50 iterations, and at this point, the model quickly concentrates towards the optimal solution in the initial stage. The curve fluctuates significantly during 150–500 iterations, indicating an unstable balance between exploration and utilization in the model. This indicates that the improved algorithm can effectively avoid falling into local optima too early, maintain a balance between multiple project management objectives such as cost, time, and quality, and optimize the overall performance of the project. The project department shall establish a decision-making level to implement decision management for the project and incorporate it into the scope of the construction SL management mechanism. The iteration results are shown in Fig. 9.

In Fig. 9, the iteration results of the improved model have 23 optimal feasible solutions, with construction costs mostly ranging from 240,000

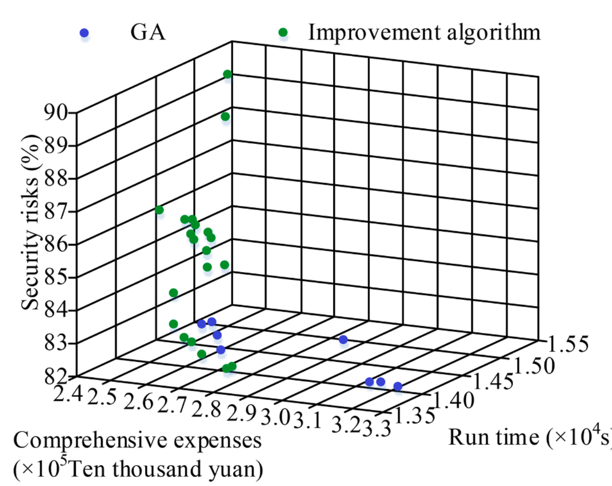
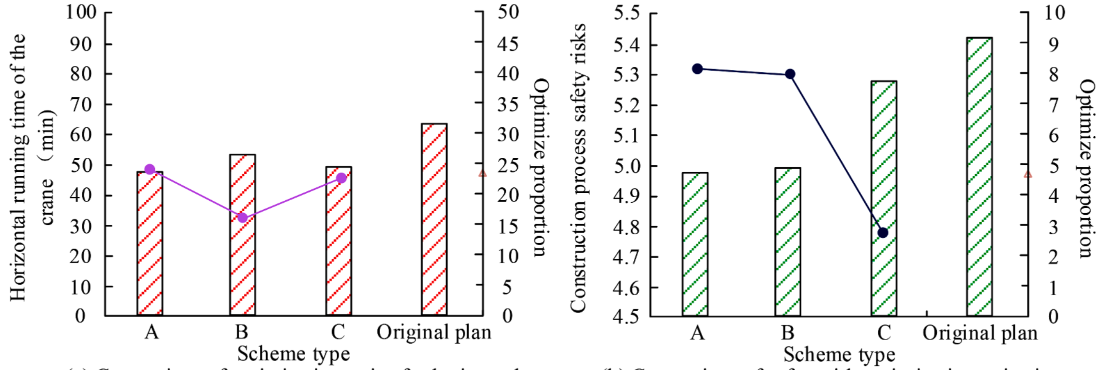


Fig. 10. Comparison of optimal solution sets for different algorithms.



(a) Comparison of optimization ratios for horizontal running time of cranes in different schemes

(b) Comparison of safety risk optimization ratios in different construction schemes

Fig. 11. Comparison of the optimized proportion of crane horizontal operation time and construction process safety risks between the three schemes and the original scheme.

Table 1
Statistical test results of objective function before and after optimization.

Multi objective optimization statistics	Average value	Standard deviation	Mean standard error	Correlation	*P*	T-test	*F*	Sig (Double tailed)
Before optimization	82.10	13.908	4.398	/	/	/	/	/
After optimization	87.00	9.832	3.109	/	/	/	/	/
Comparison before and after optimization	4.90	5.971	1.888	0.930	0.000	−2.595	21.519	0.029

to 260,000 yuan and an average safety risk coefficient of 85.65%. For removing the impact of accidental elements as much as possible, simulation tests were run 10 times and the best optimization outcomes were chosen for comparing. After all the programs have finished running, the Pareto solution set is output, and three optimization solutions are finally obtained, named Scheme 1, Scheme 2, and Scheme 3. Scheme 1 prioritizes the layout of the building materials warehouse, Scheme 2 prioritizes the layout of the mechanical and electrical equipment warehouse, and Scheme 3 prioritizes the setting up of the construction machinery warehouse. The cost of Scheme 1 is 38.34 million yuan, and the transportation time is 85,402 s. The cost of Scheme 2 is 38.49 million yuan, and the transportation time is 81,918 s. Scheme 3 has a cost of 3875 and a transportation time of 80,250. The original scheme had a cost of 40.26 million yuan and a transportation time of 85,952 s. The comparison of the OSO of different algorithms is shown in Fig. 10.

In Fig. 10, the improved algorithm has higher computational efficiency, resulting in more Pareto OSO and higher quality. In terms of computational time (CTI), the GA algorithm takes an average of 1702.0 s, while the improved algorithm takes an average of 421.0 s. In calculation outcomes, the GA algorithm obtained 9 OSO, while the improved algorithm obtained 23 OSO, which increased the quantity of OSO by 1.6 times. And the OSO obtained by the improved algorithm dominates the OSO from the GA algorithm. Consequently, the improved algorithm not only improves the efficiency of problem solving, but also optimizes the scope and quality of understanding, which is of great significance for solving complex optimization problems. The comparison between the three schemes and the original scheme in terms of the optimization ratio of crane horizontal operation time and construction process safety risks is shown in Fig. 11.

In Fig. 11, the horizontal transportation time of the crane in the original plan was 63 min, while the A, B, and C plans were 48 min, 53 min, and 49 min, respectively, saving an average of 21.83%. Overall, both in terms of the numerical value of the objective function and from the perspective of plane layout, the three optimized schemes have a certain degree of improvement compared to the original scheme. This indicates that the algorithm is indeed feasible and effective in optimizing the layout of construction sites, and has certain reference value. Regarding the evaluation and decision-making of the optimization plan, construction management personnel need to further consider various factors and make a comprehensive comparison before making a selection. Statistical analysis was conducted on the objective function before and after optimization, and the results are shown in Table 1.

In Table 1, $P = 0.000$, indicating that the improvement in transportation time and cost optimization by the improved algorithm is unlikely to be caused by random mutation. The effect of improving the algorithm is credible and statistically effective.

5. Results and discussion

To improve the rationality of OSL, a GA is used to build a construction SL model, thereby establishing an optimal objective function for cost. At the same time, Pareto ant colony GA is used to establish a MOO model for construction management SL, which optimizes the cost objective mathematical function of the SL. The results show that the OSO can be obtained through multiple iterations. The optimal value of the improved model function is 25.35×10^4. On the ground of this optimization, the corresponding solution can be obtained by placing the facilities in the corresponding positions in sequence. The iteration results of the improved model have 23 optimal feasible solutions, with construction costs mostly ranging from 240,000 to 260,000 yuan and an average safety risk coefficient of 85.65%. In calculation outcomes, the GA algorithm obtained 9 OSO, while the improved algorithm obtained 23 OSO. The number of OSO increased by 1.6 times, and the OSO from the improved algorithm all dominated the OSO obtained by the GA algorithm. Consequently, the improved algorithm obtains more and higher quality solutions with higher computational efficiency. The improved algorithm has significant advantages in both efficiency and effectiveness, and it has important practical application value for construction project management that needs to handle large-scale multi-objective optimization problems. This method can provide more high-quality decision support, which helps project managers make better choices in multi-objective decision-making environments. Although this study provides valuable insights, it does not delve into the key influencing factors in construction management. Future research should analyze the risk factors of the project in detail to more comprehensively ensure the overall feasibility and sustainability of the project.

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CRediT authorship contribution statement

Hui Yin: Writing – original draft, Software, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

No conflict of interest was declared by the author.

Data availability

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

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ARTICLES FOR FACULTY MEMBERS

MULTI-OBJECTIVE OPTIMIZATION ALGORITHM FOR AUTONOMOUS SPATIAL LAYOUT DESIGN

Multi-objective optimization of the spatial layout of green infrastructures with cost-effectiveness analysis under climate change scenarios / Zhang, X., Liu, W., Feng, Q., & Zeng, J.

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Multi-objective optimization of the spatial layout of green infrastructures with cost-effectiveness analysis under climate change scenarios

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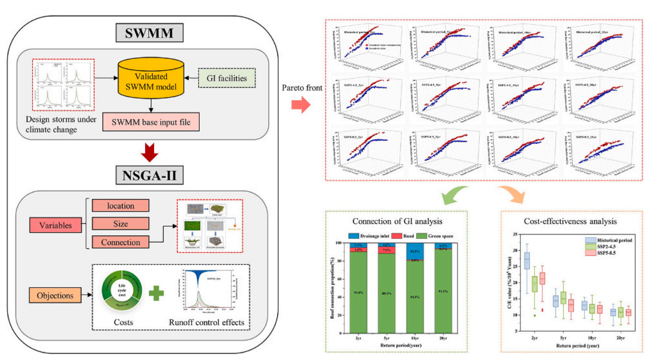
HIGHLIGHTS

- Optimizing the connection, size, and location of GI was conducted under the climate change scenarios.
- Stormwater runoff on roofs most flew through green spaces in optimal GI layouts.
- Permeable pavement accounted for the highest average area proportion in optimal GI layouts.
- The increase in rainfall intensity caused by climate change slightly weakened the cost-effectiveness of GI.

GRAPHICAL ABSTRACT



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Cost-effectiveness

ABSTRACT

Green infrastructure (GI) plays a significant role in alleviating urban flooding risk caused by urbanization and climate change. Due to space and financial limitations, the successful implementation of GI relies heavily on its layout design, and there is an increasing trend in using multi-objective optimization to support decision-making in GI planning. However, little is known about the hydrological effects of synchronously optimizing the size, location, and connection of GI under climate change. This study proposed a framework to optimize the size, location, and connection of typical GI facilities under climate change by combining the modified non-dominated sorting genetic algorithm-II (NSGA-II) and storm water management model (SWMM). The results showed that optimizing the size, location, and connection of GI facilities significantly increases the maximum reduction rate of runoff and peak flow by 13.4 %–24.5 % and 3.3 %–18 %, respectively, compared to optimizing only the size and location of GI. In the optimized results, most of the runoff from building roofs flew toward green space. Permeable pavement accounted for the highest average proportion of GI implementation area in optimal layouts, accounting for 29.8 %–54.2 % of road area. The average cost-effectiveness (C/E) values decreased from 16 %/10^5 Yuan under the historical period scenario to 14.3 %/10^5 Yuan and 14 %/10^5 Yuan under the two shared socioeconomic pathways (SSPs), SSP2–4.5 and SSP5–8.5, respectively. These results can help in understanding

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the optimization layout and cost-effectiveness of GI under climate change, and the proposed framework can enhance the adaptability of cities to climate change by providing specific cost-effective GI layout design.

1. Introduction

Rapid urbanization has led to the gradual replacement of natural permeable surfaces by impermeable surfaces, which significantly hinders the infiltration and retention of rainfall and increases the surface runoff and confluence velocity during storms (Hammond et al., 2015; Jiang et al., 2018; Shao et al., 2020). Furthermore, climate change characterized by global warming leads to frequent extreme rainfall events, which directly increases urban flooding risk (Hosseinzadehtalaei et al., 2020). Conventional gray infrastructures build pipes and ditches to discharge water rapidly (Dong et al., 2017). However, due to the difficulty and cost of retrofitting gray infrastructure, increasing its stormwater storage capacity is unsustainable, expensive, and even impractical, especially in urban areas (Qin et al., 2013). Green infrastructure (GI), also called low impact development (LID), best management practices (BMPs), sponge city (SC), and water sensitive urban design (WSUD), is well known as a solution to mitigate urban flooding risk (Wang et al., 2022; Zhang and Chui, 2018). The widely used GI facilities include green roofs, infiltration trenches, rain barrels, bioretention cells, and permeable pavements, etc., which play a significant role in urban stormwater management by simulating the natural hydrological cycle (Casal-Campos et al., 2018; Li et al., 2019).

Although previous studies have assessed the runoff retention capacity of GI facilities via field experiments and model simulations (Junqueira et al., 2021; Kaykhosravi et al., 2018; Liu et al., 2021; Liu et al., 2019), the results exhibit large variations and discrepancies, owing to different spatial layout, structural configuration, and climatic conditions. In practice, GI layout planning relies heavily on the experiences of practitioners and general guidelines, which can be subjective and result in unsatisfactory effectiveness of runoff control. Due to space and financial limitations, how to obtain cost-effective solutions for GI layout design is an important issue and challenge that needs to be addressed urgently (Eckart et al., 2018). In stormwater management programs, the high heterogeneity of urban landscapes leads to a wide variety of GI configurations in size, location, connection, and combination (Islam et al., 2021; Tang et al., 2022). However, many studies have only compared costs and benefits for a limited number of predefined GI implementation scenarios (Luan et al., 2019), which are unable to obtain complete optimal solutions and are difficult to provide scientific decision-making basis for the early-stage design of GI layout. Therefore, more efficient search algorithms are required to explore trade-offs among multiple objectives and find the optimal layout design of GI (Liu et al., 2016a; Raei et al., 2019).

Hydrological modeling coupled with multi-objective optimization methods is an effective approach to search for optimal GI layouts that meet a group of predefined objectives. Several hydrological models such as storm water management model (SWMM), long-term hydrologic impact assessment-low impact development model (L-THIA-LID), system for urban stormwater treatment and analysis integration model (SUSTAIN), and soil and water assessment tool (SWAT) have been used in optimizing GI layout (Chen et al., 2016; Hou and Yuan, 2020; Liu et al., 2016b; Tang et al., 2022). Meta-heuristic methods, including simulated annealing (SA) (Huang et al., 2018), the third evolution step of generalized differential evolution (GDE3) (Li et al., 2022), particle swarm optimization (PSO) (Duan et al., 2016), and genetic algorithms (GAs) (Giacomoni and Joseph, 2017; Sebti et al., 2016), are the most suitable techniques for multi-objective optimization. Among them, the most popular combination is SWMM and GAs, because they are accurate, efficient, and user-friendly. For example, Zhu et al. (2023) utilized non-dominated sorting genetic algorithm-II (NSGA-II) and SWMM to optimize the type, size, and location of GI to obtain the best solution, considering the objectives of life cycle cost, economic-environmental-social benefit, and runoff reduction effects. Yang et al. (2023) used the NSGA-II coupled with the SWMM calibrated by LID experiments to design optimal LID layouts at a small-scale community in Tianjin. Eskandaripour et al. (2023) coupled the slime mould algorithm (SMA) with the SWMM to optimally design LID combinations in urban areas. Lopes and Lima da Silva (2021) combined NSGA-II and SWMM to determine the most efficient LID unit areas and the thicknesses of soil and storage layers for different design storms. However, most of the current methods and tools used for optimizing GI layout focus on determining the spatial coverage of GI facilities through the consideration of their numbers and sizes, only limited research has synergistically optimized the size, location, and connection of GI.

Global warming intensifies the regional water cycle and extreme rainfall, leading to the increased frequency of urban flooding (Calvin et al., 2023; Tang et al., 2024; Yao et al., 2023). Due to the complex effects of urban heat island (UHI) on precipitation, highly developed urban areas are more sensitive to the impacts of climate change than suburban regions. GI facilities have shown great potential in mitigating the urban flood risk caused by climate change (Abduljaleel and Demissie, 2022; Demuzere et al., 2014). A comprehensive understanding of how GI reduces stormwater runoff capacity under climate change can provide a theoretical basis for the formulation of urban stormwater management policies, thereby mitigating the increasing urban flood risk and enhancing the adaptability of urban stormwater management systems to climate change (Liu et al., 2023; Sun et al., 2024; Wang et al., 2023b). Therefore, it is essential to successfully optimize GI layout to deal with possible climate change in the future (Ghodsi et al., 2020). Wang et al. (2023a) proposed a framework for evaluating the hydrological performance of urban gray-green infrastructure considering the non-stationary and nonlinear effects of long-term climate change, providing strong support for addressing climate change. Leng et al. (2021) optimized the gray-green infrastructure and explored its hydrological effects under climate change and land use change scenarios. However, due to the small spatio-temporal scales typically associated with urban drainage, characterized by temporal scales of just a few minutes and spatial scales of 1–10 km^2, most assessments of GI effectiveness were often based on rainfall data obtained from historical precipitation statistics, few studies considering the impact of climate change in precipitation (Yan et al., 2021).

After multi-objective optimization of the GI layout, a set of pareto solutions is produced, which provides decision-makers with a lot of layout designs. However, in practice, only one or a few GI layout designs are required. Therefore, it is crucial to evaluate the cost-effectiveness of the pareto solutions, which could provide guidance to decision-makers on GI planning programs. Cost-effectiveness analysis (CEA) is widely applied to identify the most cost-effective GI layouts (Liu et al., 2016a). CEA compares the life cycle costs and benefits to determine the feasibility of GI facilities (Cruz et al., 2017). The life cycle cost (LCC) analysis is a reliable method that considers all the costs incurred throughout a project's lifespan to identify the most cost-effective option. Various studies have employed LCC methods to assess and optimize the cost-effectiveness of GI (Eckart et al., 2018; Li et al., 2020; Zeng et al., 2021). For instance, Mei et al. (2018) used SWMM and LCC to optimize the design of GI. Their study revealed that the bioretention cell and vegetated swale combination was the most cost-effective option under all scenarios. Hua et al. (2020) proposed an integrated evaluation system based on LCC analysis to assess the LID runoff control capacity. The results showed that combining bioretention cells, infiltration trenches, and rain barrels can sufficiently reduce urban flooding risk. Although optimizing GI layout can significantly enhance their reduction effectiveness, few studies have evaluated the cost-effectiveness of GI under climate change (Liu et al., 2023; Pour et al., 2020; Wang et al., 2020).

In summary, little is known about the hydrological effects of synchronously optimizing the size, location, and connection of GI under climate change. This study proposed a framework for optimizing the size, location, and connection of GI under climate change by combining the SWMM model with the modified NSGA-II algorithm. The objectives of this study are: (1) to identify the most efficient GI layout designs including the location, connection, and size of GI; and (2) to analyze the cost-effectiveness of GI implementation under climate change.

2. Materials and methods

2.1. Description of optimization framework

There are three steps to assess the cost-effectiveness of the multi-objective optimal GI layout under the design storms of the historical and climate change scenarios. In the first step, the SWMM model was built based on community characteristics and validated using field experimental data, followed by inputting designed rainfall data into the SWMM model. In the second step, the SWMM model was integrated with the modified NSGA-II algorithm under the design storms of the historical and climate change scenarios to iteratively optimize the GI layout, including the size, location, and connection of GI. In the last step, based on the pareto front solution, the characteristics of GI optimization layout and the cost-effectiveness indexes of GI optimization layout under the design storms of the historical and climate change scenarios were analyzed. The study process is shown in Fig. S1.

2.2. Study site description

The study area is located in Chengguan District of Lanzhou (36°05′N, 103°91′E), the capital city of Gansu Province in northwest China. It is a typical semi-arid region characterized by dry climate and lack of rain. The annual average precipitation is 327 mm, primarily concentrated from June to September. It is a small community with a total area of 3.81 ha. Fig. S2 shows the location and land use of the community, with a percentage of 0.5 % for the entrance to underground parking lots, 21.0 % for buildings, 44.1 % for green space, 33.3 % for roads, and 1.2 % for landscape ponds.

2.3. SWMM model development

2.3.1. Model setup

The SWMM is a dynamic rainfall-runoff model primarily used for simulating the quantity and quality of runoff in urban areas (Rossman, 2010). The SWMM model divides the study area into multiple catchments, each of which is idealized as a rectangle with a uniform slope. Realize water balance by treating each catchment as a nonlinear reservoir, where the change in runoff depth over time is only the difference between input of rainfall and upstream catchment runoff and the sum of evaporation, infiltration, and runoff losses. According to land-use type, and location of drainage wells, as shown in Fig. S3, the community was divided into 120 catchments. The interior of the rectangle is divided into three parts: impervious area without depression storage, impervious area with depression storage, and pervious area. The percent of impervious area within the catchment area was calculated based on the land use types within the catchment area. The percent of impervious areas of roads, the ceilings of the entrance to underground parking lots, green spaces, landscape ponds, and roofs were 90 %, 100 %, 20 %, 100 %, and 100 %, respectively. Percent of impervious area without depression storage was 25 % in all catchments. The runoff from each part was directly discharged into the outlets of the catchment in this study. In the SWMM model, the landscape pond was simulated as the storage unit. The drainage network consisted of 85 junctions, 4 outfalls, and 85 conduits. Based on the actual situation of the community, the outlets of building roofs were the drainage well around the building roof. The Horton method was chosen for the infiltration module due to its parameters being easy to get and fitting experiment data well (Wang et al., 2021; Wang and Chu, 2020). The Dynamic Wave was chosen for the routing module. According to the main types of land use in the community (roof, road, and green space), as well as recommendations for corresponding GI in the Ministry of Housing and Urban-Rural Development (2014), three types of distributed GI facilities, including green roof, permeable pavement, and bioretention cell, were chosen as the GIs that need optimization in the community. Three types of distributed GI facilities were divided into several vertical layers, each with different parameters in the SWMM model. Parameters setting of various layers of GI facilities were referred to previous studies (Liu et al., 2023; Rossman and Huber, 2016; Zhu et al., 2023), as shown in Table S1.

2.3.2. Model evaluation

During the field monitoring experiment in 2023, a tipping-bucket rain gauge that recorded rainfall data at 1-minute intervals was placed on a building roof in the community (as depicted in Fig. S2). An automatic flow collector was installed at one of the stormwater drainage outlets of the community to record runoff volume at the same intervals (as depicted in Fig. S2). In this study, the model parameters can be initially determined by previous studies in the same region (Zhang, 2021) and the SWMM Manual (Rossman, 2010). Two rainfall-runoff data collected on September 23 and September 27, 2023 were used for model validation. The detailed information of two rainfall events is shown in Table S2. In this study, Nash-Sutcliffe efficiency (NSE) and root mean square error (RMSE) were selected to evaluate runoff simulation's accuracy in the SWMM model. The value of NSE greater than 0.5 is usually considered acceptable for the accuracy of the SWMM model. The value of RMSE approaches 0, indicating the high accuracy of the SWMM model. The formula of NSE and RMSE is shown below:

$$NSE = 1 - \frac{\sum_{t=1}^{N} \left(Q_{sim,t} - Q_{obs,t}\right)^2}{\sum_{t=1}^{N} \left(Q_{obs,t} - \overline{Q}\right)^2} \tag{1}$$

$$RMSE = \sqrt{1 \Big/ N \sum_{t=1}^{N} \left(Q_{sim,t} - Q_{obs,t}\right)^2} \tag{2}$$

where N is the number of runoff observation data; $Q_{sim,t}$ is the simulated runoff rate of SWMM model at time t; $Q_{obs,t}$ is the observed runoff rate of the field monitoring experiment at time t; $\overline{Q}$ is the average value of observed runoff rate of the field monitoring experiment.

2.4. Design storms under the historical and climate change scenarios

In this study, the design storms under the future climate change scenarios were derived by multiplying the change factor for each return period with the design storms under the historical scenarios. Then input the rainfall data for different return periods under the historical and future climate change scenarios into the rain gauge module in SWMM. The design storms under the historical scenarios were determined by the local storm intensity formula developed by (Ji et al., 2002), and the formula is shown below.

$$i = \frac{6.86(1 + 1.33lgN)}{(t + 12.70)^{0.83}} \tag{3}$$

where i is the rainfall intensity; N is the design return period; t is the rainfall duration.

In this study, a 2 h rainfall time series at 1 min intervals was generated for four return periods (2-, 5-, 10-, and 20-year) using the Chicago design storm method.

The sixth phase of Coupled Model Intercomparison Project (CMIP6) combines Shared Socioeconomic Pathways (SSPs) and radiative forcing to produce future climate prediction scenarios. In this study, two typical climate change scenarios, SSP2–4.5 and SSP5–8.5, were selected to reflect radiative forcing from moderate to high. SSP2–4.5 represents the radiative forcing that will be stably controlled at 4.5 W/m^2 by 2100 under the SSP2 (Middle of the Road). SSP5–8.5 adopts SSP5 (Fossil-fueled Development) and the radiative forcing will be the highest by 2100 among all climate change scenarios, at 8.5 W/m^2. The high-resolution downscaling model data of NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6) used in this study was published by the NASA Center for Climate Simulation (NCCS) (Thrasher et al., 2022). This dataset applied the bias correction/spatial disaggregation (BCSD) method to downscale output from CMIP6 to a spatial resolution of 0.25°. The SSP2–4.5 and SSP5–8.5 data from 2015 to 2100 under the BCC-CSM1-1-M model were adopted as the daily rainfall data under the climate change scenarios. The historical precipitation data from 1950 to 2014 under the BCC-CSM1-1-M model were adopted as the daily rainfall data under the historical scenario. Using bilinear interpolation to extract daily rainfall data under the historical and climate change scenarios in the study area.

The change factor method was used to calculate the change factor for each return period under climate change (Zhou et al., 2018). To be specific, the annual maximum daily precipitation was selected for each year of historical and future climate change periods. The daily rainfall under the historical and future climate change scenarios in each return period was then estimated separately based on the generalized extreme value (GEV) distribution. Finally, the ratio of daily rainfall under the historical scenario to that under the future climate change scenarios in each return period was calculated as the change factor, as shown in Table 1. Process maps of rainfall intensity in different return periods under the historical and climate change scenarios are shown in Fig. S4.

2.5. Multi-objective optimization module

2.5.1. Establishment of GI layout optimization function

2.5.1.1. Decision variables. Based on the site conditions, three types of GI facilities were assumed to be implemented in roads, green spaces, and roofs, including permeable pavement, bioretention cell, and green roof, respectively. Due to unsuitable materials, green roofs cannot be installed on the ceiling of the entrance to the underground parking lot. To determine the optimal size, location, and connection of GI, the decision variables were the area of GI in each catchment and outlets of building roofs. By changing the GI area within each catchment under constraints, the size and location variables of GI were generated. As shown in Fig. 1, the runoff from building roofs flows through downspouts to the surrounding green spaces, roads, or drainage inlets. By changing the outlets of building roofs, the connection variables of GI were generated. In the process of encoding variables for outlets of building roofs, since the range of values of the variables generated by the modified NSGA-II was real numbers and the names of the catchments and drainage inlets around the roof were continuous integers, the round function was used in R to map the values of the variables generated by the modified NSGA-II to integers. Thus, the real numbers generated by the modified NSGA-II can be transmitted to the SWMM model to change the outlets of building roofs. As a result, there were 131 decision variables, including 117 variables for the location and size of GI, and 14 variables for the connection of roofs.

Table 1
Change factors for different return periods storm under climate change.

	2-year	5-year	10-year	20-year
SSP2–4.5	1.13	1.09	1.07	1.04
SSP5–8.5	1.17	1.18	1.20	1.23

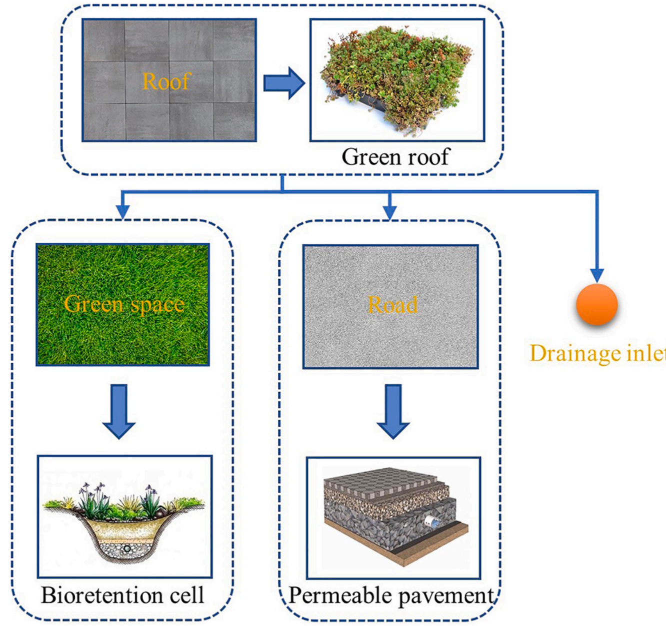

Fig. 1. The schematic diagram of possible outlets of the roof.

2.5.1.2. Objective functions. The construction of GI requires exploration of the trade-offs between cost and runoff control effectiveness. In this study, three objective functions were applied to place GI optimally: (1) minimizing the annual average cost (AAC) of GI (Eq. (4)); (2) maximizing the reduction rate of runoff volume (Eq. (5)); (3) maximizing the reduction rate of peak flow (Eq. (6)).

$$F_1 = min \sum \left[UAAC_i \cdot A_{ij}\right] \tag{4}$$

$$F_2 = max\left(1 - \frac{\text{Runoff}}{\text{Runoff}'}\right) \tag{5}$$

$$F_3 = max\left(1 - \frac{\text{Peak flow}}{\text{Peak flow}'}\right) \tag{6}$$

where $Runoff'$ and $Runoff$ are the runoff volume before and after implementing GI, respectively; $Peak\ flow'$ and $Peak\ flow$ are the peak flow before and after implementing GI, respectively; $UAAC_i$ is the unit annual average cost (UAAC) of GI$_i$; A_{ij} is the area of implementing GI in the catchment j.

Simultaneously, the constraints for multi-objective optimization are shown below:

$$A_{ij} \in \left[0, A_{Sub\,j}\right] \tag{7}$$

$$D_{\text{roof}} \in \{\text{green space}, \text{road}, \text{drainage inlet}\} \tag{8}$$

where $A_{Sub\,j}$ is the area of the j catchment, m^2; D_{roof} is possible outlets of the roof.

2.5.2. Annual average cost calculation

In this study, LCC was used to calculate the total cost of GI over its lifespan, including construction cost, operation and maintenance cost, and disposal cost. It typically uses discounted cash flow models to achieve a discounted sum of expected future costs (Bakhshipour et al., 2019; Liu et al., 2023; Mei et al., 2018). Because of different lifespans of GI facilities, comparing the total LCC was unreasonable. Therefore, it is necessary to calculate the unit annual average cost (UAAC) based on LCC (Mei et al., 2018; Wang et al., 2022). The formula of LCC and UAAC is shown in Eq. (9):

$$\begin{cases} LCC = C_C + C_{O\&M} - C_S \\ C_{O\&M} = \sum_{t=1}^{n} 1/(1+r)^t \cdot C_{O\&M_0} \\ C_S = 1/(1+r)^n \cdot (1 - 1/n) \cdot C_{O\&M_0} \\ C_{O\&M_0} = P \cdot C_C \\ UAAC_i = LCC_i/n_i \end{cases} \tag{9}$$

where C_C is the construction cost in the early stage; $C_{O\&M}$ is the operation and maintenance cost over its lifespan; C_S is the salvage value; $C_{O\&M_t}$ is the operation and maintenance cost in year t; P is the ratio of operation and maintenance cost to construction cost; where i is GI facilities; n_i is the lifespan of GI facility i.

The initial construction cost of GI was determined by the Ministry of Housing and Urban-Rural Development (2018). The UAAC of bio-retention cell, green roof, and permeable pavement are shown in Table S3.

2.5.3. Optimization algorithm

NSGA-II was widely used in GI optimal design due to its efficiency in dealing with complex, highly non-linear, discrete optimization problems (Tansar et al., 2023; Yang et al., 2023). The modified NSGA-II algorithm has similar optimization results to NSGA-II algorithm and converges faster (Monteil et al., 2019). The procedures of the modified NSGA-II optimization model are shown in Fig. S6. To start with, the modified NSGA-II algorithm generated a set of solutions for decision variables in GI. These solutions were then used to update the decision variables in the SWMM input file. Subsequently, the updated SWMM model was executed, and the output results were used to calculate three objective function values. The fast non-dominated sorting was used to obtain non-dominated solutions. After that, an offspring population was created by five rules: interpolation, extrapolation, independent sampling with a priori parameters variance, sampling for a correlation structure, and recombination. Subsequently, a new parent population was selected from the combined population of the parent population and the offspring population using the fast non-dominated sorting and the defined precision (ε) in the objective space, and a new offspring population was produced again through five rules. This process was iteratively repeated until the genetic algorithm converged to the predefined criteria or reached a set number of iterations.

2.6. Cost-effectiveness analysis

To determine the cost-effectiveness of GI in stormwater control, the reduction rate in runoff volume and peak flow per unit cost were evaluated. Due to the equal importance of runoff reduction rate and peak flow reduction rate, their mean value was calculated as the indicator for assessing the effectiveness of runoff control. The cost-effectiveness index (C/E) formula is as follows:

$$\begin{cases} V = \frac{(V_b - V_a)}{V_b} \times 100\% \\ P = \frac{(P_b - P_a)}{P_b} \times 100\% \\ C/E = \frac{(V+P)/2}{AAC} \end{cases} \tag{10}$$

where V_b and V_a are the runoff volume before and after GI implementation, respectively; P_b and P_a are peak flow before and after GI implementation, respectively; V is runoff reduction rate after GI implementation; P is peak flow reduction rate after GI implementation.

In practical applications, decision-makers usually select the layout scheme with the highest C/E value from screening the pareto solution set that meets the requirements of the runoff control objectives and investment amount. However, due to the unknown screening criteria of local decision-makers, this study selected the layout scheme with the highest and lowest C/E index in each scenario for display.

2.7. Implementation platform

The computation of climate change factors for each return period was executed through Python, involving key packages such as rasterio, glob, osgeo, and genextreme. The setup and validation of the SWMM model were completed in SWMM 5.1 software. All the coding work for multi-objective optimization was accomplished in the R studio using the R package named caRamel for the modified NSGA-II and swmmr for SWMM (Leutnant et al., 2019; Monteil et al., 2019). In the modified NSGA-II optimization iteration, the population size of the modified NSGA-II and the number of non-dominated solutions in pareto front were recommended to be set at 1000 and 200, respectively. The defined precision (ε) in the objective space was [0.001, 0.001, 0.001]. The stopping condition of the modified NSGA-II optimization model was maximum of 20,000 calls. After the above steps, the optimal layout design of GI under climate change was achieved. Then, C/E index was calculated in Excel and the visualization of optimal GI layouts was realized in ArcGIS 10.8.

3. Results

3.1. Model validation

Fig. S6 compares the observed runoff rate during the experiment with the runoff rate simulated by the corresponding SWMM model. The NSE for the model validation performance under two rainfall events was 0.85 and 0.71, and the RMSE for the model validation performance under two rainfall events was 0.14 and 0.08. This indicated that the constructed SWMM model performs well in simulating runoff in the study area. Therefore, the model parameters can be used for research, as listed in Table S4.

3.2. Overview of optimal GI layouts

The pareto front generated by different optimization variables for design storms under the historical and climate change scenarios is shown in Fig. 2. When optimizing only the size and location of GI, the average runoff reduction rate and average peak flow reduction rate were 54.8 % and 52.7 %, respectively. When optimizing the size, location, and connection of GI, the average runoff reduction rate and average peak flow reduction rate were 67.2 % and 60.8 %, respectively. Optimizing the size, location, and connection of GI can increase the maximum reduction rate of runoff and peak flow by 13.4 %–24.5 % and 3.3 %–18 %, respectively, compared to optimizing only the size and location of GI. In the scenario of optimizing the size, location, and connection of GI, the average AAC was 46.0×10^4 Yuan under the historical scenario, while it increased to 49.3×10^4 Yuan and 50.8×10^4 Yuan under the SSP2–4.5 and SSP5–8.5 scenarios, respectively. Meanwhile, the average runoff reduction rate increased from 66.5 % for the historical scenario to 67.3 % and 67.8 % for the SSP2–4.5 and SSP5–8.5 scenarios, respectively. The average peak flow reduction rate has decreased from 61.2 % for the historical scenario to 61.16 % and 60.0 % for the SSP2–4.5 and SSP5–8.5 scenarios, respectively.

3.3. Analysis of GI optimized layout

The relative proportions of roof connection in the optimized GI layout solutions under the design storms of the historical and climate change scenarios are shown in Fig. 3. More than 75.6 % of the roofs were connected to green spaces which was significantly higher than roofs connected to roads and drainage inlets, accounting for only 0.6 % to 20.1 % under the historical and climate change scenarios. This indicated that most roofs had a similar optimized connection pattern, where

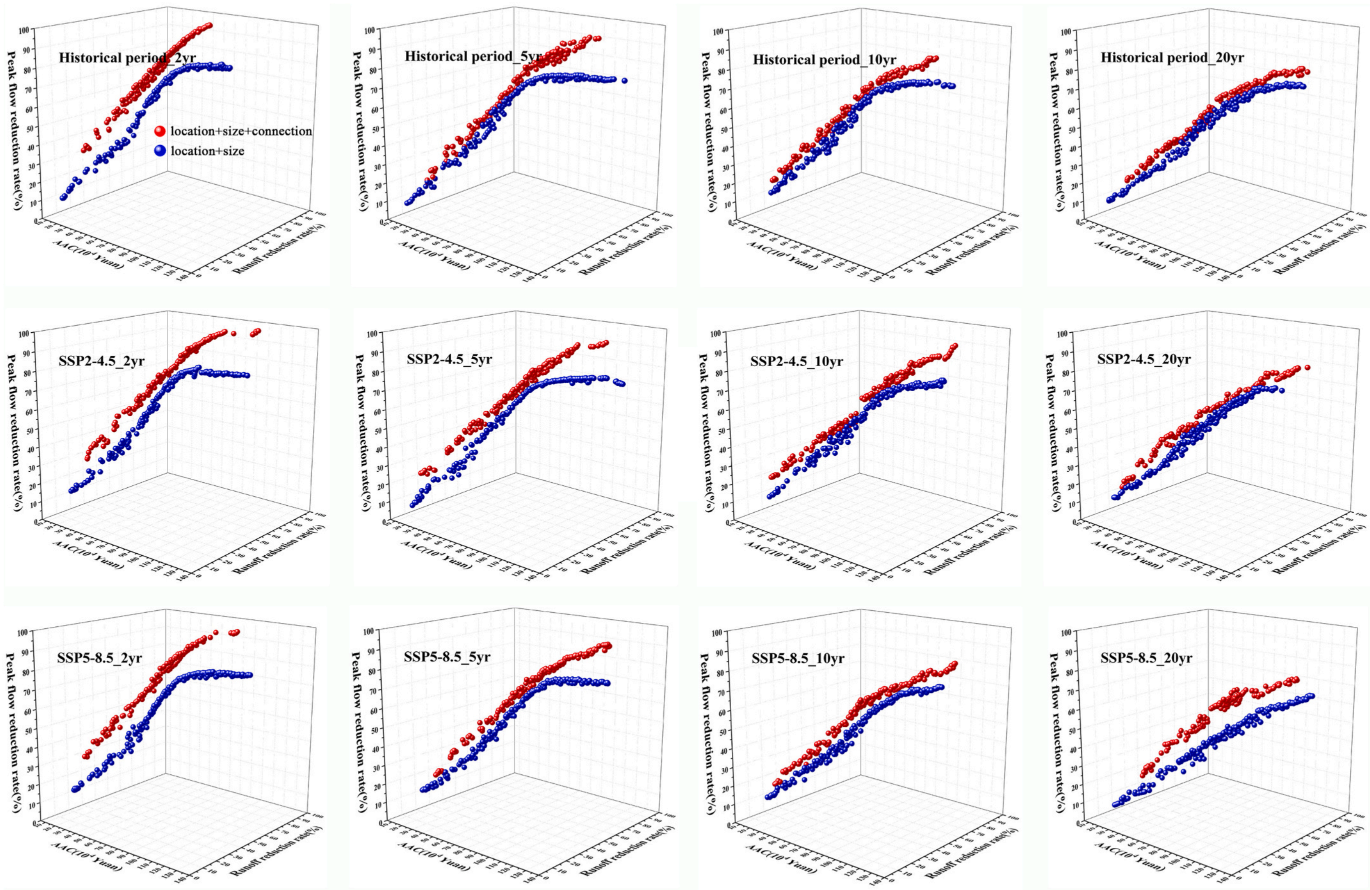

Fig. 2. The pareto front for design storms under the historical and climate change scenarios.

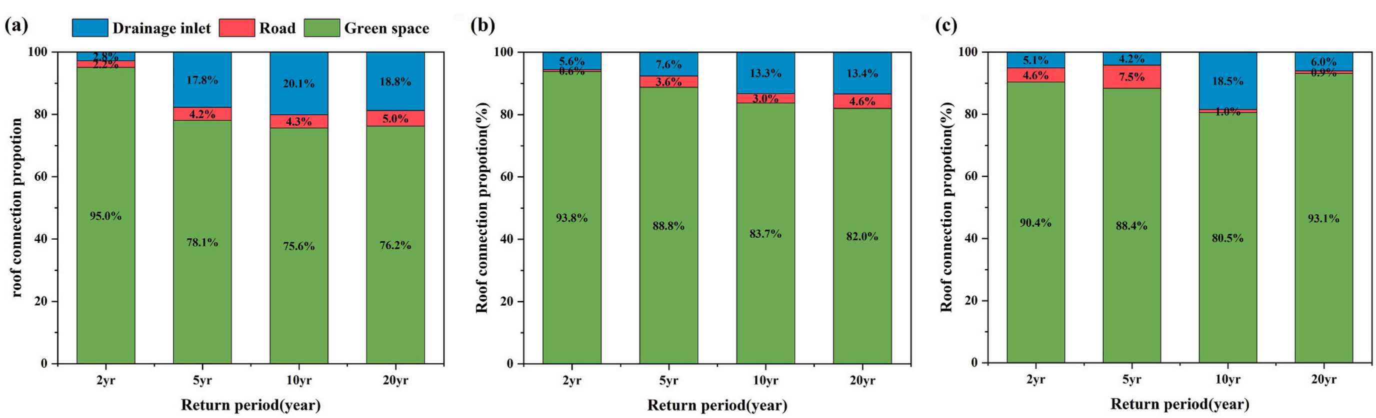

Fig. 3. Relative proportions of outlets of roofs in the optimized layout. (a) Historical period; (b) SSP2–4.5; (c) SSP5–8.5.

stormwater runoff flew through the roof, followed by green space.

The proportions of the GI facilities implementation area to the potential construction area in the optimal layout solutions under the design storms of the historical and climate change scenarios are shown in Fig. 4. The average area of GI implementation under the historical period, SSP2–4.5, and SSP5–8.5 were 1.05 ha, 1.15 ha, and 1.20 ha, respectively. For the same return period under the historical and climate change scenarios, the order of average proportion of GI implementation area was permeable pavement > bioretention cell > green roof. Specifically, Permeable pavement occupied 29.8 %–54.2 % of road area, while bioretention cell and green roof covered only 11.1 %–42.3 % of green spaces and 9.0 %–23.4 % of roofs, respectively.

3.4. Cost-effectiveness analysis of GI implementation

The C/E values of GI optimal layouts under the design storms of the historical and climate change scenarios are shown in Fig. 5. The average C/E values decreased from 16.0 %/10^5 Yuan under the historical period scenario to 14.3 %/10^5 Yuan and 14.0 %/10^5 Yuan under the SSP2–4.5 and SSP5–8.5 scenarios, respectively. Moreover, the average C/E values decreased with increasing return periods of storms. This indicated that the increase in rainfall intensity caused by climate change reduced the runoff reduction effect of GI, thereby weakening the cost-effectiveness of GI.

Simulation hydrographs of the community with no GI and GI

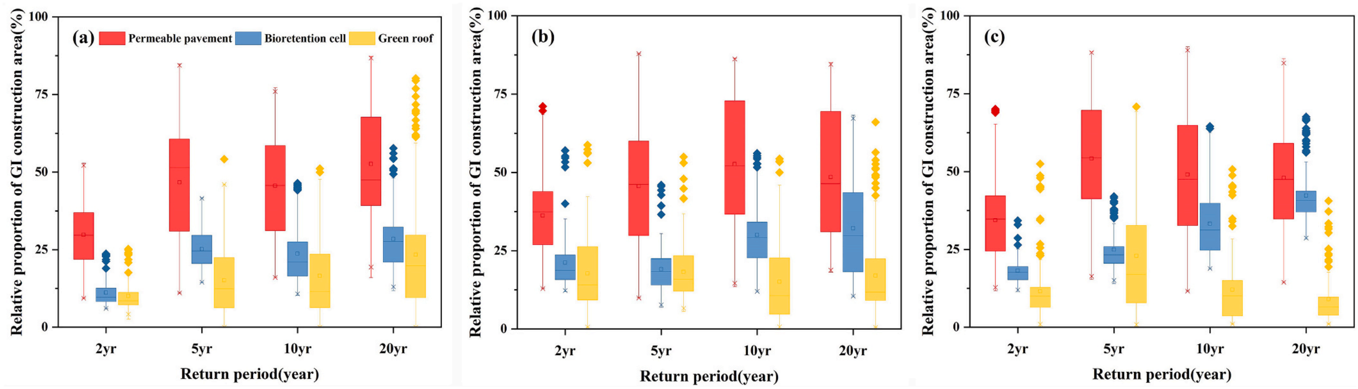

Fig. 4. Relative proportion of GI implementation area in optimal layout designs. (a) Historical period; (b) SSP2–4.5; (c) SSP5–8.5.

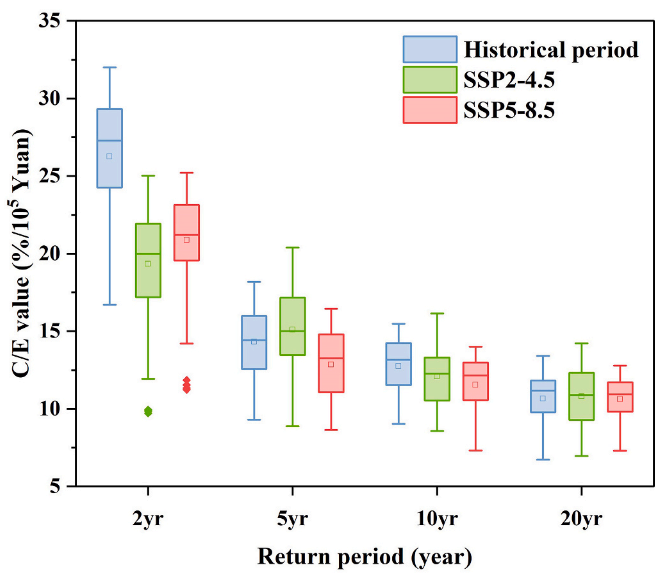

Fig. 5. The C/E indexes of GI optimal layouts under the historical and climate change scenarios.

implemented using the lowest and the highest C/E index schemes for different storms under the historical and climate change scenarios are illustrated in Fig. S7. It demonstrated the lowest and the highest C/E index schemes of GI implementation for four storms under the historical and climate change scenarios significantly reduced runoff and peak flow. Particularly, in these schemes, the peak flow reduction rate decreased as the return period of rainfall increased.

Fig. 6 illustrates the highest C/E index layout scheme for design storms under the historical period and climate change scenarios. There are notable variations in the C/E values, runoff reduction rates, and peak flow reduction rates under the historical and climate change scenarios. The average C/E value was 19.8 %/10^5 Yuan under the historical scenario, while it decreased to 18.9 %/10^5 Yuan and 17.1 %/10^5 Yuan under the SSP2–4.5 and SSP5–8.5 scenarios, respectively. Due to the limitation of cost, the average runoff reduction rate ranged from 46.8 % to 53.2 %, with the highest average runoff reduction rate observed in the SSP5–8.5 scenario. Similarly, the average peak flow reduction rate varied from 41.8 % to 45.0 %, with the highest reduction also occurring in the SSP5–8.5 scenario. Therefore, it is necessary to consider the climate change impacts in future stormwater management planning. In the highest C/E index layout scheme, permeable pavement had the highest average construction percentage at 23.9 %, followed by bioretention cell at 16.8 %, and green roof at 5.3 %. It highlighted that when the cost budget is limited, permeable pavement is a cost-effective choice to reduce runoff.

Fig. 7 illustrates the lowest C/E index layout scheme for design storms under the historical and climate change scenarios. The average C/E value was 10.4 %/10^5 Yuan under the historical scenario, while it decreased to 8.5 %/10^5 Yuan and 8.6 %/10^5 Yuan under the SSP2–4.5 and SSP5–8.5 scenarios, respectively. Additionally, the runoff reduction rate ranges from 86.0 % to 88.2 %, with the highest reduction observed in the SSP2–4.5 scenario. Similarly, the peak flow reduction rate varies from 83.5 % to 89.4 %, with the highest reduction also occurring in the SSP2–4.5 scenario. In the lowest C/E index scheme, there was a significant improvement in the average runoff reduction rate, rising from 49.0 % to 86.7 % compared to the highest C/E index layout scheme. However, this increase in effectiveness paid a substantial cost, the average AAC had increased from 26.2 × 10^4 Yuan to 98.5 × 10^4 Yuan compared to the highest C/E index layout scheme. The average construction percentage of permeable pavement, bioretention cell, and green roof was 79.6 %, 49.7 %, and 54.3 % in the lowest C/E index scheme, respectively.

4. Discussion

4.1. Optimal layout of GI in the community

Different GI optimal layout designs provide a guide for GI planning implementation in sustainable stormwater management. The results confirmed that optimizing the connection of GI can improve the runoff control capacity of GI. In previous studies, the outlets of roofs were usually used as the unchanging condition, not considered as the decision variable of the model, which underestimated the potential runoff control capacity of GI. The optimized results indicated that most roofs had a similar connection pattern, where stormwater runoff flew through the roof, followed by the green space. The results are consistent with the research conclusions of Tang et al. (2022). This connection pattern reduces the effective impervious area, which means that more runoff can be absorbed and infiltrated into the groundwater layer through natural filtration and soil absorption, thereby reducing the amount of runoff directly discharged into stormwater pipes (Wu et al., 2023). Therefore, it is important to consider reducing the effective impervious area by changing the connection of GI in practical SC projects, thus improving the runoff reduction effect of GI and enhancing the adaptability of urban stormwater management systems to climate change. For the same return period under the historical and climate change scenarios, the order of the average area proportion of GI facilities used was permeable pavement > bioretention cell > green roof. However, in the highest C/E index layout scheme, permeable pavement accounted for less installable area than bioretention cell under the 20-year return period of SSP5–8.5. This may be related to its high infiltration rate of the surface layer and the low infiltration rate of the internal layer, thus exposing the inadequacy of permeable pavement in coping with stormwater. Some

Fig. 6. The highest C/E index layout scheme for design storms under the historical and climate change scenarios.

research showed that permeable pavement was the most cost-effective measure to control runoff for high-frequency storm events among GI options (Chui et al., 2016; Wang et al., 2019; Zeng et al., 2021). This was partly due to the effective performance of permeable pavement in reducing runoff. Additionally, permeable pavement was mainly positioned in and along preferential flow paths that were characterized by a high upstream catchment area compared to bioretention cell and green roof. Since a large proportion of the runoff will flow to permeable pavement, this upstream catchment area has been proven to have a significant negative impact on the discharge volume (Rosier et al., 2023). However, the ranking of cost-effectiveness of GI may be different from other literature due to differences in climate conditions, soil property, and local labor costs in the study area.

4.2. Cost-effectiveness of GI implementation in the community

The C/E values of optimal GI layout designs under the design storms of the historical and climate change scenarios could aid decision-makers in adjusting stormwater management strategies. Due to the higher rainfall and peak values under the climate change scenarios compared to the historical scenario, future stormwater management systems will face significant challenges in mitigating and adapting to heavy rainfall caused by climate change in the study area. The trend of climate change is similar to other studies in the study area (Xia et al., 2022; Liu et al., 2023). In this study, it was found that the increased rainfall intensity under the climate change scenarios reduced the cost-effectiveness of GI. This may be related to the average annual cost remaining unchanged under three scenarios, while the increase in rainfall intensity under the climate change scenarios reduced the runoff control ability of GI, thereby weakening the cost-effectiveness of GI. Other studies have also shown that the increase in rainfall intensity caused by climate change weakened the cost-effectiveness of GI (Abduljaleel and Demissie, 2022; Liu et al., 2023). Moreover, the average cost-effectiveness ratios of GI decreased with increasing storm return periods and were relatively lower in the SSP5–8.5 scenario. Therefore, given the potential impact of climate change, planners need to reassess the design standards of existing GI and consider future climate change predictions and uncertainties, adjusting investment scale to achieve the expected effects of GI. Although, the study found that the scheme with the highest C/E value only reduced the average runoff by 49.0 % and the average peak flow by 43.0 % under the historical and climate change scenarios. It is worth mentioning that in the highest C/E value scheme, the implementation of GI only accounted for an average of 16.5 % of the total study area; the average AAC of the highest C/E value scheme is 26.2 × 10^4 Yuan, which is 26.6 % of the average AAC of the lowest C/E value scheme. Therefore, the combination of multi-objective optimization and cost-effectiveness of GI could provide cost-effective GI layout solutions for decision-makers, thereby enhancing the adaptability of urban stormwater management systems to climate change. It is obvious that the cost-effectiveness of GI could be significantly enhanced by reducing its life cycle costs. Several factors influence the life cycle cost of GI, including land costs, the structural configurations of GI, climate conditions, and local labor costs (Peri et al., 2012). In practice, it is recommended to choose local plants, substrates, and materials to directly

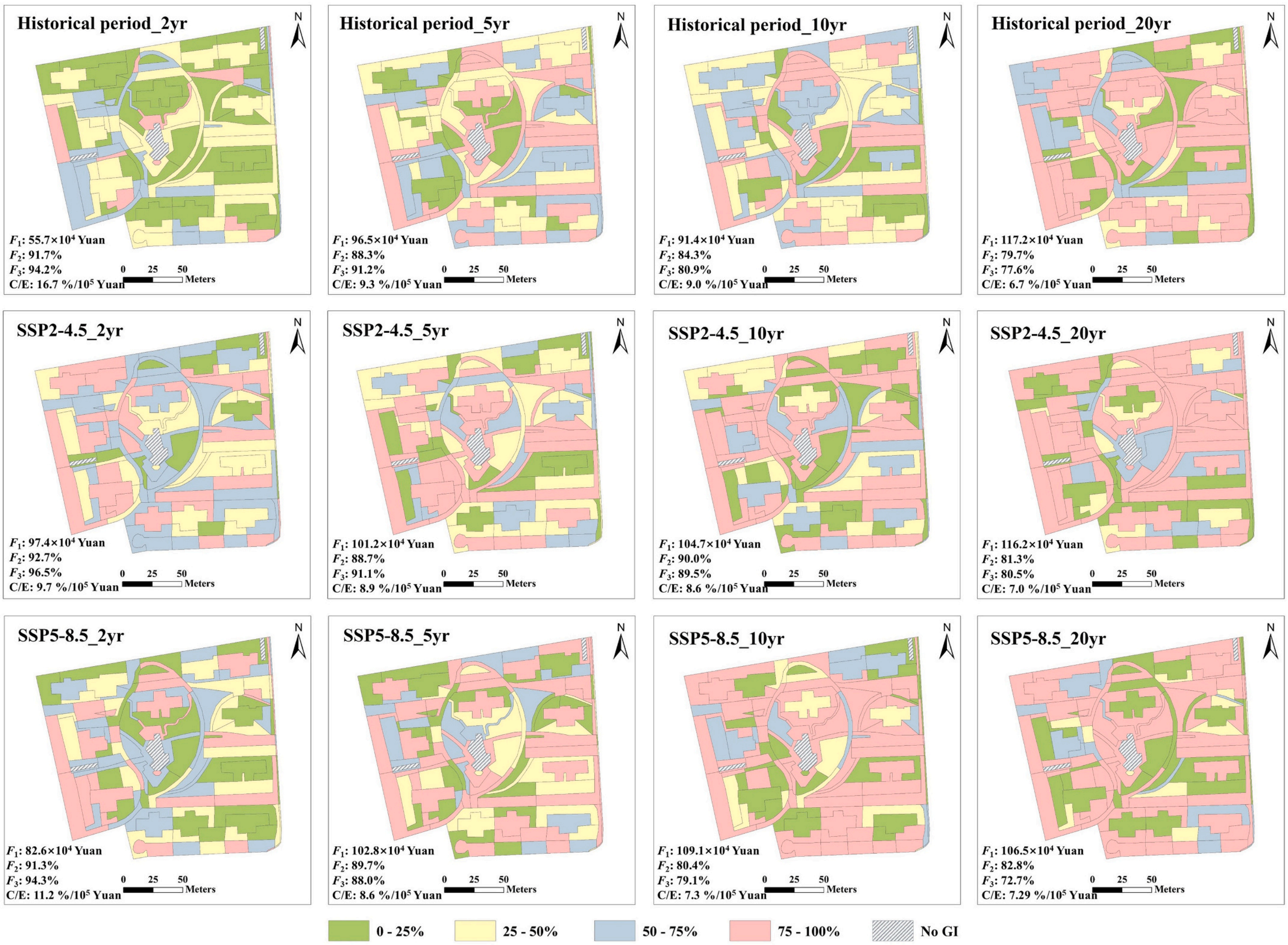

Fig. 7. The lowest C/E index layout scheme for design storms under the historical and climate change scenarios.

reduce construct costs and indirectly decrease maintenance and management costs, thereby improving the overall cost-effectiveness of GI.

4.3. Limitations and future work

There are several limitations in this study. First, considering the shortage of sub-hourly climate projections, the regional storm intensity formula parameters only changed in the daily mean intensity. Future research should focus on how to reduce the uncertainty of climate model outputs. Second, due to the incomplete comparison between the modified NSGA-II algorithm and other algorithms recently proposed (e.g., clustering-based adaptive multiobjective evolutionary algorithm, CA-MOEA; coevolutionary constrained multiobjective optimization, CCMO), it is not yet clear which algorithm performs better in the optimization of GI (Shaamala et al., 2024; Yu et al., 2022). In the future, more advanced optimization algorithms need to be selected to solve multi-objective problems through comprehensive evaluation of optimization algorithms. Third, considering many difficulties of rebuilding the sizes and layout of the existing stormwater drainage pipes, this study did not optimize the gray infrastructure. Some research concluded the green-gray combined alternative was more cost-effective than the green-only or gray-only option considering co-benefits (Alves et al., 2019; Dong et al., 2021). Therefore, the optimization of gray-green infrastructure should be improved for cities to become more sustainable and resilient to climate change.

5. Conclusions

In this study, a multi-optimization framework based on the SWMM model and the modified NSGA-II algorithm under climate change was proposed to optimize the size, location, and connection of GI, which provided decision-makers with guidance for the planning of practical SC projects in China. The results found that optimizing the size, location, and connection of GI can lead to greater runoff volume and peak flow reduction compared to only optimizing the size and location of GI. The optimized results indicated that most roofs had a similar connection pattern, where stormwater runoff flew through the roof, followed by green space, which reduced the effective impervious area. Due to its location in a high upstream catchment area and good performance in reducing runoff, permeable pavement accounted for the highest average area proportion of GI implementation in optimal layouts. Although the increase in rainfall intensity caused by climate change weakens the cost-effectiveness of GI, choosing local plants and substrates can enhance the cost-effectiveness of GI solutions. The optimal GI layout solutions and related cost-effectiveness will help in making cost-effective strategies for mitigating urban flooding caused by climate change, and contribute to improving the climate resilience of urban stormwater management systems.

CRediT authorship contribution statement

Xin Zhang: Writing – original draft, Methodology, Data curation.

Wen Liu: Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition. **Qi Feng:** Writing – review & editing, Supervision. **Jianjun Zeng:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2024.174851.

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Optimizing urban layouts through computational generative design: density distribution and shape optimization

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ABSTRACT
The density distribution in an urban matrix is one of the significant issues which affects other urban living factors such as building lighting, energy consumption and residents' interactions. The research toward achieving the optimum density distribution has received attention for the last decade. However, developing a generative approach that provides more freedom for the formation of the plans and incorporates adaptability in different land blocks is still missing. To address such a gap, this study proposes an adaptable approach developing the formation of residential blocks. This formation is according to the pre-defined size and shape of the land, and sought performance objectives. Hence, a suite of applications including Grasshopper, Python and Ladybug were applied in a residential block of Tehran as a case study. The purpose is to develop a new density distribution increasing view quality, visual privacy, and solar gain. For the optimization process, a genetic algorithm was applied utilizing the topology optimization technique. The results of the optimization process highlight the significance of this research since the developed alternatives are more efficient in terms of improving the view quality, visual privacy and increasing the solar gain. This achievement expands the potential of this research to be applied in different case studies and with different design and development objectives in order to develop better shape plans of building blocks.

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Generative design; parametric design; urban shape generation; density distribution; shape optimization; solar radiation

1. Introduction

The conventional urban shape planning, generally, relies on rigid design methods while lacks the flexibility to deal with the complexity and transformation of modern cities (Ataman & Tuncer, 2022). In contrast to traditional approaches where solutions are the result of manual iteration and experience, exploring larger design spaces is feasible through computational design methods and parametric and generative tools (Stals, Elsen, & Jancart, 2022). These methods are routinely used in architecture and engineering, typically for the optimization of discrete problems, such as building forms and facades to achieve better structural and environmental performance (Fattahi Tabasi & & Banihashemi, 2022; Fattahi Tabasi, Matin, & Rafizadeh, 2021; Haidar, Underwood, & Coates, 2019). Recently, the application of parametric and computational methods has been also utilized as a tool for design and planning objectives on neighborhood and urban scales (Mukkavaara & Sandberg, 2020; Peronato, Kämpf, Rey, & Andersen, 2017; Wilson, Danforth, Davila, & Harvey, 2019).

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A computationally optimized design solution can be substantially more efficient than the designs manually created (Shi, Fonseca, & Schlueter, 2017). Paying attention to the urban form is of high importance because through the proper buildings' density and form changes, several other factors such as livability (Martino, Girling, & Lu, 2021), social life and personal relationships (Mouratidis, 2018), air temperature (Tong et al., 2018), air quality (Kang, Yoon, & Bae, 2019), and traffic noise (Salomons & Pont, 2012) can be controlled. The importance of the density distribution in urban design and the significance of computational design in shape plan optimization (Rafizadeh, Alaghmandan, Tabasi, & Banihashemi, 2022) necessitate conducting new research. In fact, the reason behind initiating this research is to present a more integrated and adaptable methodology whose application can be applied in larger contexts. Since adaptability is the most important objective here, a cell-based approach, inspired by studies in the realm of topology optimization, was utilized. In this methodology, the design domain should be divided into a number of identical cells and the optimal topology is achieved by adding and/or removing these cells (Ghabraie, Chan, Huang, & Xie, 2010). This approach maximizes the adaptability for forming shape plans and meets architectural and structural demands (Banihashemi, Tabadkani, & Hosseini, 2018). In this study, Tehran was chosen as a case study considering the view quality, visual privacy, and solar gain as the objectives. However, this methodology can be utilized with different objective functions suitable for different case studies.

In this paper, next to the literature investigation and highlighting the contribution of this research, the research methodology is introduced. In this section, the algorithms developed in Grasshopper and Python are explained in detail. In the algorithm development process, first, a land block is divided into cells, some of these cells are then chosen based on a process explained in the following sections until it reaches the desired density distribution. In the next step, these plan layouts will be juxtaposed next to each other in the neighbor land blocks in two different arrangements to start the optimization process. In the following, the results of the optimization process are shown and compared with the baseline situation to highlight the success of this study in offering better shape plan alternatives.

2. Literature review

With respect to the literature review, several studies in the shape plan and urban layout design were investigated with a focus on the recent and most related ones.

Table A1 indicates the studies categorized and analyzed based on their scale, function, tools and optimization algorithms, objectives, procedures, adaptability and their architectural or structural perspectives to find a gap in the literature (Appendix 1, please refer to Supplementary file). In terms of scale, studies can be classified into three groups. First, there are studies considering only one building for the investigation. In this group, the focus is on a building, but with more details and analysis. For example, Zawidzki and Szklarski (2020) considered not only the outline of architectural layout but also all internal spaces design. Hence, the result of the optimization is a set of room configurations with their locations and orientations on the site. Furthermore, in the papers of J. Zhang, Liu, and Wang (2021) and Guo and Li (2017), there is a focus on the relations between internal spaces. However, the effect of the neighborhood is neglected in these studies. This is a salient drawback since objectives like energy performance, daylight, solar radiation, and view quality cannot be effectively optimized without considering neighbor buildings. The second group is the papers considering neighborhood effects in a certain site with unchangeable street locations. The third group includes studies working on urban layout generation with maximum freedom. In fact, in these papers, the streets are designed and optimized. As an example, Cheddadi, Hotta, and Ikeda (2019) provided enough flexibility for the algorithm by changing the street and plot subdivisions for optimization. In this paper, accessibility is the main objective function where the distance between each module and the nearest street was calculated to evaluate the physical accessibility and find the places for open interior spaces. Abdollahzadeh and Biloria (2022) considered the less amount of flexibility in street design. The width of streets was not a variable, but different orientations were examined. The result of these kinds of research is more suitable for new urban designs, whereas can be limited to retrofit existing urban structures.

The procedure factor investigates whether a study presents a computational design-based framework that automatically generates alternatives (generative design approach) or not. Zhang et al. (2021) proposed a performance-oriented design flow by developing a parametric generative algorithm. The final outcome of this algorithm is the evaluation and screening of generated schemes based on the spatial and energy aspects. Vermeulen, Knopf-Lenoir, Villon, and Beckers (2015) presented a method for the optimization of urban designs. The strategy was based on the distribution of blocks across a district. An evolutionary algorithm was employed to generate optimized urban blocks and receive maximum direct solar. El Ansary and & Shalaby (2014) introduced a genetic algorithm-based technique to optimally locate and orient two-dimensional layout planning of residential houses. This study is automatically considering the objective functions of minimizing the visibility between adjacent settlements and maximizing the direction of facades to a favorite view. Waibel, Evins, and Carmeliet (2019) presented a framework for the simultaneous optimization of building geometries and multi-energy systems. The study modeled four office buildings and the goal was to optimize building geometries to improve the solar potential and reduce carbon emissions. Azizi, Usman, Zhou, Faloutsos, and Kapadia (2022) introduced a framework consisting of two components. First, an automated tool was designed to convert floorplan images to attributed graphs. The attributes were designed via semantic and human behavioral features generated by a simulation. In the second component, floorplans were embedded and generated. Zawidzki and Szklarski (2020) presented a framework optimization of a floor plan of a one-story single-family house with its location and orientation. In this study, optimal and near-optimal solutions generated from the optimization process satisfy the maximization of the user's satisfaction level with the outside views, protection from external noise, and insulation preference. Xu et al. (2019) proposed a genetic algorithm-based urban layout optimization method. They generated different alternatives in order to maximize the proportion of the acceptable universal thermal comfort index range in a cold region. Cheddadi et al. (2019) studied unplanned urban fabrics for developing in a spontaneous way. In this research, firstly, a set of rules, functions, and objectives in experimental urban form-finding models were explored by studying the characteristics of urban form. Then, a parametric model was developed based on the characteristics of spontaneous urban structures in old Islamic cities in order to generate different alternatives for social housing. Guo and Li (2017) presented a method based on the combination of a multi-agent topology discovery system and an evolutionary optimization to automatically generate spatial architectural layouts. Camporeale and Mercader-Moyano (2019) conducted research to find ways to reduce the primary energy consumption of slab and high-rise housing typologies, in four different cities with different climates, through the optimization of their building shapes. A multi-objective Genetic Algorithm (GA) was implemented for buildings shape optimization based on the generative design.

However, some studies are not based on the generative design approach. For instance, Natanian, Aleksandrowicz, and Auer (2019) introduced a parametric workflow for performance-driven urban design. This parametric approach was utilized to optimize urban form, energy balance and environmental quality. Nonetheless, adding a generative aspect to this methodology can improve its impact on future studies. Abdollahzadeh and Biloria (2022) presented a parametric methodology applying multi-objective optimization to find non-automatically generated optimum design solutions. Another example of this approach is De Luca (2017) that investigated the direct solar gain of different building typologies and layouts in various urban areas with different densities. Multiple patterns of building footprints were created, and different variations were, then, delivered by changing the direction of the building in relation to the terrain. Ibrahim, Kershaw, Shepherd, and Coley (2021) highlighted the relationship between urban form design parameters, energy performance, and outdoor thermal comfort in summer and in the hot arid climate. In this paper, by changing the morphological characteristics of different blocks, various solutions were created non-generatively.

Adaptability is another analytical factor where it is essential to know whether a developed method is adaptable to different lands with different shapes and dimensions or is only limited to a case study. The literature analysis shows that this matter has been rarely considered so far. Most studies focused on predefined typologies and their limited modifications. For example, Xu et al. (2019) chose various typologies of urban blocks in Shenyang, China and examined their different placements in nine neighboring lands. In Vermeulen et al. (2015), scale, rotation, and translation were the factors used to design the shape of the nine rectangular predefined buildings as similar to Abdollahzadeh and Biloria (2022) and Ibrahim et al. (2021). Although these special typologies are suitable choices for the analyzed case studies in these studies, there is less chance for their application in different situations.

Last but not least, studies are classified into architectural and structural constraints. A suitable shape plan is one that has satisfied density distribution and is structurally and architecturally thought-out too. In fact, it should be constructible and its interior spaces should be designable with suitable connections (Banihashemi & Zarepour Sohi, 2022). This is one of the elements which has been neglected in the literature. The defined typologies present the whole picture of the building layout, yet it is not clear how the internal spaces are organized and optimal design and structure are achieved. As mentioned before, Guo and Li (2017), Zawidzki and Szklarski (2020) and Zhang et al. (2021) assessed this by the precise and dimensional design of internal spaces. The first two studies are modular and guarantee the structural design, but in the third study, there is no discussion about the optimum structure. Two studies in the literature meet architectural and structural requirements but the scale of their investigation is limited to one building and they have not utilized a parametric tool (Guo & Li, 2017; Zawidzki & Szklarski, 2020).

Eight of the investigated studies present various typologies for the density distribution with parameters limited to the dimensions and/or orientation. While these typologies are not necessarily adaptable to other cases (Abdollahzadeh & Biloria, 2022; Camporeale & Mercader-Moyano, 2019; De Luca, 2017; El Ansary & & Shalaby, 2014; Ibrahim et al., 2021; Natanian et al., 2019; Vermeulen et al., 2015; Xu et al., 2019). So, the novelty of this research lies in using the concept of generative design on the scale of the neighborhood and develops an adjustable approach for urban layout generations based on the grid system. As compared to the other studies' objective functions, this study focuses on improving the view quality, visual privacy, and the solar gain, integratively, while these objectives have not been considered before.

3. Methodology

3.1. Case study

Case study research scientifically studies a real-life phenomenon in depth and within its environmental context (Yin, 2017). No-theory/posterior study is a type of case study research design, in which the research question and hypothesis may stem from a research gap and the case or cases are chosen to test the hypothesis. In fact, this type is of great potential to offer practical insights into the phenomenon of interest. In such a study, qualitative data are inspected for aggregation and interpretation and finally, the analysis of the data is used to test the hypothesis (Eisenhardt & Graebner, 2007; Ridder, 2017). In this paper, this strategy was utilized where a research gap was initially found as explained in the literature section. The case study research strategy was then used to understand whether presenting a novel approach adaptable with different objective functions, different sites and considering the effect of the neighborhood is capable to deliver superior results in urban layouts or not. By conducting the data collection through literature, documents and report analysis, a single case study was chosen to do an in-depth analysis. In fact, a deeper description of a single case was taken priority over shallow investigations of multiple cases (Ridder, 2017).

3.1.1. Study area

To position the proposed methodology in the practical context of the shape plan optimization of residential neighborhoods, Tehran was chosen as a case study of this research. Tehran is the capital city and the largest urban area of Iran with a population of 8,700,000 (Bayat et al., 2019). The city is also ranked as one of the largest cities in Western Asia and 19th in the world. Similar to other large and dense cities in the world, Tehran faces serious air and noise pollution problems where 20% of the total energy of the country is consumed in Tehran (Carrasco, Iglesias, Amani, & Rafat, 2022). These facts justify choosing Tehran as the suitable test bed for this study. The research procedure here begins by studying the municipal laws of Tehran in order to find a suitable rule to be challenged (Figure 1). The chosen rule is the building coverage ratio (BCR) which represents the ratio of the total building area occupied by buildings, to the total land area (Soliman, Mackay, Schmidt, Allan, & Wang, 2018). According to the municipal laws of Tehran, the building must be built on the northern part of the lot with a BCR of 60% at its maximum. This rule was established in Tehran many years ago when there was no urgent need for energy consumption reduction and it has not been appropriately revised in the last fifty years (Ramyar, Ramyar, Kialashaki, Bryant, & Ramyar, 2019). In this study, this law is challenged to find a more optimized solution by integrating shape optimization and parametric design.

3.1.2. Shape optimization objectives

As mentioned in the previous sections, the main technical aim of this study is to optimize the lot coverage and density distribution in an urban matrix. The resulting pattern is expected to have the following optimization objectives:

1-The solar radiation on the exterior part of buildings should be at the maximum level (Vermeulen et al., 2015). Tehran suffers from enormous air pollution (Bayat et al., 2019), excessive amount of energy consumption (Sedaghat & Sharif, 2022) and sudden widespread power blackouts (Kalantar, Saifoddin, Hajinezhad, & Ahmadi, 2021). The reason behind increasing the received solar energy on buildings is to enhance renewable energy generation, make buildings self-sufficient and expand the solar energy capacity of the city. This not only reduces the amount of fossil fuel consumption in these buildings but also enhances the natural lighting. It should be noted that the majority of the studies conducted in the area of parametric architecture in Tehran focus on the facade design in order to optimize energy-related parameters such as daylight, thermal performance, and energy consumption (Tabadkani, Aghasizadeh, Banihashemi, & Hajirasouli, 2022). Accordingly, the potential of parametric urban layout generation for controlling the amount of solar radiation gain and consequently energy production is neglected. Some

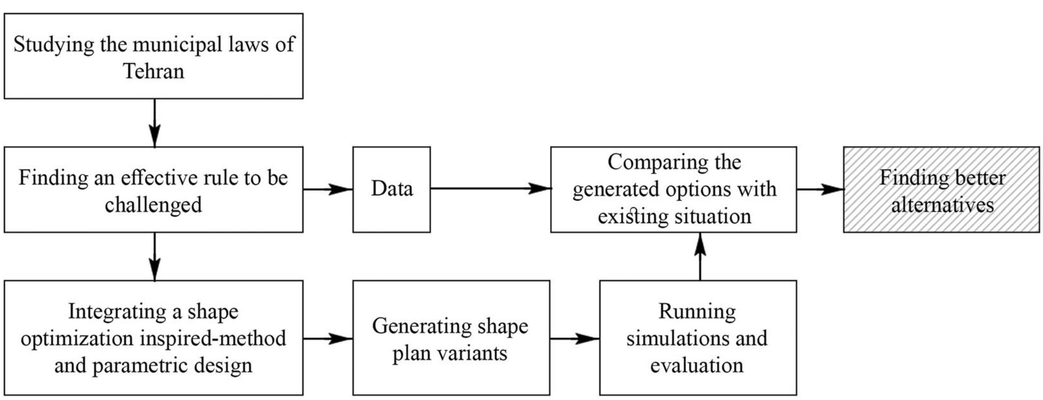


Figure 1. Research procedure diagram.

examples of the literature focusing on increasing the amount of solar radiation on buildings and the reasons behind are provided in Table A2 (Appendix 2).

2-The walls should be far enough apart. This is important for two reasons. First, it provides an opportunity to enhance the view quality (Figure 2(a)). The role of natural green spaces on human well-being, satisfaction, and social-psychological behavior is proven (Ta, Li, Zhu, & Wu, 2021). 'Researchers have generally focused on benefits gained from nearby nature, often measured as proximity to it or the amount of green space, and having a window view toward' (Irvine et al., 2010, p. 1). In the era of rapid urbanization where natural green spaces are getting diminished, having green space in residential areas can be important in contributing to the quality of human health (Shahril, Musa, Zainal, Noh, & Kassim, 2021). In the case of Tehran, unfortunately, rising land costs have pushed people toward degrading nature to earn higher profits (Mirsadeghi, 2016). On the other hand, unlike the importance of open spaces, there is no study focusing on how changing the current situation of open spaces in Tehran can deliver better results. This is why, in this study, the view quality is of potential to be enhanced by providing the view toward spaces that are suitable to be planted. Second, it provides more privacy for the occupants of these dwellings. This issue is particularly important for Tehran in light of its cultural background (Irani, Armstrong, & Rastegar, 2017) (Figure 2(b)). Iranian culture and religious beliefs accentuate the importance of visual privacy in architecture (Ravari, Hassan, Nasir, & Taheri, 2022). This is becoming more concern when the rapid growth of high-density buildings affects people's environmental quality (Fallah, Khalili, & bin Mohd Rasdi, 2015). This issue has not been paid attention in the literature from the perspective of urban layout design. This further highlights the novelty and significance of this paper.

3.2. Algorithm details

The algorithms developed in this study can be divided into three parts: the lot coverage pattern generation through Python, wall distances measurement via Grasshopper (GH) and solar radiation analysis in Ladybug plugin (Figure 3).

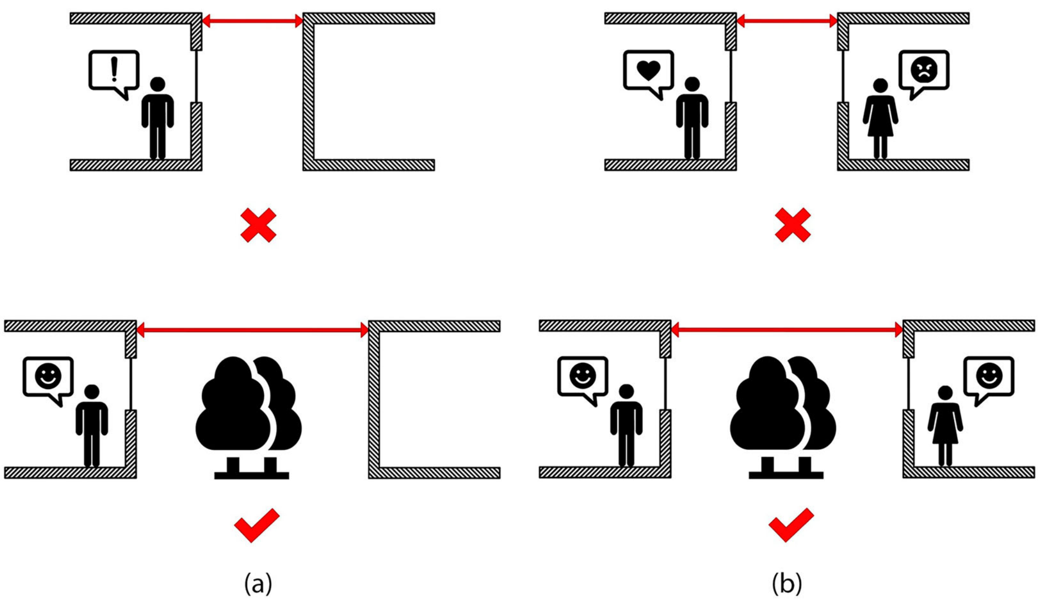
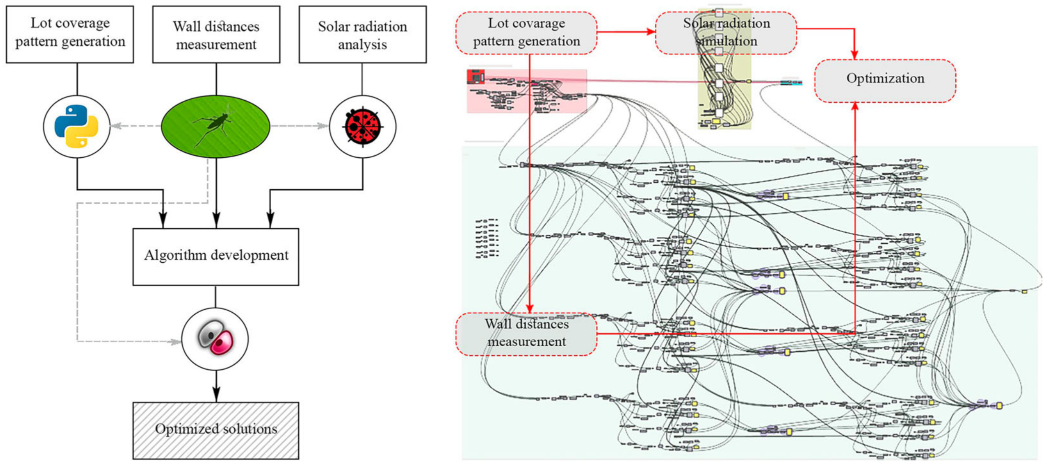


Figure 2. The importance of the view quality. (a), The importance of visual privacy in residential neighborhoods (b).

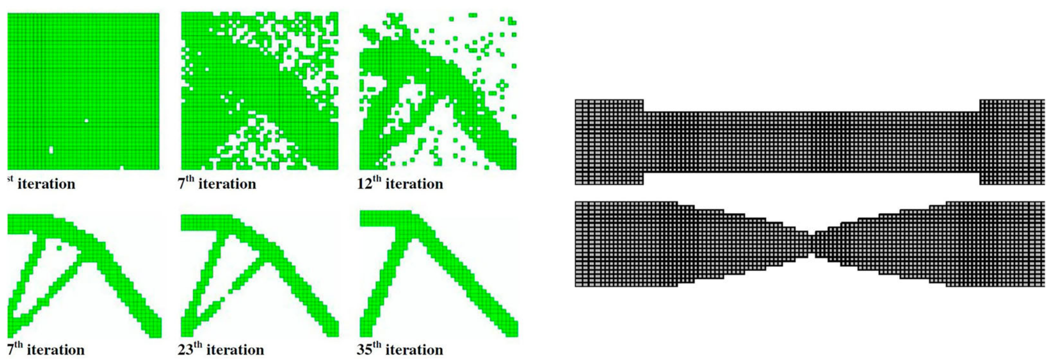


(a) (b)

Figure 3. Algorithmic method diagram (a), Algorithmic framework built in Grasshopper (b).

3.2.1. Lot coverage pattern generation

In this part, six blocks of land with a length of 30 m and width of 12 m which are the average dimensions of land block in Tehran were considered. The shape plan optimization starts from the first block and passes through the next blocks. In order to optimize the shape plan and generate the lot coverage pattern, a method used in Topology optimization studies was utilized to provide freedom for density distribution while considering architectural and structural constraints. A cells-based shape plan design assures that the structure is modularly designed and economically justifiable. Furthermore, the cell dimensions should be assessed in the way that the architectural design based on the Bottom-Up method becomes feasible (Appendix 3). Topology optimization is a tool that enables architects and engineers to find an optimal structural layout under certain conditions. Various techniques have been developed in this field such as bi-directional evolutionary structural optimization (BESO). This technique is based on the gradual removal of inefficient materials from a structure and efficient materials addition, so that the shape evolves toward an optimum one (Ghabraie et al., 2010). Two examples are provided in Figure 4(a, b) for this concept. As it is



(a) (b)

Figure 4. Examples of utilization of BESO technique for optimization, (a) Combining GA with BESO for topology optimization (Zuo et al., 2009), (b) shape optimization of a structural element (Ghabraie et al., 2010).

obvious in this Figure, the optimization process is based on the cells and their addition and/or reduction from the final shape. Therefore, in order to apply this technique, first, a grid of cells with 3m-by-3 m dimensions was designed. These dimensions were selected based on the design considerations of modular structures and the municipal laws in Tehran (Regulations, 2017). This limits the distances of the walls between two separate main spaces of residential units to at least 3 meters (this distance can be less where the spaces like kitchens place opposite together). This regulation should be met where windows are necessary for both the walls and lands of more than 200 square meters. In the following, two different approaches were, accordingly, examined.

The first method is to randomly remove 40% of the cells to enable the remaining 60% to form the shape plan (Figure 5). This method creates many alternatives but has two major drawbacks. First, it greatly increases the optimization time due to a large number of generated patterns. The second problem is that in order to achieve an acceptable shape plan, the generated shape must be integrated. This is because of the fact that some vertical and horizontal circulations are required for a residential building. Separating a building into a number of parts will increase the area of these circulation spaces. This is a waste of area and uneconomical. The algorithm developed in GH for this method is shown in Figure 6(a). As it is shown, 40% of the cells are reduced by the 'Random Reduce' component while by changing the seed, different arrangements can be achieved. A similar method was used by Cheddadi et al. (2019). In this study, a 3D grid was generated and the Random Reduce component was utilized to reduce the size of boxes based on seeds. The Pareto optimization solutions shown in this paper lack integrity and as a result, lots of buildings are not designed in an optimized way.

The second method is based on the selection of a cell and its growth in all directions in the boundary of the block to reach the BCR of 60%. In this method, disintegrated shape plans are eliminated, and optimization time can be substantially reduced. The Python component developed for this method is shown in Figure 6(b). The output of this component is creating 24 points as the central stations to generate desired cells.

The starting point is selected by defining variables in the optimization process (basex and basey). Therefore, the formation of the shape plans can be processed from all cells. By selecting the first cell, the shape can randomly grow in all directions but their different directions probability is a variable in the optimization process (left, right, up and down). The selection of cells is also controllable through

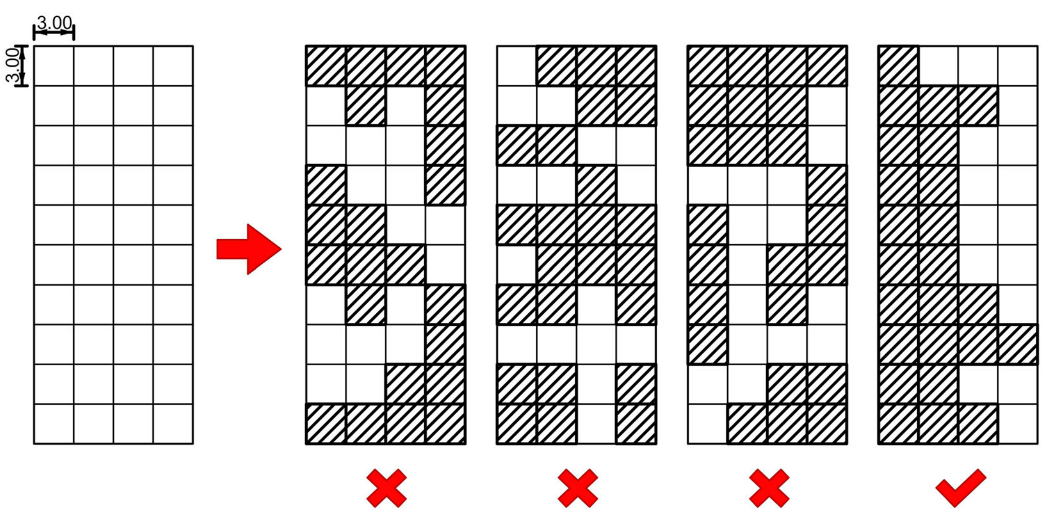


Figure 5. Based on the first approach, the random selection of 60% of the cells forms the shape plan. Some of the generated plans are not suitable to be designed due to the lack of integration.

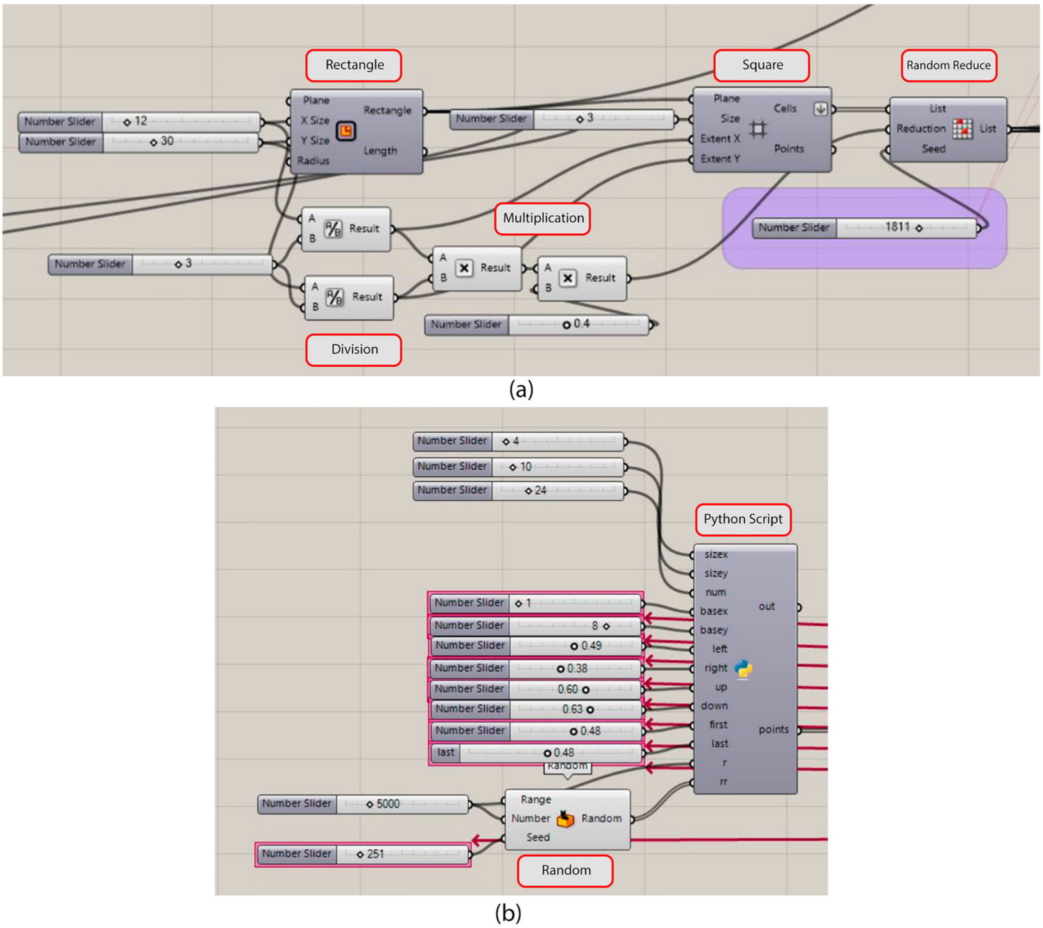


Figure 6. The algorithm developed in GH for the first method (a) and The Python component developed in GH for the second method (b).

two variables that are defined in the optimization process. These variables define the chance of the selection between primary cells or newly generated cells (first and last) (Figure 7(a-e)).

In general, this algorithm is based on the selection of a cell in the beginning and a random movement from it, while their chances of selection are the variables. By changing these variables, a wide range of shape plans can be generated. At the end of the optimization process, the generated shapes are checked against their correlation with the independent variables. The plan generation process continues until 60% of the land is occupied by the cells. Some examples of these shape plans are shown in Figure 7(f).

The next step is to extrude the shapes to create a typical 5-story residential building with 15 m of height according to the conventional building height in Tehran. Finally, the last step is to juxtapose buildings next to each other to consider the effect of the neighborhood and the exposure to sunlight and view quality. In order to examine a larger number of alternatives and achieve a more optimal result, two approaches of copy (Figure 8(a)) and mirror (Figure 8(b)) were considered to arrange buildings on the adjacent lands. In Figure 8, the building blocks colored in gray are only considered as the context buildings and the middle eight blocks (Figure 8) are the models that were investigated.

This is not the first time a grid-based methodology is being introduced to automatically generate building layouts. Zawidzki and Szklarski (2020) discussed a method based on 1.5 by 1.5 cells that enables users to input their layout-related preferences (like the list of rooms with lists of their acceptable

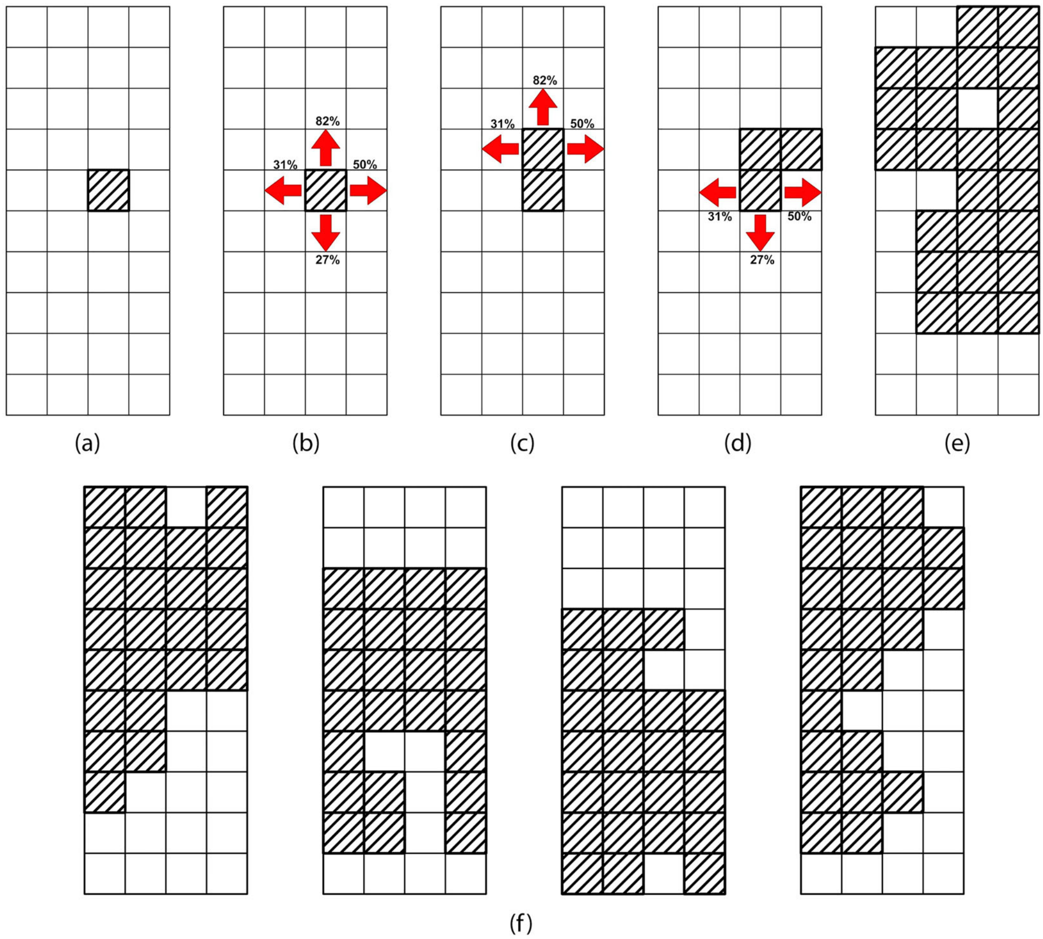


Figure 7. The second approach used in this study: selection of one of the cells as a starting point (a), the feasibility to move in all possible directions (in this case 4 directions) with different probabilities which are considered as a variable in the optimization process. (The numbers in the image are just as examples) (b), Repetition of the same process and selection of subsequent cells based on the same rule (c), Possibility of growth from the previous cells (d), a possible generated shape plan based on the algorithm (e), Some examples of the generated shape plans (f).

and preferred sizes, the size and shape of the building footprint, and the preferences regarding internal relationships) in the process. This was an adaptable approach for designing building layouts considering internal space relationships on a small scale. Guo and Li (2017) are another example that defined a 3D grid containing a number of cells. In this study, the size of the cell and the maximum number of cells were user-defined. The topology-finding process was utilized through a multi-agent system, where rooms were represented as bubble-like agents and connections as strings. Some rules were also defined to control the behavior of agents during the interaction process.

However, although these studies are valuable in terms of the architectural design on the scale of a building, there is a lack of broader investigation and generalizability of the results. What differentiates these studies from this research is the scale of the investigation; the neighborhood effect is neglected in the literature whereas this study is to fill this gap.

3.2.2. Solar radiation analysis

To evaluate the amount of solar radiation received on the outer surface of buildings (both walls and roofs), Ladybug which is a parametric environmental plugin for GH was used. Ladybug imports

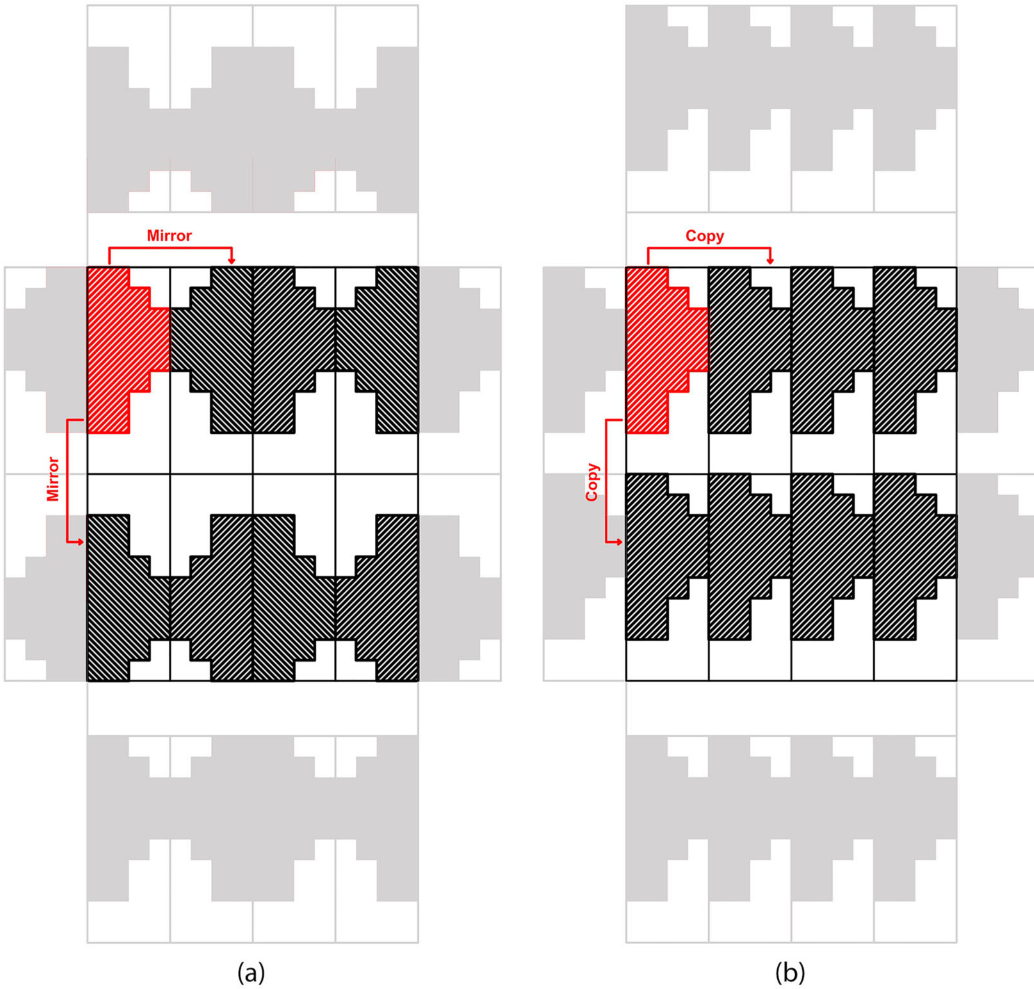


Figure 8. Two different arrangements for building juxtaposition in the adjacent lands: Mirrored (a) and Copied (b).

standard EnergyPlus Weather files (.EPW) and provides a variety of 2D and 3D designer-friendly interactive graphics. It also allows users to work with validated energy and daylighting engines such as EnergyPlus, Radiance, and Daysim (López-Cabeza, Diz-Mellado, Rivera-Gómez, Galán-Marín, & Samuelson, 2022). The solar radiation function in Ladybug uses the Cumulative Sky approach to calculate the amount of radiation of the Tregenza Skydome. With this respect, the 'RadiationAnalysis' component utilized buildings in which each building was considered as the 'geometry' and the others as the 'context'. In the end, the radiation result of these eight components was added together. The resultant figure is the first objective function in the optimization process (Zhang, Zhang, & Wang, 2016). The solar radiation on this day is at its least amount during the year (Shipman, Wilson, Higgins, & Lou, 2020) and as a result, the optimization results can be better extrapolated. A sample result from the Ladybug illustrating the amount of solar radiation on the exterior surface of the building is shown in Figure 9.

3.2.3. Wall distances measurement

To enhance the view quality and visual privacy, the distance between the walls of the adjacent buildings should be measured and increased as much as possible. To do so, the perpendicular lines, from

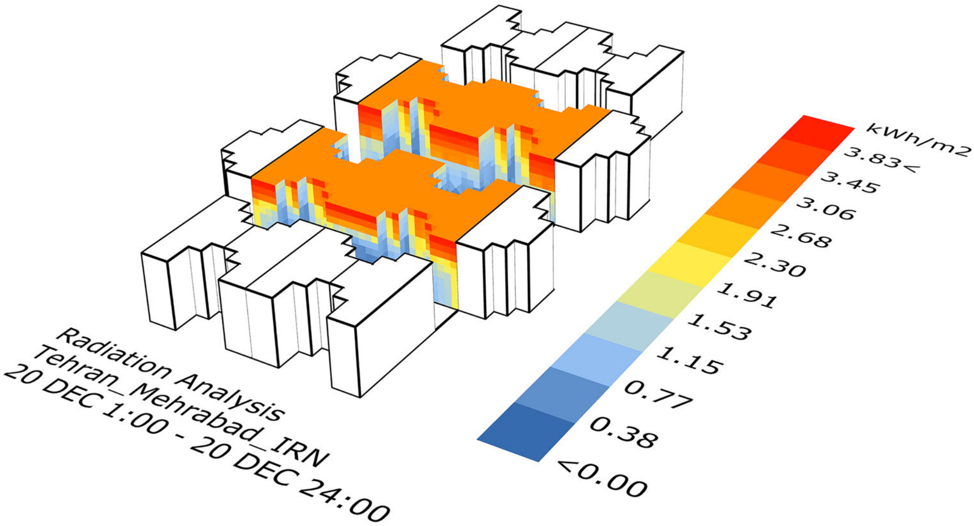


Figure 9. A sample result from the Ladybug plugin shows the amount of solar radiation on the exterior surface of the building.

the face of the walls to the first intersection by the adjacent buildings' faces, were measured (Figure 10). In fact, the sum of these distances is the second objective in the optimization process in which by increasing this value, farther apart walls can be developed.

4. Optimization

In building performance analysis, different optimization algorithms in literature have been used to find the optimal solution. Evolutionary algorithms are a group of computational search methods which are widely used in similar optimization problems (Calixto & Celani, 2015)). GA (genetic algorithm) is one of the most popular evolutionary algorithms which processes the optimization and searches for high-performing options, inspired by natural selection.

Accordingly, Galapagos Solver Function, which applies GA as its main optimization engine and is the GH-integrated tool, was applied (Huang, Chang, & Shih, 2015). Through developing the algorithms in GH, the variables and the objective functions were defined in Galapagos to find the best alternatives. As explained previously, the variables are the main actors in generating different lot coverage patterns and the objective function is to maximize both wall distances and solar radiation (Banihashemi, Golizadeh, & Rahimian, 2022). The summation of these two objectives was applied as the optimization objective function in Galapagos. Figure 11 presents the number of generations and their optimization processes for both copy and mirror approaches.

5. Results and discussion

The results of the generated and optimized urban layouts are presented from two perspectives of geometrical and numerical analysis and in terms of solar radiation, visual privacy, and view quality. These results are also compared with the existing situation and their social impacts are also discussed.

5.1. Geometrical analysis

The optimized results of the density distribution, as shown in Figure 12(b, c), are quite different from the existing density distribution in Tehran (Figure 12(a)). In the existing situation, the northern part of

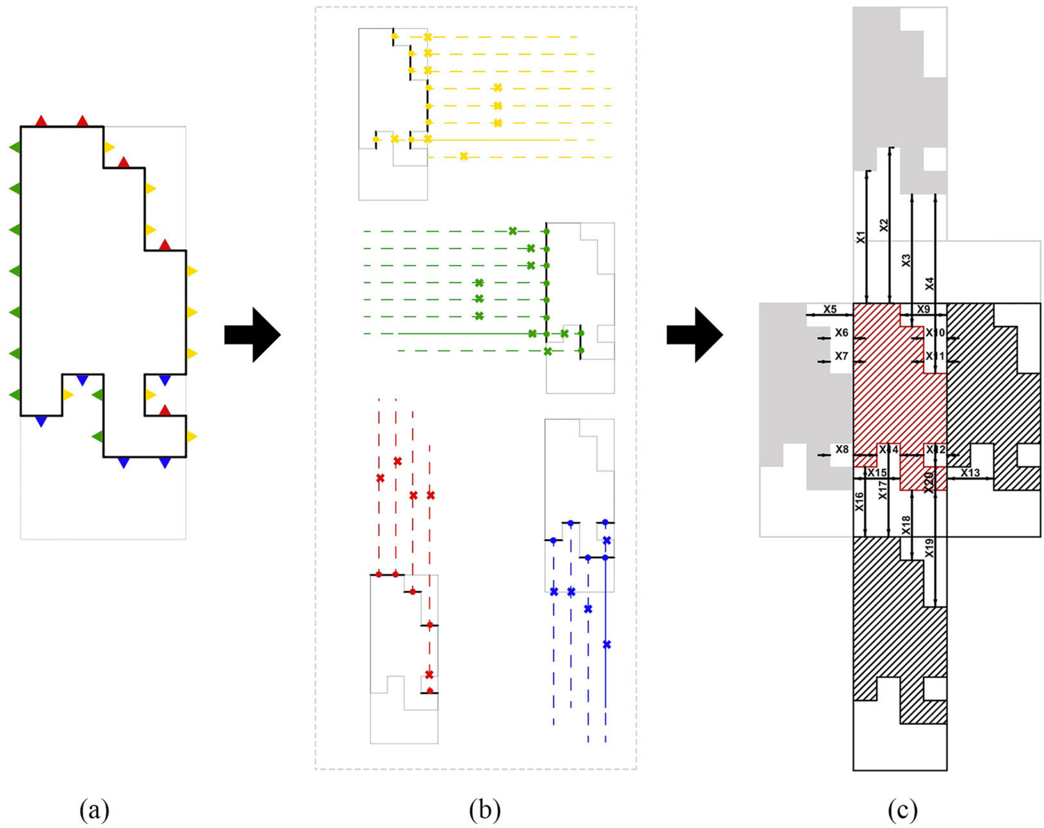


Figure 10. Wall distances measurement: all building faces (a), perpendicular lines and intersections (b), measurement of distances between area centers and intersection points.

the land is fully occupied by the building mass whereas the southern part is the open space. As a result, a clear border can be drawn between these two sections.

In contrast, in light of the developed optimization and in terms of geometry, the expansion of the building along the land is obvious, and the border between the two parts is faded. Instead of having open space with a regular shape, the yards are separated into several parts or expanded on the land with non-rectangular shapes. Depending on their size, these spaces can be used as an atrium or a courtyard. In addition, the shape plans are transformed from regular rectangular shapes to non-regular shapes. As a result of these changes, the potential of receiving daylight from the eastern and western sides of buildings is provided in most of the optimized results.

The results also show that the bounding box area (the box in which the plan is inscribed) is optimally expanded and even in some cases, it has covered the whole lot. Besides, the ratio of the circumference to the area of the shape plan is higher, delivering more optimal results. Hence, it can be inferred that the more the shape plan is spread along the land, the superior the results are. Perhaps, this outcome can be considered as a principle in future designs.

5.2. Numerical analysis

As it is shown in Figure 13, the baseline radiation simulation result is 4859 Kwh/m2 for the total solar radiation received. The numbers obtained from the optimization results show an increase in this factor. In both mirror and copy arrangements, the most optimal case shows a 2.5% and 4.3% increase compared to the baseline, respectively.

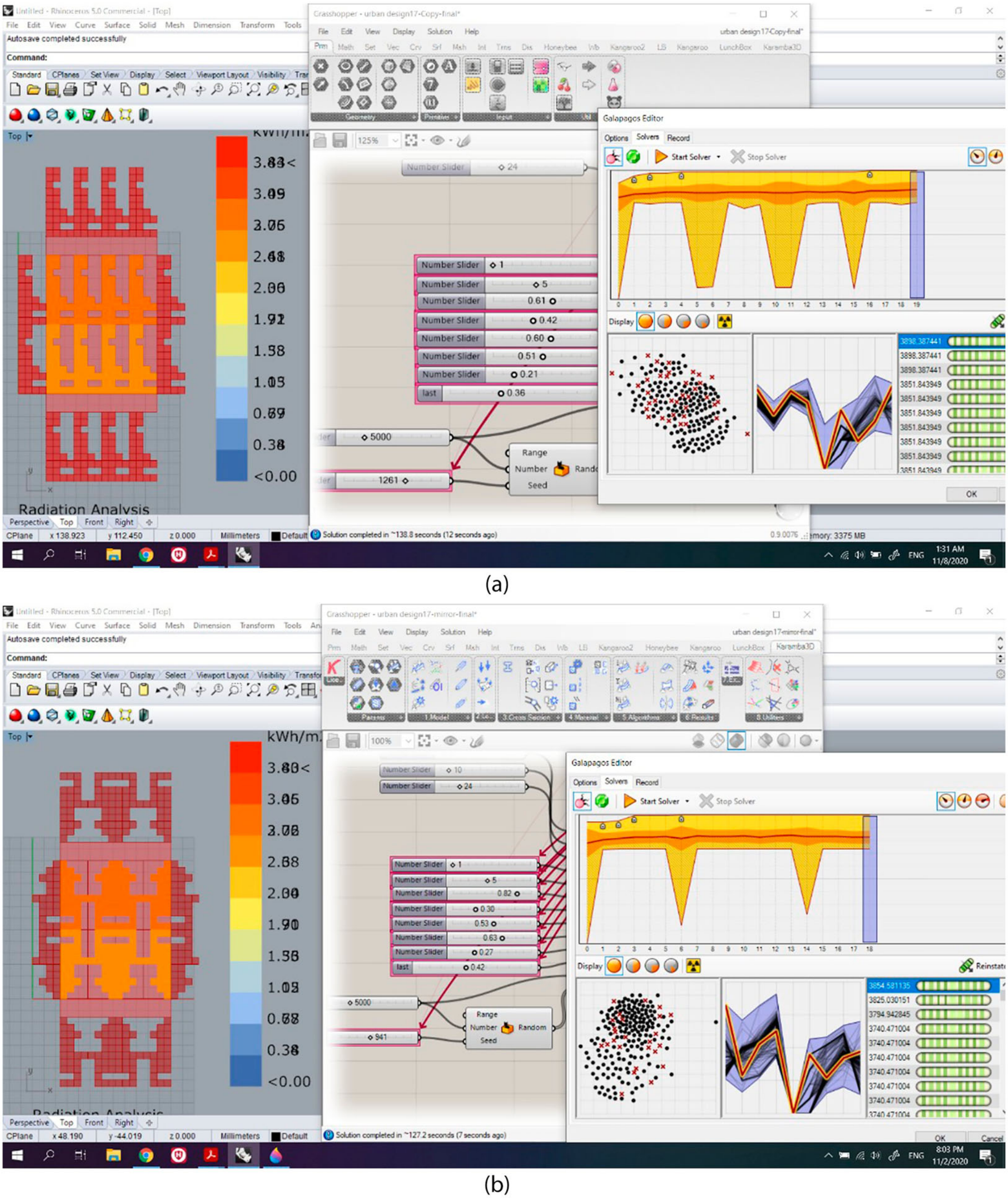


Figure 11. Galapagos solver function for the copy approach (a), Galapagos solver function for the mirror approach (b).

Furthermore, in terms of total wall distances, the results show a significant increase too. The sum of wall distances for the baseline is 832 meters. However, through the post-optimization, the sum of the wall distances for the mirror and copy arrangements are 1711.63 and 1760 meters indicating 106% and 111.5% of increase, respectively.

The comparison between the optimized results obtained from both arrangements shows that the solar radiation resulting from the copy arrangement is the highest. On the other hand, the mirror arrangement delivers more total distances between the walls (Figure 13). However, in overall and by considering the significance coefficients, the optimal results of copy arrangement are in the lead.

Figure 12. The existing situation of density distribution in Tehran (a), The top 10 optimal results with mirror arrangement (b), and The top 10 optimal results with copy arrangement (c).

5.3. Broader impacts of research

Land use is one of the important identifiers of urban sustainability which is directly affected by urban forms. Therefore, it is of vital importance to make the land use (Barbosa, Araújo, Mateus, & Bragança, 2016) optimal to enhance their sustainable and regenerative feature. Neighborhoods with row housing layouts (like the current situation in Tehran) tend to have a diminished level of social interaction between dwellers (Karuppannan & Sivam, 2011). Comparing the current situation of Tehran's density distribution with the result of the optimization process, it is obvious that an integrated open space breaks into a number of smaller ones or extends along the land. As a result of this change, not only more spaces will be exposed to greenery, but also a hierarchy of private, semi-private, and public open spaces will be created. This can provide an opportunity for more social interactions and subsequently lead to a more sustainable urban design. Moreover, being more exposed to green spaces result in more livability. This is in light of the environmental factors influencing livability such as esthetic qualities of the landscape, the presence of vegetation, and greenery (Norouzian-Maleki, Bell, Hosseini, & Faizi, 2015). Besides, by expanding the building density along the land, fewer spaces could be in direct exposure to noisy streets so that the amount of noise pollution can decrease.

5.4. Methodological contributions

One of the goals of this study was to present an adaptable methodology suiting a wide variety of cases. The adaptability of this method in comparison with the literature are more precisely discussed to highlight the potential for future research. The extent of adaptability of the proposed methodology is shown in Figure 14 in which the density distribution is based on small modular parts

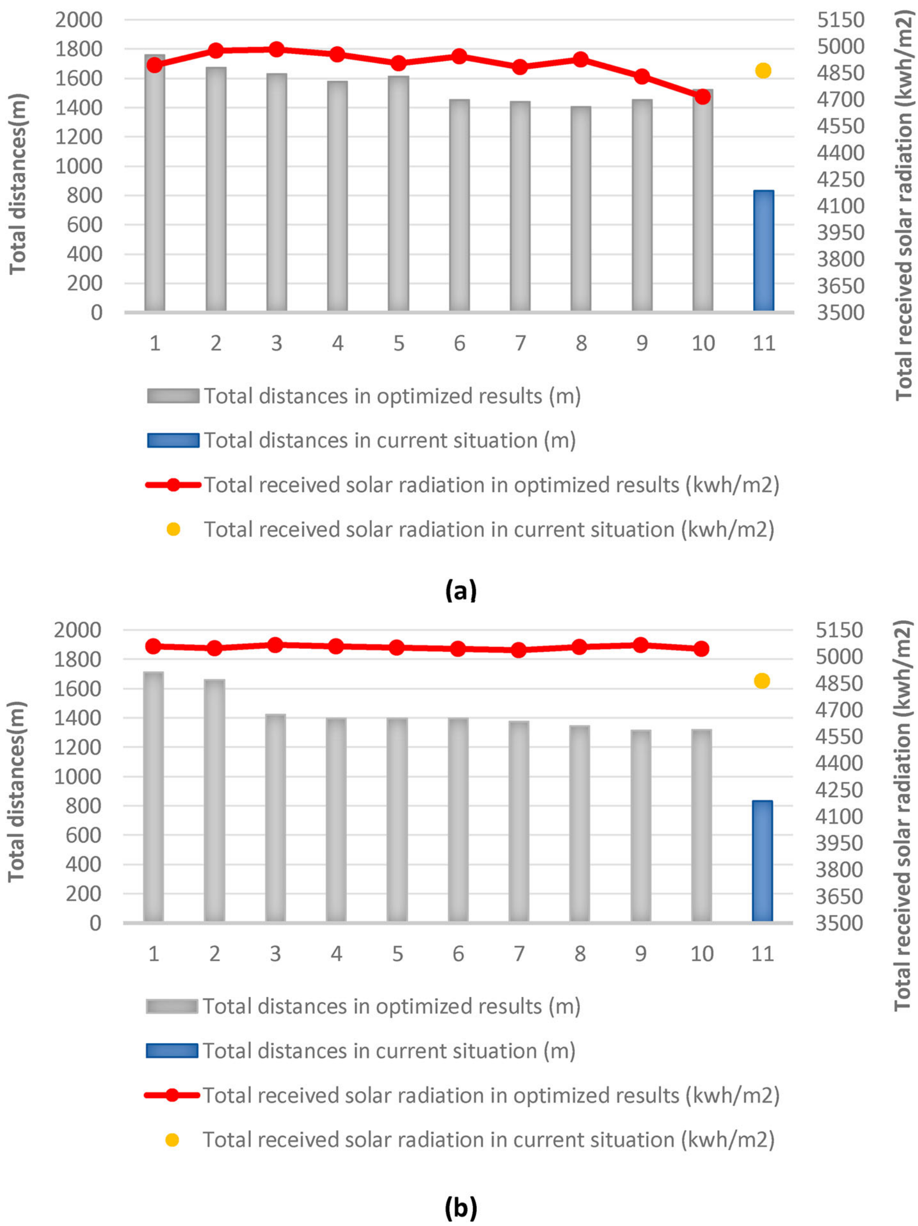


Figure 13. The objective functions in the top 10 optimal results with mirror arrangement in comparison to the existing situation (a), The objective functions in the top 10 optimal results with copy arrangement in comparison to the existing situation (b).

(cells) and provides several advantages. These modules can be fitted with the different shapes of a land including both regular and irregular ones. As an advantage, their function is not affected by the size of the land and so, fewer number of modules can fit smaller lands. Since the architectural design will be based on the bottom-up method (Appendix 3), there is no concern for the designability of the modules. Therefore, the adaptability of this approach enables changing the number of modules for other functions like social housing and considering the regulations of other cities. Another advantage of the applied cell-based method is that it is feasible to include trees in the density distribution. To maintain valuable heritage trees of the site, their location can be defined as a barrier in the algorithm. So, the cells will not be located within the defined boundaries.

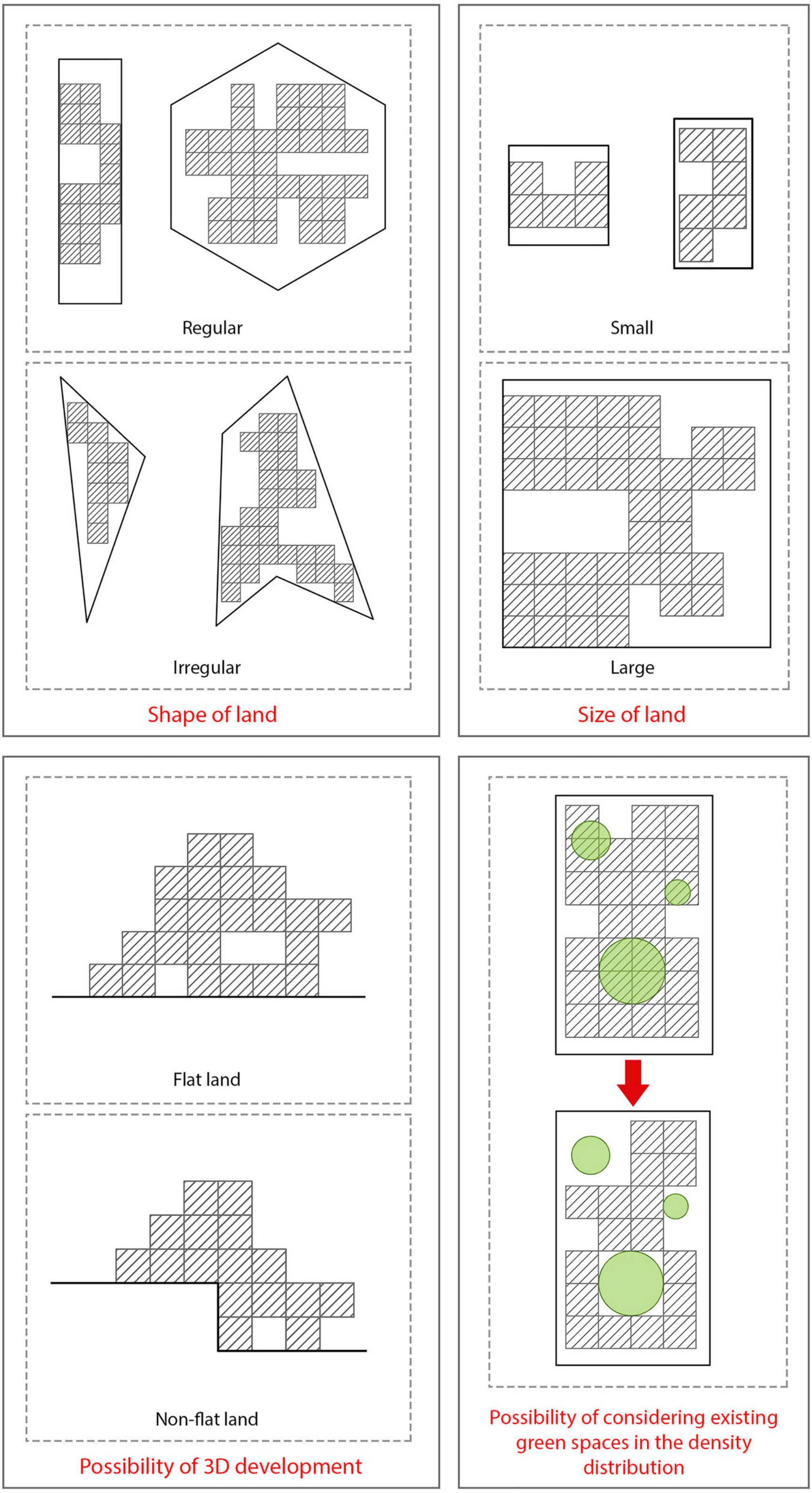


Figure 14. Advantages of the proposed modular method: adaptability to different shapes and sizes of land, provided with including the location of trees in density distribution and potential for 3D development.

In this study, a 2D approach was examined. However, there is great potential for utilizing 3D cells for both the density and volume distribution of buildings. It will not only provide maximum freedom for the formation of buildings but also make them adaptable to different types of lands comprising flat and non-flat ones.

The degree of adaptability is exactly what differentiates this study from the literature. Some of the non-adaptable approaches used in the previous studies are shown in Appendix 4. As it is obvious, in these studies, a number of typologies and some variations limited to dimensions are defined. By changing these variables through the optimization process, results are delivered. These results are definitely valuable for their applied case study. However, these integrated density distributions will not necessarily reconcile with other lands and cases with different conditions. Furthermore, changing their size to fit with other cases does not seem a good solution since it does not guarantee their designability. In fact, their potential for development in future studies is fairly limited whereas this limitation is alleviated by the presented framework in this research.

6. Conclusion

Computational design tools assist designers and architects to make better decisions in a shorter time. This research presented a new method to find superior solutions for generating more efficient urban layouts. The objective functions; increasing solar radiation received and increasing the wall distances were chosen according to the case study demands and characteristics. It was also intended to develop a new methodology that provides more freedom for shaping plans in the residential blocks according to the defined objectives and to be applied in the field. Hence, in future research and according to the chosen site, more or different design and development objectives can be defined to achieve more significant results.

In this study, although achieving freedom in shaping the urban blocks was desired, architectural and structural constraints were not compromised. This virtue was controlled and achieved via choosing the dimension of cells and designing plans which are architecturally sound and structurally modular and efficient. A parametric algorithm was designed to generate a large number of alternatives for buildings shape plans and two different arrangements of building were considered for their adjacencies. After more than one hundred hours of the simulation and optimization process, a set of results were generated. The optimization results are evidence of the significance of this study as to clearly demonstrating that by changing the distribution of the building density in Tehran, more optimal results can be achieved. These results indicate that the amount of solar radiation, gained by the optimal results, increased 2.5% in the mirror and 4.3% in copy arrangement in comparison with the non-optimized layout.

However, this study only investigated the optimization of the shape plan of a 5-story building in a dense neighborhood. Further studies can be carried out considering the shape optimization of buildings in 3 dimensions where the shape plans of different floors are not typical. Besides, in order to minimize the negative consequences of the maximum solar radiation in summer, more studies are required to include shadings and other control strategies. Including some energy-related objectives like daylight and thermal comfort and interior design-related parameters in the optimization process can further enhance the practicality of the result in future studies. Additionally, this research underlays an opportunity for increasing view quality for residents at the conceptual level. However, view quality enhancement is related to three variables including view content, view access, and view clarity (Ko, Kent, Schiavon, Levitt, & Betti, 2022). Considering the two last variables requires a more in-depth design of building details such as windows. This is another area for future research. Finally, this should be noted here that, in this paper, among the abundant of the literature in the shape plan and urban layout optimization, a very focused sphere of the research was selected for the literature analysis. Hence, all existing varieties in terms of the scale of investigation, general approach, adaptability, and architectural and structural aspects were covered. However, further research is necessary to analyze all other aspects and variables related to this field.

Disclosure statement

No potential conflict of interest was reported by the authors.

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