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AIstructure-Copilot: assistant for generative AI-driven intelligent design of building structures

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Abstract: The rapid advancement of intelligent design technology in building structures has been primarily implemented in engineering practice through the use of local or cloud-based software to offer intelligent design services. However, local intelligent design services are time-consuming and require high-end hardware, whereas cloud-based designs fail to integrate seamlessly with existing design processes. Consequently, providing convenient intelligent design support for engineering practices is challenging. To address these problems, this study proposes a local–cloud collaborative intelligent design technology called AIstructure-Copilot, which serves as a structural intelligent design assistant. In this system, the local end performs routine graphical operations that align with engineers' design habits, whereas the cloud end executes generative artificial intelligence (AI) for intelligent design, thereby enhancing efficiency and effectively combining the strengths of both services. Specifically, this technology achieves a high level of automation and intelligence throughout the entire process, encompassing architectural design, structural design, and the establishment and execution of structural analysis models. This is accomplished by constructing a local–cloud collaborative mode, introducing a comprehensive data transmission format, and developing a cloud interface for generative AI algorithms. The effectiveness of the AIstructure-Copilot model was validated using a typical case study. The results demonstrate that AI design improves design efficiency by more than tenfold, satisfies the regulatory requirements of design schemes, and exhibits a discrepancy of approximately 20% when compared with designs created by competent engineers.

Keywords: intelligent design; local–cloud collaboration; generative AI; shear wall structure; complete design process



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1. Introduction

The mainstream work mode in the building structure design industry still relies heavily on manual design, and the reliance on engineering experience poses challenges in enhancing efficiency and quality, thereby limiting industrial development. The rapid advancement of intelligent design technologies for building structures has emerged as a crucial catalyst for the development of intelligent construction. In recent years, remarkable progress has been made in generative artificial intelligence (AI)-driven methods for intelligent building structure design, as highlighted by Liao *et al.* [1], laying the groundwork for practical applications. Nevertheless, a pressing gap remains in the availability of convenient, efficient, and intelligent building structure design paradigms as well as the corresponding intelligent design tools that can be effectively employed in engineering practice.

Currently, application tools for intelligent design in building structures rely primarily on parametric modeling and intelligent optimization technologies, which can be categorized into two primary types: local-end-based and cloud-platform-based design technologies. (1) Local-end-based technologies: This approach relies on 3D graphics engines such as Rhino [2], Autodesk Revit [3], and SketchUp [4] for visualization and interaction. Visual programming languages, such as Grasshopper [5] and Dynamo [6] are used to encapsulate the required parametric and automated operation commands for structural modeling and analysis into functional modules. This enables the parametric modeling and optimization of structures. Intelligent design tools such as YJK-GAMA [7], PKPM-AID [8], Swallow [9], TigerKin [10], and Euler [11] have provided support for the digital and intelligent transformation of building structure designs. (2) Cloud-platform-based technologies: These involve the development of a cloud-based project execution platform that encompasses all design functions, including design drawings, interactive operations, and intelligent design features. The development of cloud-based platforms for architectural design has rapidly progressed, with platforms such as Xkool [12] and Pinlan [13] gaining popularity. However, relatively few cloud-based intelligent structural design technologies exist. Fei *et al.* [14] proposed a technology that integrates offline graphic operations with an online intelligent design platform. Overall, local-end tools are often time-consuming and require high-performance local computers. However, cloud-based design tools are not seamlessly integrated with existing design processes, causing engineers to switch between multiple tools, which is inconvenient. Therefore, intelligent design technologies for building structures require efficient, convenient, and user-friendly tools to enhance their usability.

With the advancement of effective intelligent methods, such as generative AI, the computational requirements of AI often exceed the capabilities of personal computers. To address this, scholars have proposed the concept of a copilot. A copilot serves as a mechanism for AI to provide cloud-based services, assuming certain aspects of the human workload while collaborating seamlessly within the existing software usage process [15]. Inspired by the copilot concept, a collaborative work approach can be adopted, utilizing local ends for lightweight tasks such as graphic operations, whereas complex and heavy processes such as AI intelligent design are executed on the cloud end. This facilitates a higher level of

intelligent design in building structures. Nevertheless, challenges remain to be overcome when realizing a copilot-driven intelligent design. First, a local–cloud collaborative work framework should be established. Additionally, the standardization of data formats for transferring multi-stage design information in local–cloud collaboration remains pending. Finally, the development of a cloud AI algorithm for intelligent design interfaces is yet to be accomplished.

This study focused on the generative AI design of shear wall structures, a topic that has been extensively researched and widely demanded in practice. An intelligent design assistant for shear wall structures, named AIstructure-Copilot, was developed and is driven by generative AI. The aforementioned problems related to intelligent design collaboration between local- and cloud-ends have been effectively addressed by establishing a local–cloud collaborative work framework, dividing the design content between the local and cloud, adopting a structured data expression in the JavaScript Object Notation (JSON) file format, and integrating the latest AI intelligent design algorithms into the cloud system. Additionally, a typical case study was conducted to thoroughly test the performance of AIstructure-Copilot, and comprehensive comparisons were made between the design results generated by AI and those produced by competent engineers. The foundation for the subsequent enhancement and progress of AIstructure-Copilot has been laid, and the practical application of technologies related to intelligent design can be explained by this study.

2. AIstructure-Copilot for shear wall structures

2.1. Introduction to local–cloud collaborative design tools

In this study, a local–cloud collaborative intelligent design tool called AIstructure-Copilot was developed specifically for shear wall structures. This tool can be seamlessly integrated into computer aided design (CAD) platforms, offering effective design solutions. The operational architecture of the tool is presented in Figure 1, which clearly illustrates its functionality. AIstructure-Copilot enables users to conveniently draw design blueprints within a CAD platform while simultaneously displaying intelligent design results. To provide intelligent design services, the tool accesses intelligent design algorithms through open application programming interfaces (APIs) using hypertext transfer protocol (HTTP) on a cloud platform. By employing a collaborative approach between local and cloud platforms, AIstructure-Copilot maximizes the advantages of local computer CAD operations and the computational power offered by cloud platforms. Consequently, it significantly enhances the design efficiency without imposing an additional computational burden on the local computer.

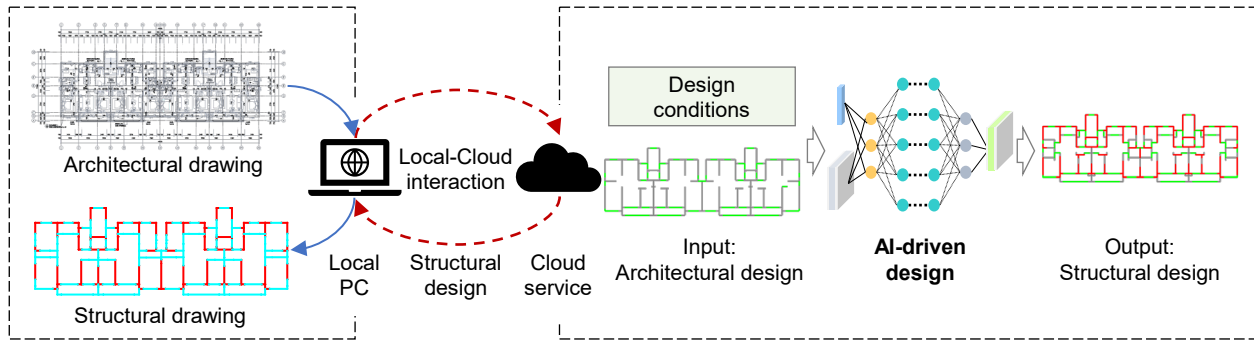


Figure 1. Local–cloud collaborative intelligent design system for shear wall structures.

When installed on a CAD platform, AIstructure-Copilot presents a user interface with various features, as shown in Figure 2. The key functionalities encompass user logins and intelligent designs specifically tailored for shear walls. The intelligent design features for shear wall structures include parameter settings, building information pre-processing, shear wall intelligent design, beam intelligent design, modeling information for the shear wall–beam structure, and intelligent material consumption prediction. For comprehensive guidance on utilizing these features, please refer to Subsection 2.2 for detailed instructions.

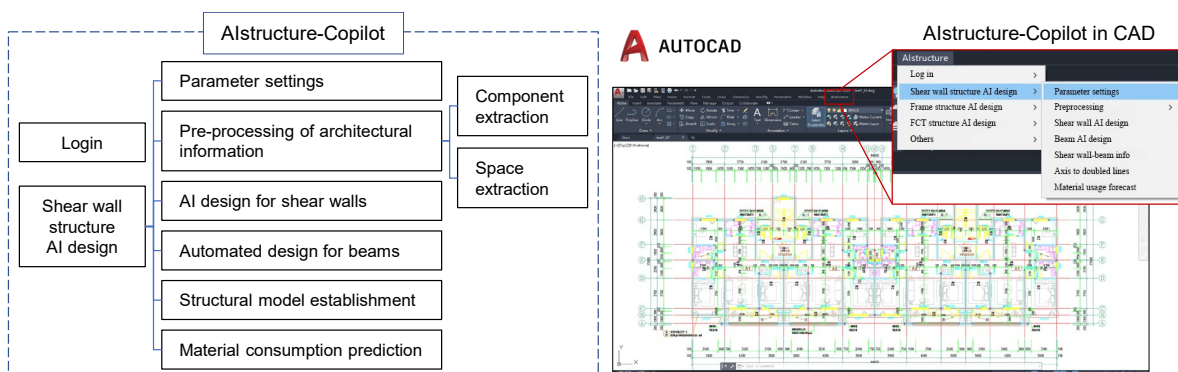


Figure 2. CAD-based AIstructure-Copilot.

AIstructure-Copilot functions as an intelligent design assistant for building structures within a CAD platform, building upon the aforementioned process. It enables engineers to conduct intelligent designs for shear wall structures directly within the CAD platform on their local computer, without requiring any modifications to existing design workflows or established practices.

The key innovation of this study lies in streamlining the laborious processes of uploading and downloading between pre- and post-processing work and cloud-based intelligent design platforms. By integrating the entire process, a complete intelligent design workflow can be executed seamlessly within the CAD environment. This achievement holds significant value for guiding the practical implementation of intelligent designs in engineering structures, thereby providing an effective blueprint for real-world applications.

2.2. Building structure intelligent design process

The workflow of AIstructure-Copilot is depicted in Figure 3. All operations can be seamlessly completed within the CAD program, eliminating the necessity for cumbersome platform switching and time-consuming upload and download processes. Consequently, an intelligent design process for shear wall structures can be accomplished within a remarkably short timeframe of 5–10 minutes.

Step (1): Pre-processing of building information (~3 minutes): First, engineers perform parameter settings, including maximum and minimum values for architectural wall thickness (mm), minimum value for architectural wall length (mm), names of architectural wall and doors/windows layers (layers can be selected by clicking on CAD elements), and specifications such as design basis earthquake (DBE) acceleration (g), structural height (m), site characteristic period value (s), standard story height (m), material grade (C), shear wall thickness (mm), beam height (mm), among others.

Next, two steps are executed: the extraction of architectural component axes and generation of building spatial profiles. The architectural component axes are accurately extracted to faithfully represent the building component objects, with any inaccuracies manually adjusted by engineers. Building spatial profiles are automatically generated based on the extraction results by assigning text attributes to key spaces, such as elevators and balconies. The pre-processing method is described by Fei *et al.* [14].

Step (2): Intelligent design of shear wall structures (~1 minute): Using the selected pre-processed architectural component axes and spatial profile data, the intelligent design of the shear walls is executed. AIstructure-Copilot leverages the cloud platform to perform an intelligent design of shear walls using three types of algorithms, completing the design process in approximately 40 seconds. Currently, users can select between a generative adversarial network (GAN), graph neural network (GNN), and a diffusion model for intelligent design algorithms. For more information on intelligent design algorithms, please refer to Subsection 3.1.

Step (3): Automatic design of beam structures (~30 seconds): By selecting the layout results of the shear wall structure, along with the architectural component axes and spatial profile information, the beams are automatically designed. AIstructure-Copilot utilizes the cloud platform to perform automatic beam design. Further details of the beam design method are available in Fei *et al.* [14].

Step (4): Intelligent prediction of material consumption (~10 seconds): Based on the layout of the shear wall–beam structural components, the corresponding cross-sectional size design of the components is automatically obtained using statistical regression results and a GAN-based design [16,17]. Additionally, AIstructure-Copilot offers a feature that enables users to customize the cross-sectional sizes of the components. The shear wall–beam layout and

cross-sectional size design are then input into the material consumption intelligent prediction module, which calls on the cloud platform for the rapid estimation of concrete and steel material consumption. For more information on the intelligent prediction algorithm, please refer to Subsection 3.2.

Step (5): Automatic construction of mechanical model (~30 seconds): Similarly, the shear wall-beam structural layout and sectional size design results are automatically converted into the corresponding PKPM and YJK mechanical analysis models. These models can be utilized for detailed analyses, performance evaluations, and material consumption calculations. For details on the automatic modeling method, please refer to Subsection 3.3.

After Steps (1)–(5), the design results and structural analysis models shown in Figure 4 are obtained, thereby facilitating rapid scheme design and comparison tasks.

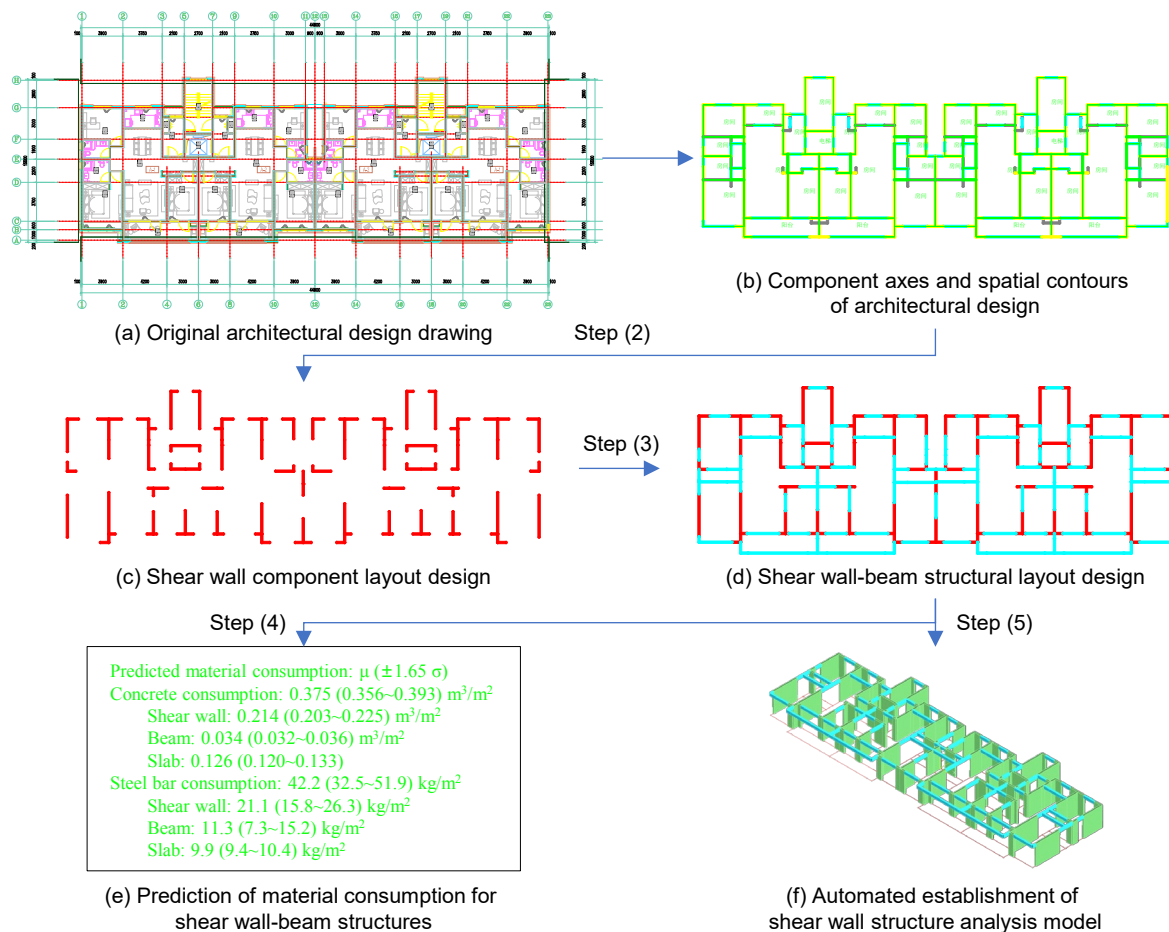


Figure 3. Intelligent design process of the shear wall structure.

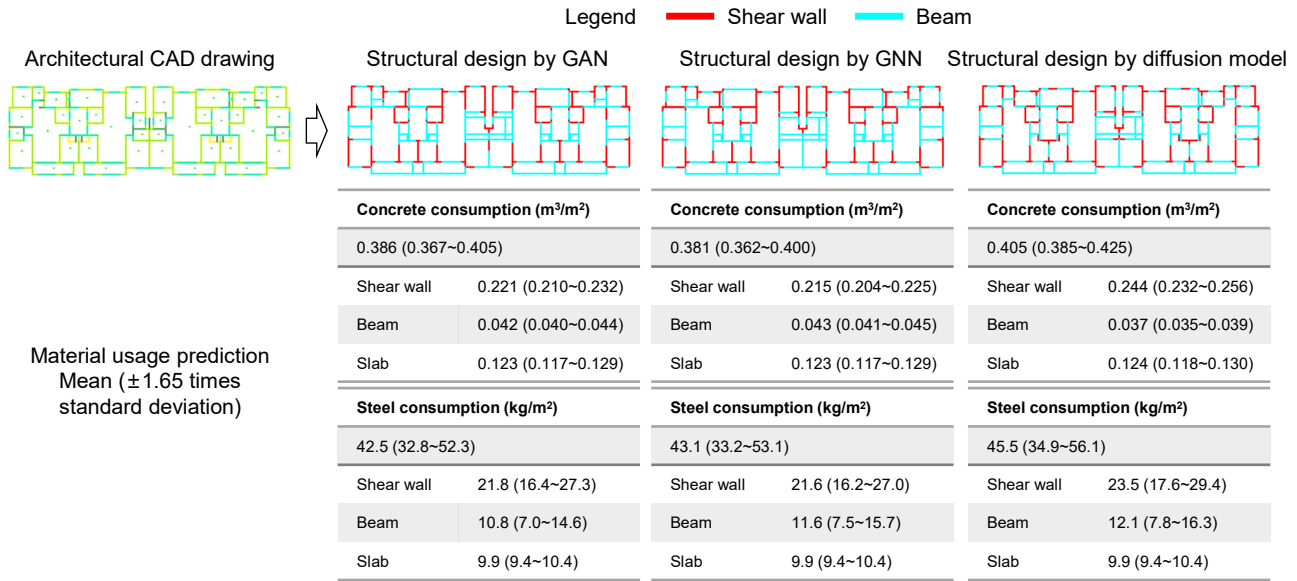


Figure 4. Astructure-Copilot-aided intelligent design of the shear wall–beam structure.

2.3. Data transfer for intelligent building structure design

To enhance the efficiency of data transfer throughout the design process and to enable flexible data manipulation for subsequent functional adjustments, this study introduces a structured data expression format that is seamlessly integrated with the design workflow. JSON files are specifically adopted for data transfer, facilitating easy modifications without disrupting other data operations such as adding, deleting, querying, and editing. Table 1 presents an example of a typical data format.

Table 1. Structured data format in JSON files.

Key	Value
DesignConditions (Design conditions)	{Intensity: float} (Design base earthquake acceleration (g)), {TotalHeight: float} (Structure height (m)), {SitePeriod: float} (Site characteristic period (s)), {NumStdstory: int} (Number of standard stories)
NaturalStories (Natural story properties)	[{NaturalStoryID (ID of natural story): int, StdStoryID (ID of standard story): int, StoryHeight (height of standard story): float},, {NaturalStoryID (ID of natural story): int, StdStoryID (ID of standard story): int, StoryHeight (height of standard story): float}]
StdStories ^a (Standard story properties)	[{StdStoryID (ID of standard story): int, Elements: Elements, ArchiSpaces: ArchiSpaces, StoryConditions: StoryConditions},, {StdStoryID (ID of standard story): int, Elements: Elements, ArchiSpaces: ArchiSpaces, StoryConditions: StoryConditions}]

^a The details of the objects in StdStories, such as Elements and ArchiSpaces, are shown in Table 2.

Table 2. Introduction for standard story parameters of JSON files.

Key	Value
Elements (Collection of component objects)	{“ArchiWalls”: [element,, element]} (Architectural walls), {“WinDoors”: [element,, element]} (Windows and doors), {“ShearWalls”: [element,, element]} (Shear walls), {“Beams”: [element,, element]} (Beams), {“CandiBeams”: [element,, element]} (Potential beams), {“Slabs”: [archispace,, archispace]} (Slabs) Where element is key-value data, element = {type, id, x1, y1, x2, y2, prop1, prop2, prop3, prop4, prop5}, where, type: string (element type, default value is None); id: int (element ID, default value is -1); x1, y1, x2, y2: float (x and y coordinate values of element 1st and 2nd nodes, respectively, default value is 0); prop1~prop5: reserved property values. Among them, the prop1 of the ArchiWalls element indicates whether it is a movable partition wall; the prop1, prop2, and prop3 of the ShearWalls element are the shear wall thickness, ID of the belonged architectural wall, and concrete material grade, respectively; the prop1, prop2, and prop3 of the Beams element are the beam section width, section height, and concrete material grade, respectively; the prop1 and prop2 of the Slabs element are the slab thickness and concrete material grade, respectively. If there is no property, it is empty.
ArchiSpaces (Collection of space objects)	{“Rooms”: [archispace,, archispace]} (spaces other than subsequent named spaces), {“Balconys”: [archispace,, archispace]} (balcony), {“Elevators”: [archispace,, archispace]} (elevator), {“Lavatorys”: [archispace,, archispace]} (lavatory), {“Kitchens”: [archispace,, archispace]} (kitchen), {“Stairs”: [archispace,, archispace]} (stairs). Where archispace is key-value data, archispace = {type, id, numnodes, xs, ys, prop1, prop2, prop3, prop4, prop5}, where, type: string (space type, default value is None); id: int (space ID, default value is -1); numnodes: int (node number of the space contour, default value is -1); xs: list (a list of x coordinates of space contour nodes, arranged in clockwise or counterclockwise order, the default value is an empty list); ys: list (a list of y coordinates of space contour nodes, the order must match the x coordinate, arranged in a consistent order with “xs”, the default value is an empty list); prop1~prop5: reserved property values. If there is no property, it is empty.

3. Key technologies of intelligent design tools

3.1. Intelligent design module based on GAN, GNN, and diffusion model

Currently, AIstructure-Copilot offers three types of intelligent design results: shear wall structural designs generated by GAN, GNN, and diffusion model algorithms. This tool extracts architectural components and spatial information from CAD files and outputs them as structured JSON files. These JSON files are subsequently uploaded to a cloud platform, where they are transformed into image and graph feature data, which are necessary for diverse generative AI algorithms. When the intelligent algorithm generates the structural

design, it is converted back into structured data and output as a JSON file, which is then transferred back to the CAD platform for drawing.

(1) A shear wall structural design method utilizing a GAN was initially proposed by Liao *et al.* [18]. Subsequent advancements have been made, including text-image fusion learning [19], mechanics-enhanced learning [16], and attention mechanism-enhanced learning [20]. After the generation of design images by the GAN, the shear wall layout is further optimized using an engineering experience encoding approach [21]. Architectural design images serve as the input data for the GAN, and the output consists of images illustrating the shear wall structural layouts, as depicted in Figure 5(a). Additionally, Fei *et al.* [14] proposed a method for mutual conversion between structured vector data and non-structured pixel image data.

(2) The shear wall design method based on a GNN was initially introduced by Zhao *et al.* [22] and was later enhanced to incorporate seismic design requirements [23]. This approach utilizes graph representation to capture both architectural and structural designs, with the GNN learning mapping rules from architectural design graphs to structural design graphs. Figure 5(b) shows this process.

In the architectural graph, nodes represent the endpoints of the architectural components, and node attributes indicate the endpoint coordinates. Edges represent the architectural components themselves, with edge attributes, including one-hot encoding of the component category, the coordinates of the two endpoints, and the component length. In the structural graph, the node features are the same as those in the architectural graph, whereas the edge features represent the attributes of the structural components. These attributes include the inward length of the shear wall components from the two endpoints. If the length of a shear wall component in the graph's edge features falls below a certain threshold, no shear wall is considered present. Because the graph itself constitutes structured data, it can be directly converted into a corresponding structured data JSON file.

(3) A shear wall design method based on the diffusion model was introduced by Gu *et al.* [24]. This approach involves converting JSON data into feature matrices representing architectural designs and constructing a diffusion model algorithm to learn the corresponding feature matrices. The diffusion model then generates the shear wall structural design features based on the trained model, as shown in Figure 5(c).

During the training process of the diffusion model, the building structure design feature tensor is gradually transformed into Gaussian white noise by adding Gaussian noise. A deep neural network predicts the distribution of added noise by inputting noisy images, thereby acquiring the ability to recover structural design images from noisy images containing Gaussian noise. The trained diffusion model progressively removes the Gaussian white noise, resulting in the final shear wall structural design feature tensor.

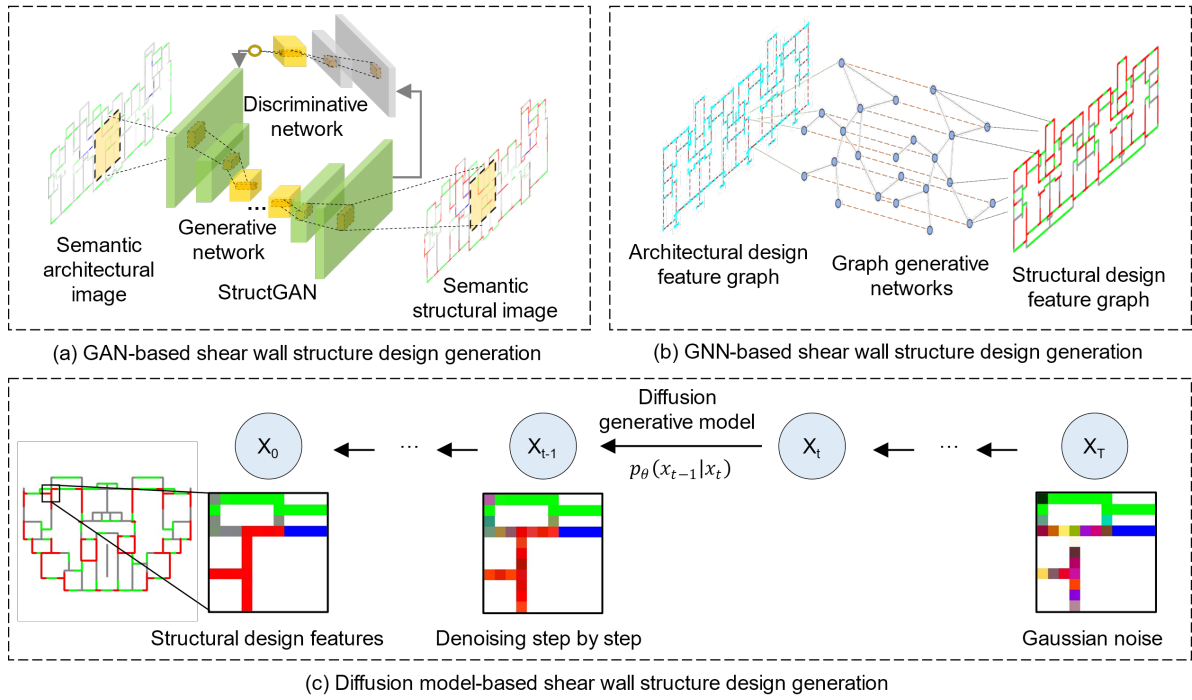


Figure 5. GAN, GNN, diffusion model intelligent design algorithms.

Each of the three algorithms exhibits distinct characteristics. The GAN captures the overall geometric features of the structural layout, the GNN is proficient in learning the topological features of shear wall structures, whereas the diffusion model can effectively consider both overall and local geometric features. Consequently, this study provides engineers with the outcomes of all three AI designs, enabling users to make selections based on the mechanical performance and material consumption.

3.2. Intelligent prediction for structural material consumption

Fei *et al.* [25] proposed an intelligent prediction algorithm using GNNs to estimate material consumption in shear wall structures. The algorithm takes the graph data representing the shear wall structural layout and dimensional design as input, along with the vector data containing structural design conditions. These inputs are processed by the trained material-consumption-prediction GNN model, resulting in a rapid estimation of the total material consumption of concrete and steel reinforcement, as well as the corresponding material consumption for shear wall components, beams, and floor slabs, as depicted in Figure 6.

This algorithm employs a unique graph structure that represents the features of structural layout, component sizes, and design conditions. The shear walls and beams are represented as edges in the graph, with the component sizes serving as the edge features. Component intersections are represented as graph nodes with their coordinates serving as node features. The design conditions are treated as global features. Additionally, a graph neural network algorithm called Graph-GEN, which integrates heterogeneous design features, was developed. The algorithm extracts global features independently, fuses and maps them with aggregated node and edge features, and ultimately determines material consumption.

Moreover, the network algorithm incorporates domain knowledge by incorporating a domain-knowledge loss function and modifying the output layer to satisfy the maximum concrete volume and minimum reinforcement ratio requirements. The maximum concrete volume accounts for the fact that the actual concrete consumption may be lower than the sum of the volumes of all components owing to component overlaps, whereas the minimum reinforcement ratio is derived from the reinforcement construction requirements specified by the standards.

Application research has demonstrated that Graph-GEN surpasses existing typical ANN, CNN, and GNN methods in terms of accuracy when assessing concrete and steel reinforcement consumption. Furthermore, its assessment efficiency is hundreds of times higher than that of commercial design software, such as YJK.

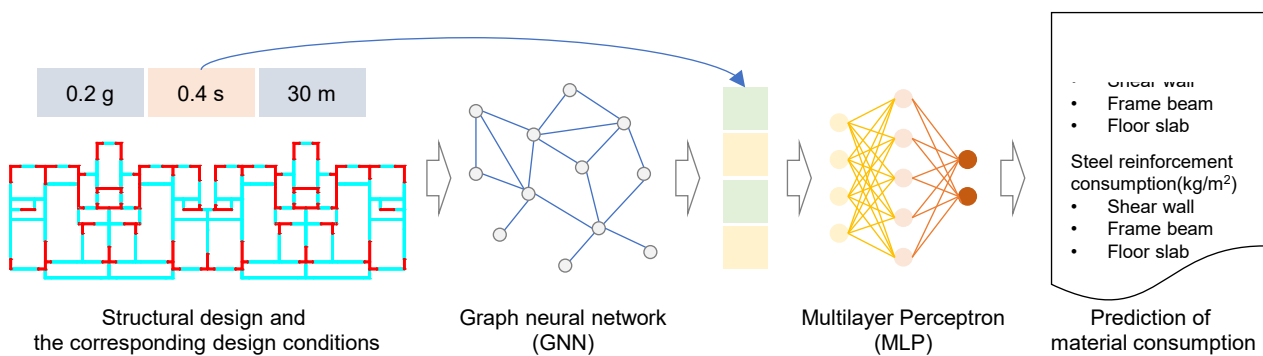


Figure 6. Intelligent prediction of material consumption for shear wall structures.

3.3. Structural mechanics model parametric establishment

After the layout and cross-sectional design of the shear wall–beam structure is complete, the corresponding structural analysis model can be efficiently established. In this method, to address potential compatibility problems when reading structural model files owing to different versions of the PKPM and YJK software, the universal SQLite database format file provided by the software is used. By parsing the SQLite file provided by the structural analysis software, rules are established for writing the shear wall and beam design parameters from the JSON file to the SQLite file. Additionally, automated construction and writing rules are established for floor slab components. This enables automated establishment of structural analysis files for PKPM and YJK, as depicted in Figure 7. The PKPM SQLite model file is saved as a ".jwd" file, which can be opened by launching PKPM, creating a new blank model file, and then importing it. In contrast, the YJK SQLite model file is saved as a ".ymd" file, which can be opened directly by clicking the file.

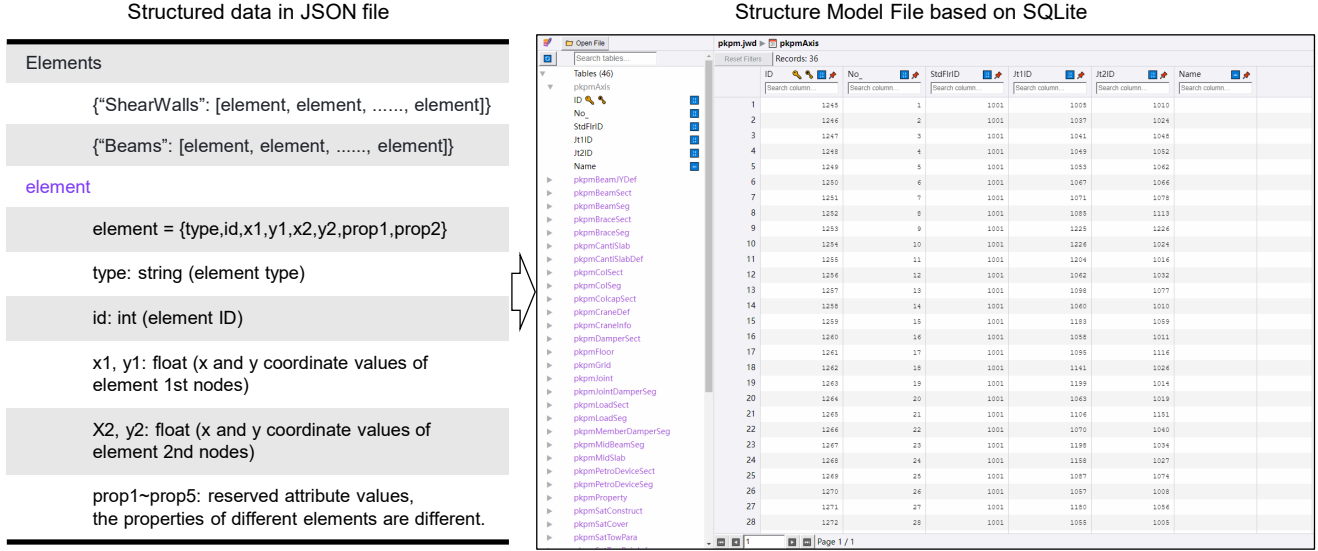


Figure 7. Data transformation from JSON file to structure model file based on SQLite.

4. Case study for AIstructure-Copilot

4.1. Evaluation method

This study evaluated the quality of AI designs based on three key aspects: planar layout consistency of the shear wall and beam components, mechanical performance of the shear wall-beam structure, and material consumption. The consistency of the shear wall and beam layouts was assessed using intersection-over-union (IoU) calculations. This measurement compares the similarity between the AI-designed and engineer-designed structural component layouts by calculating their IoU values. This approach enables a rapid and preliminary evaluation of the design results, as outlined in Equations (1)–(6) [14] and demonstrated in a study by Liao *et al.* [18]. The structural mechanical performance and material consumption were evaluated using PKPM software, which enables accurate analysis results.

$$\mathbf{M}_{\text{struct}} = m_{i,j} = \begin{cases} 0, & \text{No structural elements} \\ 1, & \text{Structural elements} \end{cases} \quad (1)$$

$$\mathbf{M}_{\text{struct}}^{\text{inter}} = \mathbf{M}_{\text{struct}}^{\text{AI}} \odot \mathbf{M}_{\text{struct}}^{\text{ENG}} \quad (2)$$

$$S_{\text{IoU}} = \eta_{\text{ratio}} \frac{L_{\text{inter}}}{L_{\text{union}}} \quad (3)$$

$$L_{\text{inter}} = \sum m_{i,j}^{\text{inter}}, L_{\text{union}} = \sum m_{i,j}^{\text{AI}} + \sum m_{i,j}^{\text{ENG}} - \sum m_{i,j}^{\text{inter}} \quad (4)$$

$$S_{\text{MIoU}} = \eta_{\text{ratio}} S_{\text{IoU}} \quad (5)$$

$$\eta_{\text{ratio}} = 1 - \frac{|\sum m_{i,j}^{\text{AI}} - \sum m_{i,j}^{\text{ENG}}|}{\sum m_{i,j}^{\text{ENG}}} \quad (6)$$

In the equations, $\mathbf{M}_{\text{struct}}$ is the matrix for structural layout positions, which in this study refers to the shear wall and beam layout design, with a matrix size of 1024×512; $\mathbf{M}_{\text{struct}}^{\text{AI}}$,

$M_{\text{struct}}^{\text{ENG}}$, and $M_{\text{struct}}^{\text{inter}}$ represent the position matrices of the intelligent design, the engineer's design, and the overlap of the two designs, respectively, with $\odot$ being the Hadamard product operator; S_{IoU} is the IoU measure of structures, L_{inter} and L_{union} are the lengths of the intersection and union of the structural layouts, respectively; S_{MIoU} is the modified IoU used to eliminate the unreasonable growth of IoU owing to the significantly increased number of structural components [18], η_{ratio} is the correction coefficient for the total length difference of structural components on IoU, $\sum m_{i,j}^{\text{AI}}$ and $\sum m_{i,j}^{\text{ENG}}$ are the total lengths of the structural components in the AI and engineer's designs, respectively.

4.2. Typical case study

For this study, an actual engineering case was selected, characterized by a seismic design intensity of 7 degrees (the corresponding design basis earthquake acceleration is 0.15g), a building structural height of 53 m, and a site characteristic period of 0.4 seconds. The case was called "Case-7.5d53m" based on its seismic design intensity and structural height. The entire scheme design process was conducted using AIstructure-Copilot, and a competent engineer was engaged in performing the corresponding structural design for comparison. The designs were analyzed and compared in terms of design efficiency, planar layout, mechanical performance, and material consumption. A comparison of the design efficiency is presented in Table 3, revealing that the AI design was approximately ten times more efficient than that of the engineer. Further detailed comparative analyses of this case are provided in subsequent Subsections 4.2.1–4.2.3.

Table 3. Design time consumption and comparison between AI and engineer designs.

Designer	Preprocess	Shear wall intelligent design	Beam automated design	Model establishment	Model analysis	Total	Total time difference (AI/Engineer)
AI	5 minutes	1 minute	1 minute	1 minute	10 minutes	18 minutes	1/11
Engineer						195 minutes	

4.2.1 Comparison of planar designs

In this study, a detailed comparison was conducted between the AI and engineer designs for Case-7.5d53m. The intelligent design process introduced in Section 2.2 was initially employed to carry out the design. The resulting architectural pre-processing is shown in Figure 7(a), which depicts a typical residential building. Figure 7(b) shows the shear wall–beam structure corresponding to the engineer's design. The AI designs are presented in Figures 7(c) to 7(e), which represent the outputs of the GAN, GNN, and diffusion models, respectively.

A visual comparison of the layouts of the shear walls and beam structural components showed that the differences between the AI designs and the engineering results were

relatively minor. Notably, a high level of consistency in the overall layout position of the shear walls, length of the structural components, and symmetry of the layout was observed. Furthermore, the layout of shear walls in critical areas, such as elevators and balconies, aligned well with design experience and established rules.

In this study, Equations (1)–(6) were utilized to calculate the IoU between the AI and engineer's structural designs. These equations enable the quantification of the differences in layout designs. The evaluation of the IoU for the shear wall and beam component layouts is presented in Table 3. Generally, S_{IoU} values greater than 0.5 indicate a relatively high similarity between the AI design and the engineer's design [18]. As shown in Table 4, the AI designs (i.e., GAN, GNN, and the diffusion model) demonstrated a generally high level of similarity with those of the engineer. However, when considering the modified IoU (S_{MIoU}), a noticeable difference was observed in the similarity between the AI design and the engineer's design, as is evident in the planar designs in Figure 8. This discrepancy was primarily because the AI design incorporated a significantly greater number and length of shear wall components than the engineer. Considering the more stringent modified IoU metric, further improvements can be made in AI designs.

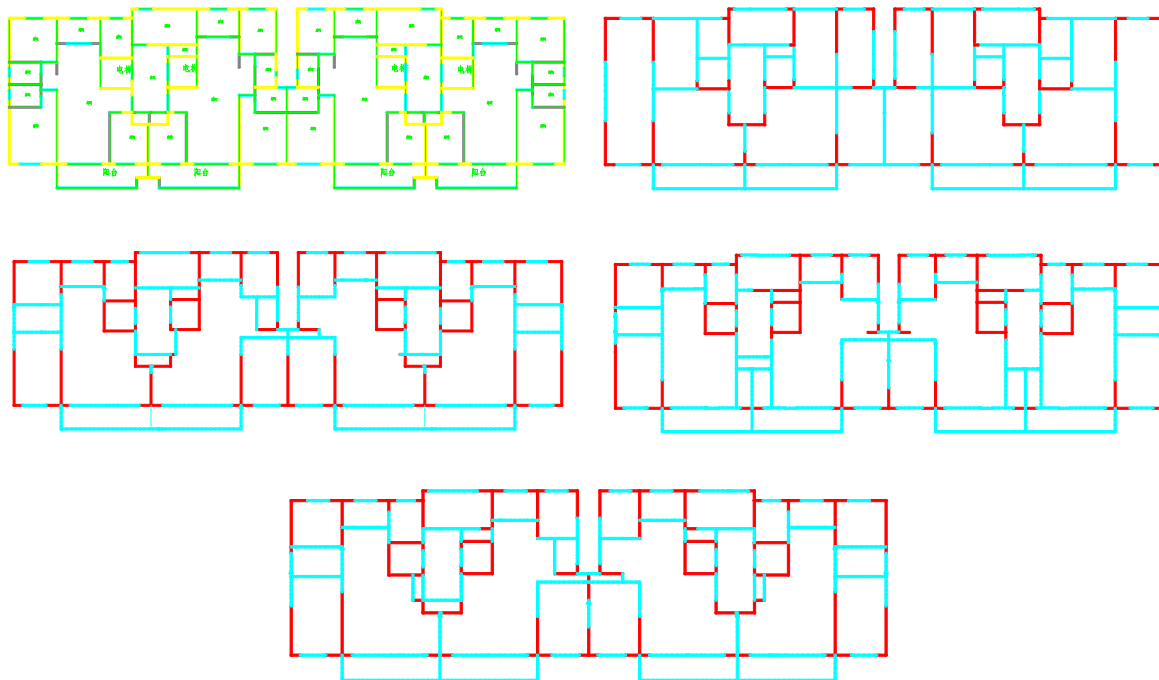


Figure 8. Case-7.5d53m shear wall–beam layout designs.

Table 4. Case-7.5d53m shear wall–beam IoU evaluation results.

AI methods	S_{IoU}^{wall} (Shear wall IoU)	S_{MioU}^{wall} (Modified shear wall IoU)	S_{IoU}^{beam} (Beam IoU)	S_{MioU}^{beam} (Modified beam IoU)
GAN	0.6338	0.3458	0.5011	0.4459
GNN	0.5412	0.4179	0.5032	0.4861
Diffusion model	0.6925	0.4352	0.5703	0.5434

4.2.2 Comparison of mechanical performance

The process began by using the PKPM analysis model generated by AIstructure-Copilot, followed by manual adjustment of the loads and subsequent verification. Subsequently, the corresponding structural models were analyzed. The mechanical analysis results from all the models indicated that the shear wall–beam structure schemes designed by the GAN, GNN, and diffusion models effectively fulfilled the overall performance requirements set by the standards [26]. Given the numerous overall indicators, this study selectively presents the comparative results of key indicators, such as the structural period and inter-story drift ratio, as shown in Table 5. Note that AIstructure-Copilot primarily focuses on designing a single standard story during the scheme design phase. Consequently, the established structural mechanical analysis model corresponds to an entire building with the same standard story.

Table 5. Case-7.5d53m shear wall–beam IoU evaluation results.

Engineer	GAN			GNN		Diffusion model	
Indicator ^a	Value	Value	Difference (vs. Engineer)	Value	Difference (vs. Engineer)	Value	Difference (vs. Engineer)
T_x^1	1.9817	1.4875	25%	1.5439	22%	1.5466	22%
T_y^1	1.8740	1.2188	35%	1.5050	20%	1.3514	28%
T_t^1	1.6508	1.0934	34%	1.0411	37%	1.1322	31%
θ_{max}^x	0.0965%	0.0666%	31%	0.0632%	35%	0.0666%	31%
θ_{max}^y	0.0897%	0.0616%	31%	0.0734%	18%	0.0633%	29%

^a T_x^1 represents the first period in the x direction. T_y^1 represents the first period in the y direction.

T_t^1 represents the first torsion period of the structure. θ_{max}^x and θ_{max}^y represent the maximum inter-story drift ratios in the x and y directions.

The differences in the mechanical performance between the three AI designs and the engineer's design ranged from approximately 20% to 35%. Notably, the first-order period exhibited a difference of approximately 20%, with the AI-designed structures exhibiting smaller periods, indicating greater stiffness. Figure 8 also shows that the AI designs generally had more layouts of the shear wall and beam components, as well as longer component lengths, compared with the engineer's design. The more conservative nature of AI designs was primarily attributed to an optimization process in which the AI-generated preliminary design is refined using a rule-encoding approach to better align with standard requirements and experience rules [21]. This optimization led to an increased number of shear wall components in the AI design and the inclusion of both primary and secondary beams in the

beam layout, resulting in an overall beam system stiffness higher than that of the engineer's design.

4.2.3 Comparison of material consumption

Moreover, the concrete and steel reinforcement material consumption for the shear wall–beam structures was calculated and compared between the AI and engineer's designs using the structural analysis model in PKPM. Table 6 presents the results. The AI designs exhibited higher overall material consumption for both concrete and steel reinforcements, as they adopted a more conservative approach compared with the engineer's designs. In particular, the material consumption of shear walls and beams in the AI designs exceeded that of the engineer. Conversely, the material consumption of the floor slabs was lower in the AI designs. This discrepancy resulted primarily from the larger number of shear walls and beam components in the AI designs, resulting in increased material consumption. Consequently, the spans of the floor slabs were reduced as they were divided into a greater number of shear walls and beam components. This reduction in span size led to smaller internal forces in the floor slabs caused by vertical loads, thereby contributing to a decrease in concrete and steel reinforcement material consumption.

Table 6. Material consumption and differences between AI and engineer designs.

		Engineer	GAN		GNN		Diffusion model	
Material	Elements	Value	Difference		Value	Difference		Value
			(vs. Engineer)			(vs. Engineer)		
Concrete (m³)	Shear wall	1579	2304	46%	1945	23%	2152	36%
	Beam	422	373	−12%	437	3%	389	−8%
	Slab	777	765	−2%	761	−2%	765	−1%
	Total	2778	3441	24%	3143	13%	3305	19%
Steel reinforcement (t)	Shear wall	139	183	31%	168	21%	185	33%
	Beam	68	77	13%	82	20%	63	−7%
	Slab	107	103	−4%	111	4%	109	2%
	Total	314	362	15%	361	15%	357	14%

AIstructure-Copilot offers intelligent predictions of material consumption. It is important to acknowledge that the primary focus of this intelligent prediction model is the analysis of high-quality structural designs crafted by engineers. By contrast, AI-designed shear wall structures exhibit greater variability and uncertainty than those created by engineers. Consequently, current prediction accuracy is relatively limited. Nonetheless, the prediction efficiency is remarkably high, with material consumption predictions generated within approximately 5 seconds. This is a significant improvement compared with the nearly 10 minutes required for PKPM calculations, resulting in a hundred-fold increase in efficiency. In the context of this case study, AIstructure-Copilot also provided material consumption

predictions for the AI design results. These predictions were then compared with the results of the PKPM calculations, as shown in Table 7.

Table 7. Comparison between AI prediction and PKPM calculation of material consumption.

Material	Elements	GAN			GNN			Diffusion model		
		AI	PKPM	Difference	AI	PKPM	Difference	AI	PKPM	Difference
Concrete (m ³)	Shear wall	1714	2304	26%	1446	1945	26%	1618	2152	25%
	Beam	287	373	23%	326	437	25%	297	389	24%
	Slab	1245	765	−63%	1245	761	−63%	1245	765	−63%
	Total	3237	3441	6%	3017	3143	4%	3160	3305	4%
Steel reinforcement (t)	Shear wall	157	183	14%	145	168	14%	153	185	17%
	Beam	75	77	2%	82	82	−1%	79	63	−26%
	Slab	94	103	9%	94	111	16%	95	109	13%
	Total	326	362	10%	321	361	11%	328	357	8%

4.2.4 Summary and discussion of case study

This study involved a comprehensive evaluation of the actual performance of AIstructure-Copilot through a real engineering case, encompassing various aspects such as layout consistency, mechanical performance, and material consumption. The results demonstrated that AIstructure-Copilot effectively executes the structural scheme design task, with the design outcomes generally conforming to the relevant code requirements. Although a certain disparity in quality remains between the current AI designs and those of an actual engineer, AIstructure-Copilot completes the entire process, from architectural design to structural design and mechanical analysis, within 20 minutes. This represents a nearly 10-fold increase in speed compared with the scheme design process conducted by human engineers. Thus, AIstructure-Copilot holds the potential to enhance design efficiency through a novel design paradigm of human-AI collaboration without requiring alterations to the existing design practices of engineers.

In addition, it is worth noting that engineer-designed schemes and AIstructure-Copilot-based schemes still differ by approximately 10%–30%. In practical engineering, AI design can be further adjusted and verified based on CAD platforms and computational software to meet the requirements of mechanical performance and engineering cost. Therefore, some minor differences between AI and engineer design are acceptable. On the other hand, it is suggested that future research include real physical mechanisms and engineer design experience to further reduce such discrepancies. This can be achieved by encoding engineer design experience, constraints on key mechanical indicators, optimization requirements for material consumption, and other relevant content into the optimization algorithm, enabling automatic optimization of AI design. This will result in AI designs that are more aligned with real design requirements and resemble engineer-designed schemes more closely.

5. Conclusions

To address the challenges associated with applying intelligent design technology to building structures in engineering practice, this study introduces AIstructure-Copilot, an intelligent design assistant specifically designed for shear wall structures. By establishing a collaborative design framework between local and cloud environments, proposing a data transfer format for a complete intelligent design process, and implementing cloud interfaces for generative AI design algorithms, a high level of automation and intelligence can be achieved throughout the entire process of shear wall structure design, including architectural design, structural design, and the establishment and analysis of structural models. The key findings of this study are as follows.

(1) AIstructure-Copilot operates locally in Autodesk-CAD, enabling operations on graphic files, whereas cloud-based components incorporate a series of generative AI-driven intelligent design algorithms. This setup enables seamless information exchange between the local and cloud environments without requiring engineers to alter existing design practices. Consequently, the AI design is effectively integrated to enhance design efficiency.

(2) The comprehensive intelligent design process facilitated by AIstructure-Copilot encompasses several steps, including pre-processing of architectural design information, intelligent layout of shear wall structures, automatic arrangement of beam components, automatic generation of sectional sizes for shear wall–beam structure components, intelligent prediction of material consumption, and the establishment of parametric structural models. While building information pre-processing is executed locally, the remaining steps are intelligently or automatically performed by cloud algorithms, leveraging technologies such as GAN, GNN, and diffusion models.

(3) The effectiveness of AIstructure-Copilot was validated through a typical case study. The AI-designed structural scheme satisfies the requirements of the relevant standards and exhibits a high degree of layout consistency with engineer-designed structures. The mechanical performance demonstrates a variation of approximately 20%–30%, whereas the material consumption varies by approximately 10%–20%. Notably, the entire design process, from architectural design to structural analysis, is completed within 20 minutes, nearly ten times faster than traditional engineer-designed approaches. This acceleration significantly enhances the design efficiency.

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Conflicts of interests

No potential conflict of interest was reported by the authors. The China Electronics Engineering Design Institute Co., Ltd. had no role in the design of the research proposal, data collection, analysis or interpretation, or manuscript writing.

Ethical statement

Ethics approval was not required for this research.

Authors' contribution

Sizhong Qin: Methodology, Software, Writing – original draft, Writing – review & editing. Wenjie Liao: Conceptualization, Funding acquisition, Software, Supervision, Writing – original draft, Writing – review & editing. Shengnan Huang: Data curation, Resources, Validation. Kongguo Hu: Data curation, Resources, Investigation. Zhuang Tan: Formal analysis, Resources, Investigation. Yuan Gao: Data curation, Investigation. Xinzheng Lu: Conceptualization, Funding acquisition, Supervision, Writing – review & editing.

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