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AI-powered automatic design of fire sprinkler layout for random building floorplans

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ABSTRACT

Fire sprinkler system is a commonly designed safety provision in modern buildings, yet the current manual drawing preparation process is burdened by time-consuming tasks, heavy workloads, and human errors. This study introduces an intelligent framework aimed at automating the drawing preparation process for fire sprinkler layout. A database of 120 sprinkler design drawings was compiled to train a pix2pixHD generative adversarial network (GAN). After training, the GAN model can generate sprinkler placement with a protection coverage of 99.5% for new and random architectural floorplans. Apart from ensuring code-compliant design, the total number of sprinklers designed by GAN is 13% lower than those arranged by professional engineers. By adopting this intelligent method, the time needed for design drawing preparation can be saved by 76%, and the cost-benefit of the sprinkler design can be improved by using reasonable fewer sprinklers.

1. Introduction

Building fire service/protection systems play essential roles in safeguarding occupants and properties in the built environment, so they are strictly regulated and require careful design and installation (Stollard, 2014). In the current design process, architects take the first step in proposing basic building drawings like building shape, floorplans and functions to deliver the fundamental design concepts and spatial arrangement of the building. After that, building services engineers or fire engineers are responsible for incorporating fire service systems as necessary to protect the building, including sprinklers, fire detectors, emergency lighting, smoke ventilation, and other elements regulated by fire codes. These engineering drawings depict the placement of fire protection equipment throughout the building, and also indicate the positions of fire emergency exits, stairwells, and other escape routes, as well as the configuration for fire compartmentation (Zeng et al., 2024a).

Despite the development of the digital design platforms such as computer-aid design (CAD) and building information modelling (BIM) (Chen et al., 2021; Schönfelder et al., 2024; Wang et al., 2015; Zhou et al., 2012), the preparation of the engineering drawings still heavily relies on the engineers on manual, such as the distribution of sprinkler heads and calculation of egress travel distance. This manual design process suffers from prolonged time consumption and low efficiency. Overruns of time and cost are commonly seen, and statistics show that although the construction industry represents 13% of global GDP, it has experienced only a 1% annual profit increase over the past 20 years (McKinsey, 2020), making it one of the slowest-growing and least profitable sectors worldwide.

Another issue is that the design of fire service systems is very complicated, with thousands of code clusters and needs to be incorporated with many disciplines such as structure, mechanical, and transportation. There are unavoidable and considerable errors in the human-lead design process. As a result, after a significant time investment on drawing preparation, great efforts are still needed on code-compliance checking of these drawings by the dedicated agency, which is also manual.

The abovementioned challenge troubles not only fire engineers but the whole architecture, engineering, and construction (AEC) industry for

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decades (Chen et al., 2018). Today, new developments of artificial intelligent (AI) technologies, especially the generative deep learning algorithm, offer a promising solution to overcome them. For example, Isola et al. (2017) proposed a conditional generative adversarial network (GAN) for the image-to-image translation tasks. To showcase the model capability, it provides a demo that, by inputting the building framework, GAN can generate a façade design including outdoor walls, balconies, and windows. It embarks the research on AI application in the building design sector. Architects first applied deep learning models to generate interior design from the basic architectural plan (Huang and Zheng, 2018). Structural engineers quickly followed up and adopted deep learning models to automate structural engineering designs (Liao et al., 2024), including allocation of shear wall (Fei et al., 2025; Liao et al., 2021, 2022, 2023; Lu et al., 2022; Qin et al., 2024a; Zhao et al., 2023a, 2023b, 2023c), beam layout (Zhao et al., 2022, 2023d), and tube framework (Fei et al., 2022; Qin et al., 2025). To improve the learning

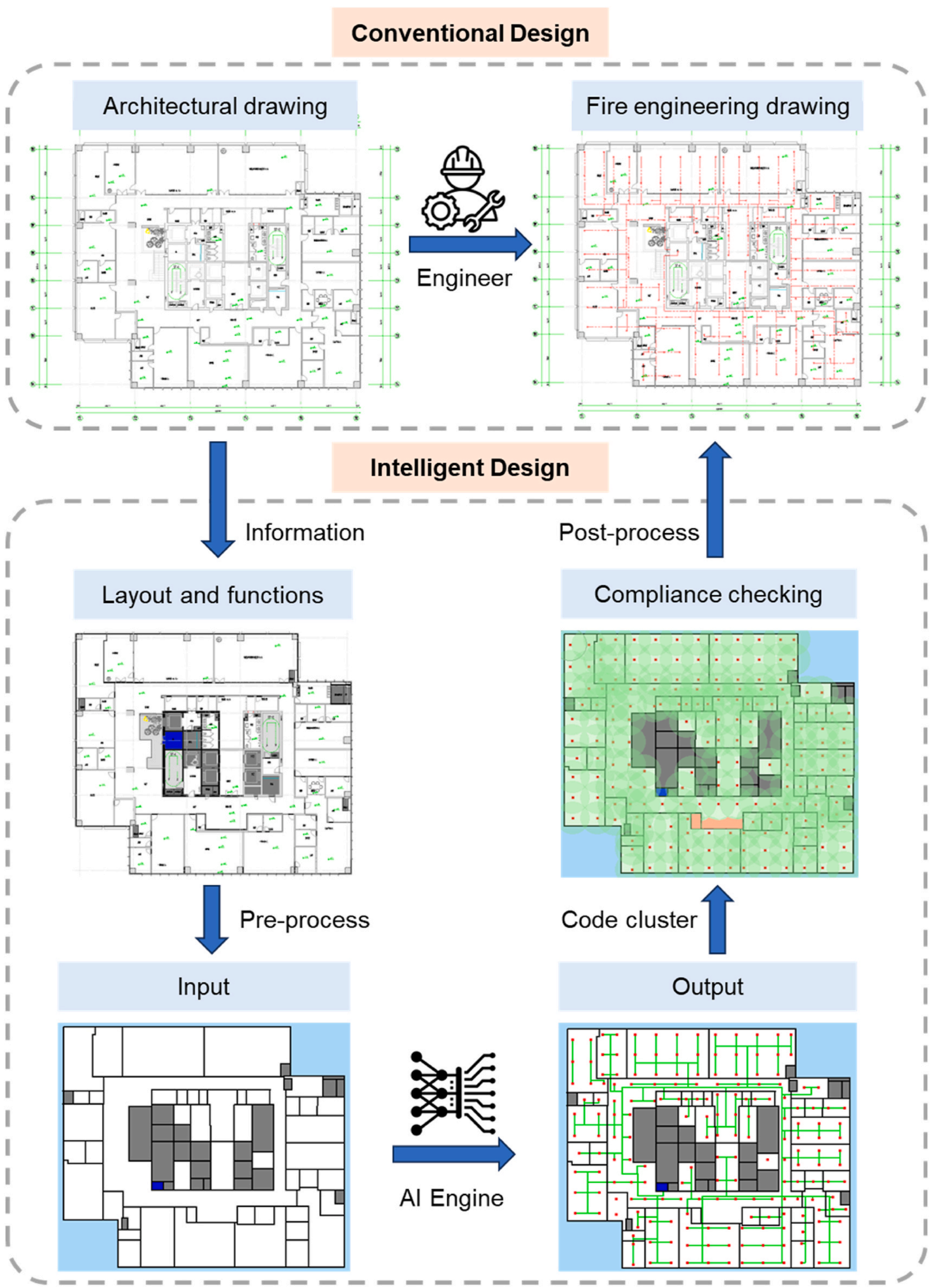

Fig. 1. AI framework for smart building fire safety design.

capability of AI under small database, several enhanced algorithms by adding expert domain knowledge and attentions have also been proposed for design drawing generation (Fei et al., 2024; Feng et al., 2023) and design code interpretation (Zheng et al., 2022, 2024). Researchers and engineers also applies generative models to predict visible deterioration in highway bridge decks (Najafi et al., 2023), detect cracks (Hu et al., 2025), and monitor health of civil infrastructure (Gwon and Jung, 2025) to ensure safety. As for the fire engineering field, AI technologies have been applied to smart firefighting and evacuation processes (Tam et al., 2022; Wang et al., 2023; Xie et al., 2025; Zhang et al., 2022a, 2022b, 2022c), as well as performance-based fire engineering analysis (Su et al., 2021; Zeng et al., 2022, 2023a; Zeng and Huang, 2024b). However, to the best of the authors' knowledge, there is still no exploration of AI method on the design drawing preparation of fire service systems so far.

This work aims to fill the research gap between the current manual drawing process for building fire safety and the ongoing intelligent development of design methods. A framework of smart fire safety design was proposed first. To demonstrate its feasibility, a case study of automatic sprinkler layout design has been attempted. A total of 120 engineering drawings of sprinkler layout were collected and pre-processed to establish the design database, which was then utilized to train a GAN model with pix2pixHD architecture (Wang et al., 2018). After the training, the GAN model was used to generate the sprinkler layout design for a new given architectural plan, and results were compared with engineers' design to demonstrate AI's efficiency and accuracy.

2. AI-assisted automatic design method

2.1. Intelligent design framework

Deep learning networks can learn from historical data to capture hidden patterns and then make quick predictions with accuracy. It has proven highly advantageous in streamlining workloads that recur frequently. Building fire safety design stands as a prime example of where AI can be effectively harnessed. In this work, a framework of intelligent design is proposed, as shown in Fig. 1, with the following several steps:

Step 1. Information extraction. There are lots of design elements from different disciplines on the original architectural drawings, and most of them are actually noise information. Therefore, the first step is to filter the unnecessary elements. To do that, the design output shall also be predefined, and only key elements that have great impacts on the design outcome should remain in the drawings.

Step 2. Data pre-process. The filtered drawings shall be pre-processed into the format that can be trained by AI, such as image and matrix, because it cannot directly process the CAD files. Mapping correlations need to be established by representing all the input design information by using different colours or encoded numbers into multiple channels. Software plugins or cloud platforms could be developed to perform convenient data transfer between AI and CAD (Qin et al., 2024b).

Step 3. Automated design generation by AI engine. By being fed with the pre-processed input matrix/image, a pre-trained AI engine is expected to generate targeted design elements automatically and promptly. Building design could be innovative and creative; thus, the adopted AI engine shall have good generalization capability to meet different design demands. Based on the previous experience (Gu et al., 2024; Liao et al., 2021; Zeng et al., 2023a), the generative deep learning models, such as GAN and diffusion model, can have better performance than traditional networks like conventional neural network (CNN) which are typically used for classification or regression tasks.

Step 4. Code compliance checking. Since the output of the AI engine is in the format of image/matrix, it also allows convenient evaluation of the design quality through the batch programming operations, which is difficult to achieve with CAD format, such as distance measurement, area calculation, and number counting. Ideally, the non-compliance issues can be highlighted in the outputted image so that the engineer can make corrections quickly. It can save a lot of labour costs for the review of the design documents.

Step 5. Data post-process. After the quick generation by the AI engine and manual correction by engineers, the outputted drawing could be post-processed into the original format of the design documents, i.e., CAD files, by using developed plugins.

Ideally, the design process can be automated through the constructed AI engine, while not only the labour cost can be greatly saved but also the design efficiency can be significantly reduced.

2.2. Case study of sprinkler layout design

The automatic sprinkler system can control fire development effectively at the initial stage (Kuznetsov et al., 2024; Zeng et al., 2019, 2023b), and it is required to be installed mandatorily in many industrial and commercial buildings (Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2022). However, it is also one of the most headache design tasks to fire engineers due to the following three major reasons:

(1) The design workload for sprinkler layout is extremely huge. The sprinkler heads shall be allocated in most of the building area to provide adequate protection, which presents a substantial amount of design work. For example, a fire compartment with 2000 m^2 requires a minimum 160 sprinklers, with a protection area of 12.5 m^2 for each head (Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2017), to be allocated manually by engineers. Moreover, most buildings have irregular areas and small room divisions that require extra attention from engineers, making it difficult to batch process the drawings.
(2) Repeated works due to changes of the building floor plan. While the sprinkler heads are designed for full coverage protection, any adjustments made to the building floor plan can potentially affect the placement of sprinkler locations (Pinlan, 2022). During the design process, design changes are quite common, leading to repeated design work and potential design errors. For example, If the walls of a room are offset by 100 mm outward, it may result in the sprinkler heads originally positioned inside being unable to protect this additional space. Moreover, the design deviations caused by these minor adjustments are difficult for engineers to detect.
(3) Difficult to review and assess. The complexity of the sprinkler system design, with numerous interconnected components and considerations such as water pressure, flow rates, coverage areas, and building layout intricacies, makes it challenging for engineers to comprehensively evaluate the design manually. Ensuring that the system meets safety standards and effectively covers all areas requires detailed analysis, which can be time-consuming and prone to oversight.

Given the abovementioned challenges, digital tools aiming to automate sprinkler design process have been developed, such as Tangent and Megdragon. These tools are developed on the basis of rule-based or expert system relying on manual programmed rules. Such system can offer clear and interpretable solutions, especially for simple and regular geometries (e.g., rectangular rooms or orthogonal layouts). However, when applied to irregular or complex geometries, such as layouts with angled walls, curved spaces, or fragmented zones, it becomes extremely challenging to define comprehensive and effective rule sets. In contrast, deep learning approaches can automatically learn implicit design rules and patterns from data and apply them across various building layouts.

This capability makes deep learning particularly advantageous as modern architectural designs increasingly feature non-standard, irregular, or innovative spatial configurations. Therefore, deep learning approach has been adopted in this study to demonstrate the potentiality of AI-assisted automatic fire safety design via example of sprinkler layout.

During the design of the sprinkler layout, sprinkler heads will be firstly placed at where needed with a certain distance to provide adequate fire suppression protection to the building (Fig. 2a). Fire regulations usually specify the maximum spacing between sprinklers, minimum/maximum distance from sprinkler to walls, the maximum protection area for each sprinkler head, etc. In many fire safety codes (British Standard Institution, 2009; Fire Services Department, 2012; Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2017; National Fire Protection Association, 2016), the spacing requirement is related to hazard class, which is categorized based on the main function of the building and its area or building height. For example, the Chinese building code categorizes commercial building with areas less than 5000 m^2 as Medium (Level-1) Fire Hazard that requires a maximum spacing of 3.6 m between sprinkler heads. The office area with a building height of less than 24 m is categorized as a Low Fire Hazard that requires a maximum spacing of 3.6 m between sprinkler heads and a 4.4 m maximum spacing (Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2017).

After the sprinkler placement, the engineer will also perform a pipeline connection task (Fig. 3). All the sprinkler heads are connected by pipes for water supply, and the pipeline connection can be further divided into sub pipe and main pipe, while the sub pipe connects all the sprinkler heads directly, and main pipe comes out from the riser shaft and connects all sub pipes.

With determined design outputs, the input attributes can be then identified. Except for the sprinkler head and the pipes, the remaining elements in Fig. 3 are defined as the model input, including the architectural plan and functional spaces that are highlighted in different colours. The white colour indicates the sprinkled space which requires the placement of the sprinkler head; the grey colour represents the rooms that do not need to install sprinkler, such as electrical shaft, elevator shaft, and stair; the blue colour indicates the riser shaft where the main pipe comes out from. As for the prior information of the hazard class, it is encoded to the background colour which will be introduced next.

2.3. Database collection and model training

An image resolution of 640 × 512 is adopted in this study, which is also the maximum size can be handled by our graphic processing unit (GPU) with 16 GB memory. A fixed distance scale of 100 mm per pixel is defined, resulting in a maximum size of 64 m × 51.2 m (3276.8 m^2) for the input architectural plan (Fig. 3). Collection of fire sprinkler drawings as the training data is the most challenging task in this work. This is because the design drawings are regarded as intellectual property with sensitive information, such as design schemes, building materials, and construction methods. Therefore, drawings are normally not publicly shared to maintain uniqueness and competitiveness of design teams in the industry. Referring to Liao et al.'s work (Liao et al., 2021) which promotes the AI-driven structural design model with a number of 63–81 training drawings for the specific seismic category, a total of 120 design drawings with different building floor plan are finally collected in this work from different design institutes, which forms the first public assessable database for fire sprinkler design (see Fig. A1 in Appendix for the full database).

These drawings contain different occupancies, such as office, school, shopping mall, and carpark. They are also categorized into three different hazard classes, i.e., Low, Medium, and High, according to Chinese code (Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2017). However, most of the original drawings are classified into Medium degree since it covers the most common-seen building volume and functionality, and only few of them are in Low and High degree. In order to have sufficient learning data on all three hazard classes for AI model training, some of the original Medium-degree drawings are redesigned to follow the code requirement for Low or High hazard class. The final data distribution is summarized in Table 1. While the AI model processes input images by analysing the RGB pixel values during training, the hazard class (Low, Medium, High) information was encoded into the images by assigning a specific background colour to the outdoor area of each input drawing: green for Low hazard class, blue for Medium, and orange for High. This encoding method was designed to integrate hazard class information directly into the pixel data, enabling the model to learn the association between hazard class and sprinkler layout.

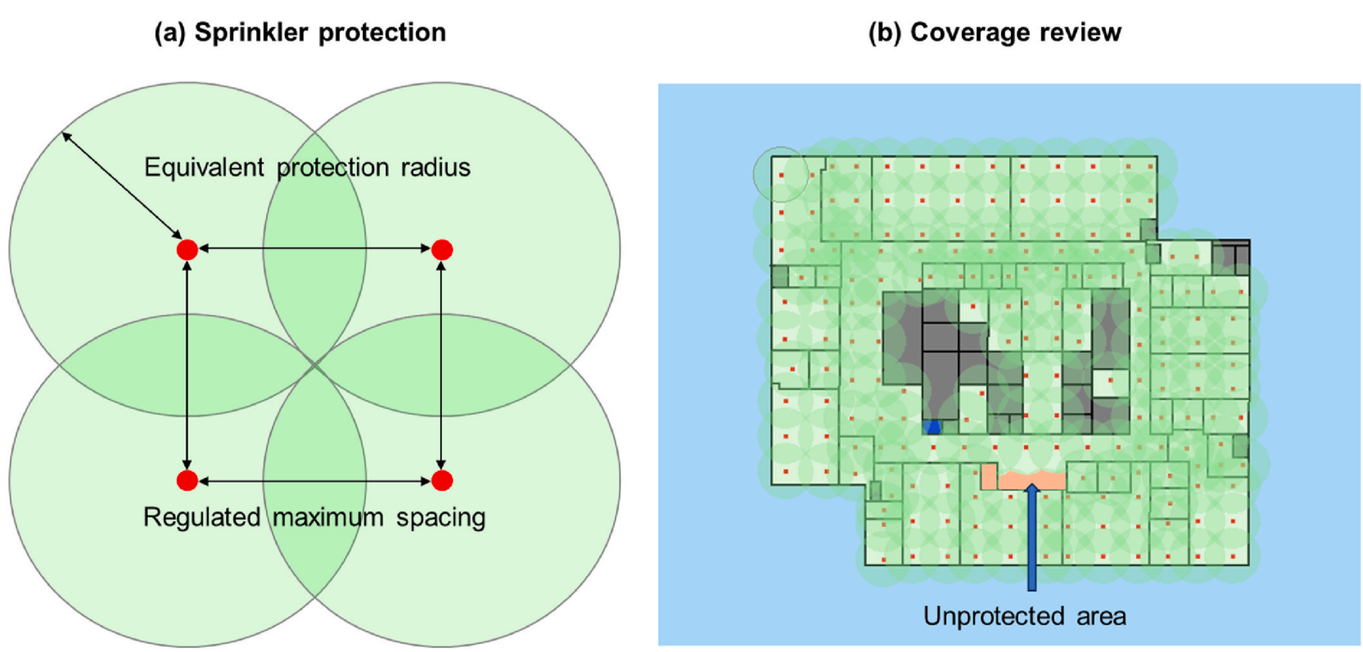

Fig. 2. (a) Sketch of sprinkler protection and (b) coverage review with equivalent protection radius.

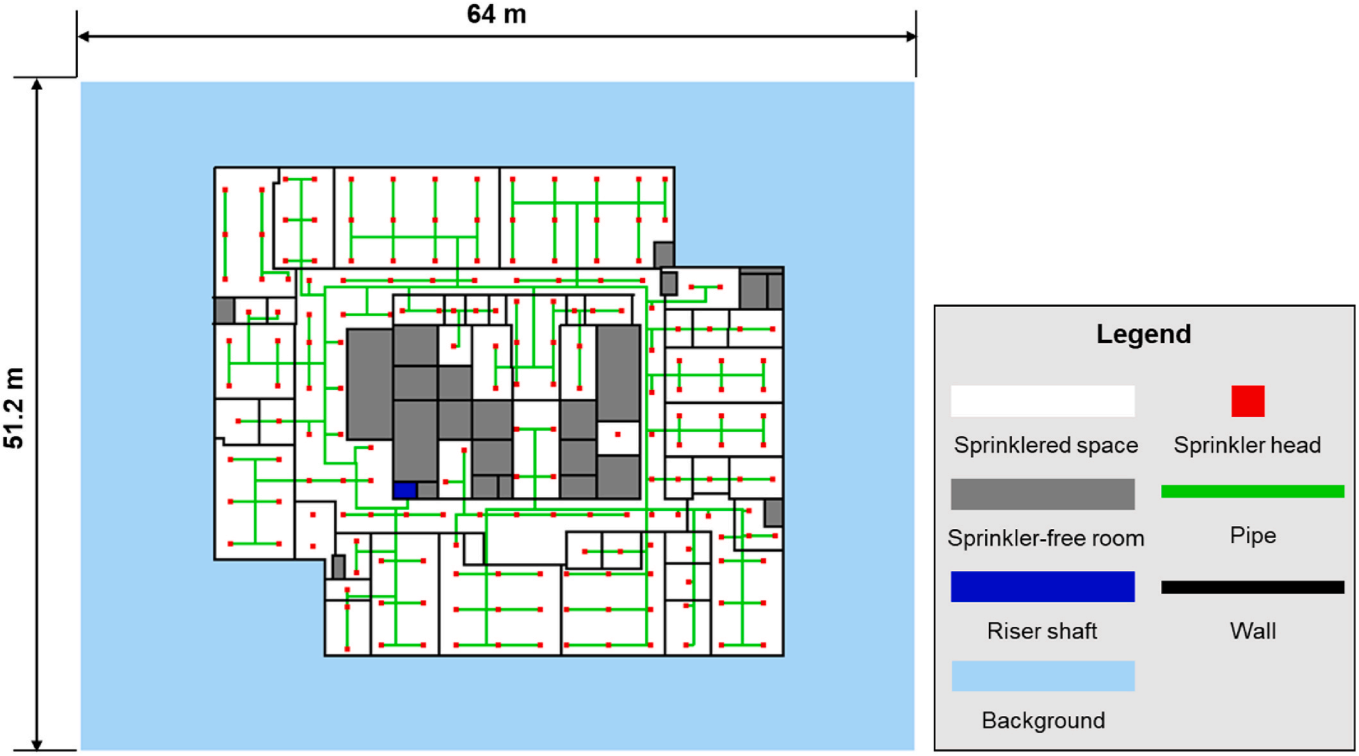

Fig. 3. Sematic image of the sprinkler layout drawing.

Table 1
Hazard class distribution in database.

Fire hazard class	Number of drawings Training (90%)	Testing (10%)	Equivalent protection radius	Encoded background colour
Low	25	3	2.1 m	Green
Medium	52	6	2.5 m	Blue
High	31	3	3.1 m	Orange

The database is further divided into training dataset (108 drawings) and testing dataset (12 drawings) with a ratio of 9:1 (Fig. A1). The training dataset is utilized for the AI model to learn the design rules and patterns, and it is further augmented by flipping the images vertically and horizontally and rotating the images at 180°. While the plan direction has no impacts on the design outcomes, the number of training samples reasonably increases from 108 to 432.

As shown in Fig. 4, the architectural input, containing information of sprinklered space, position of riser shaft, and hazard class, is fed to the AI model aiming to generate corresponding design outputs of sprinkler placement and pipeline connection. A GAN model with pix2pixHD architecture (Wang et al., 2018) is adopted in this study and detailed model configuration can be found in GitHub at https://github.com/NVIDIA/pix2pixHD.

GAN is a class of deep learning models consisting of two neural networks, i.e., a generator and a discriminator, that are trained simultaneously in a minimax game: the generator aims to produce realistic data (e.g., images), while the discriminator attempts to distinguish between real and generated data (Isola et al., 2017). Owing to their ability to learn complex data distributions, GANs are widely used for image synthesis and translation tasks. Pix2pixHD extends the traditional pix2pix conditional GAN architecture and is designed specifically for high-resolution applications. It introduces a coarse-to-fine generator comprising a global generator and a local enhancer network, which together enable the generation of images with significantly higher resolution and finer detail. In addition, its multi-scale discriminators help capture both global structure and local texture, thereby improving the realism and sharpness of the generated images (Wang et al., 2018). These features make pix2pixHD particularly suitable for tasks requiring detailed, high-resolution outputs.

In this study, high-resolution output was essential because sprinkler design spacing must be determined at a 100-mm per pixel resolution to comply with protection radius requirements (e.g., 2.1 m or 2.5 m). Unlike many deep learning applications where images are downscaled (e.g., 128 × 128 or 256 × 256 pixels) to reduce computational demands without compromising task accuracy, this work required maintaining a minimum image size of 640 × 512 pixels to preserve necessary spatial precision. Pix2pixHD is therefore adopted, as it is purpose-built for high-resolution image-to-image translation. Alternative architectures, including UNet, original GAN, or pix2pix GAN architectures, produced less satisfactory results in high-resolution image generation, while Diffusion model, although theoretically capable, required prohibitively large computational resources at this resolution. Considering both performance and computational efficiency, pix2pixHD provided the best balance for this application.

After the design generation, the results will also be evaluated. As

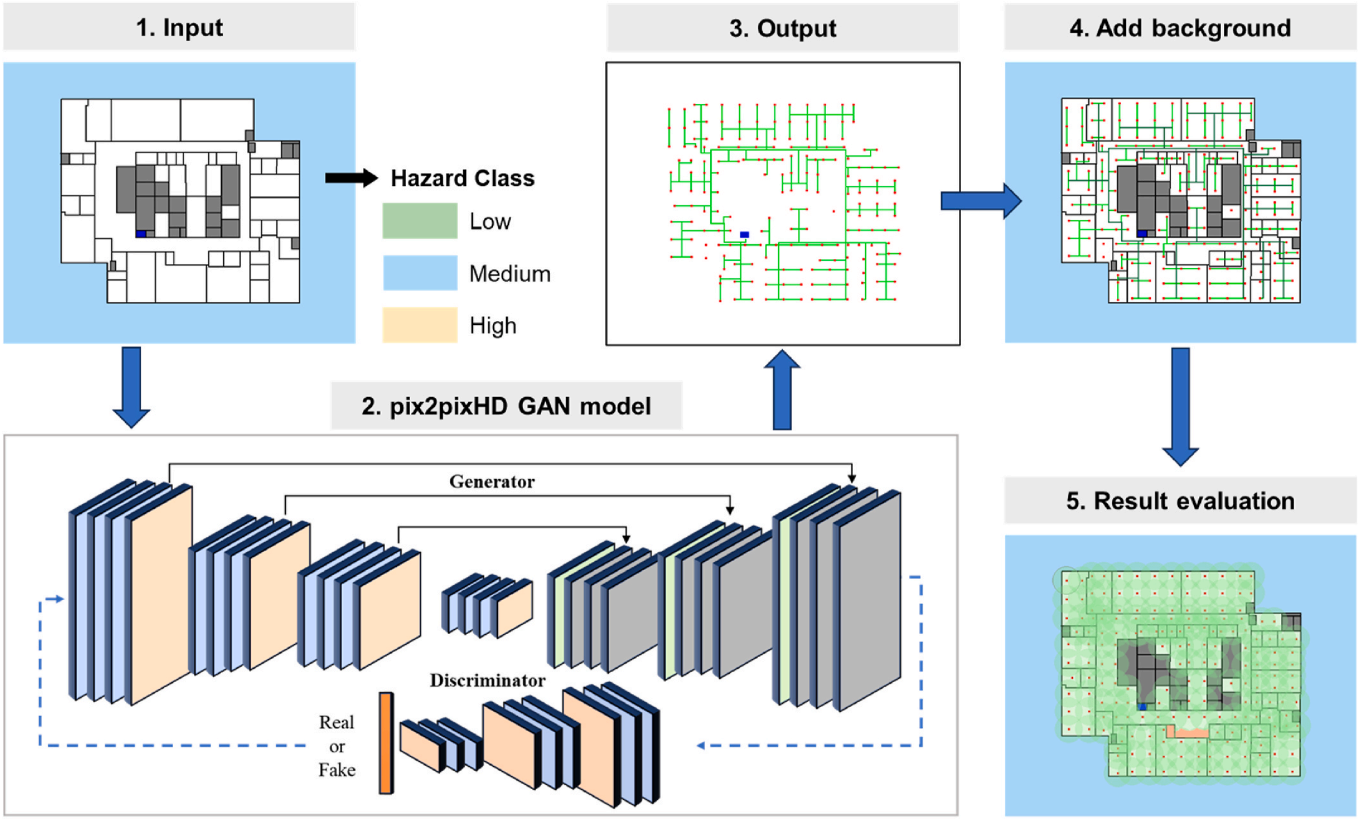

Fig. 4. Training of the AI model.

descripted in Section 2.2, the sprinkler has a very complex spacing requirement to the wall, beams, and other sprinklers. For the same hazard class, the spacing requirement is even different if the sprinklers are arranged in a square or rectangular pattern. Therefore, the detailed checking requires efforts and a more commonly used quick-checking approach in practices is to covert the spacing requirements between sprinklers to an equivalent protection radius (Fig. 2a). By drawing a protection circle for each sprinkler, areas that clearly lack sprinkler protection can be quickly identified. This approach is adopted to perform a quick code-compliance checking to the generated results (Fig. 2b) and, moreover, the total number of placed sprinklers and length of pipelines are recorded for a quantitative evaluation of the design.

3. Results and discussion

3.1. Auto-designed sprinkler placement

This section presents the generation results of the sprinkler placement by AI model for testing cases. Fig. 5 compares engineers' design and AI design for different floors in the same office tower, while the orange colour indicates the areas without sprinkler protection. In the first open-floor plan case (first row), AI can give results with a protection coverage rate up to 99.9%, which means the generated design is very code compliant and even better than engineers' design. The number of placed sprinklers is also almost same as engineer, indicating that AI places the sprinkler with reasonable usage.

In the second testing case (second row in Fig. 5), the complexity of floorplan is increased by dividing the open floor into multiple rooms. This significantly increases the difficulties of design, and both human and AI miss to add sufficient sprinklers in several small rooms. Nevertheless, AI-designed sprinkler coverage can still be up to 99.6%. Moreover, with the highlighted unprotected areas in post-processed design image, engineers are able to make quick corrections, which is not achievable in traditional CAD software. It should also be noted that engineers have greater possibilities to make errors as well when designing such complex floorplans.

Except for the quantitative evaluations of coverage rate and sprinkler number, sprinklers should be placed as much as possible in straight lines and the spacing distribution is preferred to be uniform. This is because an organized sprinkler arrangement can facilitate the connection of subsequent pipelines, allowing the pipelines to be streamlined, aesthetically pleasing, and material-saving. From this perspective, there is still room for improvement in AI results.

Fig. 6 shows the AI results for the first architectural plan under different hazard classes. The different spacing requirement leads to a significant difference in sprinkler number. Nevertheless, both results adhere to the code requirement, with sprinkler coverage over 99%. This indicates that the AI has effectively captured the design pattern for different hazard classes.

Fig. 7 compares the human and AI designs for more complex floorplans, and results for other testing cases are presented in Appendix Fig. A2. It can be seen that AI can provide code-complaint sprinkler placement in all different architectural plans including large-open plan and curved space. In most of the cases, especially with the High-hazard class, the total number of sprinkler heads designed by AI is less than by engineers, indicating the engineers' design tends to be more conservative than AI.

Upon reviewing all the testing case results, it can be observed that the model achieved higher coverage rates in layouts that were relatively regular and orderly. For example, those with rectilinear geometry, large open spaces, or continuous, coherent floor plans. In contrast, cases where the coverage rate dropped typically involved rooms with irregular geometry (such as diagonal or curved partitions) or complex spatial configurations (e.g., multiple small rooms with fragmented, narrow, or highly variable spaces).

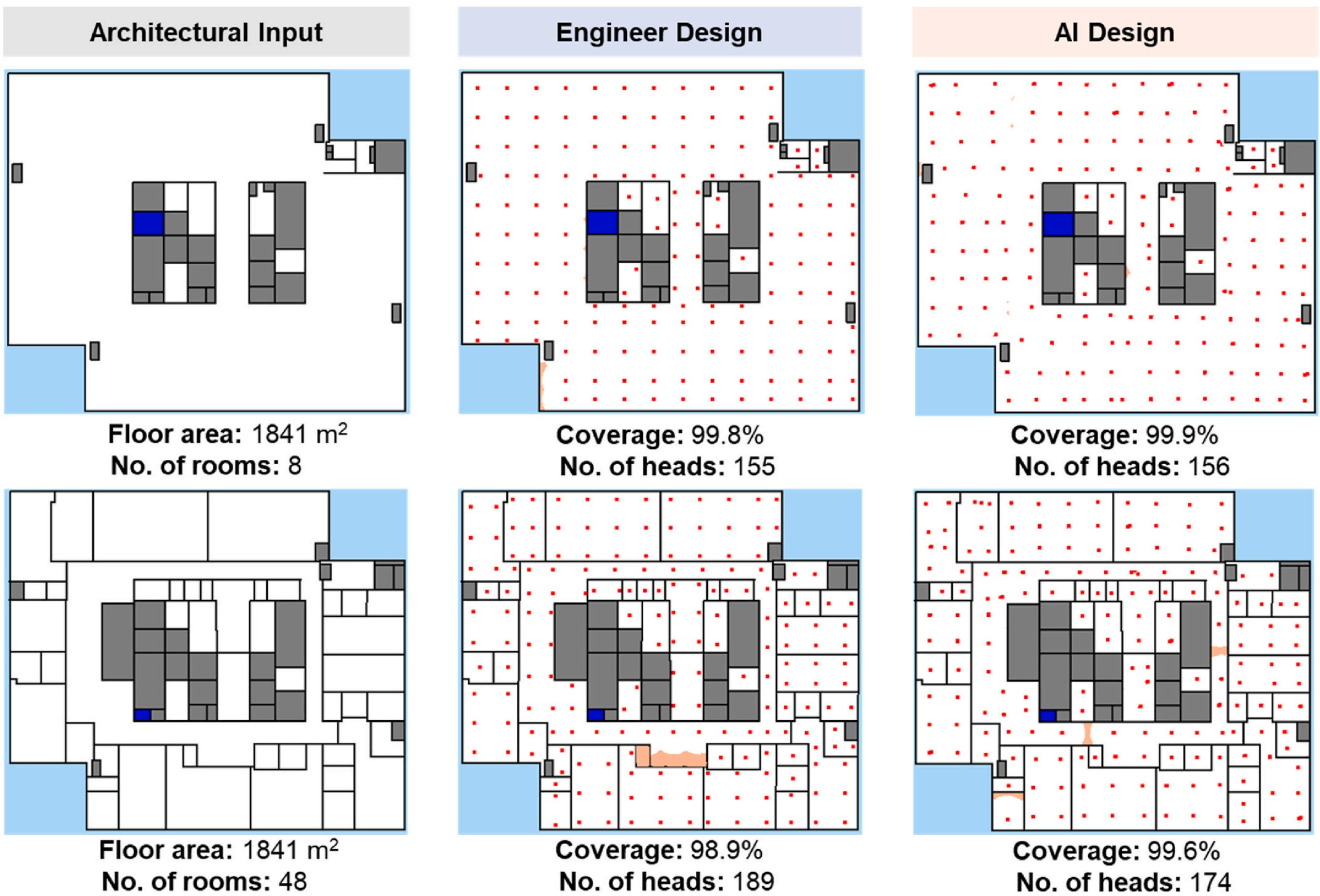

Fig. 5. Comparisons of engineer and AI designs of sprinkler placement for an office tower with different internal arrangements under Medium-hazard class, and the unprotected areas are highlighted in orange, where the first row is open floor area, and the second row is multi-room floorplan. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

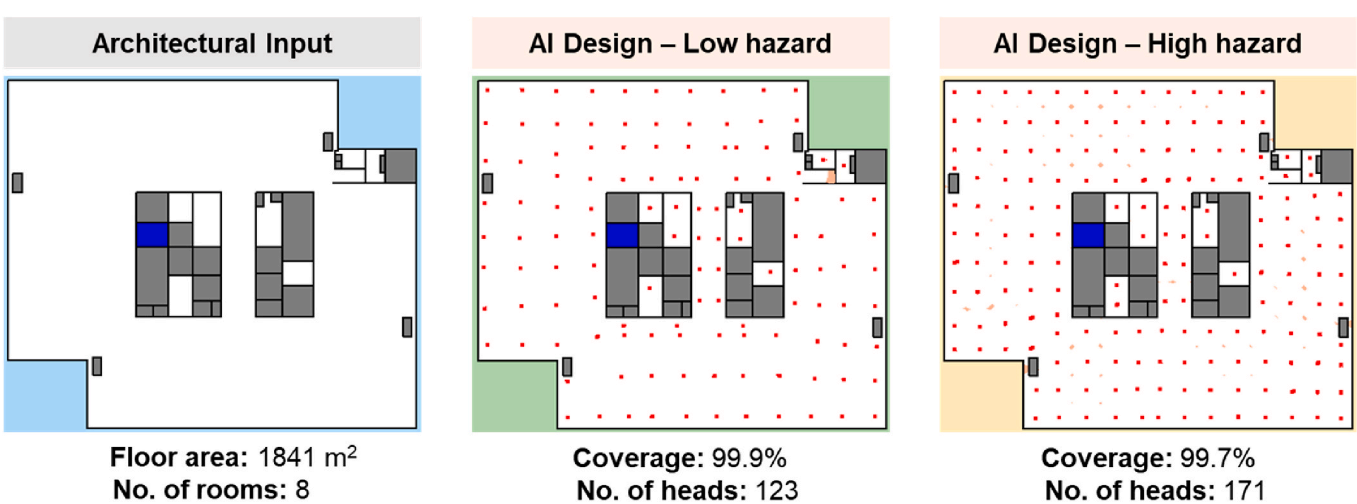

Fig. 6. AI generated sprinkler placements for different classes of fire hazards.

These findings align closely with the challenges faced by human designers in practice. Irregular layouts or those with many small, disconnected rooms are inherently more complex and time-consuming to design, increasing the likelihood of suboptimal sprinkler placement. For instance, as illustrated in Fig. 5, two cases with identical building outlines but different internal partitions demonstrate this effect: the open floor plan required only 12 min for manual sprinkler placement, while the multi-room plan took 30 min and resulted in lower coverage.

Moreover, the generated sprinkler layout for the low hazard class shows less organized compared to that of the high hazard class. It is potentially due to its larger permissible spacing between sprinklers, which leads to a significantly smaller number of sprinklers required in each design. As a result, the amount of meaningful pattern information available for the model to learn from is considerably reduced compared

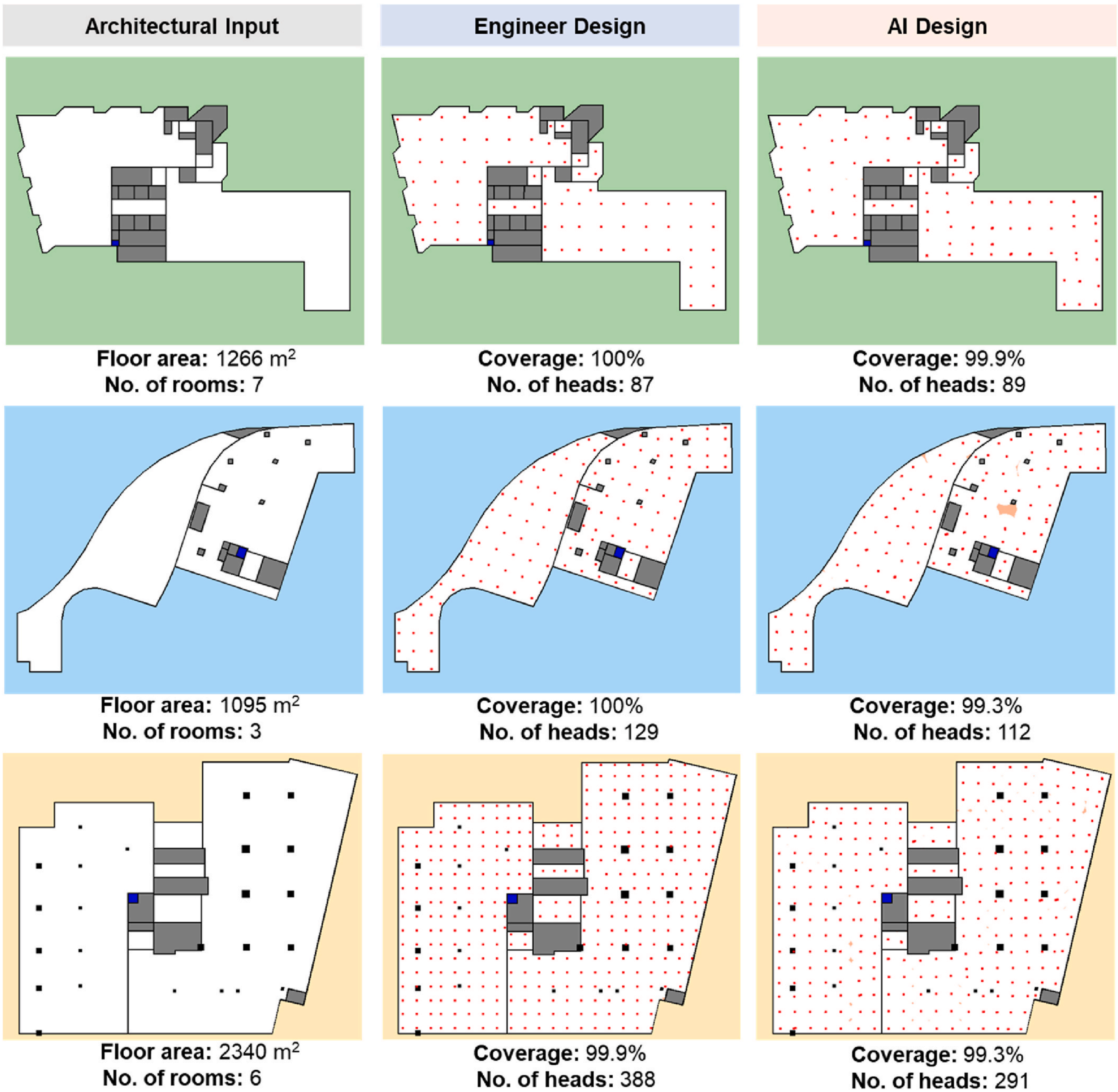

Fig. 7. Comparisons of engineer and AI designs of sprinkler placement for typical testing cases with different hazard classes (see Appendix Fig. A2 for full results).

to higher hazard classes. This lower density of learning targets in the training data limits the model's ability to generate as coherent and structured a layout as observed in the high hazard class.

In general, the proposed AI model can provide a comparable design of sprinkler placement to engineers, with an average coverage rate of up to 99.5% and a discrepancy of 13% for sprinkler number. However, it takes engineers averagely 20 min to finish one draft drawing, while AI only takes a few seconds.

3.2. Pipeline connection

Fig. 8 compares the pipeline designs by engineer and AI model for two testing cases. It can be seen that AI has firstly learnt the pattern that all the sprinkler heads should be connected with pipes. Most of the heads are grouped together by the sub pipes. However, there is a significant lack of main pipes which are supposed to connect all the main pipes and lead to the riser shaft. Despite there being several main pipes generated in AI drawing, their connections are still relatively fragmented, with a maximum of four to five sub pipes connected, rather than being linked together in a systematic manner. The total length of the AI-generated pipe is an averagely 28% less than the engineer's, which also indicates the insufficient pipeline connection.

One potential reason is that the proportion of main pipes in the entire design output is very low, which results in less learning data available for AI. AI may also assign less importance to main pipes during the training process because their impact on result evaluation is relatively minor. Moreover, unlike the sprinkler placement or the sub pipe connection, which has clear coverage demands or point-to-point linkage, the selection of the linking way for the main pipe has more flexibilities and options. As shown in Fig. 9, even for the same sprinkler

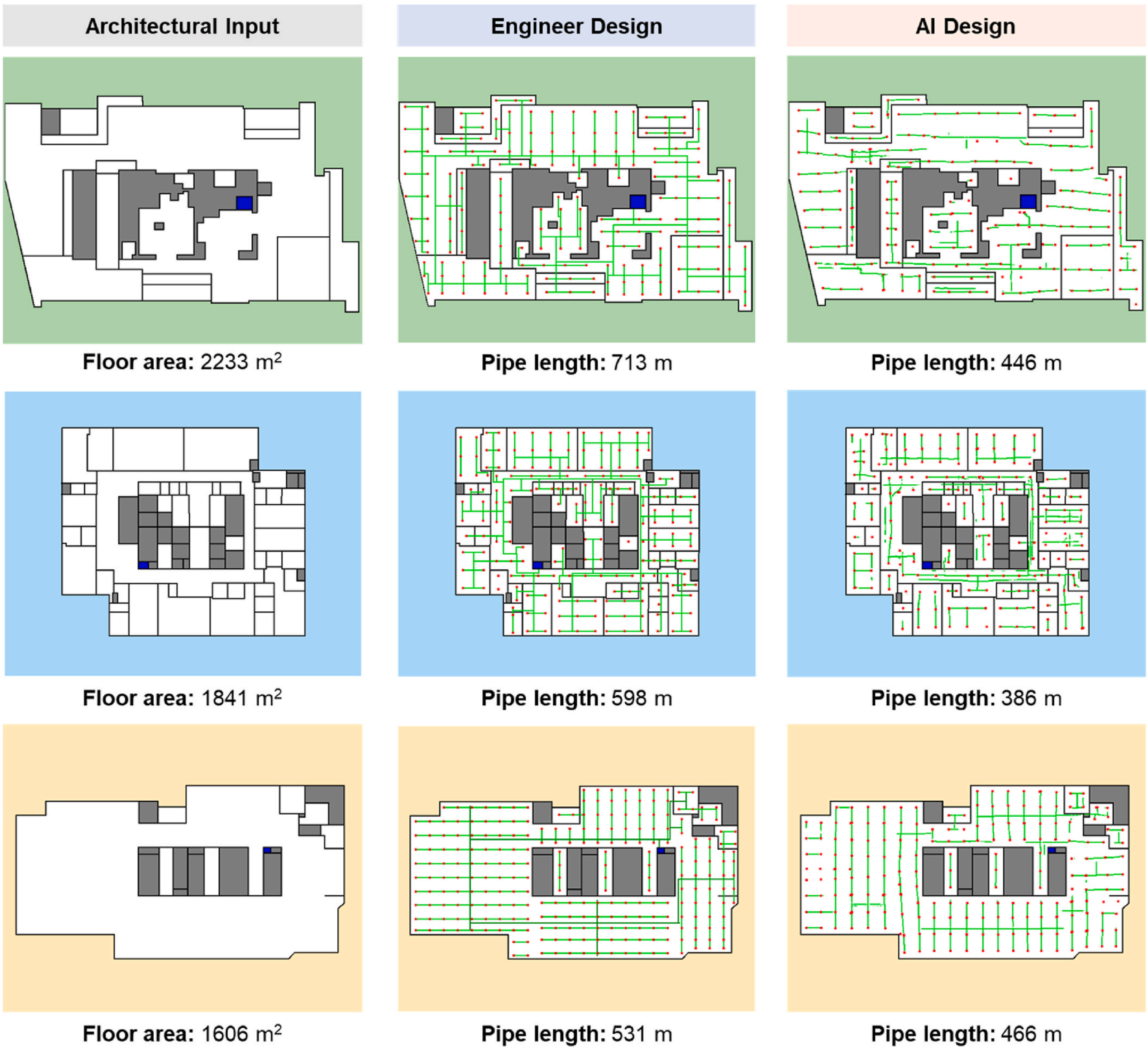

Fig. 8. Comparisons of engineer and AI designs of pipeline connection for two testing cases.

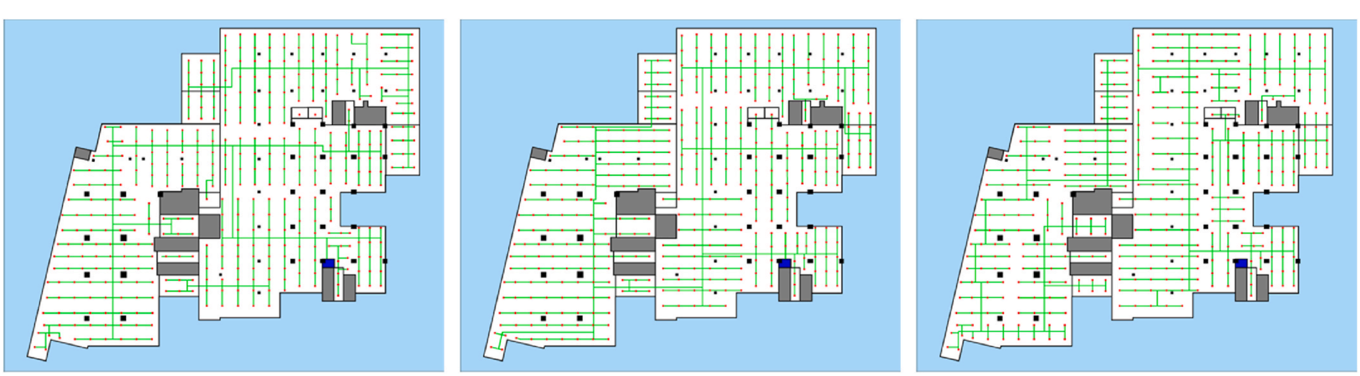

Fig. 9. Examples of different pipeline connections for the same sprinkler placement.

placement, the nozzles can be connected with different pipeline arrangements and all of them comply to fire regulations. This design flexibility makes it more challenging for AI models to capture clear connection rules or patterns.

3.3. Perspectives of AI-assisted fire service design

Although there is still demand for pipeline connection improvement, the sprinkler placement result by AI is already comparable to engineers. Table 2 compares the statistics between engineer and AI designs. While an engineer needs approximately 21 min to complete one drawing, AI takes 10 s to finish it with a high sprinkler coverage of 99.5%. Considering the time for review and manual correction of AI placement, it still needs only 5 min to get a well-designed drawing of sprinkler placement, resulting in an improvement of design efficiency by 76%. By freeing engineers from the labour-intensive and time-consuming routine drawing preparation, more efforts can be invested in impactful design tasks, such as development of the design concept and integration of sustainable strategies.

Moreover, AI gave fewer sprinklers in most of the cases, as shown in Fig. 10. It suggests that AI provides more cost-effective solutions with a reasonable number of sprinklers, which allows for opportunities of design optimization in practices. The reason is that, while the code specifies the maximum spacing requirement for sprinklers, the most cost-effective solution is that all the sprinklers are arranged with that value. However, it is a common practice for engineers to use a more conservative spacing to distribute sprinklers, rather than following the maximum value. For example, although the regulated maximum spacing between sprinklers for the Medium-hazard class is 3.6 m, engineers may place the sprinklers at a distance of 3.2 m in practice.

The reason is that the sprinkler layout design is very sensitive to the architectural plan and, meanwhile, design changes are quite common during the whole design period. If the sprinklers are maximum-spacing designed at the initial stage, they may face very frequent modifications in the following stages, which will cost them a lot. Therefore, it has become a commonly accepted practice that sprinklers are conservatively designed with tolerance for future design modification.

AI can overcome this misconduct by offering an intelligent design process that can respond to architectural changes with minor efforts. As shown in Table 2, the number of sprinklers designed by AI is on average 13 % less than the number by engineers, with up to 26 % for one High-hazard testing case, while the coverage rate remains high. It suggests that AI can provide a more cost-effective design than engineers, resulting in lower construction costs and less maintenance demands for the building operation.

It is acknowledged that, however, there are many aspects that could be improved in the future works. In terms of the effectiveness of information encoding, although the current results suggest that the model successfully distinguishes the background colour information and generates sprinklers with spacing corresponding to different hazard classes, the authors acknowledge that this approach has certain limitations. Specifically, the size of the outdoor background area varies across drawings, which may introduce potential inconsistencies in how prominently the hazard class information is represented in different images, particularly when the outdoor region is small. A potentially more robust alternative would be to encode hazard class information as a separate input channel within the input matrix, providing the model with a clearer and more consistent signal.

Table 2
Comparison between engineer and AI designs of sprinkler placement.

Features	Engineer design	AI design
Time consumption	21 min	Generation – 10 s Review and correction – 5 min
Coverage	99.8%	99.5%
Number of sprinklers	206	183

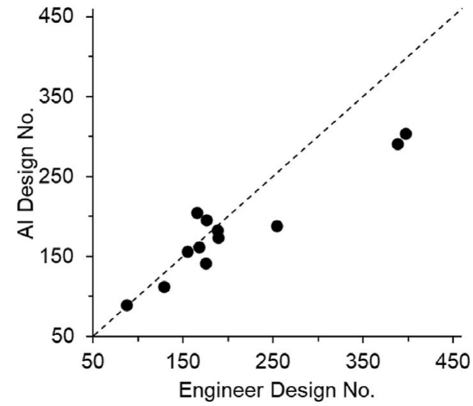

Fig. 10. Comparisons of number of designed sprinkler heads by engineer and AI for testing cases.

As for the arrangement of the sprinkler layout, one promising direction for future work is to explore more advanced generative models, such as diffusion model. While diffusion model has demonstrated superior performance compared to pix2pixHD in various image-based tasks, existing architectures are not yet well-suited for the high-resolution requirements specific to this study, as discussed in Section 2.3. Should future advancements in diffusion model design enable efficient high-resolution training, it would be highly worthwhile to investigate their applicability in this context. Another potential avenue is to develop an additional post-processing tool or model that can refine and optimize the AI-generated sprinkler layouts. Such a tool could adjust the placement of sprinklers to achieve greater alignment and uniformity while preserving coverage performance, ultimately supporting better downstream pipeline design. It is also acknowledged that the coverage rate and total sprinkler number alone do not fully capture the spatial organization and alignment of sprinklers. Additional quantitative metrics such as spacing uniformity index, nearest neighbor angle deviation, would be introduced in the future work, which can better reflect the regularity and aesthetic quality of the sprinkler layout.

To improve the AI performance on pipeline generation, one possible solution is that, instead of generating the sprinkler and pipes simultaneously, the design can be divided into two steps: (1) the first step is to generate the sprinkler placement by inputting the architectural plan and (2) the second step is to generate the pipelines by inputting the sprinkler placement. The noise for the pipeline generation can be minimized in this way and it also agrees with the natural design process by the engineer. By introducing the input of sprinkler points, deep learning algorithms of graph neural network (GNN) can also be adopted which is expected to have better performance for the point-to-point learning tasks.

While the datasets collected in this work are based on designs that comply with Chinese standards, the model is therefore applicable only to local Chinese designs, which represents one of the main limitations of this study. Nevertheless, the concept of intelligent design via deep learning models has been successfully demonstrated through the testing results, and the underlying principle and developed method could be applied to any standard, provided that sufficient and high-quality design data are available.

4. Conclusions

This study proposed a framework of intelligent fire safety design and demonstrated its feasibility by introducing a case study of sprinkler layout drawing. A database with a total of 120 engineering drawings was prepared, containing sprinkler layout designs in different architectural plans, functions, and hazard classes. This database was then utilized to train an AI model using pix2pixHD GAN architecture. By inputting the architectural plan and hazard class, the proposed AI model can complete the sprinkler placement in seconds with a high protection coverage of 99.5% for new cases, while the proposed total number of sprinklers is 13% less than the engineer's design. On the other hand, the design pattern of pipeline connections was not well captured by the proposed AI model with a significant lack of main pipe generation.

In comparison to the conventional manual design process, the AI-driven intelligent approach can improve the design efficiency of sprinkler placement by up to 76%, freeing engineers from the intensive drawing preparation so that more efforts can be made on impactful tasks such as concept refinement and sustainable development. It can also encourage cost-effective solutions with reasonable less sprinklers, reducing the construction cost and maintenance demands for the building operation.

CRediT authorship contribution statement

Yanfu Zeng: Writing – original draft, Methodology, Investigation, Formal analysis. **Xinyi Liu:** Investigation, Formal analysis. **Yifei Ding:** Formal analysis. **Zhe Zheng:** Methodology. **Tianhang Zhang:** Writing – review & editing, Resources. **Xinyan Huang:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Xinzheng Lu:** Writing – review & editing, Supervision.

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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Appendix

Fig. A1 shows the full database with 120 drawings of sprinkler layout, which is further divided into training (90%) and testing datasets (10%). This database contains designs with different geometry, function, and hazard class, presenting a great diversity of learning data. Fig. A2 presents results of AI-generated sprinkler placements for testing cases, except for cases that has already been showcased in main context. It can be seen that AI can distribute sprinklers with high coverage rate of over 99% for all new cases.

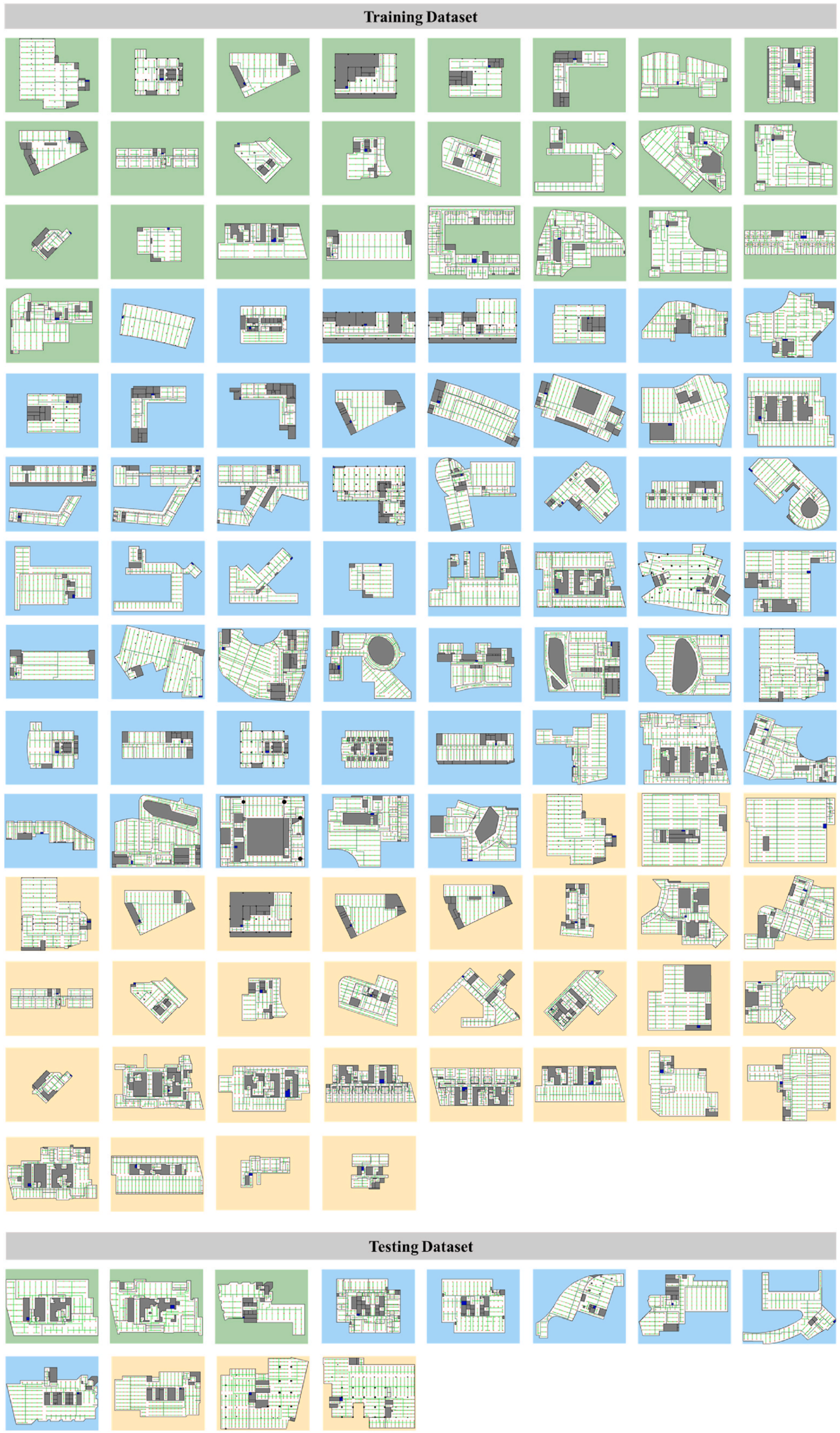

Fig. A1. Database of the sprinkler layout design.

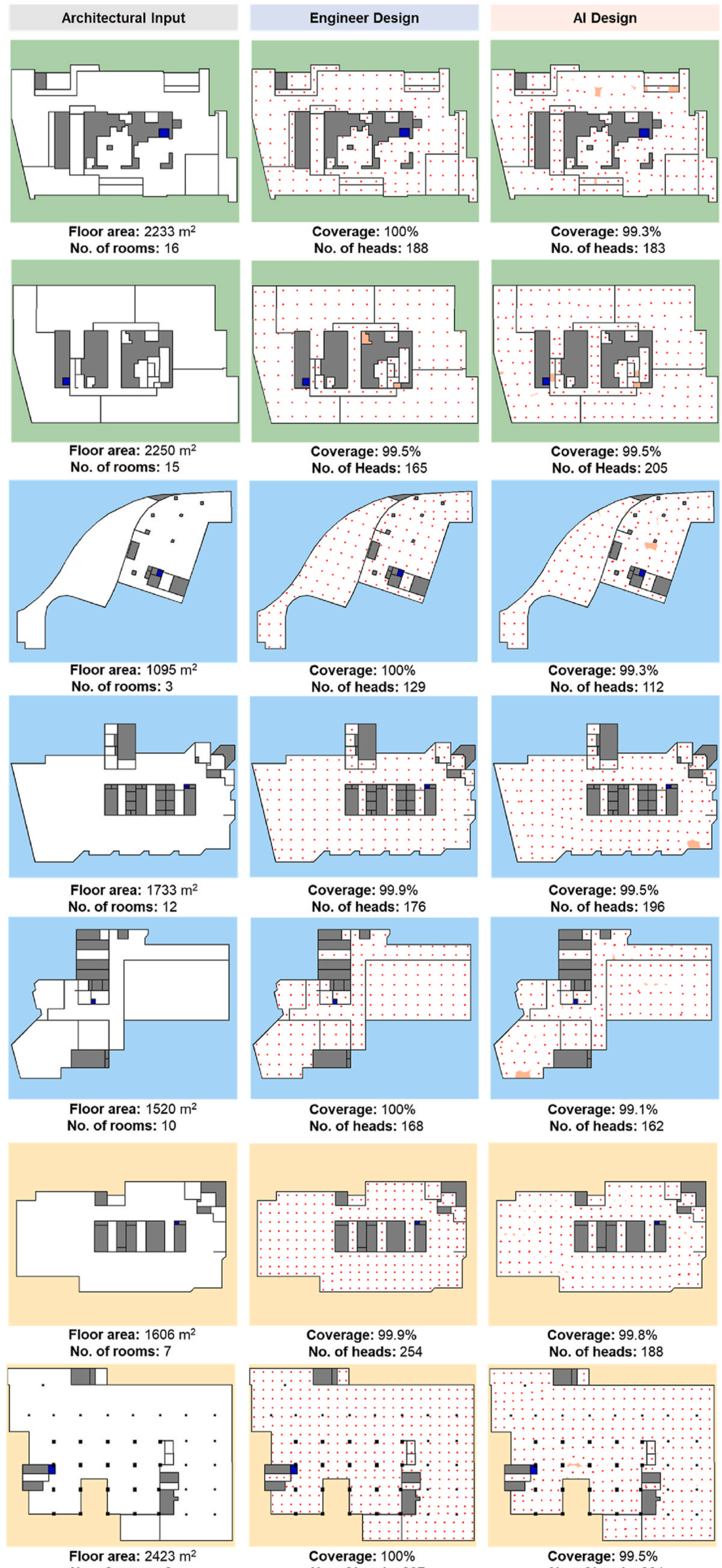

Fig. A2. AI-generated sprinkler placement for testing cases.

Data availability

The prepared training database is available on request, and adopted pix2pixHD GAN model can be found in GitHub at https://github.com/NVIDIA/pix2pixHD (Wang et al., 2018).

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