Knowledge-driven Performance-based Design for Residential Buildings Fire Safety: A Case Study of Fire Scenario Generation

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Abstract –

The high frequency of human activity in residential buildings has led to a continuous occurrence of fire accidents, which has become a prominent threat to public safety. Addressing the bottlenecks of reliance on manual experience, insufficient coverage, and low efficiency in fire scenario settings for performance-based fire design (PBFD) of residential buildings, this paper proposes a new paradigm for knowledge-driven PBFD for residential buildings. By constructing a multi-modal knowledge graph (MMKG) in the field of fire, this study systematically combines historical experience from unstructured fire accident reports with spatial semantic information from architectural drawings, realizing a fused application of knowledge graph and generative AI for fire scenario generation. Taking fire position generation as an example, this study employs a Pix2pix GAN model to automatically generate spatially plausible and interpretable fire position distributions under knowledge constraints derived from building layout and building type. The case study demonstrates that the proposed approach can effectively learn the spatial patterns of fire risk, transforming scenario construction from time-consuming manual presetting to knowledge-constrained generation. The study also discusses current limitations related to the small dataset size, manual annotation effort, and limited knowledge dimensions, and outlines future directions for optimization and expansion.

Keywords –

Performance-based fire design; Multi-modal knowledge graph; Intelligent design; Generative AI; Knowledge-driven generative design

1 Introduction

With the acceleration of urbanization in China, the scale of residential buildings continues to expand. Coupled with the diversification of lifestyles and the widespread use of decorative materials, frequent fire accidents have become a prominent threat to public safety, causing heavy losses to people's lives and property. The handling of various uncertainties in the design process has become a key bottleneck restricting the improvement of the safety level [1][2]. Due to the scene dependence of building fire risk that the smoke spread and available safe evacuation time of the same building will vary by orders of magnitude under different fire position, combustible loads, ventilation conditions and population distribution, it is often difficult to cover the combined risks of complex spatial forms and new functional business formats by relying solely on the provisions of the regulations. Thus, performance-based fire design (PBFD) has attracted wide attention.

The core value of performance-based design lies in shifting from prescriptive compliance to quantifiable safety objectives and in integrating structural fire resistance, personnel evacuation, smoke control, and fire rescue into a unified verification framework for complex buildings [3][4]. However, real fire accidents are not repeatable, and it is difficult to conduct control tests in buildings. Evacuation simulation is used to assess congestion, route selection, and pre-evacuation delay under different fire positions, personnel distribution, and blocked exits, thereby supporting performance-based life safety analysis and drill optimization [2][5]. Therefore, within the PBFD framework, the core of fire scenario simulation lies in determining performance targets and establishing quantitative criteria, such as setting a safety margin that the available safe evacuation time (ASET) must exceed the required safe evacuation time (RSET). Through a complete fire scenario setting, covering the most likely and most unfavourable situations, the comprehensiveness and robustness of ASET and RSET calculations are ensured [6]. However, the practice of this method faces a fundamental challenge: in order to comprehensively assess the fire safety performance of a complex building, the number of potential fire scenarios to be examined (such as different fire positions, fuel types, ventilation conditions) is extremely large. Performing high-fidelity CFD simulations for every scenario would incur prohibitive computational costs and time consumption, making it impractical in regular design cycles or rapid evaluations [7].

Recent research has begun to explore using generative AI to replace some high-cost simulation processes. By learning from simulation databases, near-real-time fire scenario output can be achieved, thereby improving scene coverage and design iteration efficiency. For example, Zeng et al. [8] used generative models such as Pix2pix for smoke visibility slice prediction in complex-shaped and large-space buildings, demonstrating their efficiency advantages in design analysis. Rianto et al. [9] constructed a diverse dataset by setting different fire positions within the same building. This type of work lays a methodological foundation for fire scenario analysis based on generative models in complex building layouts. However, most of the above representative approaches focus on generating simulation output fields as their core objective. Their inputs are usually regularized or engineered geometric expressions, where different fire scenarios (with fire points located in different locations) are randomly set.

However, fire position in real residential fires is not purely random. It is shaped by a combination of spatial configuration, room function, occupant activities, appliance usage, and other contextual factors [10]. The fire position selected for fire scenario simulation is supposed to be based on a deep understanding of historical fire patterns and building environment characteristics rather than assigned solely by designer intuition. If the problem is simplified to generating randomly, generative AI is prone to learning pseudo-correlations unrelated to the accident's semantics, and the generated results lack interpretability and controllability, making them difficult to trust and reuse in engineering contexts. The historical fire accident data could provide domain knowledge constraints for fire position generation, such as building type, building layout, room function, and fire cause. But such information is scattered across unstructured fire accident reports and architectural drawings. The fire accident reports are characterized by strong narrative, inconsistent terminology, and the fact that key information is often implicit or missing, while building floor plans contain precise geometric information but lack semantics. The alignment between text and images requires overcoming significant modal gaps and information incompleteness.

To address this gap, this study proposes a knowledge-driven workflow that combines a multi-modal knowledge graph (MMKG) with generative AI for fire position generation. Knowledge graph, as a type of semantic network, can formally describe concepts, entities, and their relationships in the real world, serving as the foundation for machine learning and reasoning. It can be used to merge the information described in text and the scene depicted in images into a queryable and computable semantic network [11]. This paper utilizes MMKG to represent and link historical fire accident data from different sources and at different granularities, thereby capturing datasets for the generative model. These knowledge constraints aim to improve the traceability and interpretability of generated ignition scenarios and provide a more structured basis for scenario definition. In this proof-of-concept study, knowledge constraints are used to improve the traceability and interpretability of generated fire scenarios, while only building layout and building type are operationalized in the current model due to data availability. Accordingly, this paper does not aim to provide a complete PBFD solution, but to demonstrate the feasibility of knowledge-constrained fire position generation. The main contributions include a MMKG-based representation for linking textual fire reports with floor plan semantics, a knowledge-constrained data extraction and conditional generation workflow, and an initial case study under limited data conditions. Current limitations include the small real-case dataset, partial manual processing, and restricted knowledge dimensions.

2 Methodology

The framework of the proposed methodology is illustrated in Figure 1, including two stages. First, a MMKG is constructed based on a designed domain ontology and the extraction and preprocessing of the multi-modal unstructured data to integrate text and image information in historical fire accident data. Then, this MMKG is used as a conditional compiler to extract aligned text-image dataset, which is treated as a semantically enhanced floor plan. Through a knowledge-driven conditional generative model, reasonable and easily interpretable visualized structured fire scenarios are quickly generated, thereby supporting PBFD derivation and optimization.

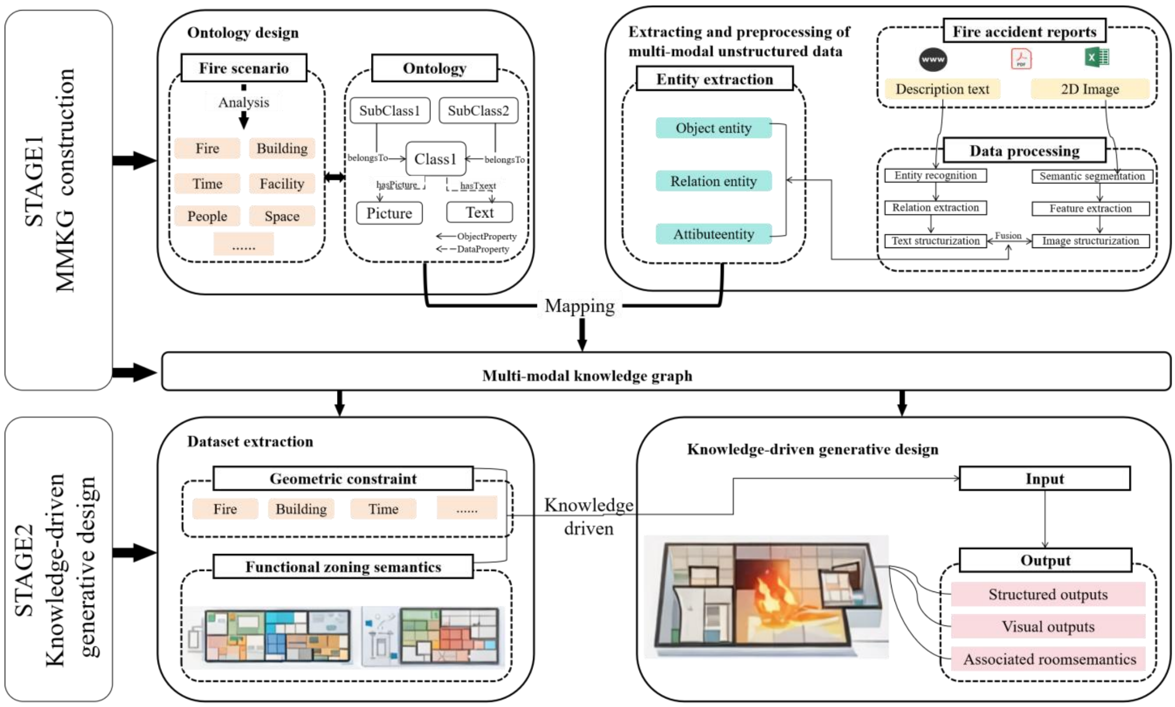

Figure 1. Framework of the proposed methodology

2.1 MMKG Construction

Considering the heterogeneity of unstructured accident report texts and planar images, the MMKG aims to carry multi-modal unstructured data with a unified semantic framework and to ensure its queryability and interpretability [12]. In this way, the empirical descriptions of fire scenario could be transformed into computable, traceable, and reusable structured knowledge, thereby supporting consistent scenario inputs in subsequent simulations and design iterations [3].

Knowledge graph usually consists of an ontology layer and an instance layer. The ontology layer could ensure semantic consistency across different systems and data sources by defining shared concepts and terminology [13]. In this paper, a top-down approach is employed to establish the MMKG. A domain ontology is designed first to describe effective fire accident information using standardized terminology and accurate concepts. Besides, the boundary delineation of the ontology concept needs to meet the PBFD, so that subsequent scenario retrieval by target and scenario assembly by constraint become executable queries and extraction operations [14].

Subsequently, the fire accident information extracted from fire accident data is stored as the triples of the instance layer based on the designed ontology. The historical fire accident data is basically classified as textual reports and visual drawings. Accordingly, the creation of the instance layer of the MMKG includes the textual information extraction, visual information extraction, and their linkage creation. At the current stage, part of the instance layer construction is manually performed, including fire position annotation, textual normalization, and cross-modal alignment, with an average processing time of approximately 30 minutes per case.

For textual information, knowledge extraction involves discovering and extracting relevant information from unstructured text, transforming it into structured data in a predefined format. For visual information, knowledge extraction involves mapping pixel information from images to low-dimensional vector representations. This provides a structured spatial semantic carrier for the "room affiliation" of the fire origin, achieving semantic storage of architectural floor plan information [15]. Finally, text information instances and image semantic elements are aligned under a unified case identifier to form a multi-modal description of the same accident instance, and a searchable and extractable dataset library is formed in the form of MMKG. In the present study, this MMKG construction is intentionally limited to the information required for fire position generation in residential PBFD, and should therefore be regarded as a proof-of-concept knowledge organization workflow rather than a fully automated large-scale knowledge extraction system.

2.2 Knowledge-driven Generative Design

2.2.1 Knowledge-constrained Dataset Extraction Based on MMKG

To ensure the generation of fire scenario is conducted based on historical knowledge, a knowledge-constrained dataset extraction is proposed based on MMKG. The extracted dataset is regarded as the input of the generative model to enable knowledge-driven fire scenario generation.

The knowledge-constrained dataset is created on the basis of knowledge query on the MMKG. In this way, each sample in the dataset consists of a floor plan image with fire position, its aligned textual conditions, and corresponding semantic segmentation results of room boundary and functions. The textual conditions and the semantic segmentation results could be regarded as the knowledge enrichment of the floor plans.

2.2.2 Generative Model Training

In this paper, the core task of fire scenario generation is defined as a deterministic or probabilistic mapping from multi-modal conditional inputs (such as building floor plan "A" and knowledge constraints "c") to scenario-based output "B". Therefore, a conditional generation paradigm based on conditional generative adversarial networks (CGAN) [16] is proposed to construct a generative AI model that integrates prior knowledge with image data. The proposed paradigm is not only a black-box data-fitting process, but also a knowledge-guided constraint generation process [17][18].

The MMKG and the generative model form a collaborative framework in which the MMKG provides structured and traceable knowledge constraints, while the generative model translates these constraints into spatialized fire scenarios efficiently.

2.2.3 Evaluation Protocol and Task-Relevant Metrics

To assess the performance of fire position generation, this study adopts both image level and task-relevant evaluation metrics. Structural Similarity (SSIM) is used to measure the structural similarity between the generated fire position annotation image and the corresponding reference image. SSIM is calculated by equation (1).

$$SSIM\,(x,y)=\frac{(2\mu_x\mu_y+c_1)(2\delta_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\delta_x^2+\delta_y^2+c_2)} \tag{1}$$

x and y represent individual sampled images from the generated and real images, respectively, μ_x and μ_y are the estimated pixel value means for x and y; δ_x and δ_y are the estimated variances, $c_1=(k_1L)^2$, $c_2=(k_2L)^2$, where L is the range of pixel values, $k_1=0.01$, $k_2=0.03$ [21]. However, because SSIM mainly evaluates image similarity, it cannot directly reflect whether the generated fire position is spatially accurate or spatially plausible. To address this limitation, two additional task-relevant metrics are introduced. The first is coordinate error (E_{coord}), reported in pixel units, which measures the Euclidean distance between the generated fire position and the annotated ground-truth fire point, as defined in equation (2):

$$E_{coord}=\frac{1}{N}\sum_{i=1}^{N}\left\|p_i^{pred}-p_i^{gt}\right\|_2 \tag{2}$$

where p_i^{pred} and p_i^{gt} denote the predicted and ground-truth fire coordinates of the $i-$th sample, respectively.

The second is valid-region hit rate (HR_{valid}), the valid-region was defined by the indoor floor plan mask derived from excluding walls and background. HR_{valid} evaluates whether the generated fire position falls within a feasible indoor region of the floor plan, as defined in equation (3):

$$HR_{valid}=\frac{1}{N}\sum_{i=1}^{N}1\left(p_i^{pred}\in\Omega_i^{valid}\right) \tag{3}$$

where Ω_i^{valid} denotes the valid indoor region of the $i-$th sample, and $1\left(p_i^{pred}\in\Omega_i^{valid}\right)$ is the indicator function.

Therefore, the final evaluation framework combines SSIM, coordinate error, and valid-region hit rate to provide a more comprehensive assessment of the proposed method.

3 Case Study

To validate the feasibility and effectiveness of the proposed method, a case study of fire position generation in the fire scenario is given in this section.

3.1 Historical Reports Collection and MMKG Construction

A total of 32 fire accident reports on residential building fires occurred in recent years, which are published on government official websites, were collected for MMKG construction. The fire accident reports contain text and images. The textual information includes detailed descriptions of the fire accident. The images in the reports are building floor plans, which are used to visually represent the building layout and fire position. Some examples of the collected fire accident reports are listed in Table 1.

Table 1. Examples of collected fire accident reports

ID	Title	Link
1	The fire accident at No. 39 Dongning Street, Yingshang Town, Fuyuan County, Qujing City	https://www.qj.gov.cn/html/2025/zhsgjy_0908/274501.html
2	The "8.8" general fire accident in Humen Town, Dongguan City, 2021	https://dgsafety.dg.gov.cn/attachment/0/100/100599/3821872.pdf

Considering both the collected historical data and the immediate needs of fire position generation, the current ontology layer is intentionally simplified to represent the minimum set of concepts that can be extracted reliably from the available cases, as shown in Figure 2. In this proof-of-concept implementation, building layout and building type are treated as the primary operational constraints for scenario generation, while accident-related textual and image information is retained as supporting attributes for case indexing and cross-modal linkage.

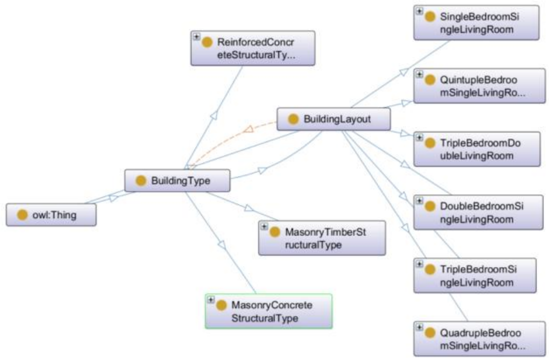

Figure 2. Ontology layer of MMKG

Based on the designed ontology layer, the text and image information are manually processed into structured data, which are then instantiated as the instance layer to form a MMKG for fire position generation. An example is illustrated in Figure 3. The instance layer construction includes a manual curation step to ensure data quality and cross-modal alignment. Specifically, the fire coordinates on the floor plan, the building type, and the building layout label are manually checked and encoded into structured triples for each case. The manual effort is mainly concentrated on identifying the fire position from report associated drawings and normalizing the textual descriptors into the predefined ontology terms. In future work, it can be progressively replaced by semi-automatic information extraction, floor plan parsing, and multi-modal entity alignment techniques to improve scalability.

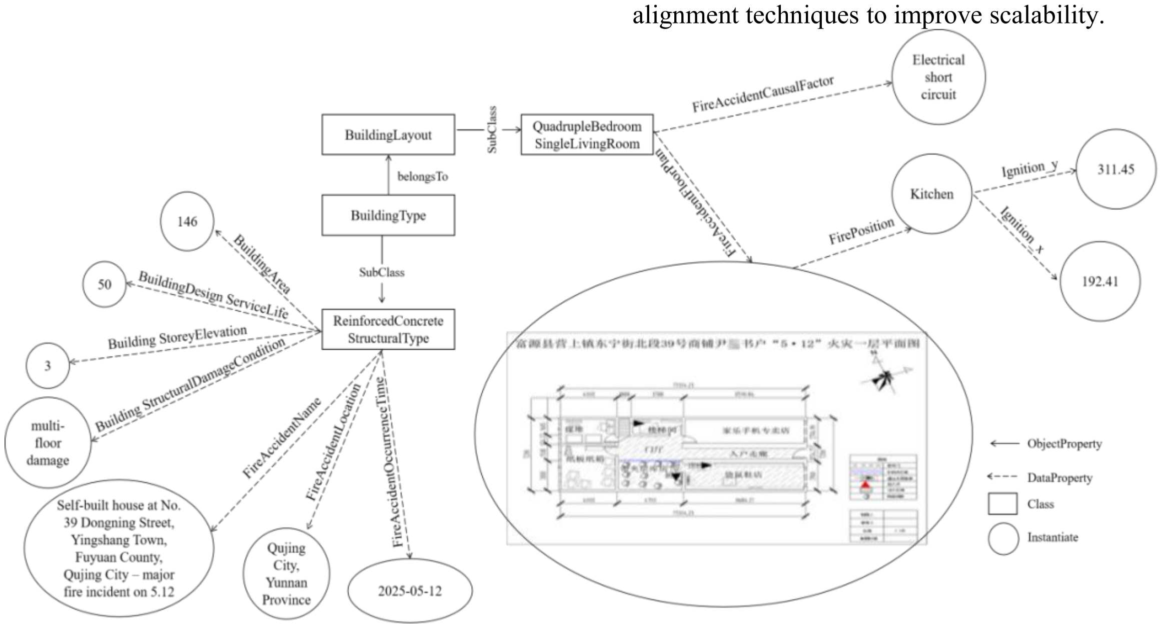

Figure 3. An example of MMKG construction

3.2 Dataset Extraction and Augmentation

In this paper, fire position in fire scenario is generated considering only the constraints of building layout and building type. Therefore, on the basis of the MMKG, the SPARQL query listed in Table 2 is utilized to extract knowledge-constrained dataset for fire position generation.

Table 2. SPARQL query to extract knowledge-constrained dataset

Algorithm
SELECT
DISTINCT ?c ?ignition_x ?ignition_y ?layout ?type
WHERE {
?c code:ignition_x ?ignition_x .
?c code:ignition_y ?ignition_y .
?c code:locates ?layout .
?c code:locates ?type .
?layout rdf:type code:BuildingLayout .
?type rdf:type code:BuildingType .
}

In addition, because training CGAN on a small dataset is prone to over-fitting and weakening generalization ability, we adopted a data augmentation method based on the original dataset, as shown in Table 3. This data augmentation method achieves image augmentation by jittering the pixel coordinates of the fire position [19]. For each planar image with pixel coordinates (ignition_x, ignition_y), random perturbation sampling is performed in the neighbourhood of the original pixel coordinates with a radius of R=3.0 to generate an image with new pixel coordinates (ignition_x', ignition_y'), while the other conditional constraints remain unchanged.

Table 3. Parameters of fire position Coordinate Jittering Augmentation

Algorithm
Input: (ignition_x, ignition_y) , R=3.0
Output: (ignition_x', ignition_y')
θ = Uniform(0, 2π)
ρ = Uniform(0, R)
d (ignition_x) = $\rho \cos \theta$
d(ignition_y) = $\rho \sin \theta$
ignition_x' = ignition_x $\pm$ d (ignition_x)
ignition_y' = ignition_y $\pm$ d(ignition_y)
return (ignition_x', ignition_y')

During the data augmentation implementation, 10 synthetic samples were generated for each real case. The 32 real cases were split at the case level into 25 training cases and 7 testing cases. All augmented variants were generated only for the training cases. This augmentation improves supervised sample density without altering layout semantics or text conditions, expanding the dataset from 32 to 352 samples, as shown in Figure 4. A grouped case-level split avoids train and test information leakage. Augmented variants stay with their original case, and only the training set uses augmentation. The test set contains held-out real cases with no overlaps. Coordinate jittering enhances local density but does not increase semantic diversity in building layout, room function, or fire context.

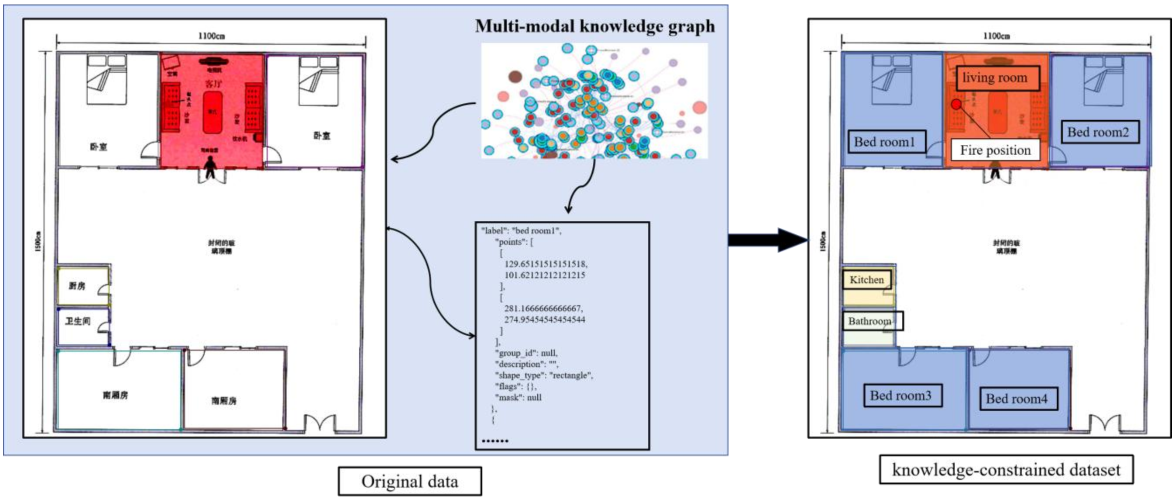

Figure 4. A sample of dataset

3.3 Knowledge-constrained Pix2pix GAN Model and Evaluation

3.3.1 Model Architecture and Training Settings

Fire position generation can be formulated as a mapping from multi-modal conditions to a spatial location. Given a combination of floor plan geometry, building type, and building layout, the model predicts and labels the fire position on the floor plan. The fire position is supposed to be predicted and labeled on the building floor plan, as shown in Figure 5.

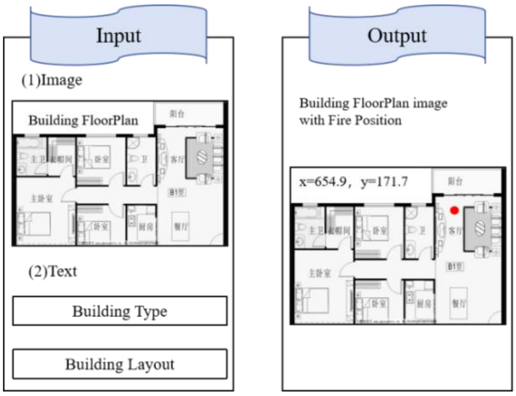

Figure 5. An example of fire position generation

Accordingly, Pix2pix is adopted as the generative model because it is well suited for paired image-to-image translations [20]. Each of the input image "A" has an aligned ground-truth target "B". As shown in Figure 6, Pix2pix can learn the conditional mapping $G : A \rightarrow B$ under CGAN framework, so the generated result follows the desired conditional distribution while preserving the spatial layout of "A". The U-Net generator performs an encoder-decoder transformation and uses skip connections to concatenate low-level encoder features with decoder features. The PatchGAN discriminator takes paired inputs $[A_{cond}, B]$ and outputs a patch-wise realism score map [17].

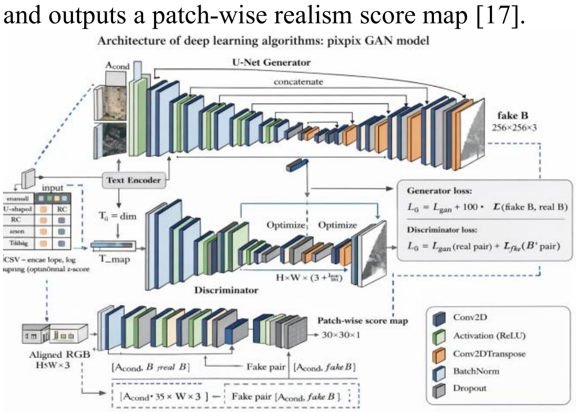

Figure 6. Architecture of Pix2pix GAN model

3.3.2 Baseline Comparison and Comprehensive Evaluation Results

To quantify the contribution of knowledge constraints, a non-constrained Pix2pix model was used as the baseline. It shares the same architecture, training settings, data split, and evaluation metrics as the proposed model, with the only difference that MMKG semantic constraints are removed and only the floor plan image is used as input. This setting provides a direct control for isolating the effect of knowledge constraints. Simpler statistical baselines will be considered in future extended evaluations. Table 4 quantifies the performance of knowledge-constrained Pix2pix and non-constrained Pix2pix.

Table 4. Quantitative comparison between knowledge-constrained Pix2pix and non-constrained Pix2pix

Method	SSIM (grayscale)	E_{coord} (pixel)	HR_{valid} (%)
Knowledge-constrained Pix2pix	0.971±0.039	6.35±2.17	98.00
Non-constrained Pix2pix	0.923±0.051	15.86±6.23	68.58

Compared with the non-constrained Pix2pix baseline, the knowledge-constrained model achieved higher SSIM, lower coordinate error, and a markedly higher valid-region hit rate. These results suggest that introducing knowledge constraints improves the spatial plausibility and task relevance of generated fire positions under the current proof-of-concept setting.

4 Conclusion

This paper presented a knowledge-driven workflow for fire position generation in residential PBFD by combining a MMKG with a conditional generative model. The proposed framework organizes heterogeneous fire report texts and floor plan information into a queryable MMKG, transforming scattered unstructured data into a structured and reusable knowledge representation. On this basis, a knowledge-constrained dataset can be extracted to support the conditional generation of fire positions on residential layouts. The case study suggests that the method can capture recurrent spatial ignition patterns and can provide a more structured and traceable alternative to purely manual scenario setup.

At the same time, the present study should be regarded as an initial proof of concept rather than a complete engineering solution. The real-case dataset remains small, and part of the MMKG construction still relies on manual curation. In addition, the currently implemented constraints are limited mainly to building layout and building type. Broader validation across more building cases and richer residential contexts is still required. Future work will focus on expanding the case base, introducing richer knowledge constraints such as room function, fire cause, fuel load, and ventilation conditions, reducing manual effort through semi-automatic multi-modal extraction, and evaluating how knowledge-constrained fire position generation can improve downstream fire scenario selection and simulation efficiency in full PBFD workflows.

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