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A Network Analysis-Based Approach for As-Built BIM Generation and Inspection

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Abstract: With the rapid advancement in Building Information Modelling (BIM) technology to strengthen the Building and Construction (B&C) industry, effective methods are required for the analysis and improvement of as-built BIM, which reflects the completed building project and captures all deviations and updates from the initial design. However, most existing studies are focused on as-designed BIM, while the analysis and inspection of as-built BIM rely on labour-intensive visual and manual approaches that overlook interdependent relationships among components. To address these issues, we propose a network analysis-based approach for managing and improving as-built BIM. Networks are generated from geometric attributes extracted from Industry Foundation Classes (IFC) documents, and network analytical techniques are applied to facilitate BIM analysis. In addition, a practical dataset is utilised to verify the feasibility of the proposed approach. The results demonstrate that our method significantly enhances the analysis and comparison of as-built BIM from model analysis and matching. Specifically, the innovative contribution leverages global information and interdependent relations, providing a more comprehensive understanding of the as-built BIM for effective management and optimisation. Our findings suggest that network analysis can serve as a powerful tool for structure and asset management in the B&C industry, offering new perspectives and methodologies for as-built BIM analysis and comparison. Finally, detailed discussion and future suggestions are presented.

Keywords: as-built BIM; network analysis; community detection; building industry; structure inspection

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1. Introduction

The Building and Construction (B&C) industry is often cited as inefficient and unproductive due to the limited integration of Internet and Communication Technologies (ICT) [1], particularly the documentation and inspection of building structures, which was a tedious and laborious task during the 2D drawing era. The advancement of Computer-Aided Design (CAD) technology facilitates data interoperability among designers, constructors, and other stakeholders throughout the entire building lifecycle and also lays the foundation of Building Information Modelling (BIM), which has received a considerable amount of attention in the B&C industry and emerged as a core enabling technology for Construction 4.0 deployment [2]. As with the traditional as-designed BIM developed during the design phase, as-built BIM has also attracted increasing attention from both industry and academia, owing to the significance of efficient BIM-enabled maintenance or facility management for building assets that were built before the existence of BIM. Many researchers have invested in as-built BIM reconstruction because of its broad potential application prospects, such as the automatic reconstruction of structures [3] and the piping system [4] from photogrammetric information or point clouds.

The increasing prevalence of as-built BIM studies necessitates the development of effective management and inspection methods to ensure a comprehensive management system for completed buildings. Efficient BIM-enabled functions for building assets that were built before the existence of BIM are highly dependent on the accuracy of as-built BIM. Such research aims to facilitate the analysis and management of as-built BIM, which is a fundamental problem arising in many BIM-based applications, such as facility management [5] and predictive maintenance [6]. Moreover, the advanced function of comparing as-designed and as-built BIMs also benefits from the improved accuracy and comprehensive analysis. Prior studies often relied on visual inspection, manual management, and a check of selective attributes [7–12]. However, such methods are time-consuming and error-prone due to the large file sizes, complex inheritance, and referencing relationships of BIM models. Although some recent studies have been developed for automatic analysis and management methods based on machine learning, their methods are sensitive to parameter tuning and exert demands on computing resources, resulting in low scalability and robustness.

To address these issues, an innovative approach based on network science is proposed for the analysis and management of as-built BIM. The proposed method starts with network component identification by extracting information from Industry Foundation Classes (IFC) files, followed by the establishment of networks for as-built or as-designed BIM. Next, topological analyses are conducted to provide more insight and reference parameters. Last, different networks are compared to identify any discrepancies or changes. Our method fully considers the correlation and relationships among building elements and effectively utilises the information from IFC files. As a result, the approach can improve comparison efficiency and reduce computational resource consumption, while its comparison process depends on network-related properties and is not sensitive to parameter tuning. Furthermore, the network analysis results are leveraged to derive management and modified recommendations for as-built BIM. Lastly, we also demonstrate potential applications of our approach in practical implementation.

The rest of the paper is organised as follows: Section 2 presents the literature review of related works on BIM inspection, while the proposed solution is detailed in Section 3. Section 4 validates the solution using practical scanning data, followed by a discussion. Finally, Section 5 summarises the contributions and suggests future work.

2. Literature Review

2.1. As-Designed BIM

The application of BIM technology has revolutionised various aspects of construction project management, extending beyond traditional inspection tasks. One significant area of impact is in project scheduling and cost estimation. Researchers have demonstrated the effectiveness of BIM in integrating time and cost dimensions, leading to the development of 4D and 5D BIM models. For example, Hallberg et al. [13] explored the application of 4D BIM for dynamic scheduling and progress tracking in large-scale construction projects, showing improvements in project coordination and timeline adherence. Similarly, Smith [14] utilised 5D BIM for detailed cost estimation and financial management, which enhanced budget accuracy and facilitated better financial planning. Moreover, BIM has been pivotal in improving collaborative workflows among project stakeholders. Turk et al. [15] discussed how BIM fosters enhanced communication and information sharing, leading to fewer misunderstandings and more efficient decision-making processes during social service. This collaborative environment is further supported by cloud-based BIM platforms, as highlighted by Pan and Zhang [16], which allow real-time access and updates to project data from multiple users, thus streamlining coordination and reducing delays. In the realm of sustainability, BIM's ability to simulate and analyse building performance has proven invaluable. GhaffarianHoseini et al. [17] investigated the use of BIM for energy efficiency assessments, enabling the optimisation of building designs to meet sustainability standards. Additionally, Stojanovic [18] highlighted the role of BIM in lifecycle assessment, where it aids in evaluating the environmental impact of materials and construction methods, thereby promoting green building practices.

Additionally, the application of BIM technology has greatly enhanced inspection tasks within the civil domain; many researchers implemented practical inspection systems for different structures and scenarios, including beam string structures [19], external walls [20], roads [21], and bridges [22,23], etc.

2.2. As-Built BIM

Ensuring the accuracy of the as-built model is a critical task for enabling as-built BIM functions throughout the building lifecycle, and most practical problems arise due to mismatching and inaccurate final as-built BIM. Lin et al. [24] developed a management system for the as-built BIM to support its inspection and modification during project closeout, while Rausch and Hass [25] proposed an automated approach for the shape and pose updating of BIM elements to reflect as-built conditions during the on-site construction phase. Furthermore, as-built BIM proves advantageous for building analysis in special scenarios, such as earthquakes [26]. As-built BIM accounts for the actual construction processes, material deviations, and modifications made during construction, providing a realistic foundation for seismic analysis. Levine et al. [27] developed a BIM-based inspection framework utilising computer vision methods for post-earthquake building inspections. Moreover, employing as-built BIM to perform comparative analyses of structures before and after earthquakes significantly enhances seismic design and improves building stability [28].

Current as-built comparison methods are mostly achieved through the element-by-element approach, which requires the utilisation of the element-matching approach. Common detected-content, vision, and IFC-enabled approaches have been widely explored by previous researchers. Yeum et al. [29] presented a visual inspection method based on the integration of the autonomous localisation algorithm and an aerial sensor system, while Bhatla [30] developed an accuracy evaluation method for as-built BIM from photographs taken by commercial cameras. IFC acquired more attention because of its versatility in the BIM field; Hamledari et al. [31] achieved the updating of BIM object information by retrieving the semantics from IFC files and discrepancy analysis automatically. Nardo et al. [32] investigated the common patterns and structures of IFC files collected in practice, while Shi et al. [33] designed software for the automatic comparison of different IFC documents, which are based on the content and hierarchical structure analysis of IFC files.

Though the element-based method has gained popularity among current researchers, the underlying logic of the element-matching approach is sensitive to the change in Globally Unique Identifiers (GUID), which results in the loss of valuable information concerning the integrity and correlation of building structures. Therefore, the introduction of network-based matching approaches from other research fields will bring significant benefits to the B&C industry. The concept of a network is commonly utilised in the linguistics field and biology engineering for text matching [34,35] or biological network exploration [36,37]. Neural network-based approaches are usually utilised as supplementary methods for network analysis and comparison, which depends on frequent parameter tuning and massive computing resources.

2.3. Research Gaps and Research Objectives

The major limitations of existing studies and the corresponding objectives are recognised as follows:

(1) Prior domain knowledge related to civil engineering is required for traditional manual or vision-based methods, resulting in the difficulty and inconvenience of the identification of specialised features and parameters during BIM inspection and comparison.

The proposed approach aims to simplify the identification process by utilising network science, making it accessible to users without extensive B&C backgrounds. This will greatly facilitate the adoption of advanced and interdisciplinary technologies.

(2) The performance of machine learning-related approaches is highly dependent on appropriate parameter settings, and wrong parameter settings result in very poor algorithm

performance. This procedure is complicated and redundant for multiple implementations for different scenarios.

The adoption of network-related properties in the new method significantly reduces the sensitivity to parameter tuning and simplifies implementation across diverse scenarios, making the process more robust and less dependent on precise parameter adjustments.

(3) Previous studies mainly focused on element-to-element comparisons without global feature consideration, adversely affecting analysis efficiency and operation time. Neighbours of critical, abnormal components are more prone to generate misidentifications.

Our approach considers the correlations and relationships among building elements by conducting topological analyses, improving comparison efficiency and reducing computational resource consumption.

3. Methodology

This section presents a network-based solution for the analysis and comparison of as-built and as-designed BIM, as illustrated in Figure 1. The input data comprise the as-designed BIM and the as-built BIM. As-built BIM is automatically reconstructed from point cloud data acquired from practical field laser scanning. As the most popular data format for BIM, the IFC data format [38] facilitates interoperability between various software platforms and is widely supported by many market-leading BIM software vendors. The network construction layer starts with the attributes extracted from IFC documents, and then the nodes and links are generated based on the calculation and analysis of attributes. The analysis and comparison will be conducted through the network analysis method, and practical implications and useful insights can be generated to guide the management of as-built BIM.

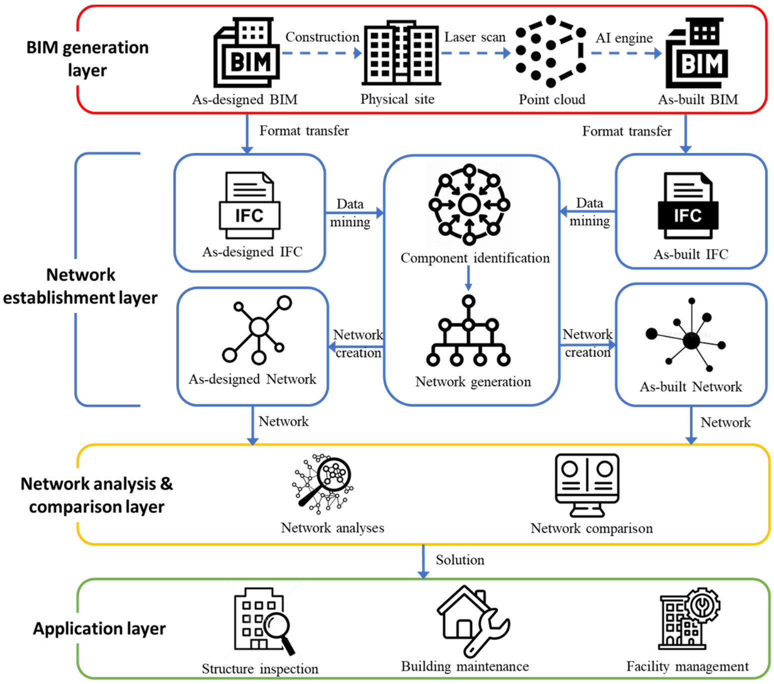


Figure 1. The network science-based framework for BIM analysis and comparison.

To further enhance the effectiveness of this network-based framework, advanced algorithms such as machine learning and artificial intelligence can be integrated into the process [36]. For instance, Convolutional Neural Networks (CNN) can be employed to process and analyse the point cloud data [39], identifying areas where the actual construction deviates from the design with high precision. Moreover, integrating this network-based approach with real-time data acquisition systems can provide continuous monitoring and updating of the as-built BIM. Utilising Internet of Things (IoT) devices and sensors on construction sites can offer real-time feedback and adjustments, ensuring that any deviations are promptly addressed [40].

3.1. BIM Reconstruction

As-built BIM is reconstructed from point cloud data using the proposed method, and the four-room apartment point cloud dataset utilised in the experiment is presented in Figure 2.

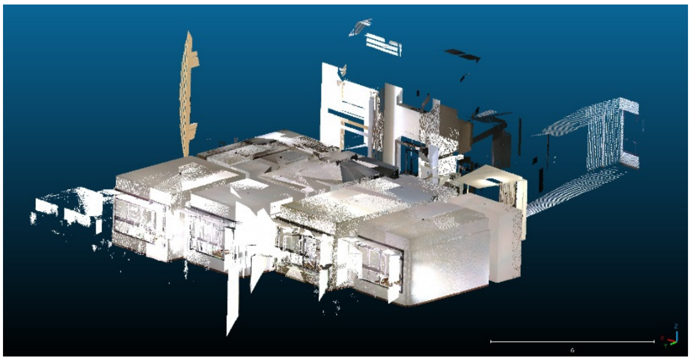


Figure 2. Four-room apartment point cloud dataset.

The process begins with the acquisition of point cloud data using laser scanning technology, while the key process is outlined as follows:

(1) Data Acquisition and Preprocessing:

Point Cloud Acquisition: High-resolution point cloud data are collected using laser scanners. These data include millions of points that capture the precise details of the building's structure.

Preprocessing: The raw point cloud data often contain noise and unnecessary points. Preprocessing steps, such as denoising and simplification, are crucial to ensure data quality. Techniques, like enhanced plane boundary line detection and corner recalibration algorithms, are employed to refine the data.

(2) Segmentation and Classification:

Segmentation: The pre-processed point cloud data are segmented into different regions corresponding to various building components such as walls, floors, ceilings, and other structural elements. Region segmentation methodology is widely used to achieve this.

Classification: Once segmented, the data are classified into recognisable building elements. This involves using domain knowledge-based heuristic methods to analyse features and associate them with specific building components.

(3) 3D Modelling and BIM Integration:

3D Model Generation: Using the classified data, 3D models of the building elements [41] and mechanical, electrical and plumbing engineering (MEP) components [4] are generated. For example, the detection of walls and doors involves template-matching algorithms to create accurate geometrical representations.

BIM Integration: The 3D models are then converted into BIM objects in the IFC format, which is compatible with various BIM software. This step ensures that the spatial relationships and geometries of the building elements are accurately represented in the BIM model.

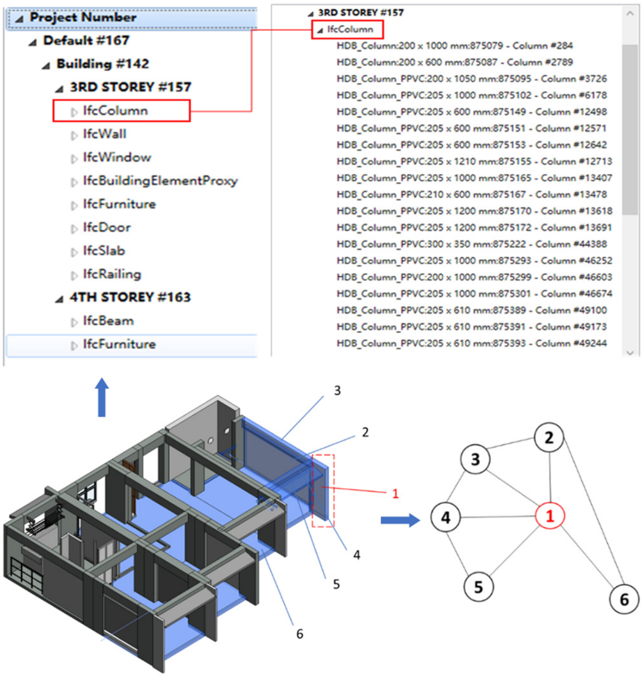
3.2. Network Establishment

The attributes extracted from IFC documents include critical details about building components, primarily focusing on their types and 3D dimensions, which are fundamental in creating a comprehensive BIM network. The types contain walls, beams, columns, windows, doors, etc., while 3D dimensions include length, width, and depth information of components. In the BIM network, the abovementioned attributes are used to create nodes and links that represent the building's structure. The network is conceptualised as follows:

Nodes: Each node represents a building element, such as a wall, beam, window, or door. The nodes are crucial points in the network where information about each component is stored and accessed.

Links: Links are the connections between these nodes, representing the physical and functional relationships between different building elements, for instance, a wall connected to a beam, a window within a wall, or a door providing access between two rooms.

Figure 3 shows the building elements (nodes) in the as-designed network. Taking one element as an example, it also demonstrates all elements associated with element one and the schematic diagram of its network.



HDB_Column:200 x 1000 mm:875079 - Column #284
HDB_Column:200 x 600 mm:875087 - Column #2789
HDB_Column_PPVC:200 x 1050 mm:875095 - Column #3726
HDB_Column_PPVC:205 x 1000 mm:875102 - Column #6178
HDB_Column_PPVC:205 x 600 mm:875149 - Column #12498
HDB_Column_PPVC:205 x 600 mm:875151 - Column #12571
HDB_Column_PPVC:205 x 600 mm:875153 - Column #12642
HDB_Column_PPVC:205 x 1210 mm:875155 - Column #12713
HDB_Column_PPVC:205 x 1000 mm:875165 - Column #13407
HDB_Column_PPVC:210 x 600 mm:875167 - Column #13478
HDB_Column_PPVC:205 x 1200 mm:875170 - Column #13618
HDB_Column_PPVC:205 x 1200 mm:875172 - Column #13691
HDB_Column_PPVC:300 x 350 mm:875222 - Column #44388
HDB_Column_PPVC:205 x 1000 mm:875293 - Column #46252
HDB_Column_PPVC:200 x 1000 mm:875299 - Column #46603
HDB_Column_PPVC:205 x 1000 mm:875301 - Column #46674
HDB_Column_PPVC:205 x 610 mm:875389 - Column #49100
HDB_Column_PPVC:205 x 610 mm:875391 - Column #49173
HDB_Column_PPVC:205 x 610 mm:875393 - Column #49244

Figure 3. Building element list and example of network establishment.

3.3. Network Analysis and Comparison

The analysis of BIM networks can be approached from two distinct perspectives: global analysis and node matching. Each perspective provides unique insights and serves different purposes in the overall evaluation and comparison of as-designed and as-built BIM models. Global analysis focuses on the overall characteristics and structure of the BIM network, including:

Global Parameters: These parameters give a holistic view of the network's structure. Examples include network density, average node degree, clustering coefficient, and path length. These metrics help in understanding the complexity, connectivity, and robustness of the network.

Community Detection: This involves identifying groups of nodes that are more densely connected internally than with the rest of the network. Community detection can reveal functional modules or subsystems within the building, such as different floors, rooms, or structural components that work together. Comparing community structures in as-designed and as-built networks can highlight discrepancies and areas where the actual construction deviates from the original design.

Node matching is the process of identifying corresponding nodes between two networks, which is crucial for the following:

Accuracy of Corresponding Relationships: Ensuring that nodes representing the same physical element in the as-designed and as-built models are correctly matched is essential for accurate comparison and analysis. This involves comparing attributes like type, dimensions, and spatial relationships of nodes.

Foundation for Future BIM Comparison: High accuracy in node matching provides a reliable basis for more detailed comparisons and analyses, such as detecting construction errors and deviations from the design and assessing the structural integrity of the built environment.

However, the parameter and property selection needs to be adjusted and determined with an in-depth study in the future. Element identification and comparison in as-built and as-designed BIM models are target functions of the above analysis and comparison, which are illustrated in the examples below.

The floor in a building structure typically has the most connections with other elements, which means the node with the highest degree in the network tends to be identified as the floor. For instance, in Figure 4, the floor is connected to most components.

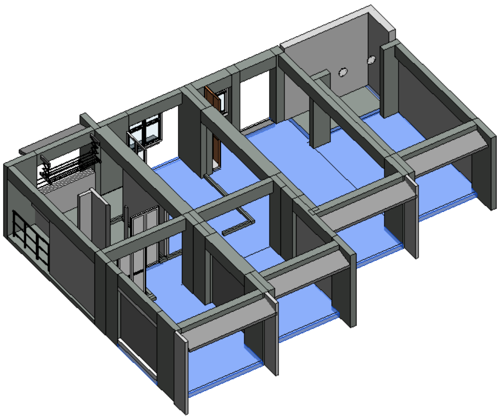


Figure 4. Floor element in Revit model.

By comparing the number of nodes in the two networks, the number of structures in the two BIMs can be analysed and compared. In practice, multiple elements in as-designed BIM are easily recognised as one in as-built BIM, which means the number of nodes in the networks will be different. As shown in Figures 5 and 6, six walls in the as-designed model are reconstructed as one in the as-built model. Global comparison and community analysis in the proposal method are instrumental in addressing the identified problems. Due to scanning accuracy limitations, as-built BIMs generally have different nodes compared to as-designed BIMs. Therefore, evaluating the number of nodes and edges provides an in-depth assessment of the scanning process. In community analysis, discrepancies are observed as isolated nodes in as-built networks, whereas they appear as clusters of adjacent nodes in as-designed networks. Consequently, analysing and comparing these network differences facilitates the detection and identification of such issues.

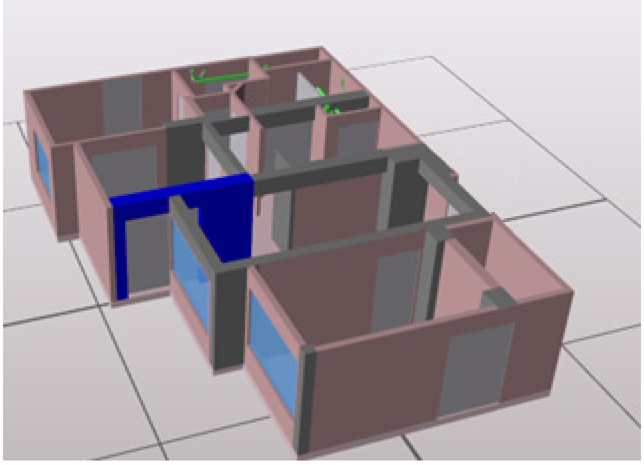


Figure 5. Elements in the as-built BIM.

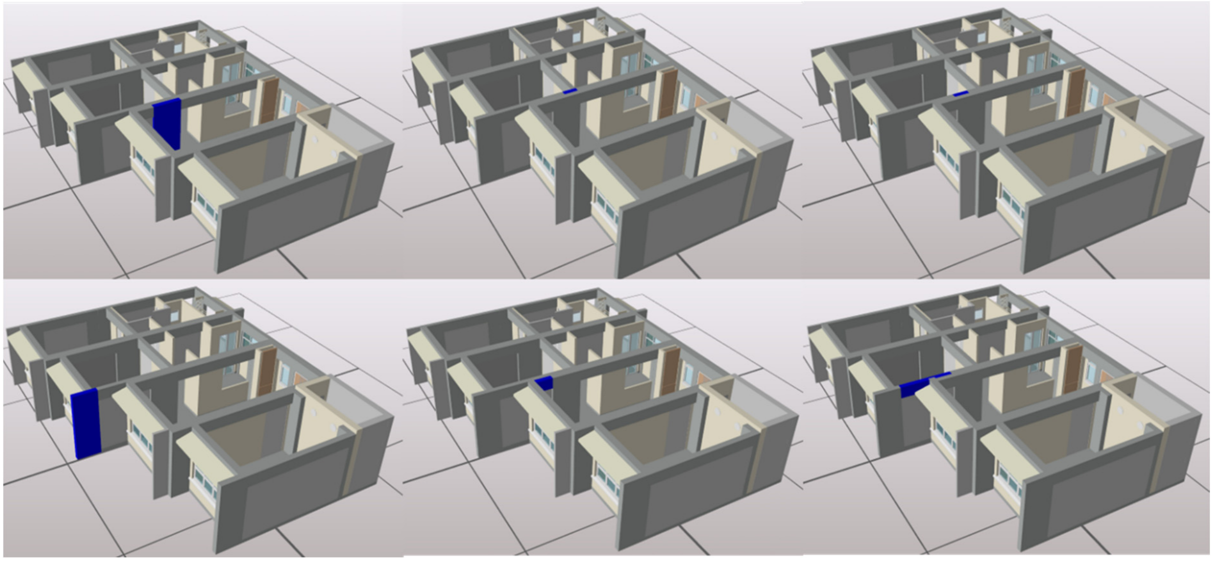


Figure 6. Elements in the as-designed BIM.

3.4. Practical Structure Analysis and Comparison

This step involves analysing the practical implications of the network analysis and comparison results, identifying structural features and generating model modification advice. The global analysis of BIM networks considers overall parameters and community detection outcomes, providing insights into the overall structure and connectivity of the building. Node matching evaluates the accuracy of corresponding relationships between nodes in the two networks, ensuring that the as-built model accurately reflects the design.

By comparing the as-designed and as-built BIM models, deviations in structural elements such as walls, beams, and columns are identified, highlighting their impact on structural performance and compliance with design specifications. The analysis results are used to provide recommendations for necessary corrections and updates to the BIM model, ensuring it accurately represents the built environment. Implementing these modifications enhances structural reliability, reduces costs by minimising rework, and improves overall project outcomes by facilitating better planning and decision-making throughout the project lifecycle.

4. Experiment

In this section, initial attempts are made to establish proof of concept by employing basic network analysis methods and node-matching techniques to a practical dataset.

4.1. Dataset Description

The dataset used in the experiment is a four-room apartment in Singapore. The as-designed BIM was provided by the Housing and Development Board of Singapore, while the as-built BIM was scanned and reconstructed by the iScan2BIM platform, as shown in Figures 7 and 8, respectively.

4.2. Network Establishment

Following the step introduced in Section 3.2, both as-built and as-designed networks are established, wherein four primary building components, namely walls, beams, columns, and slabs, have been considered to simplify the problem. It should be emphasised that, at the current stage, node attribute extraction is carried out manually through BIM authoring software, while the data mining method for IFC files requires further development in the future.

To provide a comprehensive and clear representation of building structures, distinct shapes are employed to denote various categories of building elements. Additionally, community detection is implemented using the greedy modularity method, with nodes from different communities marked by distinct colours. This visualisation method is applied to both as-built BIM and as-designed BIM, as depicted in Figures 9 and 10, respectively.

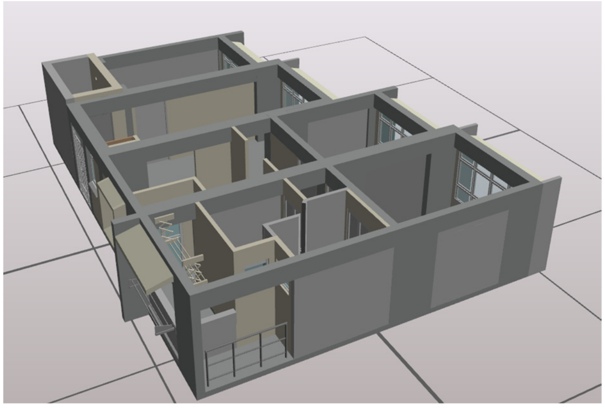


Figure 7. As-designed BIM.

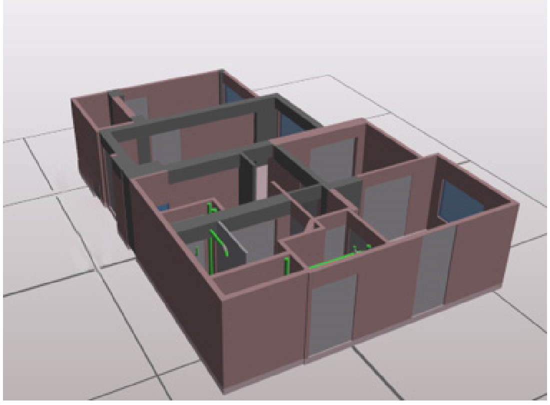


Figure 8. As-built BIM.

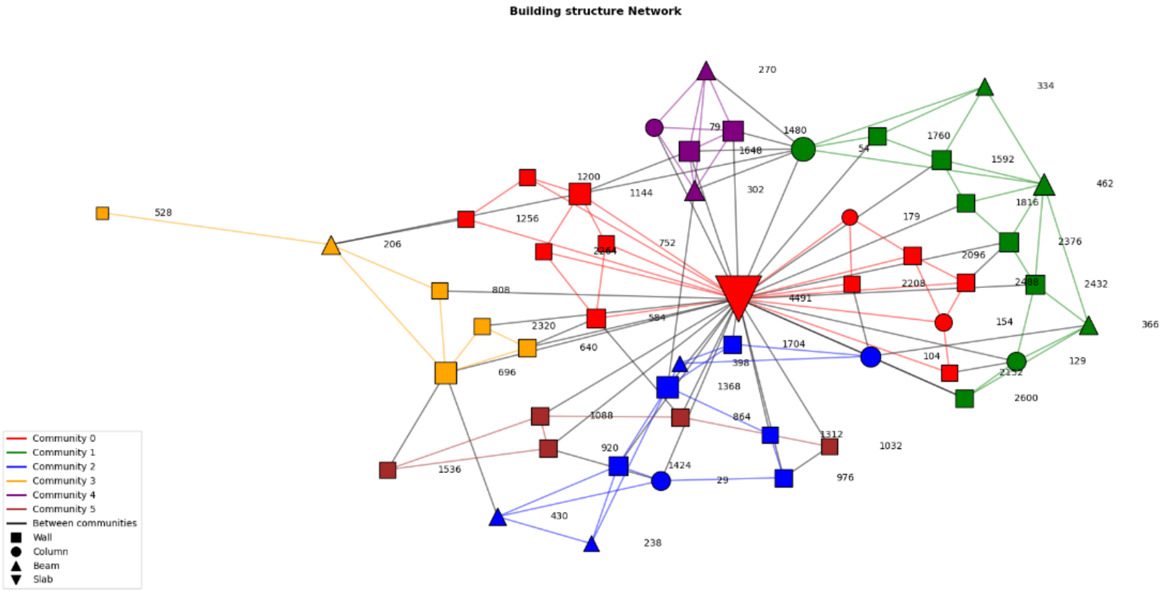


Figure 9. As-built network.

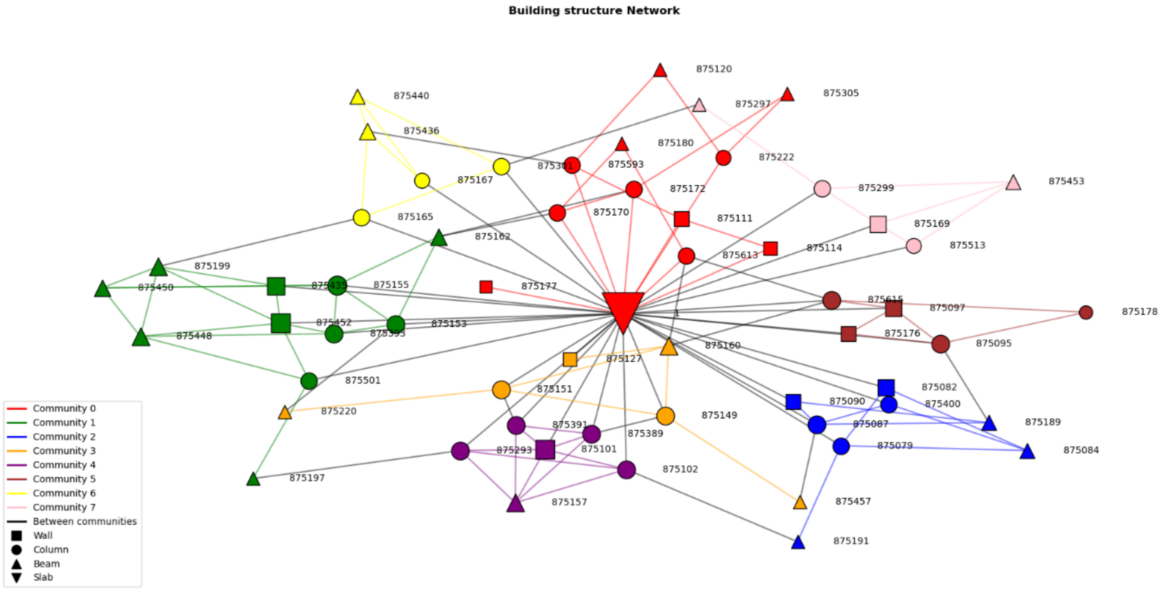


Figure 10. As-designed network.

The legend in these figures is bifurcated to enhance clarity: one section delineates the node shapes corresponding to different structural types, while the other section uses colours to represent the outcomes of the community detection process. Nodes and their connecting edges within the same community are uniformly coloured to indicate their affiliation, whereas inter-community edges are rendered in black to signify structural interactions between different communities. Additionally, each node is annotated with a code that corresponds to the structure ID in the BIM model, providing an explicit reference to the specific building element it represents. This dual-faceted approach of shape and colour not only facilitates the differentiation of structural categories but also elucidates the community affiliations within the network. The method achieves a detailed and intelligible visualisation of both the structural taxonomy and the relational dynamics within the BIM models, thereby supporting more informed decision-making in the context of building design and analysis.

4.3. Network Analysis

4.3.1. Global Analysis

The characterisation of the network's properties is crucial to understanding its structure and performances, while attributes listed in Table 1 have been selected for global matching analysis. The numbers of nodes and edges are fundamental descriptors that provide a basic overview of the network's size and connectivity. Network density quantifies the extent to which the nodes in a network are interconnected and is defined as the ratio of the number of observed edges to the maximum possible number of edges. Network transitivity refers to the tendency of nodes in a network to be connected to other nodes that are themselves connected, forming triangular structures or cycles, which means the measurement of the likelihood that two nodes that share a common neighbour will also be directly connected to each other. The average shortest path length is another essential metric that captures the average number of steps required to traverse between any two nodes in a network, while the network diameter refers to the maximum distance between any two nodes in the network. The average clustering coefficient, which is a measure of the degree to which nodes in a network tend to cluster together, is another key property that can be used to infer the network's modularity or community structure. Additionally, the average degree is a measure of the average number of edges or connections that a node has in a network, and modularity is a measure of the degree to which a network can be divided into smaller, densely connected groups or communities, which is a useful metric for identifying clusters or subgroups within a network and can provide insight into the structure and function of the network.

Table 1. Network description analysis.

Parameter	As-Designed	As-Built
Number of nodes	50	58
Number of edges	126	126
Network density	0.10	0.08
Network transitivity	0.22	0.17
Average shortest path length	2.24	2.50
Network diameter	5	4
Average clustering coefficient	0.52	0.35
Assortativity	−0.2	−0.17
Average degree	5.04	4.34
Modularity	0.42	0.49

Table 1 indicates that while the values of each parameter in the two networks are similar, they exhibit notable differences, highlighting distinctions between as-built and as-designed BIM. The numbers of nodes and edges are two core network attributes, representing the fundamental overview of the network structure. The node count is critical for analysing the accuracy of scanning processes and segmentation algorithms. Due to limitations in scanning devices, the segmentation of building structures typically differs between the as-designed and as-built models. Generally, the as-designed model contains a higher number of nodes because scanners often fail to accurately distinguish connected wall parts, erroneously merging distinct walls into a single entity. However, in this case, the as-built model exhibits a higher number of nodes, indicating that the segmentation algorithm used during reconstruction is overly aggressive, splitting many single walls into separate structures. This insight is vital for refining and improving the algorithm.

Additionally, in this experiment, a coincidental situation arises where the number of edges remains the same despite differing node counts. It indicates that as-built BIM generates numerous new connections while also losing many original links compared to as-designed BIM. New links typically form between newly added nodes due to incorrect segmentation of the same structure. The missing links are due to the situation shown in Figure 6. For connection components, as-designed BIM typically consists of numerous elements, whereas as-built BIM often recognizes these elements as a single entity, resulting in the disappearance of original links. This part is often a structural combination with a high network density. By analysing the performance of nodes and edges, it becomes evident that the connection structure of as-built BIM is relatively simple. This simplicity is attributed to its sparser network, where a greater number of nodes have an equivalent number of edges. This observation underscores the necessity for enhancing the reconstruction of as-built BIM, particularly for complex design components. Finally, other attributes can provide valuable insights, although their specific implications in real-world scenarios warrant further investigation.

The greedy modularity approach is utilised to perform community detection, which aims to obtain the optimal partitioning of nodes in a network into communities, resulting in the maximisation of the network's modularity. As depicted in Figures 11 and 12, the as-built BIM network is divided into seven communities, whereas the as-designed BIM consists of five communities. Furthermore, the percentage of component types and the distribution of volume within communities are presented. The distinct numbers of communities and their attributes between the as-built and as-designed networks demonstrate the differences between the two BIM models; however, further research is required to elucidate the specific structural differences.

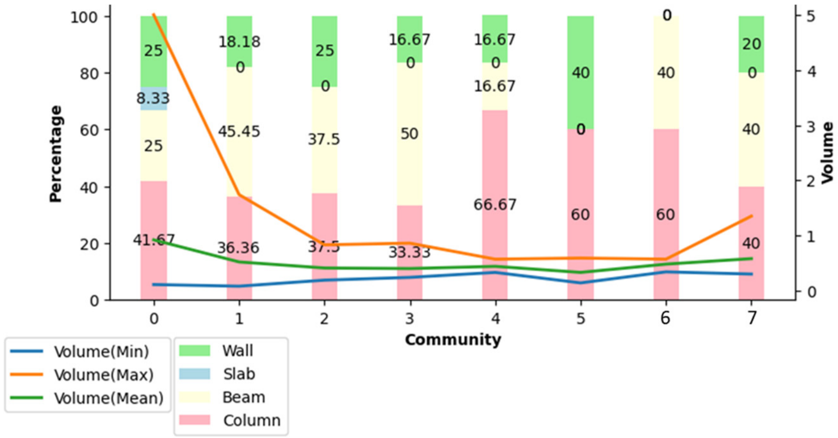


Figure 11. Statics by the community (As-built).

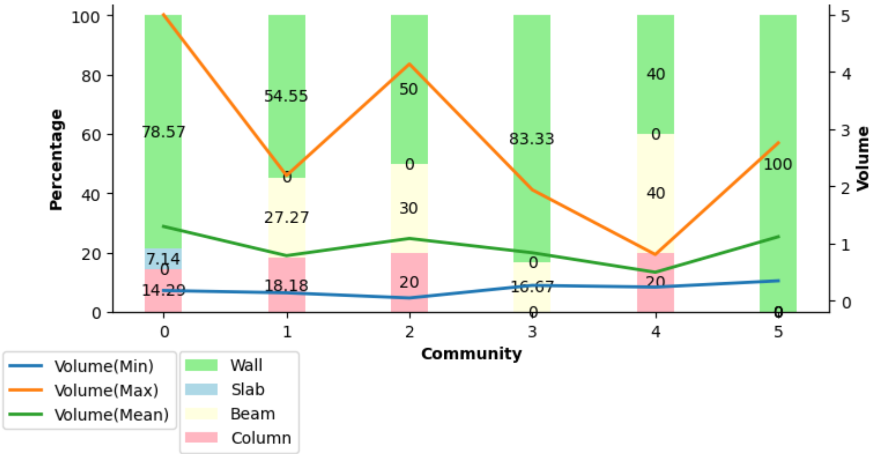


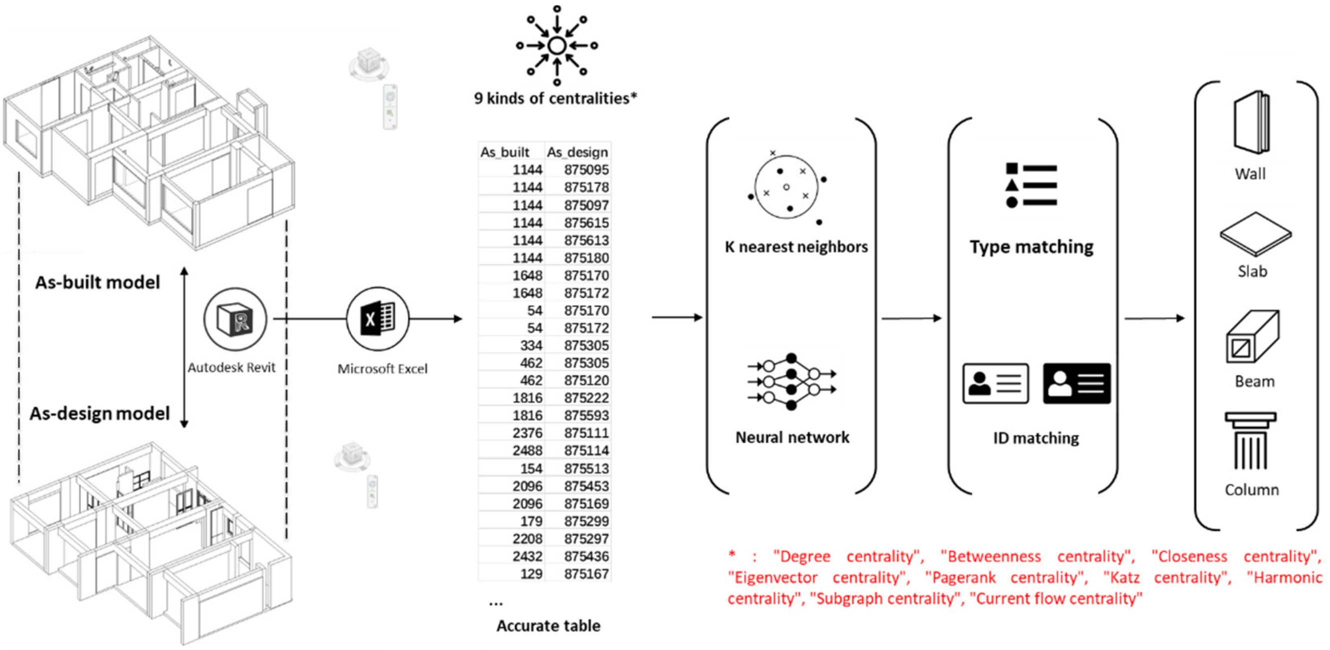
Figure 12. Statics by the community (As-designed).

4.3.2. Node Matching

Node matching is a very important process for existing element-by-element approaches because the high matching accuracy is the foundation for comparison. The pipeline of matching in the current study is illustrated in Figure 13. The first step is the generation of the accurate matching table, which is achieved by manually matching the building elements in the as-built and as-designed models. BIM authoring tools like Autodesk Revit and Xbimxplore are utilised as the visualisation platform, and the accurate matching table is created in Excel. For the initial attempts, nine types of centralities were selected as input parameters to ensure a comprehensive analysis of the network from multiple perspectives. These centralities capture various aspects of node importance and influence. The definitions are presented in Table 2.

Table 2. Definition of selected centralities.

Centrality Type	Definition
Degree Centrality	Measures the number of direct connections a node has.
Betweenness Centrality	Assesses how often a node lies on the shortest paths between other nodes.
Closeness Centrality	Calculates the average shortest path from a node to all other nodes.
Eigenvector Centrality	Evaluates a node's influence based on its neighbours' influence.
PageRank Centrality	Ranks nodes based on the structure of incoming links.
Katz Centrality	Measures node influence considering all paths, with longer paths weighted less.
Harmonic Centrality	Averages the reciprocal of shortest path distances to all other nodes.
Subgraph Centrality	Quantifies a node's importance based on its participation in subgraphs.
Current Flow Centrality	Evaluates a node's centrality based on the idea of electrical current flow.



As_built	As_design
1144	875095
1144	875178
1144	875097
1144	875615
1144	875613
1144	875180
1648	875170
1648	875172
54	875170
54	875172
334	875305
462	875305
462	875120
1816	875222
1816	875593
2376	875111
2488	875114
154	875513
2096	875453
2096	875169
179	875299
2208	875297
2432	875436
129	875167

...

Figure 13. Node matching process.

In the matching process, both the K Nearest Neighbours (KNN) and neural network methods are attempted, but ultimately, the KNN approach was selected for its higher accuracy. Type matching and ID matching were both conducted during the initial experiment. Currently, only wall, slab, beam, and column components are considered. Figure 14 presented the centralities distribution of as-built and as-designed models.

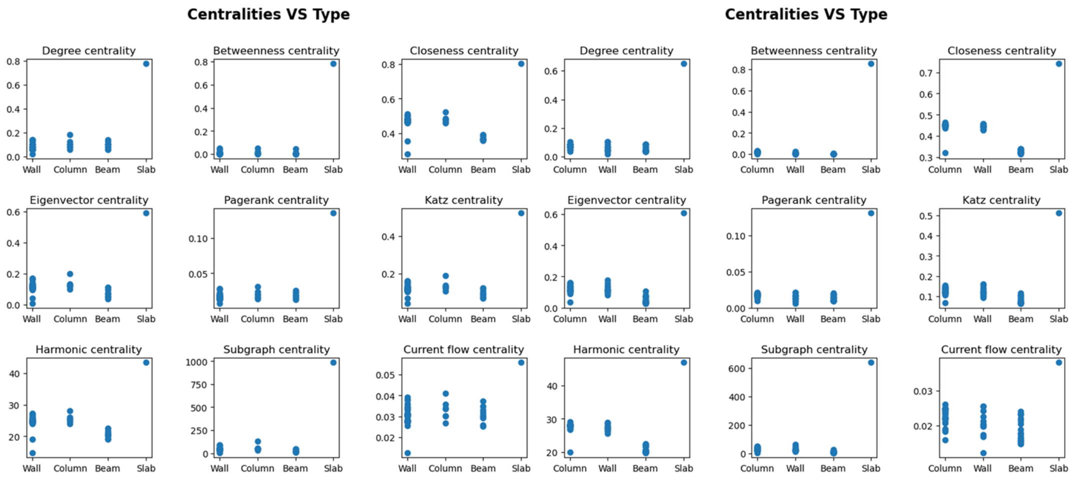


Figure 14. As-built (**left**) and As-designed (**right**) centralities.

4.3.3. Model Comparison Exploration

At present, the type matching and ID matching accuracies are 30% and 10%, respectively. The result is visualised in Figure 15, the red number represents the beam structure, and the black number refers to the column elements. Based on ground truth, an accuracy of about 40% can demonstrate the superiority of the proposed method. This is because the as-built BIM differs from the as-designed BIM due to errors generated during building scanning and model generation, and its highest matching rate is only about 50%. The current findings only serve to establish the feasibility of the method and complete the proof of concept. Although the overall accuracy is still not enough, it has been observed that all columns are correctly identified in type matching. This indicates that the parameter and algorithm selection is effective for column identification and that different types of building components may require different approach settings.

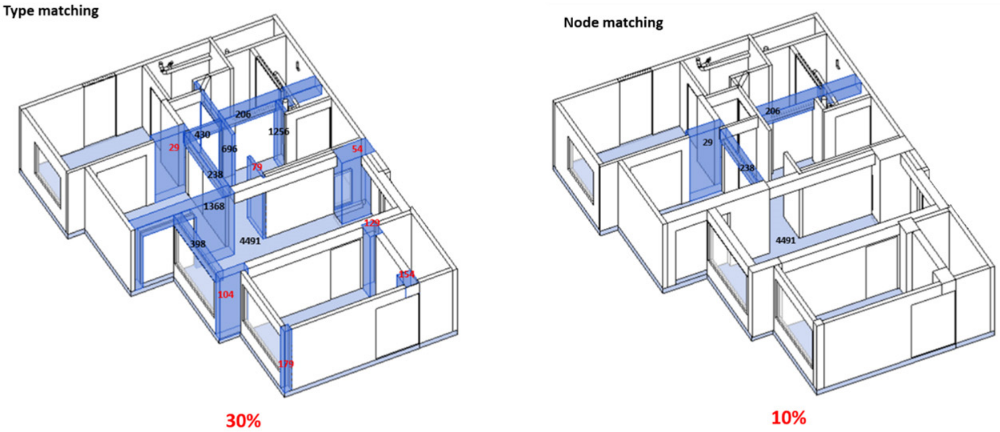


Figure 15. Accuracy result.

4.3.4. Discussion on Practical Implications and Technique Suggestions

(1) Potential Benefits for Facility Management

The findings of our study offer substantial benefits for facility management and maintenance within the B&C industry. For instance, network analysis allows for the identification of key structural components, such as columns with the most connected structures, which is critical for prioritising resource allocation and maintenance efforts. By highlighting the most interconnected and structurally significant elements, facility managers can focus on areas that require more frequent inspections or reinforcements, thereby efficiently improving overall building safety and longevity.

Additionally, the ability to compare as-designed and as-built BIM models accurately helps in assessing the quality of construction and adherence to design specifications, providing valuable feedback for continuous improvement in construction practices. Overall, the network analysis-based approach not only optimises resource management and maintenance but also contributes to the sustainability and resilience of building infrastructure.

Furthermore, reconstruction and structural detection in earthquake-related studies would also benefit from such research. By incorporating these seismic analyses and post-earthquake reconstruction models, network analysis for the BIM model can provide a comprehensive tool for both pre- and post-earthquake scenarios. This integration ensures that buildings are designed and maintained to withstand seismic events, significantly enhancing their structural safety.

In conclusion, the proposed approach not only optimises resource management and maintenance but also contributes to the sustainability and resilience of building infrastructure. By addressing both general facility management needs and specific seismic considerations, this approach offers a robust framework for enhancing the overall performance and durability of buildings in the B&C industry.

(2) Suggestions for Future Modelling

The proposed network analysis-based approach for managing and improving as-built BIM has shown considerable potential in enhancing the analysis and comparison of building projects. To further refine and expand the applicability of BIM-driven services, several suggestions on modelling can be considered.

Firstly, integrating advanced network metrics, such as centrality measures and community detection algorithms, can provide deeper insights into the structural interdependencies and critical components within the BIM. These metrics can identify key elements that significantly impact overall building performance, facilitating targeted maintenance and optimisation efforts.

Secondly, expanding the dataset to include diverse types of buildings and construction projects will validate the robustness and generalisability of the approach. This can aid in developing standardised network models for different categories of buildings, enhancing the methodology's versatility.

Lastly, developing a user-friendly software tool that incorporates this network analysis approach can make it more accessible to practitioners in the B&C industry. Such a tool could offer real-time updates and visualisations, streamlining the analysis process and aiding in decision-making.

These enhancements will not only strengthen the efficacy of the network analysis-based approach but also pave the way for its widespread adoption in the industry, ultimately leading to more efficient and effective BIM management practices.

5. Conclusions and Future Work

This research aims to develop a network analysis-based solution for as-built BIM inspection, contributing to the advancement of BIM-enabled systems in the building and construction (B&C) industry. Initially, global analysis and node matching were conducted using a practical dataset of four-room residential apartments in Singapore. Network analysis offers a fresh perspective for understanding as-built BIM models and provides a promising approach for future model comparisons. By analysing these networks comprehensively, key patterns and relationships within the data can be identified, which are crucial for optimising design, construction, and maintenance processes.

The detailed assessment of network parameters and community structures enables stakeholders to understand the interdependencies and interactions among various building components, facilitating more informed decision-making and enhanced project outcomes. The study reveals substantial benefits for facility management and maintenance within the B&C industry. For example, network analysis enables the identification of crucial structural components, such as highly connected columns, which is vital for prioritising resource allocation and maintenance tasks. By focusing on the most interconnected and structurally significant elements, facility managers can concentrate on areas that require more frequent inspections or reinforcements, thereby efficiently improving building safety and longevity.

Additionally, network analysis can reveal hidden interdependencies among different building components, enabling more effective predictive maintenance strategies. This approach also enhances fault detection by identifying anomalies in the network structure that may signal potential issues before they escalate. Furthermore, the ability to accurately compare as-designed and as-built BIM models helps assess construction quality and adherence to design specifications, providing valuable feedback for continuous improvement in construction practices.

Furthermore, the ability to accurately compare as-designed and as-built BIM models helps to assess construction quality and provides valuable feedback for continuous improvement under complex and dynamic environments. Specifically, in earthquake-prone regions such as Japan, integrating seismic considerations into BIM is imperative for comprehensive building management [42]. By borrowing as-designed and as-built BIM and comparing the approaches, stakeholders can evaluate both pre- and post-earthquake scenarios, which is crucial for ensuring structural integrity and safety during emergencies [28]. Incorporating seismic considerations into BIM analysis not only verifies adherence to design specifications but also ensures that buildings are maintained to withstand seismic events. This dual focus on design and maintenance significantly enhances the resilience and safety of building infrastructure.

Despite the discrepancies between the actual as-built BIM and the as-designed model—due to scanning inaccuracies and model generation issues—our experiments show a significant improvement in accuracy when matching specific rooms and component types. Further research and optimisation of this methodology are necessary to bridge these gaps and enhance the accuracy and reliability of the BIM inspection process.

For methodology aspects, two future directions are presented. The first line follows existing methods to improve the node-matching accuracy through the optimisation of network parameters and algorithms. Then, the network and BIM model comparison method will be easy to develop based on a node-matching result with high accuracy. The second line is more challenging, utilising the global matching method to conduct the structure difference analysis, which needs further studies to connect the global attributes with practical structural meaning. ***For implementation aspects***, a broader range of building types and larger apartments will be taken into account, necessitating the analysis of networks with a larger number of nodes. The proposed method's generalisability and robustness can be strengthened by validating it on complex network structures, which will facilitate the comparison of architectural structures.

In conclusion, the findings demonstrate that network analysis significantly enhances the understanding and comparison of as-built BIM models, offering substantial benefits for the B&C industry in terms of design optimisation, construction accuracy, and maintenance efficiency. The network analysis-based approach optimises resource management and maintenance and contributes to the sustainability and resilience of building infrastructure.

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