

# AIPDORCS: ARTIFICIALLY INTELLIGENT PRELIMINARY DESIGN OF REINFORCED CONCRETE STRUCTURES

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## Abstract

Leveraging 106 engineers' expert assessments of preliminary structural design in 48 reinforced concrete building models, we compiled two experimental Graph Neural Network (GNN) tools to demonstrate feasibility for automated classification of structural schematic layouts, a key step toward building generative artificial intelligence (AI) tools for design. Contributions include a robust project database, a model-to-graph conversion tool, and a structural design scoring application. Acknowledging limitations related to modelling assumptions and a relatively small dataset, this research clarifies the opportunity and the obstacles to AI-driven advancements in preliminary structural design.

## Introduction

The construction industry has seen remarkable advances in computational tools, from 3D modelling to finite element analysis. One critical aspect has remained relatively untouched: the preliminary design phase, a creative step where engineers propose conceptual structural layouts using heuristic rules (Caprani, 2009). Despite the availability of sophisticated tools for detailed design, the quality of results is often constrained by suboptimal preliminary designs. While optimization algorithms like genetic algorithms are available for engineering design (Katoch et al., 2021), they face challenges in execution simplicity, adapting to changing standards, and precise programming. This research explores whether deep learning can be used at the preliminary design stage to simulate the experience of senior engineers, offering faster, cheaper, and more accurate solutions. Focusing on reinforced concrete (RC) structures, we address the scarcity of AI applications in preliminary design, particularly within the construction industry (Afzal et al., 2020). The research aims to leverage recent developments in AI and machine learning to better automate the preliminary design process, with a specific focus on structural plans classification.

## Background

### Engineering Design and Automation

Engineering design, a creative and iterative process, has seen a surge in automation using AI techniques, aiming to enhance efficiency, reduce costs, and improve design quality. Expert systems, an early AI development in the 1970s and 1980s, simulated human decision-making by using a knowledge base, and were applied in various engineering fields to make decisions and solve problems (Rychener, 1988). However, the emergence of more advanced AI algorithms, such as machine learning, neural

networks, and deep learning, has surpassed the limited use of expert systems (Medsker, 1995).

The AEC (Architecture, Engineering, and Construction) industry has witnessed significant advancements in AI applications, notably in architectural layout design and generative design. The use of Generative Adversarial Networks (GANs) for architectural conceptual design (As et al., 2018), floor plan generation through rectangular dual finding algorithm (Wang et al., 2018), and automated apartment plan generation using genetic algorithms (Laignel et al., 2021) exemplify the industry's adoption of AI. AI's influence extends beyond architecture to construction, with applications like predicting labour costs (Huang and Hsieh, 2020), estimating assembly costs of flooring systems (Elhegazy et al., 2022), and employing Deep Convolutional Neural Networks (CNNs) for automated assembly of lunar construction components (Zhou et al., 2020). Start-up companies like "FIRMUS" (Abecasis and Amar, 2019), "Daisy" (Selvaraj et al., 2019), and "Structure Plus" (Jozi et al., 2019) further demonstrate the feasibility and effectiveness of incorporating AI in the AEC industry, enhancing design efficiency and optimizing structural elements.

### Artificial Intelligence and Structural Design

Over the years, AI has advanced significantly, and the integration of Building Information Modelling (BIM) has become commonplace. The rationale for employing AI in preliminary structural design is rooted in the recognition that this phase demands substantial creative input, combining engineering expertise, wisdom, and judgment (Samuel and Weir, 1999). While traditionally deemed difficult to simulate with rule-based tools, recent developments showcase the ability of advanced tools, such as Artificial Neural Networks (ANNs), to emulate these qualities by drawing inspiration from human brain neurons and incorporating engineering experience through prior data collection. Noteworthy applications include the use of ANNs for tall building design (Anwar et al., 2015), design response grammars and evolutionary algorithms for conceptual layouts creation (Boonstra et al., 2020), and reinforcement learning for optimizing plane frames (Hayashi and Ohsaki, 2020). Recent examples span diverse areas, such as accelerating the exploration of shell structure topological design (Zheng et al., 2020), designing RC columns with ANNs surpassing traditional design charts (Charalampakis and Papanikolaou, 2021), automating shear wall design for residential buildings using a method called StructGAN (Liao et al., 2021), and recommending early-stage structural design with minimal errors (Ampanavos et al., 2022). These advances collectively highlight the potential

of AI to revolutionize the structural design phase, offering expedited and precise design solutions while minimizing costs and computational resources.

### BIM and Graph-based Representation of Structures

Building Information Modelling (BIM), introduced in the seminal article "The Use of Computers Instead of Drawings in Building Design" (Eastman, 1975), has evolved into a crucial platform for detailed geometry exploration, interference resolution during early design stages and more, as evidenced by a study on modular housing design (He et al., 2021). Parametric design, integral to BIM, involves defining model families or element classes with rules controlling parameters. This approach facilitates the integration of AI in structural design by enabling computers to comprehend and control structural models. Unlike humans, computers rely on parametric objects, aligning with the principles of object-oriented programming. While the IFC schema (ISO 16739-1, 2018) is the standard for BIM data exchange, challenges persist, leading to inaccuracies and information loss (Sibenik and Kovacic, 2020). Recent solutions, such as invariant signatures (Wu et al., 2021a), and semantic enrichment via machine learning (Bloch and Sacks, 2018), aim to address these issues. Additionally, a shift towards graph-based representation in structural design, exemplified by studies like structural optimization using genetic algorithms and ANNs (Chang and Cheng, 2020), indicates a growing trend in data processing methods, offering potential for further exploration and improvement.

### Graph Neural Networks in Engineering

The advantages of graphical representation in BIM models lead to proposal of GNNs for reliable and efficient structural design using AI. GNNs, introduced in 2009 (Scarselli et al., 2009), have demonstrated significant power in various domains, such as financial networks and molecular structures (Xu et al., 2022). Practical applications of GNNs in fields like internet traffic optimization (Bernárdez et al., 2023), stock classification (Xu and Zhang, 2023), and predicting microbe-disease

associations (Jiang et al., 2023) are emerging. In the context of BIM models, which inherently possess complex relationships and dependencies, GNNs offer a natural solution for their non-Euclidean structure (Wang et al., 2021). Notably, the Graph Convolution Network (GCN) appears promising for classifying graphs representing BIM models, leveraging convolution to learn from node connections, akin to classical CNNs but tailored for graph structures (Wu et al., 2021b).

### Gaps in Knowledge and Research Aims

Despite advances in graphical representation-based AI applications, those learning directly from human input remain absent. Moreover, the scarcity of solutions for AI-driven preliminary building design, emphasizes the need for research in this crucial domain (Huang and Fu, 2019). Employing the Design Science Research (DSR) methodology (vom Brocke et al., 2020), this study aims to show the feasibility of automated preliminary classification of structural plans using GNNs and engineers' experience. In other words, can AI effectively learn from the experience and expertise of human engineers through a combination of BIM models and engineer surveys? Answering this research question involves developing a tool that transforms basic BIM structural models into actionable information, enabling accurate classification based on a knowledge base of pre-labelled engineers' structural plans.

### AIPDORCS Concept

Interviews were conducted with five senior structural engineers, each with at least a decade of experience, to establish existing preliminary design practices. The resulting process was meticulously mapped in a BPMN diagram, summarizing the preliminary design process from the architect's requirements until the completion of all preliminary design tasks by the structural engineer, as shown in Figure 1. Interestingly, the interplay of architectural requirements and structural solutions matches Maher's model of co-evolutionary design (Maher and Poon, 1996). This visualization underwent validation by eight senior structural engineers. The engineers

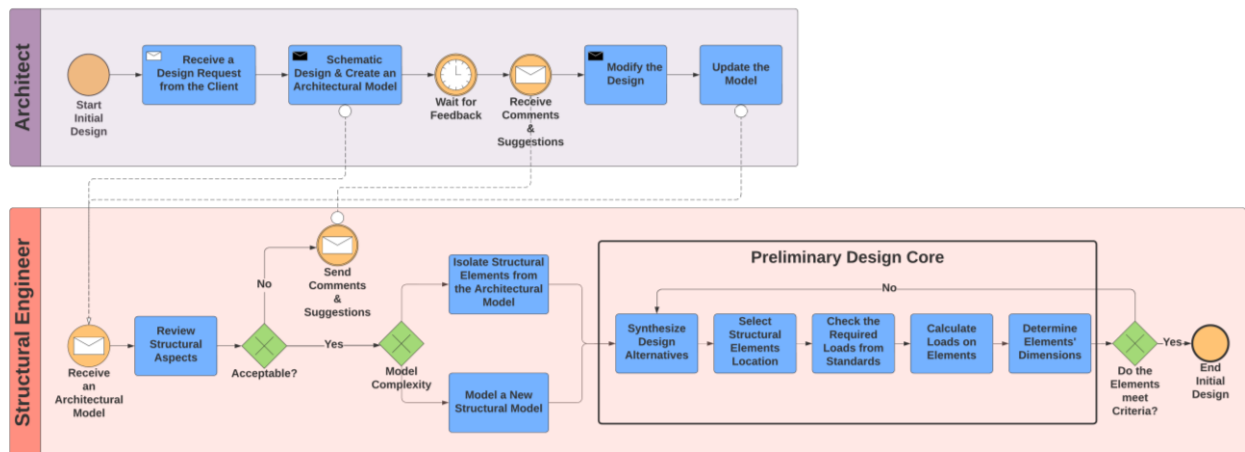


Figure 1: The process of Preliminary Structural Design, BPMN diagram.

emphasized the iterative nature of the process, likening it to a Taylor series, where each step contributes to convergence. They revealed diverse preferences in material selection, structural elements, and evaluation methods, showcasing the complexity of design choices. Notably, the interviews underscored the absence of a singular truth in structural design, with engineers prioritizing factors differently. A new concept emerged from this nuanced understanding, aiming to enhance the structural design process through AI by incorporating diverse insights and automating key aspects. We call this new concept "AIPDORCS", an acronym for "*Artificially Intelligent Preliminary Design of Reinforced Concrete Structures*." This concept comprises three stages, as shown in Figure 2. The first stage, *Data Collection & Preparation*, involves collecting and preparing data, converting structural plans into appropriate formats, addressing challenges in BIM model collection by utilizing 2D plans, and creating structured data tables for graph construction, all of which are essential for training a GNN model in the subsequent stage. The second stage, *Structural Plans Classification*, focuses on training the GNN model through engineer surveys, employing data tables and structural plans obtained from BIM models. Finally, the third stage, *Structural Design Generation*, delves into employing optimization algorithms like genetic algorithm or deep learning to evolve and refine solutions based on the previously trained classifier, iteratively until achieving optimal engineering solutions. The first two stages are the focus of this study.

## **AIPDORCS Development (Stages 1 and 2)**

### **Structural Plans Collection**

Initial attempts to gather the vast amount of data needed for training the supervised learning model, i.e. acquiring BIM models from large engineering firms, faced challenges due to legal and copyright issues. Requests for schematic plans also met with limited success. An alternative approach involved leveraging academic resources – final project plans from undergraduate students. These plans, encompassing diverse structures, were obtained with permissions from graduates, yielding 201 approved plans. The variation in quality within student designs proved advantageous, offering a spectrum for training the AI model. Subsequently, a database was constructed, filtering out non-relevant plans and ensuring anonymity by removing personal information. This database comprised around a hundred structural plans, predominantly in PDF format.

### **Plans to Models**

Structural plans in PDF or DWG format were deemed unsuitable for training the GNN model based on engineers' experience, due to their lack of essential information. The chosen solution involved manual conversion of 2D plans, of typical residential and commercial buildings, into intelligent 3D BIM models using Autodesk Revit software (Autodesk, 2022).

Recognizing the absence of flawless automatic conversion applications, a meticulous workflow was developed for manual modelling, addressing challenges of human error and maintaining a clean, uniform model database.

The modelling process started with loading a premade template into each project, resolving scale issues, and utilizing Autodesk Revit's "Snap" tool to identify and correct discrepancies. The modelling workflow included distinct steps for modelling walls, columns, beams, and slabs. Each element type was carefully modelled, considering specific rules such as ignoring windows and small openings, simplifying door modelling, addressing various complexities in columns, and modelling a separate slab for each space. Completing the models included crucial steps like "Join Geometry" automation for correct connectivity between structural elements, element numbering for referencing, manual checks by the researcher to ensure database quality, and sheet creation for later survey reference. Each model was assigned the following global parameters: building function, number of floors and gross height. Plans deemed unsuitable for the study, such as bridges or small houses, were excluded. In total, 48 projects were modelled.

### **Models to Data**

In the transition from BIM models to usable data, Dynamo (Autodesk, 2020), a visual programming language for Autodesk Revit, was employed to automate the conversion process into structured CSV files. The feature engineering aspect of this stage focused on creating an equal number of features for each structural element. Geometric properties such as dimensions in three directions and volume were considered, avoiding redundancy. Noteworthy is the decision to exclude element location coordinates, deeming them unnecessary for preliminary design as the focus was on the geometry of elements and their connections.

Feature engineering aligned with accepted design practice, was primarily based on the calculation of the "limitation of slenderness." A uniform assumption of 30 MPa concrete with limestone aggregate was made for all elements. The Dynamo script categorized objects into groups of nodes, which facilitated the extraction of global parameters, adjusted gross height, and extracted geometric properties and connections for beams, walls, columns, and slabs. Unique challenges arose in feature engineering for columns, where complex cross-section shapes were converted to equivalent rectangular cross-sections. Similarly, for slabs, irregular shapes were converted to equivalent rectangular slabs based on the largest inscribed circle's diameter, and the distance of the slab's centroid from nearest vertical support elements.

In total, each CSV file extracted for each structural element type included three geometric dimensions, volume, automatically numbered element ID, and a list of connections to different elements, forming a foundation for subsequent analysis and classification stages.

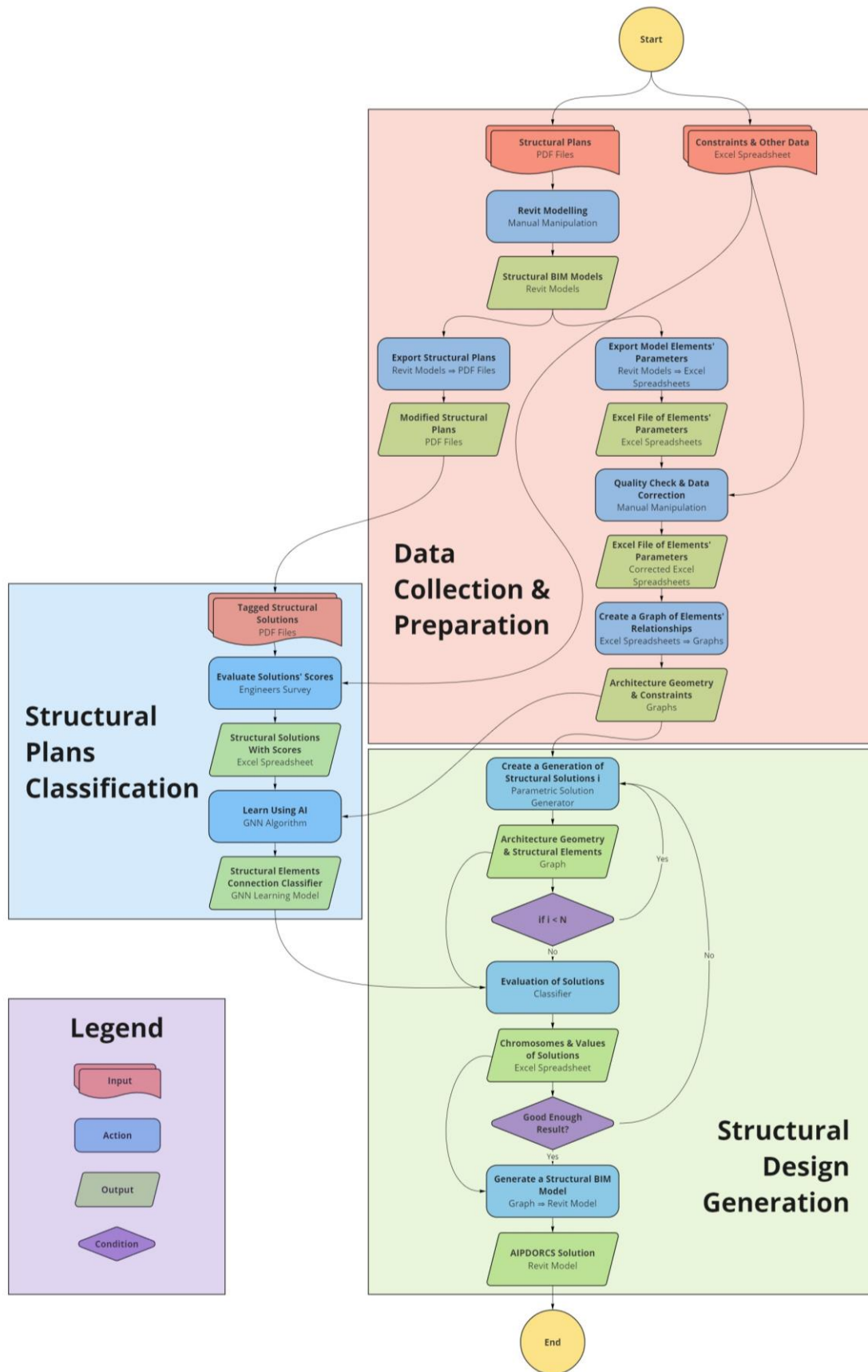


Figure 2: AIPDORCS Concept Diagram

## Engineers' Challenge

The "Engineers' Challenge" online portal was compiled to facilitate labelling of structural plans for training the GNN model. Structural engineering experts were asked to use the portal to review plans presented to them at random from the set of 48 projects, and to give scores to the overall design and to annotate the individual design elements with their design critique (by selecting design faults from a list). The result was a comprehensive dataset for automated structural design with AI.

Compilation of the portal tool required identifying the critical aspects of preliminary structural design, designing an effective and efficient user experience, and considering engineering discretion while crafting questions. Given the unique nature of the survey – requiring feedback on 48 distinct structural plans – back-end project database management and user interface considerations were paramount. No available survey compilation tool could satisfy the requirements, and thus the portal was programmed from scratch utilizing JavaScript through the Wix API (Velo, 2006).

The portal's dialogs cover project data, element comments, and general comments with an overall score. The survey is available online at the AIPDORCS's website (Argaman, 2020). Note the addition of comment properties to each element, improving results by incorporating engineering aspects such as cross-sectional area, cost, simplicity of execution, and element slenderness. Users could provide feedback on specific elements, offering a comprehensive view of the structural plans. Moreover, the general comments allow users to review the global plan as a whole, considering comments such as 'inadequate vertical support', 'uneconomical design alternative' and 'implementation difficulty'.

The survey generated valuable responses, with 112 feedbacks obtained, including scores for all 48 models. The results and analysis of the survey contributed significantly to the subsequent stages of the AIPDORCS process.

## Data to Graphs

At this stage, we utilized Python routines to construct a graph database for training the GNN model using CSV files from Revit models and *Engineers' Challenge* responses as input. To form graphs from the CSV files, preliminary data consolidation and processing were required. Each structural element from each BIM model is represented as a graph node containing features derived from exported CSV files. The natural and error-free conversion involved creating a file listing all elements as graph nodes with their respective features, incorporating both geometric and survey properties.

Creating graph edges, representing connections between nodes, was a more intricate process. The edges capture the relationships between structural elements. Given that the graph is homogeneous, i.e. all elements shared the same number of properties and dimensions, we could represent all structural elements with a single node type, named "Structural Element", as shown in Figure 3. This figure also illustrates the graph creation process from BIM models, focusing on a segment of *Project 001* from the AIPDORCS database.

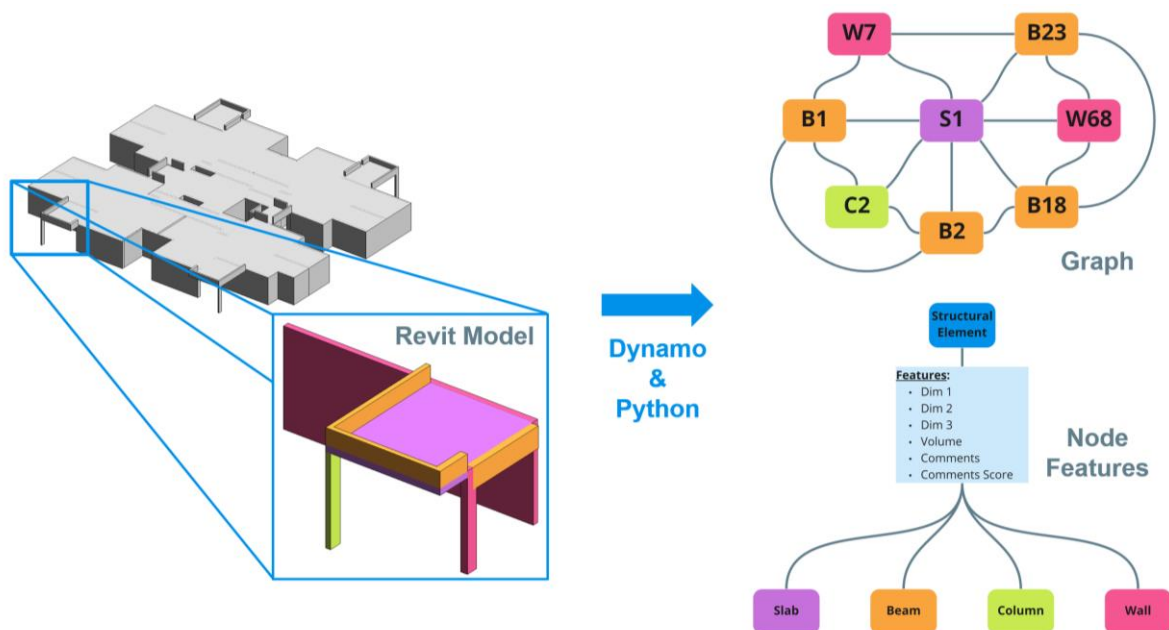


Figure 3: An illustration of the graph creation process, based on Project 001's BIM model

The Python code for this stage is organized into three files:

1. *data2graph*: The main file, orchestrating the process of building a graph database from CSV files.
2. *classes*: Defines classes for structural elements, graph nodes, and graph edges, adhering to object-oriented programming standards.
3. *websiteData*: Manages functions related to extracting and processing information from the *Engineers' Challenge* CSV file.

The code follows object-oriented programming standards, ensuring readability and maintainability for future research, and appears on AIPDORCS GitHub repository (Argaman, 2022). It uses standard Python libraries for data science, with a focus on DGL (Deep Graph Library, 2018) for creating graphs and training the GNN model.

Upon running the code, graphs are generated, exemplified by Figure 4, which shows the graph extracted for *Project 001* from the BIM models database. This visual representation exhibits element numbering and their geometric connections, providing a means for validation against the original structural plans.

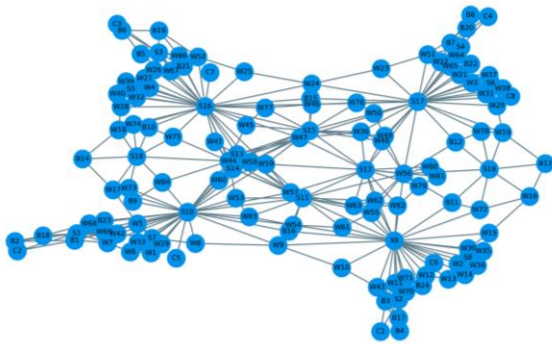


Figure 4: Graph of Project 001's BIM model

### Graph Neural Network

Two experiments were conducted utilizing GNNs, or more specifically GCNs, for classifying structural design plans with a pass/fail grade according to a certain threshold. Experiment 1 was based on geometric model graphs, where 48 graphs correspond to 48 projects, with graph nodes containing only geometric features (four features: Dim 1, Dim 2, Dim 3, and volume). Figure 5 shows the ANN structure of experiment 1.

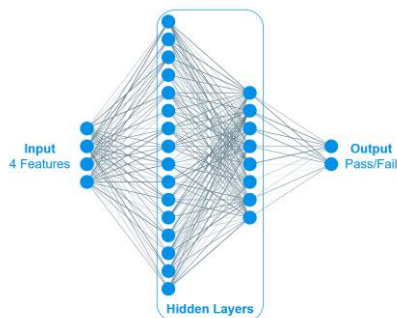


Figure 5: Experiment 1 artificial neural network structure

Experiment 2 is based on engineering feedback graphs, where 106 graphs correspond to 106 valid portal responses, with graph nodes containing all 14 features (geometric properties, survey comment properties, and points subtracted for comments). Figure 6 illustrates the ANN structure of Experiment 2.

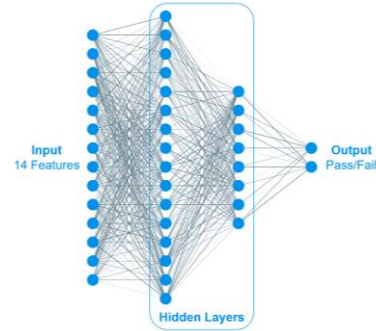


Figure 6: Experiment 2 artificial neural network structure

The architecture of the networks for both experiments is illustrated in Figures 5 and 6 respectively. The networks are structurally identical, with variations in the number of features in the input layer based on the experiment. Careful experimentation and evaluation are essential in determining the most suitable hyperparameter values for achieving the best results, and avoiding overfitting. In both experiments, the output labels were the *Engineers' Challenge* overall scores, converted to a binary value by the average score threshold. The data was split to an 80% training set and a 20% test set, and the following hyperparameters were selected by testing and tuning: number of hidden layers: 2, hidden dimensions: 16, activation function: ReLU, learning rate: 0.005, and number of epochs: 200.

## Results

### Engineers' Challenge

A total of 112 responses were gathered through the portal, six of which were deemed invalid and filtered out. The analysis of the survey results revealed insights into the engineers' perspectives and highlighted their attention to specific elements, as well as the distribution of feedback across different categories.

When comments were given on specific elements, the majority of engineers provided an average of three comments on each, demonstrating a conscientious approach to the task. Additionally, 58 written comments, categorized as "Additional Comments", required manual conversion to relevant element features, showcasing the depth of insights shared by engineers. The distribution of element comments illustrates that issues related to the size of the element's cross-section were the most frequently noted, emphasizing the significance of this aspect in the eyes of experienced engineers.

Furthermore, analysis of overall scores revealed a predominantly positive trend, with most models receiving scores above 70. Outliers with lower scores were

investigated, leading to the identification and correction of errors in feedback or potential typing mistakes. The survey results also prompted an examination of the relationship between the extent of engineers' years of experience and the scores they assigned. The findings suggested a deviation in scores based on experience, with less experienced engineers tending to give higher scores. However, the scores did not exhibit a consistent trend, emphasizing the need for further data collection to draw more conclusive insights. Overall, the *Engineers' Challenge* portal provided a valuable dataset for understanding expert opinions on structural plans, laying the groundwork for subsequent experiments with GNNs.

## Experiments

The outcomes of the GNN experiments exhibited variability across runs, influenced by both the inherent randomness in the code and the model's instability arising from limited data in the database. Focusing on the most promising runs, the analysis employed standard data science performance metrics, derived from a binary classification's confusion matrix: Accuracy, precision, recall, and F1-score.

Table 1: Experiments performance comparison

	Accuracy	Precision	Recall	F1 Score
Experiment 1	60.0%	57.1%	80.0%	66.7%
Experiment 2	68.2%	75.0%	88.2%	81.1%

The results, detailed in Table 1, highlight Experiment 2's superior performance compared to Experiment 1 across all metrics. The larger dataset and richer feature set in Experiment 2 contributed to its enhanced precision, recall, F1-score, and overall accuracy. These findings underscore the potential of GNNs in structural design classification, suggesting that leveraging extensive and diverse datasets can significantly enhance the performance of GNN-based classifiers, offering promising prospects for their application in preliminary structural design assessments.

## Discussion

The AIPDORCS concept introduces an innovative approach, setting it apart from existing works in the realm of structural engineering. Integrating AI with human expertise, this concept redefines the preliminary structural design process, offering a unique solution. In the modelling phase, which produced 48 BIM models, opportunities for improvement were identified. They included refining geometric connections and expanding the features of structural elements, which would yield a heterogeneous graph. Unequal scoring patterns revealed in survey responses necessitate further considerations, like re-scoring based on comments and normalizing scores by engineers' experience clusters. The structural plan classification experiments yielded promising results, particularly with the utilization of engineering feedback graphs, showcasing the potential of leveraging survey

data for precise structural design classification. However, employing 5-fold cross-validation emerges as a key recommendation to ensure dataset representativeness, detect overfitting, and bolster model generalization.

The technical and research limitations present crucial aspects to address. Technical limitations, such as support for specific building patterns and materials, indicate areas for improvement and expansion. Research limitations, including a small dataset and a limited number of feedbacks, underscore challenges related to generalizability and robustness. Issues like varying scales of overall scores and limited time and resources further emphasize the complexities and constraints of the study. While the two initial experiments offer valuable insights, the need for additional experiments on a larger and more diverse dataset is recognized. Notably, the use of comments as features in Experiment 2 prompted consideration of the applicability of this approach in a real-world AI tool. These limitations shape the context of the study and offer directions for future research, emphasizing the need for a comprehensive and conclusive evaluation of the proposed approach for scoring structural plans using GNN.

## Conclusion

Through the execution of two experiments utilizing GNNs, this study established the basic feasibility of automating structural plans classification, underscoring the potential to enhance accuracy and efficiency in the design process. Nevertheless, further research work is required to reliably answer the research question. Acknowledging concerns among engineers about AI's role in the creative phase of design, this study emphasizes a collaborative approach, asserting that AI can augment human capabilities without replacing them. The concluding sentiment draws inspiration from Charles Darwin's principle of adaptability, encouraging engineers to embrace AI's transformative potential in structural design, foreseeing a future where the integration of AI not only optimizes processes but also fosters innovation.

This study contributes to the field of civil engineering by proposing the AIPDORCS concept, innovatively transforming BIM models into GNN-ready graphs. Additional contributions encompass the development of a robust database, an automated model-to-graph solution, and a scoring program for structural plans. These innovations offer valuable resources, time-saving tools, and educational applications, positioning the research at the forefront of AI-assisted structural design. To conclude, this research marks a valuable step toward a future where AI and human expertise harmoniously shape the landscape of structural engineering.

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