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Development of Integrated System of Structural Design and Analysis that Includes Three Artificial Intelligence Technologies

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Abstract Our team developed structural design and analysis system "BRAINNX" BRAINNX implements three AIs. Each AI automates simple repetitive tasks. Structural engineer can spend more time doing creative things that only they can do. AI Building Research can automatically search for similar buildings based on basic project information. AI cross-section estimation can automatically estimate assumed cross-sections based on a structural model reflecting the structural plan. AI member design automatically completes member design, such as allowable stress design and calculation of lateral load-bearing capacity, based on the structural design policy set by the structural engineer. They can significantly reduce the iterative task time by the structural engineer.Based on the AI results, the average accuracy of the estimated quantity of structural elements for each of the three AIs compared to the structural engineer's design results was 98%, 105%, and 102%, respectively. We have started applying this system to practical use.

Keywords Artificial intelligence (AI), Integrated software of structural design and analysis, Machine learning, Narrow AI, Practically applicable level)

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1. Introduction

The implementation of AI in society is rapidly advancing. The use of narrow AI, such as search engines by Google and Baidu, and person identification in surveillance cameras, extends to a wide range of fields. Since the introduction of generative AI, which can be considered as a pioneering example of general-purpose AI, with the release of Chat-GPT in 2022, both the potential of AI itself and societal interest in AI have been further accelerated. Figure 1, created by the author using image generative AI (Midjourney, 2024), illustrates this. By inputting the words "building" and" structural design building" into the AI, I was able to obtain such an image in just one minute. Upon closer inspection, the left image appears to be a typical reinforced concrete structure building, but there are some concerns, such as the location of the columns on the ground floor and whether the beam sizes are appropriate for the span. The right image showcases a highly organic design, but if considered as an actual building, some unnatural aspects can be observed.



Figure 1. Building Parsing with Image Generative AI.

In this societal context, the application of AI to structural design is met with both high expectations and doubts that it cannot be applied.

In practical structural design work, there is a certain proportion occupied by specific simple tasks or repetitive tasks. The authors believe that by leveraging the latest information technologies such as AI and BIM, it is possible to improve the efficiency of these tasks and create an environment where structural engineer can focus on more creative work. In 2023, the authors developed a new integrated structural design system called BRAINNX, which incorporates AI and BIM. This paper will primarily focus on the AI capabilities of this BRAINNX.

It is important to note that the AI in this system is not a generative AI as described in Figure 1. Unlike generative AI, which automatically produces a wide range of outputs with minimal input, the goal is not to achieve automatic outputs without clear reasons. As shown in Table 1, by

Table 1. Features of narrow AI and generative AI and their adoption in BRAINNX

	Adopt	Not Adopted
Type of AI	Narrow AI	Generative AI
Target of automation	Specific tasks	Extensive tasks
Amount of output	Limited	Enormous
Explainable of output	Possible to some extent	Difficult (because of the large amount of output)

leveraging the features of narrow AI, we aim for a scenario where the AI operates based on the structural engineer's ideas and instructions. The structural engineer understands the operating rules of the AI and uses its output critically, verifying it through structural analysis.

The AI capabilities developed in BRAINNX currently focuses on standard low-rise to mid-rise buildings due to factors such as the number of datasets adopted for the AI. However, we hope that the automation of simple repetitive tasks using AI will assist in the future design of high-rise buildings.

2. Overview and Objectives of the Integrated Structural Design System BRAINNX

2.1. Overview of BRAINNX

The overview of the integrated structural design system, BRAINNX, is presented in Figure 2. BRAINNX is a next-generation version of the integrated structural design system called BRAIN, which our company has been using since 2000. BRAINNX incorporates significant improvements after a gap of 20 years. In addition to the conventional structural calculation functions, BRAINNX integrates AI and BIM capabilities. The three AI capabilities in BRAINNX provide automated support for tasks that are simple or involve repetitive processes that Structural engineer have traditionally performed. The BIM functionality facilitates clear 3D visualization of AI results and analysis outcomes and the construction of BIM datasets. The calculation functionality enables incremental analysis of elastic-plastic behavior and allows for the evaluation of our developed technologies, guiding structural engineer towards accurate assessment results.

2.2. Aim of BRAINNX

In typical projects, especially during the initial stages of design, such as the predesign planning and business feasibility study or the schematic design phase, it is common to explore multiple possibilities and conduct comparative evaluations of different design options. In conducting these evaluations, it is essential that the design options are structurally viable without any compromises and avoid unnecessary redundancies like excessive safety margins. However, there are limitations in terms of time and human-resources available for these evaluations. Achieving efficient and swift comparative evaluations while ensuring a certain level of accuracy has been a longstanding challenge in structural design.

Experienced structural engineer, drawing upon their past experiences, can minimize repetitive tasks and efficiently evaluate design options within a short timeframe. BRAINNX aims to leverage the expertise and knowledge of these seasoned professionals to automate simple and repetitive tasks in structural design. The goal is to create an environment that allows structural engineer to have more time at their disposal, enabling them to focus on tasks that require their unique judgment, such as structural planning, evaluation of design outcomes, and proposing further high-value-added solutions.

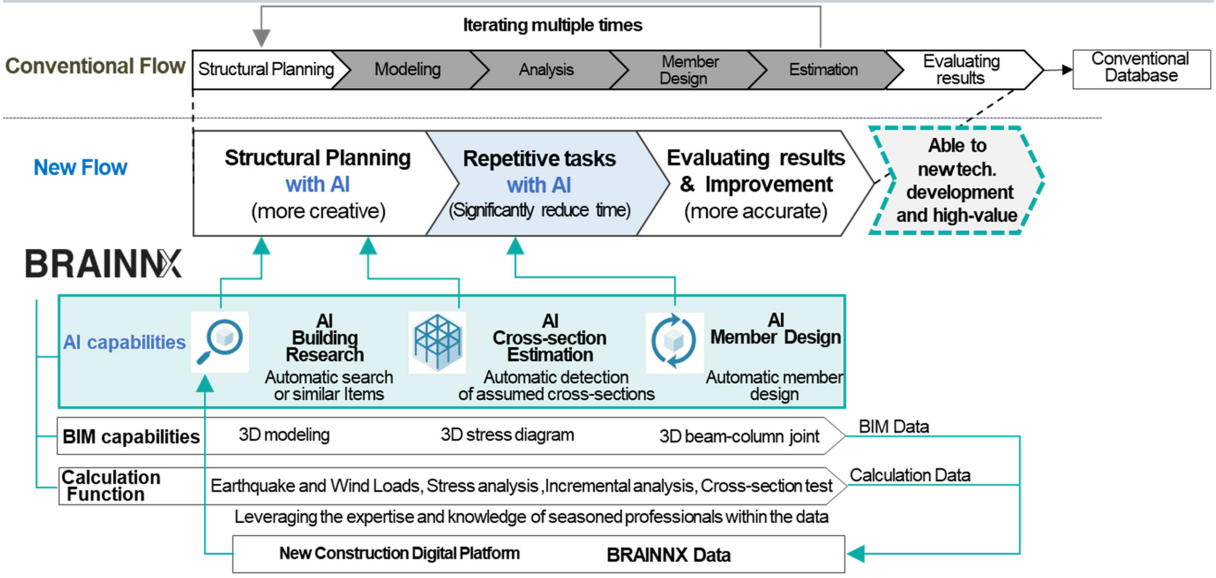


Figure 2. Overview of the integrated structural design system BRAINNX.

2.3. Challenges and solutions for AI implementation

Our team has directed its attention towards AI as a method to fulfill the potential outlined in the preceding section. While AI demonstrates remarkable speed and a certain degree of accuracy in performing specific tasks, applying it as has presented challenges. The following provides a detailed account of the problem and its corresponding solution. (Figure 3)

(1) Explainability: The output of AI is influenced by the content of the learning data and feature value that the AI focuses on and learns from. If the pursuit of accuracy leads to the adoption of numerous feature value, it becomes challenging for the structural engineer to comprehend the cause-and-effect relationship between the input and the AI's output, turning it into a black box. Through data analysis, we discovered that there are approximately 10 parameters that significantly impact accuracy, aligning closely with the main structural dimensions that structural engineer typically consider, such as span and load. By limiting the feature value utilized in the three AI systems and clearly communicating them to the structural engineer, we have avoided the black box scenario. Additionally, the rules employed in programming alongside AI are shared with users to ensure the explainability of the AI tool's output.

(2) Accuracy: While the current accuracy of AI may not match that of humans, it can still provide a certain level of accuracy when limited to simple functions. With this in mind, we identified relatively straightforward tasks and repetitive tasks in structural design and developed three narrow AI systems to address them. The accuracy of AI depends on the quality and quantity of the data used for learning, as well as the machine learning methodology employed. To ensure data quality, we leveraged our extensive collection of structural design results spanning over 20 years, utilizing approximately 500 buildings and 300,000 structural members as a dataset for AI learning. However, we discovered that the amount of data was somewhat insufficient when it came to specific member types such as columns and beams. To address this, we adopted a hybrid approach that combines the principles of structural design theory with programming techniques based on the expertise of experienced designers, rather than relying solely on AI-generated estimations.

(3) Validity: Even if the accuracy of AI output approaches that of human results, it is undesirable if the structural performance is not satisfactory. To validate the accuracy, fact-checking the AI output is an effective approach. In structural design, it is possible to combine the AI tool with the integrated structural design system to perform structural analysis, member inspection, and property checks of buildings. Additionally, the system is equipped with BIM functionality, which aids in swiftly and accurately confirming the AI's results by structural engineer, thereby supporting faster and more accurate decision-making processes.

3. Three Types of AI Functions

3.1. AI Building Research

In the early stages of a project, it is useful to refer to buildings with similar structural types, total floor area, number of floors, and purposes for cost estimation and structural planning. However, searching, assessing similarity, and organizing data from numerous past projects have historically required a significant amount of time.

AI building research utilizes t-SNE (Maaten, L., 2008) and other clustering methods to condense 10-dimensional information on key structural parameters, including span, number of floors, weight, and brace share ratio, into 2-dimensional information on a map (Figure 4). Project information is automatically positioned closer to past projects that exhibit a high degree of similarity, focusing on the study project at hand. Each project's information is linked to a building frame for cost estimation, a structural drawing for verifying the structural plan, and structural analysis results to confirm the calculations. Structural engineer can freely access and review this information from the web database.

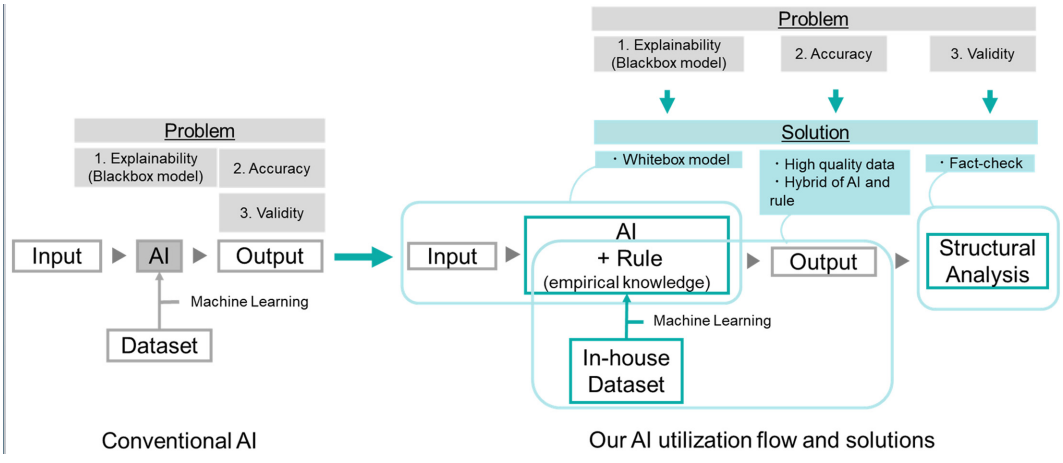


Figure 3. Problems and solutions in deploying AI in BRAINNX.

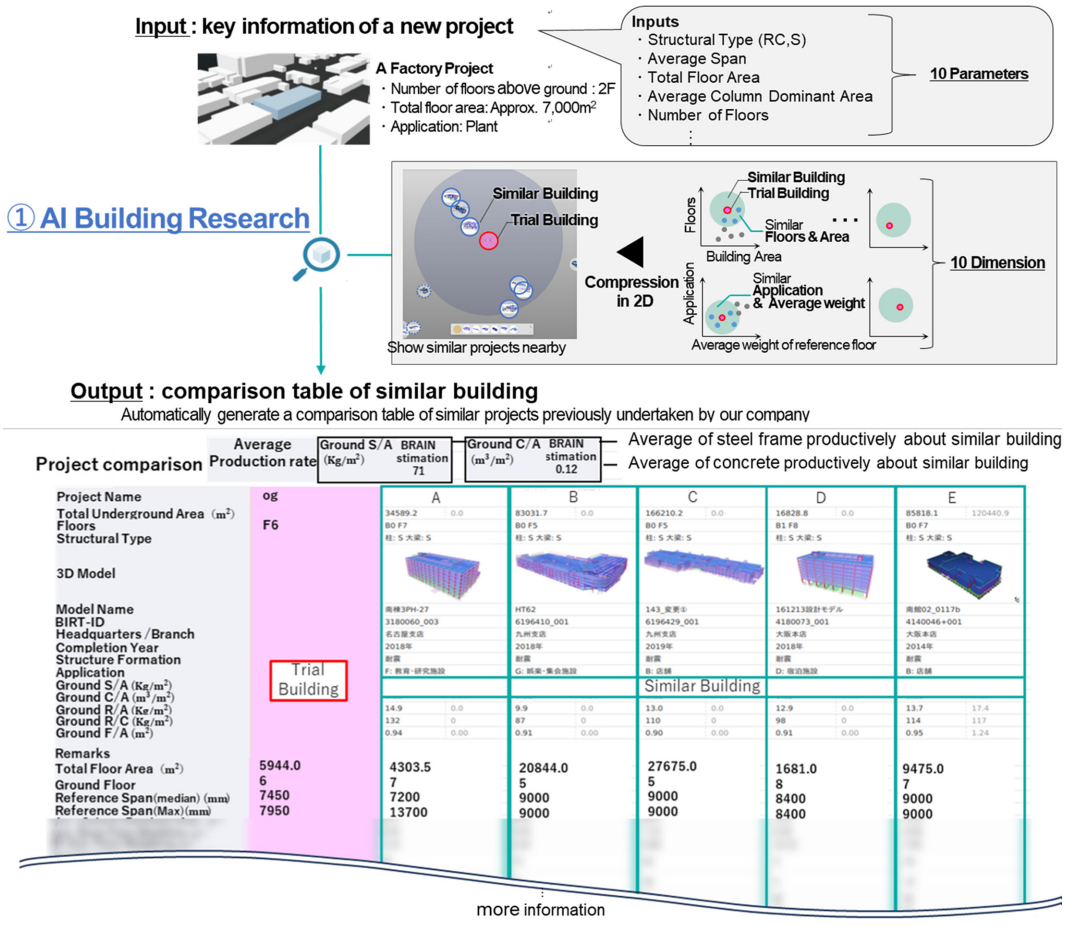


Figure 4. Overview of the AI Building Research.

Furthermore, AI building research automatically generates a table for comparing these similar buildings. The process of collecting and organizing information has been reduced from half a day to just 15 minutes. AI building research has contributed to swift and accurate calculations, serving as an effective business intelligence (BI) tool for structural engineer in structural planning.

3.2. AI Cross-section Estimation

During the schematic design, multiple structural plans are compared and evaluated to meet the diverse needs of building owners, such as a rigid frame structure with high design flexibility or a brace structure that enhances cost-effectiveness. Determining the structural plan involves deciding the member sizes based on design, functionality, and cost considerations. Quickly and accurately calculating the member sizes, or assumed cross-sections, is of utmost importance.

Experienced engineer can swiftly estimate the assumed cross-sections based on their experience and simple calculations. AI cross-section estimation utilizes machine learning to analyze datasets from structural engineers, learning structural features such as the arrangement of columns and beams and member lengths. Using methods like gradient boosting, the AI replicates the rapid estimation of assumed cross-sections in a manner akin to experienced designers (Figure 5). To estimate the assumed cross-section, the structural engineer only needs to input their structural plan model into BRAINNX, and with a single click, the AI can provide the estimated assumed cross-section. Based on this estimation, further structural evaluations are conducted, and the engineer's judgment is incorporated. The time-consuming task of examining assumed cross-sections, which used to take a day depending on the scale, can now be completed in approximately 30 minutes. This significantly supports comparative evaluations and visualizations of various structural plans.

3.3. AI Member Design

During the design development, more than 10 verification items, including bearing capacity and deformation, are examined for three external force levels: long term, short term, and ultimate. To achieve a rational structural design with excellent designability and safety, there is typically a certain degree of trial and error involved. The AI member design replicates the member design process of an experienced engineer using an original algorithm, reducing the repetition time and semi-automating the process

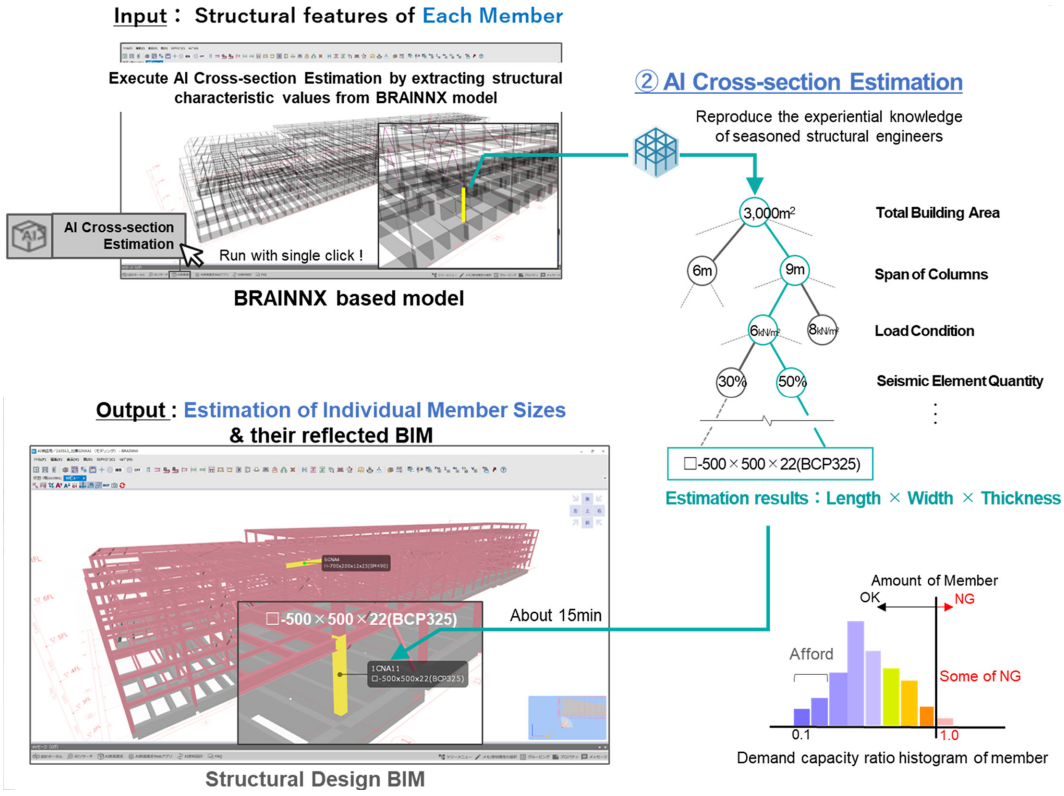


Figure 5. Overview of the AI Cross-section Estimation.

(Figure 6). However, member design is not fully automated. It operates based on the member design policy determined by the structural engineer, aligning with their intentions and objectives.

Furthermore, in the AI member design, the structural engineer performs member grouping using the k-means clustering, and multiple grouping proposals are automatically generated. The structural engineer selects proposals while considering the number of groupings and the quantity of members, and makes fine adjustments as necessary. Depending on the scale, the work that would typically take several days can now be completed in a single day, compressed to approximately 1/5 of the original time. This creates additional time that can be utilized for generating new value-added proposals.

3.4. The Validation Results of the Accuracy of the Quantity of Structural Elements for Each of the Three AIs

We conducted accuracy verification for three AI systems designed for mid-rise and low-rice reinforced-concrete and steel building structures. Table 2 provides an overview of each AI system, and Figure 7 displays box-and-whisker plots depicting the results of the accuracy verification. The verification was performed on 12 projects, all of which involved the calculation of lateral load carrying capacity. The completed design quantity set by the structural engineer for each project was 100%, considering only the upper structure without including foundation beams and foundations (Figure 7, Table 2).

For the accuracy evaluation of AI building research, intended for use during the predesign stage, the average value of the quantity of structural member per area from several past projects, identified as highly similar by AI building research, was adopted. Based on it, the overall quantity of structural member was calculated. The average quantity of structural member in the accuracy verification project of AI building research was found to be 98% of the actual project. Typically, during the predesign stage, engineer assume a margin for correspondence to unclear detailed design conditions. However, AI does not possess such a margin due to its mechanized processing.

For the accuracy evaluation of AI cross-section estimation, intended for use during the schematic design stage, the integrated value of the structural member of the assumed sections obtained through AI section estimation was used. The average result in the accuracy verification project of AI section estimation was 105% of the actual project.

For the accuracy evaluation of AI member design, intended for use during the design development stage, the integrated value of the structural members, whose design and simple column grouping were completed by AI member design, was used. The average result in the accuracy verification project of AI member design was 102% of the actual project. The main reason for projects where the accuracy of AI member design was less than 100% was the lack of

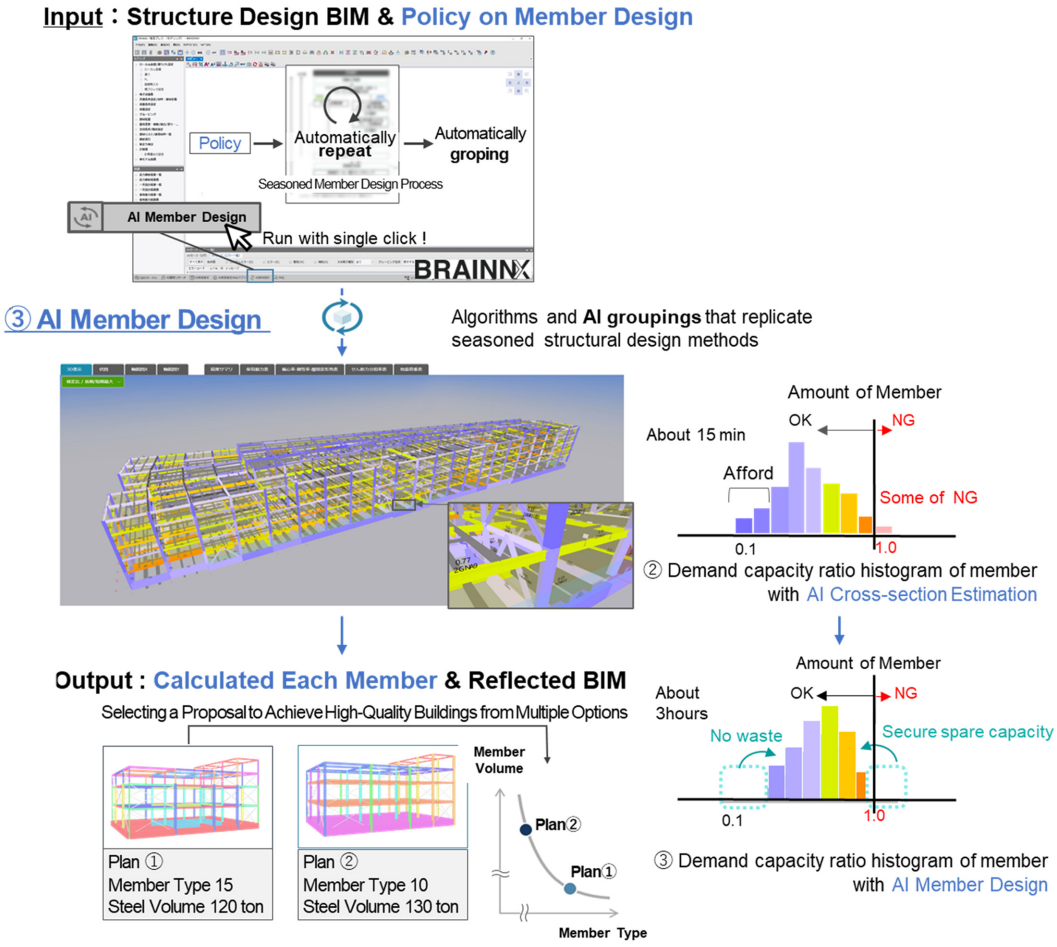


Figure 6. Overview of the AI Member Design.

Table 2. Summary of the three AI systems

	① AI Building Research	② AI Cross-section Estimation	③ AI Member Design
Utilization Phase	Predesign	Schematic design	Design development
To be considered	Building unit	Member unit	Building～Member unit
Accuracy evaluation method	Core average for highly similar projects	Accumulated core quantity for assumed cross-sections	Accumulated core quantity for members whose member design has been completed
AI Capabilities	Automatic extraction of highly similar projects	Automatic estimation of assumed cross-section	Automatic grouping of columns
Function other than AI	Comparison of highly similar projects Automatic table generation	-	Automatic repeated execution of elastic analysis, incremental analysis, member design, and calculation of lateral load carry capacity , ensuring target test ratio, story drift angle and column -beam strength ratio

consideration for design and workability in AI member design. In principle, AI member design is carried out under default condition settings. The difference between the safety factor and the number of member groupings set by the structural engineer in each project and the condition settings of AI member design also contributed to the variance in AI results.

The average values of AI systems were close to those

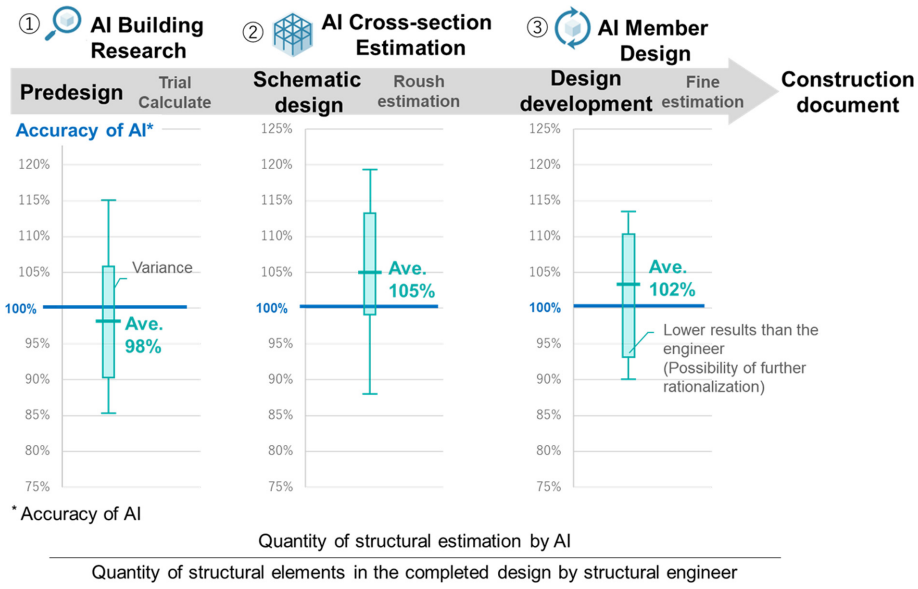


Figure 7. Results on the accuracy of three AI systems.

of the structural engineer. However, reducing variation is considered as a future challenge. Increasing the amount of learning data can help reduce variation.

4. Challenges and Expectations of Applying AI to High-rise Building

We should also consider high-rise buildings. In the structural design of high-rise buildings, a significant practical challenge is that, in addition to the issues faced by low-rise and mid-rise buildings, there are interdependent factors such as building shape, stiffness, strength, damping, wind forces, and seismic forces. These factors greatly influence each other, necessitating numerous iterations before the structural design is completed. If the design loads or stiffness distribution at the initial design stage are inappropriate, it may result in an infeasible design solution and significant rework.

The authors posit that, in addition to tools that support structural engineer, such as AI building research and AI cross-section estimation, generative AI has the potential to offer more direct guidance on suitable starting points for structural planning. Generative AI can produce multiple probable outputs based on specified inputs. The variability and range of these outputs can serve as valuable references for structural engineer when evaluating multiple structural design proposals. Research on such generative AI applications has already been published (Liao, W. 2023). Figure 8 shows design flow for high-rise building combining generative AI and multi-objective optimization.

Starting from an appropriate baseline, it is essential to adjust numerous design elements to satisfy design criteria, such as story drift angles, by iteratively feeding back the stiffness and strength of structural members obtained through member design with the design loads derived from time history response analysis. While this exceeds the current capabilities of AI, the application of multi-objective optimization is considered effective. There already exist optimization methods that, in conjunction with time history response analysis, calculate the most rational structural framework to meet design target values (Takei, H. 2023). Combining this with advanced AI member design technologies, which derive individual member sizes to realize the obtained framework for each story, can reduce the number of iterations required to complete the design. This approach also facilitates the adjustment of numerous structural members.

Currently, the availability of data for high-rise building may be limited. However, in specific applications such as high-rise residential buildings, there are some level of standard. Recently, there has been a proliferation of mixed-use high-rise building, the majority of which are intended for commercial, office, and hotel purposes. Standard structural plans may exist for each application. By leveraging existing data and making good use of it, we believe that the development and application of AI for high-rise building is feasible and can greatly assist structural engineer.

5. Conclusions

In this paper, we have presented the development objectives, functional content, and accuracy evaluation of BRAINNX, an integrated structural design system developed by our team, with a focus on AI. The following conclusions can be drawn:

(1) The aim is not to fully automate structural design using AI. Instead, AI operates under the guidance of the structural engineer, and the results are verified and

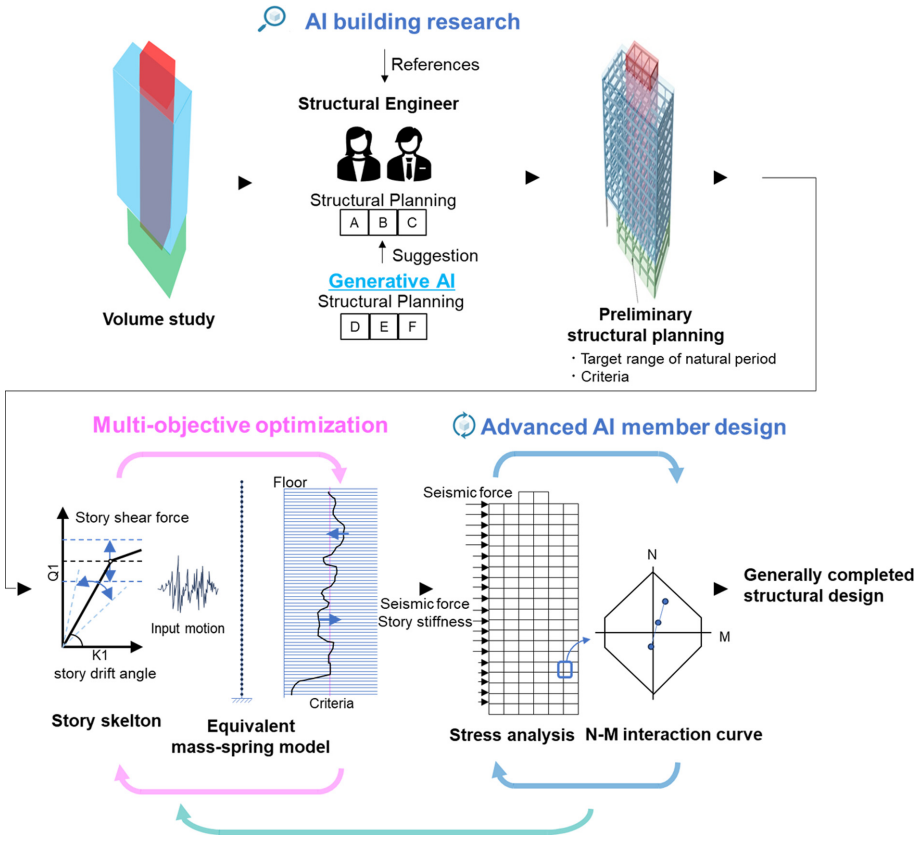


Figure 8. Design flow for high-rise building combining generative AI and multi-objective optimization.

refined by the engineer.

(2) To improve accuracy and ensure satisfaction for structural engineer using AI, we have developed three narrow AI systems tailored to specific automated design tasks. Each AI system incorporates expert knowledge to assist the AI in its operations.

(3) The AI learning data consists of approximately 500 projects and around 300,000 structural elements.

(4) In the predesign stage, we have developed AI building research, which automatically searches for buildings similar to the one being designed. The average accuracy of the estimated quantity of structural elements, obtained from buildings with high similarity, is 98%.

(5) In the schematic design stage, we have developed AI cross-section estimation, which automatically estimates the assumed section based on the structural model reflecting the structural plan. The average accuracy of the quantity of structural elements, obtained by integrating the estimated assumed sections from AI, is 105%.

(6) In the design development stage, we have developed AI member design, which performs member design and based on the structural design policy set by the structural engineer. The average accuracy of the quantity of structural elements, obtained by integrating the cross sections designed by AI, is 102%.

(7) We believe that further accumulation of learning data and rule improvements can help reduce the variance of AI.

(8) For high-rise buildings, we believe that supporting structural planning with generative AI and utilizing multi-objective optimization for member design and time history analysis training calculations can be effective.

Given the occurrence of earthquake disasters in various places this year, as structural engineer, we have a strong desire to create buildings that are resilient to such disasters. We do not overly rely on AI or disregard its capabilities. Instead, we see AI as a tool that allows structural engineer to create time for developing new technologies and fostering inventiveness. We also recognize the evolution of both humans and AI through the generation of new data by structural engineer.

Acknowledgments

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