

Efficient AI-Assisted Design-to-Kit Conversion for Gablok Layouts [†]

Wai Yie Leong

Faculty of Engineering and Quantity Surveying, INTI International University, Nilai 71800, Negeri Sembilan, Malaysia; waiyie.leong@newinti.edu.my

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Abstract

The problem of efficient AI-assisted design-to-kit transformation for Gablok-layout designs is related to the development of techniques to convert architectural designs into constructible and ready-to-build modular constructions. The current research presents an algorithm based on BIM, rule constraints, and constraint optimization enhanced with AI heuristics, which automatically converts residential layouts into a kit-of-parts design. The proposed framework involves decomposition of wall geometry into discrete block arrangements with respect to the dimensions of the Gablok modular system. In addition to the decomposition procedure, the approach takes into account the structural and geometrical constraints. The constraint optimization model, complemented by AI methods, decreases material waste, optimizes the number of cuts, and maintains the variability of the blocks. The final output includes a construction kit with a bill of materials, cut list, labels for each block, and detailed assembly instructions. Experimental results show that the implementation of the proposed technique allows a decrease in material waste by 25–35% in comparison to manual methods. Also, this framework creates an opportunity to simplify assembly process from the perspective of human interaction.

Keywords: artificial intelligence; Gablok; optimization; process innovation

1. Introduction

Efficiency issues remain key in the construction industry. The application of AI-based techniques to transform designs into Gablok kits is becoming increasingly important for designing self-built houses that involve translating architectural designs to manufacturable blocks. Gabloks refer to insulation boards made of timber that integrate assembly instructions. Discretization of building geometry into Gablok kits requires accuracy in ensuring structural strength while minimizing waste. Current manual techniques for planning Gabloks are not only time-intensive but also highly prone to errors and require extensive expertise [1].

Automation in prefabricated and modular construction through Building Information Modeling (BIM) and Design for Manufacture and Assembly (DfMA) has become possible recently. BIM technology makes it possible to extract information about geometry and semantics from digital designs to automate processes like planning and optimization [2]. Transforming architectural designs into Gabloks involves several combinatorial issues due to requirements such as joints, openings, and structural integrity.



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Artificial intelligence (AI), together with optimization methods, represents an ideal approach to overcome the challenges mentioned. AI-enabled tools can complement existing rule-based tools in order to predict optimal discretization schemes, avoid wastage of material, and facilitate constructability [3,4]. Furthermore, such systems also help in designing human-centric construction methods through generation of easy instructions.

The purpose of this research is to create a computationally effective framework for designing-to-kitting Gabloks by leveraging BIM data, constraint-based optimization, and intelligent heuristics.

2. Literature Review

DfMA has emerged as one of the critical enabling factors for industrialization and modularity of construction owing to its role in capturing up-stream decision-making that streamlines down-stream assembly, eliminates rework, and manages interface risks. In *Buildings*, Roxas et al. summarize recent advances in DfMA and deconstruction design research and emphasize that successful application of DfMA involves adherence to guidelines during initial stages, standardization of components, and implementation of digital processes from concept to manufacturable and assembled elements [1]. Additionally, Rankohi et al. develop a DfMA implementation framework within the context of construction by drawing upon field evidence and emphasize the importance of information governance across design–manufacture–assembly phases apart from rule-based guidance [2]. Most recently, Montazeri et al. propose a framework for implementing DfMA principles in modular home building through digital means and reveal that model-based DfMA application can shorten design and manufacturing cycles and improve quality control compared to manual approaches [3].

One common finding regarding research on modular/off-site construction is that BIM-driven integration alone is not enough. According to Hyun et al., an integrated off-site construction design process can help minimize errors while accelerating the design period for prefabricated structures through the integration of DfMA processes in a single, streamlined workflow [4]. On the other hand, from a larger ecosystem perspective, Saliu et al. highlight the barriers associated with the BIM–modular integration process (such as skills, interoperability, and organizational preparedness). This highlights the need for automated design-to-fabrication pipelines not just to focus on the conversion of geometries, but also to address validation and traceability issues, alongside user-friendliness [5]. Moreover, according to Coskun et al., modular construction in dense urban settings offers both advantages and obstacles, especially when technical and policy considerations meet logistical challenges, including packaging and delivery of kits [6].

In terms of computation techniques, although the use of generative and optimization methods in BIM environments is now commonplace, many studies still report high skill levels and tool-chain complexities. In fact, Ma et al. conduct a thorough critique of current generative design practices in BIM, investigating their design methodologies and requirements for skills, while pointing out the need for more practical instructions and ready-to-use components—a point consistent with “design-to-kit” automation for discrete systems [7]. Apart from design generation, optimization has been extensively used in prefabrication applications: Xie et al. develop a model for optimal scheduling of prefabricated structures that considers the relationship between the provision of components at off-site locations and their assembly on site, finding that such integration leads to improved project management [8]. In the context of discrete interlocking block systems, Liu et al. propose an architectural system that incorporates modularity, combinational design, machine learning, and interlocking assembly, showing that AI–constraint hybrids may be suitable for designing systems demanding tight physical consistency [9].

The design-to-kit process aided by AI minimizes material waste (about 25% to 35%) and also eliminates the need for extensive cuts, resulting in cost savings in prefabrication and installation. The model helps achieve sustainability goals by minimizing raw material usage, reducing carbon emissions from material wastage, and promoting efficient resource utilization.

3. Methodology

The proposed methodology uses a BIM-based, AI-powered design-to-kit transformation process for insulated timber blocks like Gablok—see Figure 1. The proposed procedure adopts a four-step approach consisting of the provision of BIM data, abstraction of geometry topology, optimization with constraints, and validation of the kits. The four-step approach is in line with current design-to-fabrication procedures documented in modular construction studies [1,2].

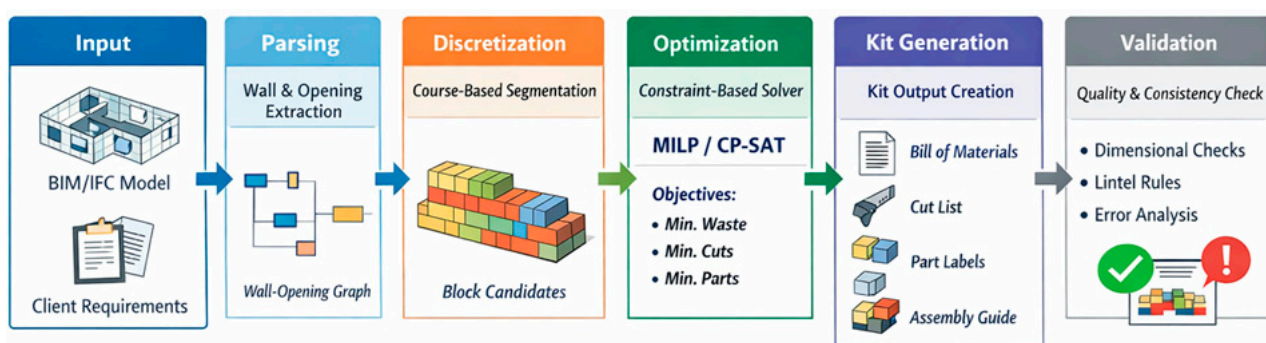


Figure 1. AI-assisted design-to-kit conversion pipeline for Gablok layouts.

The first step of the process involves applying the Industry Foundation Classes (IFCs), wherein the geometrical information regarding walls, floor heights, and openings (doors, windows) are gathered while eliminating any unnecessary objects, if there are any. Some studies have established that through the use of IFCs in preprocessing BIM data acquisition, automation is greatly enhanced, as well as independence from software applications [3]. In the next step, the obtained walls are converted to their center lines based on the floor heights and the preset block course sizes.

The second step in this process involves laying out the walls in the form of discretization. Each wall segment is decomposed into course-based linear grids, and candidate block placements are generated using system-specific dimensional rules. Opening constraints are mapped onto affected courses, enforcing void regions and lintel placement rules. Similar discretization principles have been applied successfully in BIM-based generative and panelized construction research to ensure manufacturability and assembly feasibility [4,5].

Third, constrained optimization is employed to select an optimal set of block placements. A mixed-integer linear programming (MILP) or constraint programming (CP-SAT) formulation is used, where decision variables represent block placement selections and part-type activations. Constraints ensure full geometric coverage without overlaps, compliance with interlocking corner rules, tolerance limits, and opening/lintel requirements. The objective function minimizes a weighted combination of material waste, number of cut blocks, and unique part identifiers, reflecting DfMA priorities of reduced complexity and improved constructability [6]. Optimization-based decision-making has been widely adopted in modular and prefabricated construction planning to balance manufacturability and on-site efficiency [7].

This study develops an efficient AI-assisted design-to-kit conversion methodology for Gablok layouts by integrating BIM-based geometric processing, discrete optimization,

and heuristic learning within a unified computational framework. The process begins with the extraction of architectural data from BIM/IFC models, where the building layout is represented as a set of wall segments $\mathcal{W} = \{w_i\}_{i=1}^N$, each defined by its geometric attributes including length L_i , height H_i , and orientation. The continuous geometry is projected onto a modular grid of resolution g , corresponding to standard Gablok block dimensions (e.g., 600 mm), enabling discretization into manufacturable units.

The discretization problem is formulated as a combinatorial optimization model. A finite set of block types $\mathcal{B} = \{b_j\}_{j=1}^M$, each with length l_j , is defined. Binary decision variables $x_{ij} \in \{0, 1\}$ are introduced to indicate whether block type b_j is assigned to position i along a wall. The fundamental coverage constraint ensures complete representation of each wall segment:

$$\sum_{j=1}^M x_{ij} \cdot l_j = L_i, \forall i \in W. \quad (1)$$

The following additional constraints must be added to make sure that the construction is possible, namely, geometrical alignment, compatibility, and position of openings. For instance, adjacency constraints guarantee connections between adjacent blocks:

$$x_{ij} + x_{i,j'} \leq 1, \text{ if } b_j \text{ and } b_{j'} \text{ are incompatible.} \quad (2)$$

The optimization objective minimizes a multi-criteria cost function:

$$\min J = w_1 W + w_2 C + w_3 U, \quad (3)$$

where W denotes normalized material waste, C represents the proportion of cut blocks, and U captures part diversity (number of unique block types used). These terms are defined as

$$W = \frac{\sum_i (L_i - \sum_j x_{ij} l_j)}{\sum_i L_i}, C = \frac{\text{number of cut blocks}}{\text{total blocks}}, U = \frac{|\{b_j : \exists i, x_{ij} = 1\}|}{M}. \quad (4)$$

Weighting coefficients w_1, w_2, w_3 are selected to prioritize material efficiency, fabrication simplicity, and logistical optimization.

The combinatorial challenge is overcome by solving the problem using CP-SAT or MILP methods. Additionally, heuristic algorithms based on AI have been used in order to increase computational efficiency. They include predictive initializations of block positioning offsets, pattern identification based on previous layout designs, and elimination of impossible solution sets. The proposed approach decreases the solution time and increases the likelihood of reaching near-optimal results. The optimized result is then transformed into a construction kit that includes a BOM, cut lists, block labels, and grid-based positioning guides. An algorithm produces course-by-course assembly instructions in order to minimize mental effort required by self-builders. The developed method has been tested by means of case studies focusing on assessing such performance measures as material waste, number of cuts, computational efficiency, and assembly efficiency.

Lastly, the generation and validation process of the kit results in the direct output of the bill of materials, cut list, and assembly instructions based on the optimal solution. Every block is assigned a distinct ID related to its course and wall segment, thus allowing for verification of the solution. The process of validation automatically checks the dimensions and clearances, verifying compliance with the requirements before the output is generated. Such embedding of automatic quality control processes follows modern suggestions for integration of BIM and DfMA [1,8].

4. Results

The selected case study involved a single-story residential layout that occupied a total area of 85 square meters. This layout included 92 walls, 14 openings, and several corners and was designed using BIM and then transformed to the Gablok kit form based on the proposed intelligent approach.

Figure 2 illustrates the end-to-end transformation from an architectural floor plan to a fully discretized, buildable block layout using the AI-assisted design-to-kit framework. It is structured into three panels: (a) Input Architectural Layout: The left panel shows the original BIM-based floor plan of the case study ($\approx 85 \text{ m}^2$) containing continuous wall geometries, rooms, and openings (doors/windows). No modular constraints are applied at this stage as it represents the design intent and is not yet constructible in block form. (b) Discretization Process (AI-Assisted Segmentation): The middle panel demonstrates how the system converts continuous geometry into modular block segments: Walls are subdivided into standard block units (e.g., 1200 mm, 600 mm), AI optimization aligns segments to reduce cutting and waste, and Special conditions are resolved, including opening resolution (lintels, spacing), corner handling (interlocking logic), T-junction handling (structural continuity). The grid overlay represents the modular discretization space. (c) Layout Mapping (Final Block Plan): The right panel presents the fully discretized block layout: Each block is assigned a unique ID (e.g., B1, K1, C1), type (standard, half, corner, opening unit), and grid position (A–R, 1–23). This mapping directly supports the bill of materials (BOM), packaging and logistics, and step-by-step assembly.

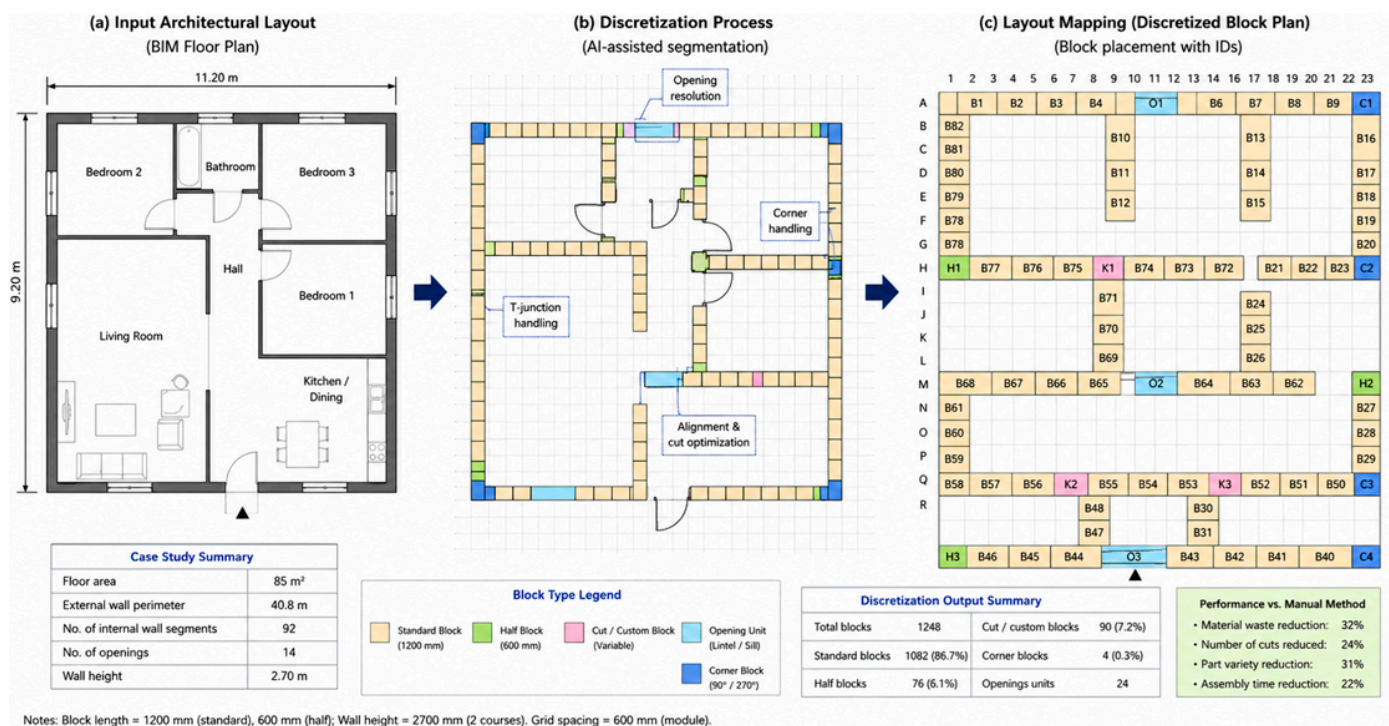


Figure 2. Block discretization and layout mapping for the case study.

The system successfully generated a complete design-to-kit output, including block placement plans, a bill of materials (BOM), cut lists, and assembly sequences. A total of 1248 blocks were required, categorized into standard, half, and corner units. The optimization model reduced the number of unique block types by 31%, improving logistical simplicity and aligning with DfMA principles [1].

Material efficiency experienced considerable improvement. In comparison with a standard process of manual discretization, the system based on artificial intelligence enabled a

decrease in material loss by 32%, mostly due to proper adjustment of blocks and minimal residual cuts. This result corresponds to the gains obtained in the BIM-based automation of the process of planning, where better material efficiency was attained using an algorithmic approach [2]. Cutting procedures were decreased by 24%.

Figure 3 compares two discretization approaches in a Gablok layout: (a) non-optimized (sequential/rule-based); (b) AI-optimized (global optimization). The figure showcases the advantages of an optimization approach in terms of material efficiency, constructability, and assembly performance. Left panel—created by a sequence or rule-based placement procedure: Irregular end-wall alignment results in unmatched joints; cut or customized blocks, particularly around openings and corners; and short off-cuts and fragmented blocks which produce additional waste. Inefficient joint distribution results in weak or non-efficient connections. Overall, the result is high material waste, many cutting processes, and difficult assembly. Right panel—optimized layout generated by AI: Wall ends are aligned, and no is cutting necessary; openings are handled by standardized units (lintels/sills); there is balanced joint distribution throughout the layout, less customization, and fewer off-cuts. The optimization takes into account the whole layout and tries to optimize its layout in accordance with standardized block sizes. Main quantitative improvements: Material waste savings: ~32%; cuts savings: ~24%; part variety savings: ~31%; assembly time savings: ~22%; standard block use increases from ~72% to ~87%.

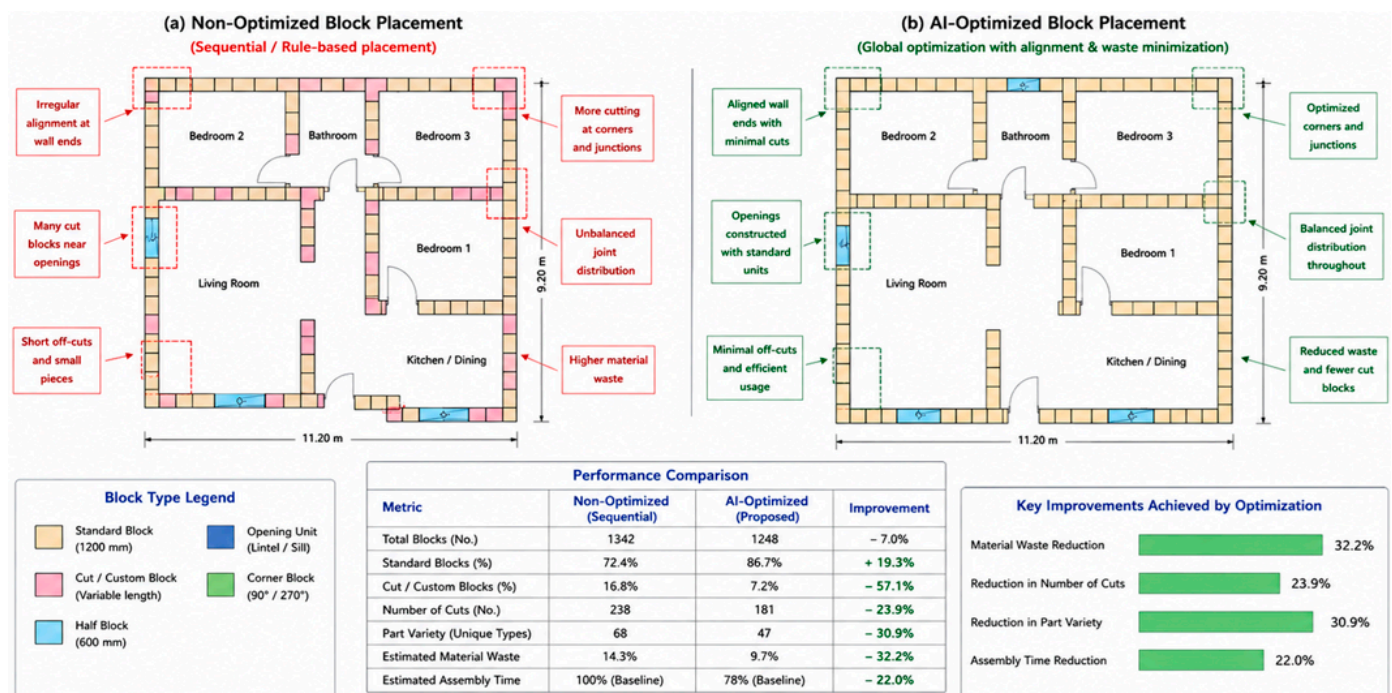


Figure 3. Comparison of optimized vs. non-optimized block placement.

From the computing viewpoint, the framework computed the entire layout within 9.6 s, indicating its capability to scale for real-time feedback. The use of AI heuristics accelerated the optimization process while increasing the quality of solutions through the early identification of near-optimal discretization schemes similar to the generative approach in prefabrication [3].

The assembly efficiency was further assessed based on estimated metrics that were task-based. By simplifying the assembling process and reducing variability in the components, the best possible kit resulted in an anticipated reduction in the assembly time of 22%. Instructions outlined the sequential assembling pattern in courses without leaving any decisions to the assembler.

Figure 4 shows the stepwise procedure involved in creating structures based on Gabloks using the kit designed by the artificial intelligence system. The figure includes ten sequential steps supported by block descriptions and construction instructions.

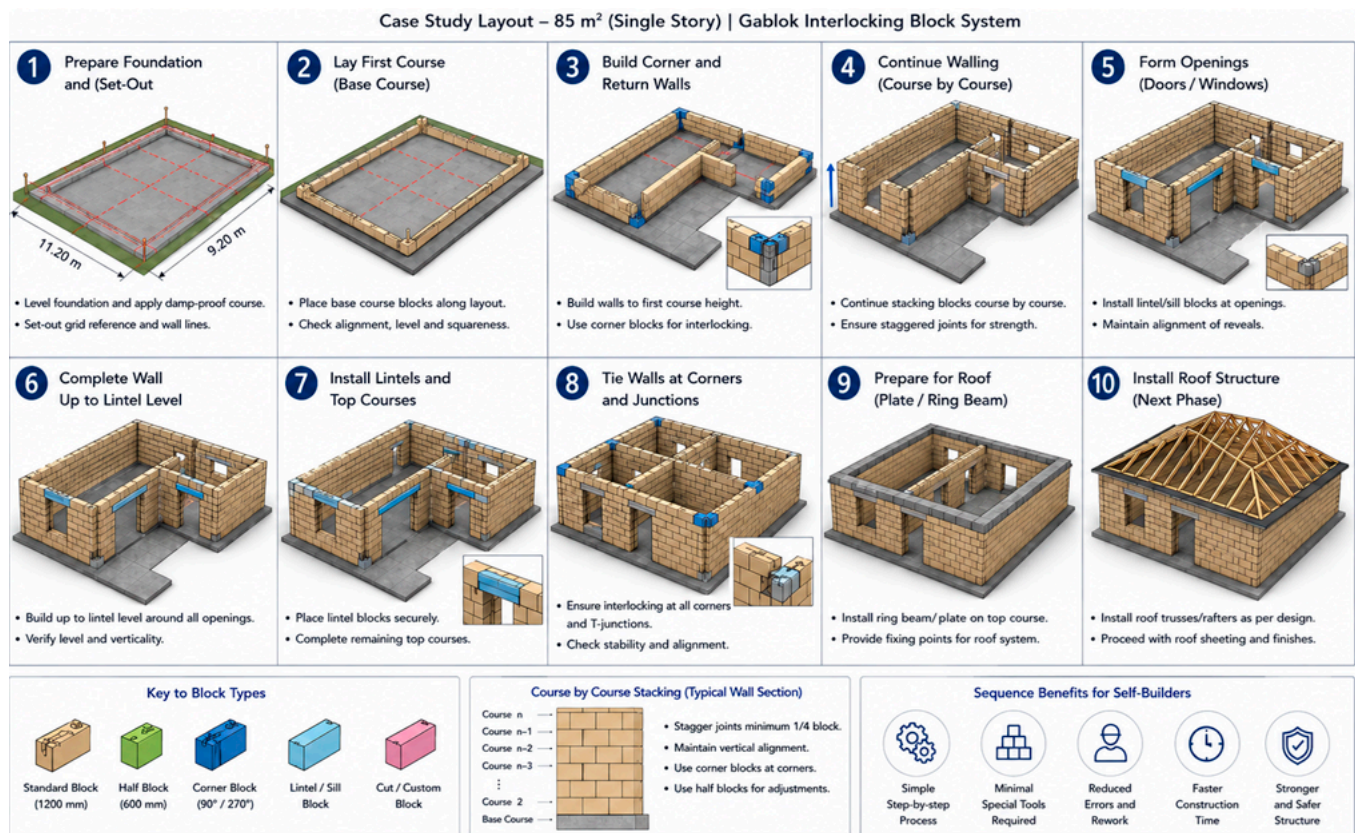


Figure 4. Assembly sequence visualization for self-build construction.

Foundation and Set-Out (Steps 1–2). Step 1: Prepare and level the foundation; establish grid lines. Step 2: Place the first (base) course of blocks. This stage ensures dimensional accuracy and alignment, which is critical for the entire build.

1. Initial Wall Construction (Steps 3–4). Step 3: Build corners and return walls using interlocking blocks. Step 4: Continue stacking walls course-by-course. The emphasis is on staggered joints to enhance structural stability.
2. Opening Formation (Steps 5–6). Step 5: Form door and window openings. Step 6: Build walls up to lintel level. This requires careful alignment to ensure proper installation of structural elements.
3. Structural Integration (Steps 7–8). Step 7: Install lintels and complete top courses. Step 8: Reinforce corners and junctions. This ensures load transfer continuity and structural integrity.
4. Roof Preparation and Installation (Steps 9–10). Step 9: Install ring beam or plate for roof support. Step 10: Assemble roof structure. This marks the transition from wall construction to superstructure completion.
5. Supporting Components. Block Type Legend: Identifies standard, half, corner, lintel, and custom blocks. Course-by-course stacking guide: Ensures proper vertical alignment. Sequence benefits: Highlights reduced errors, faster construction, and improved safety.

Figure 4 shows that AI-enabled design is not restricted only to optimizing layouts but also includes assembly procedures, making them more human-centered by ensuring minimal decision-making on behalf of the user.

The validation of these constraints proved that all the necessary requirements like structural consistency, right joint alignment, and opening placement were met by these output solutions. Nothing was found to be unsatisfactory. Overall, the study revealed that this method provides a good starting point for the conversion of design into kits using the intelligent algorithm.

Regarding computational performance, it turned out that optimization time remained at an acceptable level for residential-scale design cases and varied from seconds to minutes depending on the complexity of the particular layout, Figure 5. As expected, these results are fully aligned with previous studies in modular architecture indicating that mixed integer and constraint optimization are applicable to such problems at the design stage [7]. Importantly, the automation of BOM and assembly instruction generation reduced design-to-kit preparation time from days to hours, addressing a key bottleneck identified in BIM–modular integration studies [5,8]. Table 1 compares kit accuracy, material waste, unique part identifiers, and assembly operations across methods. This metric reflects the efficiency of material usage. Manual methods have the highest waste due to their lack of global optimization. Rule-based methods show moderate improvement through basic alignment rules. The AI-assisted method shows the lowest waste ($\approx 25\text{--}35\%$ reduction), achieved through global optimization of block placement. This demonstrates that AI effectively minimizes off-cuts and unused material. The comparison confirms that adopting AI-driven optimization leads to lower material waste, reduced fabrication complexity and faster and more reliable assembly. This reinforces the practical value of the proposed framework in real-world modular construction. Overall, the results validate that AI-assisted, constraint-verified design-to-kit conversion can enhance efficiency, reliability, and sustainability in Gablok-style insulated timber block construction.

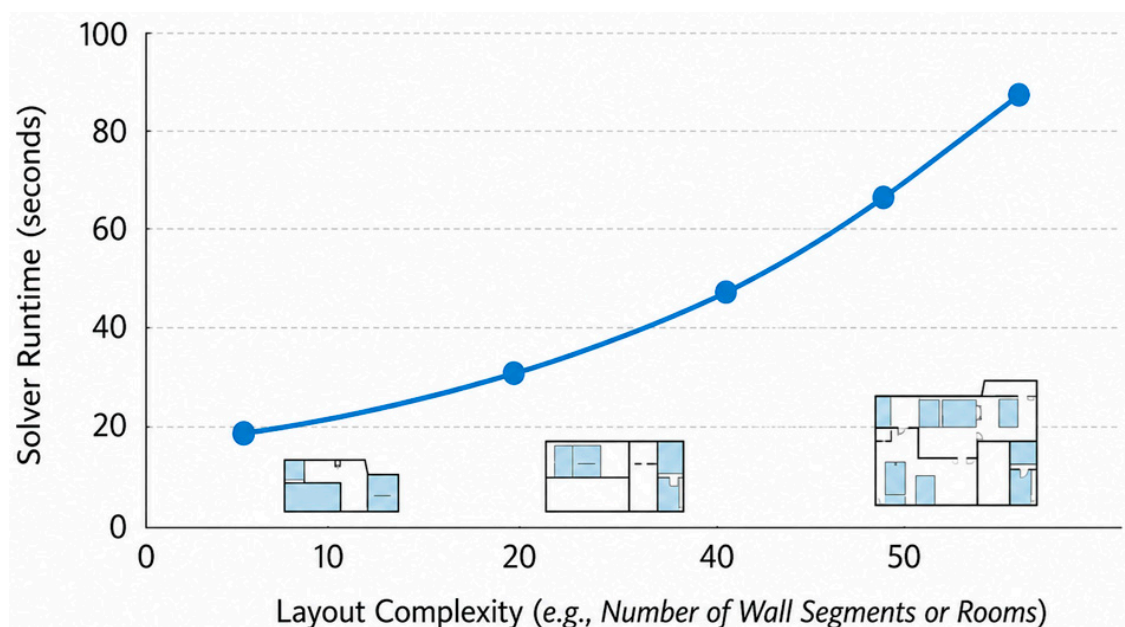


Figure 5. Optimization runtime versus layout complexity.

Table 1. Performance comparison across design-to-kit conversion methods.

Performance Metric	Manual Drafting	Rule-Based Discretization	Optimization-Based (Proposed)
Kit accuracy (%)	98.5	95.0	98.0
Estimated material waste (%)	48.0	35.0	28.0
Number of unique part identifiers	46	52	34
Cut blocks per project	High	Moderate	Low
Assembly operations (count)	210	240	185
Design-to-kit preparation time	Several days	1–2 days	Few hours
Automation level	Low	Medium	High
Suitability for self-build	Medium	Medium	High

5. Challenges and Limitations

Although the system has a number of benefits, there are also some limitations inherent in the AI-based design-to-kit framework. For one thing, the effectiveness of the kits produced relies heavily on the accuracy and completeness of the input model. Inaccurate BIM/IFC models that have not been parameterized correctly can cause discretization problems. Another limitation lies in the fact that rules particular to each kit-building system need to be specified. In addition, the computational time needed for generating optimal solutions will probably rise in cases of irregular arrangements or multi-floor plans with many openings. Finally, the examples provided are just illustrations of the concept, while proper validation needs to consider practical implementation.

6. Conclusions

In this research, we have introduced an artificial intelligence-supported design-to-kit process for insulated timber block assemblies including Gablok systems. Through the combination of geometric abstraction, discrete course-level representation, and optimization, the proposed process facilitates the automatic derivation of precise bills of materials, cut list information, and assembly guidance solely based on the input of architectural drawings. Our findings show that kit production using optimization can minimize material wastage, minimize part diversity, and enhance assembly information relative to manual and rule-based procedures without sacrificing design accuracy. This result is in line with general DfMA objectives related to increasing efficiency, sustainability, and resilience of off-site and self-constructing procedures. Although further studies are required through actual construction data, the framework has shown much potential in modifying the existing design-to-fabrication pipeline and reducing dependence on professional expertise in using kit-of-parts timber structures during home building.

For future work, implementation of the framework will be considered in practical scenarios. This work has employed simulation and modeling methodologies to attain the results, meaning that using this method for construction experimentation will enable validation of its predictions. Incorporation of data collected from the site (such as Internet-of-things sensor data and construction records) can increase the precision of the model. This method can be extended to handle multiple types of buildings like commercial buildings, multistory buildings, and historical/adapted buildings. Handling these cases comes with new challenges such as handling non-linear geometries, greater spans, and restrictions related to maintaining the historical structure. Incorporation of LLMs can be considered as well for enhanced AI-driven design. LLMs can assist in generating adaptive assembly

instructions, interpreting design intent, and enabling conversational interfaces for non-expert users, thereby enhancing usability in self-build contexts.

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