Environmental Perception-Driven Force Feedback Mechanism

A graph neural network approach in collective construction

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Abstract. Nature's collectives, like ants and bees, exhibit remarkable group intelligence, particularly in adapting to changing environments and forming self-organised structures. These phenomena have inspired new approaches in modular design and construction facing complex terrains. This study aims to address these challenges by using agent-based modelling (ABM) for decentralised decision-making. By integrating Graph Neural Networks (GNN) within ABM, we can efficiently handle large amounts of force feedback data. We show how 3D architectural components—such as corners and slabs—are generated under varying terrains and module quantities. Physical prototypes are used to validate the effectiveness of these results. Environmental data collection and simulation are conducted using the Unity3D engine. This allows for timely monitoring of overall structural stability and local mechanical data such as force, torque, and modular connectivity. The data gathered from Unity3D serves as the foundation for the training process of GNN, which optimises the outcomes to achieve stable spatial components. Additionally, an interactive platform serves as the data collection interface, where users embed their design intent, thereby providing quantifiable goals for rapid generative design. This tool achieved an accuracy of 83.6% in constructing stable structures across various terrains, enabling adaptive, rapid, scalable, and autonomous construction workflows.

Keywords. Environmental Perception, Multi-Agent System, Graph Neural Networks, Game Engine, Collective Construction

1. Introduction

The challenges of constructing in dynamic and irregular environments, such as disaster-stricken areas, extreme climates, or geologically unstable terrains, have long posed significant obstacles to achieving efficient and sustainable building practices. Conventional approaches, such as off-site prefabrication, prioritise cost and speed but fall short in adaptability, which requires significant human intervention in unpredictable settings (Petersen et al., 2019). As a result, it is urgent to construct

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autonomous systems that can dynamically respond to environmental changes and optimise structural configurations in a timely manner.

In response to this challenge, bio-inspired systems, such as the self-organising behaviour observed in ant and bee colonies (Reid et al., 2015; Smith et al., 2021), have provided valuable insights. These collectives demonstrate remarkable adaptability and coordination, which enables the way of forming adaptive structures in varying conditions. Translating these principles into construction, agent-based modelling (ABM) has emerged as a promising tool for simulating decentralised decision-making and adaptive assembly processes (Hosmer et al., 2024). However, relying entirely on ABM presents challenges in addressing the complexity of large-scale modular construction, particularly in capturing global relationships and maintaining structural stability across diverse terrains.

To overcome these limitations, Graph Neural Networks (GNNs) offer a complementary approach by leveraging graph representations to model complex relationships and predict outcomes with greater efficiency (Sanchez-Lengeling et al., 2021). However, the integration of ABM and GNNs into a unified construction framework has received limited attention. This gap presents a valuable opportunity to address critical challenges in adaptability and scalability.

This study introduces an integrated framework that combines GNNs and ABM to address challenges in adaptive construction. By incorporating self-organising mechanisms and force feedback-driven decision-making, the framework dynamically adjusts modular assemblies to maintain structural stability. A Unity3D-based simulation environment facilitates timely data collection and validation, paving the way for the training of GNNs to predict structural configurations. This approach also incorporates an interactive user interface that enables designers to embed their intent and monitor assembly processes.

This study aims to achieve the following three research objectives:

- How to develop a closed-loop control for information transmission to enable timely monitoring and feedback during construction?
- How can artificial intelligence (e.g., GNNs) be used to create reliable models for force evaluation and prediction in dynamic environments?
- How can visualisation tools and interfaces be designed to implement digital-physical closed-loop mechanisms to make sure that users can monitor and adjust construction processes in a timely manner?

2. Literature Review

In response to the challenges of complex built environments, a variety of methods have been proposed. For example, innovative mechanical tools (Leder et al., 2024) or modular components that are more suitable for the terrain (Melenbrink et al., 2020). While diverse, these methods rely on advanced and accurate computational methods to optimise and predict spatial configurations. Among them, computational methods in spatial planning (SP) may adopt two different approaches: one focuses on multi-agent systems (MAS) and adopts goal-driven strategies for specific SP tasks, while the other uses ABM to explore emergent SP patterns through agent interactions (Veloso &

Krishnamurti, 2023). For example, ABM-based algorithms, such as Wave Function Collapse (WFC) and Conway's Game of Life (GoL), are used for space-filling problems (Hosmer et al., 2020). However, their regularity often leads to overly constrained solutions, as they overlook environmental variability and lack features like autonomous agent interaction or goal-driven behaviour. This limits the ability of AMBs to explore novelty with respect to low-level design decisions(Stieler et al., 2022). In recent years, studies have highlighted the importance of autonomously adjusting structural forms to maintain stability on uneven terrain under real gravity environments (Melenbrink et al., 2017). Although the correction of stability within modular organisation has been considered, these experiments are often limited to 2D setups and lack consideration of the 3D scale.

Serving as a tool that can clearly represent the relationship between nodes and links, GNN is suited to optimise and predict global relationships within multi-agent systems (Rajeswaran et al., 2018). GNN also captures patterns in graph datasets, which allows it to generalise and manage similar tasks without needing to solve problems from scratch. For example, GNNs have been applied to predict link strength and optimise the distribution of forces in structural networks, improving overall stability (Bleker et al., 2024; M. Zhang & Chen, 2018). However, the combination of GNNs and ABMs in real-time structural optimisation is an underexplored area, especially in terms of dynamic adaptability in complex terrains.

While advancements in computational methods address force distribution and modular adaptability, most studies have overlooked the role of closed-loop environmental data transmission, one of the key links in achieving spatial emergence and self-organisation. Systems like In-situ fabrication (Dorfler et al., 2019) and the Fabrication Information Modelling (FIM) framework (Slepicka & Borrmann, 2024) highlight the importance of closed-loop communication in adaptive construction, which enables real-time corrections during 3D printing. However, these systems remain limited to specific processes, such as large-scale robotic arm printing, and some of them lack the integration of feedback mechanisms, force prediction, and real-time optimisation into a single cohesive framework. This gap has promoted research into integrating elements like closed-loop feedback, force prediction, and real-time optimisation into a unified framework for modular construction.

To address these gaps, this study proposes an adaptive framework for decentralised decision-making in modular construction. By incorporating capabilities such as self-configuration, timely force feedback, and self-reconfiguration, the framework offers a reliable and scalable solution for construction in complex and dynamic environments.

3. Methodology

Figure 1 illustrates our adaptive framework, a structural organising algorithm designed to provide stable configurations across variable terrain conditions. This framework integrates key simulation and decision-making algorithms to achieve dynamic adaptability and reliable performance.

We describe modular components and static organisation settings in Section 3.1, which form the basis for the dynamic stability control algorithm. In Section 3.2, we establish a universal analysis, simulation, and training platform. The key steps include visualisation of stress points and graph generation to represent structural connections and relative node information. In Section 3.3, we employ link prediction algorithms within a GNN model to predict the optimal sequence and location for the next structural additions. Experiments are conducted to evaluate the performance of training models to get optimised solutions. Tests are conducted across various scales and applications, including corners and bridges. Additionally, a user interface enables timely parameter adjustments for modular components to support both simulation and evaluation. Results are presented in Sections 3.4 and 4.

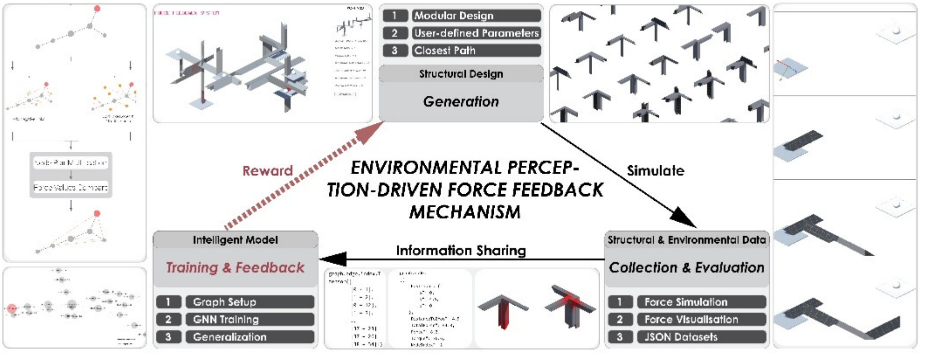

Figure 1. Force Feedback Workflow

3.1. MODULAR DESIGN AND COLLECTIVE AGGREGATION

Through enhancing component mechanical properties and aggregation rules, this study aims to generate structures with better mechanical performance. From the perspective of material properties, the approach combines mechanical joints with geometric design to create modular assembly through physical constraints. Each module features a core triangular prism with two triangular pyramids at its ends (Figure 2), equipped with connection points orientated to facilitate assembly. These points track connectivity, which allows information to flow through the physical structure for efficient assembly and structural optimisation(Tibbits & Cheung, 2012). Regarding aggregation rules, we use a hybrid approach of the top-down design process along with the bottom-up self-organising principle. A list of user-defined parameters, such as boundaries and target point, serves as the foundational rules for construction. Modules are added gradually, allowing for flexible expansion through a variety of connecting points. This approach achieves a balance between design purpose and structural performance by repositioning and reconfiguring parts as needed.

During construction, the first module calculates its optimal docking position based on endpoint orientation and distance, which serves as the input for user-defined placement. Subsequent modules select their positions by interpreting output data from previous modules, considering available connections, and preset rules to determine layout. This system constrains user placement to computed positions and orientations, ensuring logical and efficient aggregation. The process transitions from 2D surfaces to 3D volumes, which allows for the construction of diverse physical forms, such as columns, walls, and slabs, through a gradual bottom-up method.

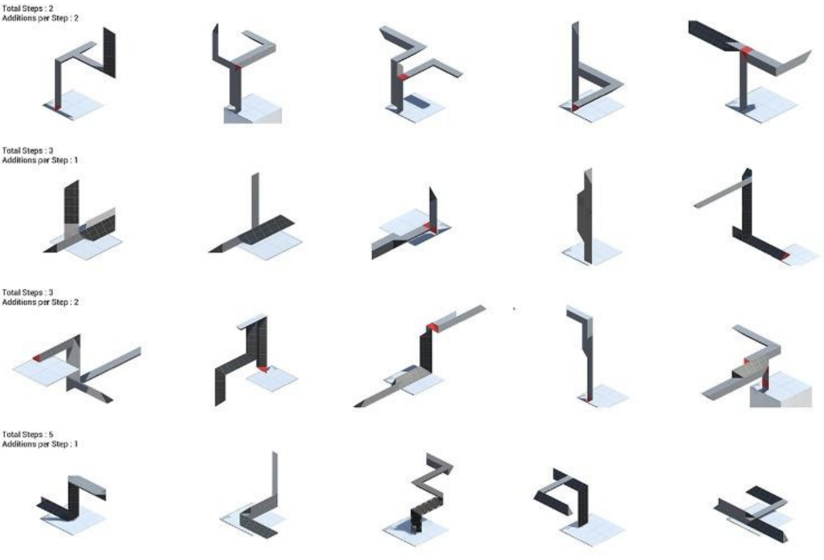

Figure 2. A set of aggregated results for testing aggregation algorithms

3.2. FORCE SIMULATION AND VISUALISATION

To confirm the reliability of the aggregated structures, we conducted static stability and force checks, which determined whether the blocks are in static stability and within the failure strength, as demonstrated in Figure 3. Specifically, our system begins by setting initial conditions and subsequently calculates structural stress and deflection during assembly process. It enables progressive and stable construction from scratch.

The Unity3D engine, combined with the Unity ML-Agents Toolkit, can simulate real-world conditions while managing visual and physical complexities(Juliani et al., 2018). Therefore, we used the Unity3D engine to simulate the environment with a focus on force simulation of building elements—columns, walls, and slabs. These elements are evaluated for performance under varying conditions, including fixed module quantities, target generation points, and loading constraints.

In Figure 3a, structures were evaluated with varying module counts, including 4, 6, 8, and more. When the number of struts is insufficient, cantilever structures exhibit instability and collapse at connection points due to inadequate support. However, as the number of struts increases, the system adapts by organising additional supports at the base and on the opposite side of the extending direction. This approach investigates how the system can employ extra modules to balance forces and improve overall stability while dynamically expanding its structural range.

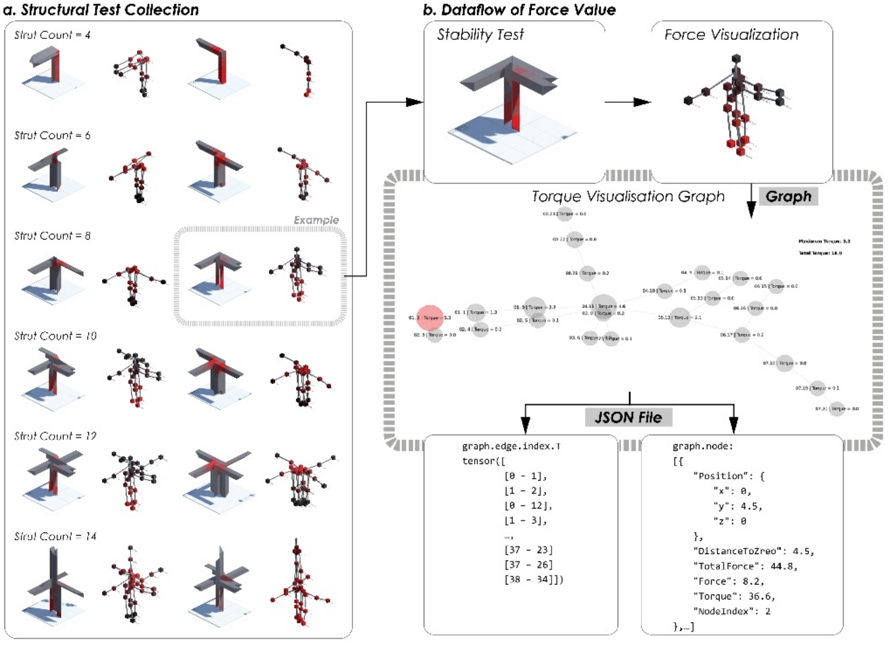

Figure 3. Dataflow of force simulation

3.3. TRAINING AND FEEDBACK OF GNN FOR ENVIRONMENTAL PERCEPTION-DRIVEN ASSEMBLY

Another key challenge is effectively organising and visualising the large-scale datasets generated during simulation. To address this, we developed structured JSON files as shown in Figure 3b to encode the connectivity data between modules, subsequently representing them as graph networks for advanced analysis and training. During the process of data preparation, each module can be simplified into three nodes, which are the two endings and one midway point. The Unity3D simulation environment capsules key information into structured datasets, which include the node features and the edge information. The node features are the world positions (x, y, z), force value, torque value, node connectivity, and node index. Each edge connects two nodes and has an associated value, which could represent the strength or type of connection.

The training model is built using the code provided by Masui (2022) and adopts the link prediction structure is originally from Variational Graph Auto-Encoders (GAEs) (Kipf & Welling, 2016). This method applies two graph convolutional layers to the input node features (x) and graph edges (edge_index), followed by the ReLU activation function. To improve the model's generalization ability, negative links and fake nodes are randomly introduced into the graph using the RandomLinkSplit module from

PyTorch Geometric (PyG). Negative links are generated by sampling node pairs that are not connected in the original graph. This augmentation forces the model to distinguish between real and fake connections, mitigating potential biases caused by the graph's inherent density.

The training process involves a binary classification task, where the predicted edge scores (out) are evaluated against the true labels, with 1 indicating connected edges and 0 representing non-connected edges. The training loss is monitored across epochs to evaluate the model's learning progress, while the accuracy is computed on the validation set to measure performance. Then we compare predicted edge distributions against true physical distributions to identify any systematic biases and to validate their reliability. This step ensures the model accurately captures the physical relationships in the assembly environment. By identifying systematic biases, the feedback loop allows for adjustments in data representation and the introduction of additional features, such as environmental constraints or dynamic interactions, to improve reliability and accuracy.

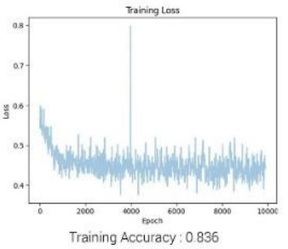

Figure 4. GNN Training Loss

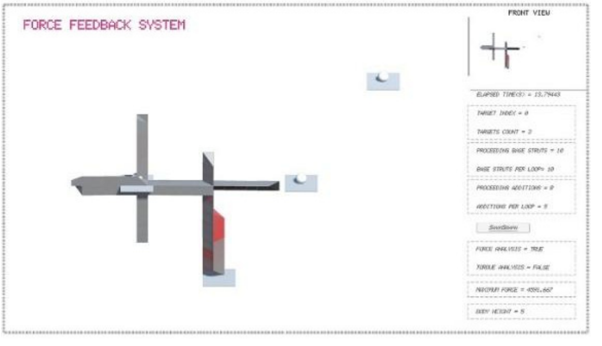

Figure 5. User-Interface for adjusting parameters.

4. Results and Discussion

Our main finding is that our adaptive model can create accurate simulations across varying quantities of struts, emergence dimensions, and span conditions. We conduct 10,000 training steps and the training result (Figure 4) achieved a validate accuracy of 83.6%. To evaluate the generalisation capacity, we developed a simulation model that allows users to interactively explore structural configurations by adjusting parameters. For the generalisation experiments, we evaluated the model under conditions that were significantly different from those during training, such as varying component counts and initial conditions (e.g., position, module orientation, etc.). This ensures broader accessibility in handling dynamically changing graph data. By continuously incorporating feedback from the physical construction environment and updating the graphical representation (K. Zhang et al., 2022), the approach ensures timely adaptability to maintain structural integrity and functionality in diverse and changing construction scenarios.

Dynamic adaptability is the key feature of our model. To ensure the entire process is visualised and can be dynamically interacted with and evaluated by users, we developed a user interface (Figure 5). The interface allows users to define starting and end points as anchor points, which can be interactively adjusted by dragging control points. Once the anchor points are set, the system automatically generates structures with long spans using the required number of modules. In our case, the user sequentially placed two destination points and specified the number of struts available for each stage. In the first stage (Figure 6a), the structure extends to the initial target with ten struts while ensuring a balanced and optimised span. In the subsequent stages (Figure 6b), after adding the second destination, the system dynamically recalculated the most stable path from the root (the foundation parts of the system) to the new target while integrating the additional 5 struts. The final structure maintained overall stability and required span dimensions throughout, dynamically updating its graph representation and edge weights in the training model. And the results were validated for stability through real-world 3D printing, assembly, and testing (Figure 7).

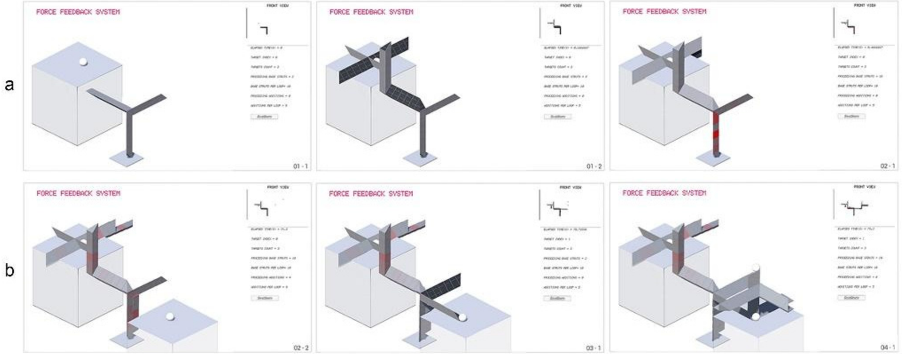

Figure 6. Adaptive aggregation process with three target points

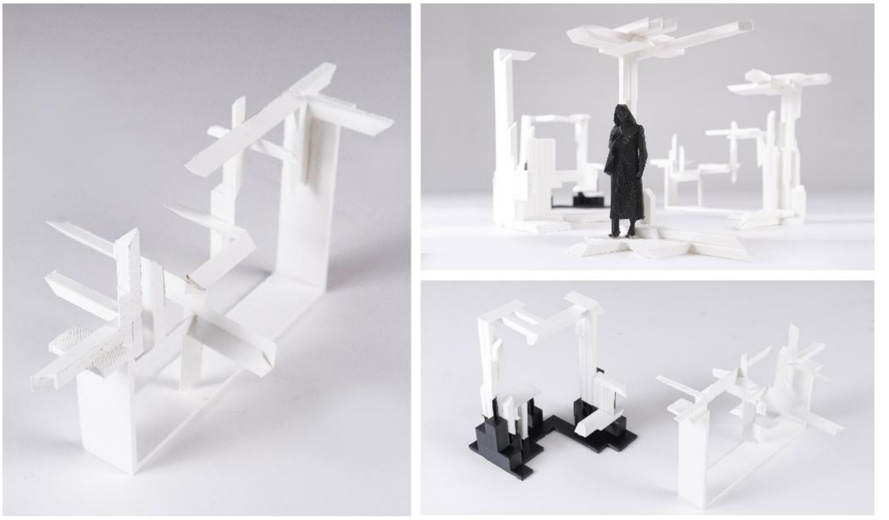

Figure 7. 3D-printed adaptive aggregation models

The integration of GNN models with this dynamic framework demonstrates a significant improvement over traditional methods that lack timely optimisation and adaptability. This aligns with previous studies, such as Slepicka & Borrmann (2024), which emphasise the importance of bidirectional feedback systems. Our feedback mechanism, which incorporates node and link prediction into structural reconfiguration, represents a novel method for ensuring adaptability during structural assembly. This approach enhances decision-making by identifying structural gaps, a capability not addressed in existing modular assembly frameworks. Moreover, from the perspective of forms, our research proved the possibility of generalising local force feedback into 3-dimensional truss structures, which has practical implications for disaster recovery or construction in extreme environments, as it ensures stable and self-optimising assembly.

5. Conclusion

In this study, we have proposed a powerful framework that integrates GNN and ABM to address the challenges of adaptive construction in dynamic and unstructured environments. The framework uses GNN to predict link strength and optimise structural stability, while ABM provides timely monitoring and feedback-driven decision-making to enable simulation of structural performance. Through a Unity3D-based simulation environment, the system demonstrates its ability to flow bi-directional information to enable timely assessment and enhancement of structural configurations and reconfigurations. This decentralised and autonomous approach not only enhances adaptability to complex terrain but also bridges the gap between digital physical integration and real-world construction challenges. By introducing advanced visualisation tools and closed-loop mechanisms, our study presents new possibilities for intelligent modular assembly and adaptive construction workflows.

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