Construction Task Scheduling for Human-Robot Collaboration Considering Human Behavior Uncertainty

Yilin Wang[1], Chao Mao[1], Jue Li[2] and Xingyu Tao[3]

[1]School of Management Science and Real Estate, Chongqing University, China
[2]School of Economics and Management, China University of Geosciences, China
[3]Department of Building and Real Estate, The Hong Kong Polytechnic University, China
nicole_wyl@stu.cqu.edu.cn, maochao1201@cqu.edu.cn, lijue16@cug.edu.cn, xytao@polyu.edu.hk

Abstract –

Human–robot collaboration (HRC) has emerged as a promising approach to improve productivity and safety in construction. However, most existing construction task scheduling methods are predominantly deterministic and fail to account for the significant uncertainty in human task execution caused by factors such as skill variability and fatigue. Such limitations can lead to unstable schedules in large-scale and dynamic construction environments, causing frequent rescheduling, inefficient human-robot coordination, and even safety risks such as spatial conflicts and unintended human-robot collisions after robots are introduced on site. To address this challenge, this study proposes a deep reinforcement learning-based uncertainty-aware scheduling (DRL-UAS) method for HRC in construction. Two key contributions are as follows: (1) task duration uncertainty associated with human workers is modeled using single-valued trapezoidal neutrosophic numbers (SVTNNs), constructed from real-world rebar binding operation data, enabling a structured and interpretable description of execution-time uncertainty; and (2) the scheduling problem is formulated as a Markov Decision Process, in which a graph attention network - proximal policy optimization (GAT-PPO) based deep reinforcement learning framework is developed to learn adaptive and uncertainty-aware scheduling strategies under dynamic HRC conditions. The proposed approach is validated through a rebar binding case and the results show that the proposed method delivers more robust schedules, exhibiting a 3.8% higher tolerance to execution-time deviations than deterministic scheduling methods. Moreover, the learned policies provide actionable insights into optimal human-robot team composition, offering practical guidance for deploying collaborative robots in uncertain and labor-intensive construction environments.

Keywords –

Construction robots; Human-robot collaboration; Scheduling; Uncertainty

1 Introduction

Construction robots can replace workers in performing hazardous and repetitive tasks, while offering advantages such as environmental friendliness and strong economic benefits [1]. However, due to the difficulty for construction robots to cope with unstructured and dynamic environments, human-robot collaboration (HRC) remains an essential approach for accomplishing construction tasks [2]. Compared with traditional construction methods, HRC enables a complementary integration of human strengths in responsiveness and intuitive decision-making with robotic advantages in repetitive operations and high precision [3]. Task scheduling for human-robot collaborative work has become an increasingly popular research topic. In particular, with the rapid development of embodied intelligence in construction robotics [4], construction sites are evolving toward multi-worker–multi-robot collaborative systems [2], where robots are increasingly capable of perceiving, reasoning, and acting within complex physical environments. Under such multi-agent and multi-level collaboration settings, effective task scheduling becomes critical for coordinating heterogeneous human and robotic resources, synchronizing interdependent activities, and ensuring both operational efficiency and on-site safety [5], [6] .

At present, a variety of task scheduling methods have been developed to support human–robot collaborative work, particularly in the manufacturing-related domains. Existing studies can be broadly categorized into optimization-based approaches [7] and learning-based approaches [8], which together provide important theoretical and technical foundations for construction HRC scheduling. On the one hand, mathematical programming methods, such as integer linear programming and constraint programming, have been applied to model scheduling problems with explicit constraints and optimization objectives [7]. On the other hand, intelligent optimization techniques, including genetic algorithms [9] and particle swarm optimization [10], have been introduced to improve solution flexibility for complex scheduling scenarios. More recently, deep reinforcement learning (DRL)–based methods have attracted increasing attention by learning scheduling policies directly, thereby enhancing computational efficiency and real-time decision-making capability in dynamic environments [7] . For example, Yu et al. [11] modeled the human–robot collaborative assembly process as a chessboard game and employed a Markov game framework combined with DQN-based multi-agent reinforcement learning to achieve real-time human–robot task scheduling in dynamic environments without relying on expert knowledge, thereby significantly reducing overall completion time. Pan et al. [12] addressed the challenge of team utility estimation in multi-robot construction scenarios characterized by heterogeneous team sizes and long task horizons by proposing a simulation-based approach that integrates cooperative board-game modeling with Monte Carlo tree search–based scheduling. By jointly minimizing completion time and maximizing robot utilization, their method effectively identified optimal robot team compositions across multiple collaboration scenarios.

Despite these advances, existing construction HRC scheduling methods still suffer from two critical limitations: (1) Limited scalability and adaptability in multi-worker–multi-robot construction settings. Many existing studies on construction HRC are primarily developed for small-scale, station-based collaboration scenarios, where fixed robotic arms assist individual workers in repetitive or contact-intensive tasks, such as grasping and placing standard components [2]. While these studies provide valuable insights into local human–robot interaction, their underlying scheduling formulations are often tailored to simplified task structures and limited agent numbers. When extended to large-scale construction environments involving multiple workers, multiple robots, and complex task interdependencies, optimization-based scheduling methods, including mathematical programming and heuristic approaches [7], [9], [10], suffer from high computational complexity. Even learning-based methods [5], [8], such as DRL, frequently assume relatively stable task sequences and execution conditions. These assumptions significantly limit their adaptability in dynamic construction settings, where task priorities, resource availability, and collaboration modes frequently change, leading to inefficient or suboptimal scheduling decisions in multi-agent scenarios. (2) Insufficient consideration of uncertainty in human–robot collaborative task execution. Most existing human–robot scheduling models are formulated deterministically, treating task durations and execution outcomes as fixed or known in advance. However, in real-world construction HRC scenarios, human task execution is inherently uncertain due to factors such as skill variability, physiological fatigue, cognitive load, and environmental disturbances [13]. Although some studies have recognized human uncertainty at the task execution level and attempted to alleviate workers' physical burden through robotic assistance [14], the impact of such uncertainty on human–robot scheduling decisions in large-scale construction environments is rarely modeled explicitly. Large-scale construction projects typically involve numerous components, equipment, and complex task interdependencies, which significantly increase scheduling complexity [12] and make human behavioral uncertainty particularly influential on scheduling stability and team productivity. Ignoring this uncertainty leads to fragile schedules that are highly sensitive to execution deviations, resulting in frequent rescheduling. Therefore, a critical research question arises: how to optimize task allocation and scheduling in multi-worker–multi-robot construction scenarios while explicitly accounting for human behavior uncertainty.

Although some methods can be referred from other domains, they cannot be directly applied to construction HRC due to fundamental differences in task characteristics and collaboration settings. Unlike factory environments with fixed workstations, stable task sequences, and homogeneous agents, construction HRC involves multi-worker–multi-robot collaboration in unstructured, dynamic environments with complex task interdependencies. Moreover, human task execution in construction is inherently uncertain, making scheduling methods that rely on deterministic assumptions or static system models inadequate for achieving robust and efficient coordination on construction sites. Therefore, this paper aims to develop a deep reinforcement learning–based uncertainty-aware scheduling (DRL-UAS) method for multi-worker–multi-robot collaboration in construction. In particular, this study seeks to answer the following two research questions:

(1) How can the time uncertainty of each task involving human workers be represented? This paper will firstly propose a single-valued trapezoidal neutrosophic numbers (SVTNNs)–based task duration modeling approach to explicitly represent human-related time uncertainty by capturing the indeterminacy arising from skill variability, fatigue, and behavioral fluctuations.

(2) How can human-robot task scheduling be optimized in the presence of time uncertainty? This paper will propose an uncertainty-aware DRL–based

scheduling framework based on a graph attention network–proximal policy optimization (GAT–PPO) architecture to learn adaptive task allocation and scheduling policies that are robust to human execution-time uncertainty in multi-worker–multi-robot construction environments.

2 Methodology

The DRL-UAS method for HRC in construction proposed in this study addresses pervasive uncertainty in construction task scheduling. The overall methodology of the proposed approach is illustrated in Figure 1. The figure presentation follows a similar visual structure to our previous work [15], while the methodology itself is newly developed in this study.

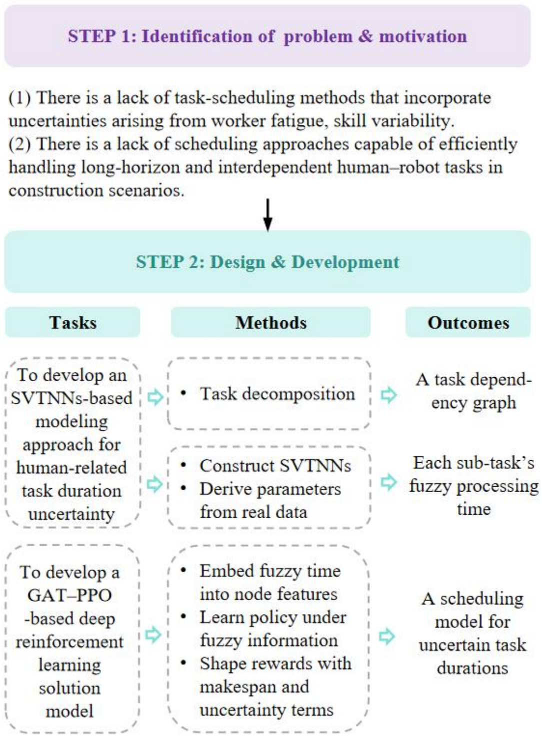


Figure 1. Methodology

In Step 1, the research begins with the identification of the problem and research motivation. Existing construction task scheduling methods fail to adequately account for uncertainties arising from worker fatigue, skill heterogeneity, and dynamic construction environments. In addition, when faced with long-horizon, highly interdependent human–robot collaborative tasks, current approaches often exhibit limited computational efficiency and insufficient scheduling quality, which restricts their applicability in complex, dynamic construction scenarios.

In Step 2, a DRL-UAS framework is designed and developed. The framework focuses on both modeling task-time uncertainty and developing a fuzzy-enhanced PPO scheduler. Specifically, the durations of decomposed construction subtasks, corresponding to atomic execution processes of the final product, are characterized using SVTNNs to represent task-time variability induced by worker fatigue, skill differences, and other human-related factors. Furthermore, a data-driven approach is proposed to construct SVTNNs from real construction data.

Building upon this uncertainty modeling, the scheduling model integrates PPO with a GAT to learn human–robot task scheduling policies under uncertainty. The GAT is employed to encode the task–human–robot interaction graph, where fuzzy task-time uncertainty is explicitly embedded into node features, enabling a high-dimensional representation of the construction system under uncertainty. Through fuzzy-time modeling, task-duration uncertainty is transformed into inputs to the reinforcement-learning environment, enabling the agent to perform interactive learning under ambiguous information and to continuously adapt task and resource-allocation strategies in response to variations in uncertainty. In addition, a reward-shaping mechanism is designed that jointly accounts for project makespan improvement and uncertainty variation, enabling a balanced evaluation of the benefits and risks of each scheduling decision and ensuring both short-term performance gains and long-term policy stability.

It should be noted that the proposed framework focuses on learning uncertainty-aware scheduling policies offline. The adaptability of the model refers to its ability to generate different scheduling decisions under varying uncertainty realizations during execution, rather than real-time policy updating.

2.1 Problem Definition

In HRC construction scheduling problems, the objective of scheduling is to determine the execution entity (construction workers or construction robots) and the execution sequence for each construction subtask, with the aim of minimizing the overall completion time.

Before scheduling, construction tasks need to be decomposed. Taking a 5×5 rebar binding task as an example (as shown in Figure 2), the rebar mesh consists of load-bearing main bars, distribution bars, supports, corner rebars, edge rebars, and middle rebars. The rebar binding process is further decomposed into eight detailed tasks, including placing supports, transporting rebars, marking rebars, placing load-bearing main bars, placing distribution bars, binding corner rebars, binding edge rebars, and binding middle rebars, as summarized in Table 1. Each task can be further divided into more specific subtasks according to the number and locations of components, such as left support and right support, or the first-column and second-column middle rebars. The precedence relationships among these tasks are illustrated in Figure 3. In this study, task decomposition is defined at the process level and follows an object-oriented perspective, where subtasks represent fundamental construction operations associated with the construction entity (i.e., the rebar mesh). Such decomposition is driven by the intrinsic structure and assembly requirements of the construction object and is therefore largely invariant to the type of executor.

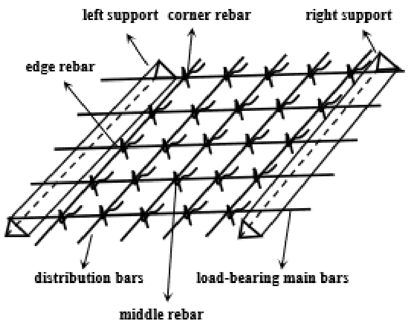


Figure 2. 5×5 rebar binding

Table 1. Rebar binding task decomposition

No.	Task decription
T1	Placing supports S11+S12
T2	Transporting rebar S21
T3	Marking rebar S31
T4	Placing load-bearing main bars S41
T5	Placing distribution bars S51
T6	Binding corner rebar S61+S62+S63+S64
T7	Binding edge rebar S71+S72+S73+S74
T8	Binding middle rebar S81+S82+S83

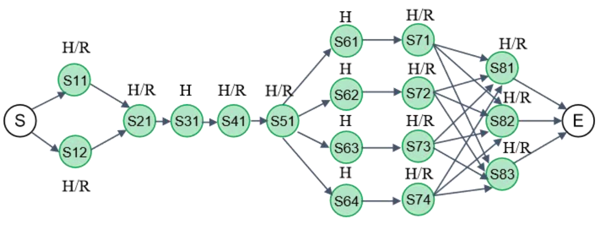


Figure 3. The task dependency diagram

The objective and constraints of the model are defined as follows: Equation (1) defines the objective function of the model, which aims to minimize the overall completion time of all construction subtasks. Equations (2)(3)(4) represent the model constraints. Specifically, Equation (2) ensures that each subtask is assigned to only one executor. Equation (3) specifies that the completion time of each subtask is determined by its start time and the processing time of the corresponding executor. Equation (4) guarantees that the start time and completion time of all subtasks are non-negative.

$$min\, C_{max} = min\left(\max_{T_j \in T} C_j\right) \tag{1}$$

$$\sum x_{jw} = 1, \forall T_j \in T \tag{2}$$

$$C_j = S_j + \sum p_{jw} \cdot X_{jw}, \forall T_j \in T \tag{3}$$

$$S_j \geq 0, C_j \geq 0, \forall T_j \in T \tag{4}$$

Where T_j denotes the jth construction subtask, and T represents the set of all construction subtasks. C_j denotes the the completion time of construction subtask T_j, and S_j denotes the start time of construction subtask T_j. x_{jw} is a binary decision variable, where x_{jw}=1 if subtask T_j is assigned to executor w, and x_{jw} =0 otherwise. p_{jw} represents the processing time of subtask T_j when executed by executor w. $C_{\max}$ denotes the maximum completion time among all construction subtasks, i.e., the makespan.

2.2 SVTNNs-Based Modeling of Human-Related Task Duration Uncertainty

In most real-world construction scenarios, construction durations tend to vary within a certain range due to various disturbances. Particularly in HRC construction settings, robots operate with predefined trajectories and relatively deterministic processing times, whereas the time required for humans to complete tasks is influenced by multiple factors, such as skill proficiency, fatigue, and psychological conditions, resulting in uncertainty in human task execution times. Consequently, the actual start or completion times of human-performed tasks often deviate substantially from the planned schedule. However, modeling and optimization of uncertainty-aware scheduling problems in human–robot collaborative construction have received limited attention in existing research. In this study, such human-related uncertainties are represented through their impact on task execution time. While human behavior also involves other factors such as learning effects and fatigue evolution, modeling these aspects explicitly would require more detailed behavioral data. Therefore, task-duration is adopted as a tractable and practically observable proxy, as it directly affects scheduling feasibility and makespan, thereby capturing the dominant effects of human variability on scheduling outcomes.

Fuzzy set–based optimization methods have been extensively applied to scheduling problems involving uncertain information. Compared with conventional fuzzy numbers, single-valued neutrosophic numbers provide a more comprehensive and refined representation of uncertainty by incorporating three independent components, namely truth, indeterminacy, and falsity. This enhanced representation extends the descriptive capability of classical fuzzy models and contributes to improved robustness and accuracy in optimization results. Accordingly, this study introduces SVTNNs to model the working time of construction workers.

Definition (Trapezoidal Neutrosophic Number).

A trapezoidal neutrosophic number is defined by three trapezoidal fuzzy numbers representing the degrees of truth, indeterminacy, and falsity, respectively. Formally, it can be expressed as

$$\tilde{n} = \langle (a,b,c,d),(e,f,g,h),(l,m,n,p) \rangle$$

where $(a,b,c,d),(e,f,g,h)$ and (l,m,n,p) denote the trapezoidal membership functions of truth, indeterminacy, and falsity, respectively, with each component taking values in [0,1] and satisfying $0 \leq T + I + F \leq 3$. A triangular neutrosophic number is a special case obtained when $b = c$, $f = g$, and $m = n$. More details can be found in [16].

2.3 GAT–PPO–Based DRL Solution Model

In **Section 2.1**, a deterministic mathematical model for human–robot collaborative task scheduling is first established. In **Section 2.2**, SVTNNs are introduced to provide a fuzzy representation of task duration uncertainty. Building upon this, the uncertainty-aware scheduling problem is formulated as a Markov Decision Process (MDP) in this section and solved using a deep reinforcement learning framework that integrates a GAT with PPO. MDP defined by the tuple $\mathcal{M} = \langle \mathcal{S}, \mathcal{A}, \mathcal{R} \rangle$.

State Representation $\mathcal{S}$.

At decision step t, the system state $s_t \in \mathcal{S}$ is represented as a graph $s_t = (\mathcal{V}_t, \mathcal{E}_t)$, where $\mathcal{V}_t$ consists of task nodes and executor nodes (workers and robots), and $\mathcal{E}_t$ encodes precedence and assignment feasibility relations. For each task node i, the feature vector includes $\mathbf{x}_i^t = [c_i^t, \tilde{d}_i]$, where c_i^t denotes completion status, $\tilde{d}_i$ is the fuzzy task duration. Executor nodes encode availability, workload.

Action Space $\mathcal{A}$.

At state s_t, the action $a_t \in \mathcal{A}(s_t)$ selects a feasible task–executor pair $a_t = (i,j), i \in \mathcal{T}_t^{\text{ready}}, j \in \mathcal{F}_i$, where $\mathcal{T}_t^{\text{ready}}$ is the set of tasks whose predecessors are completed, and $\mathcal{F}_i$ denotes the feasible human or robot executors for task i. Executing a_t assigns task i to executor j, updates resource availability.

Reward Function $\mathcal{R}$.

The reward function is designed to jointly optimize schedule efficiency and robustness under uncertainty: $r_t = - \Delta C_{\max}^t - \lambda \Delta U^t$, where $\Delta C_{\max}^t$ denotes the increase in project makespan caused by action a_t, and ΔU^t measures the change in overall schedule uncertainty induced by fuzzy task durations. The weighting coefficient λ controls the trade-off between efficiency and stability. This uncertainty-aware reward guides the agent toward scheduling decisions that are both fast and reliable.

To solve the formulated MDP, a DRL framework integrating a GAT and PPO is adopted. The framework diagram is shown in Figure 4. The system state is represented as a heterogeneous graph consisting of task nodes and human/robot resource nodes, with edges encoding precedence constraints and feasible task–resource relationships. This graph-based representation preserves the intrinsic structural information of the construction scheduling problem. By leveraging multi-layer graph attention mechanisms, the model adaptively identifies critical task dependencies and influential task–resource interactions. Task-related and resource-related features are learned in separate attention subspaces and fused through multi-head attention. The resulting node embeddings are aggregated via global pooling to form a compact and informative state representation for downstream decision-making. The encoded state representation is shared by an actor–critic architecture. The actor network outputs a probability distribution over feasible task–resource assignment actions, guiding scheduling decisions, while the critic network estimates the expected return of the current state to stabilize training. Policy optimization is performed using PPO, which constrains policy updates to avoid excessive changes and ensures learning stability under uncertainty. Through iterative interaction with the environment, the agent learns scheduling policies that balance efficiency and robustness in HRC construction scenarios.

3 Validation and results

This study selects rebar binding as the simulation task scenario. At present, various types of rebar binding robots have been deployed in construction sites, such as mobile rebar tying platforms. However, in practical operations, these robots still require human assistance for critical tasks such as positioning and material feeding, making fully autonomous execution difficult. As a result, rebar binding represents a typical and practically relevant construction scenario in which HRC remains essential.

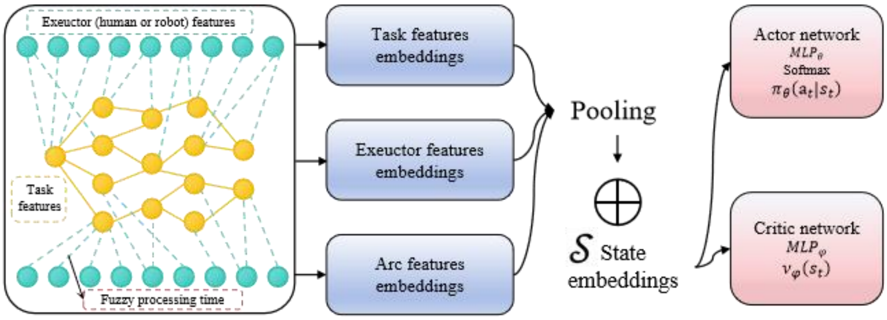


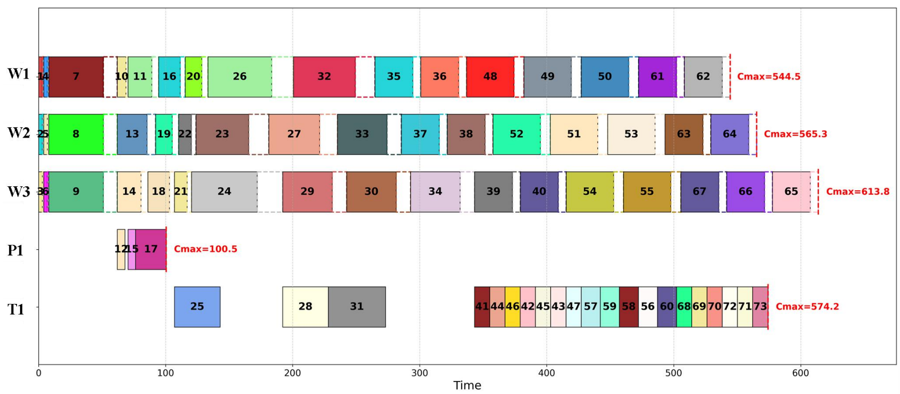
Figure 4. DRL solution framework

To characterize the uncertainty in human task execution during rebar binding, this study collected video clips of rebar binding operations from the YouTube platform. The rebar binding trade examinations shown in these videos provide real-world data for extracting uncertain processing times of individual subtasks. Based on the collected empirical data, an empirical quantile-based approach is adopted to construct SVTNNs, which are used to capture task duration variability arising from differences in worker skill levels and proficiency.

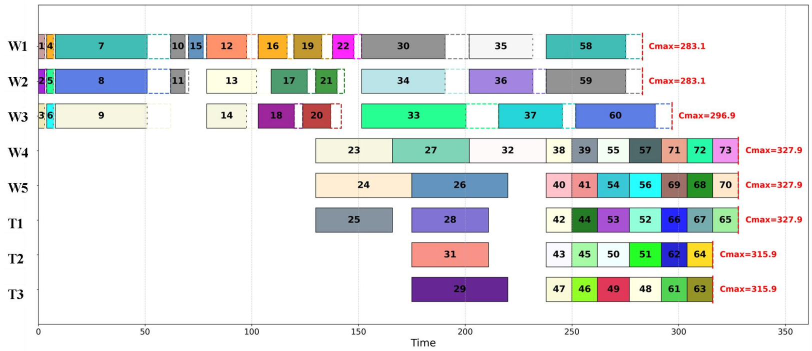
The proposed model is trained using a GAT-based actor–critic framework optimized with PPO. The GAT consists of two embedding layers with four attention heads per layer. Both the actor and critic networks contain two fully connected hidden layers with a hidden dimension of 64 and tanh activation functions. The PPO algorithm is trained for 1000 iterations with a learning rate of 3×10^{-4} and a clipping parameter of 0.2. During training, the learning process is monitored using TensorBoard by tracking both the environment loss and cumulative reward. The reward exhibits a clear increasing trend and converges to a stable value, while the loss decreases and stabilizes over training, indicating effective and stable policy learning.

Taking the 15×15 rebar mesh binding task as an example, the uncertainty-aware scheduling results for human–robot team configurations with 5, 8, and 10 executors are illustrated in Figure 5. Compared with traditional deterministic scheduling Gantt charts, the proposed uncertainty-aware schedules allow task delays caused by worker skill differences, fatigue, and other human-related factors. In the Gantt charts, the dashed-line start indicates the earliest completion time, while the dashed-line end represents the latest completion time, thereby characterizing the uncertainty range of task execution.

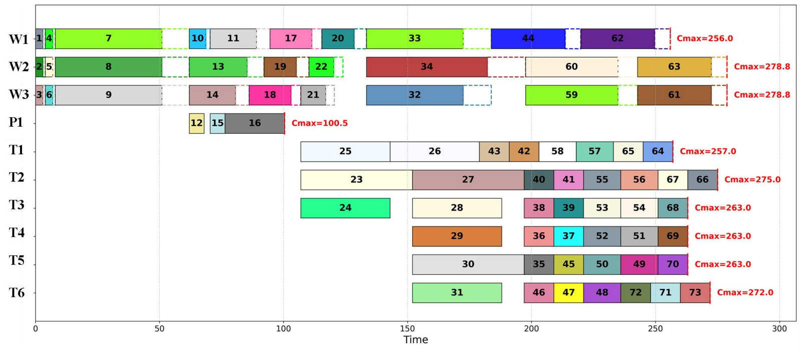
As shown in Figure 5(a), under the 5-executor configuration, the shortest makespan is achieved by a team consisting of three workers, one placing robot, and one tying robot. Figure 5(b) presents the optimal scheduling result for the 8-executor configuration, which includes three workers and five tying robots. Figure 5(c) shows the optimal schedule result for the 10-executor configuration, consisting of three workers, one placing robot, and six tying robots. In the figure, W denotes workers, P denotes the placing robot, and T denotes tying robots. Different colors correspond to different construction subtasks in the 15 × 15 rebar mesh binding task.



(a) 5-executor configuration



(b) 8-executor configuration



(c) 10-executor configuration

Figure 5. Uncertainty-aware scheduling results

From the scheduling results, it can be observed that the number of placing robots remains minimal in the optimal team configurations. This is because placing robots can perform only a limited set of subtasks, mainly related to placing supports and bars. In contrast, tying robots exhibit higher utilization due to the large number of binding-related subtasks. Workers demonstrate the highest utilization overall, as all subtasks in this scenario can be performed by human workers. These observations indicate that the development of multi-functional robots, such as humanoid robots capable of executing diverse subtasks, would further enhance the effectiveness and flexibility of HRC construction.

Follow [9], deviation is defined as the variability of makespan under uncertain processing conditions, typically measured based on the dispersion (e.g., standard deviation) of simulated makespan outcomes. Lower deviation indicates improved stability and robustness of the scheduling solution. Robustness is evaluated using the relative deviation between realized and planned makespan under uncertainty. The 3.8% improvement indicates reduced deviation compared with deterministic scheduling, reflecting enhanced stability across scenarios.

4 Conclusion

This study investigates HRC construction scheduling from an uncertainty-aware perspective. By incorporating human-related time variability into the scheduling process and embedding it within a learning-based decision framework, the proposed approach provides a systematic way to handle the mismatch between deterministic robotic execution and uncertain human performance. The results indicate that accounting for uncertainty leads to more stable and realistic scheduling outcomes and reveals the distinct roles and utilization characteristics of different human and robotic resources in collaborative construction tasks.

Despite these contributions, this study has several limitations that point to promising directions for future research. First, the proposed scheduling framework is validated through simulation-based case studies, and further empirical validation using large-scale field data would strengthen its practical applicability. In addition, the current model assumes predefined collaboration structures and does not consider dynamic changes in team composition or worker learning effects over long-term project execution.

This study models human uncertainty primarily through task-duration variability. Future work could extend this framework by incorporating richer behavioral dynamics, such as learning effects and fatigue progression, to further improve the realism and adaptability of HRC scheduling models. In addition, the study does not consider real-time policy updating or online learning during execution. Future research could incorporate online adaptation mechanisms and real-time feedback to further enhance the responsiveness and deployability of the proposed framework in dynamic construction environments. Moreover, the proposed framework is designed to scale through its graph-based representation, which can accommodate varying numbers of tasks and human-robot resources. Future work will further evaluate the approach on larger-scale and more diverse construction scenarios to comprehensively assess its scalability.

Acknowledgement

This research is supported by the Hong Kong PolyU (UGC) Start-up Fund for New Recruits (P0056204) and Zhejiang Provincial "Pioneer" and "Leading Goose" Science and Technology Plan Project (2026C04040).

References

[1] Y. Fu, J. Chen, and W. Lu, "Human-robot collaboration for modular construction manufacturing: Review of academic research," *Automation in Construction*, vol. 158, p. 105196, Feb. 2024, doi: 10.1016/j.autcon.2023.105196.

[2] M. Zhang, R. Xu, H. Wu, J. Pan, and X. Luo, "Human–robot collaboration for on-site construction," *Automation in Construction*, vol. 150, p. 104812, Jun. 2023, doi: 10.1016/j.autcon.2023.104812.

[3] F. Ranz, "Capability-based Task Allocation in Human-robot Collaboration," *Procedia Manufacturing*, 2017.

[4] J. Chen *et al.*, "EMOS: Embodiment-aware Heterogeneous Multi-robot Operating System with LLM Agents," Oct. 30, 2024, *arXiv*: arXiv:2410.22662. Accessed: Nov. 09, 2024. [Online]. Available: http://arxiv.org/abs/2410.22662

[5] W. Song, X. Chen, Q. Li, and Z. Cao, "Flexible Job-Shop Scheduling via Graph Neural Network and Deep Reinforcement Learning," *IEEE Trans. Ind. Inf.*, vol. 19, no. 2, pp. 1600–1610, Feb. 2023, doi: 10.1109/tii.2022.3189725.

[6] Y. Wang, C. Mao, and T. Wang, "A Study of Human-Robot Collaborative Construction Task Allocation Problem Considering the Level of Task Danger," in *Proceedings of The Sixth International Confer*, 2025, pp. 511–523.

[7] A. Liu, P. B. Luh, B. Yan, and M. A. Bragin, "A Novel Integer Linear Programming Formulation for Job-Shop Scheduling Problems," *IEEE Robotics and Automation Letters*, vol. 6, no. 3, pp. 5937–5944, Jul. 2021, doi: 10.1109/LRA.2021.3086422.

[8] C. Zhang, W. Song, Z. Cao, J. Zhang, P. S. Tan, and X. Chi, "Learning to Dispatch for Job Shop Scheduling via Deep Reinforcement Learning," in *Advances in Neural Information Processing Systems*, Curran Associates, Inc., 2020, pp. 1621–1632. Accessed: Mar. 23, 2025. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2020/hash/11958dfee29b6709f48a9ba0387a2431-Abstract.html

[9] Z. Jia, S. Xie, and W. Zhang, "Flexible task assignment and assembly scheduling for human-robot collaboration cell considering uncertainty," *International Journal of Production Research*, Feb. 2025, Accessed: Apr. 27, 2025. [Online]. Available: https://www.tandfonline.com/doi/abs/10.1080/00207543.2025.2469286

[10] Y. Xu, M. Zhang, M. Yang, and D. Wang, "Hybrid quantum particle swarm optimization and variable neighborhood search for flexible job-shop scheduling problem," *Journal of Manufacturing Systems*, vol. 73, pp. 334–348, Apr. 2024, doi: 10.1016/j.jmsy.2024.02.007.

[11] T. Yu, J. Huang, and Q. Chang, "Optimizing task scheduling in human-robot collaboration with deep multi-agent reinforcement learning," *Journal of Manufacturing Systems*, vol. 60, pp. 487–499, Jul. 2021, doi: 10.1016/j.jmsy.2021.07.015.

[12] Z. Pan and Y. Yu, "Optimizing heterogeneous multi-robot team composition for long-horizon construction tasks: Time- and utilization-guided simulation," *Automation in Construction*, vol. 165, p. 105520, Sep. 2024, doi: 10.1016/j.autcon.2024.105520.

[13] K. E. Stecke and M. Mokhtarzadeh, "Balancing collaborative human–robot assembly lines to optimise cycle time and ergonomic risk," *International Journal of Production Research*, vol. 60, no. 1, pp. 25–47, Jan. 2022, doi: 10.1080/00207543.2021.1989077.

[14] S. Xiang, R. Wang, and C. Feng, "Mobile projective augmented reality for collaborative robots in construction," *Automation in Construction*, vol. 127, p. 103704, Jul. 2021, doi: 10.1016/j.autcon.2021.103704.

[15] X. Tao *et al.*, "Enhancing BIM security in emergency construction projects using lightweight blockchain-as-a-service," *Automation in Construction*, vol. 150, p. 104846, Jun. 2023, doi: 10.1016/j.autcon.2023.104846.

[16] F. Smarandache, *A Unifying Field in Logics: Neutrosophic Logic. Neutrosophy, Neutrosophic Set, Neutrosophic Probability (fourth edition): Neutrsophic Logic. Neutrosophy, Neutrosophic Set, Neutrosophic Probability (fourth Edition)*. Infinite Study, 2005.