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Data-driven out-of-order model for synchronized planning, scheduling, and execution in modular construction fit-out management

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Abstract

Fit-out operations in modular construction exhibit unique features, such as limited room space and diversely distributed operations in the building. These features pose significant challenges to planning, scheduling, and execution (PSE) of fit-out activities due to operational parallelism, distributional diversity, and narrower constrained time window in modular construction. Hence, logistics-operation and multi-operations synchronizations in a real-time manner are crucial for PSE of modular construction fit-out management. With the support of cutting-edge information technologies, the real-time data inside the generated digital twins can simplify online optimization models and convert stochastic factors into deterministic parameters. This paper formulates a novel real-time data-driven Out-of-Order (OoO) model for synchronized PSE in modular construction fit-out management. Drawing inspiration from OoO mechanism in Central Processing Unit (CPU), a real-time data-driven and rolling-horizon-based OoO model is proposed for PSE of modular construction fit-out, employing a forward heuristic algorithm for solution. Time–space–state data from digital twins are updated to facilitate dynamic decision-making of managers. Through stochastic computational experiments, we demonstrate the effectiveness of OoO model in optimizing project metrics and the improved resilience in uncertain environments.

1 | INTRODUCTION

Modular construction is an industrialized approach that involves producing prefabricated modules in off-site factories and transporting them to the construction site for assembly (Lawson et al., 2012). This method results in distinct spatial building characteristics marked by precise division and arrangement, featuring rectangular shapes and geometrically structured room layouts (Lim et al., 2022; Thai et al., 2020). Moreover, due to transportation constraints, prefabricated modules are often limited in size, leading to smaller room dimensions within assembled structures, compared to traditional cast-in-situ buildings (Bertram et al., 2019). Consequently, fit-out operations need to be adjusted accordingly to accommodate these specific conditions in modular construction. Building fit-out aims to establish a tenant's internal space suitable for occupation and activities (Baccarini & Bateup, 2008; Ning, 2017). In modular construction, fit-out operations involve arranging interior spaces, encompassing various operations, such as the setup of interior spaces, mechanical, electrical, plumbing, heating, ventilation, and air conditioning, and furniture arrangement. Planning, scheduling, and execution (PSE) play crucial roles in organizing and coordinating resource supplies and operations in this specific type of fit-out. Planning aims at the long-term organization of construction project activities for global objective optimization, such as project period definition, material logistics, and crew arrangement (Karim & Adeli, 1999a). Scheduling breaks major activities into detailed work packages and determines the related sequencing and timing (Adeli & Karim, 2001; Senouci & Adeli, 2001). Execution is the operational stage to flexibly adjust task implementation and allocate operations to different workers in specific time windows (Naticchia et al., 2019).

During PSE progress in modular construction fit-out projects, several unique characteristics contribute to operational difficulty. First, fit-out activities often occur concurrently in different rooms on various floors, leading to a large decision space, compared to traditional construction methods like cast-in-situ and precast construction. Second, the smaller size of modular construction rooms intensifies the complexity of fit-out operations as each room has a limited capacity for workers and machinery. Additionally, the limited buffer area in small rooms necessitates adherence to just-in-time (JIT) rules for material delivery, emphasizing the importance of coordinating operations and logistics. Third, modular construction projects typically have shorter project durations and earlier due dates, particularly significant in locations like Hong Kong with pressing housing needs (Xu et al., 2020). This urgency further complicates the spatial–temporal complexity and uncertainty of fit-out processes due to the narrow spatial–temporal windows. Hence, effective allocation and coordination of massive resources (e.g., workers, materials, and tools) at the right time and place become crucial (Tao et al., 2020). The problem size of modular construction fit-out is substantial due to the large number of fit-out operations and heterogeneous operational types. To analyze the nature of the PSE problem in modular construction fit-out, the operational type is akin to the fixed-position assembly problem in the manufacturing area (Huang et al., 2007). Both of these two problems involve delivering materials to fixed positions (modular rooms in construction fit-out and shop-floor islands in manufacturing) for assembly and allocation with appropriate workers or machines (Guo, et al., 2020). The distinction lies in the fact that the number of modular rooms is typically much larger in a building than the number of shop-floor islands in most cases. The half-finished product in manufacturing after partial assembly could be transported from one island to another, but the modular room is always fixed, and any required material should strictly follow the spatial–temporal constraints. Hence, real-time synchronization between operations and corresponding resources is essential during modular construction fit-out PSE.

According to the definition in natural science, synchronization refers to "the adjustment of rhythms due to interaction" (Glass, 2001). Two types of synchronization are mainly applied in engineering management: multi-operations synchronization and logistics-operation synchronization (Chankov et al., 2016). Multi-operations synchronization refers to the rhythm and repetitive behaviors controlled in a certain relationship during production processes. Logistics-operation synchronization is generally defined as the coupling of operations that are under the interaction and collaboration by material flows. Synchronization allows the right materials to be delivered to the corresponding activities while meeting the spatial–temporal allocation requirements. Operations can be implemented at the appropriate time and in the correct place, which is similar as the JIT and pragmatic "Make Do" concepts observed in real-life project implementations. The synchronization of multi-operations and logistics-operations in modular construction fit-out PSE is developed based on the foundational framework of resource-constrained project scheduling problem (RCPSP), acknowledged as an Nondeterministic Polynomial (NP)-hard problem (Blazewicz et al., 1983).

Based on the inherent characteristics of this managerial problem and the unique features of modular construction fit-out, several research challenges emerge for synchronized PSE in this scenario: (1) The smaller modular space results in a restricted buffer area for material storage, leading to a narrow time window between material arrival and operation start times. Unlike traditional fixed-position assembly, fit-out operations are more spatially dispersed both horizontally and vertically. Moreover, the global space inside a building is larger than that of a factory, also requiring a longer makespan period; (2) Generating coordinated decisions that integrate fit-out operations and material supply in a real-time synchronized manner under uncertain environments remains a challenge. This challenge is common in engineering management but is exacerbated in modular fit-out construction due to the larger operational space in buildings and diverse operations. Fluctuations and changes in customer demands and operational processes are more likely, necessitating stakeholders' communication to collaboratively decide "when, where, what, and how to do?" within both the current and upcoming time windows to achieve seamless logistics-operation synchronization; and (3) Traditional optimization models like mixed integer linear programming (MILP) and metaheuristics can provide offline solutions with theoretically optimal or near-optimal values, offering a static PSE blueprint for project management. However, these solutions often struggle to handle uncertainties and require significant computational resources for rearrangement in dynamic environments such as construction sites. Hence, there is a need for more flexible and resilient online optimization models with affordable computing time to support PSE decision-making in modular construction fit-out management.

To address the above challenges, this paper proposes a real-time data-driven Out-of-Order (OoO) model for PSE of modular construction fit-out. The framework of modular construction fit-out is developed. Smart objects based on Internet-of-Things (IoT) and computer vision (CV) can collect real-time information of activities and resources to generate their corresponding digital twins. The real-time state and progress inside the digital twins could enhance the simplicity of online PSE, where many uncertain and stochastic factors are converted into deterministic parameters facilitated by the updated real-time time–space–state data (Li, Li, et al., 2023). Enhanced visibility and traceability are provided to facilitate dynamic decision-making for project managers and automatic navigations and alerts for the operators. Inspired by the OoO mechanism in Central Processing Unit (CPU), a novel real-time data-driven and rolling-horizon-based OoO model is proposed for the synchronized PSE in modular construction fit-out with improved flexibility and resilience. A forward-devised heuristic algorithm has been designed to efficiently resolve this model within acceptable computational time. Stochastic computational experiments are conducted to evaluate the OoO model under different uncertainty scenarios. Rule-based algorithms (e.g., first come first served [FCFS], shortest processing time [SPT], and earliest due date [EDD]) and one MILP algorithm are applied for the comparison with the OoO model. Sensitivity analysis about the effects of rolling time window size and workforce capacity is also implemented. Compared with other algorithms, the experiment result shows that the proposed OoO model can provide near-optimized solutions on makespan, holding time, and tardiness and also achieve higher resilience to reduce the volatility caused by uncertainties.

The structure of the remainder article is organized as follows. Section 2 reviews the prior research. Section 3 describes the digital twin-enabled environment for modular construction fit-out management. Section 4 formulates the real-time data-driven OoO model for synchronization. Section 5 reports the computational experiments. Final conclusions and limitations are presented in Section 6.

2 | LITERATURE REVIEW

The literature review of the OoO model for modular construction fit-out has two streamlines, including construction planning, scheduling, and execution, and synchronization in operations management.

2.1 | Construction planning, scheduling, and execution

PSE in construction management involves decision-making processes to allocate resources (e.g., crews, machines, and materials) to various activities for single or multiple objective optimization (Weiss, 1995). Three main types of PSE methods exist in construction management: exact algorithms, heuristic/metaheuristic algorithms, and rule-based algorithms: (1) Exact algorithms can always find the optimized solution of the combinatorial optimization problem in most cases. But in large-sized PSE problems, exact algorithms lack cost-efficiency due to the dramatically increasing computational time with the problem size, which faces the "combinatorial explosions" problem. (2) Heuristic and meta-heuristic algorithms cannot guarantee to output the globally optimized solution, but they can obtain the near-optimized solution with an acceptable computing time (Gigerenzer & Gaissmaier, 2011). Compared with the problem-dependent heuristics methods, meta-heuristics methods do not depend on the nature of the problems, so they are feasible to different problems. (3) Rule-based modeling is also a computational approach that uses a set of rules that indirectly specifies operations management problems (Chtourou & Haouari, 2008), which includes some classic algorithms, such as FCFS, SPT, and EDD. However, most of these rule-based algorithms lack the global optimization capacity and are mainly applied to solve the near-optimized problems in simple cases.

Construction PSE primarily addresses the RCPSP and resource-leveling problem (RLP; Gwak & Lee, 2021). RCPSP is widely acknowledged as NP-hard in the realm of construction project management (Zhang et al., 2006). The scheduling of activities within RCPSP takes into account resource constraints and precedence relationships to optimize predefined objectives, such as makespan, holding time, tardiness, and project cost (Ghoddousi et al., 2013; Karim & Adeli, 1999b). To achieve a globally optimized schedule with minimized construction costs, adjustments to the construction makespan are employed to address the cost–duration trade-off (Adeli & Karim, 1997; Adeli & Wu, 1998). Spatial–temporal analysis plays a crucial role in ensuring the efficacy of RCPSP within the realm of engineering management, encompassing maintenance and inspection tasks (Memarzadeh & Pozzi, 2016; Yi & Sutrisna, 2020). Considering the constraints of time and space resources, a spatial–temporal decomposition approach is applied to RCPSP in construction. Additionally, a spatial–temporal network is established to optimize total resource costs and makespan across various types of construction projects (Liu et al., 2017). For the uncertainties handling in a stochastic environment, disruptions are considered to address through mixed-integer programming to minimize project makespan or cost (Adeli & Sarma, 2006; Birjandi & Mousavi, 2019). Concurrent scheduling methods, such as the critical path method and simulation-based scheduling, are employed to compress project schedule durations (Lim et al., 2014). In the spatial domain, researchers focus on workspace limitations, establishing computational models to control and mitigate interference and traffic in construction project scheduling (Adeli, 2004; Tao et al., 2020). Given the prevalence of both renewable and nonrenewable resources in construction PSE, heuristics methods are employed to address the sequence and mode selection of tasks (Cheu et al., 2004; Li & Zhang, 2013). In contrast to analytic algorithms, while the output solution may not be the most theoretically optimized, heuristics methods offer advantages such as reduced computational complexity and increased flexibility and adaptability in configuration.

Within the domain of construction management, the RLP emerges as a pertinent challenge, notably in the intentional scheduling of repetitive construction projects to enable uninterrupted workflow from one unit to the next, minimizing preemptions and interruptions (Ponz-Tienda et al., 2017). Line-of-Balance (LoB) studies in RLP have undergone comprehensive scrutiny and refinement to achieve synchronized resource allocation, ensuring the continuity of the labor force and mitigating production rate violations. This method involves representing repetitive tasks in construction projects through single lines on a graph (Arditi et al., 2002). The natural rhythm principle, a distinctive feature of LoB, contributes to smoother resource utilization by minimizing absolute deviations in daily resource usage from standard levels, all without impacting required working hours (Damci et al., 2013). This inherent rhythm allows for the adjustment of operational start times in different units by modifying the workforce, preserving task duration in each unit, and adhering to precedence relationships among tasks. The linear scheduling method, a widely recognized linear scheduling technique, empowers stakeholders to monitor and fine-tune working rates through operation quantity versus time graphs, aligning with rigorous academic standards in the construction management field (Su & Lucko, 2016).

2.2 | Synchronization in operations management

Synchronization problem in the industry receives more attention in the last 5 years. It is more related to the reliable and accurately workable schedule and resources allocation at the right time in the right place as the JIT philosophy (Chankov et al., 2017). Real-time data derived from cutting-edge technologies, such as IoT, CV, and cloud computing, drive the synchronization in time and space among various practical applications. Massive digital twins are integrated with PSE systems to provide digitalized and automatic decision-making support to project managers (Guo, Li, et al., 2021). The concept of production synchronization contains three pillars, namely, real-time visibility and information-sharing, coordination of decision-making, and synchronized operations that are leveraged to synchronize operations and delivery with the time window on the shop floor. Simultaneity (lowest waiting times), punctuality (minimum number of tardy jobs), and cost-efficiency (lowest setup times) are the mainly considered performance indexes in synchronized PSE (Guo, Zhong, et al., 2021). Achieving proper production capacity with enhanced flexibility and responsiveness necessitates frequent changeovers and reconfigurations to align with dynamic demands in evolving project environments (Ling et al., 2022). For the data-driven model to cope with synchronization in industry, Li, Li et al. address the Production and Intralogistics Synchronization (PiLSync) problem, closely linked to scheduling issues (Li, Li, et al., 2023). While both allocating limited resources to tasks, they differ fundamentally. PilSync prioritizes spatiotemporal synchronization over rigid schedules, ensuring accurate operations by aligning resources effectively. Unlike traditional scheduling, PilSync acknowledges transparency and traceability in Industry 4.0, where real-time data monitors ongoing operations under uncertainties (Li, Guo, et al., 2023). It integrates decision-making with execution, emphasizing the immediate use of real-time data for system resilience and consistency. PilSync diverges from deterministic assumptions, recognizing the stochastic nature of the system state and ensuring seamless synchronization between production and intralogistics aspects.

In the realm of construction project management, the development of a real-time synchronization system between building information modeling (BIM) data and virtual reality equipment has been instrumental in enhancing operational efficiency through improved information sharing and fostering common understanding among stakeholders. This innovation builds upon an inventive method proposed by Du et al., which leverages BIM metadata interpretation and communication via cloud computing (Du et al., 2018). Furthermore, the integration of real-time data on resource status and project progress from digital twins has been pivotal in driving PSE models for logistics and operations synchronization during on-site assembly in prefabricated construction (Jiang et al., 2022). This approach ensures smoother coordination and timely decision-making on the construction site. In the sphere of logistics, synchronization poses a critical challenge for enhancing service quality and reducing costs. Gavriilidou and Cats have addressed this issue by developing a real-time passenger data-driven transfer synchronization control mechanism. By optimizing single-line regularity and synchronizing inter-line arrivals, this mechanism minimizes passenger transfer times, thereby improving overall transport efficiency (Gavriilidou & Cats, 2019). Moreover, a real-time data-driven mechanism is proposed to prioritize lines and positions for public transport transfer synchronization. By leveraging historical data and real-time inputs, this approach minimizes passenger transfer times within the public transport network, enhancing user experience and efficiency (Yap et al., 2019). Additionally, machine learning has enabled the utilization of historical data to forecast or monitor real-time activities. At the same time, the newly generated real-time data can be back-propagated to improve the accuracy of the previous algorithmic model for industrial synchronization (Pereira & Frazzon, 2021). Overall, these advancements underscore the importance of real-time data integration, innovative methodologies, and the application of emerging technologies in addressing synchronization challenges across various domains, ultimately driving efficiency and optimizing resource utilization.

Several research gaps have been identified in the literature review. First, a limited number of studies have delved into the PSE problem in modular construction fit-out. This particular PSE problem in modular construction presents stricter spatial–temporal constraints, a more adaptable parallel operation mode, limited operational space, and encompasses a diverse array of operations. Second, with the pervasive adoption of digital technology in engineering management, there exists an opportunity to implement forward heuristic algorithms driven by real-time data, coupled with the rolling time window method. These algorithms offer substantial flexibility and robustness to navigate through uncertain events. Although such algorithms have been developed within the manufacturing industry, there has been insufficient attention devoted to crafting related algorithms tailored specifically for the construction field. Third, in the design of real-time data-driven algorithms, previous research lacks a comprehensive analysis and discussion of some key parameters, such as the rolling time window scale. The scale of the rolling time window directly impacts decision frequency, real-time data accuracy, state prediction lead time, and system response speed to disturbances. To effectively implement this online optimization model for PSE problems, a thorough examination of these core parameter settings is imperative.

3 | DIGITAL TWIN-ENABLED SMART MODULAR CONSTRUCTION FIT-OUT

Fit-out in the modular construction mainly includes four stages: water and electricity pipeline installation phase, bricklaying phase, painting and coating phase, and furniture and household appliances installation phase. *Water and electricity pipeline installation phase* includes water and electricity disclosure, modification, and acceptance. *Bricklaying phase* mainly contains bricklaying disclosure, construction, and acceptance. *Painting and coating phase* mainly engages in wall, ground, ceiling, and other painting. *Furniture and household appliances phase* is the process where the water heater, kitchen and bathroom ceiling, range hood, floor cabinet, switch socket, and lamp and sanitary begin to be installed. Then furniture, household appliances, and decoration entered the site to gradually enrich the interior space and finally complete the overall home decoration design.

The main works of fit-out can be divided into a series of operations $\{1,\ldots, j,\ldots, J\}$ and corresponding material supplies $\{1,\ldots, m,\ldots, M\}$. From a spatial perspective, the building is vertically divided into several floors and horizontally divided into several modular units $\Delta\mathcal{E}$ based on the components division structure as shown in Figure 1. The operations and related materials are synchronized and processed in one modular area $\Delta\mathcal{E}$. From a temporal perspective, the overall PSE decision horizon H is

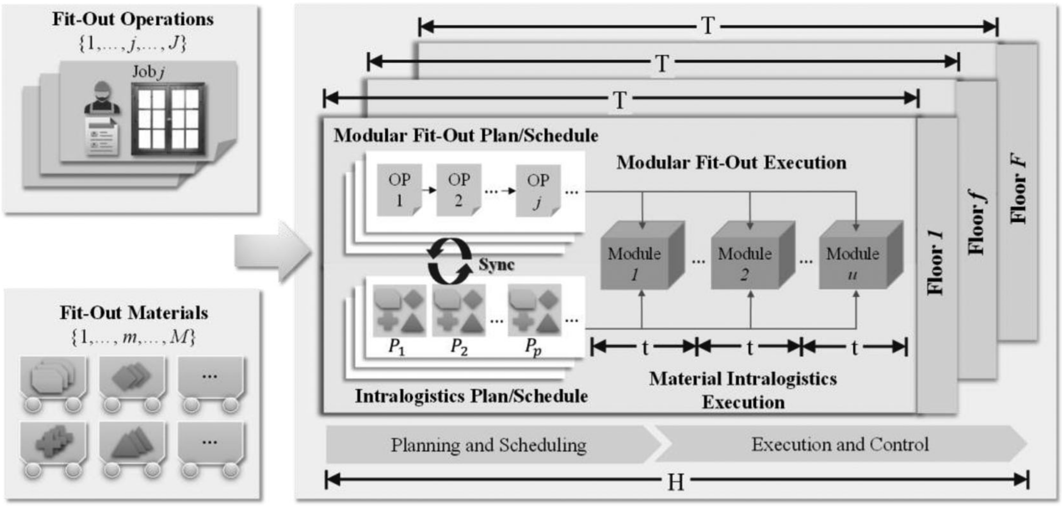

FIGURE 1 Synchronized management for operations and material supplies in modular construction fit-out.

discretized into a series of medium-length time window T, which is always 1 week or 3 days. Then time window T is discretized into short-length time interval t, which is always 1 day. Time interval t is divided into several decision cycles τ for real-time task adjustment and re-sequence, which is 10 to 60 min. Thus, the modular fit-out PSE problem is spatial–temporally discretized into an equivalent simplified system of finite space and time units.

Research Problem Definition: This study focuses on the synchronization problem, which is developed based on the scheduling problem. While both mainly aim to assign constrained resources to tasks, they differ fundamentally in their core concepts of executing operations. The two key differences are illustrated as follows.

1. Traditional scheduling approaches primarily emphasize fixed objective functions, particularly focusing on the punctuality of given tasks. In contrast, synchronization places paramount importance on achieving spatiotemporal simultaneity of resources and operations, prioritizing flexibility over rigid allocation. This concept underscores the inherent interdependence between operations and logistics, necessitating decisions that holistically consider both for seamless coordination.
2. Conventional scheduling tends to rely on probabilistic estimation and distribution models, which focuses on a priori decision-making rather than actual execution based on the current situation. In contrast, synchronization embraces a paradigm shift by fully integrating real-time data implantation driven by cutting-edge digital technologies in the smart construction domain. This transformation converts numerous uncertain variables into deterministic parameters, seamlessly integrating them into the control system.

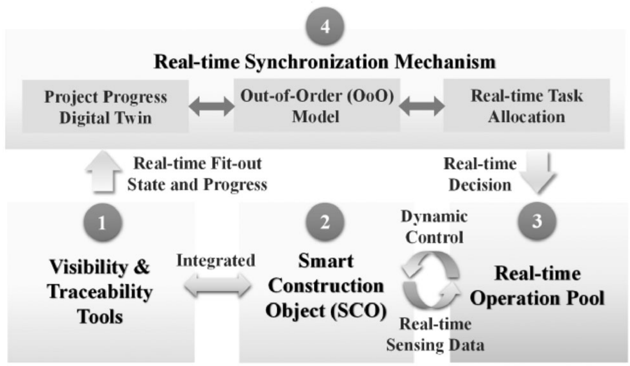

FIGURE 2 Framework of digital twin-based modular fit-out site.

Hence, the precondition of synchronization is a digital twin environment with enhanced real-time visibility and traceability. The implementation framework of digital twin-enabled intelligent fit-out construction has four key parts, including smart construction object (SCO), real-time operation pool, visibility and traceability tools, and real-time synchronization mechanism, as shown in Figure 2.

SCO is the basic element to establish high-fidelity, traceable, and hyper-connected cyber-physical construction site with enhanced real-time visibility and traceability. Physical resources on construction site are digitalized to form augmented cyber avatars, which could collect and update real-time data by IoT-based devises, such as Bluetooth, radio frequency identification, and ultra-wideband (UWB). Physical twins cooperated with the corresponding digital twins can generate SCOs, which mainly have three capacities: (1) sense the real-time status and environmental information, such as the real-time locations of fit-out resources; (2) receive and analyze the relevant fit-out operations from real-time operation pool; and (3) automatically make decisions based on the real-time states of fit-out operations, resources, and construction progress. Real-time interoperations of SCOs can be classified into two perspectives. From the vertical perspective, SCOs can receive the operation and ambient data from the operation pool and visibility and traceability tools, as well as update the analyzed decisions to other function modules; From the horizontal perspective, SCOs can interact with each other based on the dynamic instructions from stakeholders. For the real-time detection of the on-site resources and operations, CV is also utilized to identify the material types and operational time. Thus, IoT and CV can collaborate to achieve real-time information uploading about resource status and progress on the fit-out construction site. Hence, the digital twin-based site provides real-time navigations and alerts.

Real-time operation pool is applied to synchronize and coordinate the fit-out operations for SCOs based on dynamic demands. Visibility and traceability tools are used for updating the real-time operation pool through timeline, serving as the basis of spatial–temporal synchronization during digital twin-enabled fit-out PSE. To update the operation pool with time flow, the input of one SCO at the start time of the current time window contains the output of this SCO at the previous time window with the related information that occurred in the preceding window. Through real-time visibility and traceability analytics, project managers can understand the real-time states of SCOs and construction progress as the foundation for the synchronization of fit-out resources and operations. Real-time data-driven OoO model can facilitate high-level planning and scheduling and low-level executions with both spatial–temporal and data-driven decision synchronization, which will be illustrated in Section 4. For high-level planning and scheduling decision-making, the overall planning horizon of project period T is divided into multiple micro-scheduling time windows t. Based on the project demands and fit-out resource's constraints, the OoO model generates the schedule for period $t + 1$ according to the block/floor/module spatial configuration. For low-level execution, orders are released to the operation pool for each block/floor/module at the beginning of t, and the related operations and material supplies about this order are activated by a real-time synchronization mechanism. Moreover, high-fidelity digital twin models are established in real-time development engines and converted into web-based platforms to visualize the real-time construction progress with free-perspective monitoring and n-dimensional (nD) information query. Dynamic Gantt chart can visualize multiple work packages to reveal the real-time operation states based on the sensing data, which can also be manually adjusted with high flexibility by stakeholders. The iBeacon/UWB-enabled positioning visualizes the real-time states and positions of various SCOs, and analytic charts such as S-curve also provide intuitive visibility for stakeholders about the real-time fit-out construction process.

4 | REAL-TIME-DATA-DRIVEN OOO MODEL

A real-time-data-driven and rolling-horizon-based OoO model is formulated for synchronization in modular construction fit-out PSE with enhanced resilience and flexibility.

4.1 | OoO execution mechanism

The OoO execution mechanism in computer science allows the CPU to process instructions based on the availability analysis of input data and arithmetic logical unit (ALU). Hence, the OoO mechanism can avoid possible stalls during calculation, which significantly improves the utilization of spatial–temporal computing resources and processing efficiency. OoO mechanism driven by real-time data is practical and useful in online scheduling. For online scheduling, the operational and logistics data are not known in advance and only can be determined after the task completion (Weiss, 1995). In a clairvoyant online-overtime scheduling problem, stakeholders can know all the relevant data about the job when this job is sent to their hands. Clearly, the algorithms for online scheduling are different from the algorithms for offline scheduling. In offline scheduling, all the data are known in advance and can be taken into account for static optimization. OoO inspires this study to apply the real-time data-driven and rolling-horizon-based sequence and adjustment in the online scheduling model for fit-out construction management. Within a spatial–temporal unit, tasks are processed in an order determined by the availability and simultaneity of construction materials, tools, and workers.

The traditional in-order processor handles instructions sequentially in a predefined order. However, this processing mechanism has poor robustness to cope with disturbances, such as a cache miss. If the data requested for instruction is not received in the cache, it will take a long duration for Random-Access Memory (RAM) to inspect the address and retrieve the data. Due to the operation delay of this instruction, subsequent instructions must be queued. When an OoO processor is used, if a disturbance happens to one instruction, the CPU will analyze the availability of the requested parameters for the following instructions and run out of the original order to

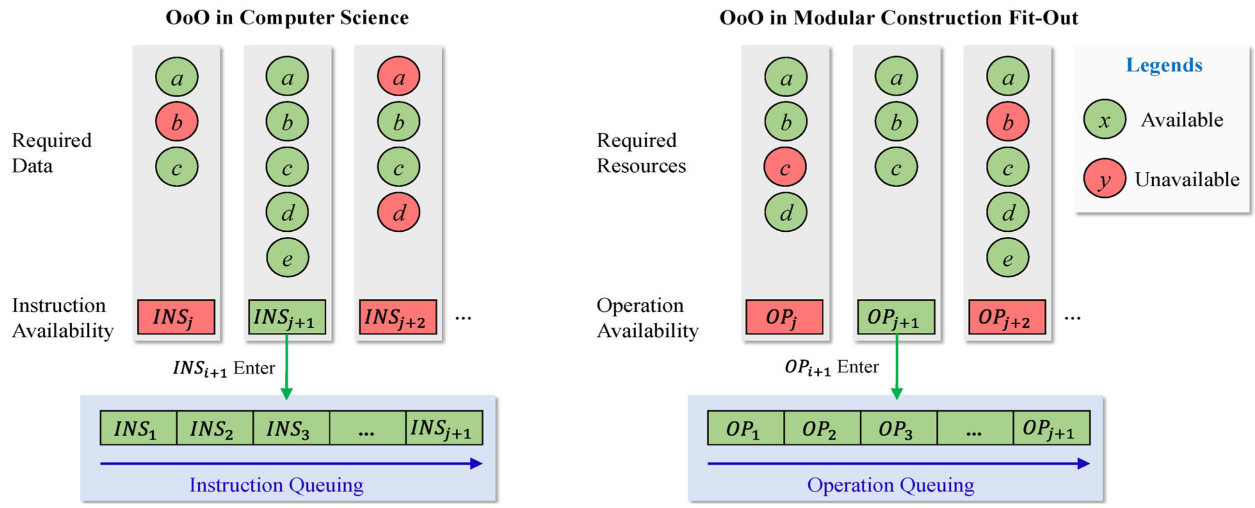

FIGURE 3 Our-of-Order (OoO) execution mechanism in CPU and modular construction fit-out.

avoid stalls. For the fit-out PSE process, OoO can also improve the robustness to disturbances, similar to a CPU, as shown in Figure 3. Only after all the preconditions of a fit-out operation (e.g., worker, tool, material, and site) are met can the operations be allowed to enter into the real-time operation pool. Afterward, operations in the real-time operation pool are sequenced for implementation in each rolling time window. For a modular area or a worker squad, when a disturbance happens such as material delay or worker absence, the operator can process another available operation in other modular areas, or the original modular area can be executed with another operation. When the real-time state data and rolling time window are considered, the OoO mechanism can provide a resilient method for dynamic operation distribution to tackle disturbances and improve the efficiency and utilization of resources in the modular fit-out PSE. Several assumptions are made for OoO model in modular construction fit-out PSE: (1) All the operational data of workers could be real-timely updated without privacy intrusion; (2) extreme data delays and signal communication disturbances would not happen in the digital twin systems; (3) in one modular area i, only one operation is permitted within a specific time window; (4) worker squads are independent, and only one operation by one worker squad within a time window is permitted; (5) some operations can only be started after certain operations are finished, which are assigned with finish-to-start (FS) precedence relationships; (6) specific fit-out operations can only be completed by specific types of workers.

The whole period of the modular construction fit-out project is a total time horizon H as shown in Figure 4. One fit-out order $OR^{i,k}$ involves a number of operations $\{OP_1^{i,k}, OP_2^{i,k} \dots OP_j^{i,k} \dots\}$, in which a particular operation contains several fit-out tasks $\{TA_{1,j}^{i,k}, TA_{2,j}^{i,k} \dots TA_{u,j}^{i,k} \dots\}$. Fit-out order $OR^{i,k}$ is a job cluster with a specific operational type in one modular area, which is allocated within a long-term rolling time window T, such as 2 weeks or 1 month. Fit-out operations $OP_j^{i,k}$ are clustered to perform within a short-term rolling time window t, which is always 1 day. Some operations are sequential with precedence constraints, and others are parallel without precedence restrictions. Time window t is divided into several decision cycles τ for real-time task adjustment and re-sequencing, which is always 10 to 60 min. The time durations of fit-out tasks are dynamic and changeable based on the real-time situation. In each time window, green arrow lines refer to the completed tasks, yellow lines denote the on-going tasks, and gray lines refer to the upcoming tasks. The schedule of operations $OP_j^{i,k}$ can be adjusted based on the real-time condition of the project progress and the resource availability state. If the materials of operation $OP_{j+1}^{i,k}$ are not arrived or the required workers are absent, the subsequent operation can be adjusted to $OP_{j+h}^{i,k}$ if the related availability conditions are fulfilled.

The overarching framework of the OoO model consists of three main phases: planning, scheduling, and execution, as illustrated in Figure 5. The planning phase encompasses the offline preparation and support for the entire project. The scheduling phase involves the operation pool generation based on the rolling horizon and the real-time operation queuing mechanism. During the execution phase, real-time information about resources and operations is fed back to the operation pool. When the status of all jobs is displayed as completed, the time window iteration ceases. The proposed model incorporates a forward heuristics algorithm, elucidated in the subsequent subsection.

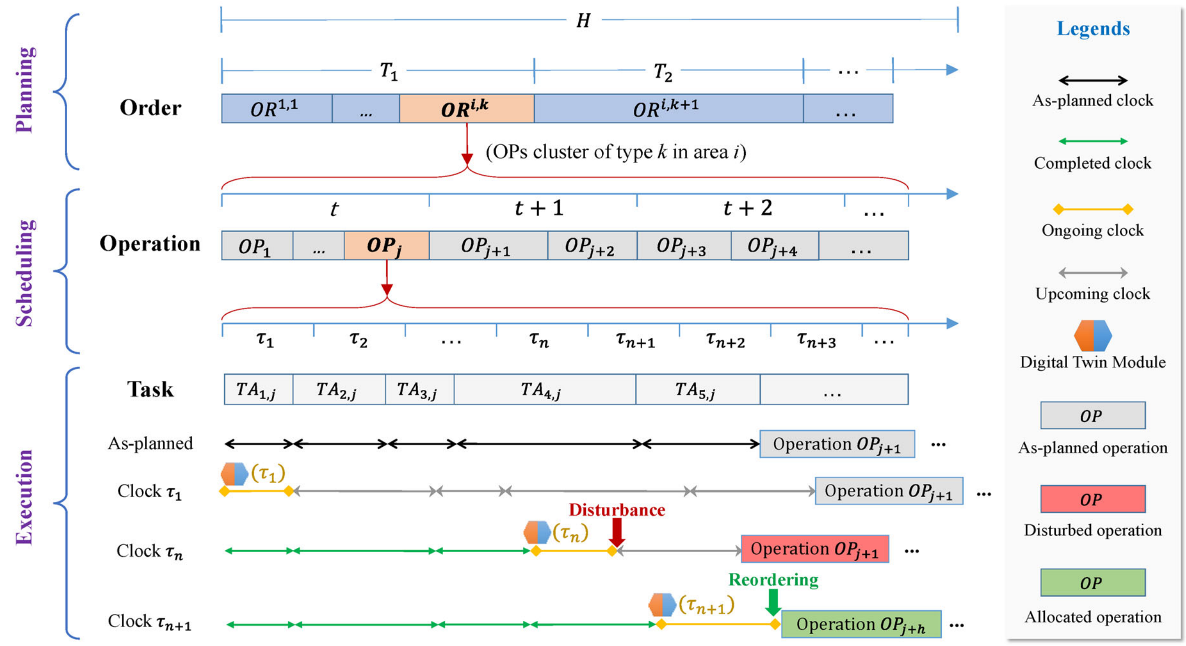

FIGURE 4 OoO-based planning, scheduling, and execution (PSE) for modular construction fit-out management.

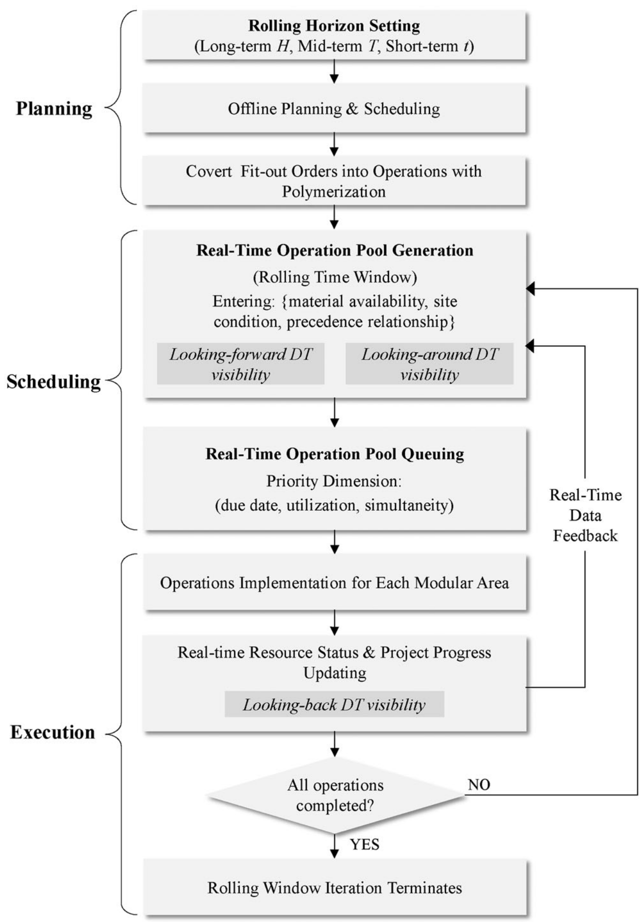

FIGURE 5 Overarching framework of OoO model for modular construction fit-out PSE.

4.2 | OoO-enabled digital twin visibility

Digital twin visibility within OoO has three flows: looking-forward visibility, looking-around visibility, and looking-back visibility, which are discussed as follows. The parameters and variables for the OoO model are shown in Table 1.

4.2.1 | Looking-forward digital twin visibility

Looking-forward digital twin visibility is realized by using the real-time data in the current time window t to estimate the upcoming time–space–state information about construction resources in the succeeding time window $t+1$. The completion time of the current operation $C^{i}_{j,k}$ is estimated based on the real-time fit-out progress to facilitate decision-making about the subsequent operations through clairvoyant online-overtime scheduling as described by Formulas (1) and (2). The next operation can be conducted only after the preceding one is completed as described in Formulas (3) to (5). Operations in the next operation type can be conducted only after all the operations in the previous operational type and the related setups are finished as described in Formula (6). The material arrival times a^{i*}_{k} can be also calculated through the real-time locations, which are collected by Global Positioning System (GPS) devices, and the related operations can be implemented only after the materials are available as described in Formula (7). All the operations involved in one work type in

TABLE 1 Parameters and variables.

Parameters	Descriptions
$OP_j^{i,k}$	Fit-out operation j of work type k for modular area i
$S_j^{i,k*}$	Start time of fit-out operation j of work type k for modular area i based on collected real-time data
$C_j^{i,k*}$	Completion time of fit-out operation j of work type k for modular area i based on collected real-time data
$p_j^{i,k}$	Processing duration estimated based on the past data of fit-out operation j of work type k for modular area i
$p_j^{i,k*}$	Processing duration of fit-out operation j of work type k for modular area i based on collected real-time data
a_k^i	Availability date of materials of work type k for modular area i
d_k^i	Due date of materials of work type k for modular area i
M	Sufficiently large constant
T^*	Start time of the real-time decision cycle in the rolling horizon
Variables	**Descriptions**
$S_j^{i,k}$	Start time of fit-out operation j of work type k for modular area i
$C_j^{i,k}$	Completion time of fit-out operation j of work type k for modular area i
$Y_{j,j'}^{i,k}$	Binary auxiliary variable for precedence relationship, 1 if operation $OP_j^{i,k}$ is processed before another operation $OP_{j'}^{i,k}$ of work type k at modular area i and 0 otherwise
$\boldsymbol{W}_m^k(T,\ t+1)$	Dynamic auxiliary set to allocate operations to worker squad m of type k in time window $(T, t+1)$
Notes	Parameters having * in the superscript represent the real-time data from digital twins

one area should be completed before the due date d_k^{i*} with a slack auxiliary variable $\theta_j^{i,k}$ as described in Formula (8). Only after the required materials and worker squads have arrived in the target buffer is the corresponding operation allowed. Each operation should be completed before the due date of the operation type in the modular area.

$$C_1^{i,k} = p_1^{i,k*},\ \forall i,\ k \tag{1}$$

$$C_j^{i,k} = S_j^{i,k*} + p_j^{i,k},\ \forall i,\ k, j \tag{2}$$

$$S_{j'}^{i,k} \geq C_j^{i,k*} - M \cdot \left(1 - Y_{j,j'}^{i,k}\right),\ \forall i,\ k, j, j' \tag{3}$$

$$S_{j'}^{i,k} \geq C_j^{i,k*} - M \cdot Y_{j',j}^{i,k},\ \forall i,\ k, j, j' \neq j \tag{4}$$

$$Y_{j,j'}^{i,k} + Y_{j',j}^{i,k} \leq 1,\ \forall i,\ k, j, j' \neq j \tag{5}$$

$$S_{j'}^{i,k+1} \geq C_j^{i,k*},\ \forall i,\ k, j, j' \tag{6}$$

$$S_j^{i,k} \geq a_k^{i*},\ \forall i,\ k, j \tag{7}$$

$$S_j^{i,k} + p_j^{i,k} \leq d_k^i + \theta_j^{i,k},\ \forall i,\ k, j \tag{8}$$

The preconditions of one operation have several indicators, including material availability standby, site condition standby, and precedence relationship standby. Only when these preconditions are fulfilled, the corresponding operation is permitted to be graduated and transferred into the real-time operation pool. An entry coordinator is deployed to analyze whether the preconditions of one operation are available. One precondition takes one credit, and the operation can be allowed to enter the real-time operation pool $\boldsymbol{P}(T, t+1)$ under time window t after the three credits are gathered. $\boldsymbol{CR}_M(T, t+1)$, $\boldsymbol{CR}_S(T, t+1)$, and $\boldsymbol{CR}_P(T, t+1)$ are three dynamic sets for the operations with qualified credits, which are, respectively, corresponded to material availability standby, site condition standby, and precedence relationship standby. Three credits are updated in each time window to judge the precondition of the operations in the pool, which are described as Formulas (9)–(11). The qualified operations are allocated into credit sets $\boldsymbol{CR}_x$ within each time window. Material availability standby means that the current operations can enter the pool only after all the required materials are available as shown in Formula (9). Site condition standby refers that operations can be started only after the site has no other work in time window $t+1$, where the binary variable Z_{t+1}^{i*} based on real-time state equals to 1 if the site is ready as shown in Formula (10). Precedence relationship standby means that operations can enter the pool only after the FS precedence-constrained tasks are completed as shown in Formula (11). After all the preconditions of one operation are satisfied, this operation is allowed to enter real-time operation pool $\boldsymbol{P}(T, t+1)$ as shown in Formulas (12)–(14). In traditional optimization programming models, binary decision variables are always applied for the allocation of operations to appropriate workers constrained by skill differentiation. Based on the concept of time–space–state modeling, dynamic state sets are applied to store the real-time states of workers (e.g., *standby*, *working*, and *abnormal*), and auxiliary variable set $\boldsymbol{W}_m^k(T,\ t+1)$ is used to record the allocated operations for worker m in time window $(T, t+1)$. Abnormal conditions, such as workers arriving late, workers being absent due to injuries, or machine breakdowns, can disrupt operations. The digital twin system could sense the abnormal states in real time and response to these disturbances. For example, another group of idle workers can be replaced to fill the current job, or the affected job can be scheduled later, which minimizes the negative impacts caused by the disturbances. If the state of the worker is *standby*, then the operation waiting in the real-time operation pool is allocated to the standby worker m as listed in Formula (15), while the related worker state is changed to *working*, which cannot be allocated with other operations until the current operation is completed.

$$\boldsymbol{CR}_M\ (T,t+1) = \boldsymbol{CR}_M\ (T,t+1) \cup \left\{ \text{Boolean}\left(a_k^{i*}\right) \cdot OP_j^{i,k} \right\},\ \forall i,\ k,\ j \tag{9}$$

$$\boldsymbol{CR}_S\ (T,t+1) = \boldsymbol{CR}_S\ (T,t+1) \cup \left\{ Z_{t+1}^{i*} \cdot OP_j^{i,k} \right\},\ \forall i,\ k,\ j \tag{10}$$

$$\boldsymbol{CR}_P\ (T,t+1) = \boldsymbol{CR}_P\ (T,t+1) \cup \left\{ \prod\nolimits_{j=1}^{J} \text{Boolean}\left(C_j^{i,k-1*}\right) \cdot OP_j^{i,k} \right\},\ \forall i,\ k \tag{11}$$

$$\boldsymbol{P}_{in}\,(T,t+1) = \cap \left\{ \boldsymbol{CR}_M\,(T,t+1),\ \boldsymbol{CR}_S\,(T,t+1),\boldsymbol{CR}_P\,(T,t+1) \right\} \tag{12}$$

$$\boldsymbol{P}_{out}\,(T,t+1)\ = \bigcup_{i=1}^{I}\bigcup_{k=1}^{K}\bigcup_{j=1}^{J} \left\{ \text{Boolean}\left(C_j^{i,k*}\right) \cdot OP_j^{i,k} \right\} \tag{13}$$

$$\boldsymbol{P}\,(T,t+1)\ =\ \boldsymbol{P}\,(T,t) \cup \boldsymbol{P}_{in}\,(T,t+1) \setminus \boldsymbol{P}_{out}\,(T,t+1) \tag{14}$$

$$\boldsymbol{W}_m^k\ (T,\ t+1) = \boldsymbol{W}_m^k\ (T,\ t+1) \cup \left\{ OP_j^{i,k} \right\},\ if\ OP_{j,k}^i \in \boldsymbol{P}\,(T,t+1)\ and\ \boldsymbol{W}_m^k\ (T,\ t+1) = \emptyset,\ \forall i,\ k, j, m \tag{15}$$

4.2.2 | Looking-around digital twin visibility

Looking-around digital twin visibility is implemented using graph-theory-based clustering. The general procedure of graph-theory-based clustering for project management can be found in the previous researches (Nascimento & de Carvalho, 2011). The disorderly and trivial operations are clustered to form orderly and complete operations, which are performed in specific modular areas within a time window. The key indicators for operation clustering are the due date d_k^i, operation type c_j^i, and three-dimensional spatial coordinates $p_j(x_j, y_j, z_j)$. The attribute of one operation $OP_{j,k}^i$ can be denoted by the following formula, $OP_{j,k}^i \overset{\Delta}{=} \{d_k^i, c_j^i, p_j(x_j, y_j, z_j)\}$. The operations within an operation cluster are also synchronized to improve resource utilization and productivity. The real-time data of statuses and progress about simultaneous operations clusters are also applied for PSE decision-making and dynamic adjustment. Operations with adjacently spatial continuity and similar types are clustered together, allowing them to be assigned to the same workers and material batches. This clustering enhances task integration, addressing the issue of fragmentation in fit-out operations. It not only improves operational efficiency but also alleviates the complexity of PSE in fit-out construction. Operations to be grouped in the current time window T are indicated by a set of vertices $V^T = \{1, \ldots, j, \ldots, \ldots, |V^T|\}$ of an undirected and weighted graph G^T. Operation pairs (u, v) denote the graph edges, the weight of the edges w_{uv} reflects the similarity between $OP_{u,k}^i$ and $OP_{v,k}^i$, where $G^T = (V^T, E^T)$, $E^T = \{(u, v), u, v \in V^T, w_{uv} > 0\}$. The due date distance $dist_{uv}^d$ is measured using standardized Euclidean distance as Formula (16). The physical location distance $dist_{uv}^l$ is measured as Formula (17) due to prioritizing fit-out rules for nearby rooms and floors, where w_h is the horizontally spatial weight and w_v is the vertically spatial weight. The required materials distance $dist_{uv}^m$ is measured using the Jaccard similarity coefficient as Formula (18), where $\boldsymbol{C}_j^a$ is the set of required materials of operation j in area a. The integrated distance $dist_{uv}$ of the operation pair (u, v) is presented in Formula (19), where w_d, w_l, and w_m are the corresponding weights for $dist_{uv}^d$, $dist_{uv}^l$, and $dist_{uv}^m$. Then $dist_{uv}$ is converted to the similarity index S_{uv} (the larger, the more similar) between $OP_{u,k}^i$ and $OP_{v,k}^i$ as described in Formula (20). The degree d_u of the $OP_{u,k}^i$ is as defined in Formula (21). Subsequently, the vertices in the graph G^T are separated into different groups based on their similarities. The problem can be redescribed as to find a partition of the graph G^T so that the edges between different clusters have very low weights, and the edges within a cluster have high weights. A typical minimum normalized cut *NCut* is used to separate G^T into operational cluster $\{OC_1, OC_2, \ldots, OC_K\}$. The volume of an OC can be calculated as $vol\,(OC) = \sum_{i \in JC} d_i$ as shown in Formula (22). The sum of edge weights between OC and OC' can calculated as Formula (23). The k-way graph cut $(OC_1, OC_2, \ldots, OC_K)$ is normolized in Formula (24), and the related minimization solution is provided by Nascimento and de Carvalho (2011).

$$dist_{uv}^d = \sqrt{\left(\frac{dt_u - dt_v}{std\,(dt)}\right)^2} \tag{16}$$

$$dist_{uv}^l = \sqrt{w_h \cdot \left(x_u - x_v\right)^2 + w_h \cdot \left(y_u - y_v\right)^2 + w_v \cdot \left(z_u - z_v\right)^2} \tag{17}$$

$$dist_{uv}^{m} = 1 - \frac{\left|\boldsymbol{C}_u^a \cap \boldsymbol{C}_v^b\right|}{\left|\boldsymbol{C}_u^a \cap \boldsymbol{C}_v^b\right|} \quad (18)$$

$$dist_{uv} = w_d\ dist_{uv}^{d} + w_l\ dist_{uv}^{l} + w_m\ dist_{uv}^{m} \quad (19)$$

$$S_{uv} = e^{\left(-Dist_{uv}^2\right)} \quad (20)$$

$$d_u = \sum_{v \in VT} S_{uv} \quad (21)$$

$$vol\ (OC) = \sum_{i \in OC} d_i \quad (22)$$

$$Cut\ \left(OC, OC'\right) = \sum_{u \in OC} \sum_{v \in OC'} S_{uv} \quad (23)$$

$$NCut\ (OC_1,\ OC_2, \dots,\ OC_K) = \frac{1}{2} \sum_{i=1}^{K} \frac{Cut\left(OC, OC'\right)}{vol\,(OC)} \quad (24)$$

4.2.3 | Looking-back digital twin visibility

Looking-back digital twin visibility means that applying the generated data during the past construction fit-out progress to evaluate the synchronization level of past operation and facilitate decision-making for current operations. Knowledge of operations and resources among the project can bring valuable insights for the adjustment of similar operations. Based on the experience from managers and supported by the data mining of the collected massive data, indicators of worker squads can be evaluated for operations allocation and spatial–temporal characteristics of the building fit-out are also analyzed. Three synchronous indicators are applied for evaluating the synchronization level in smart fit-out, including the time interval between operations and the corresponding material arrival date ($\Delta t_{LO}^{j,k,i}$), the interval of adjacent operations ($\Delta t_{OO}^{j,k,i}$) between preceded operation *j'* and succeeding operation *j*, and tardiness for overdue operations ($\Delta t_{OT}^{j,k,i}$), which are, respectively, described in Formulas (25)–(27). The corresponding weights of three performance indicators for the priority calculation of operation queuing can be flexibly adjusted based on the real-time situation.

$$\Delta\, t_{LO}^{j,k,i} = S_j^{i,k} - a_k^i \quad (25)$$

$$\Delta\, t_{OO}^{j,k,i} = S_j^{i,k} - C_{j'}^{i,k} \quad (26)$$

$$\Delta\, t_{OT}^{j,k,i} = \max\left(0,\ C_j^{i,k} - d_k^i\right) \quad (27)$$

4.3 | Real-time operation pool queuing mechanism

After the qualified operations are transferred into the real-time operation pool in each rolling time window, these operations are sequenced by a sequencing coordinator. The sequencing of operations is calculated considering several dimensions, including due date, utilization, and simultaneity. Empirical parameters λ_1 to λ_5 are predefined to facilitate the computation of the following indices, allowing for flexible adjustments based on the specific conditions of each project.

1. *Due date dimension* $Dd_{i,k}$ is a piecewise function, which reflects that the closer the current time to the due date, the more urgent the operation is. T^* indicates the real-time time point, and d_k^i is the due date of the operation type in modular area *i*. The due data dimension $Dd_{i,k}$ is described in Formula (28).

$$Dd_{i,k} = \begin{cases} \dfrac{\lambda_1}{d_k^i - T^* + \lambda_2},\ if\ d_k^i \geq T^* \\ \lambda_3 \cdot (T^* - d_k^i),\ if\ d_k^i < T^* \end{cases} \quad (28)$$

2. *Utilization dimension* $Ut_{i,k}$ aims to improve the spatial resource utilization and reduce the dispatching of workers, materials, and tools. Operations in the modular area with a faster progress and shorter remaining processing time earn higher priority, which is based on the *Shortest Remaining Processing Time First* rule. $T_{remain}^{i,k}$ represents the remaining operation time of work type *k* in the current unit, and $SOT^{i,k}$ represents the standard operation time of the current modular area based on looking-back digital twin visibility.

$$Ut_{i,k} = \frac{SOT^{i,k}}{T_{remain}^{i,k} + \lambda_4} \quad (29)$$

3. *Simultaneity dimension* $Sl_{i,k}$ means that the longer the time that is available after the materials arrive on the buffer, the higher the priority of the related operations. The simultaneity of material supplies and operations is a key point of this queuing mechanism. After the decoration materials arrive at the construction site, the inventory time should be optimized. Moreover, if some types of materials are left on the construction site for a long time, they may hinder the supply of subsequent materials. T^* is the left bound of the current time window. Parameter λ_5 is used to adjust the exponential sensitivity of the simultaneity dimension, according to the specific project conditions.

$$Sl_{i,k} = \max\left[0,\ \left(T^* - a_k^i\right)^{\lambda_5}\right] \quad (30)$$

ALGORITHM 1 Real-time operation pool pseudocode for synchronized PSE.

Input: Fit-out operation $OP^{i}_{j,k}$, real-time data from digital twins (e.g., $C^{i,k*}_{j}$, a^{i*}_{k}, Z^{i*}_{t+1}) in time window (T, t)

Output: Operation queue $OP^{i}_{j,k}$ in pool $\boldsymbol{P}(T, t+1)$, worker squad status set $\boldsymbol{W}^{k}_{m}(T,\ t+1)$

1 **Initialization**: Rolling horizon setting (Mid-term T, Short-term t)

2 Offline planning & scheduling parameter setting (e.g., a^{i}_{k} and d^{i}_{k})

3 Operations clustering into $OP^{i}_{j,k}$ based on due date d^{i}_{k}, operation type c^{t}_{j}, and spatial position $p_j(x_j, y_j, z_j)$

4 **While** $\prod_{i}^{I}\prod_{k}^{K}\prod_{j=1}^{J} Boolean(C^{i,k*}_{j}) \neq 1$ **do**
//Stopping criteria: All OPs completed

5   **For** each window $(T, t+1)$ **do**

6   Initialize operation pool $\boldsymbol{P}(T, t+1)$

7     $OP^{i}_{j,k}$ entering into $\boldsymbol{P}(T, t+1)$:
If Boolean $(a^{i*}_{k}) = 1$ & $Z^{i*}_{t+1} = 1$ & $\prod_{j=1}^{J}$ Boolean$(C^{i,k-1*}_{j}) = 1$ **then**
$OP^{i,k}_{j} \rightarrow \boldsymbol{P}(T, t+1)$
End if

8     $OP^{i}_{j,k}$ prioritized queuing in $\boldsymbol{P}(T, t+1)$:
$Pri^{(T,t+1)}_{(j,k,i)} = w_1 \cdot Dd_{i,k} + w_2 \cdot Ut_{i,k} + w_3 \cdot Sl_{i,k}$

9     $OP^{i}_{j,k}$ allocation and sequencing for worker $\boldsymbol{W}^{k}_{m}$:
If $OP^{i}_{j,k} \in \boldsymbol{P}(T, t+1)$ & $\boldsymbol{W}^{k}_{m}(T,\ t+1) = \emptyset$ **then**
$OP^{i,k}_{j} \rightarrow \boldsymbol{W}^{k}_{m}(T,\ t+1)$
End if

10   Time window rolls: $t\ =\ t+1$

11   **End for**

12 **End while**

The comprehensive priority $Pri^{(T,t+1)}_{(j,k,i)}$ of substituted operation j in modular area i is described in Formula (31).

$$Pri^{(T,t+1)}_{(j,k,i)} = \boldsymbol{w}^{\mathrm{T}} \cdot \boldsymbol{v} \tag{31}$$

where $\boldsymbol{v}\ =\ [norm(Dd_{i,k}), norm(Ut_{i,k}), norm(Sl_{i,k})]$ is the dimension vector, $\boldsymbol{w}$ is the associated weight vector, and *norm* is the normalization function for eliminating the effects of different measurement units. Conclusively, the structure of the real-time operation pool synchronization mechanism for PSE in modular construction fit-out is shown in Algorithm 1.

5 | COMPUTATIONAL EXPERIMENT

Section 5 presents the computational experiment to verify the performance of the real-time data-driven and rolling-horizon-based OoO model for construction fit-out operations. This experiment is run on a desktop computer with 3.20 GHz of Intel Core i7 CPU and 16GB of RAM. The OoO model and comparative algorithms are solved in MATLAB R2019a, where a optimization solver Gurobi 9.5.2 is applied to address the comparative MILP model.

TABLE 2 Stochastic experimental configuration.

Notations	Values
Number of floors	27
Number of modular areas per floor	4
Number of fit-out operation stage per floor	3
Number of operations per area per floor	(3/4/3)
Total number of operations	1080
Number of worker squad for each operation type	(3/4/3)
Operation processing time for op type A	U[100, 140]
Operation processing time for op type B	U[120, 180]
Operation processing time for op type C	U[80, 100]
Rolling decision cycle/time window size	60
Standard possibility of material arrival delay	8%
Standard duration of material arrival delay	U[230, 1600]
Standard possibility of operation time delay	12%
Standard duration of operation time delay	U[150, 1200]

5.1 | Motivating scenario and experimental configuration

This experiment is motivated by a modular integrated construction (MiC) fit-out project of a 27-story public residential building in Ash Street, Hong Kong, as shown in Figure 6. The batch of fit-out materials was fixed with QR codes and GPS devices for real-time information visibility and traceability. An IoT-enabled BIM platform was established for construction fit-out PSE, which has three main services, including digital twin Kanban, material tracking and tracing service, and operation scheduling service. The real-time states of workers, materials, and modular areas could be updated to the smart BIM platform for project managers in each rolling time window, and managers could make PSE decisions for task allocation and dynamic adjustment according to the real-time project demands. Considering the cost-efficiency of updating IoT data, the size of the rolling time window as well as the equivalent decision cycle is set to 60 min.

The experimental configuration is shown in Table 2. For the business workflow of this MiC fit-out project, the water and electricity lines installation phase in prefabricated modules is almost completed at the production stage. Only connection and calibration works of pipelines are

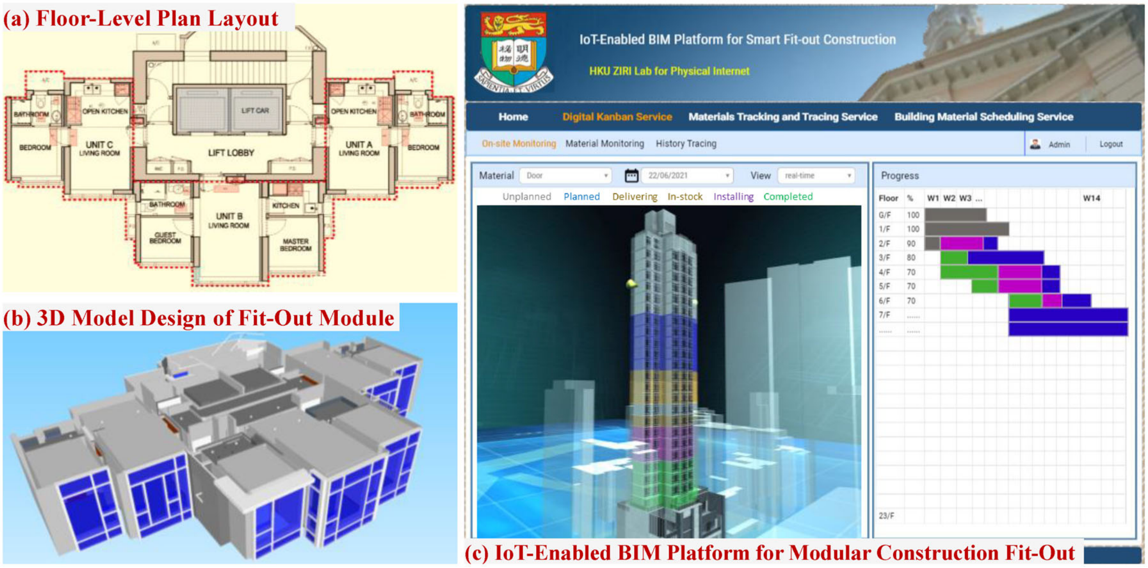

FIGURE 6 Motivating case for smart modular construction fit-out management. BIM, building information modeling; IoT, Internet-of-Things.

left for on-site operations, while some bricklaying works are also finished during the module production stage. Thus, pipelines and bricklaying operations are clustered into one fit-out phase for scheduling and execution to reduce the computational complexity. This fit-out project mainly contains three sequential stages of operations, including pipeline installation and bricklaying (Type A), painting and coating (Type B), and furniture and household appliances (Type C). Only the previous operational type is completed, the next type can be implemented with the precedence relationship (A → B → C). Different types of operations have different processing times and are assigned with different numbers of workers. Due to the standardization and integration properties of prefabricated modules, the fit-out operations in each modular area are also highly standardized. Each modular area contains 10 operations through graph-theory-based clustering and each floor has four areas, while this fit-out project totally involves 1080 fit-out operations.

For uncertainty setting, two frequently encountered types of disruptions involve delays in material arrival and extended operation durations. These disruptions are governed by two interrelated factors: the probability of delay occurrence and the severity of the delay (Su et al., 2020). In order to test the performances of OoO and other comparative methods under different uncertainty situations, this experiment sets four uncertainty levels using a scaling factor э to proportionally adjust the delay possibility rate and delay time duration: {None Uncertainties (NU) (э = 0), Low Uncertainties (LU) (э = 0.5), Medium Uncertainties (MU) (э = 1.0), High Uncertainties (HU) (э = 1.5)} (M. Li & Huang, 2021). Each performance evaluation of the PSE models is run 100 times to ensure the stability and reliability of the computational experiments.

5.2 | Comparative experiment of MILP

Conventional MILP is widely applied for the allocation and scheduling of operations and resources in construction management (Mehrabipour & Hajbabaie, 2017; Yi & Wang, 2017). An MILP model is designed for the offline scheduling optimization of PSE in modular construction fit-out, which acts as a compared scenario with the proposed real-time data-driven OoO model. The optimization solver Gurobi 9.5.2 is called into MATLAB R2019a to solve this MILP problem.

This MILP is conducted as an offline scheduling problem without real-time data support and rolling horizon scheduling. All the operational parameters are known in advance and can be taken into account at time zero to generate an optimized blueprint. New decision and auxiliary variables for operation assignment, precedence control, and operation start time are defined in this MILP, including $x_m(OP_j^{i,k})$, $y_m^k(OP_{i',j'}^{i,j})$, and $S_{j,m}^{i,k}$, which are described in Table 3. The comparative MILP model is described as follows:

Min:

$$OF = w_1 \cdot Makespan + w_2 \cdot \sum_{i}^{I} \sum_{k}^{K} \sum_{j}^{J} \sum_{m}^{M} \left(S_{j,m}^{i,k} - a_k^i \right)$$
$$+ w_3 \cdot \sum_{i}^{I} \sum_{k}^{K} \sum_{j}^{J} \sum_{m}^{M} \max\left(0,\ S_{j,m}^{i,k} + p_j^{i,k} - d_k^i\right) \quad (32)$$

TABLE 3 Parameters and variables in mixed integer linear programming (MILP) for comparative experiments.

Parameters	Descriptions
$OP_j^{i,k}$	Fit-out operation *j* of type *k* at modular area *i*
n_{FO}	Total number of fit-out operations at all the modular areas on all the floors
$p_j^{i,k}$	Processing duration estimated based on past data of fit-out operation *j* of type *k* at modular area *i*
a_k^i	Availability date of materials for operation type *k* at modular area *i*
d_k^i	Due date of operation type *k* at modular area *i*
M	Sufficiently large constant
Variables	**Descriptions**
$x_m(OP_j^{i,k})$	Binary variable for operation assignment, 1 if worker squad W_m is allocated to operation $OP_j^{i,k}$ and 0 otherwise
$y_m^k(OP_{i',j'}^{i,j})$	Binary variable for precedence relationship, 1 if operation $OP_j^{i,k}$ is processed before another operation $OP_{j'}^{i',k}$ by worker *m* of type *k* and 0 otherwise
$S_{j,m}^{i,k}$	Start time of operation *j* of work type *k* for modular area *i* processed by worker squad W_m^k
$\theta_{j,m}^{i,k}$	Auxiliary slack variable for due date constraint

S.T:

$$\sum_i^I \sum_k^K \sum_j^J \sum_m^M x_m(OP_j^{i,k}) = n_{FO} \tag{33}$$

$$S_{j',m}^{i',k} \geq S_{j,m}^{i,k} + p_j^{i,k} - M \cdot \left(3 - y_m^k(OP_{i',j'}^{i,j}) - x_m(OP_{j'}^{i,k}) - x_m(OP_j^{i,k})\right), \forall i, i', k, j, j', m \tag{34}$$

$$S_{j,m}^{i,k} \geq S_{j',m}^{i',k} + p_{j'}^{i,k} - M \cdot y_m^k(OP_{i',j'}^{i,j}) - M \cdot \left(2 - x_m(OP_{j'}^{i,k}) - x_m(OP_j^{i,k})\right), \forall i, i', k, j, j', m \tag{35}$$

$$y_m^k(OP_{i',j'}^{i,j}) + y_m^k(OP_{i',j'}^{i,j}) \leq 1, \forall i, i', k, j, j', m \tag{36}$$

$$S_{j',m'}^{i,k+1} \geq S_{j,m}^{i,k} + p_j^{i,k}, \forall i, k, j, j', m, m' \tag{37}$$

$$S_{j,m}^{i,k} \geq a_k^i, \forall i, k, j, m \tag{38}$$

$$S_{j,m}^{i,k} + p_j^{i,k} \leq d_k^i + \theta_{j,m}^{i,k}, \forall i, k, j, m \tag{39}$$

$$x_m(OP_j^{i,k}) \in \{0, 1\}, \forall i, k, j, m \tag{40}$$

$$y_m^k(OP_{i',j'}^{i,j}) \in \{0, 1\}, \forall i, i', k, j, j', m \tag{41}$$

$$S_{j,m}^{i,k} \geq 0, \forall i, k, j, m \tag{42}$$

This MILP has three minimization indexes, including makespan, material holding time, and operation tardiness, described as Formula (32). Total number of fit-out operations of all types in all areas n_{FO} is 1080, and each operation should be processed by the worker with the matched operational types, described in constraint (33). At each modular area, the next operation can be started only after the previous one is completed following the FS precedence relationship. For each worker squad, only one operation can be processed by this worker at the same time, described as Constraints (34) to (36). After the preceding operational type is finished, the successive operational type can be started, described as constraint (37). The related operations can be implemented only after the materials are available and should be completed before a predefined due date d_k^i combined with a slack variable $\theta_{j,m}^{i,k}$, described as Constraints (38) and (39). Constraints (40) to (42) are used to limit the ranges of the variables, where Constraint (40) is the binary variable for operations assignment, Constraint (41) is the binary auxiliary variable for precedence control, and Constraint (42) is the positive real variable for the operation start time.

5.3 | Performance evaluation

Classified rule-based algorithms are widely used to solve RCPSP in hybrid flow shop and job shop (Chtourou & Haouari, 2008), which can also be used for the operation allocation and scheduling in modular construction fit-out. In this experiment, three rule-based algorithms are also applied as references for the comparison with the proposed real-time data-driven OoO model, including FCFS, SPT, and EDD.

These methods are commonly used in real-life scheduling problems because they are sufficiently flexible and dynamic for application in stochastic environments. Three key indicators (makespan, holding time, and tardiness) are used for the performance evaluation of the five selected PSE methods (OoO, FCFS, SPT, EDD, and MILP) under different uncertainty scenarios. Considering the limitation of computational scale in Gurobi, the optimization of 1080 operations in the MILP model heavily consumes computational time and cannot ensure that the optimal solution is output. Thus, for the comparison between MILP-Gurobi and other algorithms, a small-sized fit-out scenario (S1) with 160 operations distributed on four floors in the target building is applied, which can be solved in an affordable computational time. In scenario S1, the initial offline schedule is set based on the output from the

TABLE 4 Performance results of stochastic computational experiments.

Makespan (min)					Average holding time (min)					Average tardiness (min)				
OoO	FCFS	SPT	EDD	MILP-Gurobi	OoO	FCFS	SPT	EDD	MILP-Gurobi	OoO	FCFS	SPT	EDD	MILP-Gurobi
None Uncertainties (NU)														
4517.6	4517.6	4517.6	4552.3	**4222.9**	558.0	558.0	558.0	573.1	**61.1**	0.3	0.3	0.3	0.3	**0.0**
Low Uncertainties (LU)														
4993.8	5125.5	5318.6	5204.2	5991.3	**616.5**	699.2	778.1	732.3	696.4	**4.0**	11.0	25.8	17.6	7.2
Medium Uncertainties (MU)														
5060.4	5349.7	5831.2	5204.2	6779.2	**683.4**	810.2	954.9	841.3	1036.3	**10.0**	26.4	68.4	32.7	115.4
High Uncertainties (HU)														
5346.9	5725.1	6506.5	6043.8	8166.2	**791.0**	953.6	1119.6	987.2	1591.5	**37.7**	89.1	179.8	113.8	390.7

Abbreviations: EDD, earliest due date; FCFS, first come first served; OoO, out-of-order; SPT, shortest processing time.

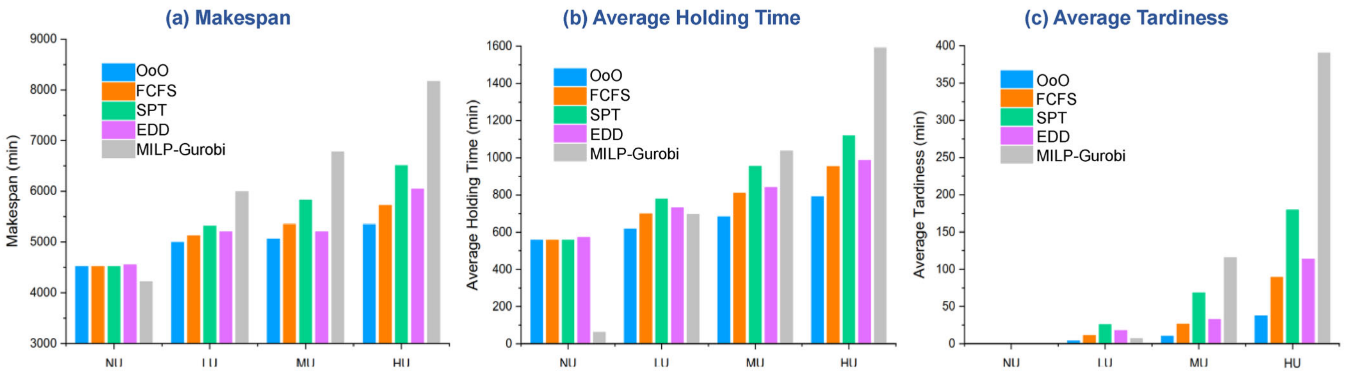

FIGURE 7 Histogram of performance results in stochastics experiments. EDD, earliest due date; FCFS, first come first served; MILP, mixed integer linear programming; SPT, shortest processing time.

revised MILP without two static temporal constraints of material available time a_k^i and due date d_k^i (Formulas 38 and 39). Combined with the lead time of materials (30 min), timing buffer between consecutive operations (30 min), and the due date lag (2000 min) for 10 temporally adjacent operations, offline a_k^i and d_k^i are determined for the online comparative experiments among OoO and other algorithms.

The average performance result of OoO and four comparative algorithms under different uncertainty levels (NU, LU, MU, and HU) in S1 is listed in Table 4, and the related histogram is displayed in Figure 7. Under the NU situation, MILP through Gurobi outperforms other algorithms in all indicators. However, with the increase in uncertainty, MILP performance indicators increase, especially in average tardiness. This result indicates that the static optimization model can solve offline scheduling when all the operational parameters can be determined in advance. However, the robustness of MILP to uncertainties and disturbances is weak. Compared with rule-based algorithms, OoO has better performance, and the related indicators increase less when the uncertainty level is higher. Tardiness is the most sensitive indicator of uncertainty due to accumulation effects, but OoO can still prevent unbalanced growth from this perspective. Thus, according to the basic mean value results, the proposed OoO model can efficiently reduce the project makespan, holding time, and tardiness in stochastic environments, providing strong robustness to disturbances in modular construction fit-out management.

The detailed performance analysis in a full-scale large-sized fit-out scenario (S2) for all floors in the target buildings is presented in Figure 8. OoO, FCFS, SPT, and EDD are compared in stochastic environments (LU, MU, and HU) to explore the managerial implications under real-life construction projects where uncertainties cannot be avoided. The parameter setting of the due date and available time is slacker and more practical to buffer uncertainties with improved robustness in real-life projects. The makespan in all PSE methods generally increases when the uncertainty level is higher due to more disturbed delays, and the OoO method outperforms the other three algorithms at all uncertainty levels. Regarding holding time, the mean value in OoO almost has no fluctuations, and the boxplot range is small. In contrast, the holding time in other algorithms is sensitive to the

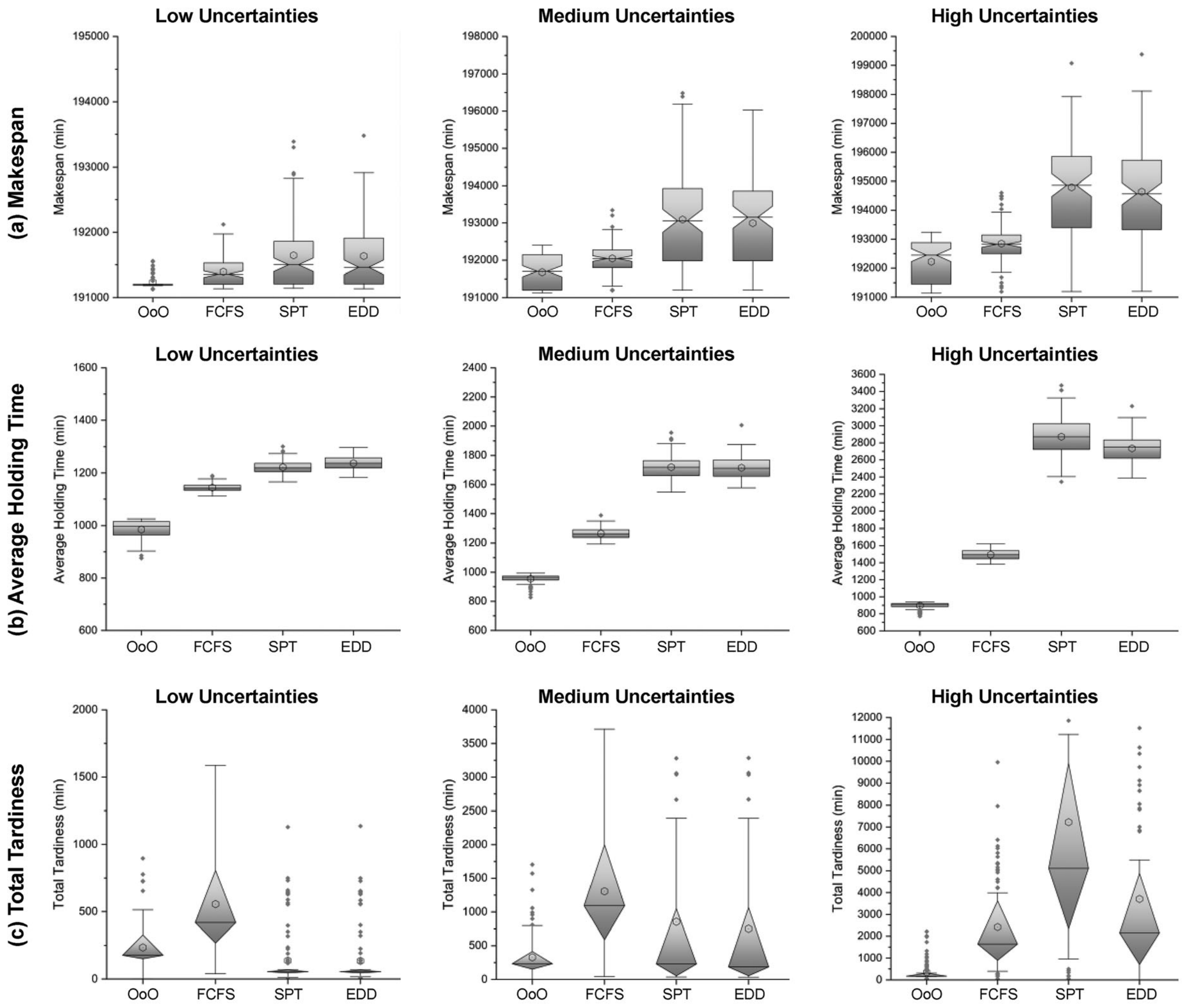

FIGURE 8 Boxplots of performance results in stochastic experiments. EDD, earliest due date; FCFS, first come first served; MILP, mixed integer linear programming; SPT, shortest processing time.

increase in uncertainty level. For total tardiness, SPT and EDD outperform OoO under a low uncertainty level, mainly due to the internal rules of SPT and EDD being more advantageous in providing a low-tardiness solution under a stable environment. However, with the increase in uncertainty level, the extent of disturbance greatly exceeds the handling capacity of SPT and EDD, whereas OoO has lower tardiness, and the value is more stable under medium and high uncertainty levels. From the perspective of the fluctuation ratio, tardiness is the most sensitive factor among the three performance indicators, mainly due to the accumulation effects of uncertainties.

For a summary of performance evaluation, based on the boxplot results, the OoO model demonstrates superior efficiency in reducing project makespan, holding time, and tardiness in stochastic environments, compared to other rule-based algorithms and the traditional MILP model. When uncertainties are absent, MILP achieves optimal performance, in line with optimization theory, by deriving theoretically optimal solutions within the solution space in undisturbed scenarios. However, MILP struggles to adapt to disturbances in uncertain environments, unless deployed in fully automated production lines with robots. On the other hand, the OoO algorithm exhibits remarkable resilience, maintaining excellent performance even in the face of disturbances. OoO model prioritizes real-time decision-making based on the actual construction process, particularly focusing on logistics-operation and multi-operations synchronization. Hence, OoO and MILP have both advantages, but OoO is more suitable for fulfilling the stochastic conditions of real-life construction management. Tardiness, as the most sensitive indicator to uncertainty due to accumulation effects, is effectively managed by the OoO model, preventing extensive and unbalanced growth in this indicator. The flexibility of the OoO mechanism enables dynamic adjustments in operation sequence and resource allocation based on updated navigations and alerts.

In addition, this experiment did not employ metaheuristic algorithms (e.g., genetic algorithm, simulated annealing, and particle swarm optimization) for the performance comparative testing. The reason lies in the internal mechanism and computational logic between metaheuristics and MILP. In the absence of considering computational time, metaheuristics algorithms do not inherently generate solutions superior to MILP. Metaheuristics relies on heuristic search strategies to explore solution spaces efficiently. These algorithms often provide near-optimal solutions through iterative improvement processes but do not guarantee optimality due to their stochastic nature and reliance on heuristics. On the other hand, MILP approaches are deterministic and aim to find exact solutions by formulating scheduling problems as linear optimization models. MILP is renowned for its ability to theoretically derive optimal solutions within the specified solution space, contingent upon the availability of ample computational resources. In the context of comparing the OoO model with global optimization algorithms, focusing on MILP as a benchmark is deemed sufficient. MILP represents a rigorous approach to offline scheduling, capturing the computational quality and optimality achievable in undisturbed scenarios. The decision not to include metaheuristic algorithms in this study acknowledges the overlap in function between metaheuristics and MILP, where MILP's function adequately represents the computational quality of offline scheduling without the need for additional comparative analysis with metaheuristics.

5.4 | Sensitivity analysis

The sensitivity analysis in this computational experiment investigates the effects of rolling time window size and crew capacity on the performance indicators to obtain more insights. Section 5.3 has proved that OoO and rule-based algorithms outperform the MILP model in real-life stochastic environments. This section only implements the sensitivity analysis for OoO, FCFS, SPT, and EDD under three-level uncertainties. For the evaluation factors, time window size is the key factor that controls the rate of iteration and affects the PSE performance within rolling horizons, and the workforce directly influences the operational efficiency and duration in modular construction fit-out projects. Both of these two inputs are vital for the output of the PSE models. The testing value of time window size is proportionally set as {15, 30, 60, 120, 240} (unit: *min*), and the testing value of worker squad number of three operational types is configured as {−2 (1/2/1), −1 (2/3/2), 0 (3/4/3), +1 (4/5/4), +2 (5/6/5)} (unit: *individual*). The effects of the input parameters on three output performance indicators are evaluated at different uncertainty levels.

For the sensitivity analysis of time window size, the makespan in the four algorithms exhibits low sensitivity to the changes in time window size in all three uncertainty levels as revealed in the results of sensitivity analysis for time window size in Figure 9. However, the effects on average holding time exhibit a proportional linear growth tendency and the growth rates in four algorithms are similar, which can be indicated that time window size directly affects the holding cost on-site buffer areas under all PSE methods. For the effects of time window size on total tardiness, the sensitivity degrees are obviously different under four algorithms in different uncertainty levels. Under low and medium uncertainty scenarios, tardiness in FCFS is significantly influenced by the increase in time window size, while the other three algorithms are basically stable when the input changes. In the high uncertainty scenario, OoO exhibits strong resilience for the increase of time window size, and the other three algorithms generate large disturbances in total tardiness. In particular, if a disturbance persists for a long period, the time window size remains likely to play an essential role in mitigating this disturbance. This is because the time window size directly affects the timeliness of detecting the disturbance. Specifically, if the time window is relatively small, there is a higher probability that the disturbance will be timely feedback to the decision-making level, allowing managers to make corresponding adjustments. If the duration of a disturbance is too long, its negative impact extent depends on whether the OoO mechanism can provide effective countermeasures. If the disturbance cannot be effectively resolved, the size of the time window becomes less critical because the temporal scale of the delay effect is already much larger than the time window scale. On the other hand, if the OoO mechanism can effectively address the disturbance, the size of the time window remains crucial as it relates to whether the decision-making layer can timely detect this disturbance, which is closely connected to the digital twin visibility module.

As shown in Figure 10, worker squad number also plays an important role in influencing the three performance indicators. For the effects on makespan, the progress delay caused by the worker capacity increases with the uncertainty level, while SPT and EDD are more sensitive than OoO and FCFS, especially in the high uncertainty scenario. Average holding time increases rapidly when the worker capacity is reduced from the standard layout (3/4/3), but it does not significantly change when the worker capacity increases with the same degree. This asymmetric

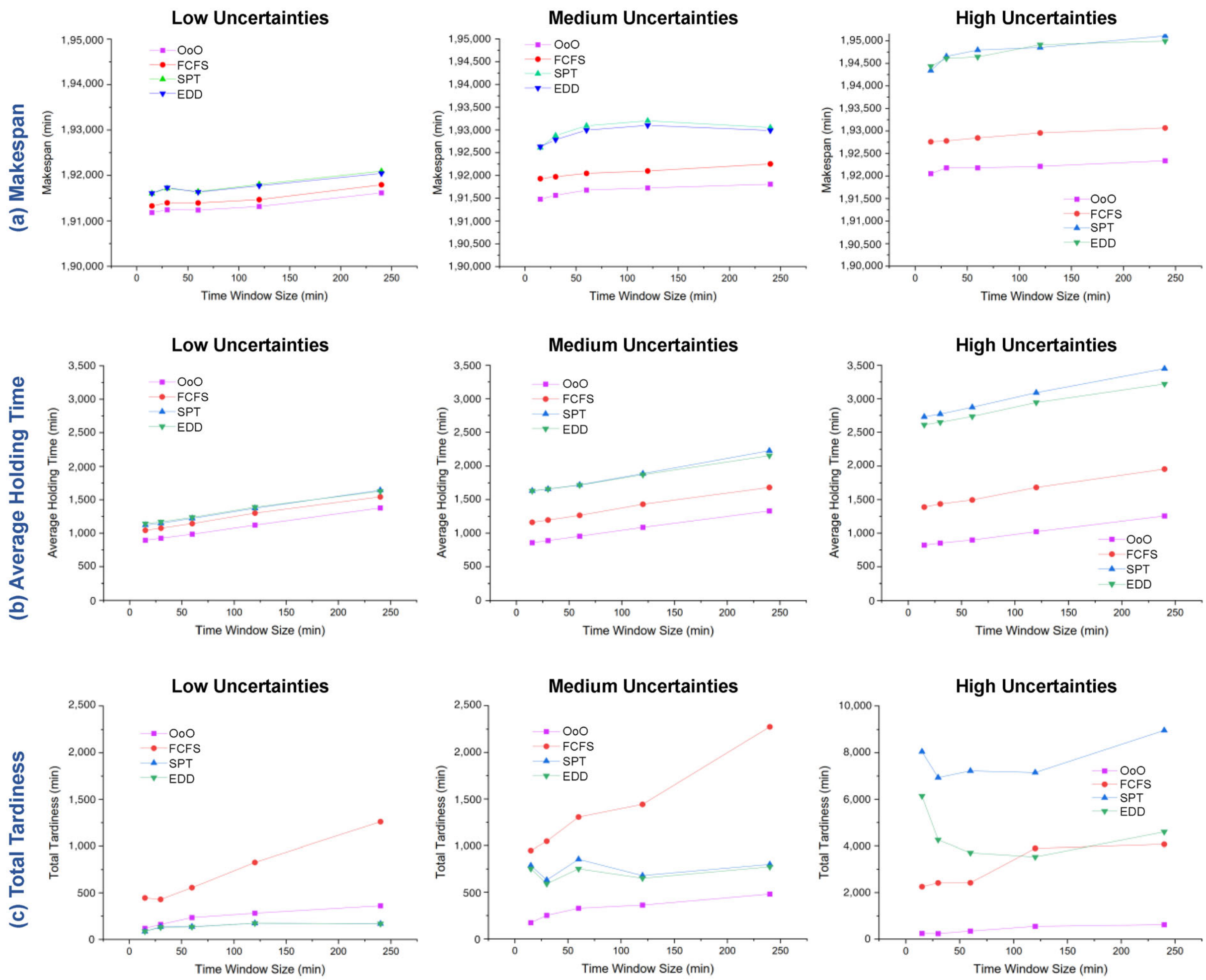

FIGURE 9 Sensitivity with rolling time window size (unit: *min*). EDD, earliest due date; FCFS, first come first served; MILP, mixed integer linear programming; SPT, shortest processing time.

performance indicates that the standard worker layout (3/4/3) occupies high cost-efficiency to save the inventory cost of fit-out materials. Moreover, few workers can cause systematic disorder and destruction for on-site fit-out material management in high uncertainty level according to the extremely increasing holding time, especially for SPT and EDD methods. However, although the holding time increases when the worker number is reduced and the uncertainty level increases, the OoO model still shows enhanced resilience for these disturbances to stabilize holding time. Total tardiness has a similar tendency as holding time when the worker capacity is changed. The total tardiness is not sensitive to the increasing of worker squad number from (3/4/3) to (5/6/5). Nevertheless, under medium and high uncertainty levels, tardiness under FCFS, SPT, and EDD greatly increases when the workforce is reduced, whereas OoO maintains high robustness to ensure that most operations could be completed before the due date. Thus, according to the sensitivity analysis, OoO is more robust to disturbances and uncertain changes in the system inputs than the other three rule-based algorithms, mainly due to its flexible rescheduling and dynamic adjustment mechanism using real-time data.

TABLE 5 Computational time analytics (100 runs).

Unit: s	TW15	TW30	TW60	TW120	TW240
OoO	310.170	150.801	76.096	35.771	18.797
FCFS	63.209	36.694	17.641	10.094	5.623
SPT	64.789	33.066	16.168	9.884	5.239
EDD	68.760	34.455	17.228	10.423	5.511

Abbreviations: EDD, earliest due date; FCFS, first come first served; OoO, out-of-order; SPT, shortest processing time.

In computational time analysis, four algorithms are tested across various time window sizes for 100 runs as shown in Table 5. The results indicate that the computational time of OoO is approximately five times longer than that of the other rule-based algorithms in each time window configuration. This discrepancy primarily

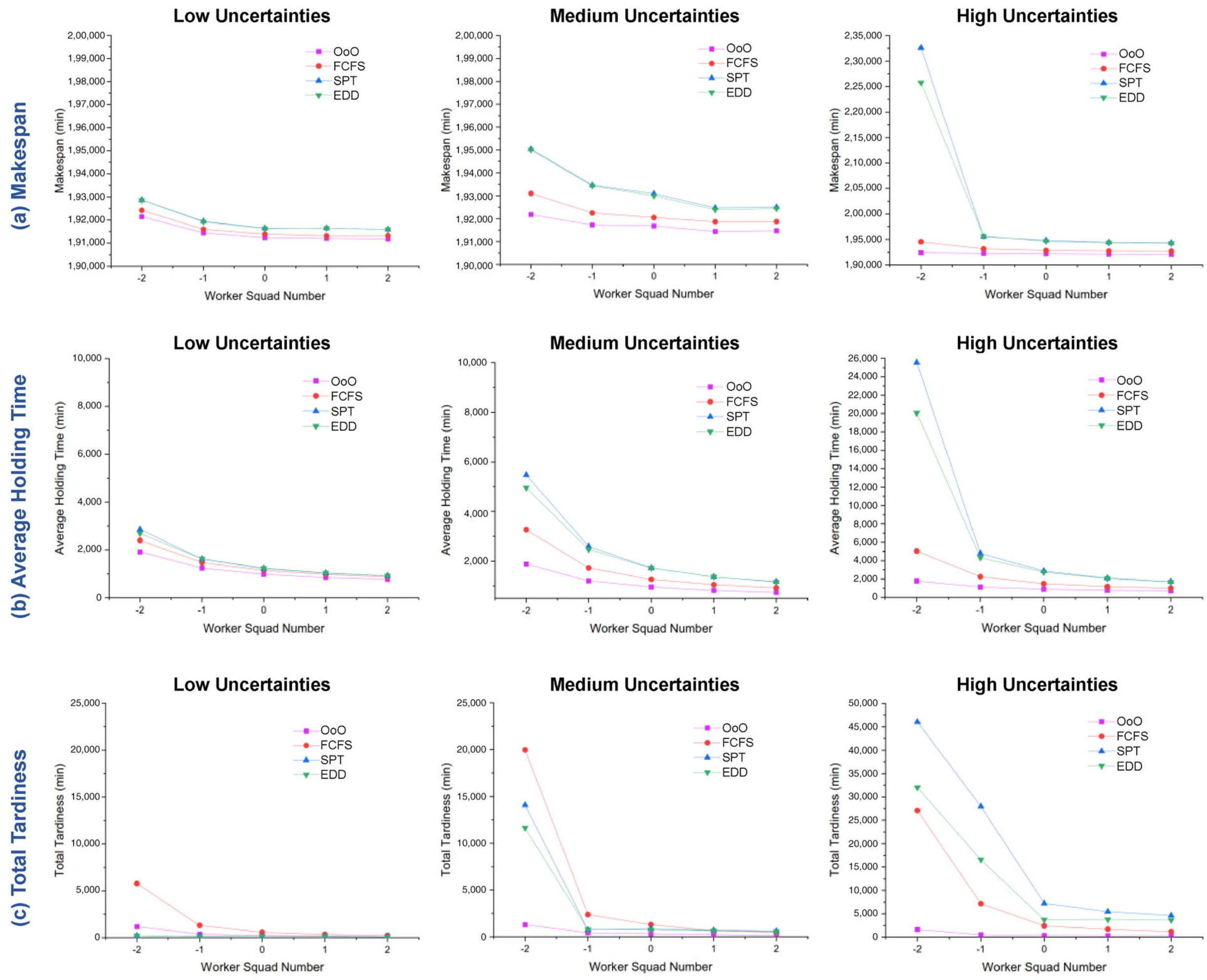

FIGURE 10 Sensitivity with workforce capacity (unit: *individual*). EDD, earliest due date; FCFS, first come first served; MILP, mixed integer linear programming; SPT, shortest processing time.

stems from the real-time state checking and resequencing mechanisms in the real-time operation pool of OoO. While FCFS, SPT, and EDD exhibit minor differences in computational time, OoO's enhanced resilience and solution quality entail additional costs. Furthermore, this experiment evaluates the computational time of MILP for the S2 scenario (160 operations), yielding a time of 3032.404 s across 100 runs. This significantly longer computational time underscores MILP's unsuitability for providing rapid responses to uncertainties and real-time solutions for digital twin systems. Additionally, the linear growth rate of computational time for OoO with changing time window sizes indicates a positive performance in terms of computational complexity. Despite implementing smaller time window sizes, OoO's computational time does not experience explosive growth, demonstrating its efficiency in managing computational complexity.

5.5 | Discussions

The proposed OoO model outperforms other algorithms in reducing project time and tardiness in uncertain environments. While MILP excels in stable scenarios, it struggles in dynamic settings. But the OoO algorithm demonstrates resilience, prioritizing real-time decision-making for efficient logistics and operations synchronization, effectively managing tardiness. Its flexibility allows for dynamic adjustments based on real-time data. For sensitivity analysis, compared with makespan and holding time, operation tardiness is more sensitive to uncertainties and changes in system configurations, such as rolling time window size. Under a high-uncertainty environment, ensuring that most operations are completed before the due dates using OoO is a challenge that managers should focus on. Time window size for real-time data collection through IoT sensors is the key controller for the iteration rate in rolling-horizon-based programming, and workforce capacity directly affects the operation efficiency. Increasing the worker number and deploying a smaller window size can improve the performance indicators, but both of these changes increase the project cost. Thus, finding the most cost-efficient parameters for the system configuration and programming design should be carefully considered in real-life modular construction fit-out management.

This paper notably excludes the utilization of machine learning techniques such as online reinforcement learning. The primary reasons for this omission can be summarized as follows. First, it is imperative to acknowledge the inherent disparities between construction sites and manufacturing facilities. Construction sites are characterized by heightened uncertainty and dynamics, along with larger spatial scales and extended operational cycles. Consequently, the collection of spatiotemporal status data relevant to scheduling poses significant challenges. This challenge is particularly daunting, compared to the context of smart manufacturing with IoT-enabled factory environments. Currently, obtaining a substantial volume of reliable and effective data on construction sites for training and validating machine learning models remains a challenging task. Second, the OoO model proposed in this study relies on real-time data within a rolling time horizon framework. Its core functionality centers on establishing consistency and simultaneity based on the present status of resources and operations. This dynamic scheduling of tasks aims to improve overall synchronization rates. Importantly, although a wealth of historical data is not an absolute requirement for driving this model in modular construction fit-out PSE, leveraging historical data can be valuable to inform decision-making. However, a prerequisite for this is the availability of sufficient and reliable datasets for training and testing within the current project. Therefore, while machine learning methods do not conflict with the OoO model proposed in this article, they have different focuses and applications.

6 | CONCLUSION

This paper formulates a novel real-time data-driven and rolling-horizon-based OoO model for the synchronized PSE in modular construction fit-out management. First, the scenario of a high-fidelity, traceable, and hyper-connected digital twin-enabled intelligent construction site is designed to provide looking-forward, looking-around, and looking-back visibility and traceability. Under the digital twin environment, logistics-operation and multi-operations synchronizations are more easily achieved to form lean and robust management under the changeable and dynamic environment. Second, a novel OoO algorithm using a real-time operation pool is proposed to synchronize and coordinate the fit-out operations based on the dynamic progress, serving as the basis of spatial–temporal synchronization during digital twin-enabled modular construction fit-out management. Third, computational experiments motivated by one MiC fit-out project of a residential building are implemented to evaluate the performances of the OoO model at different uncertainty levels. Three rule-based algorithms (FCFS, SPT, and EDD) and one MILP algorithm through Gurobi are compared to the proposed OoO model, whereas sensitivity analysis is performed to investigate the effects of rolling time window size and workforce capacity on three performance indicators. The results of the computational experiments indicate that the OoO model can achieve near-optimized solutions on makespan, holding time, and tardiness, thereby ensuring robustness to reduce the volatility caused by uncertainties.

This study makes several research contributions. First, this paper applies the concept of logistics-operation and multi-operations synchronizations to address PSE in modular construction fit-out management. In contrast to the traditional manufacturing assembly process, modular construction fit-out is more spatially dispersed. Concurrently, the modular construction fit-out project exhibits a broader modular area and an increased workload, necessitating a greater workforce and the utilization of diverse heterogeneous materials from multiple sources. Different from the traditional optimization problem, synchronization focuses more on the simultaneity rather than punctuality, which requires that suitable materials should be delivered to the right activities and operations should be implemented at the right time in the right place. This concept closely aligns with the JIT philosophy in manufacturing and the pragmatic “Make Do” concept, rooted in practical experiential knowledge, in real-life construction projects. Conventional static optimization models such as MILP can generate solutions that contain theoretically optimal value to give a static blueprint of task allocation and sequencing for managers. But many solutions provided by MILP are not capable to solve disturbances in uncertain and complex environments, such as a fit-out construction site. In contrast, the proposed OoO model fully uses real-time data through IoT and digital twins and considers more about spatial–temporal synchronization in dynamic and uncertain conditions. The updated real-time data in each rolling horizon converts the uncertain factors into deterministic parameters to provide real-time visibility and traceability, and managers can obtain what is happening in the current window and what will happen in the next time window to make related adjustments. Hence, the OoO model can output near-optimized solutions within acceptable computing time in the global regulation, and meanwhile improve the resilience and stability to handle uncertainties in advance before their severe effects actually happen.

However, there are several limitations in this study. First, the stability of the information communication environment for real-time data updating within a rolling time window remains unguaranteed due to current limitations in information communication technologies. Data transmission is susceptible to various uncertain outdoor conditions, including rain, wind speed, and dust. Therefore, it is crucial for the sensing environment to promptly collect and upload reliable real-time data, ensuring the effectiveness of the real-time data-driven OoO model. Second, in the context of optimizing operations and resources based on looking-around digital twin visibility, a more intricate graph algorithm can be employed for in-depth exploration. For instance, spatial continuity is a crucial consideration in the scheduling of both worker transitions and material transport. A judicious transfer of resources based on spatial continuity can enhance operational efficiency while concurrently reducing investment. Within the domain of fit-out operations, beyond the optimization of global or local metrics, the real-time interplay between operations and resources warrants dedicated consideration. Utilizing real-time data facilitates the representation of operations and resources as dynamic nodes within a time window, allowing the establishment of a dynamic graph. Subsequent utilization of graph optimization algorithms aims to maximize network efficiency, focusing on spatial continuity and the alignment of workers with operation metrics. A more profound investigation into this area is slated for future exploration. Third, the implementation of a digitalization framework poses potential threats to individual privacy, which gives rise to concomitant cultural and legal complexities. Addressing this concern necessitates thorough contemplation and steadfast adherence to ethical principles. This serves as a fundamental constraint, emphasizing the criticality of a deliberate approach toward safeguarding personal data. Additionally, the integration of worker perspectives is recognized as a crucial area for enhancement. This limitation underscores the importance of enhancing the inclusivity of insights within decision-making processes. Enhancing this integration becomes imperative for fostering a collaborative and inclusive working environment facilitated by a digital twin-based management system.

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