Concurrent Execution Process Modeling and Interaction Strategy among Coupled Design Tasks under EPC Mode

Ting Wang*

Logistics and E-Commerce College, Zhejiang Wanli University, Ningbo, China

INFORMATION

Keywords:
Concurrent execution
probability of information change
information interaction behavior
rework behavior
interaction strategy
EPC mode
design coupling
concurrent engineering
information transfer efficiency

DOI: 10.23967/j.rimni.2026.10.71652

Revista Internacional de Métodos Numéricos para Cálculo y Diseño en Ingeniería

Concurrent Execution Process Modeling and Interaction Strategy among Coupled Design Tasks under EPC Mode

Ting Wang*

Logistics and E-Commerce College, Zhejiang Wanli University, Ningbo, China

ABSTRACT

The concurrent execution of preliminary design and construction drawing design under the Engineering Procurement Construction (EPC) mode is an important method to achieve efficient connection in technology and deep integration in management between them, but it also faces the risk of multiple rework and information transmission caused by repeated iterative coupling and frequent information interaction. This issue leads to inefficiencies and increases project risk, particularly in managing interdependencies and mitigating rework. Unlike previous studies, this research focuses on optimizing the interaction strategies to minimize these risks and improve overall project performance in EPC projects. In view of this, on the basis of planning and quantifying the parallel execution process of preliminary design and construction drawing design, and constructing the corresponding change probability function (which is a model that predicts the likelihood of design information changes), this study introduces a novel analytical framework for predicting the likelihood of information changes and calculating their impact on task durations. A parallel execution duration decision-making model for solving the optimal information interaction strategy (the method of managing communication and decision-making to reduce delays and rework) is constructed. This model offers new decision guidelines to minimize rework and reduce delays in design tasks. Subsequently, through the numerical derivation and analysis of the change probability function, seven propositions about the interaction strategy are proposed. Through the numerical solution and analysis of the parallel execution duration model, six propositions about the interaction strategy are proposed. These propositions contribute to theory by offering a model that quantifies rework and information transfer in concurrent execution, and to practice by providing actionable insights for improving EPC project management. The results provide methodological countermeasures for discussing the interaction strategy of preliminary design and construction drawing design in the concurrent execution process from the perspective of quantitative analysis, and also provide directional suggestions for the application method of concurrent engineering concept in EPC mode.

OPEN ACCESS

Received: 09/08/2025

Accepted: 13/01/2026

DOI
10.23967/j.rimni.2026.10.71652

Keywords:
Concurrent execution
probability of information change
information interaction behavior
rework behavior
interaction strategy
EPC mode
design coupling
concurrent engineering
information transfer efficiency

*Correspondence: Ting Wang (wang_ting93@163.com).

1 Introduction

In terms of the tendering intervention time for EPC projects, the owner can base their decision on the project's characteristics and choose to award the contract after the completion of the feasibility study, scheme design, or preliminary design [1]. When the contract is awarded after the completion of the feasibility study but before the approval of the scheme design, there may be disputes over price adjustments or risk allocation for contract performance due to the inability to clearly define construction scale, construction standards, and investment limits under a fixed total price scenario [2]. When the contract is awarded after the preliminary design is completed, how can the construction drawing design be seamlessly connected with the preliminary design? How to effectively ensure the quality of construction drawing design documents? How to give full play to the architect's leading role and implement the architect responsibility system in the whole life cycle of the project? Therefore, awarding the contract after the completion of scheme design not only facilitates cost control and risk allocation under a fixed total price scenario, but more importantly, it enables the seamless integration of management for preliminary design and construction drawing design that are technically related, and maximizes the leading role of design in EPC mode [3].

However, during the project execution, despite the decision to award the contract after the completion of the scheme design, there are still disconnects in management and technical conflicts between preliminary design and construction drawing design, which lead to large-scale changes and large-scale rework behaviors between them [4]. The reason is that the serial execution method under the traditional design-bid-build (DBB) mode is still continued, and the concurrent execution method is not adopted according to the characteristics of the integration of the design process under the EPC mode [5]. Concurrent execution applies the core idea of concurrent engineering, emphasizing the maximum overlap of upstream and downstream stages without breaking the logic sequence [6,7]. This overlapping method can realize the transformation of large-scale change and high-cost rework in the traditional serial execution mode into small-scale change and low-cost rework through multiple information interaction behaviors between upstream and downstream stages [8,9]. Therefore, exploring how to apply the concept of concurrent engineering to the preliminary design and construction drawing design stages plays a pivotal role in achieving integration in the design stage.

Research Focus and Problem Statement:

While previous studies have addressed various aspects of concurrent execution in design-build phases, the optimization of interaction strategies to minimize rework and enhance overall project performance remains underexplored. While both our study and the referenced study address the challenge of managing concurrent execution between design and construction phases, our research specifically targets the optimization of interaction strategies to minimize rework and enhance project performance in EPC mode. Unlike the referenced study, which primarily focuses on the general optimization of concurrent execution, our work introduces a probabilistic framework to model the likelihood of information changes during concurrent execution. This approach enables more precise decision-making, reducing inefficiencies and mitigating project risks associated with task rework and information transmission.

2 Symbols and Definitions

Calculations involving logarithms in this work are done in the natural logarithm (base e). Logarithmic quantities (like entropy values) are made non-zero and normalized to lie between 0 and 1 to make them consistent across models and calculations. In the case of entropy, this implies that the values are normalized in such a manner that the highest value of the entropy (when the system is perfectly disordered) is 1, and the lowest value of the entropy (when there is no uncertainty) is 0, as in Table 1.

Table 1: List of symbols, definitions, and units

Symbol	Term	Definition	Unit	Allowed interval	Origin of estimate
iPD	Preliminary Design Task	The first phase of the design process, focusing on high-level concepts and overall project planning.	Dimensionless	N/A	Assumed from model
iCD	Construction Drawing Task	The second phase of the design, which involves detailed technical drawings and specifications.	Dimensionless	N/A	Assumed from model
TE	Transfer Efficiency	A measure of how quickly and accurately information is passed between tasks. Higher efficiency means faster and clearer transfer.	Dimensionless (0 to 1)	0 to 1	Estimated from model
TQ	Transfer Quality	A measure of how accurate the information is when it is transferred. Higher values mean more accurate information.	Dimensionless (0 to 1)	0 to 1	Based on entropy model
LE	Learning Effect	The improvement in task performance (speed or accuracy) over time due to experience gained from prior tasks.	Dimensionless (0 to 1)	0 to 1	Assumed from literature
WTC	Workload Transfer Coefficient	The proportion of rework caused by changes in the design information. A higher value means more work is needed to correct errors.	Dimensionless (0 to 1)	0 to 1	Estimated from model
CC	Coordination Capability	The ability of the design teams to work together effectively, reducing mistakes and improving efficiency.	Dimensionless (0 to 1)	0 to 1	Based on team studies
ID	Innovation Difficulty	The level of difficulty in incorporating new or complex ideas into the design process. More difficult innovation requires more effort and time.	Dimensionless (0 to 1)	0 to 1	Assumed from literature
H_{max}	Maximum Time-Dependent Entropy	The maximum value of entropy in a system.	nats (for natural log)	N/A	Based on theoretical model
H_t	Time-Dependent Entropy	The entropy of a system at a given time during concurrent execution.	nats (for natural log)	N/A	Based on calculation from model

3 Literature Review

As for the issue of concurrent execution between design tasks, existing literature can be roughly divided into two categories based on different research methods: one focuses on exploring the necessity and rationality of applying concurrent engineering theory to design management from a qualitative analysis perspective, and provides macro-level countermeasures and suggestions from the ideological, institutional, and technical levels [10–13]. These research results lay a theoretical foundation for the application of concurrent engineering theory in design management, but their research conclusions are all based on non-data-driven qualitative analysis methods, and there are many advocacy conclusions and few substantive and actionable conclusions. Allur's [14] research on resource allocation in cloud data centers proposes a new form of load-balancing, making use of edge computing, AI, and machine learning; thus, increasing scalability and efficiency. This approach could further extend to the EPC simultaneous operation process modeling of coupled design tasks by intelligently allocating loads among tasks and resources. This type of approach is efficient in terms of task execution, latency, and overall system performance. Zhang et al. [15] introduced that Engineering, Procurement, and Construction (EPC) projects, particularly in pumped storage hydropower, face challenges due to fragmented documentation and poor interoperability despite the use of BIM. To address this, a cross-platform EPC collaboration framework integrating IFC and Semantic Web technologies is proposed to enhance information accessibility and automate workflows through open standards.

Another type of research focuses on the concurrent execution duration between design tasks from the perspective of quantitative analysis. According to different optimization objectives, this kind of research can be divided into two categories: One focuses on the rework problem caused by concurrent execution. For example, Hossain et al. [16] proposed the equivalent rework duration calculation model considering the concurrent execution of multiple design activities by constructing the global benefit function of concurrent development duration and development cost. Based on the rework probability of design tasks, [17,18] discussed the problem of concurrent execution with sequential execution relationship and reverse feedback, and proposed that the expected reduction of rework depends on the accuracy of early information upstream and the sensitivity of downstream activities. Adaptability of the PI event trigger control has been proposed for MIMO nonlinear systems with input delays by [19]. Such systems can utilize the event-triggered mechanisms to minimize the frequency of control updates and maximize system effectiveness. This adaptive control methodology can merge into the proposed work on the concurrent process modelling of coupled design tasks in EPC mode to handle the timing and synchronization of task execution for resource efficient use and delay minimization between interdependent tasks. The realization of this strategy will lead to a more coordinated performance, reduced computation overheads and overall improved system performance in the execution of coupled design tasks. Hazini et al. [12] developed a parallel optimization algorithm based on genetic algorithms. This algorithm aims to identify which design activities require rework and to determine the parallel strategies that can minimize the rework costs. Seyednezhad et al. [20] presented a routing design in optical networks-on-chip with the use of Gray code to minimize optical loss. The strategy focused on the optimization of routing paths in order to improve the performance of optical interconnects in integrated circuits. The paper [21] focused on multitask optimization in an IoT-based green building energy system based on binary metaheuristic algorithms. The study focused on maximizing energy efficiency and sustainability in building operations by using advanced optimization techniques. Kalach et al. [22] provide information on rework probabilities based on different combinations of evolution, sensitivity, overlap strategies, and overlap percentages used between upstream and downstream activities to better understand the potential risks of rework. Koolwijk et al. [23] developed a concurrent optimization algorithm based on a genetic algorithm, which aims to find which design activities need to be executed in concurrent, and concurrent strategies that can minimize the total execution cost. The target-directed visual navigation system set forth by [24] base causal intervention in on enhancement of the navigation accuracy of intelligent vehicles. The method invokes causal attention mechanisms to mitigate the confounding effects and generalize to large populations of unknown targets and scenes for the future. By applying this causal intervention approach in addressing concurrent execution process modelling of coupled design tasks under EPC mode, shared management of task interactions ensures efficient execution and coordination among interdependent tasks. Lin et al. [25] adopted the SD method to simulate the evolution process of two kinds of rework behaviors, re-execution due to changes and reprocessing due to quality problems, and further analyzed the differences between the two kinds of rework behaviors. Lin et al. [26] discussed how to analyze multipath networks by introducing multiple precursor effects and how to analyze concurrent overlaps by introducing cascade effects, which provided inspiration for solving the overlapping time-cost trade-off and determining the optimal overlap degree. The above literature adopts different methods to study the rework problem caused by concurrency, but it still has the following shortcomings: (1) Only one-way rework caused by the possibility of information change of upstream design tasks is considered, while two-way task rework caused by information change between coupled tasks is ignored, which is not in line with the reality of a large number of coupling iterations between upstream and downstream design tasks; (2) Only the possibility of information change during concurrent execution in the design stage is considered, and the possibility of information change after the end of concurrent execution caused by the limited concurrent duration and the unpredictability of information change is ignored; (3) The influence of learning effect caused by concurrent execution on rework duration and concurrent duration is not considered.

Another type of research focuses on the information interaction duration caused by concurrent execution. Since there is no significant difference between the design stage of the construction industry and the design stage of the manufacturing industry due to different industry backgrounds, this study further extends the perspective of the literature review to the field of product manufacturing. Lin et al. [27] discussed how to determine the degree of concurrency between upstream and downstream activities and determine the frequency of information communication between them accordingly. Liu et al. [28] incorporated communication duration and cost into the concurrent strategy model to determine the optimal concurrency degree and communication strategy. Bo's research [29] on optimizing cloud environments for big data processing addresses issues concerning dynamic resource allocation, autoscaling, and load balancing for performance and scalability benefits. These strategies can be adopted in the proposed concurrent execution process modeling of coupled design tasks under EPC mode to distribute computation resources efficiently among interdependent tasks with a balanced workload and low latency. The implementation of such optimization strategies will improve task execution in terms of efficiency, scalability, and cost-effectiveness in the design process. Loch & Terwiesch [30] constructed a communication model of static information and dynamic information in the process of concurrent execution, and deduced from the model that only when the downstream work progresses to a certain extent, the upstream should communicate with each other to obtain the latest information. Dehghan et al. [10] constructed a model for multiple information release during concurrent execution in the design phase, and explored the optimal size of information release work packages under different levels of concurrency. Park et al. [31] incorporated the communication and coordination behaviors caused by rework and changes into the SD model, and considered the impact of the time taken by this behavior on the project completion date. Srour et al. [32] present a four-step process for scheduling the design phase of fast-tracked construction projects while taking into consideration information exchange among project activities. The above literature discusses the information transfer behavior in concurrent mode from different angles, but it still has shortcomings: (1) It only discusses the one-way information transfer behavior based on the concurrent situation between a single upstream and downstream activity, and does not further extend the concurrent execution situation of multiple activities and coupled activity sets; (2) The influence of mutual learning effect caused by two-way information interaction in concurrent execution mode on information communication duration and concurrent execution duration is not considered; (3) The information interaction behavior in the concurrent execution mode is not classified and discussed according to whether there is information change.

Methodological Advancements:

A key innovation of our study lies in the introduction of a change probability function that models the likelihood of design information changes and their impact on task durations. This function, which is central to our analysis, goes beyond the traditional methods used in the referenced paper by considering both upstream and downstream information changes within coupled design tasks. Additionally, we incorporate a learning effect in the task execution process, which allows our model to account for improvements in efficiency over time due to iterative feedback between tasks. This is a significant advancement over the existing study, which primarily considers one-way task rework without factoring in the dynamic learning processes that occur in real-world projects.

4 Research Objective and Scope

Based on the above analysis and combined with the research background, improvements are made from the following aspects: (1) The concurrent execution of a single design task is extended to multiple design tasks with coupling relationship; (2) Extend the case that only upstream change behavior causes downstream rework behavior to consider both upstream and downstream change behavior causes rework behavior; (3) When estimating the information change rate of upstream and downstream tasks, replace the traditional empirical estimation method with the scientific calculation method based on the rigorous probability estimation model; (4) According to the characteristics of coupled design tasks, the concurrent execution within the same design task is regarded as two-way information interaction behavior, while the concurrent execution between different design tasks is regarded as one-way information interaction behavior; (5) Using comparative analysis to explore the impact of learning effects on task concurrent execution duration and total execution duration between coupled design tasks. The model allows iterative feedback to be effective in ensuring proper communication between the preliminary design (PD) and construction drawing design (CD) tasks. These feedback processes enable communication of information during the PD stage to be communicated continuously to the CD stage and be integrated to minimize rework and make both stages in line with each other. The model, therefore, allows an easy flow of information between the stages, whereby changes in one stage are communicated to the other swiftly, avoiding mistakes and optimum execution of the entire project. The architect is very important in controlling and directing the project during the preliminary design and construction drawing phase. During the initial design stage, the architect will make sure that the design ideas comply with the general project requirements, consult with different stakeholders, and assist in creating attainable schedules. During the construction drawing phase, the architect is concerned with technical detailing and control of how to fit the design into a workable plan of construction. Their participation can see both stages through without causing much error and rework. In addition, the integration of upstream and downstream design interactions in the model ensures that feedback from preliminary design can be iteratively incorporated into downstream construction drawings to reduce rework, while downstream detailing receives stabilized upstream outputs at later stages to optimize execution time. Based on the above reconstruction of modeling methods, this study takes preliminary design and construction drawing design as two stages of concurrent execution of design tasks, and then discusses the interaction strategy of whether there is information interaction behavior or not under the influence of the learning effect in the concurrent execution duration between the two stages. In the practice of EPC projects, the two-way information exchange is usually found within one specific specialty, such as between planning of structural layout and load calculation in the initial design phase, where the iterative feedback processes can be observed in both directions. Unidirectional information exchange is used, by contrast, between specialties, such as the transfer of structural drawings to be detailed off-the-sheet by HVAC or electrical, the latter of which receives completed information and updates only infrequently.

Fig. 1 shows the overall planning diagram of Preliminary Design (PD) and Construction-drawing Design (CD) during concurrent execution. According to the key time nodes of the two in concurrent execution, the process can be divided into four time periods successively, namely, the start time of the first concurrent execution, the concurrent execution stage with two-way information interaction behavior, the concurrent execution stage with one-way information interaction behavior, and the start time of concurrent execution. Among them, the last three time periods occur repeatedly in the design life cycle with a single task as the basic division unit. The planning and quantitative analysis for the above four time periods are as follows:

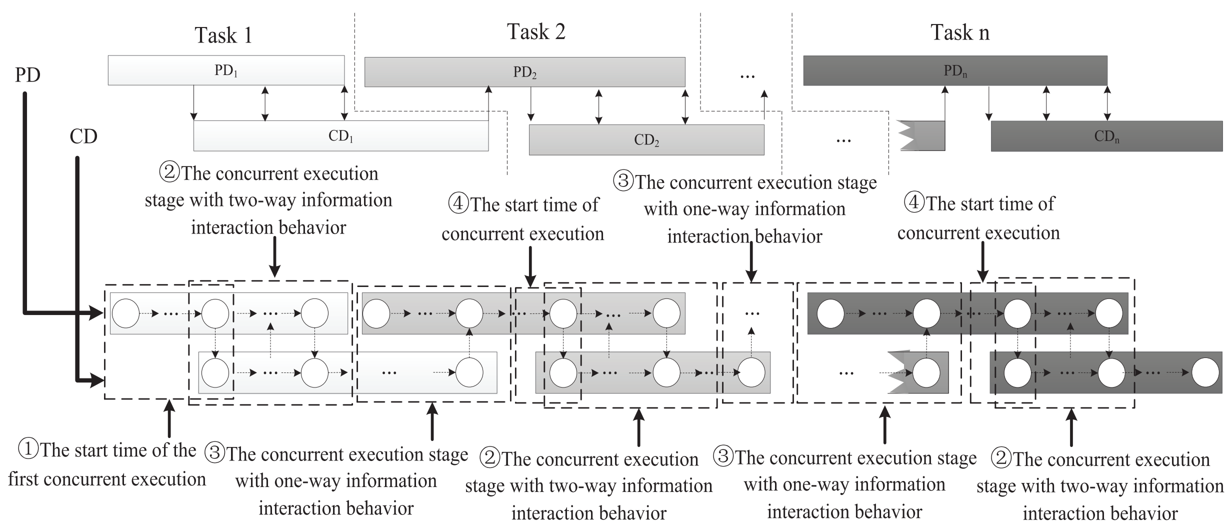


Figure 1: Concurrent execution process planning in the design phase

Key Differences from Existing Research

A notable distinction between our work and the existing studies lies in our focus on the iterative feedback process between coupled design tasks. While previous studies mainly address general optimization techniques in concurrent execution, they do not fully capture the iterative and complex interactions between upstream and downstream tasks. Our model incorporates these interactions in a more sophisticated manner, using probabilistic modeling to predict rework and communication durations. Additionally, we extend the application of Monte Carlo simulations and optimization algorithms, which were not employed in prior research, to enhance the robustness of our solution in handling project uncertainties. The inclusion of these advanced modeling techniques offers more precise decision-making capabilities and allows for the effective management of project risks associated with rework and information transmission inefficiencies. This approach addresses critical gaps in previous studies and provides a more comprehensive framework for EPC project management.

5 Modeling of Concurrent Execution Process

Proposed Proposition and Quantitative Model:

To address the challenges of inefficient task interactions in concurrent execution, we propose a new set of propositions that optimize the interaction strategy between upstream and downstream tasks. Our quantitative model is designed to minimize rework and enhance overall project efficiency by integrating two-way information interaction. Unlike traditional models that rely on one-way information transfer, our approach fosters dynamic feedback between tasks, allowing for continuous updates and reducing delays. These propositions offer actionable strategies to improve EPC project performance by identifying optimal information transfer strategies that minimize inefficiencies, rework, and project delays, providing a more robust and efficient approach to concurrent execution in EPC projects.

5.1 Planning and Quantification of Concurrent Execution Processes

5.1.1 The Start Time of the First Concurrent Execution

At the beginning of the first concurrent execution, that is, when CD_1 starts to execute, PD_1 will transmit the completed design results, that is, the design information accumulated before concurrent execution, to CD_1. At this time, PD_1 needs to spend a certain amount of information transmission duration while CD_1 needs to spend a certain amount of information receiving duration. Since the information transmission behavior and the information receiving behavior are two mutually causal phenomena in the same relationship in the concurrent execution process, the two behaviors can be regarded as the same behavior with the same duration consuming. In this study, they are regarded as the same behavior of information transmission, and the duration consuming of the behavior is mainly affected by the information transmission prescription, which measures the speed of information transmission.

Based on the above analysis, and combined with the quantitative research on the communication duration required during concurrent execution by [27,33], the starting execution duration of PD_1 is defined as 0, the starting interval between PD_1 and CD_1 is d'_{a1}, and the information transfer duration between PD_1 and CD_1 at the starting time of concurrent execution is:

$$I_1 = \theta\,(1 - E_1)\,d'_{a1} \tag{1}$$

where, θ is the coefficient of information transmission duration, which is affected by the information transfer efficiency E_1. This study borrowed the calculation method of information transfer efficiency among several organizations or departments proposed by Robert (Wang & Feng, 2022) [34], that is, by dividing the execution duration into several equal duration intervals, the execution duration can be regarded as a set composed of several duration segments. The nodes connecting several duration segments can be abstracted as several departments or organizations. As shown in Fig. 1, the dotted frame marked with ① is the duration segment abstracted from the execution duration involved in the first concurrent execution start moment, which is composed of several circle nodes. The improved calculation process of information transfer efficiency is as follows:

Step 1: Determine the contact length l_{xy}. l_{xy} is the shortest information transmission path between nodes x and y, referred to as the contact length between two nodes. If two nodes are directly connected, the length of the connection is 1. If the connection between two nodes passes through other nodes, the length of the connection increases by 1 for each node that passes through.

Step 2: The total number of aging microstates and the realization probability of aging microstates. Based on l_{xy}, the total number of aging microscopic states corresponding to *dashed box* ① and the realization probability of aging microscopic states associated with nodes x to y can be obtained as follows:

$$A_1 = \sum_{x=1}^{N}\sum_{y=1}^{N} l_{xy} \quad x, y \in dashed\ box① \tag{2}$$

$$P_1(xy) = l_{xy}/A_1 \tag{3}$$

Step 3: The maximum time-dependent entropy of information transmission based on the *dashed box* ①. The maximum time-dependent entropy represents the maximum value of entropy in a system. The total number of microscopic states calculated by Wang & Feng [34] is based on a complete organizational structure, so the maximum time-aging entropy is defined based on A_1. In this study, *dashed box* ① belongs to two systems PD_1 and CD_1, so the maximum time-dependent entropy of the *dashed box* ① can be expressed as:

$$H_{1m} = \log_2\left(A_{1(PD_1)} + A_{1(CD_1)}\right) \tag{4}$$

$$A_{1(PD_1)} = \sum_{x=1}^{N}\sum_{y=1}^{N} l_{xy} \quad xy \in PD_1, \quad A_{1(CD_1)} = \sum_{x=1}^{N}\sum_{y=1}^{N} l_{xy} \quad xy \in CD_1$$

where,

Step 4: The calculation formulas for the time-dependent entropy of information transfer between nodes x and y based on the *dashed box* ① and the total time-dependent entropy of the system are respectively:

$$H_1(xy) = -P_1(xy)\log_2 P_1(xy) \tag{5}$$

$$H_1 = \sum_{x=1}^{N}\sum_{y=1}^{N} H_1(xy) \tag{6}$$

Step 5: The calculation formula for the information transmission effectiveness based on the *dashed box* ① is:

$$E_1 = 1 - H_1/H_{1m} \tag{7}$$

This 5-step itemization is especially suitable in the context of the PD-CD interaction network, since the measure of entropy is suitable to quantify the uncertainty in, and dynamic interactions between tasks in the concurrent execution environment. Entropy as a measure of disorder assists us to know how information quality and efficiency change with time in the course of transmission. The method is appropriate in the prediction of the iterative and time-dependent feedback that exists between correlated tasks.

Other models useful in the analysis of efficiency of communication include mutual information, channel capacity, and queuing models, which, however, have a shortcoming in terms of being dynamic and iterative in the study of the PD-CD interaction. Mutual information pays attention to the common information, though it does not consider the dynamics of time of concurrent tasks, whereas channel capacity and queuing models are considered with static or unidirectional communication, which is more limited to the interdependencies of the current design process.

Based on the above modeling and analysis, the following practical recommendations for EPC practitioners are suggested:

- Optimal information interaction strategies should be adopted to minimize rework, particularly in cases of information uncertainty during concurrent execution.
- Improving coordination capabilities among design teams can reduce delays, ensuring a smoother execution process. Practitioners should establish clear communication protocols to enhance information transfer efficiency.
- Regularly evaluate the degree of concurrency between preliminary and construction drawing design tasks to align with the rate of information change, optimizing project schedules and resource allocation.

These recommendations are aimed at reducing inefficiencies and improving overall project management within the EPC framework.

5.1.2 The Concurrent Execution Stage with Two-Way Information Interaction Behavior

In the process of two-way information interaction, both PD_i and CD_i need to spend a certain amount of time on information communication, and this time is not only affected by the information transfer efficiency, but also by the learning effect, considering that communication is a subjective and mutual learning behavior [34]. Additionally, since the implementation of CD_i is based on the incomplete work of PD_i, there may be a certain level of uncertainty in the design information that has been accepted by CD_i. When uncertain information is changed, CD_i is bound to carry out positive rework on part or all of the work completed in the concurrent stage (CD_i rework triggered by PD_i information change), thus bringing about the information change duration for PD_i and the positive rework duration for CD_i. Since the behavior of information change and positive rework are two mutually causal phenomena in the concurrent execution process, they can be regarded as the same behavior with equal time consumption. In this study, they are unified as positive rework behavior. At the same time, considering that information often faces distortion in the communication process, the rework duration is also affected by the information transfer quality, which measures the accuracy of information transmission under the existing communication mode. In order to highlight the impact of rework phenomenon on concurrent execution duration, it is assumed that only when rework occurs will the impact of information transfer quality be considered.

Accordingly, the probability that PD_i does not change and the probability that PD_i changes is P_{ai} and $1 - P_{ai}$, respectively. When there is no design change, there is no forward rework duration for PD_i and CD_i during concurrent execution, but only two-way information interaction duration. At this time, the information transmission duration of two-way information interaction behavior (*TIIB*) can be expressed as:

$$I_i^{TIIB-nr} = \theta \left(1 - E_i\right) \left(1 + ci^{\alpha_1}\right) d_{abi} \quad i = 1, \cdots, n \tag{8}$$

where, the calculation method of E_i is similar to that of E_1, except that when solving l_{xy}, the nodes x and y belong to the *dashed box* ②, and the solution process can be referred to E_1. c is the difficulty coefficient of information communication, which will dynamically increase with the increase of overlapping duration based on the coefficient of information reception duration θ. α_1 is the learning effect index of information communication, i^{α_1} is the learning rate of information communication, and ci^{α_1} indicates that the difficulty coefficient of information communication between PD_i and CD_i will gradually decrease with the increase of concurrent execution duration.

When design information is changed, PD_i and CD_i have both information transfer duration and forward rework duration during concurrent execution. At this time, the information transmission duration and the forward rework duration with two-way information interaction behavior can be expressed as:

$$I_i^{TIIB-r} = \theta\left(1 - E_i\right)\left[\left(1 + ci^{\alpha_1}\right) d_{abi} + \Delta t_{ba(i,i)}\right] \quad i = 1, \cdots, n \tag{9}$$

$$\Delta t_{ba(i,i)} = m_{ba(i,i)} i^{\alpha_2}\left(1 - Q_i\right) d_{abi} \quad i = 1, \cdots, n \tag{10}$$

In Formula (9), the information interaction duration is affected by the information transfer effectiveness, concurrent duration, and rework duration. In Formula (10), $m_{ba(i,i)}$ is the workload transfer coefficient (positive transfer coefficient), which represents the rework scale caused by changes in PD_i to CD_i. The system will also dynamically increase with the increase of concurrent duration. α_2 is the workload transfer learning effect index, i^{α_2} is the workload transfer learning rate, $m_{ba(i,i)} i^{\alpha_2}$ indicates that with the increase of concurrent execution duration, the workload transfer coefficient from PD_i to CD_i will gradually decrease due to the existence of the learning effect of information communication in the concurrent stage, and eventually shorten the rework duration. Q_i represents the information transfer quality, and $m_{ba(i,i)}\left(1 - Q_i\right)$ represents the inverse relationship between the workload transfer coefficient and the information transfer quality. As shown in Fig. 1, the dotted box marked with ② represents the execution duration of the concurrent execution process involving information interaction activities, which is abstracted as a time period consisting of several connected circle nodes. The improved solution to the information transmission quality is similar to the information transmission effectiveness, and the solution process is as follows:

Step 1: Determine the contact span K_x. K_x is the number of nodes that are directly related to the x node, and $x \in dashedbox$ ②.

Step 2: Total number of quality microscopic states and realization probability of microscopic states. Based on K_x, the total number of quality micro-states corresponding to *dashed box* ② and the realization probability of quality micro-states of the x node can be expressed as:

$$B_i = \sum_{x=1}^{N} K_x \quad x \in dashed\ box② \tag{11}$$

$$P_i\left(x\right) = K_x / B_i \tag{12}$$

Step 3: The maximum quality entropy of information transmission based on the *dashed box* ②. The maximum quality entropy represents the maximum entropy of a system. The calculation formula for the total number of microscopic states constructed by Wang & Feng [34] is based on a complete organizational structure, so its maximum time-aging entropy is defined based on B_i. In this study, *dashed box* ② belongs to two systems PD_i and CD_i, so the maximum quality entropy of *dashed box* ② is:

$$L_{im} = \log_2\left(B_{i\left(PD_i\right)} + B_{i\left(CD_i\right)}\right) \tag{13}$$

$$B_{i\left(PD_i\right)} = \sum_{x=1}^{N} K_x \quad x \in PD_i, \quad B_{i\left(CD_i\right)} = \sum_{x=1}^{N} K_x \quad x \in CD_i.$$

where,

Step 4: The calculation formulas for the information transmission quality entropy and the total system quality entropy of the i th node based on the *dashed box* ② are respectively:

$$L_i(x) = -P_i(x)\log_2 P_i(x) \tag{14}$$

$$L_i = \sum_{x=1}^{N} L_i(x) \tag{15}$$

Step 5: The calculation formula of information transmission quality based on *dashed box* ② is as follows:

$$Q_i = 1 - L_i/L_{im} \tag{16}$$

5.1.3 The Concurrent Execution Stage with One-Way Information Interaction Behavior

When PD_i is completed, because the design depth of CD_i is much higher than that of PD_i, the task quantity of CD_i is far more than that of PD_i, which results in the finiteness of the concurrent execution duration of PD_i and CD_i belonging to the same specialty, that is, there are still a lot of unexecuted work in CD_i when PD_i is completed. As we all know, in order to satisfy the coordination and mutual restriction between CD_i and CD_{i+1}, which also have the same compact and contextual dependence, the execution of PD_{i+1} task not only depends on the design information provided by its compact design task PD_i, but also needs to refer to the design information provided by CD_i at the time of final completion to a certain extent. However, in order to shorten the design task completion cycle as much as possible, the succeeding design task PD_{i+1} of PD_i will start in advance without obtaining the final information of CD_i, that is, it will start at any time after the completion of PD_i, thus forming a concurrent execution mode of the remaining stage of CD_i and the early start stage of PD_{i+1}. During concurrent execution, because the two tasks belong to different stages, that is, PD_{i+1} only needs the final information of CD_i instead of the process information, there is only one-way information interaction behavior during concurrent execution, and only one one-way information transmission behavior exists at the end of CD_i. If there is a deviation between the final information delivered by CD_i and the estimated information of PD_{i+1} at this time, it means that CD_i finds the hidden design error of PD_i when it conducts detailed design based on PD_i or solves the design problem left by PD_i, and takes a change behavior. At this time, the PD_{i+1} design process, which is started in advance based on the estimated information only, will produce reverse rework behavior (PD_{i+1} design rework caused by the change of CD_i information) due to the incompatibility with the final CD_i information, and the rework workload is the correction of the incompatible part of the currently executed design task.

Based on this, the duration of the remaining stage of CD_i after PD_i is completed is set as d'_{bi}; the duration of the advanced start stage of PD_{i+1} is also $d'_{a(i+1)}$. The advanced start stage can be divided into two categories based on whether CD_i is completed before or after the task, where the duration before completion is $\rho d'_{a(i+1)}$ and the duration after completion is $(1-\rho)\, d'_{a(i+1)}$. ρ represents the proportion of concurrent execution duration of one-way information interaction behavior to the duration of the advanced start stage. The probabilities of no information change and information change happening in the remaining stage of CD_i are P_{bi} and $1 - P_{bi}$, respectively. When no information change occurs, there is no reverse rework duration for PD_{i+1}, only information receiving duration. In this case, the information receiving duration is affected by the information transmission efficiency E_i in stages d'_{bi} and $\rho d'_{a(i+1)}$, and d'_{bi}, as an important source of necessary design information for PD_{i+1}, needs to meet the information compatibility requirements with $\rho d'_{a(i+1)}$. Therefore, when ρ increases, it means that PD_{i+1}

needs to spend more time to analyze the information compatibility between $d^{'}_{bi}$ and $\rho d^{'}_{a(i+1)}$. Therefore, under one-way information interaction behavior ($OIIB$), the information receiving duration without rework duration can be expressed as:

$$I_i^{OIIB-nr} = \theta \left(1 - E_i\right) \left(1 + \rho\right) \left(\rho d^{'}_{a(i+1)} + d^{'}_{bi}\right) \quad i = 1, 2, \cdots, n \tag{17}$$

When information changes, PD_{i+1} has both information receiving duration and reverse rework duration. Therefore, the information receiving duration and rework duration with no information interaction behavior can be expressed as follows:

$$I_i^{OIIB-r} = \theta \left(1 - E_i\right) \left(1 + \rho\right) \left(\rho d^{'}_{a(i+1)} + d^{'}_{bi} + \Delta t_{ab(i,i+1)}\right) \quad i = 1, 2, \cdots, n \tag{18}$$

$$\Delta t_{ab(i,i+1)} = m_{ab(i,i+1)} \left(1 - Q_i\right) \rho d^{'}_{a(i+1)} \quad i = 1, 2, \cdots, n \tag{19}$$

In Formula (18), the information receiving duration is affected by both concurrent duration and rework duration. In Formula (17), $m_{ab(i,i+1)}$ is the workload transfer coefficient (reverse transfer coefficient), which represents the rework scale caused to PD_{i+1} when CD_i is changed. It should be noted that the reason why there is no workload transfer learning rate is that there is no mutual learning effect caused by two-way information interaction during concurrent execution. Q_i represents the quality of information transmission, and $m_{ab(i,i+1)} \left(1 - Q_i\right)$ represents the inverse relationship between the quality of information transmission and the workload transfer coefficient. As shown in Fig. 1, the dashed box marked with ③ represents the time period involved in the concurrent execution process without information interaction as the time period connected by several circle nodes. For the specific solution process, refer to Q_i.

5.1.4 The Start Time of Concurrent Execution

The concurrent execution start time refers to the concurrent execution start time of any other design task except the first design task. Based on the quantization result of concurrent execution phase without information interaction behavior, the information transmission duration under the condition of no rework behavior (Formula (20)) and rework behavior (Formula (21)) can be obtained, respectively:

$$I_i = \theta \left(1 - E_i\right) d^{'}_{a(i+1)} \quad i = 2, \cdots, n \tag{20}$$

$$I_i^r = \theta \left(1 - E_i\right) \left[d^{'}_{a(i+1)} + \Delta t_{ab(i,i+1)}\right] \quad i = 2, \cdots, n \tag{21}$$

where, the information transfer duration coefficient θ is affected by the information transfer efficiency E_i, the early start stage duration $d^{'}_{a(i+1)}$, and the possible rework duration $\Delta t_{ab(i,i+1)}$. The calculation method of E_i is similar to that of E_1, except that i and j nodes belong to dotted box ④ when solving l_{ij}, and the solving process can be referred to E_1.

Based on the above planning and quantitative analysis of the concurrent execution process of PD and CD, a quantitative schematic diagram of the concurrent execution process can be drawn as shown in Fig. 2. The execution duration of PD_i and CD_i can be divided into nominal execution duration and actual execution duration. The nominal execution duration refers to the task execution period excluding the information transfer duration and rework duration, while the actual execution duration refers to the task execution period including the two types of duration. Therefore, the nominal execution duration (actual execution duration) of PD and CD can be defined as D_a and D_b (T_a and T_b), respectively; the nominal execution duration (actual execution duration) of PD_i and CD_i can be defined as D_{ai} and D_{bi} (T_{ai} and T_{bi}), respectively; the nominal start execution time (actual start execution time) of PD_i and CD_i can be defined as d^s_{ai} and d^s_{bi} (t^s_{ai} and t^s_{bi}), respectively; and the overlapping duration of PD_i and CD_i is d_{abi}.

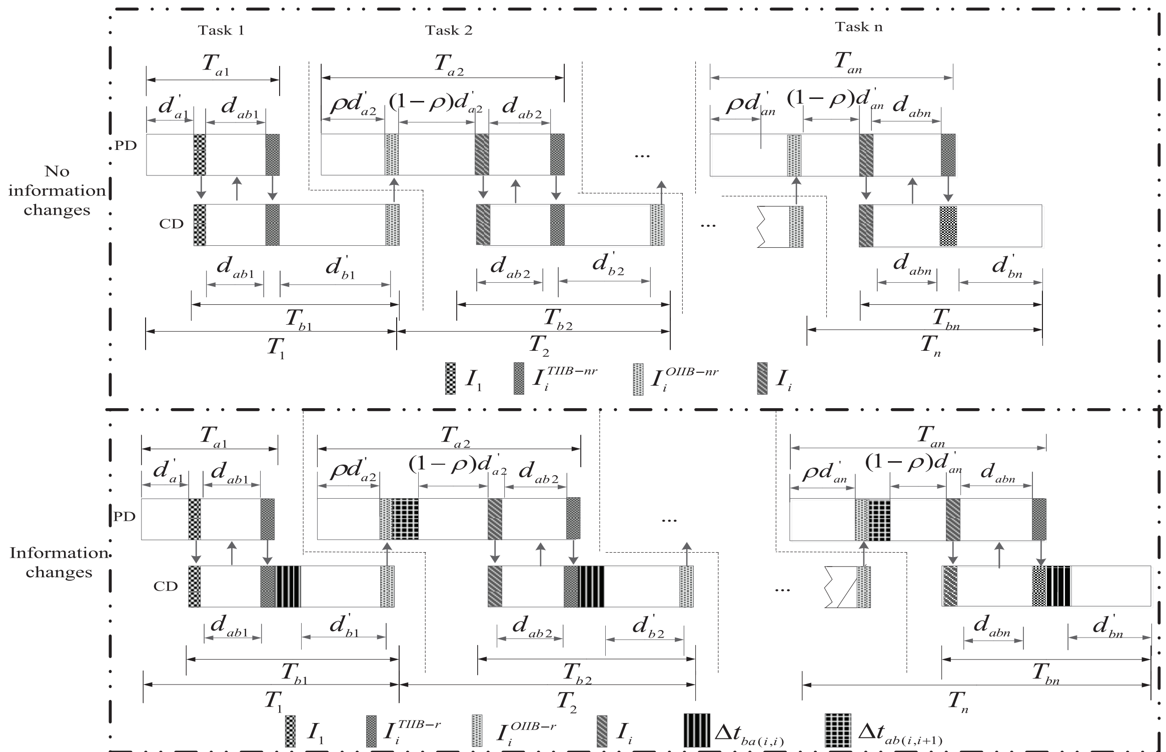


Figure 2: Quantization diagram of concurrent execution process in design stage

5.2 Practical Contributions

In addition to the theoretical contributions, this study provides practical guidelines for managing concurrent execution in EPC projects. We propose actionable strategies aimed at improving coordination capabilities among design teams, reducing delays, and ensuring smoother project execution. These strategies are based on a quantitative understanding of concurrent execution durations, rework behaviors, and information transfer efficiency—factors that are not fully addressed in previous studies. These practical contributions focus on:

- **Improved Coordination**: Establishing clear communication protocols to enhance coordination between upstream and downstream teams, thereby reducing project delays.
- **Efficient Information Transfer**: Optimizing the method and timing of information transfer to prevent rework and mitigate inefficiencies.
- **Enhanced Execution**: Applying probabilistic models and Monte Carlo simulations to predict rework and communication durations, ensuring better resource allocation and task management.
- **Rework Minimization**: Formulating methods to reduce rework by improving the accuracy and timeliness of information transfers, based on the results of the parallel execution duration model.

6 Construction of the Change Probability Function for Concurrent Execution Process

6.1 Construction of the Change Probability Function for Preliminary Design

In the concurrent execution mode, since CD_i works on the basis of incomplete information provided by PD_i, if the published information of PD_i changes, CD_i must rework part or all of the completed design link. Therefore, it is necessary to estimate the probability of PD_i changing by using a proper probability model. As a random event, the change behavior of PD_i can be predicted in a certain design stage, but the specific time node of its occurrence cannot be accurately predicted. Therefore, this behavior can be regarded as a random event subject to Poisson distribution. In addition, it is considered that the frequency of this random event is not constant throughout the PD_i stage, but constantly evolves with the deepening of the design progress. Therefore, the change behavior of PD_i should be regarded as a random event subject to a non-homogeneous Poisson distribution [35], and the corresponding probability mass function is:

$$P_{ai}\left(X=\pi\right)=\frac{{\omega_{ai}}^{\pi}}{\pi!}e^{-\omega_{ai}},\pi=0,1,2,\cdots,n \tag{22}$$

where, π represents the number of changes occurring; ω_{ai} is a non-homogeneous Poisson distribution parameter, and its value in the range of PD_i execution duration can be expressed as:

$$\omega_{ai}=\int_{d_{ai}^{s}}^{d_{ai}^{s}+D_{ai}}\lambda_{ai}\left(t\right)dt \tag{23}$$

where, $\lambda_{ai}\left(t\right)$ is the rate of information change occurrence. The idea proposed in literatures [36,37] to measure the rate of information change occurrence only considers the influence of the current task's own factors, without considering the possibility of the influence of the preceding and following tasks on it. Therefore, when defining $\lambda_{ai}\left(t\right)$, this study considers the key factors that affect the information change of CD_{i-1} during execution, and combined with the concurrent execution scenario of this study, it can be expressed as:

$$\lambda_{ai}\left(t\right)=\left(g_i\right)^{\beta_{ai}}\left[1+\left(P_{b(i-1)}\right)^{q_{i-1}}\varepsilon_i\left(2\frac{t}{D_a}-1\right)\right]t\in\left[d_{ai}^{s},d_{ai}^{s}+D_{ai}\right] \tag{24}$$

where, $g_i\in(0,1]$ represents the inherent uncertainty degree of PD_i, β_{ai} represents the technical capability index of the design team undertaking PD_i, and $\left(g_i\right)^{\beta_{ai}}$ represents the inherent uncertainty degree of PD_i will be reduced when the technical capability of the design team undertaking PD_i is improved. $\varepsilon_i\in[-1,1]$ represents the rate parameter at which PD_i changes information, which is affected by the degree of uncertainty of CD_i in concurrent execution mode. When $\varepsilon_i\in[-1,0)$, it means that the change rate gradually slows down with the progress of PD_i (rapid evolution), and the more it approaches -1, the more significant the change trend is. When $\varepsilon_i\in(0,1]$, the change trend is opposite to the above. When $\varepsilon_i=0$, it means that the rate at which PD_i changes is constant. $P_{b(i-1)}\in(0,1]$ represents the probability that CD_{i-1} does not change information, q_{i-1} is the inherent uncertainty degree of CD_{i-1}, and $\left(P_{b(i-1)}\right)^{q_{i-1}}$ represents that when the inherent uncertainty degree of CD_{i-1} is reduced, the probability that CD_{i-1} does not change information will be increased, and the rate of information change of PD_i will be reduced to some extent.

Based on the solution result of $\lambda_{ai}\left(t\right)$, the non-homogeneous Poisson distribution parameter ω_{ai} can be further obtained as follows:

$$\omega_{ai}=\left[D_{ai}\left(g_i\right)^{\beta_{ai}}\left(D_a-D_a\left(P_{b(i-1)}\right)^{q_{i-1}}\varepsilon_i+D_{ai}\left(P_{b(i-1)}\right)^{q_{i-1}}\varepsilon_i+2\left(P_{b(i-1)}\right)^{q_{i-1}}\varepsilon_i d_{ai}^{s}\right)\right]/D_a \tag{25}$$

Thus, the probability that PD_i does not change information can be finally obtained as follows:

$$P_{ai}\left\{X\left(d_{ai}^{s}+D_{ai}\right)-X\left(d_{ai}^{s}\right)=0\right\}=e^{-\omega_{ai}} \tag{26}$$

The change probability model works on the principles of forecasting the probability of design changes in parallel implementation, which makes scheduling more precise and also allows maximizing task overlaps. The model prevents the rework by estimating the number of design changes at various stages so that downstream tasks do not have to wait because of unexpected changes in upstream tasks. This lowers inefficiency in the design process and the rework effects on the execution of the whole project.

6.2 Construction of the Change Probability Function for Construction Drawing Design

From the above analysis of PD and CD in the concurrent execution stage without information interaction, it can be seen that the change of CD_i information will cause the reverse rework of PD_{i+1} task. Therefore, it is very necessary to estimate the possibility of CD_i information change by using an appropriate probability estimation model. The possibility of change in CD is the same as that in PD, which can also be regarded as a random event. The difference is that the change in CD_i is not only affected by its own factors, but also affected by the reliability of PD_i and the overall innovation of PD. The reliability of PD_i is closely related to its effective information accumulation rate, which is closely related to the actual progress of the task. Therefore, the reliability function of PD_i is defined as follows:

$$\mu_{ai}=\tau_i\left(\sum_{i=1}^{i} D_{ai}/D_a\right)^{\eta_i}+\left(1-\tau_i\right) \tag{27}$$

where: η_i is the path index of effective information accumulation and evolution of PD_i. When $0 < \eta_i < 1$, the characteristics of effective information accumulation and evolution of PD_i are first fast and then slow, and the more it approaches zero, the more significant the change trend is. When $\eta_i > 1$, the change trend is opposite to the above. When $\eta_i = 1$, the cumulative evolution of effective information of PD_i presents a linear growth trend. $\sum_{i=1}^{i} D_{ai}/D_a$ represents the effective information accumulation rate of PD_i within the nominal execution duration; τ_i is the innovation degree index of PD_i in the design process, which determines the resource intensity required for each PD_i in the design process.

Based on the definition of PD_i reliability, it is considered that the improvement of the coordination ability of the design team between PD_i and CD_i can effectively reduce the disutility caused by PD_i's low reliability. At the same time, CD_i's dependence on PD_i's design achievements and the technical capability index of CD_i's design team will both have a certain degree of influence on CD_i's change rate. Therefore, the probability that CD_i has no information change is defined as:

$$P_{bi}\left(Y=0\right)=1-\frac{u_i}{\beta_{bi}}\left(1-\mu_{ai}\right)^{v_i} \tag{28}$$

where: u_i is the degree of dependence of CD_i on the design results of p; β_{bi} represents the technical ability index of the design team that undertakes CD_i; v_i represents the coordination ability index of the design team between PD_i and CD_i.

6.3 Construction of the Target Decision Model Based on Concurrent Execution Duration

$E\left(d_{ai}\right)$ is defined as the expected execution duration of PD_i before the concurrent execution with two-way information interaction behavior, and $E\left(d_{bi}\right)$ is the expected execution duration of CD_i after the concurrent execution with two-way information interaction behavior. Its function expression can be defined as:

When $i = 1$, $E(d_{a1}) = d'_{a1} + I_1$;

When $i = 2, \cdots, n$, $E(d_{ai}) = P_{b(i-1)}\left[d'_{ai} + I_i^{OIIB-nr} + I_i\right] + \left(1 - P_{b(i-1)}\right)\left[d'_{ai} + \Delta t_{ab(i,i+1)} + I_i^{OIIB-r} + I_i^r\right]$;

When $i = 1, \cdots, n$, $E(d_{bi}) = P_{ai}\left[I_i^{TIIB-nr} + d'_{bi}\right] + (1 - P_{ai})\left[I_i^{TIIB-r} + \Delta t_{ba(i,i)} + d'_{bi}\right]$.

Define T_i as the actual execution duration of PD_i and CD_i based on the concurrent execution mode, then its functional expression is:

When $i = 1$, $T_1 = E(d_{a1}) + d_{ab1} + E(d_{b1})$;

When $i = 2, \cdots, n$, $T_i = E(d_{ai}) - \rho d'_{ai} + d_{abi} + E(d_{bi})$.

Therefore, the goal decision model based on concurrent execution duration can be written as an optimization model as shown in Eq. (29):

$$T_{min} = \sum_{i=1}^{n} T_i$$
$$s.t.\begin{cases} 0 \le d_{abi} \le min(D_{ai}, D_{bi}) \\ 0 \le d'_{ai} \le D_{ai} \\ 0 \le d'_{bi} \le D_{bi} \end{cases} \tag{29}$$

7 The Solution of the Concurrent Execution Process Model

7.1 Determination of Model Parameter Values

To explore the information interaction strategies that should be adopted by PD_i and CD_i under different change probability scenarios, this study developed a design professional, which includes five design tasks with close sequential dependencies. It is assumed that the change probabilities of PD_i and CD_i in these five design tasks decrease from high to low. Based on this, the static parameter values are developed as shown in Table 2. Among them, the static property indicates that the value of the parameter will not change with the change of concurrent execution duration d_{abi} with two-way information interaction behavior. As can be seen from Table 2: (1) With the progress of the design stage, the inherent uncertainty degree of PD_i and CD_i, namely g_i and q_i, gradually decreases; (2) The rate parameter ε_i of information change in PD_i changes from fast-to-slow to slow-to-fast, and the effective information accumulation evolution path index η_i of PD_i is transitioning from slow-to-fast to fast-to-slow; (3) The technical capability index β_i of the design team responsible for CD_i and the coordination index v_i between the design teams of PD_i and CD_i are continuously increasing as the tasks progress; (4) The innovation index τ_i of PD_i in the design process and the dependence degree u_i of CD_i on the design achievements of PD_i decrease with the progress of the task; (5) The values of information communication learning effect index α_1 and workload transfer learning effect index α_2 are -0.074 and -0.152, respectively when the improvement rate of learning curve is $s_1 = 0.95$ and $s_2 = 0.90$; (6) Under the premise of not affecting the accuracy of model solution results, the nominal execution duration of CD_i and PD_i is proposed to be 50 and 100, respectively; (7) The value range of concurrent execution duration with two-way information interaction behavior and one-way information interaction behavior is divided into $d_{abi} \in [0, 50]$ and $\rho \in [0, 1]$, and the value interval is 1 and 0.1, respectively.

Table 2: Values of static parameters

Parameter	Task 1	Task 2	Task 3	Task 4	Task 5
g_i	0.3	0.28	0.26	0.24	0.22
q_i	0.2	0.18	0.16	0.14	0.12
ε_i	-1	-0.5	0	0.5	1
η_i	3	2	2	0.5	0.1
β_{ai}	0.5	0.7	0.9	1.1	1.3
β_{bi}	0.5	0.7	0.9	1.1	1.3
v_i	0.55	0.65	0.75	0.85	0.95
τ_i	0.5	0.4	0.3	0.2	0.1
u_i	0.7	0.6	0.5	0.4	0.3
$\alpha_1 = lgs_1/lg2$	-0.074 ($s_1 = 0.95$)				
$\alpha_2 = lgs_2/lg2$	-0.152 ($s_2 = 0.90$)				
D_{ai}	50				
D_{bi}	100				
d_{abi}	0:1:50				
ρ	0:0.1:1				

The dynamic parameter values developed in this study are shown in Table 3, and their dynamics are reflected in the fact that they change with the concurrent execution duration d_{abi} of two-way information interaction behavior. The analysis of Table 3 shows that: (1) The value range of the information transmission duration coefficient θ during concurrent execution is [0.05, 0.25], and the value interval is 0.004 to form a corresponding relationship with the value interval of concurrent execution duration d_{abi}. The reason why the value range starts from 0.05 instead of 0 is that the information transmission behavior still exists when there is no concurrent execution mode; (2) The value range of information communication difficulty coefficient c during concurrent execution is [0.1, 1], and the value interval is 0.018 for the same reason as above. The reason why the value range starts from 0.1 instead of 0 is that when there is no concurrent execution mode, there are still some obstacles in the information transmission and acceptance behavior between PD_i and CD_i; (3) ci^{α_1} refers to the change of the value range and interval of the difficulty coefficient of information communication after it is affected by the learning effect; (4) The value range of forward transfer coefficient m_{bai} and reverse transfer coefficient $m_{ab(i,i+1)}$ during concurrent execution is [0.1, 0.5], and the value interval is 0.008 for the same reason as above; (5) $m_{bai}i^{\alpha_2}$ refers to the change of the value range and value interval of the positive transfer coefficient after being affected by the learning effect.

As shown in Table 4, based on the calculation method of information transfer efficiency E_i and information transfer quality Q_i, the parameter values of E_i and Q_i based on four concurrent execution stages are obtained by taking d_{abi} at intervals of 2.5 units and ρ at intervals of 0.1 units as an evaluation cycle. There is no exact measurement basis for the evaluation period of d_{abi} and ρ, and only a certain accuracy requirement needs to be met. The parameter ranges used in this research have been well chosen in accordance with industry standard in the EPC projects, specifically the execution of design activities simultaneously. These ranges are used to take into consideration the uncertainty in the initial phases of the design, which is decreasing as the design moves forward and more specific information is known. The parameters are also included in the learning effects and the enhancement in coordination and technical capability with time. These parameters were estimated by use of both empirical information on other similar EPC projects, including the case study in Saudi Arabia, and theoretical models, including Poisson distributions to estimate information change and rework on tasks. Also, the information transfer efficiency and quality values were predetermined so as to allow the model to find a compromise between accuracy and computational efficiency guaranteed realistic and reliable model simulations of the project execution.

Table 3: Values of dynamic parameters

Parameter	Task 1	Task 2	Task 3	Task 4	Task 5
θ			0.05: 0.004: 0.25		
c			0.1: 0.018: 1		
$ci^{\alpha 1}$	0.1: 0.018: 1	0.1: 0.017: 0.95	0.1: 0.0164: 0.92	0.1: 0.016: 0.9	0.1: 0.0156: 0.88
m_{bai}			0.1: 0.008: 0.5		
$m_{bai}i^{\alpha 2}$	0.1: 0.008: 0.5	0.1: 0.007: 0.45	0.1: 0.0064: 0.42	0.1: 0.0061: 0.405	0.1: 0.0058: 0.39
$m_{ab(i,i+1)}$			0.1: 0.008: 0.5		

Table 4: The solution results of information transfer timeliness and information transfer quality

TIIB Concurrent Execution Duration	①④				②				*OIIB* Concurrent Execution Duration	③			
	H_i	E_i	L_i	Q_i	H_i	E_i	L_i	Q_i		H_i	E_i	L_i	Q_i
$0 \leq d_{abi} < 2.5$	5.76	0.34	3.46	0.20	0	1	0	1	$\rho = 0$	0	1	0	1
$2.5 \leq d_{abi} < 5 or 5 \leq d_{abi} < 7.5$	5.51	0.37	3.32	0.23	1.5	0.90	1.5	0.77	$\rho = 0.1$	1.5	0.90	1.45	0.78
$7.5 \leq d_{abi} < 10 or 10 \leq d_{abi} < 12.5$	5.23	0.41	3.17	0.27	4.47	0.71	2.24	0.66	$\rho = 0.2$	3.95	0.75	2.39	0.64
$12.5 \leq d_{abi} < 15 or 15 \leq d_{abi} < 17.5$	4.92	0.44	3.00	0.31	6.41	0.59	2.72	0.59	$\rho = 0.3$	5.59	0.64	2.92	0.56
$17.5 \leq d_{abi} < 20 or 20 \leq d_{abi} < 22.5$	4.57	0.48	2.81	0.35	8.16	0.48	3.09	0.54	$\rho = 0.4$	6.85	0.55	3.30	0.50
$22.5 \leq d_{abi} < 25 or 25 \leq d_{abi} < 27.5$	4.17	0.53	2.59	0.40	9.40	0.40	3.38	0.49	$\rho = 0.5$	7.87	0.49	3.59	0.46
$27.5 \leq d_{abi} < 30 or 30 \leq d_{abi} < 32.5$	3.70	0.58	2.32	0.46	10.62	0.32	3.62	0.45	$\rho = 0.6$	8.74	0.44	3.83	0.42
$32.5 \leq d_{abi} < 35 or 35 \leq d_{abi} < 37.5$	3.15	0.64	2	0.54	11.53	0.26	3.82	0.42	$\rho = 0.7$	9.48	0.39	4.03	0.39
$37.5 \leq d_{abi} < 40 or 40 \leq d_{abi} < 42.5$	2.45	0.72	1.59	0.63	12.45	0.20	4.00	0.39	$\rho = 0.8$	10.15	0.35	4.21	0.37
$42.5 \leq d_{abi} < 45 or 45 \leq d_{abi} < 47.5$	1.5	0.83	1	0.77	13.17	0.15	4.16	0.37	$\rho = 0.9$	10.74	0.31	4.37	0.34
$47.5 \leq d_{abi} < 50$	0	1	0	1	13.9	0.11	4.31	0.35	$\rho = 1$	11.27	0.28	4.51	0.32

7.2 Case Study: EPC Project in Saudi Arabia

The project that was thoroughly case-studied was a large-scale power transmission revamp project in Saudi Arabia. This was an engineering, procurement and construction (EPC) project that was characterized by huge delays and reworks hence client relationships were not healthy. The research was conducted through a thorough review of the project management processes of the EPC contractor, which included interviews, focus groups and the audit of the project documentation like procurement, contract documents, engineering, HR management, safety and project control. The results identified the weaknesses in the ability and capabilities of the contractor in different aspects of project management [38].

Moreover, the systematic sensitivity analysis has also been performed in this case study to determine how well the parameters in the model can be applied in real-life situations. The analysis looked at the influence of changes in such major parameters as transfer efficiency and coordination capability on the project results. It was noted that variations in these parameters had a great impact on the project performance and that proper estimation of parameters to maximize design-execution process in EPC project is important.

8 Model Solving

In this study, MATLAB R2021b software was used to compile and calculate the simulation program of the above model. The choice of MATLAB was made due to its high capabilities of numerical computation and optimization particularly the probability based functions and also the model of iterative rework and the calculations involving matrices that are used in the analysis of concurrent execution. Its inbuilt Monte Carlo simulation and visualization also helped it to be efficient and clear, whereas other languages like Python or R would have been used but would need various external libraries to be used, thereby complicating the implementation process. The specific method was as follows: under the consideration of the mechanism of learning effect and without consideration, the actual execution duration of each design task in the range of d_{abi} and ρ was calculated successively, and the optimal solution of d_{abi} and ρ was determined according to the principle of minimizing the actual execution duration. Monte Carlo simulations were used numerically to capture the uncertainty in task durations and optimization algorithms were applied to find the optimal execution strategies. The two approaches were combined to be robust in the presence of probabilistic components and to improve the overall design.

8.1 Solution and Optimization of d_{ab1} in Task 1

It can be seen from the above analysis that only TIIB concurrent execution duration d_{ab1} exists between PD_1 and CD_1 of task 1, and there is no OIIB concurrent execution duration, and the learning effect has not taken effect at this stage. As shown in Fig. 3, the variation trend chart of T_1 under different values of d_{ab1} is obtained under the probability estimation of $P_{a1} = 22.37\%$. It can be observed that: (1) The shortest actual execution duration $T_1^{min} = 168.18$ is obtained when the interaction strategy is set as $d_{ab1} = 12$; (2) The actual execution duration shortening rate when $d_{ab1} \in [0, 12)$ is much smaller than the actual execution duration increasing rate when $d_{ab1} \in (12, 50]$.

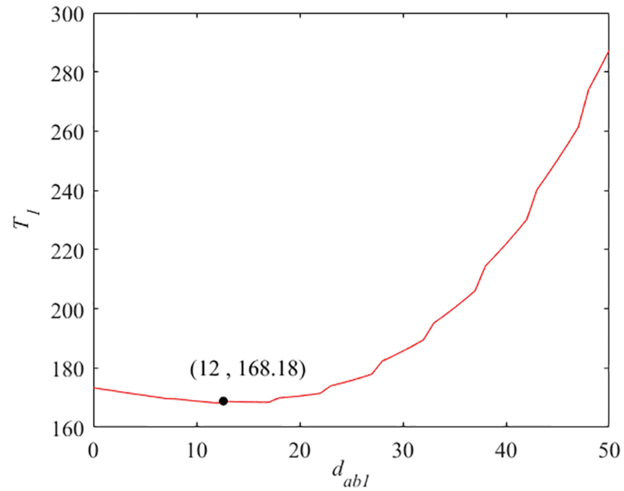


Figure 3: Trend chart of T_1 based on different values of d_{ab1}

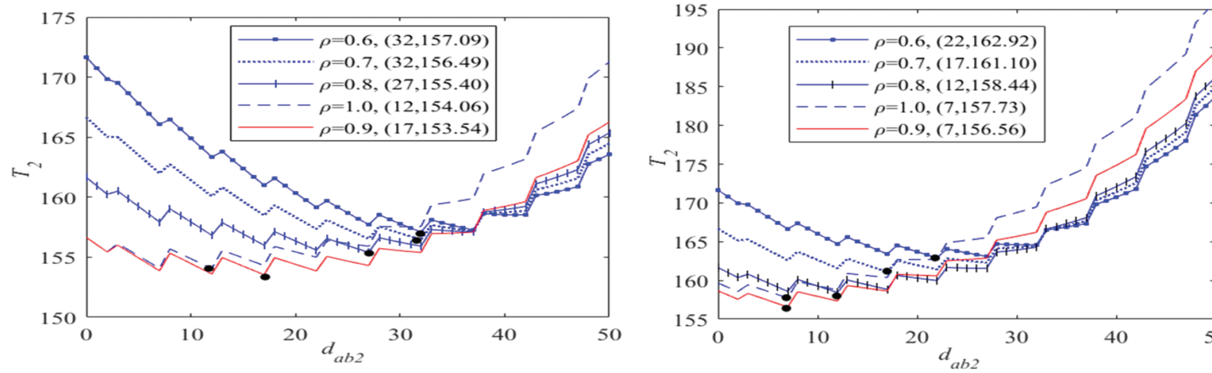
The learning effect is yet to be enforced at this stage as the changes in the information transfer strategy have not taken place. Learning effect is the ability of the task to be performed better with time following an initial experience which would ultimately lead to reduced time taken to execute the task and better quality of the work output. With increasing number of tasks performed and experience gained one should anticipate the growth in efficiency of the execution thus cutting down the duration of the tasks and the error thus improving the performance of the whole project.

8.2 Solution and Optimization of d_{ab2} and ρ in Task 2

As shown in Fig. 4, the change trend chart of T_2 based on the different values of d_{ab2} and ρ is obtained under the probability estimation condition of $P_{b1} = 32.94\%$ and $P_{a2} = 35.76\%$. It can be observed that: (1) Considering the mechanism of learning effect, the shortest actual execution duration $T_2^{min} = 153.54$ is obtained when the interaction strategy is set as $d_{ab2} = 17$ and $\rho = 0.9$, respectively; (2) Without considering the mechanism of learning effect, the shortest actual execution duration $T_2^{min} = 156.56$ is obtained when the interaction strategy $d_{ab2} = 7$ and $\rho = 0.9$, respectively; (3) The actual execution duration shortening rate for $d_{ab2} \in [0, 17)$ is about $1/2$ times the actual execution duration increasing rate for $d_{ab2} \in (17, 50]$.

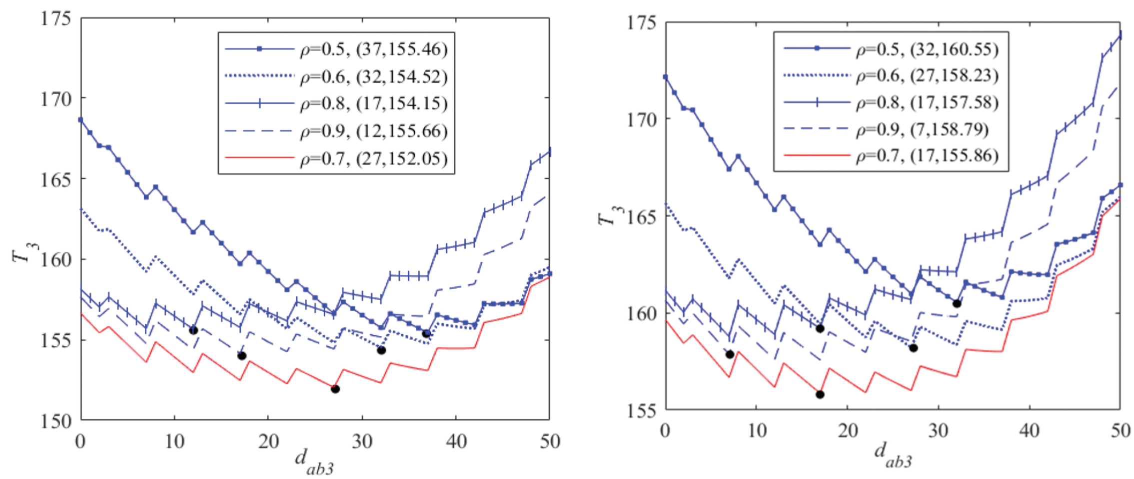
8.3 Solution and Optimization of d_{ab3} and ρ in Task 3

As shown in Fig. 5, the change trend chart of T_3 based on the different values of d_{ab3} and ρ is obtained under the probability estimation condition of $P_{b2} = 45.57\%$ and $P_{a3} = 41.18\%$. It can be observed that: (1) Considering the mechanism of learning effect, the shortest actual execution duration $T_3^{min} = 152.05$ is obtained when the interaction strategy is set as $d_{ab3} = 27$ and $\rho = 0.7$, respectively; (2) Without considering the mechanism of learning effect, the shortest actual execution duration $T_3^{min} = 155.86$ is obtained when the interaction strategy $d_{ab3} = 17$ and $\rho = 0.7$, respectively; (3) The actual execution duration shortening rate for $d_{ab3} \in [0, 27)$ is about $2/3$ times the actual execution duration increasing rate for $d_{ab3} \in (27, 50]$.



(**a**) (**b**)

Figure 4: Trend chart of T_2 based on different values of d_{ab2} and ρ. (a) considering the mechanism of learning effect; (b) without considering the mechanism of learning effect

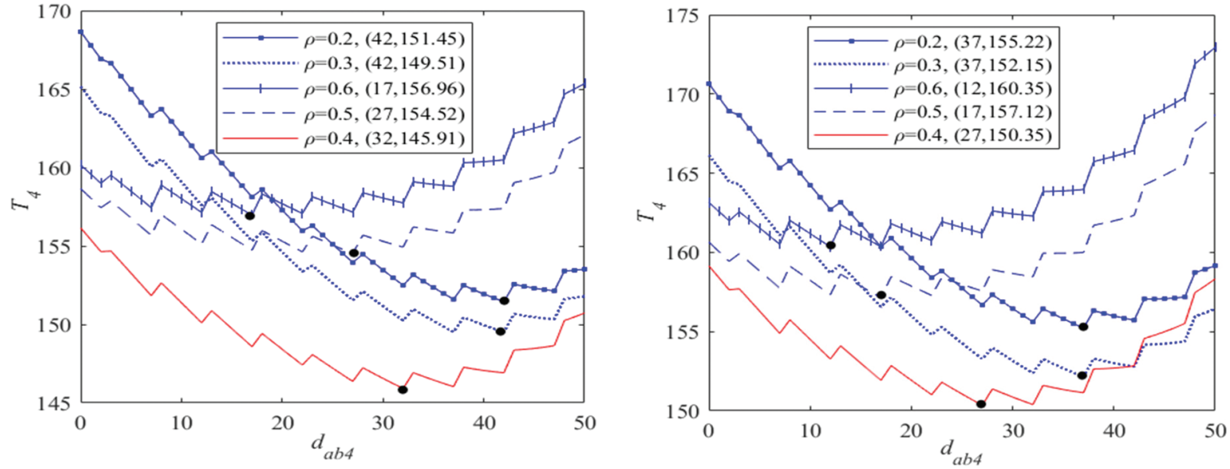


(**a**) (**b**)

Figure 5: Trend chart of T_3 based on different values of d_{ab3} and ρ. (a) considering the mechanism of learning effect; (b) without considering the mechanism of learning effect

8.4 Solution and Optimization of d_{ab4} and ρ in Task 4

As shown in Fig. 6, the change trend chart of T_4 based on the different values of d_{ab4} and ρ is obtained under the probability estimation condition of $P_{b3} = 58.42\%$ and $P_{a4} = 52.75\%$. It can be observed that: (1) Considering the mechanism of learning effect, the shortest actual execution duration $T_4^{min} = 145.91$ is obtained when the interaction strategy is set as $d_{ab4} = 32$ and $\rho = 0.4$, respectively; (2) Without considering the mechanism of learning effect, the shortest actual execution duration $T_4^{min} = 150.35$ is obtained when the interaction strategy $d_{ab4} = 27$ and $\rho = 0.4$, respectively; (3) The actual execution duration shortening rate for $d_{ab4} \in [0, 32)$ is about one times the actual execution duration increasing rate for $d_{ab4} \in (32, 50]$.

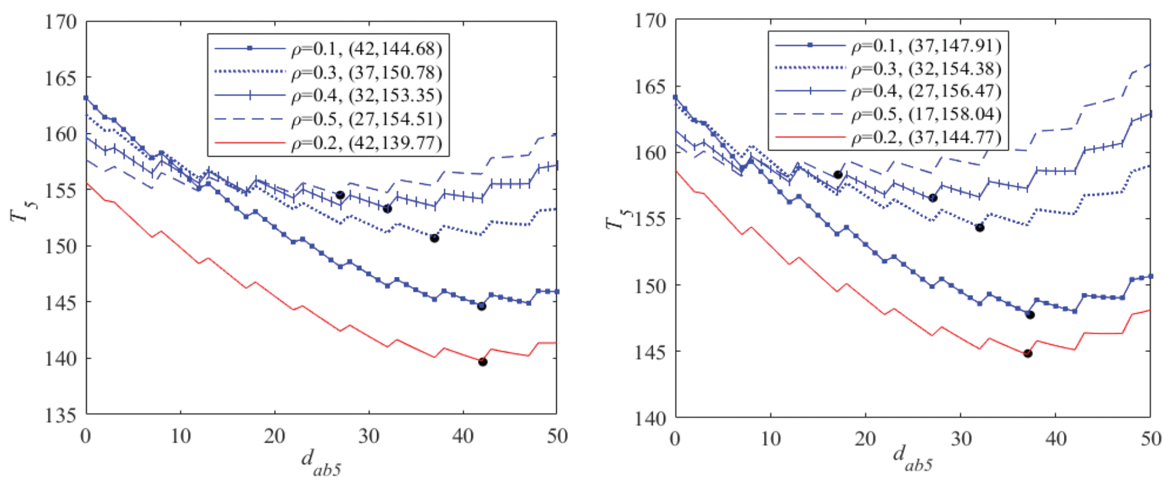


(a) (b)

Figure 6: Trend chart of T_4 based on different values of d_{ab4} and ρ. (a) considering the mechanism of learning effect; (b) without considering the mechanism of learning effect

8.5 Solution and Optimization of d_{ab5} and ρ in Task 5

As shown in Fig. 7, the change trend chart of T_5 based on the different values of d_{ab5} and ρ is obtained under the probability estimation condition of $P_{b4} = 66.37\%$ and $P_{a5} = 78.46\%$. It can be observed that: (1) Considering the mechanism of learning effect, the shortest actual execution duration $T_5^{min} = 139.77$ is obtained when the interaction strategy is set as $d_{ab5} = 42$ and $\rho = 0.2$, respectively; (2) Without considering the mechanism of learning effect, the shortest actual execution duration $T_4^{min} = 144.77$ is obtained when the interaction strategy $d_{ab5} = 37$ and $\rho = 0.2$, respectively; (3) The actual execution duration shortening rate when $d_{ab5} \in [0, 42)$ is much higher than the actual execution duration increasing rate when $d_{ab5} \in (42, 50]$.



(a) (b)

Figure 7: Trend chart of T_5 based on different values of d_{ab5} and ρ. (a) considering the mechanism of learning effect; (b) without considering the mechanism of learning effect

9 Discussion

9.1 Analysis of Change Probability Function

9.1.1 Numerical Analysis of Preliminary Design Change Probability Function

By analyzing Formula (26) and combining with Fig. 8 drawn after reasonable assignment of relevant parameters ($D_a = 200$, $D_{ai} = 100$, $d^s_{ai} = 0$, $P_{b(i-1)} = 0.9$, $q_{i-1} = 0.1$, $\beta_{ai} = 2$, $d^s_{ai} \in [0, 100]$, $\varepsilon_i \in [-1, 1]$) in Formula (26), Proposition 1 can be obtained as follows:

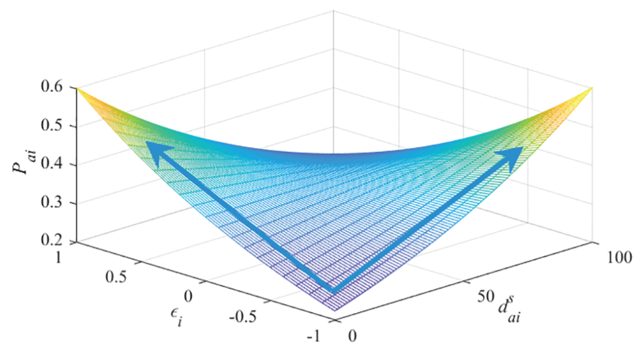


Figure 8: The influence of ε_i and d^s_{ai} on the change trend of P_{ai}

Proposition 1. *When $\varepsilon_i \to 0$, the value of P_{ai} is constant. This indicates that there is no mutual influence between the concurrent execution duration of the two-way information interaction behavior between PD_i and CD_i and the probability of information change occurring or not occurring. When $\varepsilon_i \to -1$ and $d^s_{ai} \to 100$, P_{ai} gradually increases. This indicates that in the case of rapid evolution of the information change rate, the concurrent execution start time of the two-way information interaction behavior should be postponed as much as possible. When $\varepsilon_i \to 1$ and $d^s_{ai} \to 0$, P_{ai} gradually increases. This indicates that in the case of slow evolution of the information change rate, the concurrent execution method of the two-way information interaction behavior should be started as early as possible.*

By analyzing Formula (26) and combining with Fig. 9 drawn after reasonable assignment of relevant parameters ($D_a = 200$, $D_{ai} = 100$, $d^s_{ai} = 0$, $P_{b(i-1)} = 0.8$, $q_{i-1} = 0.2$, $g_i \in [0.1, 1]$, $\beta_{ai} \in [0, 2]$) in Formula (26), Propositions 2 and 3 can be obtained as follows:

Proposition 2. *In terms of the commonality of Fig. 9a–c, during concurrent execution with two-way information interaction behavior, there are: (1) When $\partial P_{ai}/\partial g_i \leq 0$, it indicates that the higher the degree of inherent uncertainty of PD_i, the higher the possibility of its information changing; (2) When $\partial P_{ai}/\partial \beta_{ai} \geq 0$, it indicates that with the improvement of the technical ability of the design team, the possibility of information change in PD_i will decrease.*

Proposition 3. *Regarding the differences between Fig. 9a–c, by observing the representative points A and B in the figure, it can be seen that when $\varepsilon_i > 0$, P_{ai} shows an upward trend at points A ($\beta_{ai} = 0.6$) and B ($g_i = 0.7$); when $\varepsilon_i = 0$, P_{ai} shows an upward trend at points A ($\beta_{ai} = 1.3$) and B ($g_i = 0.5$); when $\varepsilon_i < 0$, P_{ai} shows an upward trend at points A ($\beta_{ai} = 1.7$) and B ($g_i = 0.4$). The above results show that during the concurrent execution with two-way information interaction behavior, when the information evolution rate ε_i gradually accelerates, when and only when the value of g_i gradually decreases and the value of β_{ai} gradually increases, the information change behavior can be transformed from a deterministic event to a random event.*

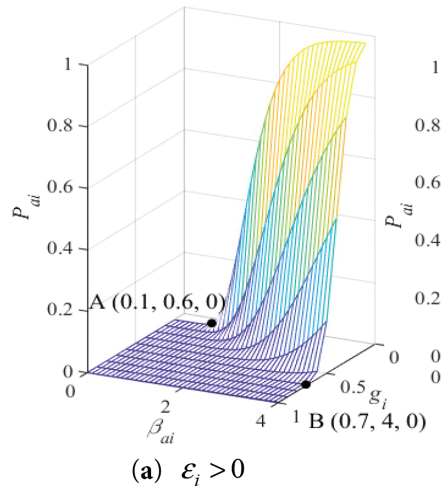


Figure 9: The influence of β_{ai} and g_i on the change trend of P_{ai}. (a) slow evolution, (b) stable state; (c) fast evolution

9.1.2 Numerical Analysis of Construction Drawing Design Change Probability Function

By analyzing Formula (28) and combining with Fig. 10 drawn after reasonable assignment of relevant parameters ($D_a = 200$, $D_{ai} = 100$, $\tau_i = 0.5$, $v_i = 2$, $u_i \in [0.1, 1]$, $\beta_{bi} \in [0, 2]$) in Formula (28), Propositions 4 and 5 can be obtained as follows:

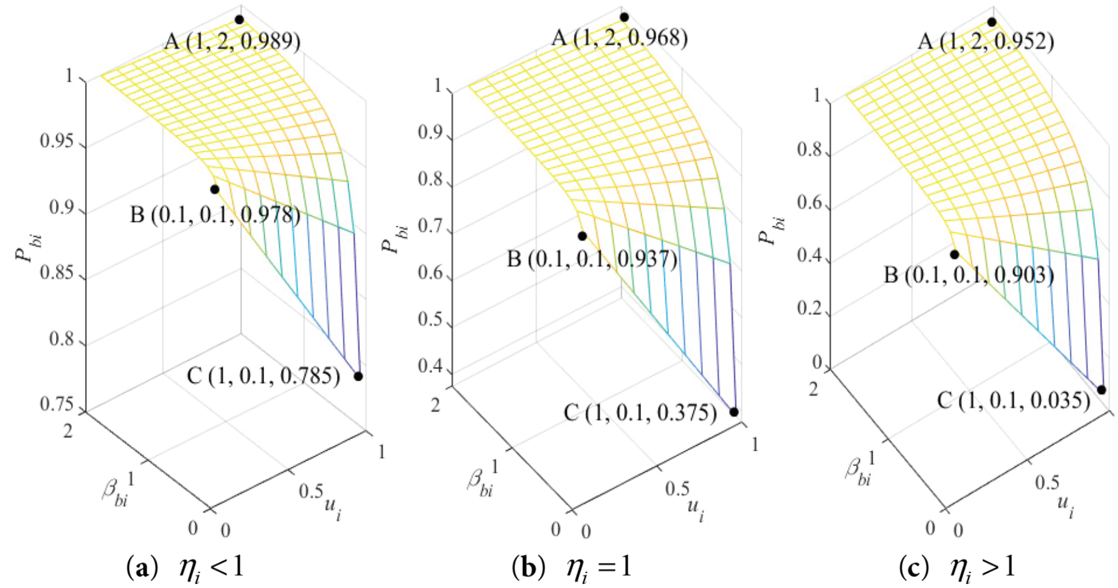


Figure 10: The influence of β_{bi} and u_i on the change trend of P_{bi} across different scenarios (a) First fast, then slow; (b) linear growth; (c) First slow, then fast

Proposition 4. *In terms of the commonalities of Fig. 10a–c, during the concurrent execution with two-way information interaction behavior, there are: (1) When $\partial P_{bi}/\partial u_i < 0$, it indicates that the probability of no information change in CD_i is decreasing with the increasing dependence of CD_i on the design achievement* *of PD_i; (2) When $\partial P_{bi}/\partial \beta_{bi} > 0$, it indicates that with the improvement of the technical ability of the design team, the possibility of information change in CD_i will decrease; (3) In terms of the value of P_{bi}, $A > B$ exists, indicating that rather than reducing CD_i's dependence on PD_i design results, more attention should be paid to improving the technical ability of CD_i design team to reduce the probability of information changes in CD_i.*

Proposition 5. *In terms of the differences between Fig. 10a–c, by observing the corresponding P_{bi} values for points A, B, and C, there exists $A_{\eta_i<1} > A_{\eta_i=1} > A_{\eta_i>1}$, $B_{\eta_i<1} > B_{\eta_i=1} > B_{\eta_i>1}$, and $C_{\eta_i<1} > C_{\eta_i=1} > C_{\eta_i>1}$. This indicates that during concurrent execution with two-way information interaction, when the effective information accumulation evolution path of PD_i is fast-to-slow, the information change rate of CD_i is lower than the linear growth and slow-to-fast scenarios, while the linear growth scenario is lower than the slow-to-fast scenario.*

By analyzing Formula (28) and combining with Fig. 11 drawn after reasonable assignment of relevant parameters ($D_a = 200$, $D_{ai} = 100$, $\beta_{bi} = 1$, $u_i = 0.8$, $\tau_i \in [0.1, 1]$, $v_i \in [0, 1]$) in Formula (28), Propositions 6 and 7 can be obtained as follows:

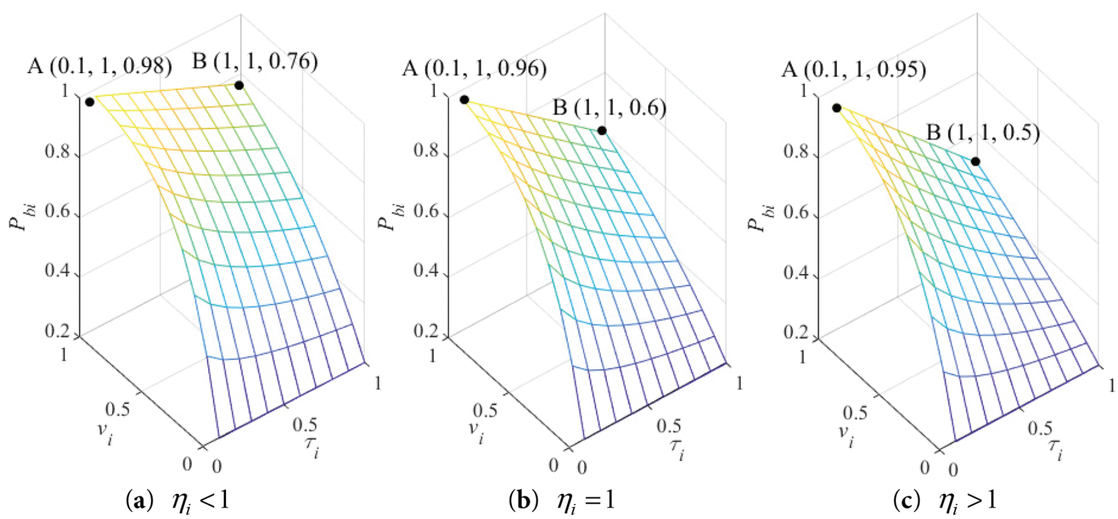


Figure 11: The influence of v_i and τ_i on the change trend of P_{bi}. (a) First fast, then slow; (b) linear growth; (c) First slow, then fast

Proposition 6. *As far as the commonalities of Fig. 11a–c are concerned, during the concurrent execution with two-way information interaction behavior, there are: (1) When $\partial P_{bi}/\partial v_i > 0$, it indicates that with the improvement of the coordination ability of the design team between PD_i and CD_i, the possibility of information change in CD_i will decrease; (2) When $v_i > 0$, $\partial P_{bi}/\partial \tau_i > 0$, indicating that if and only if the design team between PD_i and CD_i has a certain coordination ability, the probability of information change in CD_i can be reduced by reducing the difficulty of innovation in PD_i.*

Proposition 7. *In terms of the differences between Fig. 11a–c, by observing the values of p corresponding to points A, B, and C, there exists $A_{\eta_i<1} > A_{\eta_i=1} > A_{\eta_i>1}$ and $B_{\eta_i<1} > B_{\eta_i=1} > B_{\eta_i>1}$. The conclusion revealed by this proposition is the same as Proposition 5, that is, during the concurrent execution of two-way information interaction behavior, when the effective information accumulation evolution path of PD_i is fast-to-slow, the information change rate caused by CD_i is lower than the linear growth and slow-to-fast scenarios, and the linear growth scenario is lower than the slow-to-fast scenario.*

9.1.3 Analysis of the Concurrent Construction Process Model

Proposition 8. *When the design information change rate of PD_i is greater than (less than) 50%, the concurrent execution duration of two-way information interaction between PD_i and CD_i should be less than (greater than) 1/2 of the nominal execution duration of PD_i. When the design information change rate of CD_i is greater than (less than) 50%, the concurrent execution duration of one-way information interaction between CD_i and PD_{i+1} should be greater than (less than) 1/2 of the nominal execution duration of PD_{i+1}. This indicates that as the probability of information change between PD_i and CD_i in each design task decreases gradually, the corresponding trend of the optimal interaction strategy is as follows: the concurrent execution duration with two-way information interaction behavior increases, while the concurrent execution duration with one-way information interaction behavior decreases. The 50% threshold in Proposition 8 is based more on numerical evidence than an analytical argument. In model simulations, it appeared to function well as a boundary under typical projects condition. This threshold's stability has been tested across project scales: variations in task sizes and execution durations, but it has proven stable under these variations.*

Proposition 9. *When the design information change rates of PD_i and CD_i are both less than 50%, the shortest actual execution duration of the design task achieved under the optimal interaction strategy for both PD_i and CD_i is less than their nominal execution duration. This indicates that in the case of low design information change rates, concurrent execution not only reduces the non-value-added duration spent on information transfer and forward and reverse rework, but also accelerates the completion speed of the design task during the value-added period, thereby shortening the nominal execution duration.*

Proposition 10. *Taking the concurrent execution duration corresponding to the optimal interaction strategy as the benchmark, when the design information change rate of PD_i and CD_i is high (low), the negative effect of increasing the concurrent execution duration with two-way information interaction behavior is higher (lower) than that of reducing the concurrent execution duration. Proposition 10 explains the marginal benefit brought by the change rate of design information and the change of concurrent execution duration with two-way information interaction behavior to the project execution duration. In other words, under the condition of high (low) change rate, the marginal benefit brought by increasing the concurrent execution duration with two-way information interaction behavior is lower (higher) than that brought by reducing the concurrent execution duration.*

Proposition 11. *With the decrease of the change rate of design information, in the case of the same concurrent execution duration with two-way information interaction behavior, the difference between the actual execution duration corresponding to the adjacent concurrent execution duration with one-way information interaction behavior is more significant. This indicates that compared to the situation where the design information change rate is high, the actual execution duration corresponding to the design information change rate in the low case is more sensitive to the concurrent execution duration with one-way information interaction behavior. That is, when solving the actual execution duration corresponding to the optimal interaction strategy under the low design information change rate, the actual execution duration has a higher requirement for the accuracy of the concurrent execution duration with one-way information interaction behavior.*

Proposition 12. *Compared with no consideration of the mechanism of learning effect, when the mechanism of learning effect caused by two-way information interaction is considered, the concurrent execution duration between PD_i and CD_i is significantly increased, and the actual execution duration is significantly shortened. This indicates that the existence of learning effect can enhance the concurrency between PD_i and CD_i by reducing the rework duration and information transfer duration, thereby achieving the goal of shortening the actual execution duration of design tasks. Therefore, the learning effect due to two-way* *information interaction behavior can amplify the advantage of concurrent execution in shortening the task execution duration.*

Proposition 13. *The concurrent execution of PD_i and CD_i in EPC mode can shorten the actual execution duration of CD_i more than that of PD_i. It shows that concurrent execution can significantly shorten the forward rework duration brought to CD_i by design information change of PD_i, but has no obvious effect on the reverse rework duration brought to PD_i by design information change of CD_i.*

The propositions are hypothetical under the field view and based on the mathematical model developed for concurrent execution. They were made under the assumptions and variables contained in the model rather than from empirical project-execution data. Validity of these propositions in case studies-practical applicability in real EPC projects-could be checked by future work through empirical data.

10 Conclusion

When formulating the interactive strategy of the concurrent execution process of preliminary design and construction drawing design, the following factors should be considered: the rate of information change in the preliminary design stage, the effective information accumulation and evolution rate in the construction drawing design stage, the rate of information change in the preliminary design and construction drawing design stages (speed), and the learning effect generated during concurrent execution. That is, when the rate of information change in the preliminary design stage is in a slow evolution situation, the inherent uncertainty level under concurrent execution with two-way information interaction can be appropriately relaxed, and the technical capability requirements for the design team can be appropriately reduced. Conversely, the inherent uncertainty level should be controlled within a low range, and the technical capability requirements for the design team should be as high as possible. The effective information accumulation and evolution path should be arranged to perform preliminary design tasks that are rapidly (slowly) evolving during concurrent execution with one-way (two-way) information interaction. When the rate of information change in the preliminary design stage gradually decreases, the strategy of gradually increasing the concurrent execution duration with two-way information interaction should be adopted. When the rate of information change in the construction drawing design stage gradually decreases, the strategy of gradually reducing the concurrent execution duration with one-way information interaction should be adopted. The learning effect brought by concurrent execution with two-way information interaction should be paid attention to achieve the goal of shortening the design task execution cycle by reducing the information transmission duration and forward rework as much as possible.

This study focuses on exploring the impact of the inherent properties of preliminary design and construction drawing design on the interaction strategy of optimal concurrent execution, and does not further expand the research perspective to the influence of external environmental factors that can promote or hinder. Therefore, future studies can take into account the following factors: Considering the impact of ethical risk behaviors between preliminary design and construction drawing design teams with heterogeneous characteristics on interaction strategies; Considering the impact of resource constraints such as personnel and machine limitations on resource allocation policies during the concurrent execution of preliminary design and construction drawing design; On the basis of considering the information interaction duration, rework duration and concurrent execution duration as random variables, the influence of them on the stability of interaction strategy can be further discussed.

Acknowledgement: Not applicable.

Funding Statement: This research was supported by the National Natural Science Foundation of China (No. 72401162).

Availability of Data and Materials: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Austin RB, Pishdad-Bozorgi P, Garza JM. Identifying and prioritizing best practices to achieve flash track projects. J Constr Eng Manag. 2016;142(2):04015077. doi:10.1061/(asce)co.1943-7862.0001061.
2. Deng H, Shi Q, Wang Y. Joint optimization of condition-based maintenance and inventory ordering based on status monitoring for multi-unit system. 2021 [cited 2025 Jan 1]. Available from: https://www.scipedia.com/public/DENG_et_al_2021b.
3. He S, Cai W, Zhang H, Wang T, Qiao X. A fully distributed algorithm for dynamic economic dispatch of cross-regional power systems based on alternating direction multiplier method. 2024 [cited 2025 Jan 1]. Available from: https://www.scipedia.com/public/He_et_al_2024a.
4. Blacud NA, Bogus SM, Diekmann JE, Molenaar KR. Sensitivity of construction activities under design uncertainty. J Constr Eng Manag. 2009;135(3):199–206. doi:10.1061/(asce)0733-9364(2009)135:3(199).
5. Li W, Ma Y. Research on the synchronization control of fractional-order complex networks based on switching topology. 2024 [cited 2025 Jan 1]. Available from: https://www.scipedia.com/public/Li_Ma_2024a.
6. Bogus SM, Molenaar KR, Diekmann JE. Concurrent engineering approach to reducing design delivery time. J Constr Eng Manag. 2005;131(11):1179–85. doi:10.1061/(asce)0733-9364(2005)131:11(1179).
7. Bogus SM, Diekmann JE, Molenaar KR, Harper C, Patil S, Lee JS. Simulation of overlapping design activities in concurrent engineering. J Constr Eng Manag. 2011;137(11):950–7. doi:10.1061/(asce)co.1943-7862.0000363.
8. Bogus SM, Molenaar KR, Diekmann JE. Strategies for overlapping dependent design activities. Constr Manag Econ. 2006;24(8):829–37. doi:10.1080/01446190600658529.
9. Dehghan R, Ruwnapura JY. Model of trade-off between overlapping and rework of design activities. J Constr Eng Manage. 2014;140(2):04013043. doi:10.1061/(asce)co.1943-7862.0000786.
10. Dehghan R, Hazini K, Ruwanpura J. Optimization of overlapping activities in the design phase of construction projects. Autom Constr. 2015;59(2):81–95. doi:10.1016/j.autcon.2015.08.004.
11. Eggink E. A practical guide to engineering, procurement and construction contracts. Abingdon, UK: Informa Law from Routledge; 2020.
12. Hazini K, Dehghan R, Ruwanpura J. An evolutionary optimization method to determine optimum degree of activity accelerating and overlapping in schedule compression. Can J Civ Eng. 2014;41(4):333–42. doi:10.1139/cjce-2013-0194.
13. Hossain MA, Chua DKH. Overlapping design and construction activities and an optimization approach to minimize rework. Int J Proj Manag. 2014;32(6):983–94. doi:10.1016/j.ijproman.2013.10.019.
14. Allur NS. Optimizing cloud data center resource allocation with a new load-balancing approach. Int J Inf Technol Comput Eng. 2021;9(2):188201.

15. Zhang S, Zhang S, Wu Z, Wang C, Jiang Z, Wang X. Cross-platform EPC collaboration framework for construction management of pumped storage hydropower utilizing industry foundation classes and semantic web. Tunn Undergr Space Technol. 2025;163:106692. doi:10.1016/j.tust.2025.106692.
16. Hossain MA, Chua DKH, Liu Z. Optimizing concurrent execution of design activities with minimum redesign. J Comput Civ Eng. 2012;26(3):409–20. doi:10.1061/(asce)cp.1943-5487.0000150.
17. Jalili Y, Ford DN. Quantifying the impacts of rework, schedule pressure, and ripple effect loops on project schedule performance. Syst Dyn Rev. 2016;32(1):82–96. doi:10.1002/sdr.1551.
18. Ji Y, Zhu F, Li H, Al-Hussein M. Construction industrialization in China: current profile and the prediction. Appl Sci. 2017;7(2):180. doi:10.3390/app7020180.
19. Wang J, Wu Y, Philip Chen CL, Liu Z, Wu W. Adaptive PI event-triggered control for MIMO nonlinear systems with input delay. Inf Sci. 2024;677(24):120817. doi:10.1016/j.ins.2024.120817.
20. Seyednezhad R, Derakhshanfard N, Heikalabad SR. Routing design in optical networks-on-chip based on gray code for optical loss reduction. Optik. 2021;228:166198. doi:10.1016/j.ijleo.2020.166198.
21. Wang Q, Chen G, Khishe M, Ibrahim BF, Rashidi S. Multi-objective optimization of IoT-based green building energy system using binary metaheuristic algorithms. J Build Eng. 2023;68(2):106031. doi:10.1016/j.jobe.2023.106031.
22. Kalach M, Abdul-Malak MA, Srour I. Design information release under alternative design-construction modes. Eng Constr Archit Manag. 2021;28(4):969–93. doi:10.1108/ecam-02-2020-0080.
23. Koolwijk JSJ, Van Oel CJ, Wamelink JWF, Vrijhoef R. Collaboration and integration in project-based supply chains in the construction industry. J Manage Eng. 2018;34(3):04018001. doi:10.1061/(asce)me.1943-5479.0000592.
24. Zhao X, Wang T, Li Y, Zhang B, Liu K, Liu D, et al. Target-driven visual navigation by using causal intervention. IEEE Trans Intell Veh. 2024;9(1):1294–304. doi:10.1109/tiv.2023.3288810.
25. Lin J, Chai KH, Brombacher AC, Wong YS. Optimal overlapping and functional interaction in product development. Eur J Oper Res. 2009;196(3):1158–69. doi:10.1016/j.ejor.2008.05.030.
26. Lin J, Qian Y, Cui W. Managing the concurrent execution of dependent product development stages. IEEE Trans Eng Manag. 2012;59(1):104–14. doi:10.1109/TEM.2011.2132761.
27. Lin J, Qian Y, Cui W, Miao Z. Overlapping and communication policies in product development. Eur J Oper Res. 2010;201(3):737–50. doi:10.1016/j.ejor.2009.03.040.
28. Liu B, Huo T, Meng J, Gong J, Shen Q, Sun T. Identification of key contractor characteristic factors that affect project success under different project delivery systems: empirical analysis based on a group of data from China. J Manage Eng. 2016;32(1):05015003. doi:10.1061/(asce)me.1943-5479.0000388.
29. Gan B, Jin S. Research on optimization strategy of cloud computing resources in big data environment. Adv Comput Commun. 2024;5(3):177–82. doi:10.26855/acc.2024.07.004.
30. Loch CH, Terwiesch C. Communication and uncertainty in concurrent engineering. Manag Sci. 1998;44(8):1032–48. doi:10.1287/mnsc.44.8.1032.
31. Park M, Ahn C, Lee H, Yoon Y. System dynamics-based strategies to diffuse construction VE in the public sector. KSCE J Civ Eng. 2012;16(4):486–98. doi:10.1007/s12205-012-1226-0.
32. Srour IM, Abdul-Malak MU, Yassine AA, Ramadan M. A methodology for scheduling overlapped design activities based on dependency information. Autom Constr. 2013;29(3):1–11. doi:10.1016/j.autcon.2012.08.001.
33. Wang T, Tang W, Qi D, Shen W, Huang M. Enhancing design management by partnering in delivery of international EPC projects: evidence from Chinese construction companies. J Constr Eng Manag. 2016;142(4):04015099. doi:10.1061/(asce)co.1943-7862.0001082.
34. Wang T, Feng J. Modeling and optimization of concurrent execution process of coupled design-construction tasks under design-build mode. Concurr Eng. 2022;30(4):353–66. doi:10.1177/1063293x221117865.

35. Wang T, Feng J. Multi-objective joint optimization for concurrent execution of design-construction tasks in design-build mode. Autom Constr. 2023;156:105078. doi:10.1016/j.autcon.2023.105078.
36. Wang T, Feng J. Optimal review strategy for concurrent execution of design-construction tasks in DB mode. J Constr Eng Manag. 2023;149(1):04022139. doi:10.1061/(asce)co.1943-7862.0002408.
37. Yassine A, Maddah B, Nehme N. Optimal information exchange policies in integrated product development. IIE Trans. 2013;45(12):1249–62. doi:10.1080/0740817x.2012.762487.
38. Alshammari M. A case study of implementing project management processes in EPC contracts. J Constr Eng Manag. 2023;149(4):04022055.