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SCHEDULING THE PRODUCTION OF PREFABRICATION CONSTRUCTION SUPPLY CHAINS CONSIDERING VARIABLE DELIVERY TIMES

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Abstract. The application of prefabrication and modularization in the construction industry has grown significantly recently. The efficiency of prefabrication supply chains yields substantial advantages for construction projects. A challenge is the variability in delivery times, which negatively impacts the economy and reliability of prefabrication supply chains. Most construction prefabrication suppliers have difficulty adjusting their schedules in response to delivery time changes in a timely manner. Despite this critical challenge, limited research has addressed proactive and robust production scheduling to mitigate these uncertainties. This study investigates a method for proactive and robust production scheduling for construction prefabrication suppliers, particularly those with multiple fabrication shops, responding to changes in delivery times. This paper introduces a multi-objective, two-stage stochastic programming model that facilitates the production planning with multiple fabrication shops, considering variable delivery times. Computational results from an experimental study demonstrate that the proposed optimization model achieves a 14.6% cost reduction compared to the traditional EDD method. Computational results also show that the expected cost of the stochastic programming model achieves a cost reduction of 0.23% compared to a deterministic model. These findings suggest the model's capability to generate robust and flexible schedules that effectively balance cost minimization with time reduction.

Keywords: supply chain, scheduling, prefabrication, modularization, construction, optimization, uncertainty, stochastic programming.

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1. Introduction

The application of prefabrication or modularization is growing in the construction industry. A study by Dodge Data & Analytics (2020) indicated that construction prefabrication and modularization (CPM) help improve cost, schedule, quality, safety, and client satisfaction while reducing waste significantly. Both design firms and contractors who participated in the study forecasted an expanded use of prefabrication and modularization in the near future. While utilizing prefabrication and modularization benefits the construction industry, the uncertainty of construction schedules can adversely impact the operation of the prefabrication and modularization supply chain. Therefore, prefabrication suppliers and manufacturers in construction need to account for the uncertainty of construction schedules when developing their production plans.

Production scheduling under uncertainty is typically divided into reactive and proactive approaches. The reactive scheduling approach modifies the schedule only after changes to due dates are announced or unexpected events occur, based on the current conditions of the plant. However, implementing rescheduling strategies to manage disruptions can be challenging, often leading to costly or inefficient adjustments (Bonfill et al., 2008). Moreover, most construction prefabrication shops do not have sophisticated scheduling or manufacturing resource planning (MRP) systems to reconfigure their schedules in a timely manner (e.g., weekly or monthly) in response to delivery time changes. Proactive scheduling creates robust and resilient plans that take into account uncertainties and can remain unchanged even when disruptions occur. However, most of the literature in the construction prefabrication domain focuses on reactive approaches when addressing schedule uncertainty. When schedule disruptions occur, these suppliers struggle to adapt efficiently. Despite its potential, proactive scheduling in construction prefabrication remains unexplored.

Planning the production of the CPM supply chain considers cost and time as two critical factors. While reducing cost and gaining profit are essential business goals, delivering CPM products on time is vital to a reliable workflow on-site. On the one hand, delaying the delivery of CPM products can cause a stoppage of field installations and disturb the installation schedule of construction trades. On the other hand, delivering CPM products earlier than delivery due can lead to increased inventory costs and site congestion, or may result in returning the products to the shop when construction sites have limited storage space. As a result, it is necessary to evaluate the tradeoffs between reducing costs and the risks of not delivering products on time. Substantial benefits can be achieved if the CPM supply chain is equipped with a flexible production scheduling system to handle delays and reduce costs proactively. Previously, Ho et al. (2022) illustrated the benefits of optimization for the production planning of prefabrication supply chains with multiple fabrication shops. However, that study did not consider the impact of uncertainty and balancing two objectives (i.e., cost and delay reduction).

To bridge those gaps, this research aims to develop a proactive and robust production scheduling method for a construction prefabrication supplier with multiple fabrication shops that can better respond to delivery time changes. The main research questions are:

- How can production schedules be optimized under uncertainty in delivery due dates in the prefabrication construction supply chains?
- How can multiple and potentially conflicting objectives, such as reducing both cost and project delays, be incorporated into production scheduling to support more balanced decision-making?

The research team began by conducting an industry survey to study the operation of CPM supply chains, considering the impact of uncertainty (Ho, 2019). This information motivated the development of a multi-objective, two-stage stochastic programming model that incorporates uncertainty of delivery times and enables tradeoff studies between cost and delay. The model generates optimal production and delivery schedules under various scenarios representing variable delivery times. The optimization model is demonstrated through an experimental study with four scenarios about the required delivery time.

This research contributes to the theory of optimization modeling for construction prefabrication supply chain with multiple fabrication shops, using stochastic programming to address uncertainty in delivery due dates. Practically, this research contributes to improving the efficiency and reliability of the prefabrication supply chain by proactively generating robust and flexible schedules that balance cost and delay. The construction contractors and suppliers can tailor the proposed model to their data and quantify the impact of the variation in required delivery due dates.

2. Relevant studies

2.1. Uncertainties and construction schedule variations

Previous studies have recognized that uncertainty is an enemy of workflows (Koskela, 2000; Brodetskaya et al., 2013; Ma & Sacks, 2016). However, it is unavoidable in many economic sectors, especially the construction industry. Gidado (1996) claimed that the increase in complexity of construction supply chains results from uncertainties involving resources, environments, and the operational interdependence among tasks. Love and Matthews (2020) addressed uncertainty in the construction projects caused by the reworks. They found three key issues contributing to rework: the lack of a homogenous culture, the non-alignment of strategy, and corporate memory loss. Howell et al. (1993) discussed several types of uncertainties in construction projects: project objective uncertainty, project means and methods uncertainty, workflow uncertainty, and resource uncertainty. Ballard (2000) asserted that most construction short-term schedules are unreliable: major construction contractors' average weekly percent plan completion falls below 85%. Wang et al. (2023) modeled construction performance under deep uncertainties by generating prediction intervals that represent the relationship between construction planning schemes, construction planning performance and corresponding uncertainties. Their study showed that planning outcomes are significantly impacted when production contexts change from simple to complex, introducing more uncertainty.

A survey conducted in the Pacific Northwest in 2017 (Ho, 2019) revealed that many prefabrication companies operate multiple fabrication shops, and it is common for construction projects to request changes in the delivery times of prefabricated products. The survey was conducted with ten construction fabricators, including three rebar fabricators, three mechanical, electrical & plumbing (MEP) contractors, one façade contractor, one stone contractor, one exterior panel contractor, and one precast concrete contractor. The survey showed that changes in delivery times make it difficult for the fabricators to adjust the production plan, resulting in an increased cost.

Moreover, the COVID-19 pandemic exacerbated the reliability of the construction supply chain. Kisi and Sulbaran (2022) interviewed 32 construction company executive members in the United States to collect the cost and schedule impact of COVID-19. They found COVID-19 impacted project schedules and costs, disrupting building material supply chains.

Uncertainty impacts various construction supply chains. The prefabrication and modularization supply chain is no exception. Construction schedule changes lead to changes in installation times as well as delivery dues of prefabricated products. Since the delivery dues of prefabricated products are unstable or unpredictable, it poses a challenge for suppliers to respond to the changes. Kim and Lee (2024) claimed that most construction projects undergo changes to delivery dues after placing the order. The contractor's non-cooperative decisions, such as delivery time changes, often result in supply chain inefficiencies, leading to poor performances for both contractors and suppliers (Jiang et al., 2023).

2.2. Construction prefabrication scheduling

Planning and scheduling supply chain networks with multiple production stages and facilities have been investigated in several manufacturing industries (Arntzen et al., 1995; De Bontridder, 2001; Milat et al., 2021; Pinedo, 2009; Javid & Azad, 2010; Zadeh et al., 2014; Javid & Hoseinpour, 2015; Yu et al., 2015). However, few studies in prefabrication construction have addressed this problem. Unlike manufacturing sectors, construction projects are unique and job-specific, making it challenging to apply optimization models available in other industries. Few have paid attention to the coordination between multiple fabrication shops, while several studies have focused on optimization problems in job shop schedules for individual construction sites or individual fabrication shops (Chan & Hu, 2001; Hsu et al., 2018; Leu & Hwang, 2002; Nolz, 2021; Pan et al., 2011; Tserng et al., 2011; Shu et al., 2014; Matt et al., 2015; Anvari et al., 2016).

In the domain of construction prefabrication scheduling, heuristic and metaheuristic approaches have been used (Desale et al., 2015; Kim et al., 2020). Dawood (1995) carried out a production schedule model for precast concrete production using the heuristic job scheduling approach. Benjaoran et al. (2005) developed a genetic algorithm (GA) for a flow shop-scheduling model for prefabrication production with multiple molds used. Yang et al. (2016) performed a multi-objective version of a genetic algorithm to evaluate the impacts of consequential decisions from manufacturing up to assembly.

As the Architecture, Construction, and Engineering (AEC) industry moves toward a prefabrication/modular approach, there has been research on construction prefabrication scheduling that addresses uncertainties in demand or delivery times. Ko and Wang (2010) adjusted the production schedules provided by GA in response to changes in due dates. Wang and Hu (2018) developed a two-level rescheduling model for prefabrication production involving multiple production lines when due dates shift. Ma et al. (2018) proposed an approach to optimize rescheduling for shop floors handling multiple production lines during production crises, such as rush orders. Kim et al. (2020) proposed a dynamic precast concrete (PC) scheduling model that integrates a production simulation module and a new heuristic rule to handle due date changes. Du et al. (2020) used a multi-objective genetic algorithm-based dynamic flow shop scheduling model for prefabricated components production, considering demand fluctuations such as the advancement of due dates. Wang et al. (2021) employed a hybrid optimization model for rescheduling precast production to reduce costs while ensuring timely deliveries amid machine breakdown disruptions. Kim et al. (2022) developed a PC production scheduling model using a deep reinforcement learning approach to minimize total tardiness by adjusting conditions in real-time. Zhang et al. (2023) proposed a three-layer disruption management model for scheduling that handles the concurrent occurrences of order advancement and emergency order insertion in PC production workshops.

However, the existing literature largely employs a reactive approach to managing demand uncertainty. Production schedules are adjusted or rescheduled using such reactive methods only after changes occur. It is noted that most construction prefabrication suppliers lack the sophisticated scheduling systems necessary for timely adjusting their schedules when disruptions arise. Typically, fabricators create schedules on a monthly basis, during which time the schedule remains unchanged. Few studies have explored proactive or robust scheduling methods, where schedules are constructed to be resilient or less sensitive to potential changes.

Demand uncertainty regarding the required delivery time of prefabricated materials can be analyzed using stochastic programming. The literature indicates that many studies have successfully applied stochastic programming to investigate uncertainties. Cruz et al. (2024) included stochastic demand and travel time in the periodic supply vessel planning problem, determining the optimal periodic schedule and the respective fleet composition of offshore servicing. Hadid et al. (2022) proposed a clustering and stochastic optimization methodology to support the planning and scheduling of outpatient chemotherapy appointments to minimize the length of stay of patients and staff over time. Guimarans and Padron (2022) proposed a stochastic model to support the development of work plans for airport ground support resources that can mitigate flight departure delays while reducing the under- or over-utilization of equipment. Mazloumian et al. (2022) proposed a robust multi-objective integer linear programming model to minimize patent waiting times while maximizing the operating room utilization rate. Greene et al. (2024) presented an optimization model to support the ordering plans for a set of healthcare commodities during a pandemic. Yeni et al. (2025) used a two-stage stochastic programming to reduce cost and establish a resilient aquaculture supply chain by addressing the uncertainty caused by fish escape due to undercurrent and storm factors. Yilmaz et al. (2025a) developed a two-stage stochastic programming model incorporating Conditional Value at Risk and Chance Constraints to manage the risk of unsatisfied demand in a medical supply chain in the post-pandemic era. Yilmaz et al. (2025b) applied the two-stage stochastic programming to design a resilient humanitarian supply chain considering viability under uncertainty in capacity and demand. Yilmaz et al. (2025c) used unified robust stochastic programming with a two-stage approach for medical kit allocations to enhance the viability of the medical supply chain during the pandemic. Yilmaz et al. (2025d) utilized a unified robust stochastic programming to investigate the roles of strategic warehouse design and product clustering on the viability of the supply chain under the uncertainty in demand. Table 1 summarizes the studies relevant to this research.

Table 1. Summary of relevant studies

Author(s)	Research Area	Description	Research Gap
Uncertainties and Construction Schedule Variation			
Howell et al. (1993)	Uncertainty in Construction	Categorizes types of uncertainty in projects	No optimization-based solutions proposed
Gidado (1996)	Construction Planning	Measures complexity in construction production	No link to uncertainty mitigation strategies
Ballard (2000)	Construction Schedule	Shows unreliability in short-term schedules; promotes collaborative planning	No stochastic modeling of schedule reliability
Koskela (2000)	Construction Production System	Adapts manufacturing theory to construction's dynamic workflows	Lacks quantitative modeling of uncertainty
Brodetskaya et al. (2013)	Interior Finishing	Proposes pull flow control for variable finishing tasks	No integration with stochastic planning
Ma and Sacks (2016)	Construction Workflow	Uses agent-based simulation to model workflow dependencies	Limited scalability to multi-shop environments
Love and Matthews (2020)	Rework in Construction	Identifies cultural and strategic causes of rework	No predictive modeling for uncertainty
Wang et al. (2023)	Construction Planning	Models performance under deep uncertainty using prediction intervals	Does not address the production of fabrication supply chain with multiple shops
Construction Prefabrication Supply Chain			
Dawood (1995)	Precast Scheduling	Uses simulation for precast production planning	No stochastic modeling
Benjaoran et al. (2005)	Production Workflow	Proposes flowshop model for custom precast planning	Does not include stochastic programing model
Ko and Wang (2010)	Precast Planning	GA-based decision support for production planning	No uncertainty modeling, no multiple shops.
Yang et al. (2016)	Precast Production	Multi-objective GA for decisions from manufacturing to assembly	Not for prefabrication construction supply chain with multiple shops
Wang and Hu (2018)	Prefabrication Production	Two-level rescheduling model for due date shifts	Does not address multiple fabrication shops
Ma et al. (2018)	Precast Scheduling	Optimizes multi-line rescheduling during crises	Does not address multiple fabrication shops
Du et al. (2020)	Prefabricated Components	GA-based flowshop model for demand fluctuations	Does not address multiple fabrication shops
Kim et al. (2020)	Precast Scheduling	Simulation + heuristic model for due date uncertainty	Single-shop context, no stochastic programing
Wang et al. (2021)	Precast Scheduling	Hybrid model for rescheduling amid machine breakdowns	No stochastic modeling of disruptions
Ho et al. (2022)	Prefabrication Production	Surveys firms; proposes deterministic optimization model	No uncertainty, no stochastic modeling for delivery variation
Kim et al. (2022)	Precast Production	Deep reinforcement learning to minimize tardiness	No integration with stochastic demand
Jiang et al. (2023)	Construction Prefabrication	Studies crashing strategies and decisions on pricing and coordination under power structures	No stochastic framework for delivery disruptions
Zhang et al. (2023)	Precast Scheduling	Three-layer disruption management model for emergency order handling	No stochastic programming with uncertainty
Kim and Lee (2024)	Precast Scheduling	Proposes contractual scheme for stakeholder alignment	Does not cover stochastic demand and delivery changes
Planning and Scheduling Supply Chain Networks			
Arntzen et al. (1995)	Global Supply Chain	Evaluates global manufacturing and distribution strategies	Not developed for construction prefabrication supply chain
De Bontridder (2001)	Production Optimization	Uses local search for purchasing and production planning	Does not address prefabrication supply chain

End of Table 1

Author(s)	Research Area	Description	Research Gap
Pinedo (2009)	Manufacturing & Services	Reviews planning and scheduling techniques	General framework, not construction specific
Javid and Azad (2010)	Network Design	Optimizes location-routing-inventory decisions	Not stochastic programing model
Zadeh et al. (2014)	Steel Supply Chain	Models dynamic inventory and facility location	Not applied to prefabrication context
Desale et al. (2015)	General Supply Chain	Reviews heuristic/metaheuristic algorithms	No construction prefabrication with multiple shops
Javid and Hoseinpour (2015)	Distribution Network	Integrates location, inventory, and pricing	General supply chain, not construction
Yu et al. (2015)	Multiproduct Supply Chain	Combines location-production-distribution planning	Is not construction specific
Milat et al. (2021)	Construction Scheduling	Examines adaptive scheduling in construction	Does not cover construction prefabrication
Stochastic Programming with Uncertainty			
Guimarans and Padron (2022)	Airport Resources	Stochastic model for ground support scheduling	Needs adaptation for prefabrication shops
Hadid et al. (2022)	Chemotherapy Scheduling	Clustering & stochastic optimization to reduce wait times	No link to supply chain or production planning
Cruz et al. (2024)	Vessel Planning	Stochastic model for demand and travel time	Not applied to construction prefabrication
Greene et al. (2024)	Healthcare Commodities	Optimizes ordering plans under substitution and delay	No application to construction logistics
Yeni et al. (2025)	Aquaculture Supply Chain	Combines lean tools with robust optimization	Transferability to construction unexplored
Yilmaz et al. (2025a)	Medical Supply Chain	Hybrid risk framework for resilience	No construction-specific adaptation
Yilmaz et al. (2025b)	Humanitarian Supply Chain	Machine learning & viability analysis for resilient design	Not tailored to prefabrication logistics
Yilmaz et al. (2025c)	Medical Kit Allocation	Unified robust stochastic programing & machine learning to predict contagion and adjust demand	No application to construction scheduling
Yilmaz et al. (2025d)	Warehouse Design	Unified robust stochastic programing for strategic inventory planning under uncertainty	No link to prefabrication supply chain design

The research in this paper addresses the above needs and knowledge gaps by investigating two-stage stochastic programming with multiple objectives for construction prefabrication scheduling with multiple fabrication shops. Our two-stage stochastic program considers future scenarios weighted by probabilities that represent the uncertainty associated with changes to delivery dues. The first stage is proactive in that it provides fabricators with a robust schedule that is fixed for the first time period (e.g., 1st week). The first-stage schedule is designed so that the fabrication shops are well-positioned to react to future changes. The second stage of the stochastic program is reactive in that it suggests modifications to the schedule in the second time period (e.g., weeks 2–4) given the announcement of changes to the delivery due dates. This provides fabricators with information on how they might adjust the schedule when delivery dates change. The multi-objective approach within the stochastic program formulation provides the ability to explore tradeoffs between minimizing cost and minimizing delay.

The following sections introduce the research method with our optimization model, discuss an experimental study, and present research findings.

3. Research method: optimization approach

In a prefabrication supply chain, the coordination across a network of different shops must account for transportation distances, shop capacities, inventory, time, and cost. The jobs herein correspond to construction projects that need prefabricated materials. A job usually includes a set of job parts with varying delivery times. For fabrication and module assemblies with relatively short lead times, such as rebar, façade units, or MEP components, since materials are fabricated and assembled within a few days before delivery dates, the storage area for both raw materials and fabricated/assembled materials is not a concern for the supply chain. However, other construction products may require longer production time, such as the curing time for precast units or when multiple trades are needed to fabricate the modules. In such cases, storage areas can become a factor influencing both costs and schedule.

Our optimization approach incorporates the impacts of uncertainty via different scenarios regarding required delivery dates (i.e., delivery dues). It allows us to evaluate the impact of different realizations of uncertainty on the cost, delay, and schedule of prefabrication supply chains, thereby gaining insight into the relationship between uncertainty and supply chain performance.

Figure 1 illustrates the prefabrication supply chain that is used in our experimental study, with three fabrication shops at different locations, and ten jobs situated at different locations. Each job is a construction project that requires different prefabricated items (or job parts). The supply chain includes fabrication of parts at the fabrication shops and transportation to the jobs that require the parts. Each fabrication shop has a machine for each job part that is produced in that shop. The planning time horizon is four weeks. The due dates for delivery of job parts in the first week of the planning period cannot be changed.

The optimization model determines the job part allocation among the fabrication shops based on processing cost, transportation distance, and shop capacity. Two objectives are addressed: minimizing total cost and minimizing total delay. A two-stage stochastic program is developed to reflect delivery time uncertainty with different scenarios. The first stage involves determining a robust production plan for the first week of the planning period while anticipating possible future scenarios with changes in delivery dues. The second stage involves creating a production plan for the remaining three weeks of the planning period for each scenario, incorporating scenario-specific information on changes in delivery due dates.

The assumptions used in the optimization model are:

- Each fabrication shop has sufficient equipment and labor capacity to do all job parts and unlimited inventory and storage capacity; however, each shop is restricted to two 8-hour shifts per day, effectively limiting production capability.
- The supply chain has an unlimited transportation capacity.

The optimization model includes sets, parameters, and decision variables as follows:

Sets

I: Set of fabrication shops, with $i \in I$ for shop index.

J: Set of jobs, with $j \in J$ for job index.

K: Set of job parts, with $k \in K$ for part index.

SC: Set of scenarios about required delivery time, with $\xi \in$ SC for scenario index.

Parameters

D_{jk}: Demand (in unit) for job part k in job j for $j \in J$, $k \in K$.

a_{jk}: The original due date of job part k of job j at the first week of the planning period ($k \in \{1, ..., 7\}$) for $j \in J$, $k \in K$.

a_{jk} (ξ): The due date of job part k of job j given the scenario ξ for $k \in K$, $j \in J$.

p (ξ): The probability of scenario ξ for $\xi \in$ SC.

h_{ik}: Processing time (in hours) for job part k at fabrication shop i for $i \in I$, $k \in K$.

$\tilde{h}$: Number of machine hours per day available for production.

t^{end}: The last day in the considered time horizon.

c^{p}_{ik} : The cost to process a unit of job part k at fabrication shop i for $i \in I$, $k \in K$.

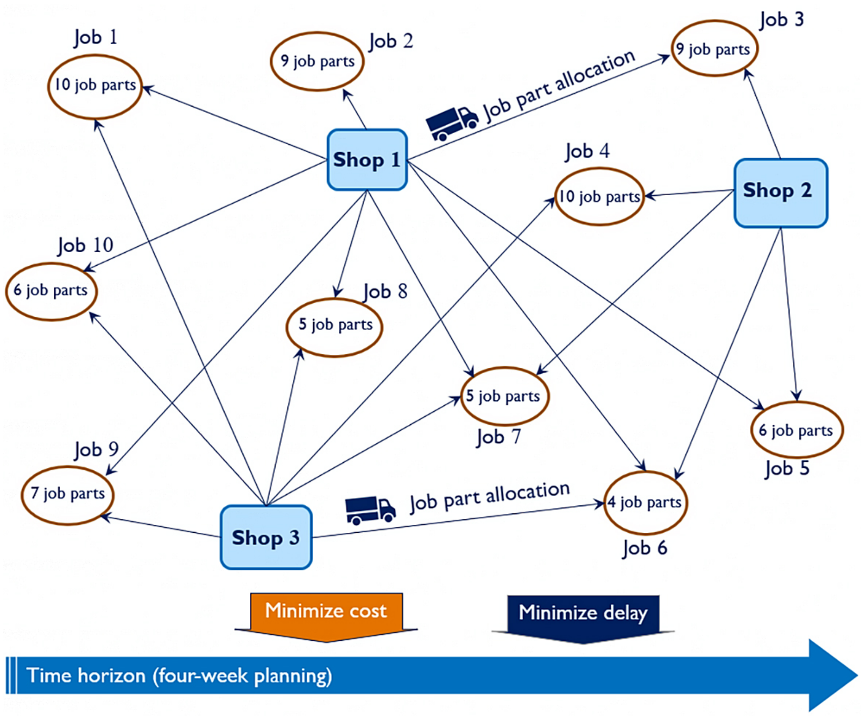

Figure 1. Job allocation of prefabrication supply chain with multiple fabrication shops

$c_k^{p_{tardy}}$: The estimated cost to process a unit of job part k that is delayed at the end of the time horizon for $k \in K$.
c_k^m: The cost to transport one unit of job part k for one km transportation distance for $k \in K$.
d_{ij}: Transportation distance (in km) from fabrication shop i to the construction site of job j for $i \in I$, $j \in J$.
d_j^{tardy}: Estimated transportation distance (in km) from a fabrication shop to the construction site of job j for the job parts that are still tardy at the end of the time horizon for $j \in J$.
w_{jk}: The tardiness (delay) cost per unit per day for an order of job part k of job j that is delayed for $j \in J$, $k \in K$.
T: Last day of time horizon (e.g., 28).

Decision Variables

$\tilde{x}_{ijkt}$: Quantity (in unit) of job part k in job j produced at fabrication shop i in time interval t for $i \in I$, $j \in J$, $k \in K$, $t \in \{1, ..., 7\}$.
$\tilde{y}_{ijkt}$: The quantity of job part k transported from the fabrication shop i to the construction site of job j at time t for $i \in I$, $j \in J$, $k \in K$, $t \in \{1, ..., 7\}$.
$\tilde{v}_{jkt}$: The quantity (in unit) of job part k that is tardy (has not arrived) at job j at the end of time interval t for $j \in J$, $k \in K$, $t \in \{1, ..., 7\}$.
$x_{ijkt}(\xi)$: Quantity (in unit) of job part k in job j produced at fabrication shop i in time interval t given the scenario ξ for $i \in I$, $j \in J$, $k \in K$, $t \in \{8, ..., T\}$.
$y_{ijkt}(\xi)$: The quantity of job part k transported from the fabrication shop i to the construction site of job j at time t given the scenario ξ for $i \in I$, $j \in J$, $k \in K$, $t \in \{8, ..., T\}$.
$v_{jkt}(\xi)$: The quantity (in unit) of job part k that is tardy (has not arrived) at job j at the end of a time interval t given the scenario ξ for $i \in I$, $k \in K$, $t \in \{8, ..., T\}$.

The two-stage stochastic programming model with two objectives is formulated as follows:

- Minimize total cost: $C = C_1 + C_2$, where C_1 represents the cost for the first week of the planning period while C_2 represents the cost for the subsequent three weeks, accounting for uncertainty across a set of weighted realized scenarios ξ:

$$C_1 = \sum_{t\in\{1,\ldots,7\}}\sum_{k\in K}\sum_{j\in J}\sum_{i\in I} c_{ik}^{p}\,\tilde{x}_{ijkt} + \sum_{t\in\{1,\ldots,7\}}\sum_{k\in K}\sum_{j\in J}\sum_{i\in I} c_k^{m}\,\tilde{y}_{ijkt} d_{ij} + \sum_{t\in\{1,\ldots,7\}}\sum_{k\in K}\sum_{j\in J} w_{jk}\,\tilde{v}_{jkt}; \tag{1}$$

$$C_2 = \sum_{t\in\{8,\ldots,T\}}\sum_{k\in K}\sum_{j\in J}\sum_{i\in I}\sum_{\xi\in SC} c_{ik}^{p} x_{ijkt}(\xi) p(\xi) + \sum_{t\in\{8,\ldots,T\}}\sum_{k\in K}\sum_{j\in J}\sum_{i\in I}\sum_{\xi\in SC} c_k^{m} y_{ijkt}(\xi) d_{ij}\, p(\xi) + \sum_{t\in\{8,\ldots,T\}}\sum_{k\in K}\sum_{j\in J}\sum_{\xi\in SC} w_{jk} v_{jkt}(\xi) p(\xi) + \sum_{j\in J}\sum_{k\in K}\sum_{\xi\in SC} c_k^{p_{tardy}}\, v_{jkt^{end}}(\xi) p(\xi) + \sum_{j\in J}\sum_{k\in K}\sum_{\xi\in SC} c_k^{m} v_{jkt^{end}}(\xi) d_j^{tardy} p(\xi). \tag{2}$$

- Minimize total delay: $L = L_1 + L_2$, where L_1 represents the delay for the first week of the planning period while L_2 represents the delay for the subsequent three weeks, accounting for uncertainty across a set of weighted realized scenarios ξ:

$$L_1 = \sum_{t\in\{1,\ldots,7\}}\sum_{k\in K}\sum_{j\in J} \tilde{v}_{jkt}; \tag{3}$$

$$L_2 = \sum_{t\in\{8,\ldots,T\}}\sum_{k\in K}\sum_{j\in J}\sum_{\xi\in SC} v_{jkt}(\xi) p(\xi). \tag{4}$$

Subject to the constraint on the availability of machines at fabrication shops:

$$\sum_{j\in J} h_{ik}\tilde{x}_{ijkt} \le \tilde{h},\ i\in I,\ t\in\{1,\ldots,7\},\ k\in K; \tag{5}$$

$$\sum_{j\in J} h_{ik} x_{ijkt}(\xi) \le \tilde{h},\ i\in I,\ t\in\{8,\ldots,T\},\ k\in K,\ \xi\in SC. \tag{6}$$

Subject to the constraint on the tardy job:

$$\sum_{\tau\in\{1,\ldots,t\}}\sum_{i\in I}\tilde{y}_{ijk\tau} + \tilde{v}_{jkt} = D_{jk},\ t\in\{1,\ldots,7\},\ t\ge a_{jk},\ j\in J,\ k\in K; \tag{7}$$

$$\sum_{\tau\in\{8,\ldots,t\}}\sum_{i\in I} y_{ijk\tau}(\xi) + v_{jkt}(\xi) = D_{jk},\ t\in\{8,\ldots,T\},\ t\ge a_{jk}(\xi),\ j\in J,\ k\in K,\ \xi\in SC. \tag{8}$$

Subject to the constraint on the total transportation quantity:

$$\sum_{t\in\{1,\ldots,7\}}\sum_{i\in I}\tilde{y}_{ijkt} + \sum_{t\in\{8,\ldots,T\}}\sum_{i\in I} y_{ijkt}(\xi) = \sum_{t\in\{1,\ldots,7\}}\sum_{i\in I}\tilde{x}_{jkt} + \sum_{t\in\{8,\ldots,T\}}\sum_{i\in I} x_{jkt}(\xi),\ j\in J,\ k\in K,\ \xi\in SC. \tag{9}$$

Subject to the constraint on transportation on each day in the time horizon:

$$\sum_{\tau\in\{1,\ldots,t\}}\sum_{i\in I}\tilde{y}_{ijk\tau} \le \sum_{\tau\in\{1,\ldots,t\}}\sum_{i\in I}\tilde{x}_{ijk\tau},\ j\in J,\ k\in K,\ t\in\{1,\ldots,7\}; \tag{10}$$

$$\sum_{\tau\in\{1,\ldots,7\}}\sum_{i\in I}\tilde{y}_{ijk\tau} + \sum_{\tau\in\{8,\ldots,t\}}\sum_{i\in I} y_{ijk\tau}(\xi) \le \sum_{\tau=\{1,\ldots,7\}}\sum_{i\in I}\tilde{x}_{ijk\tau} + \sum_{\tau=\{8,\ldots,t\}}\sum_{i\in I} x_{ijk\tau}(\xi),\ j\in J,\ k\in K,\ t\in\{8,\ldots,T\},\ \xi\in SC. \tag{11}$$

Subject to the constraint in the non-negative properties of the variables:

$$\tilde{x}_{ijkt},\ \tilde{y}_{ijkt},\ \tilde{v}_{jkt} \ge 0,\ \ i\in I, j\in J, k\in K, t\in\{1,\ldots,7\}; \tag{12}$$

$$x_{ijkt}(\xi),\ y_{ijkt}(\xi),\ v_{jkt}(\xi) \ge 0,\ i\in I, j\in J, k\in K, t\in\{8,\ldots,T\}, \xi\in SC. \tag{13}$$

To explore this problem with two objectives, we consider a set of λ values within the range [0, 1] and solve a set of optimization models with the objective function as $f = \lambda C + (1 - \lambda)L$. When $\lambda = 1$, the solution minimizes cost; when $\lambda = 0$, the solution minimizes delay. By varying intermediate values of λ, we get the set of Pareto-optimal values (non-dominated solutions) for the total cost C and the total delay L along the efficient frontier (Rardin, 1998; Winston, 2004).

The optimization model results are the decisions about times to fabricate job parts, the fabrication shop for which the parts are assigned for production, and the machine used to manufacture the parts. The outcome of the optimization objectives, including the total cost and total delay time, is also provided.

4. Experimental study

Consider a four-week planning period (28 days) of a prefabrication supply chain network that includes three fabrication shops and ten construction projects (ten jobs) situated at various locations. These jobs require diverse types of parts on different days in the 4-week planning horizon. The total number of unique job parts demanded by these jobs is fifteen. Each shop has different production times and production costs. These shops operate seven days per week, two shifts per day, and eight hours per week. As a result, the number of machine hours per day available for production is $\tilde{h}$ = 16. There is a penalty cost for each day of delay past the required delivery time for each unit of the job part. The shop managers develop schedules based on a four-week plan, including one weekly work plan for the first week and a look-ahead plan for the next three weeks. Since delivery times often change due to construction schedules, shop managers must account for uncertainty when developing their shop schedules. They must determine the job allocation, production schedules, and transportation plans for these fabrication shops, considering various scenarios for required delivery times. Their objectives are to minimize cost and delay. They also want to understand the tradeoff between cost and delay to create a flexible schedule that balances these objectives.

We developed four scenarios for the experimental study. Figure 2 illustrates the required delivery times for the ten jobs across the four scenarios. Scenario 1 indicates the original due dates (or required delivery times) agreed upon between the fabricator and the contractor. In Scenario 2, the due dates in Scenario 1 are postponed for around 30%–40% of the job parts for three days. In Scenario 3, we shifted the due dates in Scenario 1 for around 30%–40% of the job parts three days earlier. In Scenario 4, we postpone the due dates in Scenario 1 for around 30%–40% of job parts of job 1 to job 5 for three days. In Scenario 4, we also shift due dates in Scenario 1 for around 30%–40% of job parts of job 6 to job 10 for three days earlier. Since we want to develop a schedule for week 1 based on the uncertainty of the required delivery time over the next three weeks in the planning period, the due dates in Scenarios 2, 3, and 4 are limited between day 8 and day 28.

The uncertainty of the required delivery time is determined based on relevant data from the literature and our survey. Ballard et al. (1996) indicated that the percent plan complete (the percentage of the assignments completed as planned) of a case study project in their study increased from 65% to 85% after improving the reliability of job assignments. Kim (2019) investigated percent constraint removal (the number of assignments assigned in the weekly work plan compared to the number of assignments planned in the n-week look-ahead plan) based on 53 construction projects in Korea. The average percent constraint removal (PCR) identified from his study is 83% (Kim, 2019). This means that around 17% of assignments planned in the look-ahead plan do not appear in

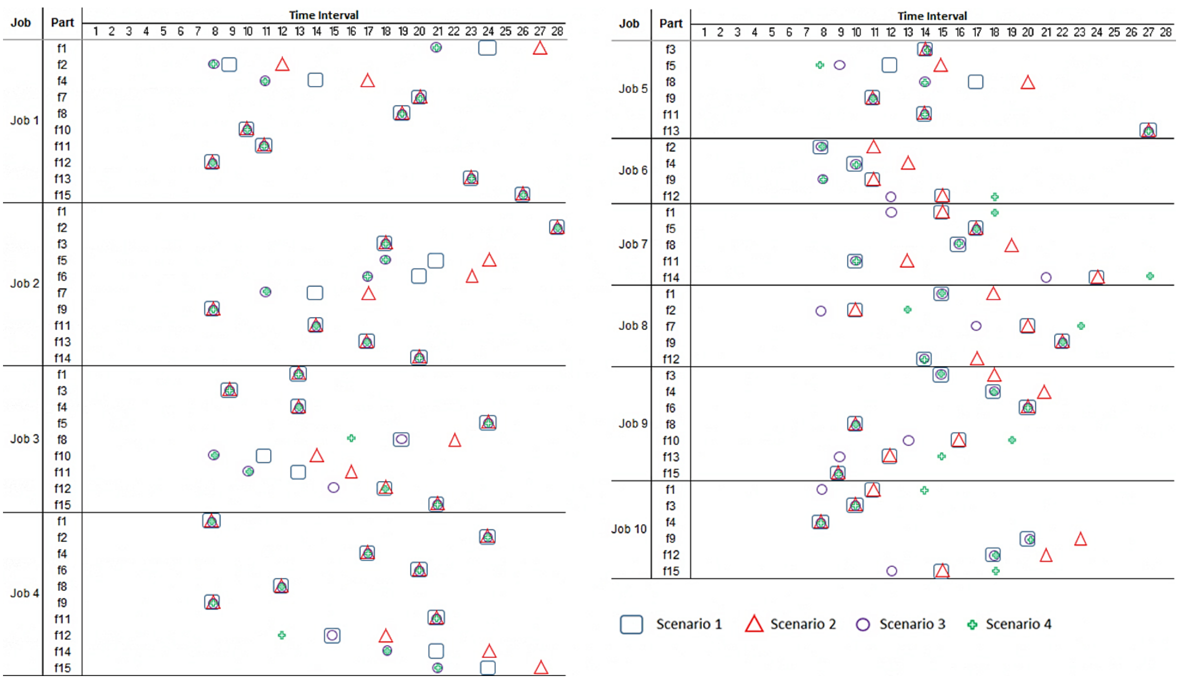

Figure 2. Required delivery times for job parts with four scenarios

the weekly plan on time. However, the PCR of the case study projects in Kim's research is higher than that of typical cases, as these construction projects have used the Last Planner System for several years. The sustained implementation of the Last Planner System has led to high-quality job assignments, significantly contributing to the elevated PCR values. On the other hand, a fabrication contractor who participated in the survey by Ho (2019) reported that their company tracks changes in the required delivery time for construction projects. Their findings indicate that after an order is released, the required delivery time changes in 30% of cases. As a result, we assumed that 30%–40% of the jobs in this example change the required delivery time.

Tables 2 to 5 describe the input data for the experimental study, including transportation distances, transportation and production costs and processing times at each shop, job demands and delay costs, and details about required delivery time in the scenarios.

Table 2. Transportation distance between construction sites and fabrication shops

Transportation Distance (km), d_{ij}			
Job j	Shop 1, i = 1	Shop 2, i = 2	Shop 3, i = 3
Job 1	50	65	10
Job 2	69	85	90
Job 3	76	79	25
Job 4	60	80	70
Job 5	79	42	150
Job 6	150	90	40
Job 7	80	70	60
Job 8	50	90	80
Job 9	130	20	40
Job 10	100	60	110

Table 3. Transportation cost, production cost, and production time at different fabrication shops

Job part k	Transportation cost ($/unit/km) c_k^m	Production time (hour/unit) p_{ik}			Production cost ($/unit) c_{ik}^p		
		Shop 1 i = 1	Shop 2 i = 2	Shop 3 i = 3	Shop 1 i = 1	Shop 2 i = 2	Shop 3 i = 3
f1	0.9	2	2	1	450	405	405
f2	0.9	3	2	3	720	720	720
f3	0.6	4	3	2	960	1152	1152
f4	0.9	2	1	4	360	288	288
f5	1.2	3	2	2	540	432	432
f6	1.2	2	2	1	480	384	384
f7	1.5	1	1	2	180	144	144
f8	0.9	2	2	1	480	384	384
f9	1.2	2	3	3	600	900	900
f10	0.6	1	2	1	180	270	270
f11	1.2	3	4	2	720	1080	1080
f12	0.3	1	1	2	180	216	216
f13	0.3	2	1	2	480	288	288
f14	0.6	5	3	3	540	864	864
f15	0.9	2	2	3	360	396	396

Table 4. Demand quantity, original due date, and delay cost of different construction projects

Job part k for job j	Demand quantity D_{jk}	Demand date a_{jk}	Delay cost ($/unit-day) w_{jk}
Job 1			
1f1	150	24	30
f2	120	9	45
f4	120	14	30
f7	70	20	60
f8	130	19	60
f10	50	10	90
f11	70	11	30
f12	45	8	45

Job part k for job j	Demand quantity D_{jk}	Demand date a_{jk}	Delay cost ($/unit-day) w_{jk}
f13	49	23	30
f15	30	26	45
Job 2			
f2	150	28	30
f3	140	18	60
f5	120	21	45
f6	150	20	45
f7	120	14	45
f9	80	8	60

Continue of Table 4

Job part k for job j	Demand quantity D_{jk}	Demand date a_{jk}	Delay cost ($/unit-day) w_{jk}
f11	110	14	45
f13	120	17	45
f14	180	20	45
Job 3			
f1	100	13	30
f3	140	9	75
f4	140	13	30
f5	60	24	45
f8	180	19	30
f10	200	11	60
f11	50	13	75
f12	150	18	30
f15	120	21	45
Job 4			
f1	110	8	30
f2	50	24	45
f4	30	17	30
f6	70	20	45
f8	100	12	30
f9	120	8	30
f11	80	21	30
f12	50	15	75
f14	80	21	30
f15	60	24	60
Job 5			
f3	150	14	45
f5	110	12	30
f8	40	17	60
f9	50	11	30
f11	130	14	45
f13	120	27	30
Job 6			
f2	20	8	30
f4	150	10	45
f9	140	11	30
f12	110	15	45
Job 7			
f1	80	15	60
f5	140	17	45
f8	150	16	60
f11	50	10	45
f14	70	24	30
Job 8			
f1	50	15	30
f2	70	10	45
f7	30	20	60

End of Table 4

Job part k for job j	Demand quantity D_{jk}	Demand date a_{jk}	Delay cost ($/unit-day) w_{jk}
f9	40	22	45
f12	70	14	60
Job 9			
f3	150	15	30
f4	200	18	30
f6	70	20	30
f8	50	10	60
f10	60	16	30
f13	80	12	60
f15	120	9	60
Job 10			
f1	90	11	30
f3	50	10	60
f4	100	8	60
f9	70	20	30
f12	60	18	30
f15	200	15	60

Table 5. Scenarios about the required delivery time

Job part k for job j	Demand Date at Scenario (SC), a_{jk}			
	SC1	SC2	SC3	SC4
Job 1	Original	Extend SC1 due date	Move back SC1 due date	Move back SC1 due date
f1	24	**27**	**21**	**21**
f2	9	**12**	**8**	**8**
f4	14	**17**	**11**	**11**
f7	20	20	20	20
f8	19	19	19	19
f10	10	10	10	10
f11	11	11	11	11
f12	8	8	8	8
f13	23	23	23	23
f15	26	26	26	26
Job 2	Original	Extend SC1 due date	Move back SC1 due date	Move back SC1 due date
f2	28	28	28	28
f3	18	18	18	18
f5	21	**24**	**18**	**18**
f6	20	**23**	**17**	**17**
f7	14	**17**	**11**	**11**
f9	8	8	8	8
f11	14	14	14	14
f13	17	17	17	17
f14	20	20	20	20

Continue of Table 5

Job part k for job j	Demand Date at Scenario (SC), a_{jk}			
	SC1	SC2	SC3	SC4
Job 3	Original	Extend SC1 due date	Move back SC1 due date	Move back SC1 due date
f1	13	13	13	13
f3	9	9	9	9
f4	13	13	13	13
f5	24	24	24	24
f8	19	22	19	**16**
f10	11	**14**	**8**	**8**
f11	13	**16**	**10**	**10**
f12	18	**18**	**15**	18
f15	21	21	21	21
Job 4	Original	Extend SC1 due date	Move back SC1 due date	Move back SC1 due date
f1	8	8	8	8
f2	24	24	24	24
f4	17	17	17	17
f6	20	20	20	20
f8	12	12	12	12
f9	8	8	8	8
f11	21	21	21	21
f12	15	**18**	15	12
f14	21	**24**	**18**	**18**
f15	24	**27**	**21**	**21**
Job 5	Original	Extend SC1 due date	Move back SC1 due date	Move back SC1 due date
f3	14	**17**	**11**	**11**
f5	12	**15**	**9**	**8**
f8	17	**20**	**14**	**14**
f9	11	11	11	11
f11	14	14	14	14
f13	27	27	27	27
Job 6	Original	Extend SC1 due date	Move back SC1 due date	Extend SC1 due date
f2	8	**11**	8	8
f4	10	**13**	10	10
f9	11	11	**8**	**14**
f12	15	15	**12**	**18**
Job 7	Original	Extend SC1 due date	Move back SC1 due date	Extend SC1 due date
f1	15	15	**12**	**18**
f5	17	17	17	17
f8	16	**19**	16	16
f11	10	**13**	10	10
f14	24	24	**21**	**27**

End of Table 5

Job part k for job j	Demand Date at Scenario (SC), a_{jk}			
	SC1	SC2	SC3	SC4
Job 8	Original	Extend SC1 due date	Move back SC1 due date	Extend SC1 due date
f1	15	**18**	15	15
f2	10	10	**8**	**13**
f7	20	20	**17**	**23**
f9	22	22	22	22
f12	14	**17**	14	14
Job 9	Original	Extend SC1 due date	Move back SC1 due date	Extend SC1 due date
f3	15	**18**	15	15
f4	18	**21**	18	18
f6	20	20	20	20
f8	10	10	10	10
f10	16	16	**13**	**19**
f13	12	12	**9**	**15**
f15	9	9	9	9
Job 10	Original	Extend SC1 due date	Move back SC1 due date	Extend SC1 due date
f1	11	11	**8**	**14**
f3	10	10	10	10
f4	8	8	8	8
f9	20	**23**	20	20
f12	18	**21**	18	18
f15	15	15	**12**	**18**

Note: The numbers in bold indicate the required delivery times that are changed compared to the original required delivery time.

5. Computational result

5.1. Computational run-time

To solve the model, we employ DOCPLEX, an IBM Decision Optimization CPLEX Modeling for Python (DOCPLEX version 2.9.141, 2019), with an Intel® Core™ i7-5500U CPU@2.40GHz laptop. We use Python (version 3.6, 2018) as an application programming interface (API) to call DOCPLEX, read data, write the problem, and present the computational results. The input data for the optimization model is written in a relational database management system named SQLite (version 3.10.1, 2016). The use of Python, DOCPLEX, and SQLite allows us to streamline the creation of input data and the analysis of computational results. The run-time for a problem with a single scenario and a single objective is approximately 10 seconds. The run-time for the two-stage stochastic program with four scenarios and a single objective is approximately 25 seconds. However, when exploring the Pareto optimal solutions along the efficient frontier with 20 values of λ and the two-stage stochastic program with four scenarios, the run-time is approximately 15 minutes because multiple models are needed to generate several points along the efficient frontier.

5.2. Production schedule: compare stochastic model vs deterministic model

To understand the performance of the stochastic model compared to the deterministic model with no uncertainty (Ho et al., 2022), we solved a deterministic model using the due dates in Scenario 1. Table 6 shows the production schedule in shop 1 for job 1 generated from the deterministic model. Table 7 shows the production schedule in shop 1 for job 1 generated from the stochastic programming (SP) model with four weighted scenarios. The weights are 40%, 30%, 10%, and 20% for Scenarios 1, 2, 3, and 4, respectively. This selection of weights is based on industry interviews and expert judgments from actual construction projects, where many changes can happen throughout the planning time horizon. The level of variation is different for projects, phases, and trades. As a result, we decided to select four scenarios with varying weights of possibility to represent the variation of schedule changes for construction projects. The complete schedules are included in the appendices of this paper. Both models are single-objective models that focus on minimizing cost. The computational results show that the minimal cost of the deterministic model (using Scenario 1 as certain) is $4,289,087, whereas the expected cost of the SP model with four weighted scenarios is $4,279,240, a 0.23% cost reduction.

Notice that the production schedules for the first seven days for the deterministic model are different from those of the SP model. This difference indicates the robustness of the SP model. As previously mentioned, this SP model addresses the issue where the required delivery time for the first week (or the weekly work plan) is fixed, while the delivery times for the following weeks are subject to change. Therefore, the SP model determines a robust production schedule in the first seven days, recognizing possible future scenarios. In addition, the SP model provides different production schedules for the remaining time in the planning horizon for different scenarios. This provides information to shop managers when developing a look-ahead plan for the next three weeks.

While the SP model generates an optimal production schedule for the first week and provides scenario-specific schedules for the following three weeks, in real life, construction fabricators typically select a solution for their monthly production process. What happens if a fabricator carries out the production process based on one scenario, but a different scenario occurs? Table 8 shows the total costs when solving the optimization model for a specific scenario and then applying that optimal schedule to a different scenario.

Row 1 in Table 8 shows the total costs when scheduling per Scenario 1, but another scenario occurs. Similarly, row 2, row 3, and row 4 show the total costs when scheduling per Scenario 2, Scenario 3, and Scenario 4, respectively, but another scenario occurs. The last column of Rows 1 to 4 in Table 8 presents the average cost that results when carrying out a schedule determined for a specific schedule but another scenario occurs (with probabilities 0.4, 0.3, 0.1 and 0.2.).

Table 6. Production schedule at shop 1 for job 1 for the original schedule (Scenario 1)

Shop	Job	Part	Days in the Planning Horizon																												Sum Produced
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	
Shop 1	Job 1	Part 01																													
		Part 02							5		1																				6
		Part 04														8	8	8		8			8	8	2	8					58
		Part 07																													
		Part 08																													
		Part 10	16		16	16						2																			50
		Part 11																													
		Part 12		16		16			13																						45
		Part 13																													
		Part 15																									8	8			16

Note: The number in each cell is the quantity produced on that day; the number in the light gray cell is the quantity produced on that day, but tardy.

Table 7. Production schedule of shop 1 for job 1 with four weighted scenarios (0.40, 0.30, 0.10, 0.20) generated by the stochastic programming model

Shop	Job	Part	Scenario	Days in the Planning Horizon																												Sum Produced
				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	
Shop 1	Job 1	Part 01	Sc I																													
			Sc 2																													
			Sc 3																													
			Sc 4																													
		Part 02	Sc I					1				5																				6
			Sc 2																													1
			Sc 3																													1
			Sc 4								5	5																				11
		Part 04	Sc I						6								8	8	8	8	8			8	8	2						64
			Sc 2															8	8	8	8		8		2							48
			Sc 3								8	8	8	8	8				8		8		8	8		2						80
			Sc 4								8	8	8	8	8		8				2	8			8	8						80
		Part 07	Sc I																													
			Sc 2																													
			Sc 3																													
			Sc 4																													
		Part 08	Sc I																													
			Sc 2																													
			Sc 3																													
			Sc 4																	8	8	8										24
		Part 10	Sc I		2						16	16	16																			50
			Sc 2								16	16	16																			50
			Sc 3									16	16																			34
			Sc 4									16	16																			34
		Part 11	Sc I																													
			Sc 2																													
			Sc 3																													
			Sc 4																													
		Part 12	Sc I	13						16	16																					45
			Sc 2								16																					45
			Sc 3								16																					45
			Sc 4								16																					45
		Part 13	Sc I																													
			Sc 2																													
			Sc 3																													
			Sc 4																													
		Part 15	Sc I																									8	8			16
			Sc 2																													
			Sc 3																								4	8	8			20
			Sc 4																								4	8	8			20

Note: The number in each cell is the quantity produced on that day; the number in the light gray cell is the quantity produced on that day but tardy.

Table 8. Total cost of scheduling per one scenario, but another scenario occurs instead

	Cases	Total Cost when Certain Scenario (SC) Occurs ($)				
		SC1 occurs	SC2 occurs	SC3 occurs	SC4 occurs	Average Cost
Row 1	Schedule per the solution for SC1	4,289,087	4,232,147	4,522,727	4,450,262	**4,327,604**
Row 2	Schedule per the solution for SC2	4,485,965	4,211,765	4,736,945	4,663,835	**4,464,377**
Row 3	Schedule per the solution for SC3	4,305,379	4,252,954	4,352,764	4,345,954	**4,302,505**
Row 4	Schedule per the solution for SC4	4,380,899	4,333,574	4,517,669	4,313,714	**4,366,942**
Row 5	SP schedule with weighted scenarios					**4,279,240**
Row 6	EDD schedule when assigning demands equally to 3 shops					**4,904,129**

Row 5 shows the average total cost when using the SP schedule and the probabilities of occurrence of Scenarios 1, 2, 3 and 4 are 0.4, 0.3, 0.1 and 0.2, respectively. Row 6 shows the total cost when scheduling based on the Early Due Date (EDD) method, assuming that demands are assigned equally to each shop. The result from Table 8 demonstrates the value of the SP schedule in obtaining the minimal cost no matter which scenario occurs. This confirms the robustness of the SP model.

Figure 3 illustrates the breakdown of different costs incurred for different scenarios. The first set of bars in Figure 3 represents the average costs associated with the SP solution (where the probabilities of occurrence of Scenarios 1, 2, 3, and 4 are 0.4, 0.3, 0.1 and 0.2, respectively). The total cost for the weighted case is $4,279,240 (see Row 5 of Table 8). The other sets of bars correspond to the diagonal costs of Table 8, where, fortunately, the same scenario occurs as used in scheduling. Scenario 2 has the lowest optimal cost of $4,211,765, while Scenario 3 has the highest at $4,352,764. The low cost of Scenario 2 is reasonable, as Scenario 2 allows extended due dates from Scenario 1, providing the supply chain with greater flexibility for scheduling.

On the other hand, Scenario 3 represents the case that the due dates are shifted earlier from Scenario 1, making it difficult for the supply chain to arrange the schedule, which results in higher costs. The optimal cost of Scenario 4 is $4,313,714, which falls in the middle. This scenario reflects a mix of some due dates shifting earlier and others shifting later, resulting in an optimal cost between the best and worst cases. Note that the model does not include handling costs for the work impacted by the changes in required delivery time. In case handling cost is included, the total cost for the scenarios subjected to the variation in required delivery time is much higher than the original scenario, as recognized by Ho et al. (2022).

5.3. Production schedule: Multi-objective optimization

Figure 4 shows the Pareto efficient frontier between cost and delay for solutions to the SP model. The figure illustrates an inverse relationship between cost and delay: as costs decrease, delays increase, and as delays decrease, costs rise. Supply chain managers must balance their risk of delay with cost.

In Figure 4, the solution labeled A was obtained by minimizing delay only, and the solution labeled D was obtained by minimizing cost only. The solution labeled B provides a reasonable balance between cost and delay.

Comparing D to B, the delay reduces from 8,455 to 8,116 (4.01% reduction), and the cost increases mildly from $4,279,240 to $4,282,179 (0.07% increase). Comparing B to A, the cost increases significantly from $4,282,179 to $4,446,133 (3.68% increase) while the delay is reduced from 8,116 to 7,790 (4.02% reduction. The trade-off curve can be used to identify diminishing returns. For example, reducing delay below 8100 (B on graph – sometimes called the "knee" of the efficient frontier) has a large increase

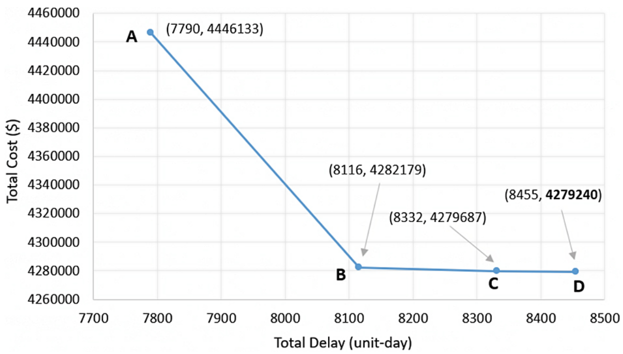

Figure 4. Pareto efficient frontier for the multi-objective SP solutions with four weighted scenarios

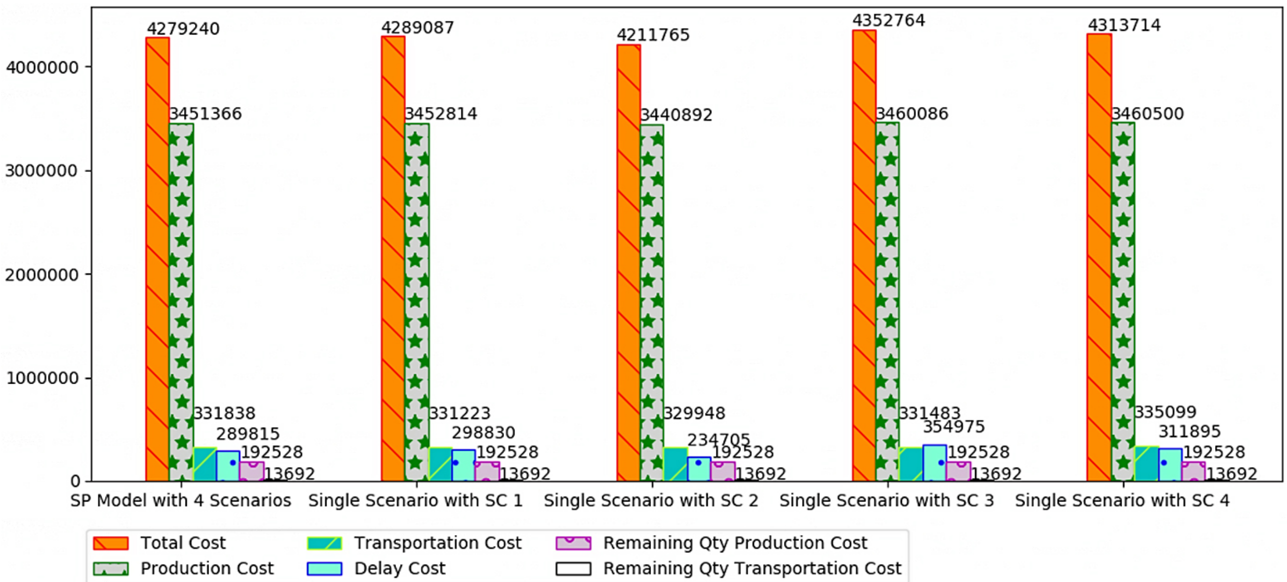

Figure 3. Optimal cost for different scenarios

in cost, whereas allowing delay increase beyond 8100 (C, D on graph) does not save much money but may impact the relationship with customers in the supply chain. By selecting the solution corresponding to B, a supply chain manager may choose to balance cost and delay with an acceptable delay and a reasonable cost.

Contrasting the multi-objective approach with the single objective of minimizing cost (as in Figure 4), we see that more work is scheduled in week 1 for the multi-objective approach. This is because performing more work early provides a production schedule in the first week that is robust enough to accommodate possible future scenarios while balancing delay and cost.

5.4. Production scheduling using the Early due date (EDD) method

We used the early due date (EDD) method to verify model performance. The EDD method prioritizes the production of the job parts with earlier due dates to avoid excessive delay. To apply the EDD method, we assumed that the job parts are assigned equally to 3 fabrication shops. Each fabrication shop is responsible for producing and transporting 33.33% of the job parts demanded by job sites. The total cost of the EDD method is $4,904,129, representing a 14.6% increase compared to the $4,279,240 total cost derived from the SP model for minimizing cost. The EDD method prioritizes reducing the total number of delayed dates without accounting for other cost factors, such as production and delay expenses. However, because of the assumption that there is no overtime (limit of 8 hours per day), and the inability to relocate the job parts to another shop that has not reached its limit, the EDD method ends up with higher unfulfilled job parts, adding further cost to the total cost.

5.5. Discussion

The proposed stochastic programming model in this research offers responses to our research questions and managerial insights. Regarding the first research question, this study addressed the challenge of balancing two objectives by incorporating a multi-objective optimization framework into the proposed model. The framework enables decision-makers to assign relative weights (ranging from 0 to 1) to cost and delay objectives according to their priorities. By generating a set of Pareto-efficient solutions, the model allows users to visualize and select a scheduling alternative that best aligns with their needs, thereby supporting more balanced decision-making in practice.

Regarding the second research question, this research addressed uncertainty in delivery due dates by developing a stochastic programming approach. The SP model integrates proactive and reactive scheduling: it first determines a robust baseline schedule for the initial planning horizon and then explores alternative reactive schedules for various possible future scenarios. This strategy improves the model's ability to adapt to unforeseen disruptions.

In addition, the study improves the accessibility and proximity between contractors' construction schedules and suppliers' prefabrication schedules. While the industry has long recommended that suppliers be actively involved in contractors' short-term scheduling processes (Ballard, 2000), it is easily noted that such integration rarely occurs in practice. Suppliers typically have limited or no opportunity to participate in the development of short-term construction schedules, and the two schedules are often managed independently. The stochastic programming model developed in this research addresses this gap by enabling suppliers and contractors to estimate the impacts of delivery due date changes on the prefabrication plans. With this capability, suppliers can provide contractors with scenario-based inputs to illustrate potential impacts, while contractors, in turn, can generate and evaluate multiple scheduling scenarios. In this interactive process, the model can serve as a decision-support tool for suppliers, allowing them to optimize production schedules by considering the likelihood of each scenario.

Moreover, the optimization framework allows contractors to be better informed about the potential impacts of schedule changes. If contractors and suppliers operate within a shared platform that integrates the SP model, suppliers could gain access to up-to-date short-term construction schedules (e.g., look-ahead plans), while contractors could retrieve suppliers' real-time capacity and lead-time data. This transparency would improve the delivery order coordination, thereby fostering a more reliable and cost-efficient supply chain between off-site suppliers and on-site contractors.

Beyond operational improvements, our findings also have potential implications for improving the equity and fairness in commercial contracts between contractors and suppliers. In current practice, many contracts impose penalties on suppliers for failing to meet agreed delivery dates, yet contractors often face no consequences for altering those dates. Our survey revealed that 30%–40% of delivery orders experience changes in delivery timing, with the resulting additional costs typically borne by suppliers (Ho, 2019). By enabling both parties to quantify the impacts of delivery date changes, the proposed model can offer a mechanism for more equitable contractual arrangements. While addressing contractual fairness is beyond the scope of this study, the methodology can provide insights that could support more balanced risk allocation.

A limitation of the proposed SP model, in addition to its simplified assumptions, is that it requires the supplier to work with a limited number of scenarios, each with a specific due date. This limitation suggests that the model becomes difficult to apply in cases where specific due date changes are unknown. The ability to set up reliable scenarios depends on either historical data on due date changes from the same contractor or on the contractor's willingness to provide information about possible due date variations. As a result, the reliability and accuracy of this model depend on the relationship between the supplier and the contractor.

For instance, if there is a long-term relationship or prior experience with similar projects, a supplier will likely accumulate data that can enhance the model's predictions. Additionally, contractors may share information on potential due date variations in a collaborative relationship. Conversely, if the contractor is unwilling to provide information regarding due date changes, the application of the proposed SP model may be less valuable as a scheduling tool but may be used to anticipate additional costs associated with due date changes.

6. Conclusions

This paper presents an optimization approach to facilitate the production planning of prefabrication construction supply chains with multiple fabrication shops under uncertainty. We present a stochastic programming model with multiple objectives that balance cost and delay reduction. The research also presents computational results for an example problem, which shows that the stochastic model changes the production schedule in the first week, adapting to various scenarios about uncertainty after the first week. The stochastic model generates a more robust solution than the deterministic model. When considering multiple objectives, the results of the stochastic program can indicate regions in the Pareto efficient frontier that balance decreasing delay with increasing cost. Recognizing these trade-offs between cost and time along the Pareto frontier allows supply chain managers to balance these objectives effectively when designing production plans.

This research is expected to contribute to improving the efficiency of production planning in the prefabrication supply chain in three ways. First, the proposed model offers prefabrication manufacturers a practical scheduling tool that proactively addresses delivery time changes. With the weighted scenarios factored in, the model allows suppliers to manage their resources better, reducing the negative impact on cost and project timelines.

Second, another key contribution of this study is the incorporation of a multi-objective optimization framework that allows decision-makers to balance cost and delay reduction objectives. By assigning customizable weights to these objectives, the model supports flexible and priority-driven scheduling decisions.

Third, the proposed model serves as a potential coordination tool for construction contractors and suppliers. Since most construction contracts transfer financial risks to the suppliers, it becomes challenging for all parties to collaborate to mitigate costs when the schedule changes. A key prerequisite for this proposed system is a shared cost and scheduling system between main contractors and suppliers.

As addressed in the discussion section, a key limitation of the proposed SP model is its reliance on a limited set of predefined scenarios with specific due dates. The model's reliability depends on the availability of historical data or the contractor's willingness to share information about possible due date changes, which may not always be feasible in practice.

We suggest that further research should focus on enhancing this model by incorporating additional constraints, such as labor and material availability, as well as different work sequences and scheduling cycles. It would also be valuable to validate the model in practice through case studies. Moreover, future studies could extend the model to account for uncertainties generated by suppliers, rather than assuming that uncertainty arises solely from the contractor's schedule, thereby better reflecting real-world dynamics of prefabrication supply chains.

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