Optimal transportation planning for prefabricated products in construction

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Abstract: *Prefabrication-based construction has several advantages such as short building time and superior quality. The transportation of prefabricated products from factories to construction sites has two key issues to consider. One is how to efficiently utilize the capacity of trucks in order to use as few trucks as possible, and the other is how to postpone the transportation of prefabricated products so as to pay for them as late as possible. This study proposes a mathematical programming model to optimize the transportation planning of prefabricated products to minimize the sum of trucking transportation costs and inventory holding costs. Extensive numerical experiments show that the optimal transport plan generated by the model outperforms the plan obtained by a greedy approach by 10% cost savings, implying the effectiveness of the model for the construction industry.*

1 INTRODUCTION

The construction industry is a labor-intensive industry. In the US, there are more than seven million construction workers (United States Department of Labor, 2018). The construction industry is also marked with high occupational illnesses and deaths. The rate of injury and illness cases of the construction industry in the US is around 3 per 100 full-time workers per year and the annual number of fatalities is around 1000. To overcome the disadvantages of conventional cast in-situ manual construction, this industry has followed a modular production model of the manufacturing industry. By using prefabrication, the construction industry takes advantage of automation in production and assembly to increase efficiency. Prefabrication is a manufacturing process that takes place at specialized factories. Some stages of the construction projects are prefabricated, i.e., they are carried out off-site. The prefabricated construction products are then transported to the construction site and assembled (installed) for completing the whole construction project. Prefabrication can be small components, to 2D panels, 3D modules, or even complete buildings. Compared with conventional construction methods, prefabrication generally has the advantages of (i) short building time, because a whole construction project consists of assembling tens of or a few hundred prefabricated construction products; (ii) superior quality, because the prefabricated construction products are produced in factories which have better working conditions than construction sites; (iii) safer construction, because of less labor requirement onsite; (iv) environmental friendliness, because of the controlled working conditions in factories; and (v) reduced cost, because of the above factors (Jaillon and Poon, 2010; Lu and Yuan, 2013; Zhong et al., 2017; Hsu et al., 2018). Due to these advantages, prefabrication has been widely used in construction in countries and regions such as Singapore

(Building and Construction Authority of Singapore, 2018), Hong Kong (Jaillon et al., 2009; Lu and Yuan, 2013), Europe and America (Hällmark et al., 2012).

Using prefabrication in construction has three essential steps: prefabrication in factories, transportation of prefabricated products to construction sites, and installation of prefabricated products onsite. The first and the third steps have been widely studied, whereas the second step has aroused little attention. This paper focuses on the second step. In what follows, for brevity, we use "prefab products" to refer to all types of prefabricated products, such as small components, 2D-panels, and 3D-volumes. Suppose that the construction company manages the transportation of prefab products from the factory to the construction site. The factory issues invoices to the construction company for the prefab products when they leave the factory. In practice, the payment terms for prefab products may vary depending on negotiation, for example, within 10 days or 30 days from the invoice date.

There are two key issues to consider in the transportation of prefab products. The first one is how to efficiently utilize truck capacity in order to use as few trucks as possible. For instance, if there are six prefab products, whose weights are 1, 3, 3.5, 4, 4.5, and 6 tons, and the capacity of a truck is 11 tons, then the best way is to use one truck to transport the three products with weights of 1, 4, and 6 tons and to use another truck to transport the other three products. The second one is how to postpone the transportation of prefab products. Ideally, the prefab products are delivered to construction sites only when they are needed. In this way, the transportation of the prefab products can start as late as possible so that the construction company can have more fluidity of its working capital, which is essentially the "just-in-time (JIT)" concept adopted in the manufacturing industry. The construction industry is capital intensive and many construction companies often face big pressure in cash flow and financing cost, so the issue is significant. Using the terms in the manufacturing industry, the construction company can save the inventory holding cost of the prefab products, i.e., to save the time value of the money tied to the prefab products that are purchased but not installed. The above two issues are intertwined. For instance, in the above example of using one truck to transport the three products with weights of 1, 4, and 6 tons, it is possible that the installation times of the products with weights of 1 and 6 tons are quite different and hence it will incur a huge amount of inventory holding cost if they are transported by the same truck (the time they are transported from the factory must follow the earlier installation time of the two components). We will develop optimization models to formulate the transportation planning problem for prefab products in construction. Solving the optimization models will provide us with the optimal solutions, that is, transportation planning decisions that incur the lowest total costs, including the transportation costs and the inventory holding costs.

1.1 Literature review

The production operations of prefab products in factories are similar to that of a manufacturing firm; as a result, a number of techniques and innovations in the manufacturing industry can be applied (Anson and Wang, 1998; Linner and Bock, 2012). There are a few studies that focus specially on the operations of prefabrication factories. Goh et al. (1986) and Burdorf et al. (1991) investigated the occupational health hazards in prefabrication factories. Lu and Yuan (2013) conducted case studies of three prefabrication factories. They demonstrated that the amount of waste by weight in prefabrication factories is not greater than 2%, which proved that prefabrication in a factory environment is more conducive to waste reduction than the conventional construction method. Kasperzyk et al. (2017) presented a robot-based prefabrication system aimed at increasing the design flexibility of prefabrication. The system allowed the automatic disassembly of a prefabricated structure and the reconstruction of the prefabricated structure according to a new design. Zhong et al. (2017) developed a building information modeling platform enabled by the internet-of-things (IoT) technologies to achieve real-time visibility and traceability of prefab products for the construction industry. This platform was applied in a public rental housing project in Hong Kong. Altaf et al. (2018) proposed a simulation-based optimization model for an integrated planning and control system for the prefabrication of 2D panels. The system could efficiently generate the optimal production schedules and the resulting waiting time, idle time, and station utilization data. Arashpour et al. (2018) formulated integer and probabilistic optimization models to reduce the cost of utilizing multi-skilled resources in prefabrication factories.

A number of studies have focused on the comparison between prefabrication construction and the conventional construction method. Prefabrication has cost advantages in many projects. Jaillon and Poon (2008) carried out case studies of seven high buildings in Hong Kong and their findings revealed that using prefabrication significantly outperforms conventional construction techniques in terms of environmental, economic and social benefits. However, prefabrication has an apparent disadvantage of lacking personalization of the buildings. Moreover, Jaillon and Poon (2010) reported that some prefabrication modules are too large and cannot fit into the space in Hong Kong. Tam and Hao (2014) pointed out that for Hong Kong the high land cost is a major difficulty for establishing a prefabrication factory and the congested roadwork affects the delivery of prefab products to construction sites. Jaillon and Poon (2010) conducted questionnaire survey and found that prefabrication is more prevalent for public residential buildings but less popular for private houses; moreover, designs for recycling and dismantling are rarely adopted in prefabrication, which means that buildings constructed with prefabrication may not be easily dismantled for repair, reuse in another location, or recycling.

Great efforts have been devoted to measures to improve prefabrication-based construction. Hsieh (1997) argued that to achieve maximum benefits from prefabrication, integrating the prefabrication subcontractor into the general contractor's organization is an effective approach. Tam et al. (2007a) conducted interviews and discovered that involving contractors and subcontractors in the design stage is vital to improve prefabrication implementation. Chen et al. (2010) proposed a construction method selection model to assist planners to evaluate the feasibility of prefabrication for a construction project; if prefabrication is infeasible, then the conventional construction method will be used. Li et al. (2016) performed a strengths, weaknesses, opportunities, and threats (SWOT) analysis of prefabrication housing production in Hong Kong. They suggested that IoT-enabled platform deploying Building Information Modeling (BIM) is significant for improving the situation in Hong Kong. Hsu et al. (2018) developed a two-stage stochastic programming model for prefab factory manufacturing planning that reacts to variations in the demand on construction sites.

In recent years, researchers have been paying more attention of waste reduction by prefabrication. Tam et al. (2005, 2007b) studied four private building projects and carried out questionnaire survey to demonstrate that the use of prefabrication can significantly reduce the amount of waste generated in construction activities such as plastering, timber formwork, concrete and reinforcement, and the reduction can be 100 per cent in some situations. Jaillon et al. (2009) administered a questionnaire survey and concluded that the average wastage reduction level by using prefabrication is about 52%. Tam and Hao (2014) further identified based on a structured survey that waste from poor workmanship can be considerably reduced by using prefabrication. They reported that prefabrication reduces 73.91% to 86.87% of waste in timber formwork, 51.47% to 60% of waste resulting from concrete, and 35% to 55.52% of waste of steel bars. Li et al. (2014) quantitatively evaluated the effect of prefabrication technology on construction waste reduction. Their model was validated based on a construction project in Shenzhen, China. The model showed that the policy of increasing the subsidy for the construction process to adopt prefabrication has a large influence on the adoption of prefabrication and waste reduction. Other than construction waste reduction, Mao et al. (2013) developed a quantitative model to analyze the greenhouse gas (GHG) emissions in construction and their results indicated that prefabrication reduces about 1.1 tons of GHG emissions per 100 m^2 of areas compared with conventional construction methods.

Lean/JIT production systems have been extensively studied and practiced in manufacturing (Monden, 2011; Zhang et al., 2016). When considering the prefab products as industrial components and the construction site as the industrial product, the prefab construction process is similar to manufacturing and can also adopt the Lean/JIT concept. Tommelein and Li (1999) analyzed two case studies to investigate whether the prefab factory or the contractor should be in charge of transportation. Pheng and Chuan (2001) found empirically that contractors in general overlooked the costs associated with the time value of prefab products. We argue that inventory costs are mainly concerned by manufacturing companies but are not common knowledge in the construction industry.

Based on the literature review, we find a gap that most studies focus on the construction site management or on prefab product manufacturing; even though some works have used simulation approaches to analyze the material flow for construction sites (Chan and Lu, 2008), very few works are devoted to operations research models for the transportation of prefab products from prefab factories to construction sites. To bridge the gap, we employ mathematical models and optimization methods to address this transportation problem for construction. Optimization models have been successfully applied to other transportation problems such as rail network maintenance (Xie et al., 2018), bus route design (Yang et al., 2017), vehicle routing (Liao et al., 2017), freeway cost minimization (Jiang and Adeli, 2003; Karim and Adeli, 2003), and road network design (Wang and Szeto, 2017) and construction problems such as cost estimation (Adeli and Karim, 2007, 2014; Karim and Adeli, 1999; Rafiei and Adeli, 2018; Senouci and Adeli, 2001), surveillance camera placement (Yang et al., 2018), structure analysis (Park et al., 2007; Acharya et al., 2018; Branam et al., 2019), sustainability (Zavadskas et al., 2018) and resource scheduling (García-Nieves et al., 2018). Both exact and heuristic algorithms are used to solve these models. We enrich the literature by applying an exact optimization solution approach to prefabricated construction process.

1.2 Objectives and contributions

This study examines the optimal transportation planning of prefab products for construction sites with the objective of minimizing the total cost. The contribution of the paper is twofold. First, to the best of our knowledge, this is the first study that develops a mathematical programming model to optimize the transportation planning of prefab products. The mathematical programming model can be solved by off-the-shelf solvers (Zavadskas et al., 2016; Bagloee et al., 2017; Ponz‐Tienda et al., 2017; Tang et al., 2018) and generates the optimal transportation plan that minimizes the sum of truck transportation costs and inventory holding costs. Second, we have conducted numerical experiments and the results show that the optimal transport plan outperforms the plan obtained by a greedy approach in that the former reduces the total cost by about 10%, implying the effectiveness of the model.

The remainder of this paper is organized as follows: Section 2 describes the problem in detail. Section 3 formulates a mathematical model, discusses a few linearization techniques, and proposes some strengthening approaches. Computational experiments are reported in Section 4. Final conclusions are drawn in the last section.

2 PROBLEM DESCRIPTION

We consider a prefab construction site. The construction project consists of a set of prefab products, denoted by J. All of the prefab products are from a factory. Each type of components $j \in J$ may have more than one piece, and we use n_j to represent the number of pieces of prefab product j. For example, if a prefab house has two washrooms, then $n_j = 2$ for the washroom prefab product. All pieces of prefab product j must be available for construction by time T_j. Note that in the previous example, if one washroom is on the first floor and the other is on the second floor, and they are installed at different times, then we will treat them as two different prefab products and each prefab product will have only one piece.

Ideally, the prefab products are transported from the factory to the construction site just when they are about to be installed. In this way, the inventory holding costs of the prefab products are minimal (i.e., the inventory holding costs are only associated with the transportation time from the prefabrication factory to the construction site). In reality, however, the prefab products are transported from the factory by truck and a truck will generally carry more than one piece of prefab products. In other words, some prefab products arrive at the construction site earlier than when they are needed because they are transported with other components on the same truck. We denote by T the time required for trucks to transport prefab products from factory to the construction site. To simplify the model formulation, we assume immediate payment terms, i.e., the payment of prefab products occurs when they leave the factory. Such a simplification does not alter the nature of the problem or the optimal solution because the payment terms are usually a fixed number of days, which will be treated as a constant if being incorporated in the model. The unit inventory holding cost of a piece of prefab product j is c_j. Then, if a piece of prefab product j leaves the factory at time t, $t \le T_j - T$, the extra inventory holding cost incurred is $c_j(T_j - T - t)$.

In addition to the inventory holding cost, the trucking cost is a significant cost component. We denote by W the weight capacity of a truck and by w_j the weight of one piece of prefab product j. We denote by V the volume capacity of a truck and by v_j the occupied volume by one piece of prefab product j. For brevity, hereafter we refer to v_j as the "volume." We further represent by C the cost of transportation by truck each time. Evidently, the number of trucks required is at least

$max\{\lceil \sum_{j\in J} n_j w_j / W \rceil, \lceil \sum_{j\in J} n_j v_j / V \rceil\}$, where $\lceil x \rceil$ means the smallest integer greater than or equal to x. The maximum number of trucks required, denoted by I, can be calculated as follows:

$$I = \sum_{j\in J} \lceil n_j / (min\{\lfloor W/w_j \rfloor, \lfloor V/v_j \rfloor\}) \rceil, \quad (1)$$

where $\lfloor x \rfloor$ means the largest integer smaller than or equal to x, $\lfloor W/w_j \rfloor$ is the maximum number of pieces of prefab product j that can be carried by one truck considering weight only, $\lfloor V/v_j \rfloor$ is the maximum number of pieces of prefab product j that can be carried by one truck considering volume only, $min\{\lfloor W/w_j \rfloor, \lfloor V/v_j \rfloor\}$ is the maximum number of pieces of prefab product j that can be carried by one truck considering both weight and volume, and $\lceil n_j / (min\{\lfloor W/w_j \rfloor, \lfloor V/v_j \rfloor\}) \rceil$ is the minimum number of trucks required to carry all pieces of prefab product j. Therefore, the I in Eq. (1) is effectively the number of trucks required to carry all pieces so that every truck carries pieces of only one type.

The construction site manager therefore needs to decide how many trucks to use, how many pieces of each prefab product to transport on each truck, and the departure time of each truck from the factory, such that all the components are delivered to the construction site on time (they are allowed to be delivered before their installation times), to minimize the total costs consisting of the trucking costs and inventory holding costs.

Regarding the uncertainties at construction sites, such as uncertain demand by crew on site, crew productivity variation, too congested site space to provide buffers for laydown yard or even for parking trailers, we can insert some buffer time (e.g., 1 day) in the formulation of the model to make the solution work in practice. Moreover, the buffer time will be different for different types of uncertainties. The proposed model can also be conducted in a rolling-horizon manner. For instance, the model can be resolved every day to take into account the latest updates in uncertainties and to adjust the buffer times used.

3 MODEL FORMULATION AND ALGORITHM

This section develops a mathematical programming formulation for the problem and proposes methods to linearize the proposed formulation. Section 3.1 lists the notation; Section 3.2 presents a nonlinear mathematical model for planning the transportation of prefab products; Section 3.3 proves that the problem is NP-hard; Section 3.4 describes linearization techniques that are used to transform the model into a mixed-integer linear programming one; Section 3.5 proposes a few strengthening techniques to improve the computational efficiency of the model.

3.1 Notation

***Sets and Indices*:**

i: index for truck;

j: index for prefab product;

t: index for time;

Z_+: Set of nonnegative integers;

***Input parameters*:**

J: number of types of prefab products;

n_j: quantity of prefab product j required for construction;

T_j: time when prefab product j is required for construction; without loss of generality, we assume that $T_1 \le T_2 \le \cdots \le T_J$ and assume that $T_1 = T + 1$, that is, the first truck will depart from the factory at time 1;

w_j: weight of one piece of prefab product j;

v_j: volume of one piece of prefab product j;

c_j: inventory holding cost of one piece of prefab product j per unit time;

I: maximum number of trucks required;

W: weight capacity of a truck;

V: volume capacity of a truck;

C: cost of transportation by truck each time;

T: time required for trucks to transport prefab products from factory to the construction site;

***Functions*:**

$\lfloor x \rfloor$: the largest integer smaller than or equal to x;

$\lceil x \rceil$: the smallest integer greater than or equal to x;

$f(a)$: 1 if $a \ge 0$ and 0 otherwise;

***Decision variables*:**

$x_{ij} \in Z_+$: number of pieces of prefab product $j = 1, \ldots, J$ transported by truck $i = 1, \ldots, I$;

$y_i \in Z_+$: time when truck $i = 1, \ldots, I$ departs from the factory;

$z_i \in \{0,1\}$: a binary variable that equals 1 if and only if truck i is used, $i = 1, \ldots, I$.

3.2 Mathematical model

To develop the optimal prefab product transportation plan, we need the following variables: z_i is a binary variable that equals 1 if and only if time truck i is used, $i = 1, \ldots, I$; y_i

is a nonnegative integer variable that represents the time when truck i departs from the factory; x_{ij} is a nonnegative integer variable that represents the number of prefab product $j = 1, \ldots, J$ transported by truck $i = 1, \ldots, I$. The prefab product transportation planning problem can be formulated as:

[M1]

$$C^* = \min \sum_{i=1}^{I} Cz_i + \sum_{i=1}^{I} \sum_{j=1}^{J} c_j x_{ij} (T_j - T - y_i) \quad (2)$$

subject to:

$$x_{ij} \le n_j z_i,\ \ i = 1, \ldots, I, j = 1, \ldots, J \quad (3)$$

$$x_{ij} \le n_j f(T_j - T - y_i), i = 1, \ldots, I, j = 1, \ldots, J \quad (4)$$

$$\sum_{i=1}^{I} x_{ij} = n_j, j = 1, \ldots, J \quad (5)$$

$$\sum_{j=1}^{J} w_j x_{ij} \le W, i = 1, \ldots, I \quad (6)$$

$$\sum_{j=1}^{J} v_j x_{ij} \le V, i = 1, \ldots, I \quad (7)$$

$$y_i \le y_{i+1}, i = 1, \ldots, I - 1 \quad (8)$$

$$x_{ij} \in Z_+,\ \ i = 1, \ldots, I, j = 1, \ldots, J \quad (9)$$

$$y_i \in Z_+,\ \ i = 1, \ldots, I \quad (10)$$

$$z_i \in \{0,1\},\ \ i = 1, \ldots, I. \quad (11)$$

In the above model, Eq. (2) minimizes the sum of trucking cost and inventory holding costs. Constraints (3) require that truck i can transport prefab product j (i.e., $x_{ij} > 0$) only if truck i is used (i.e., $z_i = 1$). Constraints (4) require that truck i can transport prefab product j (i.e., $x_{ij} > 0$) only if truck i departs from the factory no later than $T_j - T$. Constraints (5) impose that all the n_j pieces of prefab product j are transported. Constraints (6) limit the weight capacity of each truck i. Constraints (7) limit the volume capacity of each truck i. Constraints (8) eliminate symmetrical solutions by requiring truck i to depart from the factory at a time no later than truck $i + 1$. Constraints (9) define x_{ij} as nonnegative integers. Constraints (10) define y_i as nonnegative integers. Constraints (11) define z_i as binary variables.

3.3 Model analysis

In this subsection, we prove that the prefab product transportation planning problem is NP-hard. The NP-hardness of a problem means it cannot be solved in polynomial time unless all the NP problems can be solved in polynomial time.

Proposition 1: The prefab product transportation planning problem is NP-hard.

Proof: We prove this proposition by reducing the prefab product transportation planning problem to a well-known NP-hard problem, namely the bin-packing problem. In the prefab product transportation planning problem defined by model [M1], let the inventory holding cost $c_j = 0, j = 1, \ldots, J$, the quantity of pieces of prefab product j is 1, i.e., $n_j = 1$, $j = 1, \ldots, J$, all the prefab products are required for installation at the same time, and the volume capacity of a truck is infinity, i.e., $V = \infty$. Then, this special version of the prefab product transportation planning problem will become:

[M1'] $\quad \min \sum_{i=1}^{I} Cz_i \quad (12)$

subject to:

$$x_{ij} \le z_i,\ \ i = 1, \ldots, I, j = 1, \ldots, J \quad (13)$$

$$\sum_{j=1}^{J} w_j x_{ij} \le W, i = 1, \ldots, I \quad (14)$$

$$x_{ij} \in \{0,1\},\ \ i = 1, \ldots, I, j = 1, \ldots, J \quad (15)$$

$$z_i \in \{0,1\},\ \ i = 1, \ldots, I. \quad (16)$$

Note that in model [M1'], x_{ij} is a binary decision variable because each prefab product has only one piece and the decision variables y_i are removed because the inventory holding cost is 0. The model [M1'] is exactly the bin-packing problem. Therefore, if the general version of the prefab product transportation planning problem can be solved in polynomial time, the bin-packing problem will also be solved in polynomial time. This completes the proof of the proposition.

3.4 Linearization of the model

Despite of the NP-hardness of the prefab product transportation planning problem, in reality, the number of types of prefab products is not large. This is a main advantage of prefabrication in construction compared with traditional construction methods. Therefore, we can seek efficient solution algorithms to find the optimal transportation plan.

The model [M1] is nonlinear in that (i) the objective function has the multiplication of two decision variables $x_{ij} y_i$ and (ii) Constraints (4) have nonlinear functions. After careful examination, we find that we can transform the nonlinear model [M1] into a linear integer programming model, which can then be solved to optimality by off-the-shelf solvers.

3.4.1 Linearization of Constraints (4)

To linearize Constraints (4), we notice that the latest time when trucks must leave the factory can be denoted by $\hat{T} = T_J - T$. Therefore, we define u_{it} as a binary variable that equals 1 if and only if truck i departs from the factory at time t, $i = 1, \ldots, I$, $t = 1, \ldots, \hat{T}$. The role of u_{it} is to replace y_i in model [M1] and to linearize Constraints (4).

***Newly defined input parameter*:**

$\hat{T}$: latest time when trucks must leave the factory, $\hat{T} = t_J - T$;

***Newly defined decision variables*:**

$u_{it} \in \{0,1\}$: a binary variable that equals 1 if and only if truck i departs from the factory at time t, $i = 1, \dots, I$, $t = 1, \dots, \hat{T}$.

With the above definitions, the prefab product transportation planning problem can be formulated as

[M2] $$C^* = \min \sum_{i=1}^{I} Cz_i + \sum_{i=1}^{I} \sum_{t=1}^{\hat{T}} \sum_{j=1}^{J} c_j x_{ij} u_{it} (T_j - T - t) \quad (17)$$

subject to:

$$x_{ij} \le n_j z_i,\ i = 1, \dots, I, j = 1, \dots, J \quad (18)$$

$$x_{ij} \le n_j \sum_{t=1}^{T_j - T} u_{it}, i = 1, \dots, I, j = 1, \dots, J \quad (19)$$

$$\sum_{i=1}^{I} x_{ij} = n_j, j = 1, \dots, J \quad (20)$$

$$\sum_{j=1}^{J} w_j x_{ij} \le W, i = 1, \dots, I \quad (21)$$

$$\sum_{j=1}^{J} v_j x_{ij} \le V, i = 1, \dots, I \quad (22)$$

$$z_i = \sum_{t=1}^{\hat{T}} u_{it}, i = 1, \dots, I \quad (23)$$

$$\sum_{t=1}^{\hat{T}} t u_{it} \le \sum_{t=1}^{\hat{T}} t u_{i+1,t}, i = 1, \dots, I - 1 \quad (24)$$

$$x_{ij} \in Z_+,\ i = 1, \dots, I, j = 1, \dots, J \quad (25)$$

$$u_{it} \in \{0,1\},\ i = 1, \dots, I, t = 1, \dots, \hat{T} \quad (26)$$

$$z_i \in \{0,1\},\ i = 1, \dots, I. \quad (27)$$

In the objective function (17), we formulate the inventory holding costs using variables u_{it} (note that $T_j - T - t$ is a known value). Constraints (19) define that trucks that depart too late cannot transport prefab products whose installation times are early. Constraints (23) define the relation between decision variables z_i and u_{it}. Similar to Constraints (8), Constraints (24) eliminate symmetrical solutions.

It should be noted that the decision variable z_i can be eliminated since, according to Eqs. (23), it can be computed from the values of u_{it}. In this way, Constraints (23) can be eliminated and z_i in the objective function can be replaced by its expression in function of u_{it}. Also, Constraints (18) can be eliminated because they are implied by Constraints (19).

3.4.2 Linearization of Objective function (17)

The objective function (17) still has the multiplication of two decision variables $x_{ij} u_{it}$. We can linearize it without introducing new integer variables. We define v_{ijt} to be the number of pieces of prefab product $j = 1, \dots, J$ transported by truck $i = 1, \dots, I$ that departs from the factory at time $t = 1, \dots, \hat{T}$.

***Newly defined decision variables*:**

v_{ijt}: a variable that equals x_{ij} if u_{it} is 1, and 0 otherwise, $i = 1, \dots, I, j = 1, \dots, J,\ t = 1, \dots, \hat{T}$.

Model [M2] can be linearized as:

[M3] $$C^* = \min \sum_{i=1}^{I} Cz_i + \sum_{i=1}^{I} \sum_{t=1}^{\hat{T}} \sum_{j=1}^{J} c_j (T_j - T - t) v_{ijt} \quad (28)$$

subject to:

$$v_{ijt} \ge x_{ij} + n_j (u_{it} - 1),\ i = 1, \dots, I, j = 1, \dots, J, t = 1, \dots, \hat{T} \quad (29)$$

$$v_{ijt} \le x_{ij},\ i = 1, \dots, I, j = 1, \dots, J, t = 1, \dots, \hat{T} \quad (30)$$

$$v_{ijt} \le n_j u_{it},\ i = 1, \dots, I, j = 1, \dots, J, t = 1, \dots, \hat{T} \quad (31)$$

$$v_{ijt} = 0,\ i = 1, \dots, I, j = 1, \dots, J, t = T_j - T + 1, \dots, \hat{T} \quad (32)$$

$$v_{ijt} \ge 0,\ i = 1, \dots, I, j = 1, \dots, J, t = 1, \dots, \hat{T} \quad (33)$$

and Constraints (18) – (27). It should be noted that Constraints (28) – (33) will enforce v_{ijt} to be x_{ij} in the optimal solution if u_{it} is 1, and to be 0 otherwise.

Model [M3] is a mixed-integer linear program and can be solved by mixed-integer linear programming solvers including CPLEX.

3.5 Strengthening model [M3]

In this section, we propose several approaches to strengthen model [M3]. The purpose of strengthening [M3] is to make its linear programming relaxation tighter, thus accelerating the convergence of the algorithms in the search process.

First, in model [M3] we used Eq. (1) as a crude approach to identify an upper bound of the number of trucks used I. We can reduce the value of this upper bound by a greedy approach below:

Algorithm 1. *Greedy prefab product transportation planning*

Step 0: Sequence all the $\sum_{j=1}^{J} n_j$ pieces of prefab products in ascending order of installation time. Initialize the number of trucks used $i \leftarrow 0$.

Step 1: Set $i \leftarrow i + 1$. Load the remaining pieces of prefab products to truck i according to their order until the truck does not have capacity to load the next component. The departure time of the truck is the installation time of the first loaded piece minus the transportation time T.

Step 2: If all pieces of prefab products have been transported, go to Step 3. Otherwise, go to Step 1.

Step 3: Calculate the total cost, consisting of the trucking cost and inventory holding cost, denoted by

C^{Greedy}. Then, the maximum number of trucks used in the optimal solution, denoted by I, is at most $\lfloor C^{\text{Greedy}}/C \rfloor$.

Second, by time $t = 1, \dots, \hat{T}$, the departed trucks should be able to transport all the prefab products j such that $T_j \leq t + T$. Therefore, by time t, the number of departed trucks should be at least $I_t^{min} = max\left\{\left\lceil\left(\sum_{j=1,T_j\leq t+T}^{J} n_j w_j\right)/W\right\rceil, \left\lceil\left(\sum_{j=1,T_j\leq t+T}^{J} n_j v_j\right)/V\right\rceil\right\}$. We can therefore add to model [M3] the following constraints:

$$\sum_{i=1}^{I}\sum_{\tau=1}^{t} u_{i\tau} \geq I_t^{min}, t = 1, \dots, \hat{T}. \quad (34)$$

Third, because x_{ij} is an integer, we can strengthen Constraints (21) and (22) by adding the following constraints, respectively:

$$x_{ij} \leq \lfloor W/w_j \rfloor, i = 1, \dots, I, j = 1, \dots, J \quad (35)$$

$$x_{ij} \leq \lfloor V/v_j \rfloor, i = 1, \dots, I, j = 1, \dots, J\ . \quad (36)$$

4 COMPUTATIONAL EXPERIMENTS

In this section, we report the results of numerical experiments that are used to validate the effectiveness and efficiency of the proposed model. The experiments are run on a laptop computer equipped with 1.80GHz of Intel Core i7 CPU and 16GB of RAM. The mixed-integer programming model [M3] is solved by CPLEX 12.8.

4.1 An illustrative example

We first examine an illustrative example of the construction of a two-floor private house using prefab products. The purpose of the example is to demonstrate the applicability of the model.

4.1.1 Input parameters

A two-floor private house has 15 types of prefab products. Table 1 shows for each prefab product j the quantity of pieces (n_j), weight of one piece (w_j) (ton), volume of one piece (v_j) (m^3), inventory holding cost (c_j) (\$/day), and time required for construction (T_j) (day). The time required for trucks to transport prefab products from factory to the construction site $T = 4$ days. We denote by the weight capacity of a truck $W = 20$ ton. The volume capacity of a truck $V = 40$ m^3. The cost of transportation by truck each time $C = \$1000$.

Table 1 Description of the 15 prefab products

ID	Name	n_j	w_j	v_j	c_j	T_j
1	Water tank of the swimming pool	1	10.0	40.00	4.00	5
2	First batch of slabs for the 1st floor	25	1.0	0.40	0.08	5
3	Second batch of slabs for the 1st floor	25	1.0	0.40	0.08	7
4	First batch of panel walls for the 1st floor	5	1.4	0.56	0.15	10
5	Second batch of panel walls for the 1st floor	5	1.4	0.56	0.15	13
6	Bathroom for the 1st floor	1	3.0	20.00	2.50	13
7	First batch of slabs for the 2nd floor	25	1.0	0.40	0.08	18
8	Second batch of slabs for the 2nd floor	25	1.0	0.40	0.08	20
9	Staircase	2	1.0	3.00	0.20	25
10	Panel walls for the 2nd floor	6	1.4	0.56	0.15	25
11	Bathroom for the 2nd floor	2	3.0	20.00	2.50	27
12	First batch of facades for the 1st floor	10	1.5	0.60	1.00	35
13	Second batch of facades for the 1st floor	10	1.5	0.60	1.00	38
14	First batch of facades for the 2nd floor	10	1.5	0.60	1.00	41
15	Second batch of facades for the 2nd floor	10	1.5	0.60	1.00	44

4.1.2 Optimal solution

We first use Eq. (1) to calculate the maximum number of trucks required $I = 19$. Without using the strengthening approaches in Section 3.5, the computation time required to obtain the optimal solution is 51 s. Applying Algorithm 1, we calculate $C^{\text{Greedy}} = \$14{,}574.55$, and the maximum number of trucks required is reduced to $I = 14$. The latest time when trucks must leave the factory $\hat{T} = T_J - T = 44 - 4 = 40$. By time t, the minimum number of departed trucks I_t^{min} is shown in Table 2. After strengthening, the computation time to solve model [M3] is 39 s. Therefore, the proposed model can be solved efficiently and the proposed strengthening approaches are effective. Moreover, the minimum total cost is $C^* = \$111{,}22.19$, which is 24% lower than the cost obtained by the greedy approach in Algorithm 1. This demonstrates the effectiveness of the proposed model.

Table 2 Minimum number of departed trucks $\boldsymbol{I_t^{min}}$

t	I_t^{min}	t	I_t^{min}
1	2	21	7
2	2	22	7
3	3	23	8
4	3	24	8
5	3	25	8
6	4	26	8
7	4	27	8
8	4	28	8
9	4	29	8
10	4	30	8
11	4	31	8
12	4	32	8
13	4	33	8
14	6	34	9
15	6	35	9
16	7	36	9
17	7	37	10
18	7	38	10
19	7	39	10
20	7	40	11

In the optimal solution, a total of 11 trucks are used, and their workloads and departure times are shown in Table 3. It can be seen that a truck may carry more than one prefab product. Moreover, trucks do not carry the prefab products in the sequence of their required installation time. For instance, truck 4 carries products 3, 4, and 7. In this way, the capacity of trucks can be better utilized. There is the reason why the proposed model outperforms the greedy approach in Algorithm 1.

Table 3 Optimal solution

Truck	Departure time	Product ID	Number of pieces
1	1	1	1
2	1	2	20
3	1	2	5
		3	15
4	3	3	10
		4	5
		7	3
5	9	5	5
		6	1
		7	2
		8	8
6	13	7	7
		8	13
7	14	7	13
		8	4
		11	1
8	20	9	2
		10	6
		11	1
		12	1
9	31	12	9
		13	4
10	34	13	6
		14	7
11	37	14	3
		15	10

4.1.3 Sensitivity analyses

In this section we numerically examine the sensitivity of the total cost with the input parameters. First, suppose that the prices of prefab products increase due to inflation. We hence multiply the inventory holding cost c_j by a ratio of 100%, 110%,…, 150%, and plot the total costs in Figure 1. We can see that the total cost almost increases in a linear way with the inventory holding cost ratio. Next, suppose that the trucking freight rate fluctuates with the relative magnitude of supply and demand. To reflect this situation, we multiply the cost of transportation by truck each time C by a ratio of 80%, 90%, 100%, 110%, 120%, and plot the total costs in Figure 2. We can see that the total cost increases in a linear way with the trucking transportation cost ratio. Figure 1 and Figure 2 show that when the inventory holding cost ratio and the trucking transportation cost ratio change within a small range, the optimal solution structure, namely how many trucks to use, the departure time of each truck, and the prefab products transported by each truck, hardly changes.

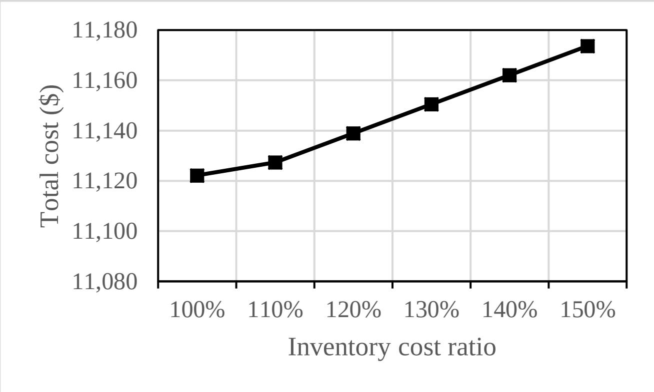

Figure 1 Sensitivity with the inventory holding cost ratio

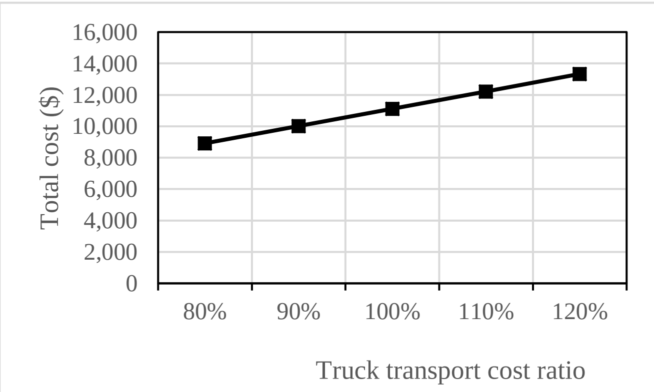

Figure 2 Sensitivity with the truck transport cost ratio

The trucking industry has been demanding the government to allow trucks that are longer and heavier to be operated. We hence analyze the results when the truck capacity (both W and V) is multiplied by a ratio of 100%, 110%,…, 150%. Suppose that the cost of transportation by truck each time C does not change. Note that the purpose of this assumption is to facilitate the analysis of the total cost with the truck capacity as we have already analyzed the sensitivity of the total cost with the truck transport cost. The total costs are plotted in Figure 3. According to Figure 3, increasing the truck capacity can in general significantly reduce the total cost. It seems that when truck capacity is extremely large, the marginal cost reduction is lower. This phenomenon may be because more pieces of prefab products must be aggregated on one truck and hence some prefab products have to be transported much earlier than their required installation time. Since in practice, the truck transport cost C increases with the capacity, using larger trucks is not always optimal.

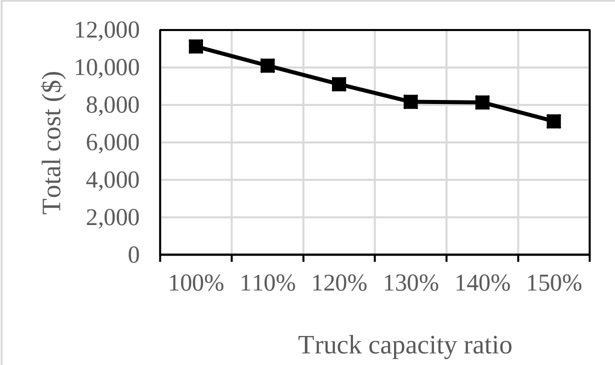

Figure 3 Sensitivity with the truck capacity ratio

We have further examined the solutions obtained in the above three groups of sensitivity analyses. We find that the optimal solutions are very similar and often identical under scenarios with different inventory holding cost ratios and different truck transport cost ratios. However, the optimal solutions differ significantly under scenarios with different truck capacity ratios. This demonstrates the robustness of the solutions whenever the trucks used to transport the prefab products do not change.

4.2 Randomly generated instances

This section reports the results of randomly generated instances. We first consider a total of 4 groups of instances with the types of prefab products $J \in \{5, 10, 15, 20\}$. In each group, we randomly generate 4 instances. In each instance, the parameters for the prefab products are randomly generated as follows: (i) the quantity of pieces of each prefab product is between 1 and 10; (ii) the weight is between 1 and 20; (iii) the volume is between 0.4 and 40; (iv) the inventory holding cost is between 0.10 and 5.00; (v) $T_{j+1} - T_j$ is between 1 and 3. The parameters for the trucks are the same as the case in Section 4.1.

Table 4 reports for each instance the number of types of prefab products J, the instance ID, the total cost by the greedy approach C^{Greedy}, the optimal total cost C^*, their gap defined as $\left(C^{\text{Greedy}} - C^*\right)/C^{\text{Greedy}}$, and the standard deviation of the four gaps for the four instances of each J. We can see that when the number of types of prefab products is small, the greedy approach performs excellently. However, when there is a large number of types of prefab products, the gap between the greedy approach and the proposed model is significant. It can be expected that the proposed model can reduce 10% of the total cost compared with the greedy approach. Moreover, when the number of types of prefab products is small, the standard deviation of the gaps between the solutions yielded by the greedy approach and the optimal ones is large. This should not be surprising for the following intuition. Suppose that for a given J, the gap between the solution yielded by the greedy approach and the optimal one, which is random, has a standard deviation σ. Then when the number of types of prefab products is $2J$, assuming that the first J and the second J types cannot be transported by the same truck and that the characteristics of the first J and the second J types are independent, then the gap between the solution yielded by the greedy approach and the optimal one will have a standard deviation $\sigma/\sqrt{2}$. In sum, a stable improvement over the greedy approach can be expected when the number of types of prefab products is large.

We then consider five large-scale randomly generated instances with the types of prefab products $J = 50$. We set the maximum CPU time for solving each instance at 10 minutes, that is, the algorithm will stop and output the best solution found once 10 min's computation time is used up. The results are shown in Table 5. It can be seen that although the optimal solutions may not be guaranteed for large-scale instances, the solutions obtained by the mathematical programming model still significantly outperform those yielded by the greedy heuristic. This further demonstrates the effectiveness of the proposed model.

Table 4 Computational results of randomly generated instances

J	Instance	C^{Greedy}	C^*	Gap	Gap_sd
5	1	17,011	17,011	0.00%	0.110
	2	12,003	12,003	0.00%	
	3	31,000	24,197	21.94%	
	4	41,000	41,000	0.00%	
10	1	54,011	54,011	0.00%	0.085
	2	36,020	36,015	0.01%	
	3	53,115	45,383	14.56%	
	4	51,000	43,429	14.85%	
15	1	75,011	66,276	11.64%	0.036
	2	57,115	50,777	11.10%	
	3	75,000	65,050	13.27%	
	4	69,016	55,960	18.92%	
20	1	100,032	89,873	10.16%	0.021
	2	106,016	94,651	10.72%	
	3	88,071	75,394	14.39%	
	4	118,097	101,829	13.78%	

Note: "Gap_sd" is the standard deviation of the four gaps for the four instances of each J.

Table 5 Computational results of large-scale randomly generated instances with 50 types of prefab products

Instance	C^{Greedy}	C^*	Gap
1	226013	216764	4.09%
2	238000	224580	5.64%
3	252003	220064	12.67%
4	224000	202177	9.74%
5	229076	226796	1.00%

5 CONCLUSIONS

This study has applied a nonlinear programming model to optimize the transportation planning for prefabricated products from factory to construction site with the objective of minimizing the total costs. We have proposed a few techniques to linearize the model to make it solvable by off-the-shelf mixed-integer linear programming solvers. We have further proposed some strengthening techniques to improve the computational efficiency of the model. We have used an illustrative example to demonstrate the applicability of the model. Sensitivity analyses demonstrate that the total cost increases almost linearly with the daily inventory holding cost of the prefabricated products and linearly with the trucking transportation cost each time. We have further carried out extensive randomly generated numerical experiments. The results of numerical experiments show that the proposed model reduces the total cost by 10% in comparison with a greedy approach. This implies considerable cost savings for the construction industry.

In this study, we have only considered the weight and occupied volume of a prefab product. In reality, we need to consider the three-dimensional features of the prefab products. For instance, if the volume capacity of a truck is 2.5m×2.5m×6m=37.5m^3, and the volume of a prefab product is 2m×2m×2m=8m^3, then the truck cannot carry four pieces of prefab products but can only carry three. In the future, we will optimize a detailed truck loading plan in prefab product transportation planning.

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