Cross-docking truck scheduling with the arrival times for inbound trucks and the learning effect for unloading/loading processes

Alireza Amini*, Reza Tavakkoli-Moghaddam and Aschkan Omidvar

School of Industrial Engineering and Research Institute of Energy Management & Planning, College of Engineering, University of Tehran, Tehran, Iran
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Cross-docking is a technique firstly proposed to reduce the storage space and flow time, simultaneously. This paper addresses a truck scheduling problem, in which a position-based learning effect is taken into consideration for unloading and loading tasks done by human labors in many related environments. The goal of the given problem is to minimize the mean completion time of outbound trucks. Therefore, a mathematical model is proposed inspired by an available model in the literature of this field. Furthermore, four heuristic algorithms are developed along with a simulated annealing (SA) algorithm in order to overwhelm the complexity of large-sized problems. The performance of the proposed algorithms is compared with the optimal solutions obtained by a complete enumeration method.

Keywords: cross-docking; truck scheduling; inbound truck; learning effect; mathematical model

1. Introduction

Cross-docking is a system, in which the concepts of both warehouses and distribution centers are considered. In such systems, delivered goods to cross-docking centers by inbound trucks should be unloaded, sorted, and labeled to prepare required items for outbound truck. A remarkable reduction in the amount of holding items within the warehouse and achieving an appropriate speed of distributing functions can be mentioned as the most significant advantages of employing cross-docking systems in supply chains. However, sufficient evaluations are required to determine whether cross-docking is an apt strategy to implement or not (Apte & Viswanathan, 2000). There are some well-known areas to study on this kind of distribution systems, such as locating cross-dockings, determining the optimum number of cross-dockings and the number of receiving and shipping doors, designing facilities layout within a cross-dock and scheduling inbound and outbound trucks at cross-docking terminals.

Numerous researchers have embedded mentioned areas; however, it is required to have more studies about truck scheduling because of the wideness of uncovered issues in sequencing problems and the key role of an optimum sequence to design pre-specified plans prepared by top managers. It is worth mentioning that a suitable truck scheduling strategy leads to control all associated operations well to satisfy desired targets. As a result, this paper discusses a scheduling problem in a cross-docking environment. In real cases, there are different demands with different conditions,
depending on the next stage nodes, which need making suitable decisions not to lose them as the potential customers in future.

Consequently, cross-docking should attempt to assign effective priorities to inbound and outbound trucks for visiting all demands through a superior technique. Since unloading/loading operations are completed by human labors in many systems, we can consider the learning effect that affects the procedure of identifying the sequence of any inbound and outbound trucks, obviously. To illustrate, this paper concentrates on developing a linear mathematical model for a truck scheduling problem at cross-docking terminals with the effect of learning in unloading and loading processes.

In fact, researchers tend to study scheduling problems, in cross-docking centers, by considering different assumptions. This will be on account of the importance of optimizing scheduling problems in different conditions. Even, a number of scheduling problems in these centers are taken into account where there is uncertainty (e.g. Konur & Golić, 2013; Larbi, Alpan, Baptiste, & Penz, 2011; Shakeri, Low, Turner, & Lee, 2012). Despite the presented studies about the ‘learning effect’ in machine scheduling problems, there is a lack of mentioned issue in truck scheduling within cross-docking terminals. This can be important because unloading/loading processes are accomplished by labors. So, they can learn how to work better by experiencing more. To approach the reality, unit unloading/loading times and inbound trucks arrival times are not assumed to be the same.

As a result, the paper, on hand, considers a truck scheduling problem at cross-docking terminals, in which there is a learning effect for unloading/loading processes in shipping and receiving doors. In fact, it is desired to develop a mathematical model for this aim and solve that. First of all, literature of this body of study is reviewed and then a mathematical model is proposed and examined by this paper.

In the following section, a brief literature review is brought, and in Section 3, the problem is explained in detail. Sections 4 and 5 present the solution approaches and numerical results, respectively. Finally, conclusion and future studies are discussed in Section 6.

2. Literature review

Cross-docking centers deal with different types of problems, such as location (e.g. see Mousavi & Tavakkoli-Moghaddam, 2013; Ross & Jayaraman, 2008), vehicle routing (e.g. see Dondo, Méndez, & Cerdá, 2011; Lee, Jung, & Lee, 2006; Liao, Lin, & Shih, 2010; Mousavi, Tavakkoli-Moghaddam, & Jolai, 2013; Mousavi et al., 2014; Santos, Mateus, & Salles da Cunha, 2011), and truck scheduling (Boysen & Fliedner, 2010; Van Belle, Valckenae, & Catry, 2012). This section deals with presenting the background of the truck scheduling problem in cross-docking and a brief literature of learning effect in scheduling problems.

2.1. Cross-docking truck scheduling

Truck scheduling in cross-docking centers has been an interesting area of the study in recent years. In fact, it is desired to determine places, in which trucks are unloaded/loaded and their respective times (Stephan & Boysen, 2011). To exemplify truck scheduling problems, Boysen and Fliedner (2010) classified cross-dock scheduling problems based on door environments, operational characteristics, and objective functions. Additionally, Van Belle et al. (2012) discussed about various problems of cross-docking
centers, including truck scheduling. One of the earliest studies is presented by Yu and Egbelu (2008), due to the work accomplished by Yu (2002), who considered a truck scheduling problem in the presence of temporary storage in front of the shipping door. Furthermore, Boysen, Fliedner, and Scholl (2008) introduced a base model to schedule trucks at cross-docking terminals in order to present an efficient insight for such problems. Maknoon and Baptiste (2009) addressed a study on sequencing inbound and outbound semi-trailers to improve the efficiency of cross-docking platforms.

As a matter of fact, some kinds of products (e.g. those are relevant to food industry) have high potential to be perished in an environment with non-appropriate temperature. On account of the importance of considering the mentioned situations, Boysen (2010) presented a cross-docking environment, where holding stocks is prohibited. Moreover, Vahdani, Soltani, and Zandieh (2009) investigated another approach of cross-docking scheduling, in which the temporary storage is not allowed.

Truck scheduling has been found complex (2008); therefore, different approaches are required to solve large-scale problems. For instance, Yu and Egbelu (2008) proposed some heuristics to find the optimum sequence of inbound and outbound trucks with a receiving and a shipping door. Another efficient approach is to develop meta-heuristics. Boloori Arabani, Fatemi Ghomi, and Zandieh (2011) employed meta-heuristics in order to overwhelm the complex nature of truck scheduling problems. Forouharfard and Zandieh (2010) designed an imperialist competitive algorithm (ICA) in order to minimize a number of products that visit the temporary storage. Vahdani and Zandieh (2010) and Soltani and Sadjadi (2010) utilized the design of experiments (DOE) to have robust meta-heuristics in truck scheduling problems. Additionally, Liao, Egbelu, and Chang (2012, 2013) used meta-heuristics in a truck scheduling problem within a cross-docking center. Finally, Vahdani, Soltani, and Zandieh (2009) proposed a GA and an electromagnetism-like algorithm (EMA) as the efficient methods to solve the given problem.

2.2. Learning effect

The very first attempt to introduce learning effects in an industry was by Wright (1936). He studied the learning effects on productivity in an aircraft industry. Jaber, Bonney, and Guiffrida (2010) proved that the learning curve is the S-curve, and divided this curve to three phases, namely incipient, learning, and maturity. In the first phase of the learning process, the worker gets used to the job and becomes familiar with the tools. In the second phase, the learning progress occurs rapidly and finally, in the third phase, the worker or machine is mature enough to perform a job in an optimal operation time. It is obvious that the speed of learning in the first and third phases is not as rapid as the second phase. Learning effects can be described in many different fields of industries, such as lot-sizing, scheduling, economy, management, service sectors, and many other branches.

Learning effects in scheduling are very popular, and researchers have modeled various kinds of scheduling problems with learning effects (e.g. see Biskup 1999, 2008; Hosseini & Tavakkoli-Moghaddam, 2012; Mosheiov, 2001, Qian & Steiner, 2013). The first attempt to consider the learning effect in scheduling problems was by Biskup (1999) who proposed a kind of the learning effect in a single machine scheduling problem. Main reason of considering such an effect in a scheduling problem is to approach the fact stating that functions of a scheduling problem are more likely done in shorter times than those that are assumed constant at the first point of planning. Qian and Steiner (2013) believe that it will limit the applicability of models if processing times are always assumed constant, and some changes are expected during the process, such
as having new workers and buying new machines. Two different approaches of considering learning effects in scheduling problems are the learning effect dependent on the number of jobs (i.e. position-dependent learning effects) and dependent on total processing time (i.e. time-dependent learning effects) (Mosheiov & Sidney 2003). Although most of the researches have theoretical points of view, for studying the learning effect and it does not have practical applications, it seems necessary not to neglect this phenomenon. The leading reason of perusing the learning effect attempts to reach an applicable approach.

3. Problem definitions

There is a cross-docking center, in which an exclusive receiving door and an exclusive shipping door are designed to do unloading and loading tasks, respectively. Inbound trucks, which carry the sent items from the first stage of a three-echelon supply chain (i.e. suppliers, cross-docking center, and customers), have arrival times that differ from a truck to another. Thus, a sequence of inbound trucks should be determined to unload all received items completely. After that, the assigned items should be sent to be loaded within outbound trucks. Unloading and loading procedures, which are done by manpower, require type-dependent times for each item. The following sub-section gives brief information about the learning effect.

3.1. Learning effect of the model

The idea of the learning effect attempts to find the relationship between the processing times needed to perform a job and the number of repletion of that job. It is shown, that the operation time decreases when the experience in that job increases. This kind of improvement is called learning by doing. From this idea, several curves have been developed, which represent the rate of learning for an activity.

This paper supposes that unloading and loading processes are done by manpower. By considering the nature of human and due to the above-mentioned information, it is assumed that labors are more efficient in doing their tasks in the case of being experienced enough. It means that requisite times for unloading and loading procedures will decrease based on the number of doing same job before. Figure 1 illustrates an example of learning effect performances.

![Figure 1](image-url)  
**Figure 1.** Effect of position-dependent learning in a decreasing processing time of a job.
This paper assumes a position-dependent learning effect for unloading and loading items. Equation (1) presents how this kind of learning effect is calculated in some scheduling problems, derived from the idea introduced by Biskup (1999). We consider a simple scheduling problem, with a machine and \( n \) jobs, to explain Equation (1). Suppose that \( P_{kl} \) is the processing time of job \( k \) in position \( l \), which clearly is dependent on the position, where job \( k \) is assigned. Here, \( \alpha \) is a number between the range \([-1, 0]\), which causes the conversion of a positive integer number to a positive number between 0 and 1. Obviously, a smaller amount of \( \alpha \) in the mentioned range results in having a smaller quantity in comparison to choose an \( \alpha \) closer to 0.

\[
P_{l[k]} = P_l \times k^2; \quad -1 < \alpha < 0
\]  

3.2. Model development

There is a cross-docking center with one exclusive receiving door for inbound trucks and one exclusive shipping door for outbound trucks. A temporary storage exists next to the shipping door. The capacity of this storage place is assumed to be infinity. Each inbound truck arrives at the center in a specific time called arrival time. Also, unloading and loading times of each item’s unit differ from one type to another. As mentioned before, there are some functions within cross-docking centers. Here, we assume that all functions are completed in a specific time which is not dependent on items’ type. In an overview, some assumptions are considered as follows.

1. All trucks are ready at their arrival times.
2. There is a receiving and a shipping door.
3. Inbound (outbound) trucks should be unloaded (loaded) completely to leave the receiving (shipping) door.
4. There is a temporary storage in front of the shipping door.
5. Pre-emption is not allowed.
6. There is no limitation for capacity of temporary storage.
7. Sequence of the unloading (loading) items form (to) inbound (outbound) trucks is determined.
8. Operational time within the cross-docking center and truck changeover times are assumed constant and same for all items.
9. Breakdown of trucks is not considered.
10. The following information is assumed to be known.
   (a) Number of items from each type for inbound and outbound trucks.
   (b) Unloading and loading times for items.
   (c) Truck changeover time.
   (d) Operation time within the cross-docking center.

Yu and Egbelu (2008) presented a mathematical model for truck scheduling at cross-docking systems to minimize the makespan. This paper develops a mathematical model based on their introduced model. In the new model, unloading and loading process times and the effect of learning on them are considered. To design the model, it is needed to define some notations.
3.2.1. **Parameters**

- $R$ Number of inbound trucks
- $S$ Number of outbound trucks
- $N$ Number of items’ types
- $r_{ik}$ Number of units item type $k$ in inbound truck $i$
- $s_{jk}$ Number of units item type $k$ in outbound truck $j$
- $t_k$ Unloading time of item type $k$
- $t_k'$ Loading time of item type $k$
- $\alpha$ Rate of learning
- $A_i'$ Arrival time of inbound truck $i$
- $D$ Truck changeover time
- $V$ Operational time within cross-docking center
- $M$ A significant big number

3.2.2. **Variables**

- $c_i$ Entering time of inbound truck $i$ at receiving door
- $F_i$ Leaving time of inbound truck $i$ at receiving door
- $d_j$ Entering time of outbound truck $j$ at receiving door
- $L_j$ Leaving time of outbound truck $j$ at receiving door
- $X_{ijk}$ Number of items type $k$ transferred from inbound truck $i$ to outbound truck $j$
- $\nu_{ij}$ A binary variable which equals 1, if any transformation from inbound truck $i$ to outbound truck $j$ is existed
- $p_{ij}$ A binary variable that is 1, if inbound truck $i$ precedes inbound truck $j$
- $q_{ij}$ A binary variable that is 1, if outbound truck $i$ precedes outbound truck $j$

Based on the defined notations, the mathematical model is built below.

3.2.3. **Mathematical model**

\[
\min \sum_j L_j/S \quad (2)
\]

s.t.

\[
\sum_i X_{ijk} = r_{ik}; \quad \forall i, k \quad (3)
\]

\[
\sum_i X_{ijk} = s_{jk}; \quad \forall j, k \quad (4)
\]

\[
X_{ijk} \leq M\nu_{ij}; \quad \forall i, j, k \quad (5)
\]

\[
F_i \geq c_i + \sum_k t_k' r_{ik} \left( 1 + \sum_j \{1 - p_{ij}\} \right)^z; \quad \forall i \quad (6)
\]

\[
c_j \geq A_i - M(1 - p_{ij}); \quad \forall i, j \quad \text{and} \quad i \neq j \quad (7)
\]
\[
c_i \geq A_i; \quad \forall i
\]  
\[
c_j \geq F_i + D - M(1 - p_{ij}); \quad \forall i, j \quad \text{and} \quad i \neq j
\]  
\[
c_i \geq F_j + D - Mp_{ij}; \quad \forall i, j \quad \text{and} \quad i \neq j
\]  
\[
p_{ij} = 0; \quad \forall i
\]  
\[
L_j \geq d_j + \sum_k t_k^0 s_{jk} \left(1 + \sum_i \{1 - q_{ij}\}\right); \quad \forall j
\]  
\[
d_j \geq L_i + D - M(1 - q_{ij}); \quad \forall i, j \quad \text{and} \quad i \neq j
\]  
\[
d_i \geq L_j + D - Mq_{ij}; \quad \forall i, j \quad \text{and} \quad i \neq j
\]  
\[
q_{ij} = 0; \quad \forall j
\]  
\[
L_j \geq c_i + V + \sum_k X_{ijk} \left(t_k^0 \left(1 + \sum_l \{1 - q_{ij}\}\right)^x + t_k^1 \left(1 + \sum_l \{1 - p_{il}\}\right)^x\right) - M(1 - v_{ij}); \quad \forall i, j
\]  

All variables are non-negative.

Objective function (2) aims at minimizing the mean completion time of each outbound truck. Here, \(L_j\) is the completion time of outbound truck \(j\) and \(S\) is number of outbound trucks. Constraints (3) and (4) illustrate the balance approach, i.e. demonstrating that the total number of items received by inbound trucks is equal to the total number of the sent items by outbound trucks. Constraint (5) guarantees not to transfer any items between an inbound truck and an outbound truck that do not have any relationship. This assurance is obtained by giving a big coefficient to \(v_{ij}\), which is a binary variable used to show the relationship between inbound truck \(i\) and outbound truck \(j\). Constraints (6)–(16) calculate the completion times of trucks. Here, \(M\) is assumed as a large number employed to relax one of Constraints, (9) and (10), and also one of Constraints, (13) and (14). Arrival times affect the model through Constraints (7) and (8). Constraint (7) guarantees that each inbound truck has to work after the arrival time of all its predecessors. In fact, if \(p_{ij} = 1\) this constraint plays a role in the model, else it is be relaxed. Then, Constraint (8) states that the start time of inbound trucks is not smaller than their arrival times. Moreover, Constraints (11) and (15) are put to declare that there is no transportation from each truck to itself. Finally, Constraint (16) presents that leaving time of an outbound truck has to be equal or more than the leaving time of all inbound trucks, which transfer items to that outbound truck in addition to operational time within the center and unloading and loading times (i.e. for all \(i\) by which \(v_{ij} = 1\) for outbound truck \(j\)).

As a matter of fact, the sequence-dependent effect of the learning is apparent in Constraints (6) and (12). In fact, \(\sum_k t_k^0 r_{ik}\) is the total unloading times for inbound truck \(i\), and similarly, \(\sum_k t_k^0 s_{jk}\) represents the total loading time for outbound truck \(j\). On the
other hand, \( \sum_j \{1 - q_j\} \) and \( \sum_j \{1 - q_j\} \) denote the total number of inbound and outbound trucks assigned before inbound truck \( i \) and outbound truck \( j \), respectively. Thus, the priority of all trucks in respective sequence can be determined by adding amount 1 to the aforementioned expressions; it is done on account of considering inbound truck \( i \) and outbound truck \( j \) in the sequence. Then, the learning effect is calculated by the procedure explained in Equation (1). Figure 2 illustrates how the paper, on hand, determines the place of trucks in the sequence through an example of five trucks.

As a matter of fact, the mathematical model differs from the model presented by Yu and Egbelu (2008) in some aspects. Constraints (7) and (8) are added to the model to consider arrival times of inbound trucks. Moreover, Constraints (6), (12), and (16) are modified in comparison with the based model. This modification is taken into account to measure the learning effect. Other constraints are similar to those developed in based models.

4. Solution approaches

In order to obtain the exact solutions, a complete enumeration approach is employed for small- and medium-sized problems. In fact, due to the \( R \) inbound and \( S \) outbound trucks, there are \((R!)(S!)\) possible solutions in total. Obviously, the computational time increases significantly by an increase in a number of trucks. This paper proposes a heuristic approach, and also a simulated annealing (SA) algorithm to obtain optimal or near-optimal solutions in large-sized problems in an acceptable time. First, four heuristics are designed by the concept of the processing time for trucks. Then, the proposed SA algorithm is developed with regard to the characteristics of the problem.

4.1. Processing times-dependent methods

Sequencing jobs based on their processing times, as heuristic methods, are frequently used in machine scheduling problems. Therefore, the processing time of trucks is taken into account to introduce novel heuristic methods for inbound and outbound truck scheduling. First of all, it is necessary to define the concept of the processing time of a truck as given below, in which \( P^I_i \) and \( P^O_j \) are the processing times of inbound truck \( i \) and outbound truck \( j \), respectively (both of them are proposed in Equations (17) and (18)).

\[
P^I_i = \sum_k t^I_k r^I_{ik} + D; \quad \forall i
\]
Due to the discussed concept of a truck processing time, the two following approaches can be employed for inbound and outbound trucks separately, which means 4 (i.e. $2 \times 2$):

- Truck with a shorter processing time (SPT) is assigned earlier.
- Truck with a longer processing time (LPT) is assigned earlier.

### 4.2. Simulated annealing

Simulated annealing (SA) is a meta-heuristic method, which locates an acceptable sub-optimal solution for a NP-complete problem or large search space. This method produces better results when the feasible area is discrete, for instance the scheduling problem; however, SA does not guarantee the best global solution. The origin of the name ‘simulated annealing’ comes from a process in Metallurgy. In an annealing technique, materials are heated in order to melt the substance and then cooled slowly to the vicinity of a freezing point. So that, they crystallize with less defects and bigger crystal shapes. The method was introduced by Kirkpatrick, Gellat, and Vecchi (1983) based on the work presented by Metropolis, Rosenbluth, Rosenbluth, Teller, and Teller (1953).

The SA algorithm begins with the point $s$ in a feasible area and moves step by step close to the optimal solution. Each step calculates the current objective function value (OFV) and then moves to a new neighborhood solution. If the new solution is better than the current solution, then the algorithm chooses the new solution as an optimal solution; otherwise, the current solution with the acceptance probability of $\exp(-\Delta E/T)$ will be chosen. Here, $\Delta E$ is the difference between the current OFV and neighborhood solution. Also, $T$ is the global parameter of temperature.

In the primary steps of SA, the temperature is too high. Therefore, more undesired solutions may be produced and accepted. This high temperature guarantees that the algorithm does not trap in local optima. When the temperature gradually decreases, there is less chance to accept worse solutions and as a result, a good feasible solution would be obtained in the final steps or in a low temperature when the temperature reaches a steady state or thermal equilibrium.

In this problem, as it is obvious in Figure 3, we design a row to define any solution. Moreover, Equations (20)–(22) describe the assumed features of the developed meta-heuristic method. Note that $\delta$ is the SA parameter that is typically lower than 1.

$$T_0 = 10 \times \text{OFV}_0$$  \quad (19)

$$T_F = T_0 \times 10^{-\delta}$$  \quad (20)

![Figure 3. Considered row to define each solution.](image-url)
\[
\text{Max } It = \left\lfloor \frac{\log(T_F/T_0)}{\log(\delta)} \right\rfloor
\]  

(21)

Here, SA includes Max \textit{It} external iterations and Max \textit{Itln} internal iterations per external iteration. It means that there are Max \textit{It} \times Max \textit{Itln} iterations. In fact, a random solution is generated as the initial point with objective value OFV\textsubscript{0}. Then, the first external iteration with Max \textit{Itln} internal searches begins. Remember that a solution replacement procedure of internal searches is as same as that mentioned above. It means that a better solution is chosen and a worse solution is selected with the presented probability.

5. Numerical experiments

To clarify the effectiveness of the proposed methods, 20 numerical examples of Yu (Yu, 2002) are considered. Basic information of these problems is indicated in Table 1. In addition, unloading and loading times are distributed uniformly in the range [1 100], and likewise, inbound truck arrival times are generated in the range [1 500]. Transportation time between receiving and shipping doors is assumed 100 and truck changeover time is 75. Furthermore, the learning rate is considered to be –.1, –.5, and –.9, separately, to see the proficiencies in different rates of learning. Problems are solved by coding all specified algorithms (i.e. enumeration, heuristics, and SA) on the MATLAB software on a desktop Core 2 Duo PC, 2.67 GHz with 4 MB RAM. Table 2 reports the best, mean, and worst solutions of each problem. An average computational time is given for each problem, as shown in Table 2.

As it was expected, objective values decrease by increase in the learning rates. Also, optimum sequences are affected by the learning rates in some problems. For instance,

| No. of problem | No. of inbound trucks | No. of outbound trucks | No. of types | No. of products |
|----------------|-----------------------|------------------------|--------------|----------------|
| 1              | 4                     | 5                      | 4            | 990            |
| 2              | 5                     | 4                      | 6            | 1030           |
| 3              | 3                     | 3                      | 8            | 890            |
| 4              | 5                     | 5                      | 8            | 1000           |
| 5              | 5                     | 3                      | 8            | 960            |
| 6              | 4                     | 4                      | 5            | 1020           |
| 7              | 5                     | 4                      | 6            | 980            |
| 8              | 3                     | 5                      | 7            | 890            |
| 9              | 4                     | 4                      | 8            | 900            |
| 10             | 3                     | 4                      | 9            | 930            |
| 11             | 5                     | 4                      | 6            | 1620           |
| 12             | 6                     | 4                      | 6            | 1950           |
| 13             | 5                     | 6                      | 8            | 1610           |
| 14             | 5                     | 5                      | 8            | 1680           |
| 15             | 6                     | 5                      | 4            | 2030           |
| 16             | 5                     | 6                      | 6            | 1690           |
| 17             | 4                     | 4                      | 7            | 1180           |
| 18             | 6                     | 6                      | 7            | 1770           |
| 19             | 5                     | 5                      | 10           | 1720           |
| 20             | 6                     | 6                      | 9            | 2020           |
Table 2. Results from the complete enumeration method.

|      |   $\alpha = -0.1$ |      |   $\alpha = -0.5$ |      |   $\alpha = -0.9$ |      | Time (s) |
|------|-------------------|------|-------------------|------|-------------------|------|----------|
|      | Best  | Mean  | Worst | Best  | Mean  | Worst | Best  | Mean  | Worst | Best  | Mean  | Worst |        |        |
| 1    | 64094.65 | 93875.12 | 122053.9 | 59443.2 | 89088.52 | 114872.5 | 56635.94 | 85941.2 | 109757.2 | .299 |
| 2    | 228712.5 | 334447.3 | 411,738 | 204477.9 | 305236.5 | 400773.7 | 190919.8 | 286384.4 | 393034.6 | .347 |
| 3    | 139310.8 | 166774.7 | 184993.3 | 135477.7 | 160723.2 | 177366.8 | 132807.3 | 156435.3 | 171,773 | .004 |
| 4    | 240018.9 | 387966.8 | 503321.3 | 218478.7 | 363324.8 | 487909.8 | 206457.3 | 347466.1 | 476355.4 | 1.899 |
| 5    | 153283.2 | 249212.9 | 311,512 | 131,658 | 226329.8 | 281021.1 | 119092.6 | 211503.3 | 264813.2 | .081 |
| 6    | 202961.7 | 279382.8 | 33235.6 | 191,313.5 | 261082.6 | 310,657 | 184063.7 | 248799.7 | 295621.7 | .06  |
| 7    | 99845.83 | 190859.4 | 325765.3 | 96767.07 | 183523.7 | 315230.6 | 95095.42 | 178791.2 | 307432.3 | .334 |
| 8    | 269084.3 | 287683.6 | 313210.6 | 268175.6 | 283257.1 | 305,624 | 267576.8 | 280,188 | 300257.1 | .087 |
| 9    | 118245.5 | 171965.8 | 260650.4 | 117502.2 | 170957.9 | 259436.7 | 117053.7 | 170304.6 | 258632.1 | .064 |
| 10   | 101877.5 | 159279.8 | 235014.4 | 95686.8 | 152364.1 | 227041 | 91501.22 | 147515.8 | 221,343 | .016 |
| 11   | 258,246 | 418957.4 | 611805.6 | 250477.4 | 399392.3 | 583,029 | 240091.9 | 386774.5 | 563314.2 | .345 |
| 12   | 435288.7 | 570022.3 | 692366.1 | 408268.9 | 538351.1 | 648746.4 | 389082.1 | 51860.73 | 620313.6 | 2.186 |
| 13   | 180113.1 | 313323.4 | 48809.2 | 176664.6 | 326538.1 | 481,526.8 | 174783.2 | 323567.3 | 477066.5 | 11.419 |
| 14   | 147438.1 | 316341.7 | 437434.2 | 123161.3 | 284056.1 | 395888.2 | 109,458 | 263,259 | 365868.6 | 1.901 |
| 15   | 181459.6 | 308836.2 | 508057.7 | 172,108 | 295646.7 | 490000.3 | 167071.3 | 287474.3 | 478442.7 | 10.539 |
| 16   | 201,795 | 282948.6 | 331657.7 | 197751.7 | 273452.7 | 316990.6 | 195598.4 | 267401.3 | 306914.3 | 11.631 |
| 17   | 136144.5 | 150296.4 | 166001.3 | 134390.1 | 148079.7 | 164332.2 | 133289.6 | 147680.4 | 163214.2 | .059 |
| 18   | 277339.2 | 400772.3 | 645536.8 | 266089.8 | 383763.4 | 620998.1 | 260,330 | 373302.6 | 603477.8 | 72.628 |
| 19   | 353896.7 | 560,286 | 1,117,138 | 349650.8 | 549101.2 | 1,100,811 | 347326.4 | 541945.5 | 1,089,588 | 2.051 |
| 20   | 138,382 | 440718.3 | 685529.7 | 96516.17 | 389204.8 | 647583.7 | 74725.09 | 357293.2 | 619873.4 | 77.444 |
the optimum sequence of trucks in problem 1 is (R: 4-2-3-1, S: 5-1-4-2-3) for \( \alpha = -0.1 \), (R: 4-2-3-1, S: 5-2-1-4-3) for \( \alpha = -0.5 \), and (R: 4-2-3-1, S: 5-4-3-2-1) for \( \alpha = -0.9 \). However, some problems are not influenced by different learning rates to find optimum sequences.

Table 3. Results of the heuristics where \( \alpha = -0.1 \).

|   | SSPT    | SLPT    | LSPT    | LLPT    |
|---|---------|---------|---------|---------|
| 1 | 72533.32| 73113.71| 120864.9| 120012.6|
| 2 | 237703.3| 239712.8| 400543.1| 401254.4|
| 3 | 141694.9| 142056.3| 176712.6| 176793.6|
| 4 | 241232.3| 240624.3| 502253.8| 503218.2|
| 5 | 154982.3| 153283.2| 290298.2| 292480.9|
| 6 | 210723.1| 209869.3| 317568.5| 314083.5|
| 7 | 118680.4| 119238.8| 303877.2| 305259.6|
| 8 | 269084.3| 269241.7| 300583.9| 300145.5|
| 9 | 119,602  | 119262.7| 260242.8| 259563.8|
|10 | 109187.1 | 108580.1| 234883.7| 234,955  |
|11 | 326513.1 | 325798.4| 582936.4| 583028.1|
|12 | 492129.5 | 493226.1| 672503.2| 672925.4|
|13 | 185260.6 | 184772.3| 485,080 | 485439.1|
|14 | 148739.7 | 147,561 | 359,581  | 359012.7|
|15 | 205083.1 | 202307.2| 490898.4| 490,301  |
|16 | 210690.5 | 209039.1| 318394.1| 319,814  |
|17 | 136663.5 | 136518.9| 165421.6| 164,987  |
|18 | 296042.8 | 295,768 | 643516.1| 643516.1|
|19 | 378471.3 | 376588.8| 1,087,491| 1,086,978|
|20 | 188916.8 | 187,606 | 631291.7| 631786.2|

Table 4. Results of the heuristics where \( \alpha = -0.5 \).

|   | SSPT    | SLPT    | LSPT    | LLPT    |
|---|---------|---------|---------|---------|
| 1 | 65791.1 | 66760.16| 113756.2| 113587.1|
| 2 | 213396.6| 215170.4| 391090.7| 392042.5|
| 3 | 137,573 | 138182.6| 169958.1| 170287.3|
| 4 | 219049.8| 219081.5| 486668.8| 487773.8|
| 5 | 132775.7| 131,658 | 274399.8| 276392.8|
| 6 | 196025.7| 196,365 | 298707.3| 297507.8|
| 7 | 112336.1| 112,794 | 295813.6| 298026.3|
| 8 | 268175.6| 268,813 | 294612.1| 294613.8|
| 9 | 118518.7| 118,764 | 258641.5| 258485.4|
|10 | 101586.8| 101402.1| 226547.9| 226844.1|
|11 | 296521.3| 297373.2| 554919.2| 557052   |
|12 | 448836.4| 44960.3 | 630,631  | 631,419  |
|13 | 179837.4| 180073.6| 477926.8| 480001.4|
|14 | 123913.1| 123296.2| 345108.2| 344,877  |
|15 | 190542.2| 188995.4| 475,257  | 476,564  |
|16 | 203453.4| 202464.7| 307597.8| 308918.5|
|17 | 134853.8| 135280.3| 163192.4| 163,531  |
|18 | 277214.7| 277284.1| 618504.3| 619946.4|
|19 | 369328.5| 368717.3| 1,074,644| 1,076,285|
|20 | 134328.8| 133692.2| 593568.3| 594586.3|
5.1. Heuristic solutions

As mentioned before, four heuristics are developed to solve the given problems. To simplify, we name the processing times as follows.

1. Shortest inbound trucks processing times – Shortest outbound trucks processing times: SSPT
2. Shortest inbound trucks processing times – Longest outbound trucks processing times: SLPT
3. Longest inbound trucks processing times – Shortest outbound trucks processing times: LSPT
4. Longest inbound trucks processing times – Longest outbound trucks processing times: LLPT

Table 5. Results of the heuristics where $\alpha = -0.9$.

|    | SSPT    | SLPT    | LSPT    | LLPT    |
|----|---------|---------|---------|---------|
| 1  | 61424.4 | 62465.28| 108703.7| 108,903 |
| 2  | 198968.7| 200592.8| 384940.2| 386049.4|
| 3  | 134646.1| 135415.6| 165360.9| 165850.1|
| 4  | 206,757 | 207150.2| 475,057 | 476227.7|
| 5  | 119961.9| 119227.7| 262948.2| 264813.2|
| 6  | 186795.8| 187823.8| 285841.4| 286063.4|
| 7  | 107551.7| 107961.5| 291206.4| 293,883 |
| 8  | 267576.8| 268523.1| 290803.1| 291051.8|
| 9  | 117827.4| 118426.9| 257,577 | 257749.5|
| 10 | 96180.23| 96242.32| 220658.4| 221106.7|
| 11 | 275835.8| 278,500 | 537706.2| 541001.6|
| 12 | 420793.1| 421969.5| 604770.7| 605703.1|
| 13 | 176,737 | 177325.1| 473,105 | 476042.8|
| 14 | 109997.4| 109,707 | 335336.3| 335328.2|
| 15 | 181052.9| 180228.9| 465938.9| 468356.6|
| 16 | 199252.4| 198691.7| 300210.8| 301436.6|
| 17 | 133670.8| 134423.5| 161715.7| 162537.6|
| 18 | 266995.5| 267254.4| 600977.7| 602882.9|
| 19 | 362778.3| 362914.6| 1,067,293| 1,070,022|
| 20 | 101892.2| 101,558 | 571408.5 | 572715.6|

5.2. SA solutions

Considering the three parameters of SA (i.e. $\text{Max\ ItIn}$, $\delta$, and $\theta$) that should be tuned, a Taguchi design is employed. Three levels are determined for each parameter. Table 6 presents the selected levels. Considering L27 design, 27 trials are prepared. Each trail is run for five times to find the OFV and computational time. Then, the final response is calculated based on Equation (22) where $\text{OFV}_{e,r}$ and $\text{Time}_{e,r}$ denote the OFV and computational time of examination $e$ in run $r$, respectively. Also, $\text{OFV}_{e}^\text{min}$ and $\text{Time}_{e}^\text{min}$
represent the minimum amounts among OFVs and computational times in run \( r \), respectively.

\[
\text{Response}_{e,r} = \frac{1}{2} \left( \frac{\text{OFV}_{e,r} - \text{OFV}^{\text{min}}_{r}}{\text{OFV}^{\text{min}}_{r}} + \frac{\text{Time}_{e,r} - \text{Time}^{\text{min}}_{r}}{\text{Time}^{\text{min}}_{r}} \right)
\]  

(22)

Problem 20 is selected to be examined by the designed experiments with the learning rate of .5. Due to Equation (23), signal to noise (S/N) ratio is derived. Here, \( y_a \) is the response value in replication \( a \) and \( n \) is the number of replications. Levels with smaller S/N ratios are preferred. So, optimum levels of parameters are found as their first level, as shown in Figure 4.

\[
S/N = -10 \log \frac{\sum_{a=1}^{n} Y_a^2}{n}
\]

(23)

Table 7 represents the mean of obtained results of SA among five independent runs. Besides, the standard deviation of five different results could be observed by Table 7. It can be interpreted that SA is able to find acceptable solutions.
5.3. Methods evaluation

Some numerical examples are solved by a complete enumeration method, four heuristics and the proposed SA. Tables 8–10 summarize Gap and Interval Gap of the proposed SA and heuristics based on Equations (24) and (25). Here, Interval Gap helps to evaluate the performance of a method in an interval, in which it can find a solution.

\[
\text{Gap} = \frac{\text{Best heuristic result} - \text{Best exact result}}{\text{Best exact result}} \times 100 \tag{24}
\]

\[
\text{Interval Gap} = \frac{\text{Best heuristic result} - \text{Best exact result}}{\text{Best exact result} - \text{Worst exact result}} \times 100 \tag{25}
\]

Additionally, Tables 8–10 illustrate that the LSPT and LLPT cannot find results as well as two other heuristics and SA. It means that the long-processing time first rule for inbound trucks is not an apt choice when it is needed to find minimum mean completion times for outbound trucks. So, the LSPT and LLPT are deleted, and three other methods are evaluated by three Paired-T examinations. In fact, the examinations identify if a method is performed as same as another one. Table 11 reports the \( p \)-value of all three examinations. Since the confidence level is .95, the SSPT and SLPT are found same for all the learning rates. Also, SA is not as same as SSPT and SLPT, and it can perform better than heuristics subject to the results presented by Tables 8–10. As a result, it could be concluded that SA outperforms other heuristics subject to final results.

| \( \alpha = -.1 \) | \( \alpha = -.5 \) | \( \alpha = -.9 \) |
|----------------|----------------|----------------|
| \( M \) | \( SD \) | \( M \) | \( SD \) | \( M \) | \( SD \) |
| 1 | 64119.123 | 44.215 | 59480.550 | 49.744 | 56743.886 | 127.257 |
| 2 | 228712.518 | 0 | 204477.855 | 0 | 190919.817 | 0 |
| 3 | 139310.824 | 0 | 135776.669 | 0 | 132807.299 | 0 |
| 4 | 240022.830 | 5.443 | 218538.288 | 58.744 | 206548.815 | 87.406 |
| 5 | 153905.950 | 348.135 | 131748.525 | 123.904 | 119119.612 | 60.422 |
| 6 | 203893.136 | 1275.435 | 191313.536 | 0 | 184064.558 | 2.015 |
| 7 | 99898.215 | 47.822 | 96900.293 | 30.806 | 95190.380 | 104.821 |
| 8 | 269085.613 | 2.767 | 268175.904 | 0.364 | 267577.106 | 0.361 |
| 9 | 118245.502 | 0 | 117502.195 | 0 | 117053.705 | 0 |
| 10 | 101883.278 | 8.059 | 95686.799 | 0 | 91501.221 | 0 |
| 11 | 258328.497 | 184.535 | 250720.862 | 111.011 | 241318.625 | 2519.002 |
| 12 | 437850.554 | 3508.246 | 408296.426 | 37.709 | 389215.862 | 214.548 |
| 13 | 180160.935 | 64.908 | 176763.747 | 81.383 | 174889.722 | 111.466 |
| 14 | 147483.422 | 78.893 | 132220.909 | 26.469 | 109560.945 | 15.869 |
| 15 | 181492.101 | 22.453 | 172320.254 | 159.767 | 167095.071 | 53.209 |
| 16 | 201848.980 | 49.388 | 197840.527 | 129.442 | 195611.656 | 29.577 |
| 17 | 136151.038 | 6.0105 | 134424.869 | 77.666 | 133289.629 | 0 |
| 18 | 277501.444 | 90.034 | 266220.269 | 85.829 | 260393.529 | 39.606 |
| 19 | 353903.688 | 10.149 | 349687.723 | 24.153 | 347331.902 | 12.396 |
| 20 | 138495.042 | 147.832 | 96803.862 | 104.094 | 74813.995 | 63.208 |
Table 8. Error percentages of heuristics and SA where $\alpha = -0.1$.

|     | SSPT |     | SLPT |     | LSPT |     | LLPT |     | SA   |     |
|-----|------|-----|------|-----|------|-----|------|-----|------|-----|
|     | Gap  | Interval Gap | Gap  | Interval Gap | Gap  | Interval Gap | Gap  | Interval Gap | Gap  | Interval Gap |
| 1   | 13.17 | 14.56 | 14.38 | 15.91 | 88.57 | 97.95 | 87.24 | 96.48 | 0    | 0    |
| 2   | 3.93  | 4.91  | 4.81  | 6.01  | 75.13 | 93.88 | 75.44 | 94.27 | 0    | 0    |
| 3   | 1.71  | 5.22  | 1.97  | 6.01  | 26.85 | 81.87 | 26.91 | 82.05 | 0    | 0    |
| 4   | 0.51  | 0.46  | 0.25  | 0.23  | 109.26 | 99.59 | 109.66 | 99.96 | 0    | 0    |
| 5   | 1.11  | 1.07  | 0     | 0     | 89.39 | 86.59 | 90.81 | 87.97 | 0    | 0    |
| 6   | 3.82  | 6     | 3.4   | 5.34  | 56.47 | 88.65 | 54.75 | 85.96 | 0    | 0    |
| 7   | 18.86 | 8.34  | 19.42 | 8.58  | 204.35 | 90.31 | 205.73 | 90.92 | 0    | 0    |
| 8   | 0     | 0     | .06   | .36   | 11.71 | 71.39 | 11.54 | 70.39 | 0    | 0    |
| 9   | 1.15  | .95   | .86   | .71   | 120.09 | 99.71 | 119.51 | 99.24 | 0    | 0    |
| 10  | 7.17  | 5.49  | 6.58  | 5.03  | 130.56 | 99.9  | 130.62 | 99.96 | 0    | 0    |
| 11  | 26.43 | 19.31 | 26.16 | 19.11 | 125.73 | 91.83 | 125.76 | 91.84 | 0    | 0    |
| 12  | 13.06 | 22.11 | 13.31 | 22.54 | 54.5  | 92.27 | 54.59 | 92.44 | 0    | 0    |
| 13  | 2.86  | 1.67  | 2.59  | 1.51  | 169.32 | 99.05 | 169.52 | 99.17 | 0    | 0    |
| 14  | .88   | .45   | .08   | .04   | 143.89 | 73.15 | 143.5 | 72.96 | 0    | 0    |
| 15  | 13.02 | 7.23  | 11.49 | 6.38  | 170.53 | 94.75 | 170.2 | 94.56 | 0    | 0    |
| 16  | 4.41  | 6.85  | 3.59  | 5.58  | 57.78 | 89.79 | 58.48 | 90.88 | 0    | 0    |
| 17  | .38   | 1.74  | .28   | 1.25  | 21.5  | 98.03 | 21.19 | 96.6  | 0    | 0    |
| 18  | 6.74  | 5.08  | 6.64  | 5.01  | 131.86 | 99.32 | 132.03 | 99.44 | .01  | .01  |
| 19  | 6.94  | 3.22  | 6.41  | 2.97  | 207.29 | 96.12 | 207.15 | 96.05 | 0    | 0    |
| 20  | 36.52 | 9.24  | 35.57 | 9     | 356.19 | 90.09 | 356.55 | 90.18 | .01  | 0    |
Table 9. Error percentages of heuristics and SA where $\alpha = -.5$.

|   | SSPT | SLPT | LSPT | LLPT | SA |
|---|------|------|------|------|----|
|   | Gap  | Interval Gap | Gap  | Interval Gap | Gap  | Interval Gap | Gap  | Interval Gap | Gap  | Interval Gap |
| 1 | 10.68 | 11.45 | 12.31 | 13.2 | 91.37 | 97.99 | 91.09 | 97.68 | 0 | 0 |
| 2 | 4.36 | 4.54 | 5.23 | 5.45 | 91.26 | 95.07 | 91.73 | 95.55 | 0 | 0 |
| 3 | 1.55 | 5 | 2 | 6.46 | 25.45 | 82.31 | 25.69 | 83.1 | 0 | 0 |
| 4 | .26 | .21 | .28 | .22 | 122.75 | 95.57 | 109.93 | 96.9 | 0 | 0 |
| 5 | .85 | .75 | 0 | 0 | 108.42 | 95.57 | 109.93 | 96.9 | 0 | 0 |
| 6 | 2.46 | 3.95 | 2.64 | 4.23 | 56.13 | 89.99 | 55.51 | 88.98 | 0 | 0 |
| 7 | 16.09 | 7.13 | 16.56 | 7.34 | 205.7 | 91.11 | 207.98 | 92.12 | .12 | .05 |
| 8 | 0 | 0 | .24 | 1.7 | 9.86 | 70.59 | 9.86 | 70.6 | 0 | 0 |
| 9 | .87 | .72 | 1.07 | .89 | 120.12 | 99.44 | 119.98 | 99.33 | 0 | 0 |
| 10 | 6.17 | 4.49 | 5.97 | 4.35 | 136.76 | 99.62 | 137.07 | 99.85 | 0 | 0 |
| 11 | 18.38 | 13.85 | 18.95 | 14.27 | 121.54 | 91.55 | 122.4 | 92.19 | .07 | .05 |
| 12 | 9.94 | 16.87 | 10.21 | 17.34 | 54.46 | 92.47 | 54.66 | 92.79 | 0 | 0 |
| 13 | 1.8 | 1.04 | 1.93 | 1.12 | 170.53 | 98.82 | 171.7 | 99.5 | 0 | 0 |
| 14 | .61 | .28 | .11 | .05 | 180.21 | 81.38 | 180.02 | 81.3 | .03 | .01 |
| 15 | 10.71 | 5.8 | 9.81 | 5.31 | 176.14 | 95.36 | 176.9 | 95.77 | 0 | 0 |
| 16 | 2.88 | 4.78 | 2.38 | 3.95 | 55.55 | 92.12 | 56.22 | 93.23 | 0 | 0 |
| 17 | .35 | 1.55 | .66 | 2.97 | 21.43 | 96.19 | 21.68 | 97.32 | 0 | 0 |
| 18 | 4.18 | 3.13 | 4.21 | 3.15 | 132.44 | 99.3 | 132.98 | 99.7 | .01 | .01 |
| 19 | 5.63 | 2.62 | 5.45 | 2.54 | 207.35 | 96.52 | 207.82 | 96.73 | 0 | 0 |
| 20 | 39.18 | 6.86 | 38.52 | 6.75 | 514.99 | 90.2 | 516.05 | 90.38 | .19 | .03 |
Table 10. Error percentages of heuristics and SA where $\alpha = -0.9$.

|    | SSPT Gap | Interval Gap | SLPT Gap | Interval Gap | LSPT Gap | Interval Gap | LLPT Gap | Interval Gap | SA Gap | Interval Gap |
|----|----------|--------------|----------|--------------|----------|--------------|----------|--------------|--------|--------------|
| 1  | 8.45     | 9.01         | 10.29    | 10.97        | 91.93    | 98.02        | 92.29    | 98.39        | 0      | 0            |
| 2  | 4.22     | 3.98         | 5.07     | 4.79         | 101.62   | 96           | 102.21   | 96.54        | 0      | 0            |
| 3  | 1.38     | 4.72         | 1.96     | 6.69         | 24.51    | 83.54        | 24.88    | 84.8         | 0      | 0            |
| 4  | 0.15     | 0.11         | 0.34     | 0.26         | 130.10   | 99.52        | 130.67   | 99.95        | 0      | 0            |
| 5  | 0.73     | 0.6          | 0.11     | 0.09         | 120.79   | 98.72        | 122.36   | 100          | 0      | 0            |
| 6  | 1.48     | 2.45         | 2.04     | 3.37         | 55.29    | 91.23        | 55.42    | 91.43        | 0      | 0            |
| 7  | 13.10    | 5.86         | 13.53    | 6.05         | 206.23   | 92.22        | 209.04   | 93.48        | 0      | 0            |
| 8  | 0        | 0            | 0.35     | 2.9          | 8.68     | 71.07        | 8.77     | 71.83        | 0      | 0            |
| 9  | 0.66     | 0.55         | 1.17     | 0.97         | 120.05   | 99.25        | 120.2    | 99.38        | 0      | 0            |
| 10 | 5.11     | 3.6          | 5.18     | 3.65         | 141.15   | 99.47        | 141.64   | 99.82        | 0      | 0            |
| 11 | 14.89    | 11.06        | 16       | 11.88        | 123.96   | 92.08        | 125.33   | 93.1         | 0      | 0            |
| 12 | 8.15     | 13.71        | 8.45     | 14.22        | 55.44    | 93.28        | 55.67    | 93.68        | 0      | 0            |
| 13 | 1.12     | 0.65         | 1.45     | 0.84         | 170.68   | 98.69        | 172.36   | 99.66        | 0      | 0            |
| 14 | 0.49     | 0.21         | 0.23     | 0.1          | 206.36   | 88.09        | 206.35   | 88.09        | .03    | .01          |
| 15 | 8.37     | 4.49         | 7.88     | 4.23         | 178.89   | 95.98        | 180.33   | 96.76        | 0      | 0            |
| 16 | 1.87     | 3.28         | 1.58     | 2.78         | 53.48    | 93.98        | 54.11    | 95.08        | 0      | 0            |
| 17 | 0.29     | 1.27         | 0.85     | 3.79         | 21.33    | 94.99        | 21.94    | 97.74        | 0      | 0            |
| 18 | 2.56     | 1.94         | 2.66     | 2.02         | 130.85   | 99.27        | 131.58   | 99.83        | .01    | .01          |
| 19 | 4.45     | 2.08         | 4.49     | 2.1          | 207.29   | 97           | 208.07   | 97.36        | 0      | 0            |
| 20 | 36.36    | 4.98         | 35.91    | 4.92         | 664.68   | 91.11        | 666.43   | 91.35        | 0      | 0            |
6. Conclusion

This paper has addressed a truck scheduling problem at cross-docking terminals in order to minimize the mean completion time of outbound trucks. Unloading/loading times for receiving and shipping items have affected by a phenomenon, called learning effect. In fact, this assumption could be imperative, because in many situations, unloading/loading processes have been accomplished by manpower. This paper has developed a mathematical model and proposed four heuristics (i.e. SSPT, SLPT, LSPT, and LLPT) based on the shortest and longest processing times of trucks. Furthermore, a simulated annealing (SA) algorithm has been employed to obtain high-quality solutions for the given problem in large-scale instances. The computational results of heuristics and SA for 20 test problems have been compared with the exact solutions obtained by a complete enumeration method. SA has been found as a capable method to obtain optimum or near-optimum solutions. Also, the LSPT and LLPT have not been appropriate for the considered objective function. As for future studies, it is advised to work on different types of learning effects, in which the learning rate is different depending on the position and time periods. Sometimes learning effect exists based on turn of a truck in the sequence and it could be considered to study. Additionally, implementing such assumptions in real cases, such as the effect of arrival times on sequencing, breakdown probability for trucks and several inbound and outbound doors, is proposed strongly.

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