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Optimal berth reservation problem under flexible time slot system

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ABSTRACT

Traditional method of setting a reservation frame for each truck, which is used in many distribution centers, does not consider the delay in the arrival time of the truck, and the waiting time tends to increase. To solve this problem, a method for setting the reservation time frame for multiple trucks was proposed. The behavior in each reservation frame was modeled as an M/M/k type queue, and the expected stay time in the system was derived. The optimal truck berth reservation frame was determined for each supplier, which was formulated as 0-1 integer programming with an objective function of minimizing the sum of expected stay times. In the numerical experiments, a data set based on a survey conducted by the authors was created and its effectiveness was verified in the real world. The effects of the transportation unit and the number of berths were also considered.

Keywords: berth reservation problem; queueing system; optimization; stochastic system; logistics

1. INTRODUCTION

Logistics plays an important role in supporting industrial competitiveness and the wealthy lives of people by connecting entities in a supply chain to manage the movement of goods and information effectively. In recent years, the number of freight movements has rapidly increased along with the growth of e-commerce and omni-channels. However, the substantial lack of workforce, due to the decreasing working-age population in many countries, makes it unclear whether the logistics system will continue to keep pace with future traffic demands. Therefore, increasing delivery efficiency is critical for sustainable logistics.

An important problem in increasing delivery efficiency is reducing the waiting time for unloading in warehouses. It is known that the waiting time is often long, for example, one or two hours, and reduces delivery efficiency. The optimization of berth allocation has been extensively studied in the field of container yards (Bierwirth and Meisel, 2015). This problem is called the berth allocation problem (BAP). The BAP is categorized as discrete or continuous BAP, depending on how the berth layout is organized. To consider the BAP in the context of the reservation system in truck unloading at a warehouse, the discrete layout modeling was focused in this study, because most of the truck sizes in our application were not significantly different.

Imai et al. (1997) first presented the discrete berth allocation problem (DBAP). Imai et al. (2001) presented a dynamic DBAP in which ships may arrive at the port during the planning horizon. Lalla-Ruiz and Voss (2016) proposed an integrated approach of metaheuristics and mathematical programming. Nishi et al. (2020) proposed an integrated approach for metaheuristics and dynamic programming. Agra and Oliveira (2018) presented a mixed-integer programming (MIP) approach for integrated berth allocation and quay crane assignment and scheduling problems. Kramer et al. (2019) proposed a time-indexed formulation and an arc-flow formulation. Schepler et al. (2019) considered the stochastic arrival time in DBAP and proposed a framework combining the proactive and reactive phases. Wawrzyniak et al. (2020) proposed a method for selecting algorithms for large BAPs.

Another study focused on truck scheduling at cross-docking terminals. Recently, this has received considerable attention. Recent papers by Ladier and Alpan (2016a) and Theophilus et al. (2019) showed that there has been a notable increase in attention on this topic. Theophilus et al. (2021) and Castellucci et al. (2021) proposed an optimization model to determine the truck scheduling, that is, the assignment of dock and time, to minimize makespan or cost, given the deterministic scheduled arrival time of each truck. The popular solution approach is metaheuristics such as ant-colony optimization (Luo and Ting, 2017; Zhang et al., 2018), evolutionary algorithms (Behnamian et al., 2018; Dulebenets, 2018; Zhang et al., 2018), harmony search (Wang et al., 2018), variable neighborhood search (Dulebenets, 2019), and memetic algorithms (Dulebenets, 2021).

A few studies have considered the uncertainty of the arrival time. Konur and Golias (2013) studied the truck scheduling problem to minimize the total service time under arrival time uncertainty. They proposed a solution algorithm based on a genetic algorithm. Ladier and Alpan (2016b) studied the robustness of truck scheduling under uncertain transfer times, unloading times, or truck arrival times. They proposed a problem to minimize the expected realized cost and worst-case performance based on a robust optimization technique. Heidari et al. (2018) studied a problem in which both the inbound and outbound trucks arrival is random. They proposed a multi-objective model to seek the optimal truck scheduling problem to minimize the average and range of total service costs. They applied two meta-heuristics, multi-objective differential evolution and non-dominated sorting genetic algorithm-II to derive a set of Pareto solutions. Xi et al. (2020) proposed a model called the conflicting robust optimization model, in which the conflict is defined by the overlapping time assigned to multiple trucks. They presented a model to minimize the total penalty cost, measured by the sum of the waiting and tardiness costs of all trucks and conflicts.

Previous research on a Japanese grocery chain, which the waiting time at the truck berth in a distribution center (DC), was analyzed (Japan Industrial Vehicle Association, 2018). This DC is a central depot from which items are delivered to 4022 stores through 18 regional transfer centers. The survey took three days to analyze 577 trucks. Figure 1 presents the waiting times of trucks at the DC. The average waiting time is 35 minutes, and some truck drivers wait for over three hours, which shows that the efficiency of the logistics work is greatly hindered.

A major cause of this long waiting time is that, as shown in Figure 2a, the trucks arrive at random, and the arrival time overlaps, so-called a random-arrival system. To avoid such overlapping arrival times, the reservation system for truck berthing has been drawing attention. In the reservation system, as shown in Figure 2b, each truck makes a reservation for the time slot in advance, which intends to leverage the workload and reduce the waiting time, so-called a dedicated reservation system.

The DC has introduced a dedicated reservation system, but not all trucks make use of reservations, and some trucks arrive without reservations. Table 1 compares the waiting times with and without reservations. Surprisingly, the average wait time remained unchanged at 35 minutes for both random arrival and dedicated reservations.

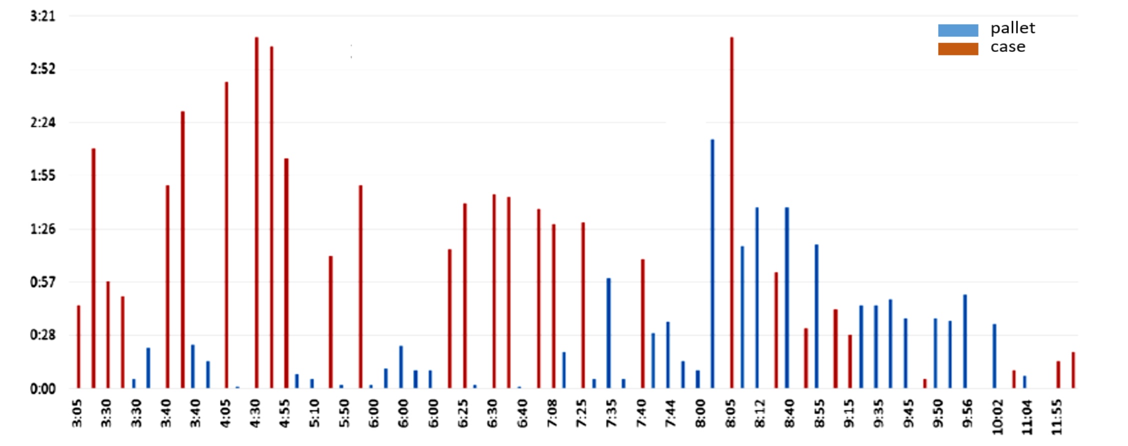

Figure 1. Waiting time of the trucks at a real-world distribution center (68 trucks)

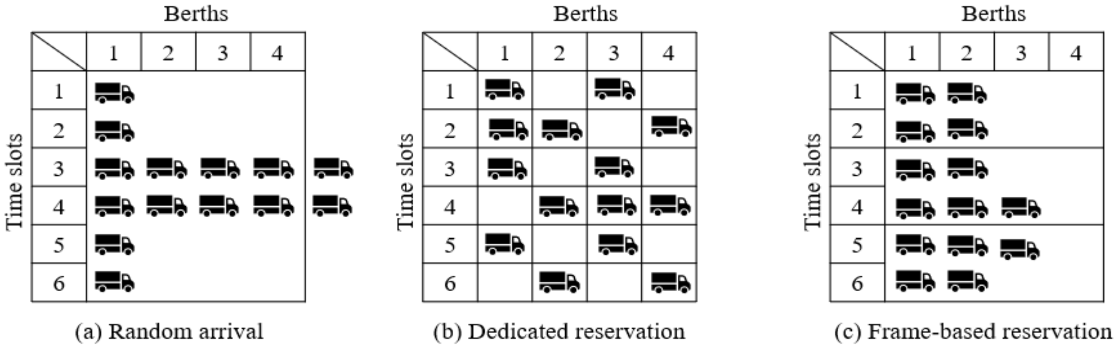

Figure 2. Comparison of reservation system

Table 1. Average waiting time of the trucks at a real-world distribution center (for 3 days)

System	Number of trucks	Percentage	Average waiting time
Without reservation (random arrival)	493	85.4%	35
With reservation (dedicated reservation)	84	14.6%	35
Total	577	100.0%	35

This is mainly due to the uncertainty of the arrival time. Figure 3 shows the difference between the reserved and arrival times. Positive values indicate late arrival and negative values indicate early arrival. While most trucks arrive shortly before reservation, some trucks deviate more than two hours from the reservation time. Therefore, even with the reservation system, the waiting time is not reduced.

To solve this problem, we proposed a new reservation system in which the reservation time frame was assigned to multiple trucks, as shown in Figure 2c. In this system, a time frame is assigned to each supplier, and each supplier can deliver any time within the assigned time frame. This system is called a frame-based reservation system. While the dedicated reservation system sets a strict arrival time for each track, the frame-based system is flexible in terms of arrival time. By doing so, it is possible to absorb the uncertainty of the arrival time. However, a new operational challenge of this system is the allocation of suppliers with different arrival rates to each reservation frame to minimize the waiting time of each reservation frame.

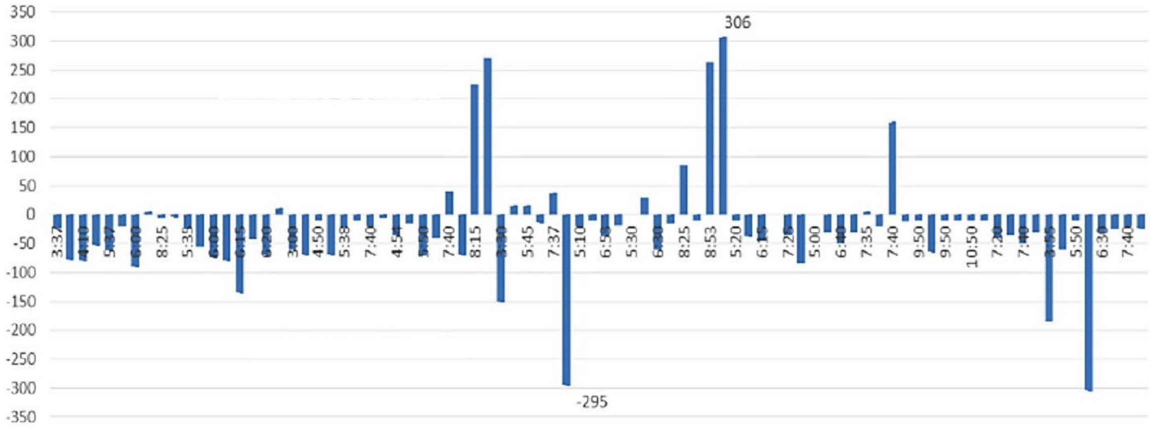

Figure 3. Difference between the reservation time and the arrival time

In this paper, the design problem was investigated to seek the optimal assignment of suppliers to the reservation frame based on the reservation system described above. The behavior in each reservation frame was modeled as an $M/M/k$ type queue, and the expected stay time in the system was derived. It was then formulated as 0-1 integer programming with an objective function of minimizing the sum of the expected stay times. In the numerical experiments, we created a data set based on a survey conducted by the authors and verified its effectiveness in the real world. We also considered the effects of the transportation unit and the number of berths.

The main contributions of this study were as follows: a new reservation system that allows to minimize the waiting time of trucks while maintaining higher berth utilization was proposed. A new version of the BAP in the context of a truck unloading reservation system in a warehouse was also proposed. In this context, the stochastic nature of the arrival time is very different from that of ship unloading, as considered in Schepler et al. (2019). In truck unloading, most trucks may arrive within a 10-20 minute difference from the initial schedule, whereas the ship arrives one or more days behind the initial schedule. This stochastic nature led to propose a different modeling approach based on the $M/M/k$ type queueing model. A nonlinear 0-1 integer programming formulation with an objective function that minimizes the sum of the expected stay times was presented. This problem can be reformulated to the mixed linear integer programming via linear relaxation and the method of Lagrange multipliers, and thus, can be solved very efficiently by off-the-shelf solvers. The proposed system was applied to a real-world company at the national distribution center of a supermarket chain.

2. MATERIALS AND METHODS

2.1 Problem model

In this section, we presented the modeling framework. A supply chain consisting of one DC and n suppliers is shown in Figure 4. A set of contracted suppliers was known in advance. The goods were delivered from supplier i to DC. Trucks were assumed to travel between each supplier and DC by a full truck load (FTL), and routing was not considered. The number of trucks from each supplier was random, depending on the daily demand.

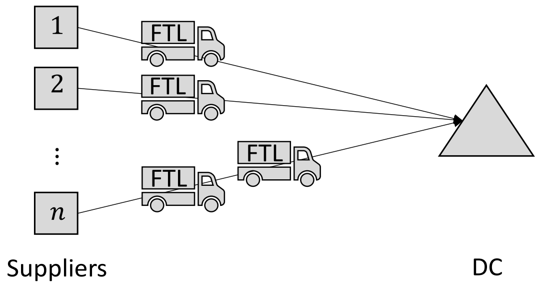

Figure 4. Illustration of supply chain

The operation of the warehouse is shown in Figure 5. First, the trucks from each supplier arrived. If the track berth in the receiving dock was full, a truck was placed in the waiting line. When a truck was assigned to a berth, the items in the truck were unloaded. The truck will leave as soon as the unloading is completed. This can be modeled as a typical $M/M/k$ type queuing model.

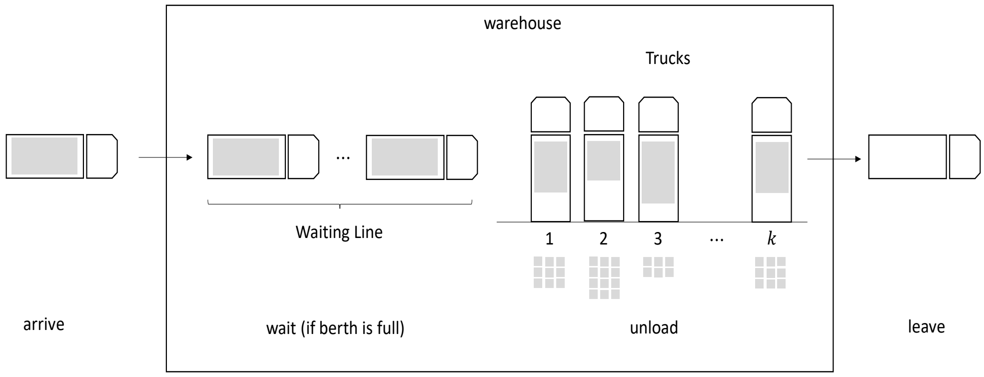

Figure 5. Illustration of warehouse operation

The available time per day was divided into T reservation frames. The duration of each reservation frame was identical. Each supplier was assigned to one reservation frame. Let x_{it} be a binary variable that takes the value of 1 when supplier i is assigned to reservation frame t, and 0 otherwise. It is assumed that a truck arrives from supplier i with an average arrival number of λ_i^{sup} Poisson. The total average number of arrivals λ_t^{time} is calculated using Equation (1).

$$\lambda_t^{\text{time}} = \sum_i x_{ij}\lambda_i^{\text{sup}}, t = 1, \cdots T \qquad (1)$$

Equation (1) shows that the arrival rate of each time frame t is the sum of the arrival rates of the suppliers assigned to time frame t.

The DC has k berths, and each berth has an average μ processing capacity. The utilization rate ρ_t, and system stay time W_t of each reservation frame t are calculated as in Equations (2) and (3), respectively.

$$\rho_t = \lambda_t^{\text{time}}/k\mu, t = 1, \cdots, T \qquad (2)$$

$$W_t = \rho_t/(1-\rho_t)\mu, t = 1, \cdots, T \qquad (3)$$

From Equation (3), W_t is an increasing function of ρ_t. Therefore, the system stay time increases as the arrival rate increases, and the waiting time decreases as the processing capacity of each berth and the number of berths increases.

The problem of determining the optimal reservable frame can be formulated as follows.

$$\text{minimize} \quad \sum_{t=1}^{T} W_t \qquad (4)$$

$$\text{subject to} \quad \lambda_t^{\text{time}} = \sum_i x_{ij}\lambda_i^{\text{sup}},\ t = 1, \cdots T \qquad (1)$$

$$\rho_t = \lambda_t^{\text{time}}/k\mu,\ t = 1, \cdots, T \qquad (2)$$

$$W_t = \rho_t/(1-\rho_t)\mu,\ t = 1, \cdots, T \qquad (3)$$

$$\sum_{t=1}^{T} x_{it} = 1,\ \ i = 1, \cdots, n \qquad (5)$$

$$\rho_t < 1,\ \ t = 1, \cdots, T \qquad (6)$$

$$x_{it} \in \{0,1\},\ i = 1, \cdots, n, t = 1, \cdots, T \qquad (7)$$

The objective function (4) indicates the minimization of the sum of the expected stay times in each reservation frame.

Constraint (5) indicates that each supplier is allocated to one reservation frame. Constraint (6) indicates that the usage rate of each reservation frame is limited so as not to exceed 1 to avoid overflow of the system. Constraint (7) indicates the binary condition of decision variable x_{it}.

2.2 Solution method

The proposed method for solving problems (1)-(7) was presented here. Because the model is nonlinear integer programming, it is generally difficult to find a solution.

We considered an approximation problem in which the arrival rate of each time frame λ_t^{time} was the continuous decision variable, as follows:

$$\text{minimize} \quad \sum_t [\lambda_t^{\text{time}}/(k\mu - \lambda_t)\mu] \tag{8}$$

$$\text{subject to} \quad \sum_t \lambda_t^{\text{time}} = \Lambda \tag{9}$$

$$\lambda_t \geq 0 \tag{10}$$

where $\Lambda = \sum_i \lambda_i^{\text{sup}}$. The objective function (8) indicates the minimization of the sum of the expected stay times in each reservation frame, which is equivalent to (4). This is obtained by substituting (2) and (3) into Equation (4). Constraint (9) indicates that the total arrival rate of time frames must be equal to the total arrival rate of the suppliers.

Taking Lagrangian, we had the relaxed problem (11), as follow:

$$\text{minimize} \quad \sum_t \left[\frac{\lambda_t^{\text{time}}}{(k\mu - \lambda_t^{\text{time}})\mu}\right] + v\left(\Lambda - \sum_t \lambda_t^{\text{time}}\right) \tag{11}$$

where ν is the Lagrange multiplier for constraint (9). Deriving partial derivatives of function (11) and setting to zero yields the following optimality condition:

$$\frac{\partial}{\partial \lambda_t^{\text{time}}} \sum_t \frac{\lambda_t^{\text{time}}}{(k\mu - \lambda_t^{\text{time}})\mu} + \frac{\partial}{\partial \lambda_t^{\text{time}}} v\left(\Lambda - \sum_t \lambda_t^{\text{time}}\right) = \frac{k\lambda_t^{\text{time}}}{(k\mu - \lambda_t^{\text{time}})\mu} - v = 0, \ \ t = 1, \cdots, T \tag{12}$$

$$\frac{\partial}{\partial v} \sum_t \frac{\lambda_t^{\text{time}}}{(k\mu - \lambda_t^{\text{time}})\mu} + \frac{\partial}{\partial v} v\left(\Lambda - \sum_t \lambda_t^{\text{time}}\right) = \Lambda - \sum_t \lambda_t^{\text{time}} = 0, \tag{13}$$

$$\frac{\partial}{\partial \lambda_t^{\text{time}}} \frac{\lambda_t^{\text{time}}}{(k\mu - \lambda_t^{\text{time}})\mu} = \frac{(k\mu - \lambda_t^{\text{time}})\mu + \mu\lambda_t^{\text{time}}}{(k\mu - \lambda_t^{\text{time}})^2 \mu^2} = \frac{(k\mu - \lambda_t^{\text{time}})\mu + \mu\lambda_t^{\text{time}}}{(k\mu - \lambda_t^{\text{time}})^2 \mu^2} = \frac{k\lambda_t^{\text{time}}}{(k\mu - \lambda_t^{\text{time}})} \tag{14}$$

where the partial derivative of the first term in Equation (12) with respect to λ_t^{time} can be derived as shown in Equation (14).

We then solve the Equation (12) as (15).

$$\frac{k\mu - u_t}{k\mu - \lambda_t^{\text{time}}} - v = 0$$

$$\Leftrightarrow k\mu - u_t = (k\mu - \lambda_t^{\text{time}})v$$

$$\Leftrightarrow k\mu(1 - v) - u_t = -v\lambda_t^{\text{time}}$$

$$\Leftrightarrow \lambda_t^{\text{time}} = \frac{u_t - k\mu(1 - v)}{v}, \ \ t = 1, \cdots, T \tag{15}$$

This means that λ_t^{time} takes the same value under the optimal conditions. Combining this result with Equation (9) leads to the optimal solution of problem (8) and (9).

$$\lambda_1^{\text{time}} = \cdots = \lambda_t^{\text{time}} = 1/\Lambda. \tag{16}$$

Equation (16) indicates that the optimal solution of the approximated problem requires that the arrival rate of each time frame be the same. This leads to the following theorem.

Theorem: The arrival rate of each time frame should be the same in the optimal solution of the approximated problems (8)-(10).

The relationship between the waiting time and utilization rate is shown in Figure 6. As ρ_t approached 1, the stay time increased sharply. Therefore, to reduce the overall waiting time, it is not desirable to perform an unbalanced allocation such that the utilization rate of one timeframe is high, and the utilization rate of another is low. This is because even if the utilization rate is lowered to some extent, it does not significantly contribute to the reduction in the overall waiting time. On the other hand, if the utilization rate is exceeded to some extent, the waiting time increases sharply, leading to deterioration of the overall waiting time. Therefore, to reduce the overall waiting time, it is desirable to perform a balanced allocation so that the utilization rate of each time frame is the same.

Therefore, the original problem only needs to be assigned so that the difference between λ_t^{time} is minimized. An optimal solution can be obtained by solving the following problem:

$$\text{minimize} \quad \max_t \lambda_t^{\text{time}} \tag{17}$$

$$\text{subject to} \quad \lambda_t^{\text{time}} = \sum_i x_{ij}\lambda_i, \ \ t = 1, \cdots T \tag{1}$$

$$\sum_{t=1}^{T} x_{it} = 1, \ \ i = 1, \cdots, n \tag{5}$$

$$\lambda_t^{\text{time}} < k\mu_t, \ \ t = 1, \cdots, T \tag{6}$$

$$x_{it} \in \{0,1\} \ \ i = 1, \cdots, n, t = 1, \cdots, T \tag{7}$$

The objective function (17) represents the minimization of the maximum arrival rate of all the time frames. This means load leveling in each time zone. This problem is linear integer programming, and thus, can be solved efficiently by off-the-shelf solvers.

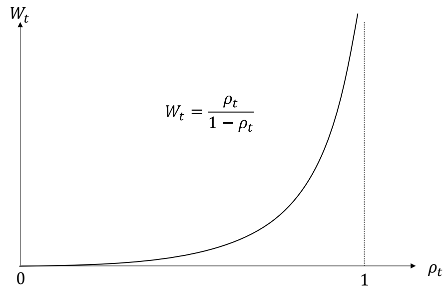

Figure 6. Relationship between the waiting time and the utilization rate

3. RESULTS AND DISCUSSION

3.1 Data set

The model presented was motivated by the work that we did for a national distribution center of a supermarket chain. The daily loadable time was 9 h from 3: 00 AM to 12: 00 AM, and $T = 9$. The number of suppliers was set to $n = 80$ and divided into four groups, as shown in Table 2. The total of λ_i was 47.8 trucks/day, which was close to the actual value of 47.5 trucks/day. The number of berths was $k = 7$, and the average service rate per berth was $\mu = 1.8 / h$.

The model was coded in Julia run on a personal computer with Intel (R) Core (TM) i7-8700 CPU, 3.20GHz, 3.19 CPU with 32.0 memory.

Table 2. Supplier group features

Group	Delivery frequency	i	λ_i
N_1	7 times/week	$\{1,\cdots,30\}$	1.00
N_2	4 times/week	$\{31,\cdots,50\}$	0.57
N_3	2 times/week	$\{51,\cdots,65\}$	0.28
N_4	1 time/week	$\{66,\cdots,80\}$	0.14

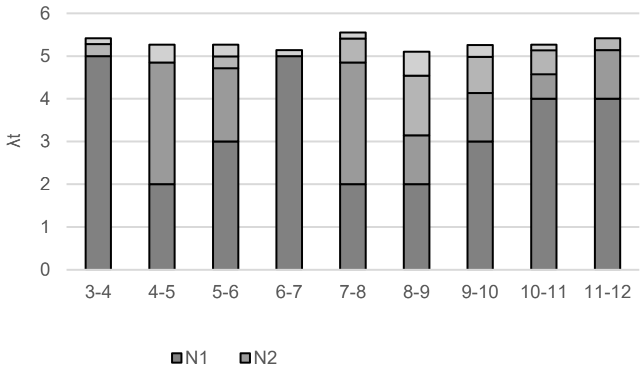

Figure 7. Arrival rate of each reservation frame

Table 3. Expected stay time

Time frame (t)	3-4 (1)	4-5 (2)	5-6 (3)	6-7 (4)	7-8 (5)	8-9 (6)	9-10 (7)	10-11 (8)	11-12 (9)	Sum	Ave
λ_t	5.42	5.27	5.27	5.14	5.55	5.1	5.26	5.27	5.42	47.7	5.30
W_t	25.2	24.0	24.0	23.0	26.2	22.7	23.9	24.0	25.2	218.0	24.2

3.2 Baseline case

Figure 7 shows the number of reservations for each reservation frame for each supplier group. Table 3 presents the expected stay times for each time frame.

From Figure 7, by combining suppliers with different frequencies, the arrival rate for each reservation frame can be equalized. From Table 3, the expected stay time for all trucks were 24.2 minutes in the proposed system. This was much less than the 35 minutes in the real-world average waiting time, in which random arrival and dedicated reservation system were mixed. These results indicated that the proposed system can reduce the stay time, compared with traditional operation systems.

3.3 Sensitivity analysis

The effects of changes in the number of berths and packages were analyzed, considering the number of berths $k = 4,\cdots,10$. Regarding the transportation unit, a customized pallet (bulk/beer pallet) and standard pallet were considered. At present, both pallets were mixed. In the case of the customized pallet only, transfer occurred, so $\mu = 0.6$. In the case of the standard pallet only, $\mu = 8.7$, because there was no transfer.

Table 4 shows the expected stay time when the number of berths and packing style were changed. From Table 4, the effect of the change in the number of berths and packages was calculated. A feasible solution cannot be obtained using only the exclusive package. Standardizing the packing style was found to be more effective than reducing the number of berths. In general, the loading ratio of the dedicated package was higher, but the waiting time was correspondingly longer, which suggested that it is necessary to quantitatively examine the trade-off between the two.

3.4 Managerial implications

The results presented in this study examined a comprehensive set of reservation problem, mathematical model and a solution algorithm relevant to the logistics operations management. It is revealed that the reservation system had a significant impact on the stochastic nature of the unloading operations at warehouses, which resulted in a greater waiting time for unloading and lower operational efficiency. This finding is beneficial to companies bringing more awareness of importance of how to design the reservation system.

The mathematical formulation based on the $M/M/k$ queuing model presented in this study could capture the stochastic nature of random arrival and quantify the average waiting time of truck berths. This can support the decision-making of how to allocate suppliers to each time frame; what type of transportation unit to be used; and how many berths to operate at a track yard in warehouse. Another important issue is how to find an optimal solution to the problem addressed. This algorithm provided the optimal solution with a real-world application data. Other algorithms that could solve the problem to optimality was a family of exact algorithms such as dynamic programming, branch and bound, and Bender's decomposition. However, instead of these general-purpose algorithms, the problem can be solved more efficiently by exploiting the special structure of the problem. It should also be noted that while the approximated algorithms, such as meta-heuristics (Heidari et al., 2018 and Xi et al., 2020), can be applicable, these methods do not guarantee that the solution obtained is optimal. Therefore, the proposed algorithm is more suitable in terms of the optimality guarantee.

Finally, the application to a real-world case study revealed that the proposed system significantly reduced the expected stay time of the unloading operations at warehouse. Along with the use of standard pallet, the unloading time was reduced from 35 minutes to 1.3 minutes. This is in line with the physical internet perspective (Dong and Franklin, 2021), where standardized container is used to operate the entire logistics system in the future. The proposed system brought several other implicit advantages over the traditional dedicated reservation system. In the traditional dedicated reservation system, the time frame is so small, which impose the narrow time window constraints in their vehicle routing planning. In the study of vehicle routing problem with time window (VRPTW), imposing narrow time window constraints is likely to reduce the routing efficiency. In the proposed system, time window was much wider, and drivers did not need to worry about arriving on time. Also, in the proposed system, drivers did not need to make a reservation every time they visit. Further, the proposed system did not require greater software support.

Table 4. Expected stay time per time frame

Number of berths	Expected stay time		
	Present	**Customized pallet**	**Standard pallet**
4	N/A	N/A	1.3
5	47.8	N/A	1.0
6	32.1	N/A	0.8
7	24.2	N/A	0.7
8	19.4	N/A	0.6
9	16.2	N/A	0.5
10	13.9	N/A	0.4

Note: N/A indicates overflow

4. CONCLUSION

In this study, a new reservation system to minimize the waiting time for trucks was developed. In the proposed reservation system, reservation frames were set for a plurality of trucks. Each truck may come at any time within the assigned reservation-time frame. It can be modeled as a typical $M/M/k$ type queuing system. The allocation of the reservation time frame for each supplier had to be determined so that the overall waiting time was minimized.

In this study, we formulated this problem as a 0-1 integer programming. This problem is nonlinear and cannot be solved using a standard solver. Therefore, we considered an approximated problem in which the arrival rate of each time frame was modeled as a continuous variable. The optimal conditions were obtained by using Lagrangian relaxation. As a result, it was found that the operation can be performed with a system stay time of approximately 30% less than the actual waiting time. This study provides a framework for discussing the effectiveness of each measure. Future research on the length of time in the time frame and the case in which all trucks are not reserved should be performed.

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