Flexible Services and Manufacturing Journal (2023) 35:416–454
https://doi.org/10.1007/s10696-021-09432-9

Performance analysis of a drop-swap terminal to mitigate truck congestion at chemical sites

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Accepted: 5 October 2021

Abstract

Truck congestion at chemical sites is a persistent problem that is difficult to solve, even using a truck appointment system. This study presents an alternative solution to improve the flexibility of chemical sites by creating a drop-swap terminal adjacent to the site location. The terminal serves as an intermediate depot where the trucks can drop empty containers and swap them with preloaded containers without entering the site. This study aims to evaluate the performance of such a solution in mitigating truck congestion at chemical sites. The problem is modeled as a nonstationary semi-open queueing network with time-varying arrivals. We propose a combination of a fluid-flow approximation and a decomposition-aggregation method to estimate the time-dependent performance of the system. A chemical site in the Netherlands is presented as a case study. Several scenarios are tested and evaluated. Numerical results show that a drop-swap terminal can effectively reduce truck idling time and increase logistics efficiency at chemical sites. We also found that swapping containers on chassis is a cheaper and greener option to operate the terminal. However, the investment needed to support the operation should not be overlooked to sustain the benefits. The study concluded with several key messages for site operators who wish to maximize the benefit from a drop-swap terminal.

Keywords Truck congestion · Containers · Drop-swap · Chemical site · Semi-open queuing network

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1 Introduction

Compared to other industries, the supply chain in the chemical industry is exceptionally complex. The transport lead times are long, the supply network is highly inflexible, and the transport modes are limited (Husain et al. 2006). These constraints contribute to a high inventory carrying cost and a highly inefficient chemical supply chain. The European Chemical Industry Council (CEFIC/ECTA 2009) report highlights that several trucks in Europe experienced a long idling time at chemical sites due to the growing demand from industries. This queuing problem decreases truck productivity and increases the risk of accidents (CEFIC/ECTA 2007, 2009). In chemical sites, a small accident could lead to a major catastrophe and harm the neighboring population. One of the latest accidents occurred at a chemical site at Port Neches, Texas, where 15 people were killed, and at least 50,000 people were evacuated due to the explosion (Toal et al. 2019). Moreover, the green-houses gasses from the idling truck engines, such as particular matters, carbon oxide, and nitrogen oxide, can also cause health problems among the neighboring population (Giuliano and O’Brien 2007; Chen et al. 2013a).

The truck congestion problem is not unique to chemical sites. Similar problems can also be found at seaport container terminals (Torkjazi et al. 2018; Zhang et al. 2019b; Yi et al. 2019). Previous studies have implied that the truck congestion in container terminals is a complex problem that is not only driven by the capacity issue but also by truck availability and equipment reliability (Chen et al. 2013b; Dekker et al. 2013). The conflict of interest between stakeholders in the terminals also intensifies the complexity of the problem (Lange et al. 2017). On the one hand, the terminal operator often aims to maximize terminal capacity utilization, which causes higher traffic and inflexibility in the loading/unloading operations (Zhao and Goodchild 2010). On the other hand, the trucking companies want to improve truck productivity, which requires the terminal operator to put more flexibility in the operations (Huynh et al. 2016). This conflict of interest between the stakeholders triggers a persistent truck congestion problem on the terminals.

Several studies have proposed the implementation of the Truck Appointment System (TAS) to mitigate the truck congestion problem (e.g., Zehendner and Feillet 2014; Phan and Kim 2016; Li et al. 2018). The TAS requires trucking companies to book an appointment with the terminal operator before the actual truck arrivals. The objective is to streamline the availability of the trucks and the terminal capacity through a scheduling system. It has been widely proposed as an effective solution to reduce traffic congestion in container terminals. However, several empirical studies evaluated that the implementation of TAS did not solve the traffic congestion in container terminals effectively (Giuliano and O’Brien 2007; Huynh et al. 2016). This outcome is caused by the high resource dependency and process variability in the existing logistics operations, which are difficult to address through rigid scheduling (Huynh et al. 2016; Huiyun et al. 2018). Wibowo and Fransoo (2020) conducted a multi-stakeholder analysis of the problem and found that the TAS primarily benefitted the terminal operator. The direct benefits for trucking companies are trivial, making them less motivated to adopt TAS.

This complex truck queuing phenomenon can be conveniently analyzed from the queuing theory perspective. Scheduling job arrivals based on server availability (as in the TAS) is one of the key strategies in queuing theory to minimize idling time and maximize server utilization (Franz and Stolletz 2012; Selinka et al. 2016). However, this strategy cannot effectively solve the queuing problem when the terminal operator cannot control the exact truck arrival time (due to road traffic or truck availability) and the equipment availability (due to equipment reliability issues). This unmatched availability between the trucks and the handling equipment leads to a substantial idling time in the logistics operation (Huynh et al. 2016; Li et al. 2018; Azab et al. 2020).

Our study presents an alternative solution to mitigate the truck congestion problem at chemical sites by developing a drop-swap terminal (DST). The DST serves as an intermediate depot nearby the site where an external truck can *drop* an empty container and *swap* it with a preloaded container without entering the site. This operation requires the site operator to dedicate a few internal vehicles to preload the containers and carry them to the terminal. By decoupling the logistics process, the site operator and trucking companies can operate independently and flexibly. The trucks can save some time since the containers are preloaded, making them more productive. The trucks can also avoid encountering disruptions (e.g., equipment failures) that occasionally occur during the loading/unloading activities. Besides, the reduced traffic on-site can help protect the chemical plant from detrimental events, such as truck crashes or other accidents. Due to its many potential benefits, a DST could be a promising solution for mitigating traffic congestion at chemical sites.

This study aims to evaluate if developing a DST could be a viable solution to the truck congestion problem on chemical sites. We examine the performance of a DST based on various criteria such as operational efficiency, emissions, and the associated logistics costs. Evaluating such a system could provide key evidence for managerial decisions on logistics operations at chemical sites. We developed a nonstationary queuing approximation as a method to achieve the research objective. A chemical site setup in the Netherlands is presented as a case study for numerical analysis.

The main contributions of this study can be summarized as follows:

- It explores the truck congestion problem at chemical sites, which is still underrepresented in the literature.
- It provides a detailed analysis of the performance of a DST to reduce the waiting time of external trucks at a chemical site. The evaluation includes the operational efficiency, the emission, and the associated cost resulting from implementing a DST.
- It extends the application of a fluid-flow approximation to solve nonstationary semi-open queuing networks based on a decomposition-aggregation approach.
- It gives several key messages for terminal operators who wish to maximize the benefit from a DST to mitigate truck congestion problems.

We organize the rest of this paper as follows. Section 2 provides a literature review on chemical logistics, truck congestion problems, and available methods in performance analysis. Next, we describe the problem and the mathematical model in Sect. 3. Section 4 discusses the proposed method to estimate the performance of the systems. In Sect. 5, we provide a numerical analysis based on a case of a chemical site in the Netherlands. Finally, Sect. 6 concludes the paper.

2 Literature reviews

2.1 Chemical logistics

In chemical logistics, the products are often handled in tank containers that allow hazardous chemicals to be shipped through multimodal transport in a safe manner. However, one of the challenges in managing tank containers is the imbalance of supply and demand across regions. The demand for multiple container types and the cleaning process also complicate the managerial process.

Many existing studies on container management focuses on dry containers and in a seaport context. Only a few studies address the problem in the context of the chemical industry. For example, Erera et al. (2005) propose a multi-commodity network flow model to improve global intermodal tank container management. The model helps to route booked containers and reposition the empties with regard to the supply and demand across the globe. Karimi et al. (2005) extend the network flow model to manage the tank container by considering container cleaning, non-uniform holding cost, and revenue management. Wu et al. (2011) introduce a decision support model based on a vehicle routing problem to determine a quick and feasible route and stowage plan for chemical cargoes across the globe. Xing et al. (2019) took a further step by considering multiperiod operational decisions and capacity constraints in tank container planning. The model consists of two-stage optimization: tactical container repositioning and dynamic job acceptance/rejection decisions in the quotation-booking process.

Even though most chemical products are shipped by truck, raw and intermediate materials in the upper supply chain are primarily shipped via pipeline, ship, or rail. Compared to other modes of transport, rail transports are more flexible but require more organizational and technical efforts. Kirschstein (2018) proposes a heuristic based on a rolling-horizon decomposition to solve the multi-commodity rail transportation planning problem. The model also considers realistic constraints such as transport time and handling capacity. Meisel et al. (2013) introduce integrated production and intermodal transport planning, including production setups, cargo consolidation, and capacity booking of rail and road transports.

Due to its global supply chain network, chemical transport also largely contributes to greenhouse gas emissions worldwide. Many initiatives and policies have been proposed to reduce emissions by promoting the use of intermodal transport, swap arrangements for commodity products, and logistical collaboration (McKinnon and Piecyk 2010). Unfortunately, emissions are not the main driver for logistics service providers (LSPs) to change their operations. Cichosz (2017) surveyed LSPs' perspective on green chemical logistics and found that LSPs have a low interest in emission reduction. LSPs' motivation to join a green logistics initiative such as intermodal transport is mainly due to cost efficiency and convenience.

To summarize, most studies in chemical logistics are centered on strategic and tactical decisions, such as network optimization and intermodal transport planning. Only a few studies address the logistical issues in the operational level, such as the truck congestion problem. A report from (CEFIC/ECTA 2009) states that a long truck queue has been spotted in many chemical sites in Europe. However, academic literature almost completely overlooks the issue. One of the possible causes is that it has some similarities to the truck congestion problem in container terminals. Therefore, it only receives little attention from scholars. Nonetheless, the on-site logistics at chemical sites also have few distinct features, such as short site operating hours, long service time, uncertain truck arrivals, and high regard for safety and security (Wibowo and Fransoo 2020).

As an effort to reduce the truck idling time in chemical sites, Zhao et al. (2020) propose an IoT-enabled smart indoor system. The device helps drivers to track and locate the right vehicle and equipment in the parking lot. Excessive time and human effort spent locating the equipment lead to significant delay and congestion and cause extra emissions. Wibowo and Fransoo (2020) also evaluate the effectiveness of TAS to reduce truck congestion at chemical sites from a multi-stakeholder perspective. The result suggests that the benefit of TAS for trucking companies is trivial therefore does not change their behavior. This study contributes by exploring an alternative solution to the truck congestion problem at chemical sites, which is still underrepresented in the literature.

2.2 Truck congestion problem

A long truck queue is a complex phenomenon occured in several logistics sites, such as seaport container terminals and air cargo terminals. The rapid growth of demand, combined with the limited handling capacity, stimulates heavy workloads at the terminal. Besides, the random arrival of external trucks also complicates the problem, causing a significant truck idling time at the terminal. This problem has gained wide attention from scholars since it reduces logistics efficiency and increases freight costs at terminals (Gracia et al. 2017; Zhang et al. 2019b). The idling engines also create pollutants that can harm the health of the population nearby (Giuliano and O'Brien 2007; Chen et al. 2013a).

Numerous efforts have been undertaken to solve the problem. The effort can be divided into three major streams: (1) managing truck arrivals, (2) improving coordination, and (3) expanding the terminal handling capacity. Scholars in the first stream believe that the random truck arrivals at the terminal are the root cause of the problem. Therefore, it attempts to change the truck arrival behavior through several incentives, such as time-varying tolls, time-windows assignment, and TAS implementation. Time-varying tolls aim to reduce truck arrivals at the gate during the busy period by charging different fees during peak and off-peak hours (Chen et al. 2011; Zhang et al. 2019a). Time-windows assignment aims to shorten the truck waiting time by allocating specific time windows for truck arrivals to match storage space availability (Chen et al. 2013b; Chen and Jiang 2016). TAS aims to distribute the truck arrivals by requiring the trucking companies to book an appointment before the actual arrival (Gracia et al. 2017; Li et al. 2018; Torkjazi et al. 2018; Yi et al. 2019). While the design of TAS has gained popularity in the literature, empirical studies found that its effectiveness in real-world situations still needs to be verified further (Giuliano and O'Brien 2007; Huynh et al. 2016).

Scholars in the second stream believe that the root cause is the lack of coordination between the terminal operator and the trucking companies. Therefore improving coordination between the stakeholders should help to mitigate the truck congestion at the terminals. The coordination aims to align the availability of trucks and handling equipment by continuously updating and exchanging their availability status through an advanced information platform (Phan and Kim 2016; Azab et al. 2020; Im et al. 2021). Although it seems a viable solution, the benefits may not pay off the technical and organizational efforts required to operate such a system.

Scholars in the third stream think it is impossible for the terminal operator to control the exact truck arrivals and ensure availability of equipment. Several random events can occur during the process and disrupt the established plan. Therefore, instead of increasing control over uncertain variables, some scholars propose expanding the terminal handling capacity, such as utilizing the off-peak hours via night delivery (Bentolila et al. 2016) or developing a chassis exchange terminal decouple the operation (Dekker et al. 2013). Both initiatives require terminal operators to invest in new resources. Therefore, a careful analysis is needed to evaluate whether the operational benefit can justify the investment.

Currently, there are only a few available studies within the third stream category. Our study gives additional insight into this category by assessing the performance of a DST to expand the handling capacity at a chemical site. We also provide an analytical framework and evaluation of the operational benefits, safety, emission, and cost performance of the DST. To our knowledge, this is the first time such a solution has been evaluated in detail.

2.3 Decoupled logistics operation

The idea of decoupling logistics operations in a highly congested area is not new. Similar concepts have also been proposed and implemented in the context of seaport terminals. Dekker et al. (2013) introduced Chassis Exchange Terminal (CET) concept at a seaport terminal in Rotterdam to mitigate truck congestion. CET is a type of off-dock terminal that works as an extended gate where the trucks can exchange the containers on chassis during the day. The containers are transferred from the seaport terminal to the CET at night. The study claims that the CET can reduce the truck turnaround time and increase the terminal's capacity utilization. However, the implementation also requires substantial investment in the seaport area, which is rather expensive. Unfortunately, the study does not offer details of the cost analysis. It only reports that an additional 45 euro per container is required to support the investment to break even. Chassiakos et al. (2017) investigate the impact of CETs on the distribution network in the greater area of Los Angeles and Long Beach ports.

They found that an optimal network configuration of CETs could reduce the truck travel time up to 20%, subsequently improving the truck efficiency to perform more jobs in the area. Due to its advantages, CET has also been referred to as the future trend in the container terminal layout (Gharehgozli et al. 2020).

The concept of dry ports in the seaport terminal also offers a comparable concept. A dry port is an inland intermodal terminal directly connected to a seaport by road or rail that serves as a transshipment hub of sea cargo to inland destinations. The primary purpose of a dry port is to relieve the congestion at the seaport due to increased container flows (Roso et al. 2009). Port authorities can mitigate the traffic congestion at the seaport, improve the hinterland accessibility, and alleviate the associated environmental problems by decoupling the distribution facilities and value-added service to dry ports (Nguyen and Notteboom 2019). A recent empirical study by Jeevan et al. (2019) suggests that the development of dry ports in Malaysia has significantly improved the seaport terminals' competitiveness, including enhancing their capacity and increasing the trade volume.

The trend of decoupling logistics operations can also be observed in city logistics. The accessibility issues and high delivery failure rate in urban areas provide substantial challenges for LSPs to provide exceptional delivery services to/from customers (Weltevreden 2008; Kedia et al. 2020). One of the emerging solutions to this problem is introducing collection-and-delivery points (CDPs) in city logistics. A CDP is a third-party location that facilitates the delivery and pick-up locations of items to/from dense areas. Instead of directly delivering the item to the customer, the carrier could drop the item to CDPs and let the customers pick it up at their convenience time. The introduction of CDPs helps avoid additional costs associated with failed delivery (Cárdenas et al. 2017; Kedia et al. 2020). They also reduce time and distance-based costs retrieved by consolidating several small orders from the customers (Kin et al. 2018; Janjevic et al. 2019).

Despite being a popular approach to mitigating traffic congestion, the notion of decoupling logistics operations at chemical sites still lacks representation in the literature. This fact is unfortunate since the chemical supply chain plays an essential role in many economies. Our study contributes to the literature by providing insights on the performance of decoupled logistics operations to reduce truck congestion at chemical sites.

2.4 Performance analysis methods

The truck congestion problem at logistics sites is typically modeled as nonstationary queuing systems. In this queuing system, the trucks serve as customers who arrive stochastically at the gate, waiting to be served by the site operators within a specific operating hour. In the literature, we observe two main approaches to evaluate the performance of such a system, namely simulation methods and queuing approximations.

Franz and Stolletz (2012) use a discrete simulation (DES) model to evaluate the performance of a slot-based appointment system to reduce truck turn time truck at air cargo terminals. The authors found that small shifts in the truck arrival distribution could significantly reduce the truck waiting time. Using a simulation model, Gracia et al. (2017) evaluate the impact of lane segmentation and booking levels on truck congestion at a container terminal. The result implies that providing dedicated lines for trucks with an appointment effectively reduces the average truck waiting time. Li et al. (2018) use a simulation model to seek a proper response strategy to counteract the impact of disruptions on the established plan. They found that the disruption in the truck arrival time has a significant effect on the terminal productivity. Azab et al. (2020) combine a DES with an optimization model to evaluate the effectiveness of a dynamic collaboration between trucking companies and the terminal operator.

In contrast to simulations, queuing approximations have less flexibility to develop complex design scenarios. However, the methods typically allow for elegant and compact expressions to measure the mean performance of queuing systems. Such expressions are easily implemented in practice because they can be included in commonly used tools such as Microsoft Excel. Besides, queuing approximations allow for rapid computation and scenario evaluation. The methods have also been widely used to assess the performance of logistics operations with high accuracies.

For example, Chen et al. (2013c) developed an extension to the point-wise stationary fluid-flow approximation (PSFFA) (Wang et al. 1996), called B-PSFFA, to solve a nonstationary queuing system with multi-servers. They use Cosmetatos's approximation (Cosmetatos 1976) with a bisection method to derive the service utilization rate from the fluid-flow expression. To improve model accuracy, the authors introduce a correction factor γ that needs to be carefully tuned for each case. The model was implemented to evaluate the effectiveness of TAS in a container terminal setting. Ji et al. (2014) developed a point-queue model based on the PSFFA method. The authors successfully overcome the non-negativity of queue length from the original model. The numerical results show that the proposed method can achieve acceptable accuracy, but the computation speed is relatively low, restricting the use for rapid evaluations. Zhang et al. (2019a) extend the application of B-PSFFA to determine the optimal toll rates in a container terminal. The objective is to minimize the truck waiting times by optimizing different toll rates for different periods. They use bi-level programming, which combines B-PSFFA and memetic heuristics to measure the system performance and optimize the toll rates. Hu et al. (2019) combine the PSFFA method with a generalized expansion model to solve a nonstationary queuing model with time-varying arrivals and state-dependent service. The model is implemented to assist in designing traffic circulation systems (e.g., vehicle roads and pedestrian corridors). Wibowo and Fransoo (2020) developed an approximation based on the B-PSFFA method, called WB-PSFFA, to solve a nonstationary queuing model with general distributions. Their model overcomes the need for correction factors in the original model by replacing Cosmetatos's approximation with Whitt's approximation (Whitt 1993). The method was implemented to evaluate the effectiveness of TAS in reducing truck idling time at chemical sites.

Stolletz (2008) introduces stationary-backlog carryover (SBC) as an alternative solution for time-dependent nonstationary queuing systems. The method has been implemented in various cases, such as in the airport and cargo terminals (Stolletz 2011; Stolletz and Lagershausen 2013; Selinka et al. 2016). SBC was also shown to perform well during a critical traffic intensity. However, when the traffic intensity temporarily goes beyond one, the method quickly becomes impractical.

Jia and Heragu (2009) combine a matrix-geometric method with a decomposition-aggregation approach to solve a stationary semi-open queuing network (SOQN). The advantage of the method is apparent when the number of servers in the network is large. It has also been applied to several warehousing and manufacturing systems (Ekren et al. 2014; Roy et al. 2015; Kumawat and Roy 2021). Dhingra et al. (2018) extend the method to solve a nonstationary SOQN based on a truck congestion problem in a container terminal. The authors use a Markov-modulated Poisson Process to characterize the truck arrival behavior and develop a matrix-geometric method to solve the queuing network. The result shows that the proposed method has a 15% higher accuracy than the stationary method. Unfortunately, the authors do not compare the performance with any of the existing queuing approximations. Therefore, it is hard to judge its relative performance.

Our method was developed based on WB-PSFFA to solve a nonstationary SOQN with time-varying arrivals. Wibowo and Fransoo (2020) showed that WB-PSFFA has higher accuracy than other approximation methods like SBC and PSFFA. However, the method was originally designed to solve a nonstationary queuing model in an open network configuration. This study extends the application of WB-PSFFA to solve a mixed network configuration by integrating the method with a decomposition-aggregation approach. We contribute by providing an alternative method to solve a nonstationary SOQN with a fluid-flow approximation.

3 Problem descriptions

3.1 Existing logistics operation

A chemical site represents a complex area comprised of multiple manufacturing plants that produce several chemical products. The logistics operation in the site involves loading and delivery activities from the plant to the associated customers. The site operator typically works with several LSPs that offer the required service and equipment to perform these functions. The site is usually equipped with a large parking area and an entrance gate to control the access to the site facility. Most of the chemical sites in Europe open for 8–12 h during the day (CEFIC/ECTA 2002).

Every day, external trucks from LSPs arrive at the site to perform the loading/unloading operation in the manufacturing plants. Based on the historical data from an LSP, we found that most of the trucks in Western Europe prefer arriving early in the early morning. CEFIC/ECTA 2002 has also reported a similar arrival pattern based on a survey of several chemical sites in Europe. This unique truck arrival pattern is partly driven by the trucking companies' interest in maximizing truck productivity. They recognize that the success of afternoon appointments highly depends on the accomplishment of morning operations (Huynh et al. 2016). Thus, to reduce the risk of being transferred to the following day, the trucks prefer to arrive early in the morning and wait in front of the gate.

Chemical sites typically implement strict safety regulations for any visitors. The entrance gate controls a truck's entry into the site to visit a specific plant. Every truck wanting to enter a site must have a permit and conform to a safety standard. After finishing the check-up, the truck proceeds to the destination plant to load the requested product. If the loading station in the plant is still occupied with other jobs, the truck waits in a queue until the station becomes available to serve the truck. Note that equipment failures often occur unpredictably during the loading process. The failures can cause unexpected delays and increase truck idling times. Based on data from an LSP in Western Europe, we found that, on average, trucks typically spend 2.48 h at the chemical sites, where 48% of the time is spent idling. Along with the growing demand, truck idling times at chemical sites are likely to increase considerably in the near future. Without any immediate action, on-site truck congestion will be a crucial problem in the chemical supply chain.

3.2 Design of a DST

The cause of the truck congestion at chemical sites can be rooted in the unmatched availability between the external trucks and the site capacity. Unfortunately, aligning the availability through an appointment system is less likely to solve the problem due to the high uncertainty in truck arrivals and service time. There is also a conflicting interest between the site operator and the trucking companies, which makes the problem persists (Wibowo and Fransoo 2020). Therefore, decoupling the logistics operations with a DST could be an alternative solution to improve flexibility at the chemical site.

A DST is an intermediate depot located adjacent to the chemical site where external trucks can drop and swap the containers. To support the DST, the site operator must dedicate a few internal trucks to preload the containers at the plants and carry them to the terminal. Figure 1 illustrates the logistics operations with a DST in the chemical site. By implementing a DST, the on-site operation can be decoupled into two main logistics activities: external activities and internal activities. Both activities are described as follows:

(1) *Internal activities* include shuttle service between the chemical site and the DST. The activities require a few dedicated trucks to load empty containers and drop them at the terminal. Since the trucks are considered internal resources, they do not need to perform the document and safety check-up whenever they enter the chemical site. Internal trucks also improve the plants' safety since they are more familiar with the site design and operations. The internal activities are relatively independent processes. Therefore, the internal trucks can preload the containers during off-peak hours and let the external trucks pick up the containers the day after.

(2) *External activities* include picking up containers at the DST and carrying them to the customers. These activities are performed by external trucks provided by the LSPs. Unlike conventional operations, the trucks do not need to enter the chemical site and load the product themselves. They can just drop an empty

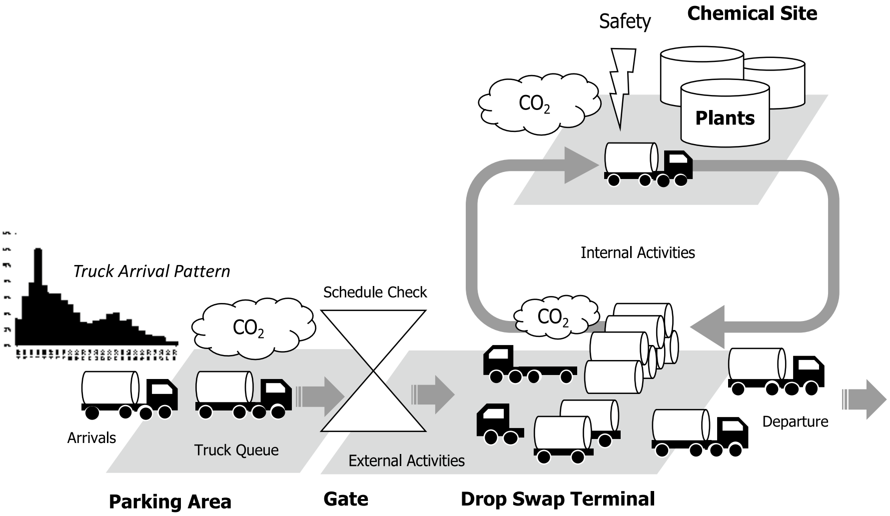


Fig. 1 The drop-swap operations in a chemical site

container in the DST and swap it with a preloaded container. Since the operations are performed outside of the chemical site, the external trucks do not need to perform a complete safety check-up, thereby saving some time. The trucks just need to check in to the terminal, pick up the preloaded containers, and carry them to customers.

The DST operations can also be designed based on the following scenarios:

(1) *Drop-Swap on Container (DS/C).* In this scenario, the truck exchanges a container in the terminal with the help of a reach-stacker. The reach-stacker lifts empty containers from the trucks and stacks them in the storage area. It also helps to stack the preloaded containers from the storage to the truck's chassis. Since an empty container can be stacked up to three levels, this method requires less space. Based on the data from an LSP, we found that it takes 11 min, on average, to perform a single drop-swap process on a container.
(2) *Drop-Swap on Wheels (DS/W).* In this scenario, a truck performs the container exchange on the chassis instead of the container itself. The truck can perform this process independently without needing a reach stacker. The process typically takes about 6 min, much faster than swapping on the container. However, since a chassis cannot be stacked up, this method also requires more space to store all the chassis and the containers.

From the explanations, it is clear that both scenarios have their advantages and disadvantages. Thus, it will be interesting to evaluate the performance and the tradeoff between the expected benefits and the required investment in the DST.

3.3 Mathematical model

We modeled the drop-swap operation in the chemical site as a SOQN. The system consists of two network types: an open queuing network (OQN) and a closed queuing network (CQN). The OQN represents the external logistics activities, consisting of two serial queuing systems in the parking area and the DST. The CQN represents the internal logistics activities consisting of two queuing systems at the DST and the chemical site. Both networks were combined into a SOQN, as illustrated in Fig. 2. It represents the complete drop-swap operations in the chemical site. The list of the parameters, notations, and variables has been provided in Table 1.

3.4 Model assumptions

The model has the following assumptions:

- The system state is assumed to be the average number of vehicles L_t at time t, which values in the continuous state space. This is an approximation since the system state is actually the number of vehicles that value in the discrete state space.
- The inter-arrival time of external trucks is assumed to follow general distributions with a time-varying rate of λ_t. The service time is also assumed to follow general distributions. Therefore, it creates a GI(t)/G(t)/m(t) queuing model.
- Truck arrival distributions at the chemical site and the DST are assumed to follow a similar pattern. This assumption may not be the case since providing a

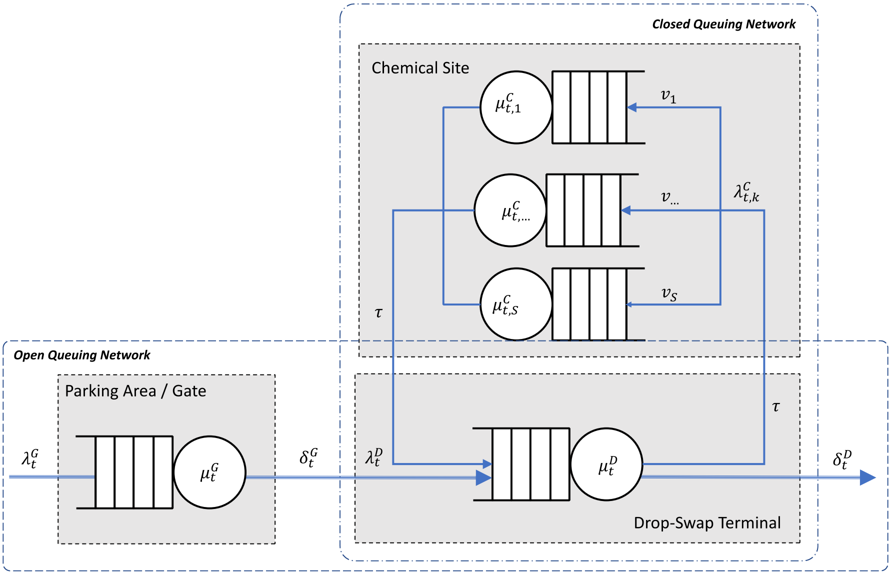


Fig. 2 A SOQNs with time-varying arrivals for the drop-swap operations

Table 1 List of parameters, notations, and variables

System	Symbol	Description
General	t	Index of time interval $t = 1, \ldots, T$
	n	Number of time intervals within period T
	s	Index of loading station at the chemical site,$s = 1, \ldots, S$
	k	Population size in the CQN (truck), $k = 1, \ldots, K$
	A	Area needed to store a container (32 m^2)
	X	Number of jobs scheduled within period T
Gate, G (parking area)	λ_t^G	Arrival rate at the gate at time t (truck/hour)
	δ_t^G	Departure rate from the parking area at time t (truck/hour)
	m^G	Number of servers at the gate
	μ_t^G	Service rate at the gate at time t (truck/hour)
	c_e^G	Coefficient of variation of service time at the gate
	c_a^G	Coefficient of variation of interarrival time at the gate
	ρ_t^G	Server utilization rate in the gate at time t
	W^G	Average truck cycle time at the gate (hour)
	W_q^G	Average truck waiting time at the gate (hour)
	L_t^G	Expected number of trucks at time t at the gate (truck)
DST, D	λ_t^D	Arrival rate at the DST at time t (truck/hour)
	m^D	Number of reach stackers at the DST
	μ_t^D	Service rate at DST at time t (truck/hour)
	$\hat{\mu}_t^D$	Adjusted service rate at time t in the DST (truck/hour)
	ρ_t^D	Server utilization rate in the DST at time t
	W^D	Average truck cycle time at the DST (hour)
	W_q^D	Average truck waiting time at the DST (hour)
	L_t^D	Expected number of trucks at time t at the DST (truck)

Table 1 (continued)

System	Symbol	Description
The chemical site, C	$\lambda^{C}_{s,t,k}$	Expected throughput in the plant s at time t with k trucks in the queuing system C (truck/hour)
	$\lambda^{C}_{t,k}$	Expected system throughput at time t with k trucks in the queuing system C (truck/hour)
	m^{C}_{s}	Number of loading stations in the plant s
	$\mu^{C}_{s,t}$	Service rate in the plant s at time t at the chemical site (truck/hour)
	v_s	The proportion of demand flow to the plant s in the chemical site
	$\hat{\mu}^{C}_{s,t}$	Adjusted service rate in the plant s at time t in the chemical site (truck/hour)
	$\rho^{C}_{s,t}$	Server utilization rate in the plant s at time t in the chemical site
	$W^{C}_{s,t,k}$	Truck cycle time in the plant s at time t with k trucks in the queuing system C (hour)
	$L^{C}_{s,t,k}$	Expected number of trucks in the plant s at time t with k population in the queuing system C (truck)
	t^{C}_{start}	Starting time of operations at the chemical site
	t^{C}_{end}	Ending time of operations at the chemical site
	$\Pi_{s,t,k}$	Probability of waiting in the plant s at time t when there are k trucks in the queuing system C
	τ	Average travel time from the DST to the chemical site (hour)
	K^{*}	The optimal number of internal trucks in the CQN

Table 1 (continued)

System	Symbol	Description
Cost variables	ϕ_{LO}	Cost to perform the loading operations (60 €/hour)
	ϕ_{IT}	Cost to acquire and operate the internal trucks (40 €/hour)
	ϕ_{ET}	Cost to acquire and operate the external trucks (48 €/hour)
	ϕ_{RT}	Cost to acquire and operate the reach stacker (48 €/hour)
	ϕ_{CN}	Cost to rent the required container (10 €/day)
	ϕ_{CS}	Cost to rent the required chassis (10 €/day)
	ϕ_{SR}	Cost to rent the space for a DST (0.75 €/m^2/day)
	E_{CO2}	Carbon emission equivalent from truck engines (kg/hour)

DST may change the external truck arrival behavior. However, since the actual truck arrival data at the DST were not available, we assume the behavior is similar to the truck arrival distribution at the site.

- The amount of jobs that go into an individual plant follows a steady flow proportion v_s. This is an approximation since the actual flow may vary over time.
- The service rate distribution is assumed to be unvarying during the site operating hours. The service begins on a prescheduled start time and ends when no jobs are left in the queue ($L_t = 0$). Therefore, when the planned operating hours have been passed, and there are still jobs in the queue, the corresponding server will go overtime until no jobs are left.
- All queues in the system operate with the "First In, First Out" (FIFO) principle. A truck may enter a corresponding station in a plant whenever it is available. However, the services between plants are not interchangeable. This assumption is realistic since each plant typically offers different types of products. Therefore the trucks should queue at a specific corresponding plant to complete the order.
- There are ample spaces in the chemical site and the DST. Therefore, the queuing capacity is assumed to be infinite.

4 Methodology

Since chemical sites typically have a finite operating hour and the trucks arrive at varying times, the system performance cannot be analyzed using a simple stationary approximation. Such a method often overestimates the performance of a nonstationary queue (Massey and Whitt 1994; Wang et al. 1996). Therefore, we propose an approximation method to estimate the time-dependent performance of such a system. The method is developed based on the combination of WB-PSFFA with a decomposition-aggregation method to solve a nonstationary SOQN. The details of the proposed method are given in the following subsections. We first explain the method to solve the individual network in the SOQN, i.e., OQN and CQN. Afterward, we describe the method to solve a nonstationary SOQN along with its relevant performance indicators. The validation of the proposed method is provided in the Appendix.

4.1 OQN

The OQN represents the external activities at the DST, where the external trucks carry the external, empty containers to be swapped with the preloaded containers at the terminal. The system consists of two serial queues, representing the check-in process at the parking area/gate and the drop-swap process at the DST, as shown in Fig. 3.

Let consider the queuing system at gate G as an example. WB-PSFFA works by dividing a period of T in the queuing system into n number of small intervals t. The fluid-flow conservation principle controls that for any time t, the number of trucks L_{t+1}^G should be equal to the difference between the arrival rates λ_t^G and the departure rates δ_t^G. The fluid-flow approximation for the nonstationary queuing system with multi-servers is formulated as follows:

$$\frac{dL^G}{dt} = \lambda_t^G - \delta_t^G \tag{1}$$

$$\delta_t^G = m^G \mu_t^G \rho_t^G \tag{2}$$

$$L_{t+1}^G = L_t^G + \lambda_t^G - \delta_t^G \tag{3}$$

Equation (1) is the fluid flow balance function of the queuing model. Equation (2) is the exit flow function for departure rate δ_t^G, and Eq. (3) is the transition rule to update the state of analysis to the subsequent time interval.

The number of trucks L_t^G can be estimated based on a stationary performance of a queuing system for each time t. WB-PSFFA employs Whitt's approximation (Whitt 1993) to estimate the GI/G/m queue performance, as demonstrated in Eq. (4).

$$L_t^G = \left(\frac{\left[1 + \left(c_e^G\right)^2\right]\left[\left(c_a^G\right)^2 + \left(\rho_t^G\right)^2\left(c_e^G\right)^2\right]}{2\left[1 + \left(\rho_t^G\right)^2\left(c_e^G\right)^2\right]} \right)\left(\frac{\rho_e^{G\sqrt{2(m^G+1)}}}{m^G\left[1 - \rho_t^G\right]} \right) + m_t^G \rho_t^G \tag{4}$$

The utilization rate ρ_t^G in Eq. (4) can be simply estimated with a numerical approach such as the bisection method. The bisection method is a simple approximation for root-finding of a continuous function on a constrained interval. It consists of repeatedly bisecting the interval and then selecting the subinterval where the function changes sign and therefore must contain a root. Repeat the process until the subinterval range converges to an acceptable margin. In our case, the iteration stops when the subinterval range has reached a lower than 0.001. The advantage of using Eq. (4) as an approximation is that it is compatible with PSFFA's framework. It has also been shown to provide a more accurate estimation than other queuing approximation methods such as SBC and PSFFA, especially when the system utilization rate is temporarily overloaded (Wibowo and Fransoo 2020).

Once the utilization rate ρ_t^G is found, we can estimate other performance measures such as the average truck cycle time W^G and the average truck waiting time W_q^G by using Little's Law, as follows:

$$W^G = \frac{1}{n}\sum_{t=0}^{n} \frac{L_t^G}{m^G \mu_t^G \rho_t^G} \tag{5}$$

$$W_q^G = \frac{1}{n}\sum_{t=0}^{n} \left(\frac{L_t^G}{m^G \mu_t^G \rho_t^G} - \frac{1}{\mu_t^G} \right) \tag{6}$$

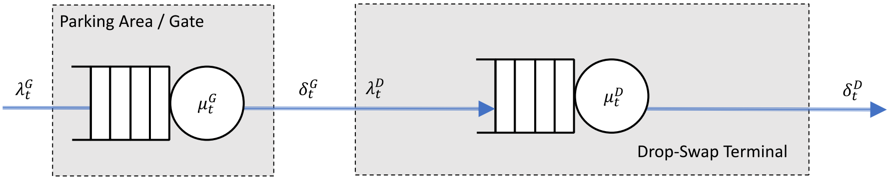


Fig. 3 The OQN at a chemical site with a DST

In this paper, we omit the detailed formulation for the queuing system at the DST to save some space. The performance can be approximated with the same approach as in the queuing system at the gate. The only difference is that the departure rate from the gate, δ_t^G, should be treated as the arrival rate to the DST, λ_t^D.

4.2 CQN

The CQN represents the internal logistics activities where a few dedicated trucks provide a shuttle service to fill empty containers in the chemical sites and drop the full containers back to the DST (see Fig. 4). In a closed network, the queuing system is relatively steady. Therefore the time-dependent performance can be estimated using a stationary approximation like in *Mean Value Analysis* (MVA) (Reiser and Lavenberg 1980). MVA is an efficient algorithm to analyze queueing networks and obtain mean values such as queue lengths, throughput, and cycle times. However, the method does not compute the joint probability distribution for queue lengths. It only gives the mean performance. Thus the variance computation is not possible using this technique. However, in most performance evaluation situations (as in our case), the mean values are the main performance metrics of interest.

Consider a CQN consisting of S manufacturing plant, numbered $s = 1, 2, \dots, S$. The number of internal trucks K represents the size of the population in the system. In MVA, the system performance is evaluated iteratively based on the population size in the system ($k = 1, 2, \dots, K$). Let us define $W_{s,t,k}^C$, and $\lambda_{s,t,k}^C$ as the cycle time and the throughput at plant s at time t with k trucks in the system. We also define $\Pi_{s.t,k}$ as the probability of waiting in plant s at time t when there are k trucks in the closed queuing system. The transportation time from the plant to the DST is denoted as τ, and the proportion of truck flows to each plant s are denoted as v_s. Thus, the MVA procedure for a nonstationary CQN with multi-servers is given as follows:

$$\Pi_{s,t,k-1} = \frac{\frac{1}{m_s^C!}\left(\frac{\lambda_{s,t,k-1}^C}{\mu_{s,t}^C}\right)^{m_s^C}}{\left(1 - \frac{\lambda_{s,t,k-1}^C}{m_s^C \mu_{s,t}^C}\right) \sum_{i=0}^{m_s^C-1} \frac{1}{i!}\left(\frac{\lambda_{s,t,k-1}^C}{\mu_{s,t}^C}\right)^i + \frac{1}{m_s^C!}\left(\frac{\lambda_{s,t,k-1}^C}{\mu_{s,t}^C}\right)^{m_s^C}} \tag{7}$$

$$W^{C}_{s,t,k} = \frac{\Pi_{s,t,k-1}}{m^{C}_{s,t}\mu^{C}_{s,t}} + \frac{1}{m^{C}_{s}\mu^{C}_{s,t}}\left(L^{C}_{s,t,k-1} - \frac{\lambda^{C}_{s,t,k-1}}{\mu^{C}_{s,t}}\right) + \frac{1}{\mu^{C}_{s,t}} + 2\tau \tag{8}$$

$$\lambda^{C}_{s,t,k} = \frac{kv_s}{\sum_{s=1}^{S} v_s W^{C}_{s,t,k}} \tag{9}$$

$$L^{C}_{s,t,k} = \lambda^{C}_{s,t,k} W^{C}_{s,t,k} \tag{10}$$

The MVA procedure starts by estimating the probability of waiting $\Pi_{s.t,k}$ at each plant when there is only one internal truck at the system, as expressed in Eqs. (7). The waiting probability measures the mean performance of the closed queuing systems, as shown in Eqs. (8)-(10). The results are then used as inputs to measure the new probability of waiting, $\Pi_{s.t,k}$, when the population size, $k=2$. The procedure continues iteratively until the population size k is equal to the number of internal trucks, K. Once the procedure is completed, it is now possible to calculate the system throughput $\lambda^{C}_{t,k}$ in the CQN as follows:

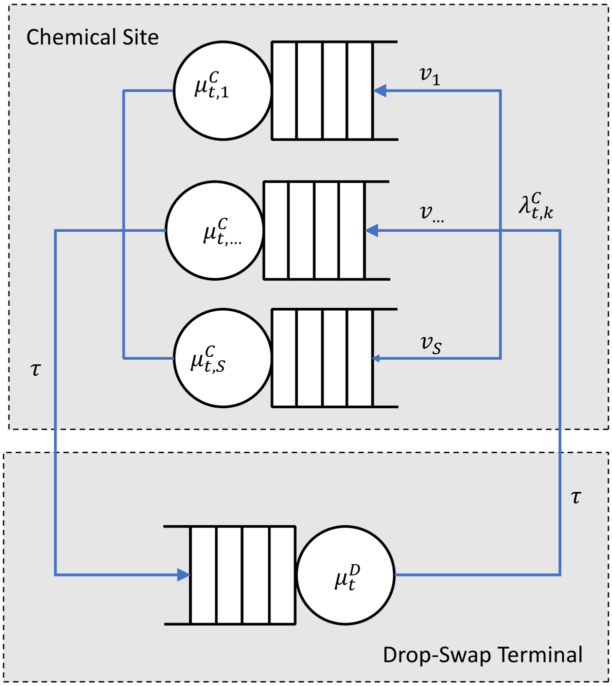


Fig. 4 The CQN at a chemical site with a DST

$$\lambda_{t,k}^{C} = \sum_{s=1}^{S} \lambda_{s,t,k}^{C} \tag{11}$$

4.3 SOQN

As discussed in Sect. 3.3, the drop-swap operation consists of two interacting queuing networks that form a SOQN (see Fig. 2). To evaluate the time-dependent performance of the network, we followed a decomposition-aggregation approach based on the work of Bruell et al. (1984). The procedure is performed by iteratively adjusting the service rate in the OQN and the CQN based on the observed utilization in the individual network. In this approach, each network is evaluated separately at the beginning. Then, for each time step t, their performance is combined to estimate the time-dependent performance of the whole system. The details of the procedure are:

- *Step 1* For a time t, estimate the server utilization ρ_t^D in the OQN based on Eq. (4).
- *Step 2* Adjust the initial service rate of each server $\mu_{s,t}^C$ in the CQN based on the server utilization ρ_t^D.

$$\hat{\mu}_{s,t}^{C} = \mu_{s,t}^{C}\left(1 - \rho_t^{D}\right) \tag{12}$$

- *Step 3* Use the adjusted service rate $\hat{\mu}_t^C$ to compute the average server utilization ρ_t^C in the CQN.

$$\rho_t^{C} = \frac{1}{S} \sum_{\mathrm{s}=1}^{S} \frac{\lambda_{s,t,k}^{C}}{m_s^{C} \hat{\mu}_{s,t}^{C}} \tag{13}$$

- *Step 4* Adjust the service rate μ_t^D in the OQN based on the server utilization ρ_t^C.

$$\hat{\mu}_t^{D} = \mu_t^{D}\left(1 - \rho_t^{C}\right) \tag{14}$$

- *Step 5* Recalculate the performance in both queuing systems based on the adjusted service rates $\hat{\mu}_{s,t}^C$, and $\hat{\mu}_t^D$.
- *Step 6* While $t < T$, repeat the procedures for the next time step, $t + 1$.

4.4 Number of internal trucks

To support the DST, the site operator dedicates a few internal to provide shuttle service between the terminal and the chemical site. Obviously, the more internal trucks being employed, the lesser the time to finish all the jobs. However, since the service capacity in the plant is limited, there should be a limit where adding one more internal truck would not increase the system throughput but lengthen the truck waiting time instead. Therefore, the optimal number of internal trucks K^* can be estimated based on the tradeoff between internal trucks and the system throughput. It is formulated as follows:

$$K^* = \arg\min_k \left[\frac{X}{\lambda_k^C} \left(k\phi_{IT} + \phi_{LO} \right) \right];\ k = 1, 2, \dots K \tag{15}$$

where X is the number of jobs scheduled, ϕ_{IT} is the operational cost of internal trucks, and ϕ_{LO} is the operational cost of loading stations. To determine the optimal number of trucks K^* in the system, we used a greedy optimization by iteratively increasing the number of trucks in the system until it cannot bring down the total cost further.

4.5 Containers/chassis requirement

The implementation of DST requires additional containers and chassis to support the operations. We assumed that the number of containers and chassis required in the operations equals the number of jobs per day (X). This number should support drop-swap operations during the regular season. The site operator may procure additional containers from a logistics service provider during the peak season to address the shortage.

4.6 Land requirement

The land requirement for a DST is measured based on the number of containers to support the operation. In the DS/C scenario, we assumed the minimum land requirement equals the number of orders multiplied by the area needed to store a container. Note that it is possible to stack up the containers to three levels with the help of a reach stacker. In the DS/W scenario, the space requirement is larger than in the DS/C scenarios because, unlike containers, chassis cannot be stacked up in levels. Thus, we assumed the DS/W scenario requires three times the area needed to store one container to ensure movement flexibility.

4.7 Performance indicators

4.7.1 Truck cycle time

The traffic congestion at chemical sites increases the truck cycle time and reduces truck productivity. The longer a truck spends time on a site, the fewer jobs it can accomplish in a day. Therefore, the truck cycle time is an important criterion to measure the efficiency of a logistics operation. The total cycle time for external trucks can be estimated by measuring the expected time for a truck to pick up a loaded container at the DST, W^D, plus the time for queuing at the gate, W^G.

4.7.2 Safety

Ensuring a safe operation is one of the primary concerns of the site operator, especially in a high-risk area such as a chemical site. Measuring the safety level of an operation is not an easy job. Safety is a complex measure that requires multifaceted analysis with multiple criteria. Our study used the average number of trucks in the chemical site as an indicator for operational safety. While it may not serve as an excellent indicator for safety measurement, it fits the queuing model properly. We assume that the higher traffic in the chemical site stimulates a higher risk of accidents. Consequently, reducing truck traffic would improve site safety. We measure the site traffic L_k^C by finding the average number of trucks at the chemical site during a period of T, as shown in Eq. (16).

$$L_k^C = \frac{1}{n}\sum_{t=0}^{T}\sum_{s=1}^{S} L_{s,t,k}^C \tag{16}$$

4.7.3 Emissions

EPA (1999) determines that an hour of an idling truck engine equals 4.46 kg of CO_2 emission. Based on this rule, the total carbon emissions per day, CO_2, can be estimated by multiplying the number of jobs, the truck cycle time, and the emission factors E_{CO2}.

$$\mathrm{CO}_2 = \mathrm{X}\left(\left[W^G + W^D\right] + \frac{1}{\lambda_k^C}\right)E_{\mathrm{CO2}} \tag{17}$$

4.7.4 Logistics cost

The logistics costs included in this study comprise seven components: the site operational cost ϕ_{LO}, the internal truck cost ϕ_{IT}, the external truck cost ϕ_{ET}, the reach stacker cost ϕ_{RT}, the container rent cost ϕ_{CN}, the chassis rent cost ϕ_{CS}, the land rent cost ϕ_{SR}. The objective is to measure the average cost to perform a single job given an operational scenario.

As previously discussed, each DST design requires a different investment. The DS/C scenarios require reach-stackers to assist the container handling in the terminal, and the DS/W scenarios require a larger terminal space to store the chassis. Hence, the average logistics cost is formulated separately. The logistics cost for the DS/C scenarios is measured based on Eq. (18), while the logistics cost for the DS/W scenarios is measured based on Eq. (19).

$$\mathrm{LC}_{\mathrm{DSC}} = \left(\left[W^G + W^D\right]\phi_{ET} + W^D\phi_{RT}\right) + \frac{\left(\phi_{LO} + \phi_{IT}\right)}{\lambda_{\mathrm{K}^*}^{\mathrm{C}}\mathrm{K}^*} + \phi_{CN} + 2\mathrm{A}\phi_{SR} \tag{18}$$

$$\mathrm{LC}_{\mathrm{DSW}} = \left(\left[W^G + W^D\right]\phi_{ET}\right) + \frac{\left(\phi_{LO} + \phi_{IT}\right)}{\lambda^{\mathrm{C}}_{\mathrm{K}^*}\mathrm{K}^*} + \left(\phi_{CN} + \phi_{CS}\right) + 3\mathrm{A}\phi_{SR} \quad (19)$$

There are four terms in the cost equations. The first term in Eqs. (18) and (19) measures the logistics cost at the DST, affected by the cycle time to pick up a loaded container at the terminal. Note that in Eq. (18), there is an additional cost for the reach-stackers. The second term measures the logistics cost at the chemical site, affected by the truck cycle time to perform internal logistics activities. The third term is the cost needed to rent additional containers/chassis to support the drop-swap operations. The last term measures the cost needed to acquire the land needed to build a DST. Note that DS/W scenarios require a larger area than DS/C scenarios because the space needed to store a chassis is larger than to store a container.

5 Numerical results and discussion

We created a numerical experiment based on a real chemical site setting in the Netherlands to evaluate the DST performances. The site has three manufacturing plants with a single access gate. The gate opens 10 h per day from 8 AM to 6 PM. Trucks arrive stochastically at the gate with a time-varying distribution, as shown in Fig. 5. A DST is planned to be constructed about one kilometer away from the chemical site to mitigate the truck congestion. It was estimated that a truck could reach the DST within five minutes from the site. Table 2 provides the parameter setting of the queuing model for the logistics operations at the chemical site. Note that the drop-swap operation can be performed on containers (DS/C) and on wheels (DS/W). Besides, the site operator can also choose to perform the internal activities during the off-peak hours (e.g., 13:00 –23:00) to avoid the traffic in the terminal.

In this study, we compared the "business as usual" (BAU) scenario, in which external trucks enter the chemical site directly to load/unload the products, against four alternative DST design scenarios, namely:

(1) DS/C-M: the drop-swap operation is performed on containers, and the internal loading activities are performed in the morning (08:00 – 18:00)
(2) DS/C-A: the drop-swap operation is performed on containers, and the internal loading activities are performed in the afternoon (13:00 – 23:00).
(3) DS/W-M: the drop-swap operation is performed on wheels, and the internal loading activities are performed in the morning (08:00 – 18:00)
(4) DS/W-A: the drop-swap operation is performed on wheels, and the internal loading activities are performed in the afternoon (13:00 – 23:00).

We evaluated the performance of all scenarios using the proposed methods in Sect. 4. The model was implemented in Visual Basic Application with Microsoft Excel version 16.48. The solver add-in in the Microsoft Excel software was used to solve Eq. (15). The results are shown and summarized in Fig. 6 and Table 3.

Figure 6 shows the time-dependent performance for all scenarios. Note that the spike of queues in the morning is caused by the truck behavior that arrives before the terminal opening hour (08:00 AM). We assume the truck arrival distribution in the model is given and cannot be controlled. The performance comparison between design scenarios is summarized in Table 3. The detailed analyses for each performance indicator are discussed in the following subsections.

5.1 Truck cycle time

Our results suggest that implementing a DST can effectively reduce the average cycle time for external trucks by 77%, from 2.34 h to 0.53 h, especially when the DST is designed under DS/W scenarios. The significant reduction in the truck cycle time is feasible since the external trucks do not need to enter the chemical site to load the containers. The containers are already preloaded and stored at the terminal. The time needed to swap containers is much shorter than loading them at a station, resulting in a shorter truck cycle time. Besides, the external trucks do not need to perform a full-length safety check-up to enter a terminal (as they do when entering a chemical site), thus saving some queuing time at the gate.

The results also show that operating a DST can effectively reduce the site operating hours up to 28%. Without a DST, the on-site logistics strictly rely on external trucks' availability to load/unload the products from the tanks. When the expected truck is not available at the designated time, the jobs will be deferred, thereby extending the site operating hour. In contrast, with a DST, the trucks are always available to perform the jobs, thereby maximizing site utilization. The numerical results suggest that a DST can increase site utilization up to 32%, creating opportunities for the operator to compress the operating hours and minimize the total cost. Alternatively, the spare time can also be utilized by inviting more jobs to increase site productivity.

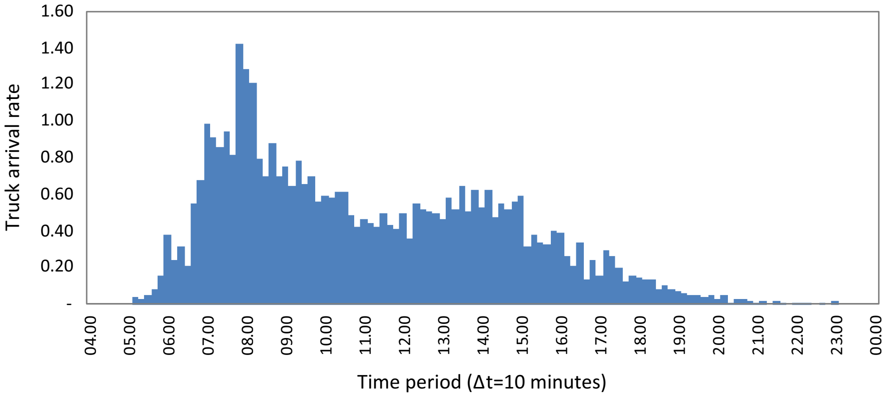


Fig. 5 Empirical truck arrival distribution at a chemical site in the Netherlands

Table 2 Parameter setting of the queuing model

Parameter	Value
Site operating hour (planned)	*Morning*: 08:00–18:00 (10 h) *Afternoon*: 13:00–23:00 (10 h)
Number of plants	3 plants
Time interval (Δt)	10 min
Chemical site gate	
Number of lanes	1 lane
Average service time	8 min
Standard deviation	3 min
Plant 1	
Number of loading stations	2 stations
Average loading time	52 min
Standard deviation	16 min
Average number of orders per day	16 orders
Plant 2	
Number of loading stations	2 stations
Average loading time	66 min
Standard deviation	21 min
Average number of orders per day	14 orders
Plant 3	
Number of loading stations	1 station
Average loading time	39 min
Standard deviation	12 min
Average number of orders per day	10 orders
Terminal gate	
Number of lanes	1 lane
Average service time	2 min
Standard deviation	2 min
Drop-swap terminal	
DST operating hour (planned)	*Morning*: 08:00–18:00 (10 h) *Afternoon*: 13:00–23:00 (10 h)
Average drop-swap time in DS/C scenarios	11 min
Standard deviation of drop-swap time in DS/C scenarios	3 min
Average drop-swap time in DS/W scenarios	6 min
The standard deviation of drop-swap time in DS/W scenarios	2 min
Average travel time to reach the DST	5 min

5.2 Safety

By operating a DST, the traffic in the chemical site can be reduced up to 36%, as indicated by the average number of vehicles in Table 3. Less traffic at the plants entails a higher safety since it creates enough space for vehicles' movement. The traffic reduction is possible since the external trucks are not allowed to enter the chemical site. Only a few trained internal trucks can enter the site and load directly from the plants, thus increasing operational safety.

From Fig. 6, we can observe that all DST scenarios effectively decrease traffic in the chemical plant. However, we should note that most of the traffic is shifted to the DST. Amongst DST scenarios, the DS/W-M gives the highest traffic at the terminal, with 9.38 vehicles on average. This outcome is expected since the scenario requires additional vehicles (i.e., reach stackers) to assist the container handling in the terminal. Therefore, the terminal operator should ensure ample space is available to ensure a safe operation. The traffic can be reduced further by shifting the internal logistics activities to the afternoon. Otherwise, one can also implement DS/W scenarios to minimize the traffic at the DST since the designs do not require reach-stackers to help with container handling.

5.3 Emissions

Figure 7 shows the cumulative emissions resulting from the operations. The result suggests that DS/C scenarios produce higher emissions than the BAU. The emissions are almost twice the emissions in the BAU scenario. Although the DS/C can effectively reduce external truck cycle time and site operating hours, it also operates more vehicles and handles more activities than other scenarios. Our model estimates that the operations require seven reach stackers in the DS/C-M scenario and four reach stackers in the DS/C-A scenario. The fewer vehicles required in the DS/C-A scenario are feasible since there is less traffic from external trucks in the afternoon. Therefore, the DST does not need a lot of handling capacity to handle both internal and external trucks in the morning.

In contrast, the DS/W scenarios generate 5–10% lower emissions than the BAU scenario. The reduction is possible since DS/W scenarios minimize the average number of vehicles in the DST and the chemical plants. It also does not require reach-stackers to assist the container handling, thus resulting in lower total emission. Our analysis suggests that the DS/W-A scenario is the greenest option to minimize total emissions. It utilizes the off-peak hours at the DST to minimize the truck idling time and reduce the number of vehicles required to support the operation.

5.4 Logistics cost

Figure 8 displays the cost structures for each design scenario. As expected, the BAU scenario emerges as the cheapest solution. Although the external truck cost is substantially higher, the BAU scenario does not require additional land and equipment costs, resulting in a lower total cost. Therefore, if costs are the primary concern of the stakeholders, a direct loading could be the best option. This result may explain why a DST is not a popular solution for many chemical sites since it is more expensive than the BAU.

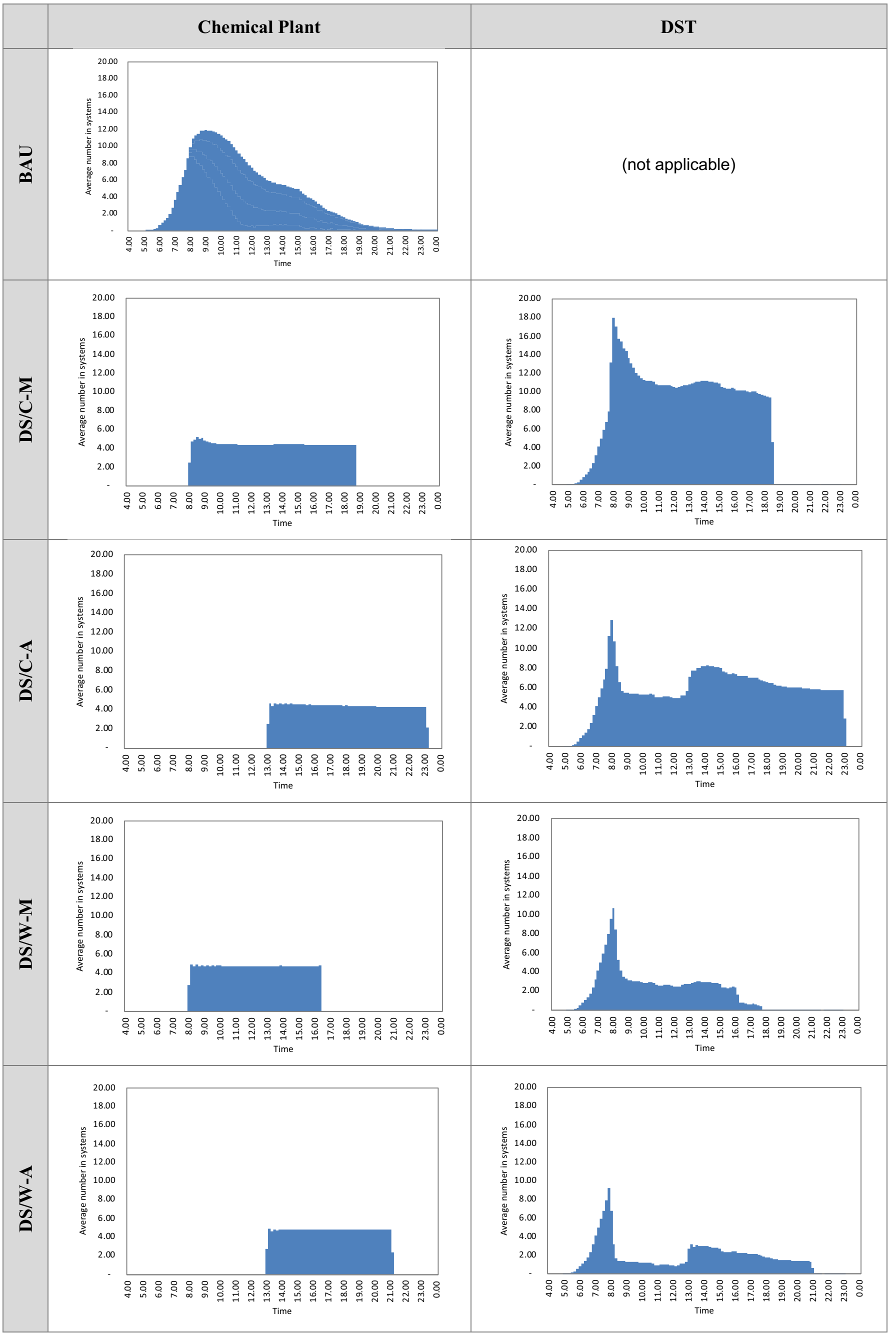


Fig. 6 The time-dependent performance of queuing systems across design concepts

Table 3 Performance comparison of BAU, DS/C, and DS/W scenarios

Performance Indicators	BAU	DS/C-M	DS/C-A	DS/W-M	DS/W-A
Chemical Plant					
Truck cycle time (hour)	2.34	2.2	2.15	1.81	1.8
Truck waiting time (hour)	1.21	0.74	0.73	0.53	0.53
Operating hours (hour)	11.5	10.67	10.17	8.33	8.17
System utilization	0.64	0.81	0.79	0.85	0.85
Average number in systems	6.77	4.44	4.31	4.75	4.69
DST					
Truck cycle time (hour)	–	0.63	0.58	0.36	0.23
Truck waiting time (hour)	–	0.33	0.28	0.2	0.01
Operating hours (hour)	–	10.67	15.16	10	13.1
System utilization	–	0.35	0.38	0.07	0.05
Average number in systems	–	9.38	4.69	3	2.02
Required Investment					
Number of Internal Trucks	–	6	6	6	6
Number of Reach-Stackers	–	7	4	0	0
Number of Containers	–	40	40	40	40
Number of Chassis	–	–	–	40	40
Land (m^2)	–	2600	2600	3900	3900
Average cost (€/job) *	238.28	368.70	349.94	263.74	259.30
Total Emissions (kg/day)	355.65	786.61	672.19	336.63	320.47

Nonetheless, if we analyze the cost structure in more detail, the operational efficiency gained from a DST also saves some costs. Our result suggests that operating a DST saves a significant amount of external truck costs. The saving in this category can even cover the internal trucking cost required to support a drop-swap operation. The saving in the site operator cost can also pay off the additional operator cost required in the DST. Thus, the main challenge to justify the DST is how to cover the costs for reach-stackers and the land. Dekker et al. (2013) proposed a subsidy of 45 euro per handling to justify the development of a CET in the case of container terminals. In our case, the subsidy required to justify a DST varies between design scenarios. Amongst the available designs, DS/W scenarios offer the closest total cost to the BAU. They require an additional 25 euro per handling or about 10% of the current BAU cost. Note that the costs in our study are based on the estimates of one chemical site. The total cost may vary from site to site, depending on its configuration.

Besides, we also found that performing internal activities during the off-peak hour (as in DS/C-A and DS/W-A) can reduce the external truck cost and the reach stacker cost. The saving comes from the reduction in the truck idling time at the DST due to the less traffic in the afternoon. As a result, the off-peak hour operation can also reduce the number of reach-stackers required in the DS/C scenarios.

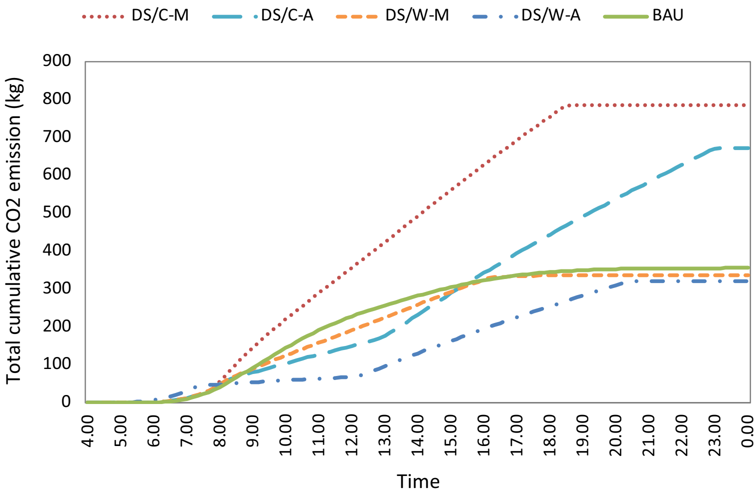


Fig. 7 Total cumulative CO2 emissions across design scenarios

5.5 The impact of truck loading time on the total cost

To further draw managerial insights from the experiments, we evaluated the impact of truck loading time on the total cost. For a fair comparison, we kept the capacity occupancy rate to 70%. The result of the analysis is displayed in Fig. 9. It shows the effect of truck loading time on total costs relative to the BAU scenario. The positive value indicates a higher cost than BAU and vice versa. Our experiment shows that the benefit of a DST is more prominent when the average truck loading time is long, e.g., 90 min or more. A longer loading time induces higher variability in the process, increasing truck congestion and

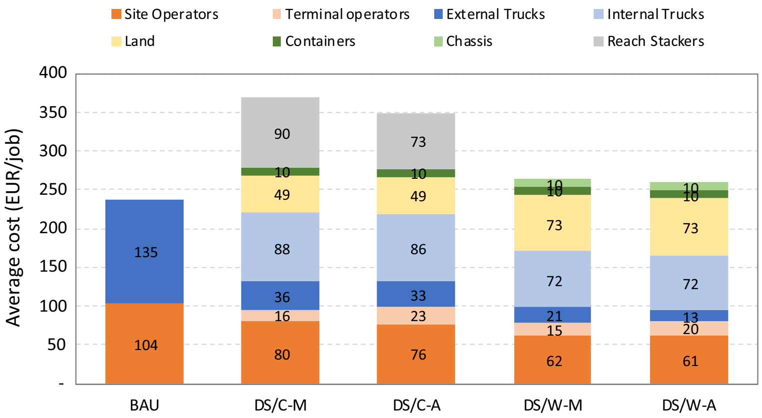


Fig. 8 The cost comparison across design scenarios

reducing capacity utilization. The availability of internal trucks in DST scenarios also helps to cope with the process variability and optimizes the site capacity. As a result, logistics efficiency rises, and the total operational cost decreases.

5.6 The impact of travel time to DST on the total cost

The impact of travel time to DST on total costs is exhibited in Fig. 10. The result shows that the longer the travel time, the higher the total cost. The trend is consistent across design scenarios. This outcome is reasonable since the cycle time of internal trucks significantly affects the site operating hours and the required amount of internal trucks. Therefore to minimize the total cost, a DST must be strategically located near the chemical plants.

5.7 Managerial implications

Our findings provide the following managerial consideration for stakeholders who wish to gain benefit from implementing a DST in a chemical site:

- Sufficient space should be available and strategically located near the chemical site. A site with abundant vacant space would benefit from implementing a DST, both in terms of cost and operational efficiency.
- Performing internal logistics activities during the off-peak hours (e.g., in the afternoon) can help to reduce the truck cycle time and the number of reach stackers needed to support the drop-swap operation.
- Swapping containers on wheels (as in the DS/W scenarios) is greener and more cost-efficient than swapping on containers. It also gives shorter process time which increases operational efficiency for internal and external logistics activities. However, swapping on wheels also requires more space to store the truck chassis and containers.
- The benefit of a DST is prominent for a plant with a long truck loading time (i.e., 90 min or more). The presence of internal trucks at the chemical site can optimize the available capacity and minimize the site operational time.
- A DST may be more suitable for a chemical site with a large transport volume and steady demand due to the high investment needed to support it. The site operator and the trucking companies should carefully plan and analyze the feasible product streams for this solution. Low transport volume and irregular demand could reduce the economies of scale of a DST and result in expensive operations.

6 Conclusions

This study analyzes the performance of a DST to mitigate truck congestion in chemical sites, which is still underrepresented in the literature. The drop-swap operation was modeled as a nonstationary SOQN with time-varying arrivals. We proposed a combination of a WB-PSFFA and decomposition-aggregation approach to estimate

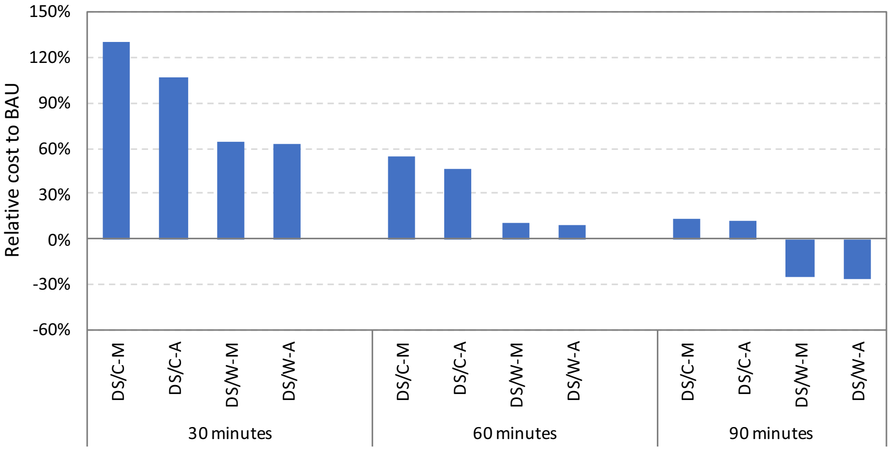


Fig. 9 The effect of truck loading time on total cost relative to the BAU scenario

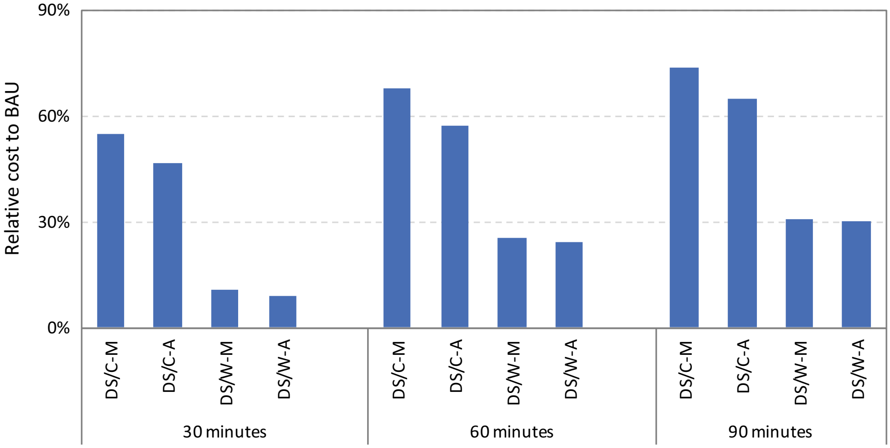


Fig. 10 The effect of travel time to a DST on the total cost

the time-dependent performance of the systems. The method provided higher accuracy than other approximations such as SBC and PSFFA (see Appendix for details). It also extends the application of fluid-flow approximation to solve a nonstationary SOQN model.

Several design scenarios were evaluated and compared. Each scenario was analyzed based on various performance indicators, i.e., truck cycle time, safety, emissions, and average logistics cost. The result suggests that implementing a DST at chemical sites can effectively mitigate the truck congestion and reduce the external truck cycle time by 77%. Although a DST may not come as the cheapest option, it also entails several benefits. The shorter cycle time provides opportunities for the trucks to perform additional jobs and improve their productivity. Besides, the DST also helps optimize site utilization, allowing for shorter site operating hours. From an environmental perspective, we also found that swapping containers on wheels (as in the DS/W scenario) produces lower emissions than the conventional operation. A DST can also improve site operational safety by mitigating 30% of truck traffic to the terminal. Based on these findings, we can conclude that the development of DST at chemical sites would benefit all the stakeholders.

Even so, the development of a DST requires a long-term investment in land and equipment. Our analysis suggests that the saving gained from implementing a DST can sufficiently cover the internal trucking cost and terminal operator cost. However, it does not have enough to cover the total costs, especially to justify the rent and reach-stacker costs. To minimize the total logistics costs, site operators can design the DST with DS/W scenarios where the containers are swapped on wheels. This scenario works best when the average loading time is long and vacant space is abundant at the site. Alternatively, the site operator and trucking companies may utilize the gained efficiency to serve more jobs and increase truck productivity. The stakeholders may also perform a joint investment to support the DST and sustain the benefits for all parties.

We also have some directions for further study. Considering that several chemical plants are usually co-located and clustered, one may extend the analysis to evaluate the benefit of a DST for a cluster of chemical sites. Such a study could provide a greater rationale for the trucking companies to grasp the benefit of a DST at the aggregate level since the total saving in freight cost would be significant. Future studies may also address the joint-investment scheme and gain sharing mechanism between the site operator and the trucking companies to fund a DST in a chemical cluster. This effort could reduce the burden of procuring the space and the required equipment to develop a DST.

This study has some potential limitations. The associated costs included in the study were based on data provided by one chemical site. Although the logistics costs amongst chemical sites are relatively comparable, in some cases, the cost structure may be significantly different due to the variation in site configuration and location.

Appendix

Model validation

This study proposed an approximation method to solve a nonstationary SOQN based on WB-PSFFA and a decomposition-aggregation approach. To validate the performance, we compare its performance against simulation results and other approximation methods, such as SBC and PSFFA. We created a simple illustrative case of a nonstationary SOQN with time-varying arrivals to mimic the drop-swap operation at a chemical site (see Fig. 11). The network consists of two queuing systems: A and B. The service time in A has a triangular distribution $T(2,4,6)$ with two interchangeable servers. The service time in B also has a triangular distribution $T(1,3,5)$ with three interchangeable servers. Both systems have an infinite queue capacity. There are two trucks classes in the system: (1) external trucks that went through the OQN and (2) internal trucks circulating over the CQN. The number of external arrivals was limited to 15, and the number of internal trucks was three. The interarrival time of external trucks was generated based on a joint distribution of two triangular distributions to create a dynamic truck arrival time, as shown in Fig. 12. The data and the parameter setting of the case are publicly available in https://doi.org/10.7910/DVN/CRM4DG.

First, we evaluated the accuracy of our methods in each type of queuing network. Then, we evaluated the accuracy of the decomposition-aggregation approach to estimate the time-dependent performance resulting from the interaction of OQN and CQN. The accuracy was measured based on two indicators: the mean absolute percentage error (MAPE) and the R-square. The result from the simulation model (50 replications) is treated as the baseline performance. We implemented the approximation methods in Visual Basic Application of Microsoft Excel version 16.48 and the simulation model in AnyLogic version 8.2 PLE. The results are summarized as the following.

Figure 13 displays the performance WB-PSFFA to estimate the time-dependent performance of the OQN under two scenarios: low and high traffic intensity. The result suggests that WB-PSFFA has the best accuracy in both scenarios, and SBC performs the worst in terms of MAPE and R-square. From the figure, we can also see that the advantage of WB-PSFFA is prominent during a higher traffic intensity. The effectiveness of MVA to estimate the transient behavior of a CQN with high accuracy is shown in Fig. 14. Note that the simulation setup caused the discrepancy at the beginning of the period. Once the system enters a steady state, the MVA can predict the mean performance accurately.

Figure 15 depicts the performance of the decomposition-aggregation approach to solve a SOQN. It shows that WB-PSFFA tends to slightly overestimate the average number of customers in queuing system B (OQN) when configured in mixed queuing networks. Conversely, the PSFFA gives a lower number than the simulation result. However, both WB-PSFFA and PSFFA can produce higher accuracy estimates when combined with the decomposition-aggregation approach than the SBC. These results validate the performance of the proposed method to estimate the nonstationary SOQN with time-varying arrivals.

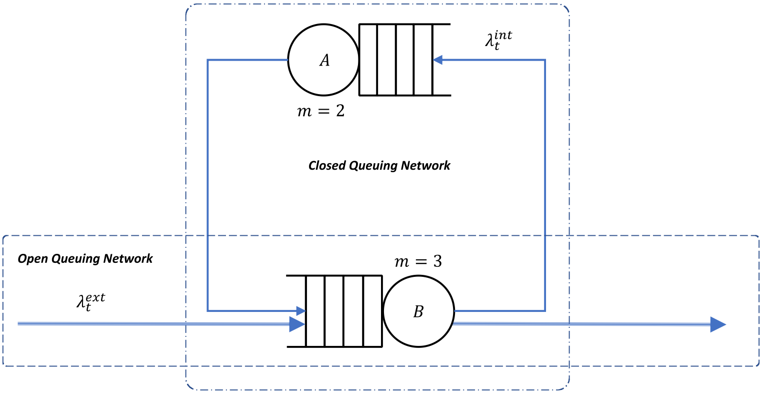


Fig. 11 The queuing system configuration for the illustrative case

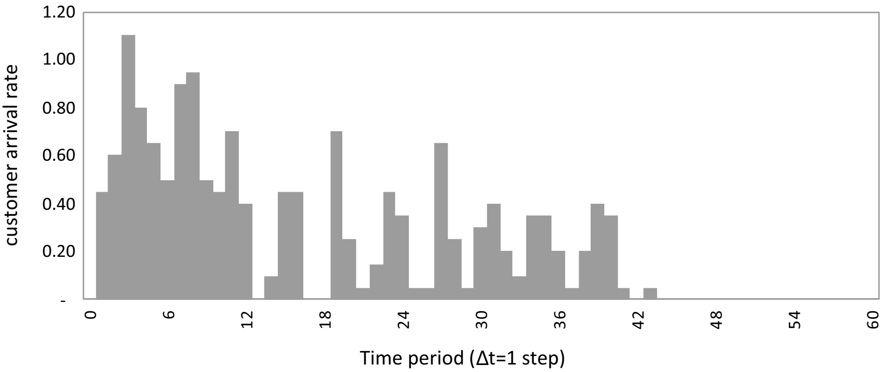
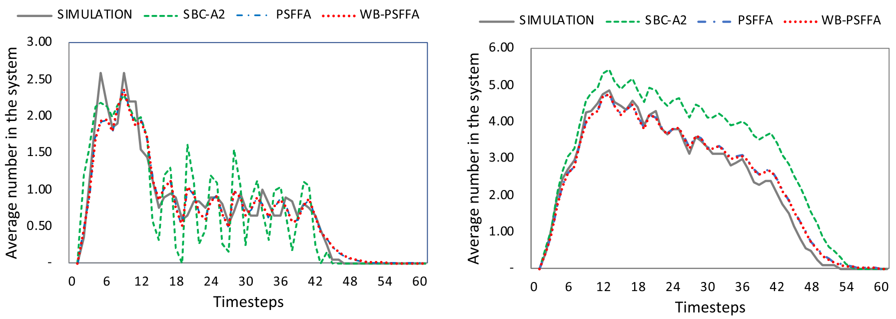


Fig. 12 Arrival distribution of external customers in the illustrative case



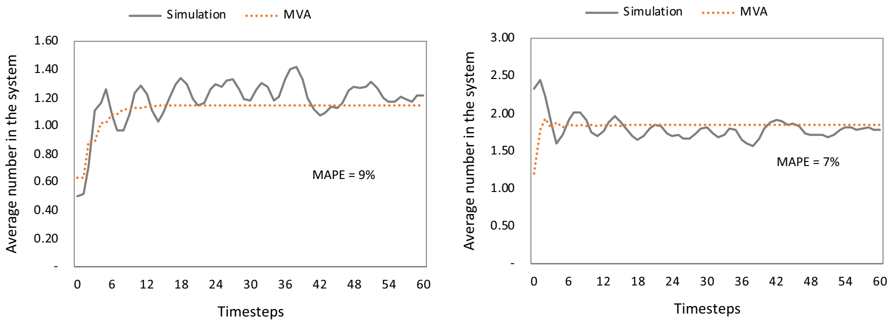
R-Square		MAPE	
SBC	88%	SBC	32%
PSFFA	97%	PSFFA	12%
WB-PSFFA	97%	WB-PSFFA	12%

(a) low traffic intensity ($\rho = 0.25$)

R-Square		MAPE	
SBC	97%	SBC	32%
PSFFA	99%	PSFFA	14%
WB-PSFFA	99%	WB-PSFFA	13%

(b) high traffic intensity ($\rho = 0.75$)

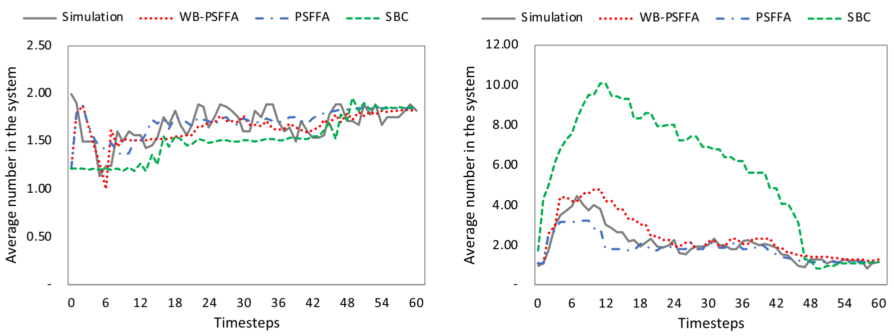
Fig. 13 Performance comparison of approximation methods to solve a nonstationary OQN



(a) Queuing system A

(b) Queuing system B

Fig. 14 Performance of MVA to solve a nonstationary CQN



R-Square	
SBC	53%
PSFFA	43%
WB-PSFFA	49%

MAPE	
SBC	11%
PSFFA	8%
WB-PSFFA	7%

(a) Queuing system A

R-Square	
SBC	76%
PSFFA	91%
WB-PSFFA	93%

MAPE	
SBC	165%
PSFFA	14%
WB-PSFFA	15%

(b) Queuing system B

Fig. 15 Performance comparison of approximation methods to solve a nonstationary SOQN

Funding This study is partially funded by the Dutch Institute of Advanced Logistics (DINALOG) as part of the 4c4chem project.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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