Joint-Optimization of a Truck Appointment System to Alleviate Queuing Problems in Chemical Plants

Citation for published version (APA):

DOI:
10.1080/00207543.2020.1756505

Document status and date:
Published: 01/06/2021

Document Version:
Accepted manuscript including changes made at the peer-review stage

Please check the document version of this publication:
• A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
• The final author version and the galley proof are versions of the publication after peer review.
• The final published version features the final layout of the paper including the volume, issue and page numbers.
Link to publication

General rights
Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognize and abide by the legal requirements associated with these rights.
• Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
• You may not further distribute the material or use it for any profit-making activity or commercial gain
• You may freely distribute the URL identifying the publication in the public portal.

If the publication is distributed under the terms of Article 25fa of the Dutch Copyright Act, indicated by the “Taverne” license above, please follow below link for the End User Agreement:
www.tue.nl/taverne

Take down policy
If you believe that this document breaches copyright please contact us at:
openaccess@tue.nl
providing details and we will investigate your claim.
Joint-Optimization of a Truck Appointment System to Alleviate Queuing Problems in Chemical Plants

Budhi S. Wibowo and Jan C. Fransoo

1Universitas Gadjah Mada, Yogyakarta, Indonesia, budhi.sholehwibowo@ugm.ac.id
2Kuehne Logistics University, Hamburg, Germany, jan.fransoo@the-klu.org

Numerous studies have proposed the use of a Truck Appointment System (TAS) to alleviate traffic congestion at logistics sites. Unfortunately, the implementation of such a system was often optimized based on the interest of a single stakeholder. Meanwhile, long truck queues have been observed in many chemical plants. This study aims to evaluate the TAS performances to mitigate traffic congestion in chemical plants from the multi-stakeholder perspective. We proposed a joint-optimization model to accommodate various interests on the site. An improved fluid-flow approximation was developed to estimate the time-dependent performance of the system. The results suggest that the benefit of TAS is mostly enjoyed by the site manager through the reduction of site overtime, while the benefits for trucking companies are found to be marginal. Through numerical experiments, we show that the proposed joint-optimization model is effective in redistributing the benefits of TAS across the stakeholders, while keeping the total logistics costs to a minimum.

Keywords — traffic congestion; logistics; non-stationary queue; chemical plant; truck appointment system.

1 Introduction

Traffic congestion has been regularly observed in various logistics sites and evidently creates severe problems. Not only does it create a perceptibly long truck queue, but also increases the freight cost and lowers the truck efficiency (Zhang, Zeng, and Yang 2019;
Lange, Schwientek, and Carlos Jahn 2017). Besides, higher traffic can also increase the risks of accidents on site (CEFIC/ECTA 2007; Zhao and Goodchild 2010) and limit the site productivity (Zhao and Goodchild 2010; Chen, Govindan, and Yang 2013). From an environmental perspective, the idling truck engines also generate dangerous pollutants such as sulfur oxide (SOx), nitrogen oxide (NOx), and particular matters (PM), which can bring serious health problems to the population nearby (Giuliano and O’Brien 2007). In the United States alone, heavy trucks were accountable for more than 20% of the greenhouse gas emission in the transportation sector (EPA 2017). Due to these problems, many related stakeholders and scholars are investing much effort in solving traffic congestion at various logistics sites.

Many studies have investigated the traffic congestion problem in the port container terminals, as summarized by Lange, Schwientek, and Carlos Jahn (2017) and Huynh, Smith, and Harder (2016). However, the study of the truck queuing problem in the chemical plant is still lacking in the literature. As at other logistics sites, long truck queues have been observed in various chemical plants too (CEFIC/ECTA 2009). Logistics sites have several distinct characteristics that make them unique, some of which as follows:

- The operations are thoroughly regulated with high safety standards and operating procedures (CEFIC/ECTA 2007). Every truck which enters the plant should pass a document checkup and conform to the safety standards.

- The plant typically opens for a short period during the day for 8 to 12 hours (CEFIC/ECTA 2002).

- The effective loading time is relatively long. It also varies significantly from 30 to 90 minutes due to the wide variant of product properties (CEFIC/ECTA 2009).
• Equipment failures often occur unpredictably during the loading process, which can trigger unexpected delays and increase the truck idling time.

Nevertheless, the traffic congestion in the chemical plants is instigated not only due to the characteristics of the site logistics, but also due to the behavior of the stakeholders in the system, i.e., trucking companies and the site manager. Since the opening hour in the chemical plant is relatively short, trucks often prefer to arrive early at the gate to avoid delays. This behavior consequently creates a morning traffic congestion at the chemical plant (CEFIC/ECTA 2002; Huynh, Smith, and Harder 2016). Meanwhile, due to the growing demand, the site manager also attempts to maximize site productivity by scheduling more jobs to the available capacity (Zhao and Goodchild 2010; Lange, Schwientek, and Carlos Jahn 2017). This behavior, intended to improve site productivity, also intensifies the traffic congestion at the chemical plant and results in a persistent queuing problem.

From the illustration, we can conclude that conflict of interests amongst the stakeholders in the chemical plant does exist. On the one hand, the site manager is expected to maximize site productivity by implementing a rigid schedule. On the other hand, the trucking company wants to minimize the truck turn-around time, which requires the site manager to be more flexible. Moreover, there are also social planners, such as the government, with their agenda to reduce the emissions from the idling trucks, since they can bring health problems to the citizens nearby.

Due to the very nature of the problem, it is difficult to address the issue solely from a single stakeholder perspective. The multi-stakeholder analysis is required to avoid a single solution that can benefit only specific stakeholders, while harming others. Previous studies on the truck queuing problem focused mainly on a single stakeholder perspective, either from the trucking company or the site manager (Lange, Schwientek,
and Carlos Jahn 2017). Our study aims to find the optimal TAS configurations at chemical plants from the multi-stakeholder perspective. The study brings a broader evaluation of the TAS by considering multiple interests in the logistics operation, as well as their trade-off and limitations.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature on the truck queuing problems and the available methods to analyze such a problem. The characterization of the logistics process at chemical plants is provided in Section 3. Section 4 describes a joint-optimization model and the method to estimate the model performance. The model verification is given in Section 5. In Section 6, we present a case study based on a chemical plant in the Netherlands, to estimate the performance of the proposed solution. Lastly, the conclusions of the study are given in Section 7.

2 Literature Review

2.1 Truck Congestion Problem

Truck congestion is a problem commonly found in many logistics sites. Numerous studies have attempted to reduce the truck waiting time by promoting a collaborative job scheduling (Phan and Kim 2016; Azab, Karam, and Eltawil 2019), off-peak operations (Bentolila et al. 2016), and the implementation of TAS (Zhang, Zeng, and Yang 2019; Torkjazi, Huynh, and Shiri 2018; Zehendner and Feillet 2014).

Amongst these alternatives, TAS is the solution that garnered the most attention from scholars, partly because its implementation has been widely adopted in many container terminals since the early 2000’s. Consequently, several variants of TAS have been proposed as alternatives to alleviate traffic congestion at logistics sites. For
instance, Guan and Liu (2009) evaluated the gate congestion problem in container terminals by using a multi-server queueing model, which showed that by controlling the interval of truck arrivals, the terminal authority could significantly reduce the average truck waiting time in the terminal. Zehendner and Feillet (2014) developed a mixed-integer linear programming model to determine the optimal number of quotas in the TAS. They suggested that providing more quotas in the less-busy or non-peak hours could significantly reduce truck congestion. Azab, Karam, and Eltawil (2019) developed a simulation-based optimization model to minimize the truck turn time based on a dynamic-collaborative TAS. They argued that the truck congestion problem at container terminals could be mitigated by continuously adjusting the schedule based on the recent condition.

However, despite the asserted benefits, the empirical study from Giuliano and O’Brien (2007) at the Port of Los Angeles and Long Beach came to a different conclusion. Their study implied that the implementation of TAS had no significant impact on reducing the truck waiting time and air pollution in container terminals. Huynh, Smith, and Harder (2016) also conducted an empirical study on TAS performance in four container terminals and found the terminal's inability to fulfill on-time appointments in the afternoon as one of the main reasons for the poor performance. The delayed appointments create inconveniences for the trucking companies in improving their productivity, which makes them less motivated to follow the appointed schedule.

Thus, in order to design a successful TAS implementation, it is necessary to develop a model that accommodates multi-stakeholder interests in the system. Many existing studies related to TAS focused only on the perspective of terminal authority and less on the trucking companies (Lange, Schwientek, and Carlos Jahn 2017; Azab,
Karam, and Eltawil 2019). This study contributes to the literature through the elaboration of multi-stakeholder considerations in the design of TAS at chemical plants.

2.2 Queuing Model for Site Logistics Operations

Recently, queuing models have gained interest among researchers as a tool to analyze logistics operations at various sites. Due to the nature of the problem, the on-site logistics operation is often modeled as a non-stationary queue, with time-varying arrivals. Many studies have proposed the use of approximation methods as a tool for analyzing the queuing problem at logistics sites (e.g., Zhang, Zeng, and Yang 2019; Selinka, Franz, and Stolletz 2016; Chen, Govindan, and Yang 2013). Compared to the simulation method and the exact approaches, approximation methods are typically simpler, more computationally efficient, and do not require a large number of repetitions.

Green and Kolesar (1991) pioneered the work of estimating the performance of a non-stationary queuing system, by proposing a "pointwise stationary approximation" (PSA). PSA divides a timeframe of interest into small-time intervals and uses a stationary queuing model to approximate the transient behavior in each time interval. Wang et al. (1996) later extended the PSA method by proposing a "pointwise stationary fluid flow approximation" (PSFFA). It combines the PSA method with a fluid-based approximation, which successfully improves the model accuracy, even though its precision deteriorates when the traffic intensity is closer to 1. Stolletz (2008) proposed a new approach to solve the non-stationary queuing model, by using a "stationary backlog carryover" (SBC). Unlike PSA, SBC was shown to perform well during a critical traffic intensity. However, the method was ineffective in estimating the queuing performance, when the traffic intensity temporarily went beyond 1.
To address the problem, Chen, Govindan, and Yang (2013) further enhanced PSFFA by introducing the B-PSFFA method. They relaxed the requirement of invertible formulae in PSFFA, by using a bisection method to achieve higher accuracy during an overload situation. However, despite the improved accuracy, their method also created a notable performance discrepancy, when a different arrival distribution was used. To address this problem, they introduced an additional correction factor $\gamma$ to improve the accuracy of the B-PSFFA method, which too could be problematic, as it should be fine-tuned every time a different distribution model is used.

Our study provides a methodological contribution by tackling the limitation of the B-PSFFA method, so that it can be used without a correction factor. The new method can be employed as a tool to evaluate the performance of a time-dependent multi-server queuing system with general distribution, which is commonly found in the logistics site operations.

3 System Characterization

3.1 Logistics Operations at a Chemical Plant

The logistics site in a chemical plant typically consists of two main areas: parking area and plant area (see Fig.1). The parking area is located outside the plant, which is used as a place to park the trucks before entering the plant area, which has one entrance gate with multiple lanes leading to several non-identical loading stations. These two areas can be treated as a series of two queuing systems representing the operations in the parking area and the plant area.

[Fig.1 near here]
In the parking area, the trucks arrive stochastically at their preferred time. The entrance gate controls whether a truck is allowed to enter the loading station area according to a pre-determined schedule. The waiting space in front of the gate is assumed to be ample for accommodating an all-day queue. This assumption is based on the behavior of the truck that would wait on the roadside when there is no more space in the parking area. Thus, even though the actual parking area may be limited in size, the queuing space is theoretically infinite. In the case of no-show, the available trucks in the parking area are permitted to fill in the available slots on a first-come-first-served (FCFS) basis. Based on the characteristics mentioned above, we modeled the queuing system at the gate as a $G_t/G/m$ queue.

After finishing the physical checkup and paperwork at the gate, the truck proceeds to a corresponding loading station within the plant area. Usually, there are several loading stations in the plant area, each serving only certain product types. Therefore, the services between loading stations are not interchangeable. When the intended loading station is occupied, the truck should wait in a queue until the loading station becomes available to serve. We assumed that the waiting space within the plant is ample, and the number of servers in each loading station does not vary over time. Thus, the queuing system in the loading station could be modeled as a $G_t/G/m$ queue. The list of parameters, notations, and decision variables in the model are provided in Table 1.

[Table 1 near here]
3.2 TAS

TAS is a system that aims to smooth out the arrivals of trucks by requiring trucking companies to make appointments before the actual arrivals. Based on support from a logistics service provider, we collected historical data of truck performance from 52 chemical plants in Western Europe. The data shows that there was no significant performance difference between the plants that implemented TAS and the plants that did not (Fig. 2). In both the systems, the truck waiting time was found to be around 1.20 hours on average. We also observed that there is a similar pattern in the truck arrival distribution between the two systems, as shown in Fig. 3. An early morning peak is observed in both systems, regardless of whether or not AS has been implemented. This morning peak instantaneously creates a long truck queue at the gate, which subsequently affects the total truck turn time.

[Fig. 2 near here]

[Fig. 3 near here]

This evidence suggests that the existing TAS implementation is not entirely effective at smoothing out truck arrivals and alleviating the congestion in the chemical plants. As shown in Fig. 3, the trucks tend to arrive early and wait before the gate, regardless of the appointments. This is because the trucking companies are aware that the success of afternoon appointments largely depends on whether the schedule in the morning has been adhered to (Huynh, Smith, and Harder 2016). Thus, arriving in the morning is a response from the trucks to minimize the risk of getting delayed or being transferred to the next day. These concerns dissuade trucking companies from arriving
on-time according to the appointed schedule (Azab, Karam, and Eltawil 2019). As a result, the truck arrival behavior is more appropriate to be modeled based on its historical arrival pattern, as suggested by Chen et al. (2013). This modeling approach allows researchers to consider the additional waiting time resulting from the difference between the actual truck arrival time and the appointed time from TAS.

### 3.3 Stakeholders’ Interest

Our study considers three stakeholders in the problem, namely the trucking company, the site manager, and the social planner. Each stakeholder is assumed to be rational and serve as an independent agent that aims to maximize their gain. The individual interest of each stakeholder is discussed in the following subsections.

#### 3.3.1 Trucking Company

Truck productivity is determined by the average number of trips accomplished per day (Huynh, Smith, and Harder 2016; Lange, Schwientek, and Carlos Jahn 2017). The more time a truck spends on a site, the fewer trips it can achieve during the day. Consequently, the existence of traffic congestion in the chemical plant would substantially lengthen the truck turn time and reduce truck productivity. Based on this consideration, we modeled the interest of the trucking company as the minimization of the total truck waiting time to improve truck productivity.

The total truck waiting time on site can be divided into two components: the waiting time at the station $W_q^S$ and the waiting time at the gate $W_q^G$. The waiting time at the station $W_q^S$ results from the non-availability of capacity at the loading stations, while the waiting time at the gate $W_q^G$ results from the difference between the truck arrival time at the gate and the actual entrance time to the plant. The measurement of
$W_q^G$ is based on the consideration that the trucks often arrive at their preferred time regardless of the appointments. Therefore, based on the measures above, the interest of the trucking company can be formulated as follow:

$$Z_L = \text{minimize} \left( D \left[ W_q^G + \frac{1}{k} \sum_{j=1}^{k} W_{q_j}^{S} \right] \phi_d \right) \quad (1)$$

where $Z_L$ is the objective function of the trucking company; $W_q^G$ is the average truck waiting time at the gate, and $W_{q_j}^{S}$ is the average truck waiting time at station $j$. We defined $\phi_d$ as the cost of the truck waiting time per hour, which is based on the driver cost and truck utility.

### 3.3.2 Site manager

The site manager typically has two objectives: maximizing the site productivity (Zhao and Goodchild 2010; Sharif, Huynh, and Vidal 2011) and maintaining the operational safety of the plant (CEFIC/ECTA 2007). To maximize the site productivity, the site manager would fit more jobs during the hours the site is open, without doing overtime. The unfinished jobs at the end of the day will mean extra work for the logistics operators. Let us define the site overtime cost $OC$ as the total cost to perform additional work beyond the site opening hours. The overtime cost can be calculated as follows:

$$OC = \phi_o \left[ m^G + \sum_{j=1}^{k} m_j^S \right] T_{ov} \quad (2)$$

where $m^G$ is defined as the number of available servers at the gate and $m_j^S$ as the number of identical servers available at the loading stations. We also defined $\phi_o$ as the site operational cost and $T_{ov}$ as the expected overtime duration.
Further, the site manager is also required to maintain operational safety within the plant. High truck traffic increases the risks of accidents, which could endanger the population nearby. The manager can reduce the risks by minimizing the truck traffic in the plant to ensure movement flexibility. Since it is not easy to directly measure the cost of safety, we used the expected number of trucks within the plant and the associated space rental cost as proxies. The space rental cost $SC$ is defined as the cost of providing the required space to accommodate the maximum number of trucks within the plant area. The cost can be calculated as follows:

$$SC = \phi_p \left[ \max \left\{ \sum_{j=1}^{k} L_{j(t)}^S ; \ t = 1, ..., n \right\} \right]$$

(3)

where $\phi_p$ is the space rental cost per truck per day, and $L_{j(t)}^S$ is the total number of trucks in station $j$ in period $t$. Based on these two costs, we modeled the objectives of the site manager $Z_S$ as a desire to minimize the expected overtime cost $OC$ and space rental cost $SC$, as shown in Equation (4).

$$Z_S = \minimize (OC + SC)$$

(4)

3.3.3 Social Planner

The idling trucks in the chemical plant produce dangerous pollutants that can harm the environment. Social planners are responsible for alleviating such externality. Thus, their objective is to minimize the total emission resulting from the logistics operations (Giuliano and O’Brien 2007; Li et al. 2018). The emissions from the idling trucks can be estimated by multiplying the truck waiting time with the engine idling emission factors $E_{CO2}$ as proposed in EPA (1999). EPA also determined that an hour of truck idling time is considered to be equal to 4.46 kg of CO$_2$ emissions. Based on that, the objective of the social planner is represented as follows:
\[ Z_E = \text{minimize} \left( D \left[ W_q^G \times \frac{1}{k} \sum_{j=1}^{k} W_q^S \right] \times E_{CO2} \right)_{CO2} \] (5)

4 Methods

In this study, we first investigated the logistics performance when the TAS is optimized based solely on a single stakeholder perspective. The result was then compared to the logistics performance that considered multi-stakeholder perspectives through a joint-optimization model. The extent of levels explored in the research framework is depicted in Fig. 4, and the details of the methods are provided in the following subsections.

[Fig. 4 near here]

4.1 Performance Approximation

We modeled the site logistics operations at the chemical plant as a series of non-stationary queueing systems with time-varying arrivals. In order to approximate the performance of the queueing systems, we proposed a new method, namely WB-PSFFA. WB-PSFFA is an extension of B-PSFFA (Chen, Govindan, and Yang 2013). The method provides an approximation to the transient behavior of a non-stationary queueing system with better accuracy, by estimating the queuing performance at each time step through a combination of a fluid flow principle and stationary approximation method from Whitt (1993).

Consider an open queuing network with a stochastic arrival process. WB-PSFFA divides a period of \( T \) into \( n \) number of small intervals \( t \). Based on the fluid flow
conservation principle, the rate of change in the number of trucks in the system $L_t$ should be equal to the difference between the average arrival rates $\lambda_t$ and the average departure rates $v_t$. The fluid approximation for a non-stationary queuing model can be as follows:

$$\frac{\partial L}{\partial t} = \lambda_t - v_t$$  \hspace{1cm} (6)

$$v_t = m_t \mu_t \rho_t$$  \hspace{1cm} (7)

$$L_{t+1} = L_t + \lambda_t - v_t$$  \hspace{1cm} (8)

Equation (6) is the fluid flow balance function of the queuing model. Equation (7) is the exit flow function for departure rate $v_t$, and Equation (8) is the transition rule to update the state of analysis to the subsequent time interval of interest. The illustration of a fluid-flow approximation for a queuing system is given in Fig. 5. It shows the flow conservation principle between the arrival rate $\lambda$, the average number of customers $L$, and the departure rate $v$ in the system at time $t$.

[Fig. 5 near here]

To determine the number of trucks $L_t$, the original B-PSFFA method adopted Cosmetatos’s approximation (Cosmetatos 1976), which assumes a Markovian arrival in a stationary queue. This approach has some limitations, since it requires a correction factor $\gamma$ to improve its accuracy performance. The setting of parameter $\gamma$ could be tricky, since it should be fine-tuned case by case. To avoid the use of a correction factor, WB-PSFFA enhanced the original B-PSFFA method by replacing Cosmetato’s approximation with Whitt’s approximation (Whitt 1993), as shown in Equation (9). Whitt’s approximation assumes a general interarrival time distribution, which provides more flexibility for researchers to consider various distributions in the arrival process.
\[ L_t = \left[ \frac{(1 + c_e^2)(c_a^2 + \rho^2 c_e^2)}{2(1 + \rho^2 c_e^2)} \right] \left[ \frac{\rho^2 \sqrt{m(t+1)}}{m_t(1 - \rho_t)} \right] + m_t \rho_t \]  

(9)

To derive the utilization rate \( \rho_t \) from Equation (9), one can use a numerical approach, such as the bisection method based on the fluid flow principle introduced in Equation (6). Then, the average truck time spent on-site \( W \) and the average truck waiting time \( W_q \) can be estimated based on Little’s Law as given in Equation (10) and (11).

\[ W = \frac{1}{n} \sum_{t=0}^{n} \frac{L_t}{m_t \mu_t \rho_t} \]  

(10)

\[ W_q = \frac{1}{n} \sum_{t=0}^{n} \left( \frac{L_t}{m_t \mu_t \rho_t} - \frac{1}{\mu_t} \right) \]  

(11)

4.2 Joint-Optimization Model

To consider the interests of various stakeholders, we developed a joint-optimization model. In this model, the stakeholder’s interests were translated into a single cost function, as shown in Equation (12). The objective is to minimize the total associated cost in the system with respect to the available constraints. The joint-optimization model for the problem is formulated as follows:

**Objective function:**

\[ \text{minimize } Z_L + Z_S + Z_E \]  

(12)

**Decision Variable:**

\[ x_t^g = \begin{cases} 1, & \text{if the gate is open at time } t \\ 0, & \text{if the gate is closed at time } t \end{cases} \]  

(13)
Subject to:

\[ \sum_{t=1}^{n} \lambda_t^G = \sum_{j=1}^{k} \sum_{t=1}^{n} v_j^S(t) \]  
(14)

\[ 0 < D < \sum_{j=1}^{k} T \mu_j^S, \quad D \in integer \]  
(15)

\[ x_t^G \geq 0, \in integer, \forall t \]  
(16)

Equation (13) is the decision variable that determines whether the gate is open or not at a specific time step. If the gate is open, the available trucks are permitted to enter the plant area, and if the gate is closed, the trucks are expected to wait in the parking area.

Equation (14) is the flow conservation equation which guarantees that all the trucks that enter a chemical plant will exit the plant. Equation (15) ensures that the number of scheduled orders should not exceed the theoretical capacity of the loading stations; otherwise, there will be infinite queues at the end of the day.

The optimization model was implemented in Visual Basic Application (VBA) and solved by using the COIN-OR Bonmin solver through the Open Solver application. The solver is capable of providing a high-quality solution for a mixed-integer non-linear problem within a reasonable time.

5 Verification of the Proposed Method

A simulation was carried out to verify the performance of WB-PSFFA. The result of the simulation was compared to other methods such as SBC and B-PSFFA. We conducted the comparison under two settings, labeled as Case 1 and Case 2. Each method was evaluated based on Rooted Mean Squared Error (RMSE) and \(R^2\) measures.
In Case 1, we set all customers to arrive simultaneously at the gate. This setting was intended to evaluate the performance of a queuing system within a high overloading situation. In Case 2, we set the customers to arrive at the gate with a deterministic inter-arrival time, mimicking the ideal situation of TAS. The performance comparison between the methods is depicted in Fig. 6, and their accuracy performance is summarized in Table 2.

The result in Table 2 shows that WB-PSFFA delivers a high level of accuracy in both cases. In Case 1, WB-PSFFA accurately estimates the transient behavior of a highly-overloaded queue with RMSE of 0.54, leaving SBC with the worst performance. We also found that when the queuing system is highly overloaded, SBC tends to underestimate the queuing performance. In Case 2, both WB-PSFFA and SBC performed very well with $R^2$ of 0.97, whereas B-PSFFA failed to provide an accurate estimation. It is to be noted that the B-PSFFA is implemented without a correction factor. This result verifies that the proposed WB-PSFFA method has successfully improved the accuracy of B-PSFFA without having to use a correction factor.

6 Numerical Experiments

This study used the setting of a chemical plant in Western Europe as an example for numerical experiments. The chemical plant has a single entrance gate with two loading stations inside the plant area. Each loading station serves a different type of product;
hence, their services are not interchangeable. The site operates for 10 hours per day, and the gate is open from 8 AM to 4 PM. The observed truck arrival pattern at the chemical plant is shown in Fig 7. The figure is summarized based on truck performance at the plant for one month. The plant has not implemented the TAS. Thus, after running through a safety check-up, a truck may directly enter the plant area and drive to the intended station. The configuration of the queuing systems in the site logistics operations is summarized in Table 3.

We considered the existing process in the chemical plant as the base scenario. By using the WB-PSFFA method, we estimated the average truck turn time in the plant to be 2.71 hours, while the actual truck turn time in the site was found to be 2.80 hours on average. Since we did not consider the transportation time inside the chemical plant, the 0.09 hours difference between the actual and the approximation could be ignored. This tiny performance discrepancy suggests that the proposed method can deliver an accurate approximation of the performance of a non-stationary queuing system in the chemical plant.

Table 4 provides more details about the results. It shows that the expected site overtime in the base scenario is 1.87 hours per day, and the CO₂ emissions are about 7.64 kg per truck. The model also estimated that the total logistics cost for the base scenario is 857.42 per day. It is noteworthy that the associated costs included in the model were based on real estimates provided by the site manager and a trucking
company in the chemical plant, while the emission cost was based on the CE Delft report (Maibach et al. 2008).

6.1 Scenario Analysis

We developed four scenarios to analyze the impact of stakeholder's interest on TAS performance. Scenario 1 was developed based on the trucking company’s interest, while Scenario 2 and Scenario 3 were developed based on the interests of the site manager and the social planner, respectively. Scenario 4 presents the situation when TAS is optimized through a joint-optimization. The result for each scenario is summarized in Table 4, while the estimated total costs are shown in Fig. 8.

The result suggests that the implementation of TAS can significantly improve the site logistics performance in the chemical plant. Through the experiments, we showed that TAS was capable of reducing the truck waiting time by 54% and cutting the site overtime duration by 82%. TAS also has the potential to reduce the truck queue by 34% and cut the CO2 emissions resulting from the idling trucks by 54%.

From Fig. 8, we also evaluated that the cost discrepancy between the scenarios is relatively small. Even though the cost performances across Scenarios 1–4 are relatively similar, the single-stakeholder optimizations seem to favor the interest of the corresponding stakeholder, as shown in Table 4. For example, the optimal solution in Scenario 2 successfully minimizes the site's overtime duration. However, the reduction comes in exchange for a longer truck turn time and higher CO2 emissions. Similar tradeoffs were also found in Scenario 1 and 3.
Further, we also found that the optimal solution in Scenario 4 provides a more balanced performance across all the key indicators. The solution also gives a minimum cost, even though the total is not substantially lower compared to other scenarios. It is to be noted that Scenario 4 was developed under a joint-optimization model that considers interests of the various stakeholders. From this result, we concluded that the main advantage of a joint-optimization is not to achieve a higher cost-saving, but to redistribute the benefits of TAS across the various stakeholders in the system.

Fig. 8 depicts the expected total cost of each scenario. The figure shows that the benefit of TAS is gained mainly from the cost reduction from the truck waiting time and the site overtime. Therefore, the implementation of TAS could be beneficial to both trucking companies and the site manager. However, one should note that the cost-saving from the truck waiting time is shared across a number of trucking companies. As a result, each truck achieves a saving of only one hour on average from the TAS implementation. With only one hour spared, it would be tough for the truck to take additional jobs in the day. This is why the empirical data in Fig. 2 suggest that TAS is not entirely effective in alleviating the truck queuing problem at the chemical plant. The benefit gained is thus insignificant and not enough to change the behavior of the trucking companies. Consequently, the trucking companies tend to disregard the time allotted by the site manager and prefer to arrive at their preferred time. Therefore, the benefit of TAS is enjoyed mostly by the site manager due to the significant reduction in overtime, while the benefit for the trucking companies depends on their capability to utilize the spare time.
Further, the cost comparison in Fig. 8 also suggests that the saving from the emission cost is almost negligible, compared to the saving from other costs. Therefore, it would be difficult for social planners to influence the behavior of other stakeholders, if they use emissions as the sole justification. This result indicates that the roles of the site manager and the trucking companies are still dominant in the chemical plant.

The time-dependent performance resulting from each scenario is exhibited in Fig. 9. The figure shows that each scenario returns a distinct optimal solution. In Scenario 1 (the trucking company's perspective), the optimal solution is to align the time window’s duration in TAS to be at least the same length as the service time (see Fig. 9b). This solution minimizes the expected truck waiting time in the site by allowing the truck available at the gate to enter the plant, just as the loading process of the preceding truck is finished. Nonetheless, one should note that this solution also induces a longer truck queue at the gate, since many of the trucks prefer to arrive early in the morning.

In Scenario 2 (the site manager's perspective), the optimal solution is to provide more time-slots in the schedule by making the duration for each slot shorter than the average loading time (see Fig. 9c). This solution is in line with the interest of the site manager, which is to maximize the utilization of the site capacity without doing overtime. A shorter time slot will allow the available trucks at the gate to immediately enter the plant area, even before the preceding truck finishes the loading process. Despite the risk of creating a longer truck queue within the plant, this strategy also captures the opportunity when the actual loading time in the station is shorter than
expected. As a result, the available truck can be served immediately, once the loading station is free. This solution provides the site with better capacity utilization and less site overtime. However, it also potentially increases the risk of accidents, since it induces higher traffic within the plant. This result is driven by the fact that under the existing cost structure, the site operational cost $\phi_o$ is notably higher than space rental cost $\phi_p$. Thus, the optimization tends to compromise the space rental cost in exchange for a greater saving from the overtime cost.

Scenario 3 (the social planner's perspective) provides an optimal solution similar to Scenario 1 (see Fig. 9d). These identical solutions arise because of the mutual interest of the trucking company and the social planner. Both stakeholders basically aim to reduce the truck idling time in the chemical plant. For the social planner, the reduction of the truck waiting time can mitigate the pollution generated from the idling engine. As for the trucking companies, the reduction of the truck waiting time can improve truck time performance and truck productivity. Consequently, a similar optimal solution emerges from these two scenarios.

A distinct optimal solution can be found in Scenario 4, where a joint-optimization model is employed to consider the various interests in the system. In Scenario 4, the optimal solution is to offer the trucking companies fewer time slots during the busy period and more slots during the less-busy period (see Fig. 9e). Despite creating a slightly longer queue at the gate in the morning, it reduces the average waiting time in the afternoon and minimizes the site overtime. Consequently, it minimizes the total cost associated with the operations, benefiting all the stakeholders in the system. A similar solution was suggested by Zehendner and Feillet (2014), who aimed at determining the optimal number of appointments based on the overall workload and the available handling capacity of container terminals. The result
encourages the site manager to offer fewer quotas in the morning and more in the afternoon.

The effectiveness of the solution in Scenario 4 arises from the fact that it copes with the unexpected delays from the morning appointments, so that the impact would not spread to the appointments in the afternoon. This strategy helps to mitigate some inconveniences for the trucking companies resulting from the implementation of TAS. The improvement would also encourage the trucking companies to arrive at the site according to the appointed time, as scheduled by the TAS.

6.2 Sensitivity Analysis

Due to the growing demand from customers, high traffic is often unavoidable in several chemical plants. Thus, to evaluate the robustness of the proposed solutions, we investigated their performance across various levels of traffic intensity. Fig. 10 demonstrates the effect of traffic intensity on logistics performance. We omitted Scenario 3 in Fig. 10, since the result has shown the same behavior as in Scenario 1, for the same reason as discussed in the previous subsection.

As expected, traffic intensity provides negative impacts on all logistics performance indicators. Higher traffic not only raises the truck turn time, but also increases the total emissions and the site overtime. The implementation of TAS could help to moderate the impact of traffic, and without it, the truck idling time and the site overtime would rise exponentially as the traffic increases. This impact is especially experienced when the traffic intensity increases beyond 50%. TAS also benefits all the
stakeholders in the chemical plant by keeping the total logistics cost low, especially when the site traffic is below 80%.

### 7 Conclusions

Many previous studies on TAS addressed the truck queuing problem only from a single stakeholder perspective. Our research contributes to the literature by providing a multi-stakeholder approach to the problem through a joint-optimization model. This study investigates the benefits of TAS implementation in the chemical plant setting, which is still under-represented in the literature. To evaluate the performance of TAS, we also proposed a new approximation method, namely WB-PSFFA that provides better and more accurate performance compared to B-PSFFA and SBC methods.

The findings from the study confirm the potential benefits of TAS to mitigate truck congestion in the chemical plants. Even in the single stakeholder scenarios, TAS was found to be effective in reducing the truck turn time, decreasing the site overtime, and mitigating the related emissions from idling engines. However, we also found that the benefit of TAS was enjoyed mostly by the site manager from the reduction of site overtime, whereas the benefit for the trucking companies was found to be insignificant. Therefore, the implementation of TAS might not directly change the trucks’ arrival behavior at the chemical plant, since the incentive for the trucking companies is trivial.

The proposed joint-optimization scenario was found to be effective in redistributing the benefits across the stakeholders. Under the joint-optimization scenario, the optimal solution was to offer more time slots during the less busy period, and fewer time slots during the busy period. Even though the solution did not lead to significant cost savings, it helped to mitigate unexpected delays in the afternoon due to the deferred workload from the morning appointments. This quality can help to
motivate the trucking companies to change their behavior and encourage them to arrive at the appointed time.

Nonetheless, in order to perform a joint-optimization in practice, the trucking companies and the site manager are expected to share the costs related to the site logistics operations. Information such as truck arrival pattern and the actual service time plays a vital role in determining the optimal strategy for reducing the traffic congestion. Thus, a stronger collaboration between trucking companies and the site manager is expected to maximize the benefits of TAS across the stakeholders.

Further, the results from the sensitivity analysis also bring some managerial implications to the stakeholders in the chemical plant. The analysis suggests that the site manager is expected to maintain the site traffic between 50% and 80% to enjoy the benefit of TAS. If the site traffic is lower than 50%, TAS might not bring many benefits, compared to the effort required to implement such a system.

This study has some potential limitations. First, the analysis was conducted based on the cost structure shared by a chemical plant and a trucking company. Even though the costs in logistics operations are arguably comparable, there might be some cases with a different cost structure. For instance, if the plant was located near an urban area, the parking rent might be significantly higher than that included in the study. The dissimilarity in cost structure can affect the optimization of the proposed solution. Second, this study evaluated the performance of TAS based on a non-stationary queuing model. Even though the model is effective for capturing the macroscopic behavior of a logistics operation, this approach may not be suitable to represent the actual day-to-day operations in the chemical plant, which are sometimes disrupted by unexpected events with severe impacts, such as equipment failures or machine breakdown. Therefore, further study may validate the benefit of TAS through a more detailed representation.
One may also continue the research by conducting an in-depth sensitivity analysis on the cost parameters and the weights in the objective function. It will be interesting to see how different weights and cost parameters affect the optimal solution to mitigate the traffic congestion problem at chemical plants.

Acknowledgment

Part of this study has been funded by the Dutch Institute of Advanced Logistics (DINALOG) as part of the 4c4chem project.

References


CEFIC/ECTA. 2009. How to Reduce Time Spent by Drivers on Site and Improve Their Treatment: Recommendations for Loading and Unloading Sites.


Zhao, Wenjuan, and Anne V. Goodchild. 2010. “The Impact of Truck Arrival Information on Container Terminal Rehandling.” *Transportation Research Part*
Table 1. List of Parameters and Notation Definition

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T$</td>
<td>Period of interest (hour)</td>
</tr>
<tr>
<td>$G$</td>
<td>Queuing system in the gate</td>
</tr>
<tr>
<td>$S$</td>
<td>Queuing system in the loading station</td>
</tr>
<tr>
<td>$k$</td>
<td>Number of loading stations in the system</td>
</tr>
<tr>
<td>$n$</td>
<td>Number of time intervals within period $T$</td>
</tr>
<tr>
<td>$t$</td>
<td>Index of time interval $t = 1, ..., n$</td>
</tr>
<tr>
<td>$j$</td>
<td>Index of station $j = 1, ..., k$, where $k$ is the number of loading stations</td>
</tr>
<tr>
<td>$\delta t$</td>
<td>Time interval period in the queuing system</td>
</tr>
<tr>
<td>$D$</td>
<td>Number of orders scheduled in a day</td>
</tr>
<tr>
<td>$T_{Oh}$</td>
<td>Site opening hour (hour)</td>
</tr>
<tr>
<td>$T_{ov}$</td>
<td>Site overtime (hour)</td>
</tr>
<tr>
<td>$E_{CO2}$</td>
<td>CO$_2$ emission factor of truck engine idling (4.46 kg/hour)</td>
</tr>
<tr>
<td>$\phi_{CO2}$</td>
<td>CO$_2$ emission cost (0.04/kg)</td>
</tr>
<tr>
<td>$\phi_d$</td>
<td>Waiting time cost (20/hour)</td>
</tr>
<tr>
<td>$\phi_o$</td>
<td>Site operation cost (40/hour)</td>
</tr>
<tr>
<td>$\phi_p$</td>
<td>Space rental cost (20/truck/day)</td>
</tr>
<tr>
<td>$W_{qj}$</td>
<td>Average truck waiting time in front of the loading station $j$</td>
</tr>
<tr>
<td>$W_qG$</td>
<td>Average truck waiting time in front of the gate</td>
</tr>
<tr>
<td>$L_{q(j,t)}^S$</td>
<td>Average number of trucks in loading station $j$ at time $t$</td>
</tr>
<tr>
<td>$L_{q(j,t)}^G$</td>
<td>Average number of trucks in the queue in loading station $j$ at time $t$</td>
</tr>
<tr>
<td>$L_qG$</td>
<td>Average number of trucks in front of the gate at time $t$</td>
</tr>
<tr>
<td>$m_j^G$</td>
<td>Number of identical servers in the loading station $j$</td>
</tr>
<tr>
<td>$m^G$</td>
<td>The number of servers available in the gate</td>
</tr>
<tr>
<td>$\lambda_{qG}^t$</td>
<td>Average truck arrival rate to the gate at time $t$ (truck/hour)</td>
</tr>
<tr>
<td>$\psi_{j(t)}^G$</td>
<td>Average truck departure rate from the loading station $j$ at time interval $t$</td>
</tr>
<tr>
<td>$\mu_j^G$</td>
<td>Average service rate at the loading station $j$ (truck/hour)</td>
</tr>
<tr>
<td>$x_t^G$</td>
<td>Binary variable indicating whether to open or close the gate (0,1)</td>
</tr>
<tr>
<td>$L$</td>
<td>Average number of customers in the system</td>
</tr>
<tr>
<td>$\lambda_t$</td>
<td>Average customer arrival rate at time $t$</td>
</tr>
<tr>
<td>$\nu_t$</td>
<td>Average customer departure rate at time $t$</td>
</tr>
<tr>
<td>$m_1$</td>
<td>Number of identical servers available at time $t$</td>
</tr>
<tr>
<td>$\mu_1$</td>
<td>Average service rate of identical servers available at time $t$</td>
</tr>
<tr>
<td>$\rho_t$</td>
<td>Average capacity utilization at time $t$</td>
</tr>
<tr>
<td>$c_a$</td>
<td>The coefficient of variation of the inter-arrival distribution</td>
</tr>
<tr>
<td>$c_e$</td>
<td>The coefficient of variation of the service time distribution</td>
</tr>
<tr>
<td>$W$</td>
<td>Average customer time spent in the system</td>
</tr>
<tr>
<td>$W_q$</td>
<td>Average customer time spent in the queue</td>
</tr>
</tbody>
</table>
Table 2. Performance Comparison of WB-PSFFA, SBC, and B-PSFFA

<table>
<thead>
<tr>
<th>Measures</th>
<th>Method</th>
<th>Case 1</th>
<th>Case 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>WB-PSFFA</td>
<td>0.54</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>SBC</td>
<td>1.19</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>B-PSFFA</td>
<td>1.02</td>
<td>1.41</td>
</tr>
<tr>
<td>$R^2$</td>
<td>WB-PSFFA</td>
<td>0.99</td>
<td>0.97</td>
</tr>
<tr>
<td></td>
<td>SBC</td>
<td>0.98</td>
<td>0.97</td>
</tr>
<tr>
<td></td>
<td>B-PSFFA</td>
<td>0.96</td>
<td>0.55</td>
</tr>
</tbody>
</table>
Table 3. The configuration of the queuing system in the chemical plant

<table>
<thead>
<tr>
<th>Queuing System</th>
<th>Number of servers, m</th>
<th>Service rate, ( \mu )</th>
<th>Coefficient of variation, ( c_e )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gate G</td>
<td>1</td>
<td>12 truck/hour</td>
<td>0.6</td>
</tr>
<tr>
<td>Loading Station S1</td>
<td>1</td>
<td>1.05 truck/hour</td>
<td>0.41</td>
</tr>
<tr>
<td>Loading Station S2</td>
<td>1</td>
<td>1.05 truck/hour</td>
<td>0.36</td>
</tr>
</tbody>
</table>
### Table 4. Performance Comparison between Scenarios

<table>
<thead>
<tr>
<th>Performance Indicators</th>
<th>Base Scenario</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
<th>Scenario 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. Truck Waiting Time (hour)</td>
<td>1.71</td>
<td>0.77</td>
<td>0.85</td>
<td>0.77</td>
<td>0.79</td>
</tr>
<tr>
<td>Avg. Number of Trucks (truck)</td>
<td>3.92</td>
<td>2.58</td>
<td>2.84</td>
<td>2.58</td>
<td>2.64</td>
</tr>
<tr>
<td>Avg. Site Overtime (hour)</td>
<td>1.87</td>
<td>0.46</td>
<td><strong>0.19</strong></td>
<td>0.46</td>
<td>0.23</td>
</tr>
<tr>
<td>CO2 Emission (kg)</td>
<td>7.64</td>
<td><strong>3.44</strong></td>
<td>3.81</td>
<td><strong>3.44</strong></td>
<td>3.51</td>
</tr>
<tr>
<td><strong>Total Cost</strong></td>
<td>857.42</td>
<td>364.71</td>
<td>358.61</td>
<td>364.71</td>
<td><strong>341.72</strong></td>
</tr>
</tbody>
</table>
Fig. 1. Characteristics of site logistics operations at a chemical plant
Fig. 2 Average truck turn time performance on chemical plants with and without TAS
Fig. 3 Truck arrival distribution on chemical plants with and without TAS
Fig. 4. Research framework
Fig. 5. Illustration of a fluid-flow approximation for a non-stationary queuing system
Fig. 6 Performance comparison of queuing approximation methods
Fig. 7 The observed truck arrival distribution at the chemical plant
Fig. 8 Comparison of cost structure between the scenarios
Fig. 9 Comparison of the average truck waiting time behaviors in Base Scenario (a) Scenario 1 (b), Scenario 2 (c), Scenario 3 (d), and Scenario 4 (e)
Fig. 10 The impact of traffic intensity to (a) the average truck waiting time, (b) the average site overtime, (c) CO₂ emissions, and (d) the total relevant cost