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EFFECT OF REAL-TIME TRUCK ARRIVAL INFORMATION ON THE RESILIENCE OF SLOT MANAGEMENT SYSTEMS

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ABSTRACT

Traffic congestion is uncertain and undesirable in logistics and leads to arrival uncertainty at downstream locations engendering disruptions. This paper considers a loading facility that uses Truck Appointment System (TAS) for slot management and faces incoming truck arrival uncertainty due to traffic congestion. Due to the recent advancements in cyber-physical systems, we propose an adaptive system that uses the real-time truck Estimated Time of Arrival (ETA) data to make informed decisions. We develop an integer mathematical model to represent the adaptive behavior that determines the optimal reschedules by minimizing the average truck waiting time. We developed a simulation model of the adaptive system and reported the estimated benefits from our initial experiments.

1 INTRODUCTION

Modern enterprises require quick adaptations in response to disruptions caused by a variety of change drivers and are increasingly becoming complex (Kulkarni et al. 2019). Any system with the ability to adjust/respond to achieve a specific goal to external disturbances is known as an adaptive system (Meyer et al. 2021). In the context of Industry 4.0, social networks, supply chains, healthcare networks, smart cities are examples of complex systems where entities and the environment interact to achieve the system goals (Szabo 2019).

In Supply Chains (SC), loading facilities play a crucial role in facilitating the loading/unloading activities at different SC terminals such as production facilities, warehouses, cross-docks, railways, and seaports. Some of these loading facilities are very complex as they involve both inbound/outbound product flows, different products, multiple loading bays, safety procedures for loading/unloading processes, different operating hours, etc. (Wibowo and Fransoo 2021). These facilities connect terminals with transportation or vice versa and involve many stakeholders such as facility/site managers, logistics providers, and product owners.

Most facility managers, especially at container terminals, use a Truck Appointment System (TAS) to manage the timeslot assignments. Customers have to reserve a time slot in advance and arrive accordingly at the plant for loading. The reservation happens using web-based platforms where a truck operator can reserve or modify their reserved timeslot based on the availability of slots. According to Wibowo and Fransoo (2021), 29 out of 52 chemical plants that they investigated in Europe implemented a TAS system at their loading facilities. Trucking companies and site operators plan their operations to optimize total costs based on the assumption that trucks arrive according to their reserved slots. But in practice, these facilities are operated in uncertain and dynamic environments (Rahmani and Ramezanian 2016), and the efficiency of their initial plan is affected by road congestions and associated truck arrivals at loading terminals. Late

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truck arrival requires rescheduling to find a new slot for the late truck. Every reschedule may directly result in a significant increase in truck waiting times, thus affecting the delivery time to the customer. From a slot management point of view, it results in the under-utilization of the loading facility and reduces the availability of buffer slots in future slot reservations.

Both unplanned road incidents such as accidents, vehicle breakdowns, cargo spillages, and uncleared debris and planned events such as road works limit the road capacity (Zografos et al. 2002) thus increasing the road congestion. The effects of road congestion propagate into all the connected logistic terminals and create severe problems (Wibowo and Fransoo 2021). Typical effects at loading facilities include late truck arrivals, long truck queues, increased pollution, and associated safety issues. The carrier can book a new slot when a truck misses its slot using the TAS portal. Alternatively, the slot manager can reschedule it to a new timeslot. The rescheduling is currently done manually with limited information that is sub-optimal when looked at the system level.

Recent developments in ICT technologies enable real-time data sharing among stakeholders. Several research articles in the literature discussed the apparent benefits of Industry 4.0 concepts in manufacturing systems. Along with real-time information availability, it is essential to build advanced techniques such as prediction and optimization models to extract the maximum value from the real-time data (Leonard et al. 2017).

In this article, we focus on a scheduling system at a chemical plant facing uncertain arrivals times, study the effect of incoming truck ETAs on the rescheduling procedure, and estimate the benefits in terms of several KPIs.

The remainder of the paper is organized as follows. Section 2 presents the relevant literature. The proposed approach is described in Section 3. Section 4 explains the conceptual model of the proposed system. Details of the simulation model are presented in Section 5. The experiment settings and initial results are discussed in Section 6, followed by conclusions in Section 7.

2 RELATED WORK

Several articles in the literature focus on disruption management problems related to different domains such as manufacturing, transportation, healthcare and logistics terminals. For example, Rahmani and Ramezanian (2016) proposed a reactive approach for a flexible flow shop system with the unexpected arrival of new jobs to optimally reschedule all jobs. Ghaleb et al. (2020) studied a flexible job shop facing uncertain arrival of new jobs and machine breakdowns and investigated the following questions associated with real-time scheduling systems (RTS). Firstly, to what extent the availability of real-time information can enhance scheduling decisions? When and how can such information be utilized to advance scheduling decisions? Whether it is beneficial to use real-time system updates to assess continuous rescheduling? To address these questions, they proposed mathematical models by explicitly considering the complexities of job shop and showed the advantage of real-time information. One assumption in their study is that there is no disruption to the availability of current jobs. Ebufegha and Li (2021) developed a simulation model of an intelligent manufacturing system (flexible job shop) where machines and parts are explicitly modeled as autonomous agents to negotiate and make real-time adjustments to the planned operations to maximize machine utilization and reduce part flow.

Disruptions in public transportation services creates a propagation effect and requires specific correction actions to mitigate negative effects of disruptions and bring their operations to normality. Several researchers studied disruptions in public networks such as railways (Huang et al. 2018; Binder et al. 2017), bus (Drabicki et al. 2022), and trams (Lai and Leung 2018), and focused on timetable adjustment, rerouting, rolling stock rescheduling, and crew rescheduling problems simultaneously (Dekker et al. 2021; Lai and Leung 2018). Huang et al. (2018) presented a mixed integer mathematical model for the online rescheduling of rail schedules in the presence of expected delay information by minimizing the weighted cost of the energy consumption and travel delay under delay scenarios. Lai and Leung (2018) proposed mathematical models to dynamically revise the schedules in real-time to avoid motorman meal-break delays and overtime, and to maintain high route coverages and service levels of tram network.

The disruptions raised by truck arrival uncertainty at loading facilities such as warehouses and chemical plants also got some attention in the literature. According to Chen et al. (2019), loading and unloading activities at chemical industrial parks account for 11% of fire-related accidents. Thus, they researched the safety incidents during loading/unloading operations and presented an escalation capability index of these loading facilities. Nasiri et al. (2022) proposed a periodic rescheduling of both inbound and outbound truck assignments based on truck delay information. They assumed that the delay information of incoming trucks is known for a few trucks when the drivers inform the plant operator. They investigated the developed models using a set of problem instances. Elbert and Roeper (2021) presented an exchange platform for carriers that use TAS systems to exchange their assigned slots with desired timeslots to optimize their overall operations.

Even though few articles focused on slot management problems at other logistic terminals, there is no research article focused on loading facilities at petrochemical manufacturers with real-time truck location information. Considering constraints such as product and loading bay mappings is crucial in the rescheduling process of chemical loading facility operations. Here, a product and loading bay mapping inform whether a particular product can be loaded on a loading bay. Further, researchers such as Ghaleb et al. (2020) and Nasiri et al. (2022) proposed mathematical models for rescheduling decisions and compared them using a set of predetermined problem instances. To understand the long-term value of real-time vehicle arrival information in rescheduling, we proposed using a discrete-event simulation model. This simulation model analyzes the rescheduling process based on different rescheduling rules. Prakoso et al. (2022) presented an integrated ML classifier and mathematical model approach to optimally reschedule the timeslots at a loading facility facing truck arrival uncertainty. This article is an extension of our previous work (Prakoso et al. 2022) 1) to present our simulation modeling approach and 2) to extend the study to test the effect of rescheduling rules such as the flexibility to reshuffle time slots of on-time trucks on the overall system performance.

3 PROPOSED RESCHEDULING SYSTEM

In this article, we focus on a petrochemical loading facility located in the port of Antwerp, whose logistic operations are similar to the one described in Wibowo and Fransoo (2021). The loading facility under study uses the TAS system to streamline the truck arrivals. Once the customers/carriers reserve a slot in advance, it is expected that they send their truck and reach the loading facility on time to get the loading service. Due to the uncertain traffic conditions en route to the loading facility, especially on Antwerp's ring road, the loading facility faces truck arrival uncertainty which increases early or late arrivals. The road congestion on Antwerp's ring road is expected to increase in the coming years due to the planned construction activity. Both early and late truck arrivals affect all the stakeholders and may disrupt the planned operations, especially when there is no prior information.

In this article, we propose an approach (as shown in Figure 1) to use real-time truck ETA information to mitigate the adverse effects of traffic congestion. In the proposed approach, all the incoming trucks are assumed to provide real-time locations to an ETA predictor algorithm which estimates the expected ETAs for all the incoming trucks. Further, the estimated ETAs are used in a mathematical model which optimally reschedules the assigned slots as described in the subsection 4.2. In addition to the estimated truck ETAs, the rescheduling model requires the current slot assignments, operational constraints such as product-loading bay mapping, and other preferences.

3.1 Main Stakeholders and Their Interests

There are mainly three stakeholders involved in the system with possibly different priorities. These are the loading facility manager, customers, and carriers. The loading facility manager's objective is to have

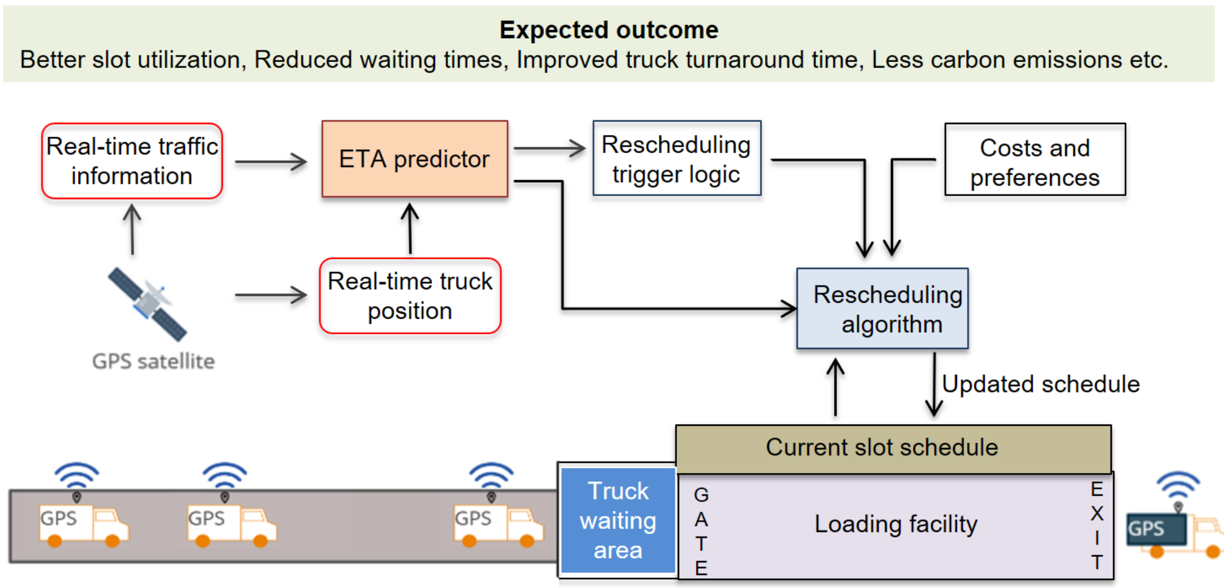

Figure 1: Proposed system overview.

smooth operations and thus increase facilities utilization. The plant's customers buy products from the plant and most probably outsource the transportation to 3PL players such as carriers. The plant customer aims to have on-time delivery of the product. But, in the current study, we limit the focus to the incoming arrival uncertainty and don't consider transportation from the plant to the customer's location. Thus, we didn't consider customers' KPIs in this study. Carriers provide logistics services to their customers and prefer to minimize disruptions to their operation plans, i.e., minimize truck turn time. Based on the stakeholder's preferences and the scope of the current research, we focus our comparative study on different KPIs as presented in Table 1.

Table 1: Selected KPIs.

Actor	KPI	Description
Carriers	Truck turn time	the total duration spent between plant arrival and plant exit
	Gate waiting time	the duration between plant gate entry time and parking area (outside gate) entry time
Loading facility	Finish time (or makespan)	it is the latest time to complete the service for all the trucks

4 CONCEPTUAL MODEL

This study aims to determine the added value of real-time truck ETA information in the rescheduling process. The presence of inherent uncertainty in demand, congestions (thus truck arrivals), loading durations, and rescheduling decisions makes the proposed system very complex to model and difficult to compare with the current operations of the loading facility. This reason justifies the selection of simulation as a tool to model and analyze the current system. In this section, we explain the main components of simulation modeling process.

In developing a simulation model, it is crucial to study the underlying system first and prepare a conceptual model. The conceptual models are developed by balancing research objectives and required model fidelity. In this study, we developed a process flow diagram of the loading system is shown in Figure 2.

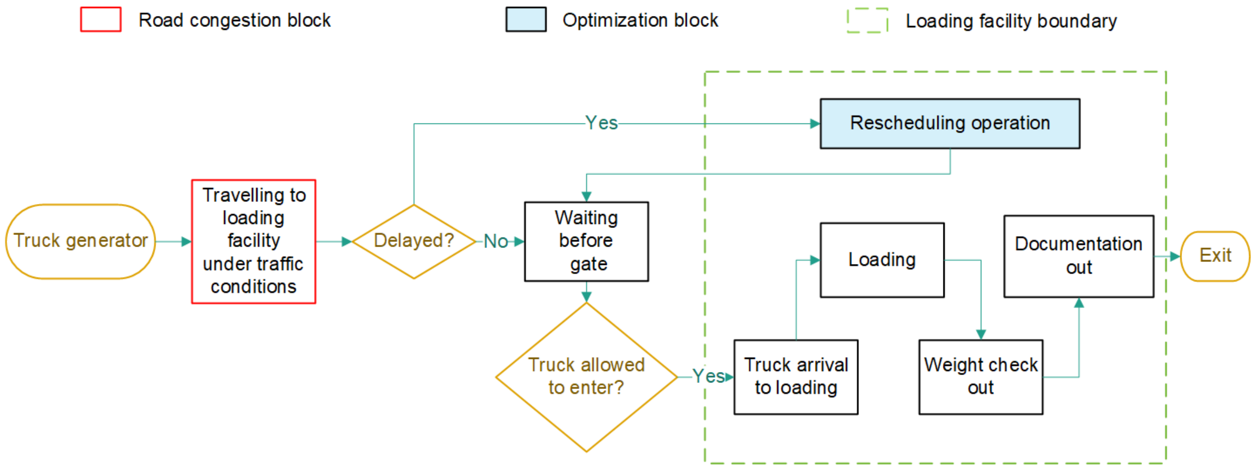

Figure 2: Process flow diagram of loading operations.

The source terminal in the process flow diagram (truck generator) generates trucks (entities). The primary decision here is related to the quantity and timing of the truck generation. Initial schedules (number of trucks and their attributes such as type of the product, assigned loading bay, trip origin, and timeslot) are generated based on the historical data obtained from our industrial partner. In this study, the trucks with slot reservations are presumed to arrive according to the initial slot assignments. In practice, no truck arrives to the loading facility without a prior slot reservation. Thus, our study also do not consider any truck arrivals without prior reservation.

While deciding on the timing of truck generation, we considered the fact that the trucks which are far away from the facility don't affect real-time slot adjustments. This is justifiable as the probability of performing next reschedule in the next 5 hours is very high in this case. Also, the quality of ETA prediction improves as truck moves closer to the destination thus it is not advisable to take decisions based on 5-hour prior ETA status. Secondly, the loading facility in this research is close to the primary source of road congestion (Antwerp's ring road). Thus, we choose to generate trucks 5 hours before the reserved slot. In other words, we are only considering the last 5 hours of the journey of trucks while traveling to the loading facility.

4.1 Modelling Congestion

The next block in the process flow is traveling from the trip origin to the loading facility through traffic congestions. Road congestion essentially means increasing vehicles' travel times, which logically changes the ETAs. Further, the triggering of the rescheduling model requires ETAs of trucks at that time. From our industry partner, we received the arrival timestamps of past trucks at the loading facility. When comparing these timestamps against their reserved slots, we obtained the truck arrival information facing real road congestions. We used this empirical data set to replicate the truck arrivals in the road congestions. Further, as road congestions are uncertain and dynamic, we decided to mimic the randomness of the road congestions by randomly modifying the truck arrival times generated from the data set. Thus, we selected a random walk approach to imitate uncertainty and correspondingly update truck ETA during the trip using the Equation (1).

$$Y_t = Y_{t-1} - stepsize + randomchoice(-1,1) \tag{1}$$

Where Y_t represents the ETA at any discrete-time point t and step size is the frequency of the ETA update. The random choice function is a random function that randomly selects either -1 or 1 with equal probability. As we focus on the last 300 minutes of the journey, we can update ETA after each minute. In this case, the step size is 1. If the frequency changes to 5 minutes, there will be 60 steps in the trip. In this case, the step size will be 5 minutes.

4.2 Rescheduling Algorithm

In the proposed approach, late truck arrivals trigger rescheduling to get a new slot by considering the expected delay. Here, the difference between the estimated ETA and the truck reserved slot is regarded as the expected delay. Based on the availability of ETA, objective function, and flexibility to reschedule on-time trucks or not, rescheduling will have different results. Firstly, we assume that only delayed trucks are allowed to reschedule and refer to this scenario as *restrictive*. The other scenario where all the trucks are allowed to reschedule is referred to as a *flexible* scenario.

4.2.1 Restrictive Scenario

The objective of the rescheduling activity in this scenario is to optimally reschedule the delayed trucks to minimize the total waiting time without disturbing the schedules of other on-time trucks. We now present some of the assumptions of the model followed by the mathematical formulation of the restrictive scenario.

Assumptions:

- There are multiple loading bays in the loading facility and time slots are fixed on each loading bay.
- The slot duration's can vary among loading bays.
- Only one truck can be allowed for loading on any loading bay at any timeslot.
- The facility can load different types of products.
- Each loading bay can only load some predetermined set of product types only.
- The delayed trucks can't be assigned before the ETA.

Sets:

P : Set of product type, $P = \{p_1, p_2, ...\}$
L : Set of loading bays, $L = \{l_1, l_2, ...\}$
J : Set of trucks or jobs, $J = \{j_1, j_2, ...\}$
$\ddot{J}$: $\subseteq J$ representing delayed trucks that need to be rescheduled
$\hat{J}$: $\subset J$ representing on-time arriving trucks
T : Set of time slots, $T = \{t_1, t_2, ...\}$

Parameters:

C_{ljt} : Current schedule of truck j at time slot t on loading bay l (in binary values)
R_{lj} : Truck and loading bay mapping based on the product type (in binary values)
Y_j : Minimum time difference required between new slot and old slot based on the delay information

Decision variable:

$$X_{ljt} \quad : \quad \begin{cases} 1, & \text{if truck j is rescheduled at time slot t on loading bay l,} \\ 0, & \text{otherwise.} \end{cases}$$

$$Minimize \quad Z : \sum_{j \in J, l \in L, t \in T} ((X_{ljt} \times t) - (C_{ljt} \times t)) \tag{2}$$

subject to,

$$\sum_{l \in L, t \in T} X_{ljt} \quad = \quad 1 \quad \forall j \in \ddot{J} \tag{3}$$

$$X_{ljt} + C_{ljt} \leq 1 \quad \forall j \in \ddot{J}, l \in L, t \in T \tag{4}$$

$$X_{ljt} - C_{ljt} \geq 0 \quad \forall j \in \hat{J}, l \in L, t \in T \tag{5}$$

$$\sum_{j \in J} X_{ljt} \leq 1 \quad \forall l \in L, t \in T \tag{6}$$

$$X_{ljt} \leq R_{lj} \quad \forall j \in \ddot{J}, l \in L, t \in T \tag{7}$$

$$\sum_{l \in L, t \in T} ((X_{ljt} \times t) - (C_{ljt} \times t)) \geq Y_j \quad \forall j \in \ddot{J} \tag{8}$$

$$X_{ljt} \in \{0,1\} \quad \forall j \in J, l \in L, t \in T \tag{9}$$

The objective function (equation (2)) represents the sum of truck delays after rescheduling, which is similar to the sum of the difference between old and new slots. The objective function value converts to the average waiting time by multiplying with respective timeslot durations. Constraint (3) ensures that all delayed trucks are rescheduled to one new slot. Constraint (4) ensures that the new slot is different from the old slot for all delayed trucks. Constraint (5) doesn't allow the slots of the on-time trucks to change. Constraints (6) ensure that only one truck can be assigned to every loading bay on each slot. Constraint (7) is to assign the truck only to a loading bay that can load a particular product type that it will carry. Constraint (8) will maintain the minimum slot difference between new and old slots of delayed trucks based on their ETA information. Constraint (9) is a binary variable constraint. This mathematical formulation is a binary integer programming model known as 0-1 integer programming.

4.2.2 Flexible Scenario

All trucks can be rescheduled in the flexible scenario to minimize the overall waiting time. If we remove constraint (5) from the restrictive scenario formulation, it becomes the flexible scenario.

5 SIMULATION MODEL

A simulation model is developed in Anylogic simulation software based on the conceptual model. The rescheduling formulation is modeled in the Gurobi Java interface and solved using the Gurobi optimization solver. We developed the necessary integration of the mathematical model using the custom function element in Anylogic software.

5.1 Input Data

Input data is required to develop the conceptual model and as an input for the simulation. From our industry partner, we received historical data for 70 days between November 2021 to March 2022. The data contains the details of product demand, truck reservations, reschedule information, timestamps of trucks at multiple activities, etc.

5.2 Verification and Validation

To build the credibility of the simulation model, we conducted the model verification primarily using the tracing method. Throughout the simulation model, print statements were added with timestamps, which enabled us to check that the progress flow logic's and methods functioned as intended. Face validity of the rescheduling algorithm was checked by observing both input and output values at multiple instances. Additionally, we created and utilized animation to observe the simulation behavior. We also documented the verification and validation process. We achieved reasonable confidence that the simulation model was built as intended using these methods.

6 SIMULATION EXPERIMENTS AND ANALYSIS

As explained in subsection 4.2, we developed models for restrictive and flexible scenarios based on willingness to reshuffle on-time trucks. We further created two more scenarios based on ETA information as shown in Table 2. Here, *restrictive - no ETA* refers to the scenario where ETA information is not known for any incoming truck (still on the journey), and only delayed truck is allowed to reschedule. The scenario of *restrictive - ETA* refers that the ETA information is known for all incoming trucks but only delayed trucks are allowed to reschedule. Similarly, ETA information is not available and available respectively for *flexible - no ETA* and *flexible - ETA* scenarios where the rescheduling of on-time trucks is allowed.

Here, *restrictive - no ETA* scenario represents the current rescheduling process at the loading facility and should be considered as base case. The base case scenario is to be compared with *restrictive - ETA* and *flexible - ETA* scenarios to estimate the benefits of ETA information in the restrictive and flexible cases respectively.

6.1 Initial Results and Discussion

We conducted simulation experiments for all the four scenarios for 6 months and collected the output of the KPIs described in Table 1. The summary of the output as mean (standard deviation) of each KPI are shown in Table 2. Please note that the standard deviation is shown inside parentheses. From the results, it can be seen that the availability of ETA information improves the average waiting time by 21% and 20% in restrictive and flexible scenarios, respectively. Similarly, in restrictive and flexible scenarios, the truck turn time is improved by 26 (17%) minutes and 19 (13%) minutes. There is an improvement of 90 (5%) minutes and 16 (0.85%) minutes for finish time for restrictive and flexible scenarios, respectively.

It is evident from the results that the availability of ETA data improves the performance of all three KPIs in both restrictive and flexible cases. When comparing against the restrictive scenario in the presence of ETA, the average finish time increases in the flexible scenario, whereas the average waiting time and the average truck turn time improve. This result is because, in the flexible scenario, the on-time trucks are also rescheduled in order to improve the overall performance. In the case of *no ETA*, both average waiting time and truck turn time relatively decreases in the flexible case, whereas the standard deviation of finish time increases. These results infer that the flexible scenario might slightly increase the finish time at any day to improve the overall loading operations.

Table 2: Results from the comparative study.

Experiment setting / KPI	Restrictive		Flexible	
	no ETA	ETA	no ETA	ETA
Average waiting time (in minutes)	89 (154)	70 (145)	87 (153)	70 (143)
Truck turn time (in minutes)	152 (140)	126 (113)	145 (126)	126 (109)
Finish time (in minutes)	1872 (74)	1782 (240)	1872 (105)	1856 (157)

7 CONCLUSIONS

This article proposed an adaptive slot management system to investigate the added value of real-time ETA information in improving loading operations. The loading facility in this study faces truck arrival uncertainty due to road congestion. We developed a simulation model to emulate the adaptive system where the adaptive decisions are determined using a mathematical model. We compared the proposed approach with different scenarios generated from the data obtained from our industrial partner. Our initial results prove that the availability of ETA information will reduce the average truck waiting time by 20% and improve all KPIs. The next steps in this research include conducting a sensitivity analysis of the proposed system against changes in demand and congestion levels.

Further the applicability of this research can be extended to different industries by customizing the mathematical model with any case-specific complexities. For example, some industries might have fixed setup or cleaning time in between consecutive loading's that should be modelled. Additionally, some loading processes might include loading operations sequentially on multiple loading bays which should be captured in the model.

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