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APPLYING SIMULATION TO ESTIMATE WAITING TIMES AND OPTIMIZE THE BOOKING SIZE FOR OVERSEA TRANSPORTATION VESSELS

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ABSTRACT

The aim of this research is to determine the booking size for vessels in oversea delivery to minimize transportation costs. In the studied setting, a producer must book transportation space in advance, whereby the arrival processes for containers and vessels are stochastic. Analytical approaches of queueing theory are inconvenient in this case, and a discrete event simulation is therefore used to estimating the objective function. Moreover, the booking size is optimized for a static and a simple dynamic booking policy using a discretization of the solution space. The results show that the higher the variance in the shipping cycle, the higher is the optimal booking size and the total transportation costs. The dynamic booking policy significantly outperforms the static policy and indicates potential for future research.

1 INTRODUCTION

Managing oversea deliveries is a difficult issue, because several uncertainties arise in the transportation. The process is intermodal, provided the production facility and retailer are not located directly at a seaport. Focusing on delay minimization for improving on-time delivery reliability, several sources of uncertainty can be detected. For example, the vessel lead time is not certain, since it depends on weather conditions (Halvorsen-Weare et al. 2013). This study investigates a different source of uncertainty, which is the waiting time for the next vessel that is scheduled on a specific route, connecting two international ports. Suppose a company sends goods from several production plants into all parts of the world. For every vessel connection, goods arrive at the port of departure (POD) in irregular time intervals and in varying quantity. Moreover, vessels leave the POD in different shipping cycles, with distinct capacity in general. The addressed waiting time is measured for each piece of goods on one vessel shipping section as the difference between the time of arrival of the goods at the port and the time of departure of the vessel, on which it is shipped. Therefore, the question of how the company – or its logistics service provider – should book capacity on vessels of a route is of major interest. The booking capacity affects the waiting time and therefore the delivery time. If this effect of booking size on delivery time is known, the total delivery costs can be optimized.

Similar problems have already been investigated with various applications. For example, in inventory management, the question is how to determine the optimal ordering policy, such that the demand can be fulfilled and the ordering and storing costs become minimal (Karmarkar 1987). In the problem of this article, a demand for transportation is considered. This demand can be fulfilled by the booked vessel capacities. In comparison to the inventory model, unused capacity cannot be shifted to the next period, while unused inventory can. The corresponding case of inventory management would be perishable goods, which cannot be stored very long.

In the order batching problem, the goal is to determine the number of orders that, if carried out together, result in most efficient processing. Le-Duc and Koster (2007) modeled order batching in a 2-block warehouse as a queueing system and gave an analytical approach of finding the optimal batch size in order to minimize the average throughput time in the system. However, the service in order batching is started only if the batch is full.

In this article, the effect of batch size on the waiting time distribution is investigated. In other words, we ask the question how the booking size affects the waiting time distribution. To the best of the authors' knowledge this question has not yet been investigated. The knowledge about this relation will be used to find the optimal booking size per vessel to minimize resource and delay costs. This booking size is assumed to be constant for all shipping cycles in a first step. Second, a simple dynamic booking policy is deployed, showing the potential for future research of other dynamic policies. Since the focus is on delays, it is not sufficient to have the mean waiting time (Wein 1991; Hafızoğlu 2013). Deliveries arriving early would compensate late deliveries in the mean and skew it. This would not correspond to reality, as early deliveries do not compensate the costs for delays. This is the first contribution, considering the whole waiting time distribution, which is needed to calculate the respective total costs. As justified in the next section, it is not practicable to calculate the waiting time distribution analytically and we, therefore, use simulation to estimate it. The simulation approach has many advantages and allows to consider realistic models instead of too simplistic ones.

The paper is organized as follows. In section 2 a literature review is given, and the limitations of queueing theory are presented. It is explained why the analytical calculation of the waiting time distribution is not applicable in the optimization problem of this paper. In section 3 the problem is defined, and the considered model is presented. Next, the process of determining the model parameters by use of empirical data is described in section 4. The optimization approach is presented in section 5 and the numerical study in section 6. The conclusion is drawn in section 7 and an outlook to future research is given.

2 LITERATURE REVIEW

This work is related to optimization problems in transportation, where costs are minimized in terms of capacity booking or penalties for bad service level. Therefore, literature with delay minimization and capacity constraints is relevant. In addition, a specific type of queueing system is reviewed to show that simulation is a better choice for estimating waiting time. Finally, some optimization problems for this type of queueing system are reviewed to estimate the difference to the optimization problem in this article.

Many articles are available considering minimization of delays in transportation. For example, Högdahl et al. (2019) investigated on finding the optimal timetable for railway transportation. They used a simulation-optimization approach to minimize the overall travel time and expected delay. Another issue is finding the optimal transportation mode when different modes are available. Altendorfer and Minner (2017) considered transportation of containers from oversea port to final destination at the customer. They discussed the choice of optimal transportation mode with the goal to minimize transportation and delay costs. However, no research is available, considering the delay of transport with varying capacity.

Capacity constraints in transportation are considered by Shen and Zhao (2017) who modeled the accessibility of highspeed rail infrastructure. They used a queueing approach to consider capacity constraints of the trains, which reduces infrastructure accessibility if the system is in a high loaded situation. They used simulation to estimate the waiting time distribution for different timetables of the trains and different load factors, adjusted by the arrival rate of passengers, but did not consider changes in the capacity of the trains. Here, the capacity of the vehicles is not varied from one train to the other within one simulation scenario.

Much work has been done on queueing systems, including batch service (sometimes bulk service or batch processing) and different types of batch service policies (Neuts 1967; Aalto 2000; Hanschke and Zisgen 2011; Claeys et al. 2013; Banerjee et al. 2015). The most common policy is the full-batch policy, where service is started only if the capacity of the server is reached (Dümmler and Vicari 1999). If less entities are in the queue the server waits and stays idle. The *[a,b]*-policy models the case where the server starts if at least *a* units are available. Between *a* and *b* all units are taken for service and if more than *b* are in queue, the remaining entities have to wait for the next service period (Neuts 1967; Gold and Tran-Gia 1993). Chaudhry and Templeton (1983) considered the full-batch policy and *[1,b]*-policy in their important work, where they derived an analytical calculation of the waiting time distribution. This calculation was used by other scholars to calculate the mean waiting time. *[1,b]* accounts for the case where the server waits only if the queue is empty. This is almost the policy that we need in our model, differing only in the fact that a scheduled vessel never waits for goods of one company, because there are many other goods that must be shipped.

Shen and Zhao (2017) considered exactly the policy that we need in our research, which can be denoted by *[0,b]*. They modeled the transportation of passengers with highspeed trains, limiting the capacity of each train. Although the distribution of the waiting time in such $M/G^b/1$ queues can be calculated analytically for certain distributions of G (Chaudhry 1992), the waiting time distribution was estimated by simulation in the work of Shen and Zhao (2017). The reason is, that the analytical calculation involves Laplace-Stieltjes integrals, which are hard to transform backwards (Chaudhry 1992). In the work of Yu and Tang (2018) several examples are given, showing the inconveniences of the analytical calculations. The study on hand extends the research on batch service queues with *[0,b]*-policy by investigating the effect of changes in the batch size on the waiting time and by optimizing the batch size to optimize the efficiency of the system.

Optimization of the batch size to minimize the waiting time was considered by Le-Duc and Koster (2007) and Chang (2006). However, in their models, the service time depends on the batch size, modeling the processing of a set of orders one after the other. Moreover, the service time is equal to the cycle of processing batches and consequently the optimization problem is different to the one of oversea transportation. Nonetheless, it is interesting that those problems were solved by analytical approximations. Le-Duc and Koster (2007) argue that they used a well-known approximation formula, since the exact computation is very time expensive. In their numerical elaborations, they found that the average throughput time is a convex function of the batch size. Chang (2006), who proposed a model to determine the optimal batch size that minimizes the mean steady waiting time under full-batch service, used a different approach to approximate the average waiting time, which is coarsely described as approximating the zeros of the generating functions of the steady state probability. With this approximation, the existence of an optimal batch size follows again from the fact that the average waiting time is convex in the batch size.

Altogether, minimization of delay in batch service queues with *[0,b]*-policy is a clear extension to the existing literature, since only the mean waiting time was minimized before and a dynamic booking policy (i.e., different batch size for each service period) has never been considered. In the next section, the problem under consideration is explained in detail and the optimization problem is formulated mathematically.

3 MODEL DEVELOPMENT & PROBLEM DEFINITION

Consider a pair of ports – port of departure (POD) and port of arrival (POA). Vessels arrive at POD with a certain series of shipping cycles and product entities (here: cars) arrive at POD with a specified rate of arrivals per day, which follows a lognormal distribution. The goal is to minimize the transportation costs by optimizing the booking size, which is assumed to be equal for all shipping cycles. The two conflicting goals are to minimize the booking cost on the one hand and to minimize the delays at POA on the other hand. To calculate the sum of delay of all entities, we need the waiting time distribution. We assume that all cars have equal target time from the plant to the retailer, which is constant and not optimized. Moreover, we assume the following facts for the model:

- There is only one type of product (here: cars).
- The number of car arrivals per day follows a Log-Normal distribution, and the arrivals are assumed to be independent.
- The capacity of the vessel is modeled as batch service (representing the number of cars on each vessel), therefore the vessel dispatching process is modeled as a batch service queueing system.

- The service times (representing the shipping cycle of vessels) follow a truncated normal distribution.
- The vessel transportation time is constant although in reality it is assumed to be uncertain.
- The waiting room is unlimited (i.e., no goods get lost because of limited storage area).

Let X_i be the random variable, describing the number of car arrivals on day i $(i = 1,2, \ldots)$, with $\ln(X_i) \sim N(\widehat{\mu_X}, \widehat{\sigma_X^2})$. And assume that the vessel shipping cycles V_j follow a truncated normal distribution $V_j \sim N(min, max, \mu_V, \sigma_V^2)$. Moreover, we assume, that the X_i and the V_j are independent and identically distributed (iid) respectively. We denote the mean value of X_i by μ_X and the standard deviation by σ_X. Let u be the waiting time of a car from arrival at port of departure to arrival (= departure) of the vessel where it is shipped with. Therefore, no loading time is considered. To model the objective function, we use the waiting time distribution of the described queueing system, which depends on the arrivals of cars and vessels and is estimated by simulation. Let d be the target delivery time and t be the constant vessel shipping time. Then, $d - t$ is the maximal waiting time, where no delay costs arise. For a waiting time, bigger than $d - t$, the costs are c_d per product and day that is delivered too late. Then the expected delay costs for one car can be calculated as follows:

$$D(b) = \int_{d-t}^{\infty} (t - d + u)\, c_d\, f_{W(b)}(u)\ du. \tag{1}$$

Where $f_{W(b)}(u)$ is the waiting time distribution for given booking amount b, car arrivals per day, and vessel shipping cycle as described above.

Next, we model the resource costs per car, which are the booking costs divided by the actual transported products per shipping cycle. Note that based on the booking size, on average more than one slot is booked per car which leads to:

$$R(b) = c_b \cdot \frac{b}{\mu_X \mu_V}.$$

In Table 1, we summarize the model variables.

Table 1: List of model variables.

$X_i = X$	The iid family of random variables, describing the number of car arrivals on day i
μ_X	Mean value of the car arrivals per day
σ_X	Standard deviation of the car arrivals per day
u	Waiting time at port of departure to be shipped
$D(b)$	Delay costs for booking size b
$R(b)$	Resource costs for booking size b
$C(b)$	Total costs for booking size b
b	Booking size
$V_j = V$	Random variable of the vessel shipping cycle
μ_V	Mean value of the vessel shipping cycle
σ_V	Standard deviation of the vessel shipping cycle
t	Fixed vessel shipping time
d	The target delivery time
c_b	Costs for one car being booked on a vessel
c_d	Costs for every day that a car is delivered too late
$f_{W(b)}$	The probability density function of the waiting time at booking size b

For the optimization we consider the objective function

$$C(b) = R(b) + D(b) \to \min_{\boldsymbol{b}} \tag{2}$$

subject to $b > \mu_X \mu_V$, i.e., the booking size is greater than the average demand between two shipping cycles. This restriction is similar to stability conditions in queueing theory. If the long-term rate of arrivals is larger than the long-term service rate, the queueing system is said to be instable, since the length of the queue will tend to infinity on the long-term (Shortle et al. 2018).

4 DETERMINING THE MODEL PARAMETERS FROM EMPIRICAL DATA

The estimation of operational parameters of transportation networks, modeled as queueing systems, was investigated by Gillen and Hasheminia (2016). They showed that estimation of capacity of trains, schedules of departure and other parameters is possible although data is available only for snapshots of container movements on micro-level. Since for the study of this article a complete data set was available from a car manufacturer (OEM) in Europe, it was possible to extract real vessel departure timetables and transportation times. Moreover, the arrivals of products at POD are fully described by the data. For computational experiments, realistic parameters for the simulation were derived from the empirical data.

The big data set covers the worldwide distribution of cars, starting from 15 production plants, up to more than two thousand retailers. Six months are covered by the data, recording the delivery of about one million cars up to retailers in all continents of the world. At the beginning and end of each process step, there are time stamps for each car delivered, enabling to track the shipping process very detailed.

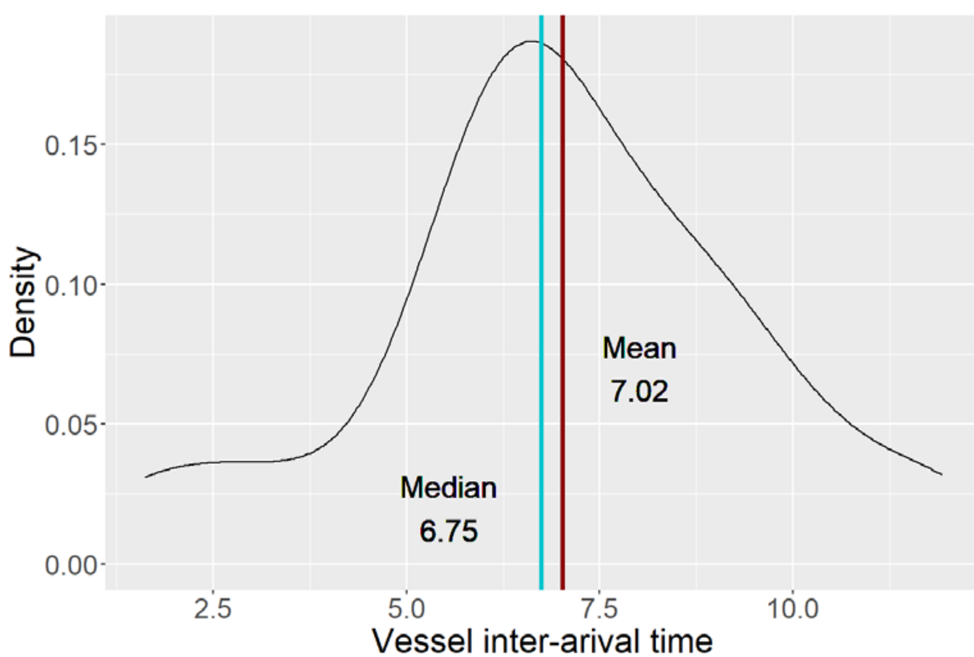

Figure 1: Distribution of shipping cycles for the chosen connection.

At a single seaport, cars arrive by vessel, coming from other seaports, or arrive by truck or train, coming from inland production plants. The cars, that arrive by vessel, may be further transported by vessel, or be proceeded by truck or train to the dealer, possibly going over a vehicle distribution center. The cars, that arrive by truck or train, are loaded on a vessel to the planned destination. Focusing on the vessel dispatching process, there are several queues, where cars arrive and wait for a vessel. Here, it is assumed that all vessels have a fixed route on which they approach all destinations in each cycle. Therefore, each queue is filled by an arrival process, which is stochastic in general. The data revealed that those arrivals vary per day and per departing vessel. Most production plants have an approximately constant outcome per day, which would result in constant arrivals if all cars had the same destination, which is not true. Accordingly, this was not confirmed by the data (i.e., the arrivals were not constant). However, to explore the main dynamics in the system of consideration, the arrivals of cars at the POD are assumed to have constant mean and low standard deviation. Enabling a variation of the standard deviation with constant mean, the lognormal distribution was used for modelling.

The vessels with the same origin and destination form separate arrival processes since they can be seen as the server of the respective queueing system for each destination. The shipping cycles of vessels departing on a certain POD and targeting a certain POA are modeled with the truncated normal distribution. Omitting values below zero, the lognormal distribution would also have been possible, but since the mean of the shipping cycles is quite low the truncated normal distribution was a better choice to avoid skewness. Figure 1 shows the empirical density of shipping cycles on a certain vessel connection including the mean and median. Assuming the mean to be 7 the parameters for truncated normal distribution were set to be $0{,}14{,}7$, indicating the min, max and mean. The standard deviation was varied from 0 to 10, which covers the range of standard deviations found in the data, e.g., the one in Figure 1 was found to be 2.5. Having a standard deviation of 10 results in very different shipping cycles already, such that the booking-size of each vessel cannot be assumed to be constant anymore. This motivates the usage of a dynamic booking policy. Before the results are presented, the methodological approach is clarified in the next section.

5 SIMULATION-BASED OPTIMIZATION

The determination of $f_{W(b)}(u)$ in equation (1) is crucial, but not easily done in a closed form. To identify the relationship between standard deviation in vessel shipping cycle, the booking size and $f_{W(b)}(u)$, a preliminary simulation experiment is conducted. From the respective results in Figure 2, it can be seen, that there is no functional dependence of the density as a function of the booking size. Therefore, the simulation of these densities cannot be improved by using some regression technique with an explicit function in the regression model. It can also be seen from the graphic that the higher the standard deviation of the vessel shipping cycle, the higher is the effect of the booking size on the waiting time distribution.

From the literature review we know that a practicable analytical solution for the waiting time distribution does not exist. Therefore, it is proper to solve the stated optimization problem (2) using a simulation-based optimization approach. We simulate the process for different parameter combinations and enumerate an appropriate solution space for the booking size for each parameter combination. This allows to calculate the costs and plot the objective function stepwise to evaluate the impact of a change in the booking size. Moreover, we present the impact of changes in the process variation on the optimal booking size and optimal costs. To calibrate the simulation model, the parameters are derived from real process data as described in section 4.

The model was built in AnyLogic® 8.7.5 for simulation. We used discrete event simulation, because the process can be completely described by the events of product arrivals and vessel arrivals. The simulation was used to model the waiting times for cars at the port and evaluate the respective waiting and booking costs. This was done for an enumeration of the decision parameter (i.e., the booking size) between a max and min value. The min was taken to be $\mu_X\mu_V$, which ensures stability of the queueing system. The max was taken by testing, such that the interval of booking sizes under consideration includes the optimal value and shows the trend of the objective above the optimum. The total costs were calculated in the following way.

If n is the index for the n^{th} simulated car of a certain simulation run. Then, the mean delay is

$$\frac{1}{N}\sum_{n=1}^{N}\max\left(0, u_{n,b} - d\right).$$

N is the number of simulated cars, where the transport was completed within the simulation run and $u_{n,b}$ is the waiting time for the n^{th} car simulated with booking size b and the target delivery time d. Note, that we set the transportation time $t = 0$ without loss of generality. Having $t > 0$ would lead to a delivery time $d + t$. Multiplying the mean delay with the cost for one unit of delay we get the delay costs

$$D(b) = \frac{c_d}{N} \sum_{n=1}^{N} \max(0, u_{n,b} - d).$$

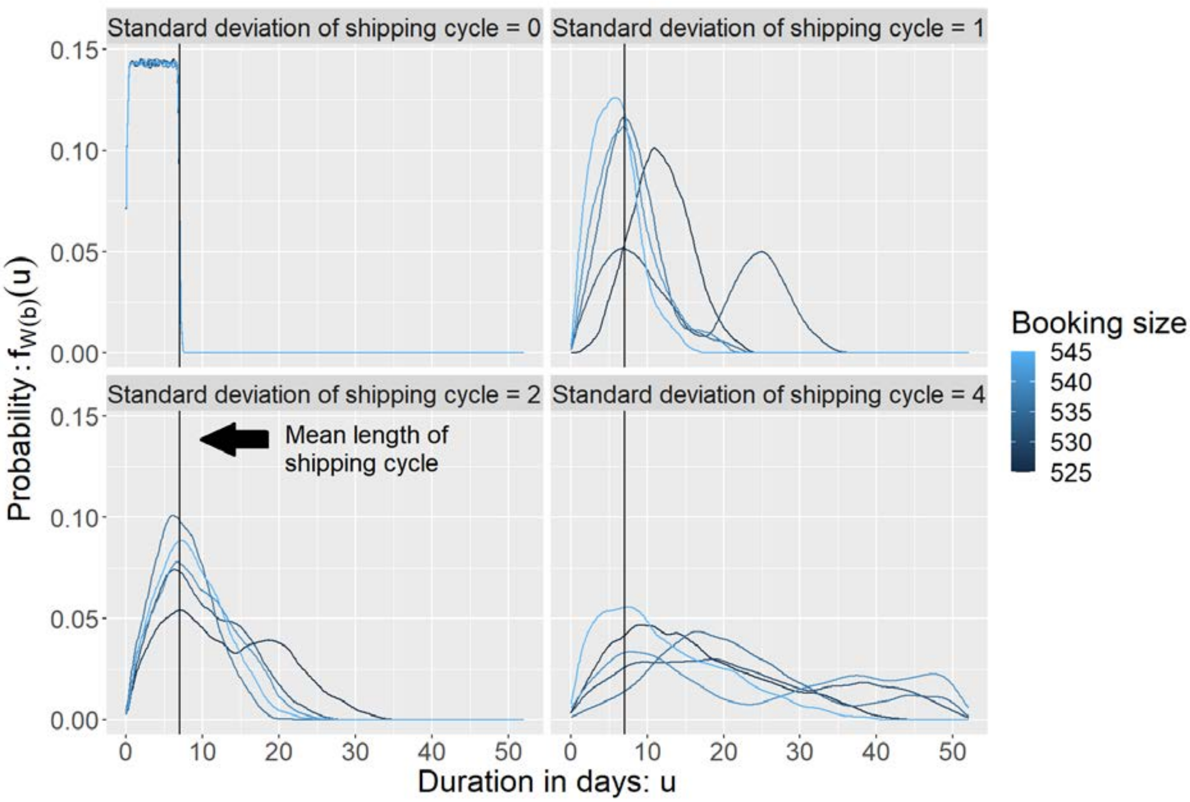

Figure 2: Waiting time distributions for different parameter configurations.

6 COMPUTATIONAL EXPERIMENTS AND RESULTS

As stated above, in this research, the car arrivals are assumed to follow a lognormal distribution. We assume a constant mean number of arrivals for cars per day of 75, mean shipping cycle of 7, and starting values of the standard deviation in the vessel shipping cycles and arrivals of cars per day, of 0 respectively (i.e., $\sigma_X = \sigma_V = 0$). We simulate booking sizes from 525, to 695 and set the step size to 10 yielding an enumeration of 18 points. The minimal booking size was set to the mean car arrivals per mean shipping cycle, i.e., such that $\mu_X \mu_V = b$. Additionally, we run the simulation for all combinations of booking size, standard deviation in the car arrivals per day ($\sigma_X = 0, 4, 10, 40$), and standard deviation in the vessel shipping cycle ($\sigma_V = 0, 1, 2, 3, 4, 5, 10$). The simulation time of each iteration was 625 days and for each parameter setting, we run 750 replications, since the stochastic simulation gives different results for every run.

Figure 3 shows the objective function for booking sizes according to the enumeration and combinations of (σ_X, σ_V) as described above. The respective optimum for every parameter setting is marked black in the diagram. All curves seem to be convex, which indicates the existence of a unique minimum for each parameter combination of (σ_X, σ_V).

In the case of $\sigma_V = 0$ and $\sigma_X = 0$, representing the deterministic system, the optimal booking size equals the average number of arriving cars per mean shipping cycle, which is $7 \cdot 75 = 525$. Increasing the variation in the shipping cycle, the booking size must be increased to reach the optimum where the total costs, in the broad view, are higher too. This is intuitively clear and underlines the validity of the model. The higher costs at the respective optima account for the higher uncertainty in the system. For example, at $\sigma_X = 0, \sigma_V = 2$ the minimal costs are reached at a booking size of 575. On the other hand, a precise consideration shows that an increase in the variation of car arrivals do not always increase the costs. Except of the case $\sigma_V = 0$, the optimal costs at $\sigma_X = 0$ are slightly higher than at $\sigma_X = 4$. While at $\sigma_X = 10$ the costs have increased only slightly, at $\sigma_X = 40$ the optimal costs are clearly higher than at every other parameter setting. Therefore, at low values of variation in the car arrival process, changes do not make much difference. This is also supported by the optimal booking size, which does not change between $\sigma_X = 0$ and $\sigma_X = 4$. However, to yield more exact results, the step size in the enumeration must be reduced.

The results in Figure 3 further show that parsimonious booking (booking size below optimum) leads to a higher increase in total costs than generous booking (above optimum). This is caused by the exponential increase in waiting times if in every cycle more cars arrive than can be transported.

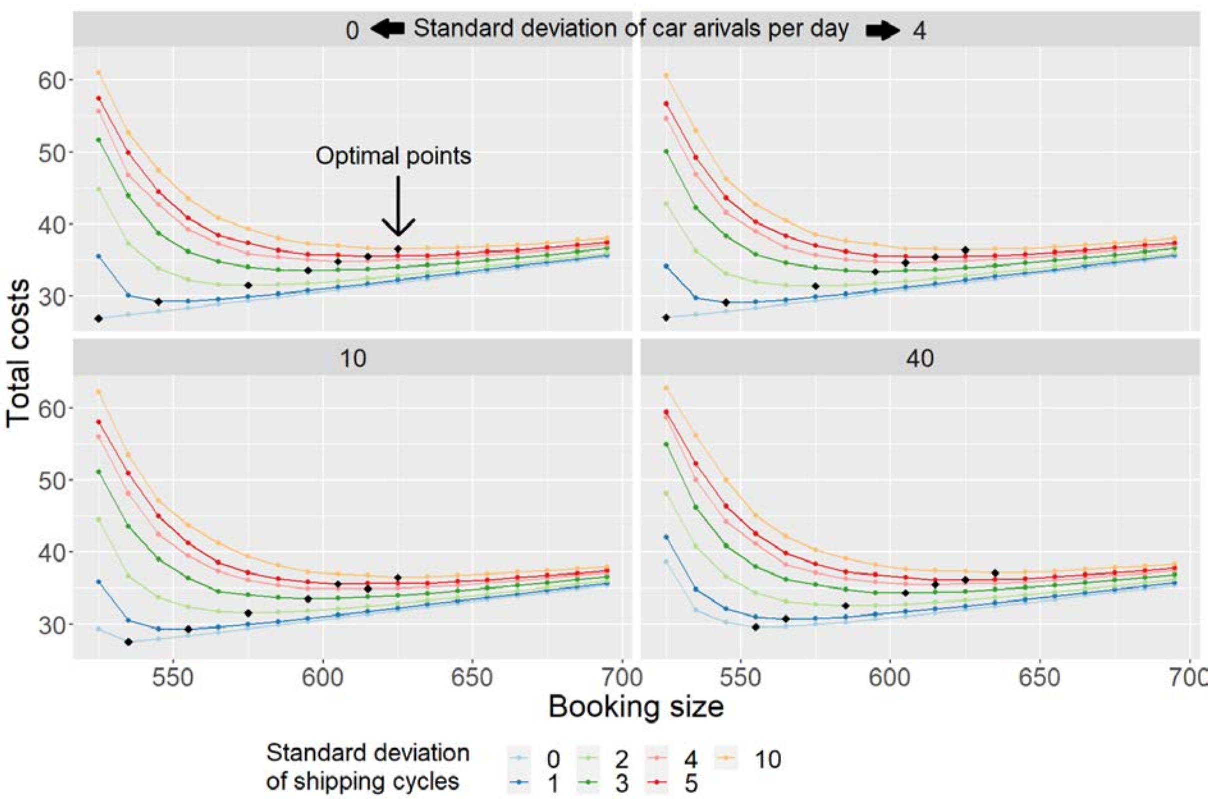

Figure 3: Variation of the parameters in the simulation of the objective.

These results are in line with the waiting-time paradox (Avineri 2004), where a higher variation in bus cycles lead to higher expected waiting times for passengers. The reason for this effect is, that variation in the cycle length leads to smaller and larger cycles. Since the mean arrival rate of passengers is constant over all days, the probability to arrive in a large cycle is higher than the probability to arrive in a short one. In other words, more passengers wait for buses that arrive after a long cycle.

To give a perspective on dynamic booking policies, where the booking size is not necessarily equal for all shipping cycles, a simple dynamic policy was implemented. In this policy, the queueing length after a vessel departure is added to the booking size of the subsequent shipment. The added bookings are added to the booking costs at an equal price as the basic bookings. This policy is intuitively motivated by the idea that it might be helpful to book additional slots if a backlog occurred in the last cycle. The optimal points using this simple dynamic policy are compared to the optimal points of the static policy in Figure 4.

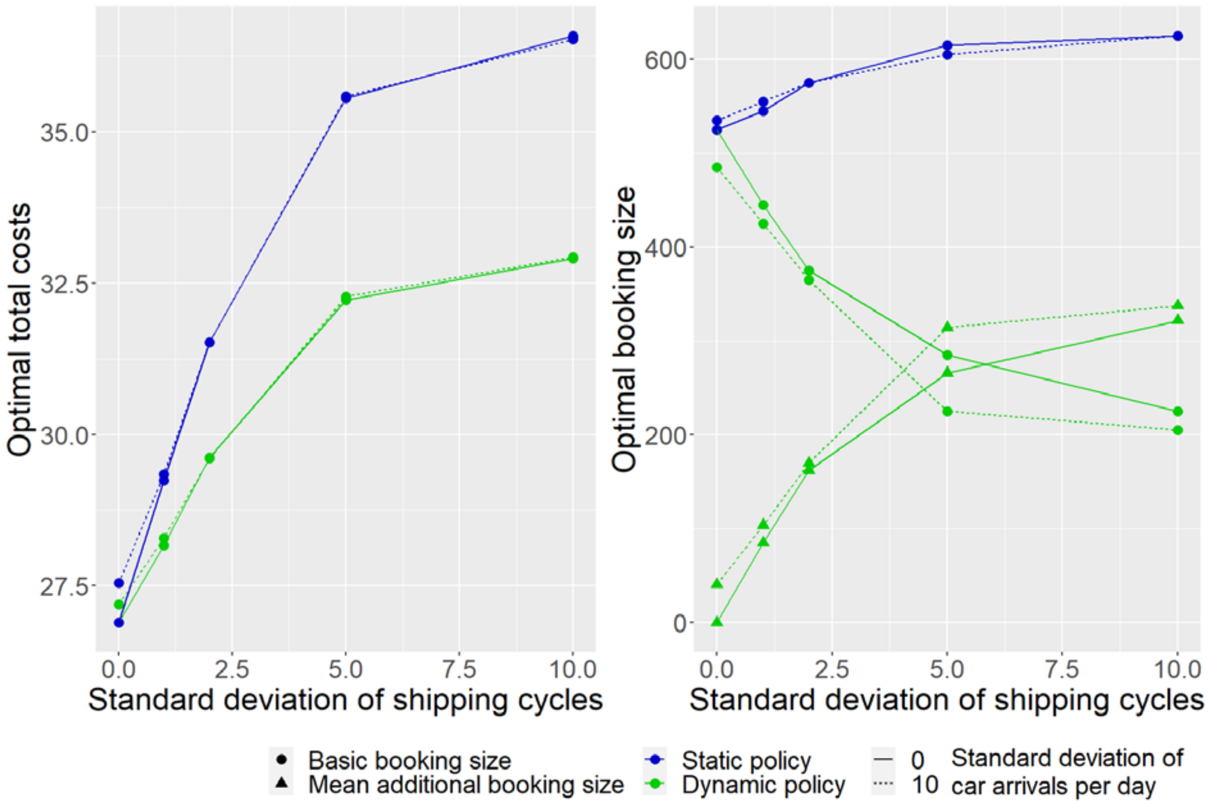

Figure 4: Objective functions for static and dynamic booking policy.

Using the dynamic policy results in lower optimal total costs in all cases with some uncertainty (i.e., except of the deterministic case). This means such a simple dynamic policy can already improve the performance of the system and in further research more sophisticated dynamic policies could be investigated. However, it is still true that the optimal costs increase with the variation in the shipping cycle. The optimal basic booking size of the dynamic policy decreases at higher uncertainty, which is compensated by the dynamic additional bookings. This means that short-lasting congestion is accepted and not avoided by larger basic booking volumes. Note that the used model allows unlimited dynamic booking. Summing up the basic and additional bookings in Figure 4, the booking size is still lower than using the static policy. This results in the lower total costs.

7 CONCLUSION AND OUTLOOK

In this article, the waiting time distribution at the port of departure of oversea shipping was simulated using discrete event simulation. Searching for the optimal costs of delays and bookings, the total costs were estimated on a grid of possible booking sizes. The impact of changes in the variation of car arrivals per day and shipping cycles on the optimal booking size and total costs was investigated. This is new since existing studies have either simplified the real situation by use of queueing models or investigated the effect of different vessel departure timetables or arrival rates of passengers on the waiting time distribution without changing the booking size. An analytical approach for the model of this article, using queueing theory would be inconvenient since the waiting time distribution in this model cannot be represented explicitly as a function of the booking size.

The present study shows that the optimal booking size increases with the variation in the shipping cycle. At the same time the total costs increase. This is known as the waiting-time paradox, where a higher variation in (e.g.) bus cycles lead to higher expected waiting times for passengers. Moreover, the experiment demonstrates that parsimonious booking leads to a higher increase in total costs than generous booking. This effect can be mitigated by using a dynamic booking policy instead of a static one. Adding the leftover cars to the booking size of the next shipment in regular intervals serves this purpose and also lowers the optimal total costs.

To further exploit the potential of dynamic booking policies, other types of it could be utilized and compared. Future research could also seek to optimize the booking sizes in delivery networks, where goods are shipped between many pairs of POD and POA. Uncertainties in the delivery time of complex supply chain networks (or delivery networks) may occur at many nodes of the network. Future research could shed more light on the interdependencies of uncertainties at several points in delivery networks. Moreover, since the future transportation demand at a node depends on the actual transportations at previous nodes, this information of current transportations can be used to optimize the capacity reservation policy at those downstream nodes. This leads to advance demand information models. In such a system, the utilization of dynamic booking policies is likely to yield a more robust performance and lower costs than a static booking policy.

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