Exploring the Impact of Overbooking Strategies in Barge Container Transport: A simulation study

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Abstract

Barge container transport faces significant capacity management challenges due to no-show uncertainty and arrival time deviations, leading to underutilized capacity on barges. This research investigates the application of overbooking strategies in barge transportation to address these challenges and provides decision support for managing uncertainty in barge operations. A discrete-event simulation model was developed using Arena software to evaluate different acceptance strategies, allocation methods, and overbooking rates under varying no-show conditions. The study reveals that overbooking effectiveness is highly dependent on the allocation strategies effectiveness and the no-show rates. With poor allocation strategies the penalties incurred from overbooking increases significantly. At lower no-show rates, overbooking provides limited benefits with disproportionately high trucking increase, while at higher rates, overbooking restores capacity utilization while incurring less trucking. The trade-off analysis establishes a framework to find opportunity cost thresholds for accepting additional orders, enabling operators to evaluate economic viability based on their competitive position. This research extends overbooking theory from traditional service industries to barge transportation and provides a framework for capacity management in barge container transport with overbooking, offering practical decision support tools for terminal operators to improve profits.

Contents

1. Introduction

Intermodal transportation represents a logistics approach where cargo moves through multiple modes of transport within standardized containers, enabling transitions between maritime, rail, road, and inland waterway networks (Hanssen et al. 2014). This integrated system forms the backbone of global supply chains, characterized by complex nodal interactions at transfer points such as maritime terminals, inland container depots, and rail hubs (Rozic et al. 2016). The efficiency of these transfer points significantly impacts the performance of the entire transportation network. Intermodal terminals function as critical capacity-constrained resources where multiple transport modes converge, necessitating coordination mechanisms to maximize throughput and minimize congestion (Bektas et al. 2007).

Barge transportation presents complex capacity management challenges due to the distinct operational characteristics of inland waterway systems (Behdani et al. 2016). Barge operators face problems in level of utilization decreases influenced by no-shows, late shipments, and transit times creating substantial uncertainty in planning barges and accepting and assigning shipments to barge services (Gumuskaya et al. 2020). Terminals serving barge traffic must therefore develop planning strategies that account for these inherent system variabilities while maintaining operational efficiency (Notteboom et al. 2021). Traditional static planning approaches fail to address the dynamic nature of container arrivals, delays, and no-shows that characterize real-world barge operations.

Overbooking strategies in passenger and hospitality sectors address similar no-show risks through probabilistic booking limits to improve capacity utilization. Van Ryzin et al. (1999) formalized the foundational revenue-management framework that balances expected denial costs against marginal booking benefits in transportation, while Subramanian et al. (1999) extended this to multiple fare classes and Gupta and Denton (2008) applied overbooking principles to healthcare with obligated versus discretionary customers. In freight transport, Feng et al. (2015) developed a dynamic programming model for decision support in railway freight overbooking, demonstrating improved capacity utilization and revenue compared to first-come-first-served methods. Wu (2019) extended this work using a simulation by studying the trade-off of booking in extended periods. In container logistics, Wang et al. (2019) examined slot allocation strategies for already-accepted orders in container terminals, focusing on how overbooking can optimize berth allocation when cancellation and no-show behavior create unused capacity. The combination of uncertainty and dynamism in barge terminals creates a complex planning environment that requires adaptive decision-making capabilities (Gumuskaya et al. 2020). Dynamism emerges from the continuous evolution of these uncertain conditions, where new information becomes available throughout the operational horizon. Traditional static models treat these factors as fixed parameters, failing to capture the interactive effects between uncertain events and dynamic system responses.

This research addresses the capacity management challenge faced by barge terminals operating under uncertainty and dynamism. Barge terminals must make sequential accept/reject decisions for incoming container orders without complete knowledge of future demand, while managing other sources of unknown information in a dynamic environment. Unlike traditional overbooking contexts where excess demand results in service denial, barge terminals possess a unique operational flexibility through truck transport substitution (Behdani et al. 2016), where, when barge capacity is exceeded, containers can be shipped via more expensive truck alternatives, ensuring continuous service delivery but at higher costs. The sequential nature of booking decisions creates a trade-off where operators must balance capacity utilization, order accommodation, and trucking usage while serving demand. This context requires decision support tools for determining overbooking strategies and explores the trade-offs between unused barge capacity due to no-shows, increased trucking reliance from capacity exceedance, and rejected orders. This thesis will develop a discrete-event simulation to examine the performance of overbooking strategies under uncertainty and dynamism. The model will replicate booking arrivals, cancellations, arrival time deviations, and container arrival assignments, while incorporating different booking strategies to analyze their performance under various conditions.

The remainder of this thesis is organized as follows. Section 2 reviews the literature on overbooking and container on barge. Section 3 details the problem setting. Section 4 defines the methodology being used. Section 5 the computational experiments done in the simulation, and Section 6 and 7 present the conclusion and discussion.

2. Literature Review

In this section, we provide an overview of available literature on overbooking. We first define overbooking and review how overbooking has been studied in literature. Then we further review the literature on overbooking for container transport. Lastly, we review the literature that researches the container on barge problem.

2.1 Application Cases of Overbooking

Overbooking is an operational strategy that has been adopted in several industries to mitigate the inefficiencies associated with uncertain demand (Gallego et al. 2019). At its core, overbooking is based on the idea that not all customers who make a reservation ultimately utilize the service. By accepting reservations more than the actual physical capacity, service providers can improve overall utilization rates. Van Ryzin et al. (1999) were among the first to develop a formal framework for revenue management that includes overbooking decisions on yield management. Their approach relies on probabilistic models that estimate no-show and cancellation rates, with the fundamental principle being to equate the expected marginal cost of additional bookings (calculated by considering the cost of compensating customers who are denied service) with the expected marginal benefit of increased occupancy. This cost-benefit analysis framework is essential in setting an overbooking limit that maximizes revenue while keeping the risk of service disruption at an acceptable level. This thesis builds on their cost-benefit analysis framework and applies it to the problem in hand where excess demand triggers service substitution through truck transport rather than service denial, creating different trade-off dynamics where customers maintain service delivery but at higher operational costs. In comparison, the thesis will also examine a third trade-off metric in the analysis which is the rejection of a customer for booking.

In both airline and healthcare industries, the overbooking process is analyzed by statistical analysis and the use of probabilistic models. A consistent finding across the literature is that overbooking strategies can succeed based on the costs for compensation of service denial, benefit from increased occupancy and the opportunity cost of denying booking; and booking beyond overbooking limits can yield diminishing returns due to the increasing probability of service denial and the associated penalties. The competitive pressures in such sectors also drive firms to adjust their overbooking thresholds based on market conditions. For example, if customer loyalty and market share are at risk, firms may choose to increase their overbooking levels, even at the expense of some revenue, to maintain long-term competitiveness (Van Ryzin et al., 1999, Fard et al. 2019).

2.2 Container Terminals (Intermodal) and overbooking

Wang et al. (2019) focus on slot allocation strategies for already-accepted orders in container terminals, examining how overbooking can be applied to optimize berth allocation when cancellation and no-show behavior create unused capacity. Their work addresses reallocating slots among orders that have already been confirmed, developing strategies to maximize utilization when some bookings fail to materialize. Our research examines the earlier stage of this process, the initial acceptance decision when orders first arrive at the terminal, before they enter the slot allocation phase that Wang et al. address.

Feng et al. (2015) produced the only research conducted in this phase and developed a dynamic model for railway freight overbooking to improve revenue in the Chinese railway freight industry. The authors formulated a Markov decision process (MDP) model with an overbooking limit level as the control policy. Their model considers a train with capacity C and an overbooking pad D that represents the maximum bookings allowed for different classes. The reservation process is divided into multiple decision periods, with customers able to cancel bookings before departure or become no-shows. Their approach establishes the foundation for overbooking decisions on freight transport by demonstrating how acceptance and rejection decisions can be evaluated through a sequential decision-making process. They compare their MDP approach to the existing first come first serve (FCFS) methods without overbooking used in the industry to verify the effectiveness of overbooking decision processes, showing that overbooking policies improve capacity utilization and revenue. However, their dynamic programming approach requires six nested loops making it computationally burdensome for real-world problems, even when considering the acceptance and rejection decisions of a single train with no deviations, immediate order arrivals, and a single stage reservation. The authors acknowledge that expanding their model to include multiple reservation stages would significantly increase the complexity of data collection, analysis, and parameter estimation, limiting practical applicability (Feng et al., 2015).

The thesis of Wu (2019) builds on Feng's work by using simulation to address overbooking in inland freight transport systems when dealing with increased system complexity. Unlike Feng's single-day approach, Wu considers multiple stages of barge departures to observe general system performance over extended periods to analyze overbooking strategies, allowing analysis of how booking decisions accumulate and interact across multiple departure cycles. Her approach uses simulation to handle multiple stochastic variables including possible deviations, and to capture long-term system dynamicity that emerges from repeated interactions between booking decisions and uncertain realizations (Wu 2019). Wu's approach maintains Feng's structure where once an order is accepted it becomes immediately available in the system without estimated arrival times, and the due dates of the order are set to the next available barge in the period. Her research also establishes that overbooking can increase utilization and profit for barges, though resulting in higher usage of trucks. However, a shortcoming of her study is that she uses a FCFS approach as orders that arrive in the system are immediately available and their due date is to the next available barge. Our methodology follows Wu's simulation approach but extends her operational framework by incorporating temporal uncertainty through estimated arrival times that may deviate from schedules, and orders are not directly available in the system. Additionally, we introduce varying order sizes rather than using single TEU per order and implement stochastic due date assignments rather than orders being automatically due for the next available barge.

2.3 Container on Barge

Studies that have employed planning in real-time such as van Riessen et al. (2016), and Mes and Iacob (2016) disregard the possibility of no-shows or delays happening in a stochastic manner. Van Riessen et al. (2016) developed decision trees for instantaneous allocation of incoming orders to suitable services without the need for continuous planning updates, creating a decision support system that is implementable in current container transportation practice. The authors specifically note that earlier proposed centralized methods can find optimal solutions for intermodal inland transportation problems in retrospect but are not suitable when information becomes gradually available. Their approach addresses the gradual information availability problem by creating decision rules for immediate allocation decisions, but assumes all incoming orders are accepted and focuses on service allocation rather than acceptance decisions. This study similarly addresses gradual information availability but focuses on the acceptance decision rather than allocation decision, incorporating no-show and cancellation uncertainties that van Riessen et al. do not consider. We make allocation less constraining to improve utilization as an order allocated to a certain barge slot can change its allocated barge based on feasibility. Rivera and Mes (2017) use probabilistic knowledge about future freights in their multi-period optimization approach, but their method also optimizes orders that are already known in the system. Their approach operates under the binding constraint that all orders arriving to the system must be served, focusing on freight selection and routing decisions rather than initial acceptance decisions. While they address uncertainty in freight availability, they do not consider no-show behavior or cancellation uncertainty from already-accepted orders. Both dynamic and deterministic studies operate under the binding constraint that all orders arriving to the system must be served.

Gumuskaya et al. (2020) developed a 2-stage stochastic MIP for dynamic barge planning addressing uncertainty in container arrival times and possible deviations. Their work focuses on uncertainty and dynamism that leads to limited information availability during planning. They employ arrival time deviation distributions to model the uncertainty between estimated and actual container arrival times, which reflects real-world operational challenges in barge planning. The simulation methodology used in this thesis also employs the same arrival time distributions employed in their study. Their method evaluates long-term performance over one year by solving the stochastic program at the end of each week for optimal allocation decisions, then simulating the orders in the upcoming week to demonstrate the dynamism of actual operational conditions. Their results show that uncertainty has an impact of up to 53% and dynamism up to 20% on total costs, highlighting the significant role of uncertain conditions in barge operations.

As we discussed in sections 2.1, and 2.2, existing overbooking literature has primarily focused on service industries with capacity constraints that result in service denial. Wu (2019) addressed that in intermodal terminals, service substitution is possible rather than service denial with a change of mode in transport. The performance of overbooking strategies in logistics environments with service substitution capabilities represents still an underexplored area of academic inquiry. Container terminals can maintain continuous service delivery even when barge capacity is exceeded by redirecting containers to truck transport (Behdani et al. 2016). Literature consistently incorporates trucking as a penalty cost in optimization models for slot allocation, as trucking costs are relatively higher than operating costs of a barge (Fazi et al. 2015, Behdani et al. 2016, Zweers et al. 2019, Gumuskaya et al. 2020). This study leverages this service substitution capability to examine how acceptance decision timing affects the trade-off between barge utilization and trucking.

This operational flexibility creates distinct planning dynamics compared to traditional service industries. When terminals reach capacity limits, operators can accommodate excess demand by loading containers onto trucks, ensuring uninterrupted service delivery to customers. This capability alters the planning problem under uncertainty, as the penalty for exceeding barge capacity is not service denial but rather increased operational costs through trucking penalties. Unlike traditional overbooking scenarios where capacity exceedance results in customer denial, this operational flexibility enables exploration of overbooking decisions that balance capacity utilization with penalty cost management.

2.4 Literature Summary

Service industries have established cost-benefit analysis as the foundation for overbooking decisions, balancing expected denial costs against marginal booking benefits (Van Ryzin et al. 1999). Customer heterogeneity significantly affects overbooking effectiveness, whether through fare class differentiation (Subramanian et al. 1999), contractual versus spot market customers (Levin et al. 2012) or obligated versus discretionary service requirements (Gupta and Denton 2008). These studies demonstrate that optimal overbooking levels exist, with diminishing returns beyond certain thresholds due to increasing denial costs.

The problem studied in this thesis is most similar to Feng et al. (2015) and Wu's (2019) studies, which address freight overbooking through sequential acceptance and rejection decisions under no-show uncertainty. Feng et al. established the foundation using MDP formulation for railway operations, developing a model for acceptance and rejection decision processes to determine optimal overbooking levels and demonstrating that overbooking policies improve capacity utilization and revenue. However, their approach focuses on single-day operations with immediate order arrivals and single-stage reservations. Wu (2019) extended this by using simulation to address increased system complexity, considering multiple barge departure stages and capturing long-term system dynamicity through repeated interactions between booking decisions and uncertain realizations. Unlike Feng's MDP approach, the developed simulation aims to capture the dynamicity of the system over time as booking decisions accumulate across multiple departure cycles, which would be computationally too burdensome to model in an MDP. This thesis builds on Wu's simulation approach but incorporates temporal uncertainty through estimated arrival times that may deviate from schedules, varying order sizes rather than single TEU per order, and stochastic due date assignments similar to the Gumuskaya et al. (2020) study rather than orders being automatically due for the next available barge. It also touches on one of the future research recommendations Wu (2019) has for the simulation methodology by enabling splitting an orders' containers into different transport modes.

Container-on-barge research fails to address no-show uncertainty and operates under the assumption that all incoming orders are automatically accepted. This constraint prevents investigation of overbooking strategies despite barge terminals possessing unique operational characteristics that make overbooking particularly viable. As mentioned in the literature review, in traditional service industries overbooking leads to service denial, but barge terminals can maintain continuous service delivery through truck transport substitution. Literature acknowledges trucking as a penalty cost mechanism as a trade-off for directing service with trucking instead of barges (Fazi et al. 2015, Behdani et al. 2016, Zweers et al. 2019, Gumuskaya et al. 2020), creating different trade-off dynamics between capacity utilization and operational costs rather than service denial scenarios.

Building on the problem foundations established by Wu (2019) and Feng et al. (2015) and incorporating the arrival time deviation uncertainty studied by Gumuskaya et al. (2020), this thesis examines how overbooking strategies can be studied in barge terminals given their unique service substitution capabilities. The research investigates the main features and trade-offs of overbooking strategies in barge transport, develops a discrete event simulation to capture system dynamicity with random orders and varying due dates, and analyzes how overbooking affects terminal performance under no-show, cancellation, and arrival time deviation uncertainty.

The table compares the most relevant studies in terms of their approach to uncertainty modeling, order processing assumptions, analytical scope, decision-making capabilities, and methodological frameworks. The comparison shows how each study addresses uncertainty factors, whether orders become immediately available in the system or have estimated arrival times, the time horizon of their analysis, whether they incorporate acceptance/rejection decisions, and their chosen modeling approach.

Study	Uncertainty Factor	Order Availability Once in System	Analysis Period	Accept/ Reject Decision	Modeling Approach
Feng et al. (2015)	No-show probabilities	Immediate availability	Single day	✅	MDP
Wu (2019)	No-show probabilities, Arrival time deviations	Immediate availability	Multiple periods	✅	Simulation
Gumuskaya et al. (2020)	Arrival time deviations	Estimated arrival times	Multiple periods	❌	Stochastic MIP + Simulation
This study	No-show probabilities, arrival time deviations	Estimated arrival times	Multiple Periods	✅	Simulation

Table 2.4: Comparison of similar studies

2.5 Research Questions

Based on the literature review and identified research gaps, this research examines overbooking strategies in barge terminals with the following research questions

Main Research Question

How to develop a decision support system that supports understanding overbooking strategies and the management of no-shows and delays in an inland container transport system?

Sub-Research Questions

SRQ1: What are the main features of a booking system to manage orders and its dynamics in a barge transport system? What are the main trade-offs?

SRQ2: What methodology can better capture the dynamicity of the system with stochastic parameters?

SRQ3: Do overbooking strategies affect barge terminal performance under no/show, cancellation and arrival time deviation uncertainty?

3. Problem Setting

3.1 Problem Description

The problem considers an inland barge terminal in the Netherlands that operates 24/7 under conditions of inherent uncertainty. Container orders arrive continuously throughout real-time, each carrying specific requirements for pickup timing, delivery deadlines, and capacity needs. The system must process these orders sequentially, making acceptance and scheduling decisions without complete information about future order arrivals or the ultimate realization of orders that have already been accepted. This creates a dynamic environment where each decision influences the system's capacity to accommodate subsequent orders.

When a container order arrives at the system, the operator faces a binary accept or reject decision based on current capacity. This decision must be made with incomplete information, as the operator cannot know with certainty when future orders will arrive, whether accepted orders will materialize, or if orders will arrive at their estimated times. Accepted orders enter the system with estimated arrival times and due date requirements, and different TEU sizes. Upon order arrival, the system evaluates available capacity against existing booking commitments. Orders that pass the initial capacity assessment are accepted and assigned to departure schedules based on their due date requirements.

The barge departures operate on a fixed schedule with predetermined departure times throughout each operational day. Barges have limited capacity and depart according to this schedule regardless of their loading level. When a barge approaches its departure time, all orders that have physically arrived at the terminal are available for loading. The system must decide which containers to load onto the departing barge within its capacity constraints. Containers not selected for barge transport with due date constraints are forced to be shipped by truck, and it is possible to split an order with more than 1 TEU between a barge and a truck if needed. The barge departs according to its fixed schedule once loading decisions are made.

Orders that have been accepted into the system progress through multiple stages where uncertainties resolve in a specific sequence. As each order approaches its estimated arrival time, the system first learns whether the actual arrival will deviate from the original estimate, revealing any timing adjustments that must be incorporated into capacity planning. These arrival time deviations may require schedule modifications and capacity reallocation across different departure windows. Once the system reaches the order's actual arrival time, it then discovers whether the order will materialize or become a no-show, resolving the demand realization uncertainty that has been carried since acceptance. Orders that successfully materialize and arrive at the terminal enter the holding queue and become available for loading decisions to the barge. If an order cannot be loaded into the barge before its due date, due to the barge being over capacitated, then it is forced to be trucked so that the order can be served before its deadline.

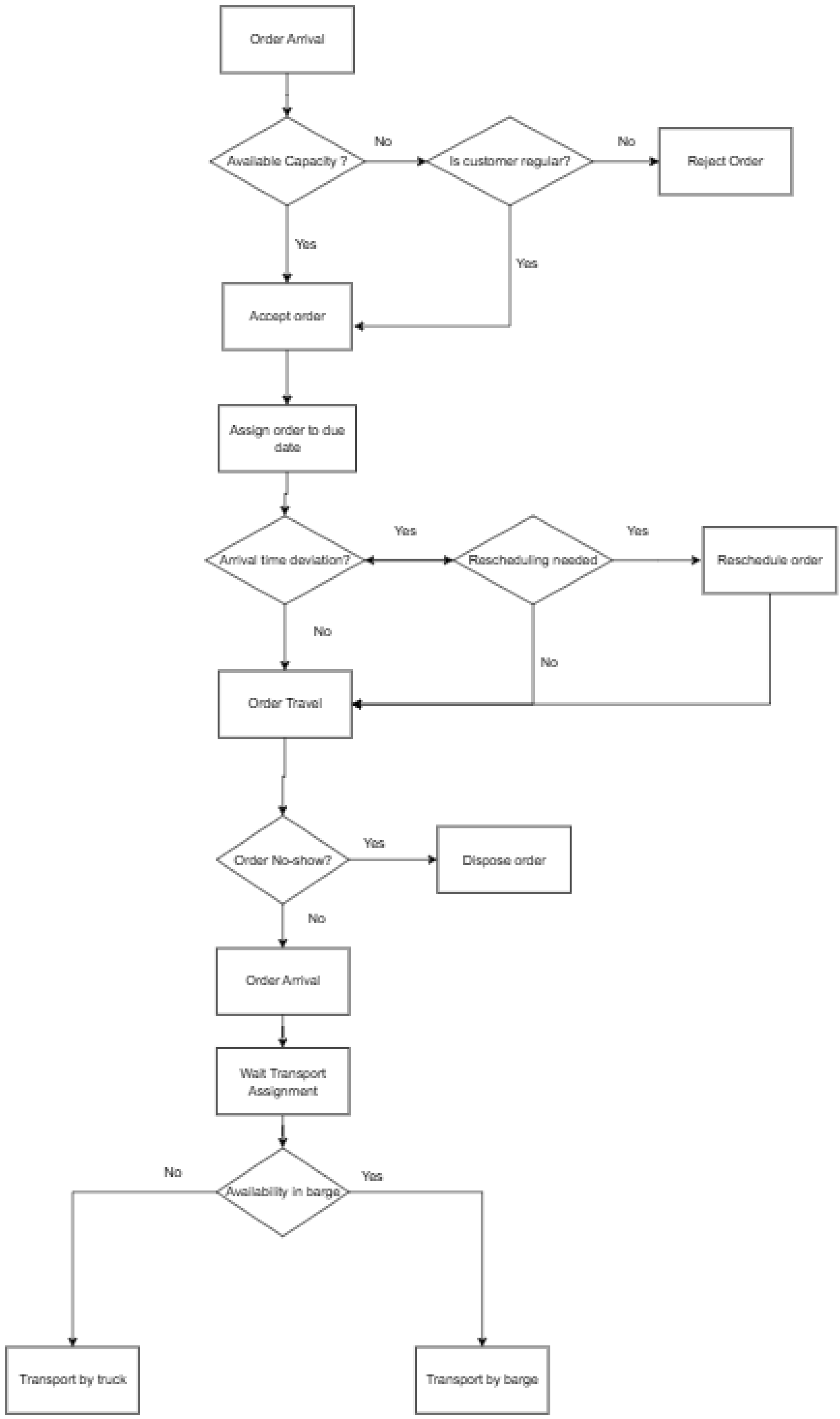


Figure 3.1: Flowchart describing the process for all orders

3.2 Performance Measurement

Different metrics are used to evaluate systems operational efficiency. The 3 metrics discussed here are identified from the literature of overbooking strategies and container on barge problems. Barge capacity utilization measures the percentage of available barge capacity that is used during each departure throughout the operational period, calculated as the ratio of loaded containers to total barge capacity. Order rejection rate tracks the proportion of incoming orders that cannot be accommodated within the system's capacity constraints and are therefore declined. Trucked containers measure the number of containers that are shipped via truck rather than barge.

Metric	Formula	Unit
Barge Capacity Utilization per period	(Total Loaded TEU to barge / Total Available Barge Capacity) × 100	%
Order Rejection Rate	(Rejected Orders / Total Orders) × 100	%
Trucked Containers	Total TEU transported by Truck	TEU

Table 3.2: Performance Metrics

3.3 Model Assumptions

The model development requires several assumptions that simplify the complexity of barge container transport and terminal operations while preserving the dynamics necessary for meaningful analysis. Operational assumptions establish the basic framework within which the system operates, including the presumption that barges operate according to predetermined schedules with consistent and reliable departure times (Gumuskaya et al. 2020, Fazi et al. 2015, Zweers et al. 2019, Wu 2019). Another operational assumption involves the immediate availability of truck transport alternatives when barge capacity is exceeded (Behdani et al. 2016, Wu 2019, Gumuskaya et al. 2020). This assumption is used in different models in literature based on that truck transport typically offers greater flexibility and availability than barge services, allowing operators to maintain service commitments even when barge capacity is fully utilized.

The model also assumes that all accepted orders that arrive must ultimately be served before its due date, either through barge transport or truck alternatives, reflecting the service commitment inherent in accepting customer orders. All container units are treated as homogeneous revenue generators regardless of their characteristics. For the homogenous revenue assumption, we additionally assume customers that place orders intend their container to be transported by barge and generate revenue accordingly. The last cost assumption is that the revenue of an order is lost if the order is a no/show or cancellation. Physical loading constraints are simplified to pure capacity limits, ignoring stowage requirements, and finally when the due date of orders deviates, orders are assigned a new due date so that an order never arrives at the terminal after its due date which would force trucking. The final destinations of orders are not considered, so any set of available orders that fit the barge capacity can be loaded into the barge. Finally, the information of a no-show happening to an order is revealed at the time of the ETA to the operator.

4. Methodology

This section presents the detailed design and implementation of the discrete-event simulation model developed to analyze overbooking in barge container transport. The model translates the problem setting from Section 3 into a functioning simulation using Arena software, incorporating the modules used in Arena, decision logic, and parameters identified in the problem setting. This section will also explore parts of SRQ 1 and 2 defined in section 2.5, identifying the main features to consider for booking systems in barge terminals, explaining the main trade-offs caused by employing different strategies, and how a discrete event simulation can capture the dynamicity of the system.

4.1 Simulation Design

This study examines how overbooking strategies can be applied in barge container transport systems to address no-show and arrival time uncertainty while managing the trade-offs between capacity utilization, order rejection, and truck substitution costs. Discrete event simulation (DES) allows the study of and experimentation with complex systems, helps in gaining knowledge that could lead to system improvement, and enables evaluation of different circumstances by changing inputs and observing resultant outputs (Sharma, 2015). According to literature studies on DES, benefits of analysis through simulation include obtaining better understanding of systems through detailed observation over long periods, studying effects of policy changes, experimenting with new situations about which only weak information is available, and identifying driving variables that performance measures are most sensitive to (Maria, 1997). Additionally, discrete event simulation is suitable for exploring and comparing strategies in complex systems under inherent uncertainty (Neagoe, 2021). For these reasons, discrete event simulation is employed in this study to evaluate different overbooking strategies under no-show and arrival time deviation uncertainty. Analytical or mathematical models were not chosen given the high dynamicity and the interplay between too many different random variables which would have made the model too complex.

The model evaluates system performance across varying overbooking rates, no-show rates, and different allocation and order acceptance strategies. Using a simulation to model enables exploration of these interactions over extended periods. The simulation tracks orders from booking requests through acceptance decisions, arrival time realizations, no-show determinations, and final allocations to barge or truck transport. The structure of the simulation and the employed rules to evaluate will be further explained in section 4.2.

4.1.1 Arena Software

Arena is used as a simulation and modeling platform that allows users to build detailed simulation models, run experimental scenarios, and produce analysis reports. The software has become widely adopted in supply chain and logistics sectors because of its ability to model complex operational systems and assess different strategic and tactical decisions (Rockwell, 2019). Arena's discrete-event simulation environment provides the flexibility to represent sequential decision-making processes, stochastic system behaviors, and dynamic scenarios that characterize real-world logistics operations. The software's modular approach for decisions and processes allows for the construction of models that can capture the temporal dependencies with clearly defined strategies, making it suitable for analyzing problems under uncertainty.

4.1.2 Arena Modules

Different Arena modules that are used in the building of the model will be explained in this section to ensure the reader can understand the technical background of the simulation, if they wish to create a similar model in the future with the same software. The create module generates order arrivals by producing entities at specified intervals and quantities. Upon creation, orders are processed through assign modules that establish order attributes including estimated time of arrival, due date, and TEU amount. The Assign modules also perform calculations throughout the simulation for updating capacity and maintaining accurate tracking of container counts. The booking acceptance logic is implemented through Decide modules that function as conditional statements within the simulation flow. The Decide modules operate like an if statement in traditional programing and are also used to handle schedule adjustment logic and barge capacity assessment when an order needs to be shipped. The hold modules are used to represent the temporal aspects of order processing by holding entities inactive until the conditions to process them are met. The Search and Remove module is used to select orders by searching orders in the simulation that meet specific criteria and removing them to redirect them for a different process. This module enables the selection of orders that we intend to process. The clone module is used to split orders into container level for order allocation, and finally the batch module is used to represent a barge where container level entities are stored until barge departure.

4.2 Conceptual Model

The simulation models the decision-making process that barge operators face when managing container bookings. The operator makes two distinct types of decisions: first, whether to accept or reject incoming orders, and second, how to allocate arrived containers to available transport capacity when barges prepare for departure. Figure 4.2 shows the IDEF0 diagram of the conceptual model.

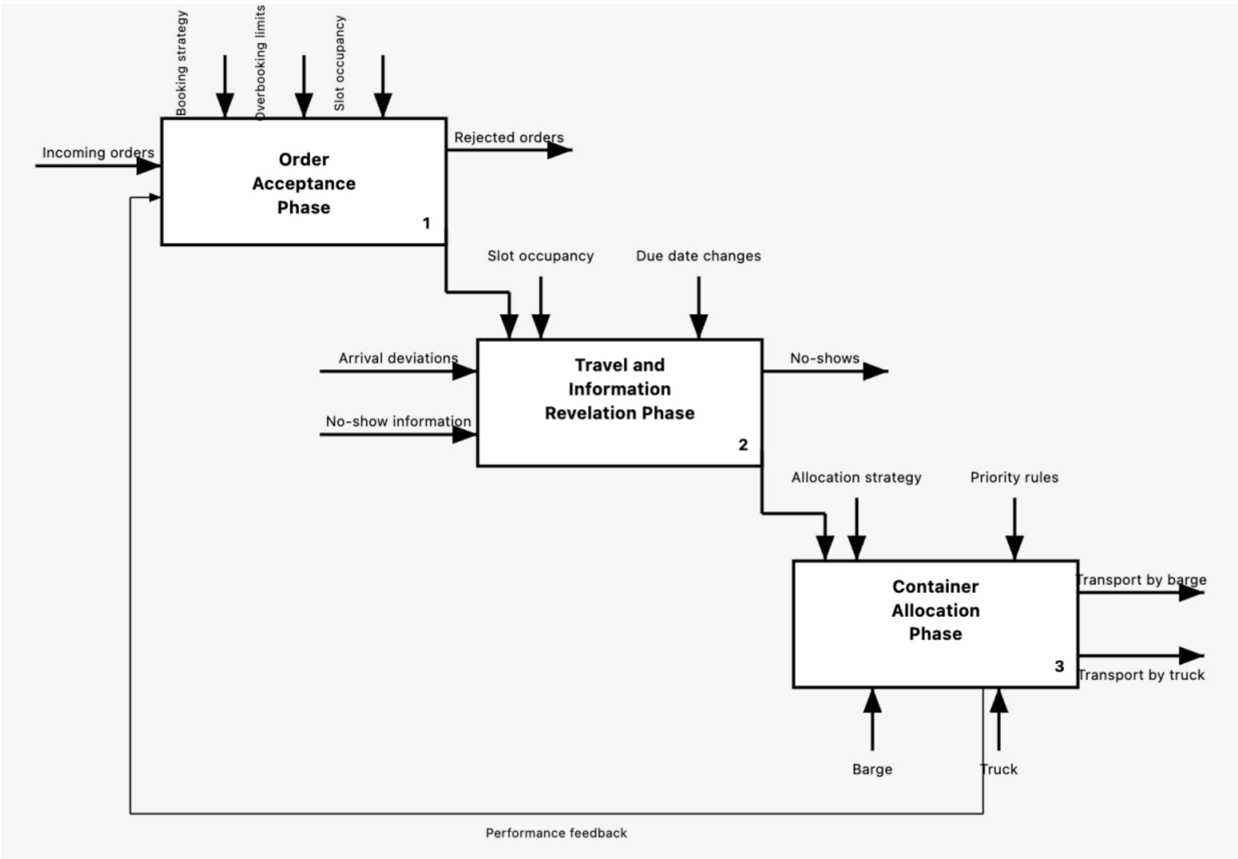


Table 4.2: IDEF0 Diagram of the conceptual model

4.2.1 Order Acceptance Phase

Orders arrive at random intervals throughout the simulation period with varying characteristics. Each order has three attributes known to the operator at the time of the acceptance decision: estimated time of arrival (ETA), due date, and TEU size.

These attributes are assigned to each order using probability distributions in the simulation. The operator must make the acceptance decision based on the information from these attributes plus the current state of the occupancy of barge slots. When making acceptance decisions, operators can employ different strategic approaches ranging from conservative to aggressive booking and increased overbooking rates. Conservative strategies accept orders only when ample capacity exists, minimizing the risk of future capacity conflicts. Aggressive strategies accept more orders despite potential future complications, aiming to maximize capacity utilization and order acceptance at the cost of increased trucking possibility.

Two specific dimensions are tested in the acceptance phase. The first dimension involves overbooking limits: Operators can set capacity limits for departure slots either at more conservative levels or at higher levels compared to the barge capacity (or at none if the operator does not intend to overbook any slots). Higher overbooking limits allow acceptance of more orders, providing protection against no-shows but creating risk of capacity exceedance. Lower overbooking limits protects the operator from more trucking usage but risks having less barge utilization and rejects more orders. The second strategic dimension involves flexibility in slot assignment when accepting orders. The conservative acceptance strategy is more selective, initially allocating each order only to its originally requested departure slot, as determined by the order's due date. For example, if a customer requests a shipment on Tuesday's first barge, the order is either accepted into that barge slot (if capacity is available) or rejected outright. Even if an earlier Monday slot has unused space and the order would arrive in time, it is not considered. By contrast, the aggressive acceptance strategy is less selective, allowing orders to be reassigned into earlier departure slots with available capacity, provided that the order's estimated arrival time makes such an allocation feasible. For example, a customer requesting Tuesday's departure could instead be initially accepted into Monday's departure if the shipment is expected to arrive at the terminal before Monday. This broader acceptance rule enables the operator to smooth out imbalances in slot demand, fill underutilized departures, and ultimately accept a larger volume of orders overall. The tradeoff is that it introduces exposure to uncertainty: if the order is subject to deviation, it may have to be shifted back into its original Tuesday slot, which could now be filled by other orders. Such reassignments create risks of capacity exceedance or additional trucking.

When an order is accepted, the operator commits capacity from the appropriate departure slot based on the order's TEU size. This slot assignment is not final, as orders can be reassigned to different departure slots during later phases to improve capacity utilization or accommodate arrival deviations.

4.2.2 Travel and Information Revelation Phase

After acceptance, orders begin traveling to the terminal. During this phase, additional information about each order is revealed that may require adjustment of the original capacity assignments. First, arrival time deviations are assigned using the probability distributions studied from the Gumuskaya et al. (2020) study. These deviations represent the difference between estimated and actual arrival times, creating scheduling uncertainty that can disrupt planned capacity allocation. When arrival time deviations occur, the operator may be forced to reassign orders to different departure slots to maintain feasibility. If an order's new arrival time makes its original departure slot infeasible to accomodate, the order is moved to the earliest feasible slot. In cases when there are no feasible slots available, the reassignment may force orders into slots that are already at capacity, creating capacity exceedance in the departure slot.

The final piece of information revealed is whether the order materializes or becomes a no-show. The no-show rate is a predefined parameter in the system that determines the percentage of an accepted order materializing. When orders become no-shows, their allocated capacity is freed up in the assigned departure slots, potentially creating unused capacity if no other orders can utilize the released space.

Information About Order	**Description**	**When Revealed**
TEU Size	Number of containers in the order	At booking request
Estimated Time of Arrival (ETA)	Projected arrival time at terminal	At booking request
Due Date	Deadline for order departure	At booking request
Arrival Time Deviation	Difference between estimated and actual arrival	During order travel phase
No-show Status	Whether order materializes or cancels	At scheduled arrival time

Table 4.2: Information About Orders Revelation Throughout the Simulation

4.2.3 Container Allocation Phase

When orders successfully arrive at the terminal, they enter the allocation phase where operators must assign arrived containers to specific transport modes. The simulation maintains the constraint from section 3.3 that all arrived orders must depart before their due dates, either by barge or truck transport. Every time a barge is set for departure, urgent orders are prioritized first by the simulation. An urgent order is classified as an order which, if it does not depart with the next available barge, will miss its due date. Since these orders will be trucked if not loaded on the barge, they are allocated to the barge first. If the amount of TEU that are urgent exceeds the capacity of the barge due to extensive booking or deviations, then the excess TEU above barge capacity are forced into trucking.

If the barge capacity does not fill up when all urgent orders are loaded, the operator needs to employ a strategy to fill up the unutilized spots on the barge. The operator can employ different allocation strategies for non-urgent orders. The simplest form of allocation strategy is first-come-first-served, which allocates orders based on their arrival sequence at the terminal. The other possible strategies that can be implemented by the operator include loading orders that are closest to their due date but not urgent, loading the smallest orders first to maximize the number of orders loaded in the barge, and loading the largest orders first to get rid of high TEU orders initially. All allocation strategies are compared to assess their performance using the performance metrics identified in section 3.2 to determine how these different strategies operate under different uncertainty conditions and overbooking strategies.

4.3 Model Validation and Verification

Due to the limited resources available in this study, model verification using real-world data comparison was not feasible. For the verification of the model, the model was built step by step, and each segment of the model was tested after construction with the supervisors. Additionally, single orders are created and tracked through the entire model to test the operation of the simulation. All testing of the different stages is performed under the same set of conditions. The model's face validity is established through supervisors' review and comparison with container on barge problems described in the literature. It is important to acknowledge that this validation occurs within the assumptions of the defined problem setting. The effectiveness of different strategies that are tested in the model is contingent upon these problem characteristics, and alternative decision-making approaches may prove more effective under different operational contexts or problem configurations. This represents a limitation of the study, as strategy effectiveness cannot be generalized beyond the scope of the modeled system without further validation under different problem settings, however the approaches used in this study serve as a baseline and can be tested or changed on specific problem-settings that can be constructed in other studies. Two extreme cases are tested to further validate the model. Additional validation of system behavior can be observed on Section 5 as well during the sensitivity analysis.

Validation Test 1: Perfect information

To validate the model's capacity tracking and order acceptance logic, the system was tested under perfect information conditions with 0% no-shows, no arrival time deviations, and no overbooking. Under these conditions, barge departure slots can never be over capacitated, and all excess demand should result in order rejections rather than truck transport. The test was conducted for both acceptance strategies using the first-come-first-served allocation strategy to verify their operational logic and provide baseline comparison. As we discussed in the previous section, the conservative acceptance strategy allocates orders only to their requested departure slots based on due dates, while the aggressive acceptance strategy allows orders to be allocated to earlier departure slots with available capacity when their original slots are full.

Acceptance Strategy	Barge Utilization	Order Rejection Rate	TEU Trucked
Conservative Acceptance	91.87%	27.92%	0
Aggressive Acceptance	95.96%	23.75%	0

Table 4.3.1: Perfect Information Baseline Validation Results

The results validate the model behavior under perfect information conditions. Both strategies achieve zero trucking, verifying that the capacity tracking system prevents over capacitation when no uncertainty exists. The performance difference between strategies shows that when orders can be allocated to earlier available slots, the system achieves better capacity utilization (95.96% vs 91.87%) and lower rejection rates (23.75% vs 27.92%) demonstrating that allocating orders to empty slots with earlier due dates improves both utilization and order accommodation without more trucking penalties when no operational uncertainties interfere with the allocation process.

Validation Test 2: Reduced Capacity

To validate that the model responds correctly to capacity constraints, the system was tested by reducing barge capacity to 10 TEU per departure while maintaining perfect information conditions (0% no-shows, no arrival time deviations, no overbooking). This test confirms that the model's acceptance logic correctly adjusts to different capacity levels and that performance metrics respond proportionally to capacity changes.

The test was conducted using both acceptance strategies with first-come-first-served allocation to isolate the impact of capacity reduction on system performance.

Acceptance Strategy	Barge Utilization	Order Rejection Rate	TEU Trucked
Conservative Acceptance	99.55%	67.31%	0
Aggressive Acceptance	99.72%	66.86%	0

Table 4.3.2: Perfect Information Low-Capacity Barge Validation Results

Both strategies achieve zero trucking as expected under perfect information, showing that capacity tracking prevents over capacitation regardless of capacity levels. The substantially higher rejection rates demonstrate that the model correctly responds to reduced capacity by rejecting more orders. We can also observe that utilization and the rejection rate are much closer for both strategies as it is very likely to fill up all the departure slots with the incoming orders.

5. Computational Experiments

5.0 Numerical Section

This section presents the parameters used in the discrete-event simulation model that were previously explained in the problem setting but were not numericized. These parameters are derived from established literature, industry data sets, and assumptions from previous container on barge studies. We use a barge capacity of 28 TEU for this study to the Fazi et al. (study). The capacity that can be accommodated is set at 27 TEU per vessel, based on an industry dataset that indicates that these 28 TEU capacity barges typically can carry a maximum of 27 TEU of containers due to stowage constraints, thus a 27 TEU capacity is also applied in this study. The daily departure schedule consists of 2 scheduled departures, consistent with the acquired dataset on the operations of 28 TEU barges and reflecting typical barge schedules in the Netherlands. Truck transport is assumed to have unlimited capacity and instant availability due to it being much more flexible than a barge (Gumuskaya et al. 2020, Behdani et al. 2016, F. Nab 2018). The availability can be seen in the Fazi et al. (2015) study as they set the travel time for trucks to 4.5 hours, while the travel time by barge is 22 hours on the same leg. Finally, the arrival time deviation is fixed to the distribution DISC(0.4, 0, 0.7, 1, 0.9, 2, 1.0, 3) days based on the Gumuskaya et al. (2020) study.

5.1 Results Compared to other strategies

To evaluate the effectiveness of different operational strategies, this study implements a comparative analysis that tests multiple strategy combinations under identical simulation conditions. This approach compares to the study of Feng et al. (2015) where they compare their developed MDP results to a FCFS strategy. The comparative analysis examines different strategies through the two primary decision components discussed in the methodology: order acceptance strategies and order allocation strategies. The acceptance component comparison evaluates the aggressive acceptance strategy against the conservative acceptance strategy. The allocation component comparison evaluates the maximum order count loading strategy, FCFS loading, largest order first loading, and earliest due date loading strategies to assess the impact of different capacity utilization approaches. Each strategy combination operates under identical system conditions including the same no-show probability, arrival time deviations, and overbooking rate configurations. Performance comparison focuses on the established metrics to assess how different strategies impact operational outcomes.

5.1.1 0 no-show uncertainty and no overbooking

The following table presents the first experimental scenarios tested. All experiments utilize identical parameters: 0% no-show rate, 0% overbooking, DISC(0.4,0,0.7,1,0.9,2,1.0,3) arrival time deviations.

Experiment	Acceptance Strategy	Loading Strategy
Test 1	Aggressive Acceptance	Maximum Order Count Loading
Test 2	Aggressive Acceptance	FCFS Loading
Test 3	Aggressive Acceptance	Largest Orders First Loading
Test 4	Aggressive Acceptance	Earliest Due Date Orders Loading
Test 5	Conservative Acceptance	Maximum Order Count Loading
Test 6	Conservative Acceptance	FCFS loading
Test 7	Conservative Acceptance	Largest Order First Loading
Test 8	Conservative Acceptance	Earliest Due Date Orders Loading

Table 5.1.1.1: Table of experiments to compare the performance of different strategies

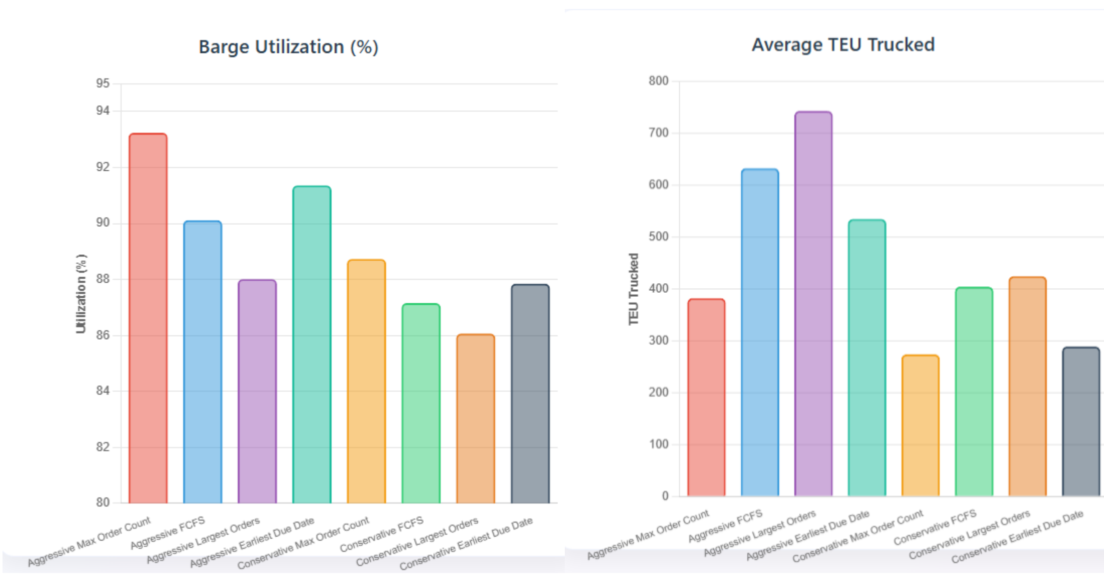
The table below provides the results of the different experiments under the given parameter specifications

Experiment	Acceptance Strategy	Loading Strategy	Barge Utilization (%)	Avg. TEU Trucked	Order Rejection Rate (%)
Test 1	Aggressive Acceptance	Maximum Order Count Loading	93.24	382.00	25.92

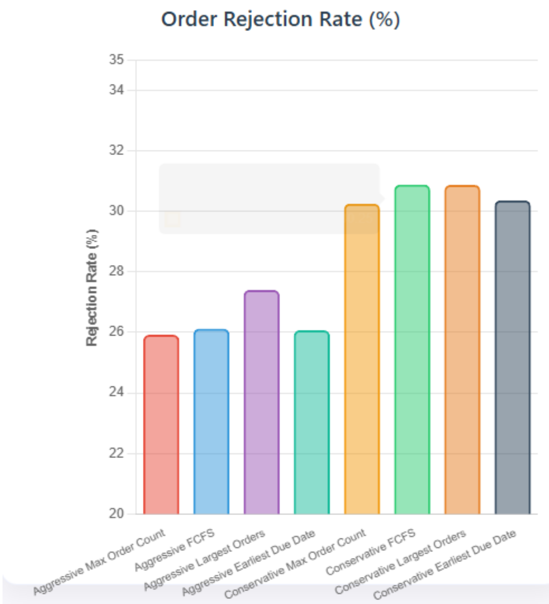
Test 2	Aggressive Acceptance	FCFS Loading	90.12	632.25	26.12
Test 3	Aggressive Acceptance	Largest Order Loading	88.01	742.45	27.40
Test 4	Aggressive Acceptance	Earliest Due Date Loading	91.36	534.20	26.07
Test 5	Conservative Acceptance	Maximum Order Count Loading	88.73	273.75	30.25
Test 6	Conservative Acceptance	FCFS Loading	87.16	404.10	30.88
Test 7	Conservative Acceptance	Largest Order Loading	86.07	424.15	30.87
Test 8	Conservative Acceptance	Earliest Due Date Loading	87.85	288.75	30.36

Table 5.1.1.2: Results Table of Experiments to Compare the Performance of Different Strategies

Out of the aggressive acceptance strategies, the maximum order count loading performs the best with the highest barge utilization (93.24%), the least TEU trucked (382.00), and the lowest order rejection rate (25.92%). As expected, compared to the conservative acceptance strategy, the aggressive acceptance strategy performs much better on barge utilization and order rejection rate metrics than the conservative acceptance strategy but performs worse on trucking usage. Between the loading strategies tested, the maximum order count loading performs much better on trucking and utilization than other loading strategies on both aggressive and conservative acceptance. This could possibly mean that having fewer orders in the queue of orders waiting for allocation to the barge creates more flexibility for future allocation of orders. An interesting remark comes from the comparison between the FCFS loading and the largest order loading on both conservative and aggressive acceptance strategies. We can observe that the FCFS loading performs better in both trucking and utilization than the largest orders first loading. On aggressive acceptance, FCFS (Test 2) achieves 90.12% utilization with 632.25 TEU trucked while largest order first (Test 3) achieves only 88.01% utilization with 742.45 TEU trucked. Similarly, on conservative acceptance, FCFS (Test 6) achieves 87.16% utilization with 404.10 TEU trucked while largest order first (Test 7) achieves 86.07% utilization with 424.15 TEU trucked. This is in line with the simulation performing much better when we use maximum order count loading for allocation, as it can be observed that trying to allocate the larger orders first creates complications for further allocation while allocating smaller orders first to decrease the number of orders in the queue creates flexibility. The earliest due date loading performs at closer levels to the maximum order count loading when the conservative acceptance strategy is applied. Under conservative acceptance, earliest due date loading (Test 8) achieves 87.85% utilization with only 288.75 TEU trucked compared to maximum order count (Test 5) with 88.73% utilization and 273.75 TEU trucked, performing similarly in trucking and slightly worse on utilization. However, under aggressive acceptance strategy, maximum order count loading performs much better, with Test 1 achieving 93.24% utilization and 382 TEU trucked compared to earliest due date loading (Test 4) with 91.36% utilization and 534.20 TEU trucked. The differences in performance between loading strategies are much more pronounced under aggressive acceptance compared to conservative acceptance, as aggressive acceptance amplifies the impact of loading strategy choices and increases the importance of loading decisions. Under conservative acceptance, the loading strategies perform closer to each other.



Figures 5.1.1.1-2-3: Barge Strategy Performance Analysis Graph



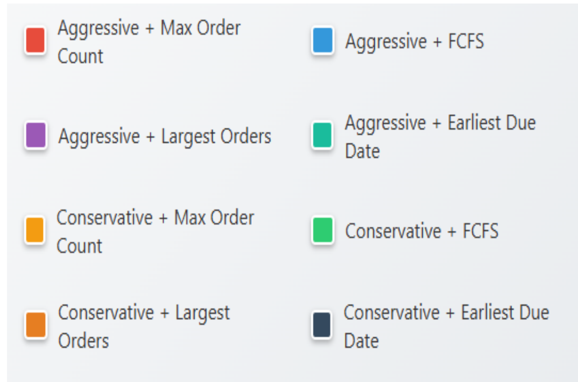


Figure 5.1.1.4: Color Schemes of performance graphs

5.1.2 10% no-show uncertainty and 10% overbooking

Since this study aims to investigate overbooking strategies to manage no-shows and delays, we conduct another comparison test under an intuitive 10% no-show uncertainty and 10% overbooking scenario. This configuration represents a more realistic hypothetical scenario where terminals face moderate no-show levels and employ corresponding overbooking strategies to maintain capacity utilization.

Experiment	Acceptance Strategy	Loading Strategy	Barge Utilization (%)	Avg. TEU Trucked	Order Rejection Rate (%)
Test 1	Aggressive Acceptance	Maximum Order Count Loading	91.11	485.35	19.06
Test 2	Aggressive Acceptance	FCFS Loading	88.83	680.50	19.62

Test 3	Aggressive Acceptance	Largest Order Loading	86.99	813.00	20.93
Test 4	Aggressive Acceptance	Earliest Due Date Loading	89.75	598.20	20.35
Test 5	Conservative Acceptance	Maximum Order Count Loading	87.04	228.10	25.26
Test 6	Conservative Acceptance	FCFS Loading	85.53	378.60	25.17
Test 7	Conservative Acceptance	Largest Order Loading	84.73	408.90	25.41
Test 8	Conservative Acceptance	Earliest Due Date Loading	86.15	247.75	25.55

Table 5.1.2.1: Results Table of experiments to compare the performance of the strategies with no-show and overbooking

Introduction of 10% no-show uncertainty and 10% overbooking shows that aggressive acceptance continues to achieve higher barge utilization and lower order rejection rates across all loading strategies, though the more aggressive acceptance strategy results in increased average trucked TEU as more orders are processed through the system. When overbooking and no-shows are part of the system, we observe that the penalties for trucking increase in aggressive acceptance even when utilization is dropping compared to the 0% no-show scenario.

We see similar trends regarding the performance of different order loading methods as maximum order count loading performs the best and largest order loading performs the worst again. This reinforces the finding that prioritizing larger orders first creates allocation complications that persist even when uncertainty and overbooking are introduced. We can also see that when overbooking and no-shows are introduced, the order rejection rates decrease compared to the previous configuration of 0% no-show and no overbooking. The uncertainty and overbooking conditions change the performance differences between aggressive and conservative acceptance strategies, making the choice of acceptance strategy more critical for terminal performance under realistic operational constraints.

The comparison between scenarios reveals that aggressive acceptance performs better under perfect information conditions than when uncertainty and overbooking are introduced. When no-show uncertainty enters the system and overbooking is applied as a countermeasure, the two acceptance strategies present distinct trade-offs as seen in figure 5.1.2. The arrows show the comparison between the scenarios with no uncertainty, and scenarios with uncertainty and overbooking on different strategies.

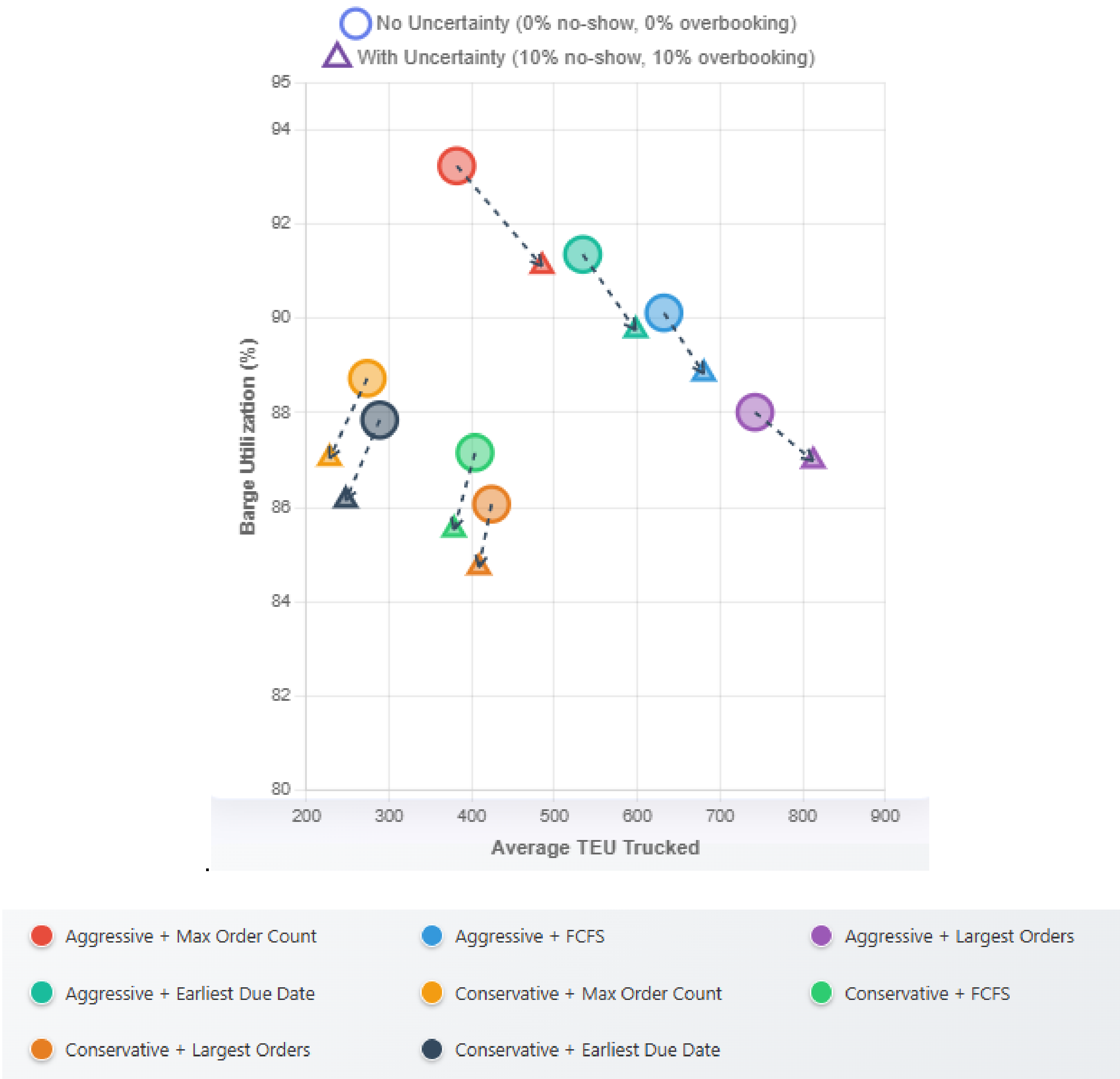


Figure 5.1.2: Performance Comparison change between scenarios: Barge Utilization vs TEU Trucked

5.2 Different No-show Uncertainty and Overbooking Rates

The comparative analysis on section 5.1 showed that maximum order count loading performs better than FCFS loading, largest order first loading, and earliest due date loading under both aggressive and conservative acceptance strategies. This pattern holds across different uncertainty conditions. Since maximum order count loading consistently outperforms the alternatives on the performance metrics, all further experiments regarding different will use this loading strategy. This allows focus on other aspects of the system without retesting allocation methods.

To examine performance across different conditions we use the parameters overbooking rate, and no-show rate, as changing them does have a direct effect on our performance metrics where we can make a trade-off analysis. Overbooking rates range from 0 to 20% in 0.05 increments (0%, 5%, 10%, 15%, 20%). The 5% increment size allows examination of performance changes while maintaining a manageable number of experimental conditions. No-show rates span from 0% to 20% in 5% increments (0%, 5%, 10%, 15%, 20%), covering the range from perfect demand realization to high uncertainty conditions.

Table 5.2: Experimental Parameters

Parameter	Level 1	Level 2	Level 3	Level 4	Level 5
Overbooking Rate	0%	5%	10%	15%	20%
No-Show Rate	0%	5%	10%	15%	20%

We additionally test the two proposed acceptance strategies with the different overbooking and no-show rates, as they create different trade-offs in different overbooking rate and no-show rate configurations

Acceptance strategy
Aggressive Acceptance
Conservative Acceptance

5.2.1 No-show Impact Without Overbooking

This section examines how introducing no-show uncertainty affects system performance when no compensating strategies are employed. By maintaining the no overbooking strategy while introducing progressive no-show rates, the analysis isolates the impact of no-shows on the performance metrics.

The following tables presents the performance of aggressive and conservative acceptance with maximum order count loading across different no-show rates with 0% overbooking:

Table 5.2.1.1: Aggressive Acceptance Strategy Performance

No-Show Rate	Barge Utilization (%)	Avg. TEU Trucked	Order Rejection Rate (%)
0%	93.24	382.00	25.92
5%	90.88	285.30	25.51
10%	87.92	212.45	24.93
15%	84.26	150.25	24.54
20%	79.07	112.20	23.93

Table 5.2.1.2: Conservative Acceptance Strategy Performance

No-Show Rate	Barge Utilization (%)	Avg. TEU Trucked	Order Rejection Rate (%)
0%	88.73	273.75	30.25
5%	86.42	165.40	30.28
10%	83.31	100.80	30.11

15%	79.28	60.60	30.16
20%	73.79	39.30	30.02

From 0% to 20% no-shows, the first trade-off pattern can be observed when no-shows are introduced to the system. On both conservative acceptance and aggressive acceptance strategies, there is a drop in utilization but also a drop in trucked TEU. This simultaneous decline in both metrics represents the impact of uncertainty on the trade-off between performance metrics. Since arrival time deviation is a part of the system that causes trucking, having some no-shows in the system creates a degree of flexibility to the operator that causes less trucking but decreases utilization. The no-shows free up departure slots that were previously reserved, allowing the system to accommodate customers who experience arrival time deviations without resorting to trucking alternatives.

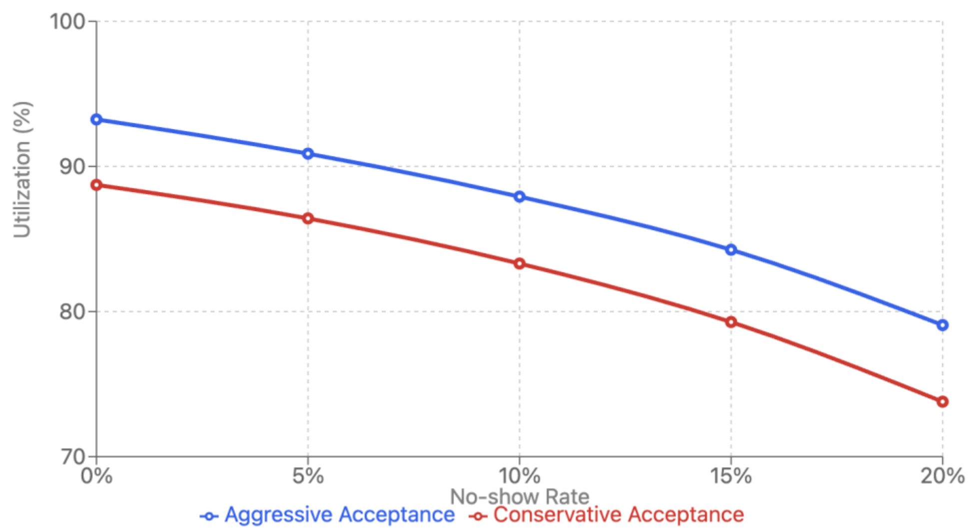


Figure 5.2.1.1: Decrease on Barge Utilization When No-show Rate Increases

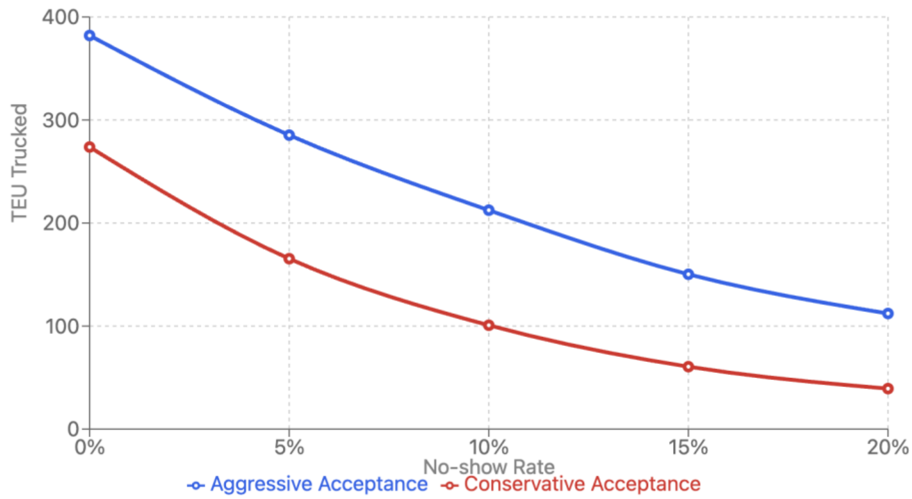


Figure 5.2.1.2: Decrease on Trucked TEU When No-show Rate Increases

As shown in Figures 5.2.1.1 and 5.2.1.2, the utilization decrease becomes exponential while the decrease in trucking becomes logarithmic as no-show rates increase. This relationship indicates that system performance gets exponentially worse when no-shows increase in the system without overbooking as a counter measure on both acceptance methods. From both the figures we can observe that the gap between performance on both acceptance strategies on different no-show uncertainty remains similar. This observation shows that both the strategies respond to no-show uncertainty without overbooking similarly.

Regarding the order rejection rate performance metric, seen in Figure 5.2.1.3, on the aggressive acceptance strategy the order rejection rate drops slightly, from 25.92% to 23.93%, as no-show uncertainty is increased while there is no significant change in order rejection rates on the conservative acceptance strategy. This indicates that the aggressive acceptance strategy can fill the gaps in departure slots caused by no-shows by accepting more orders while conservative acceptance can't. This is the only metric where we see a difference on the trend between the two strategies.

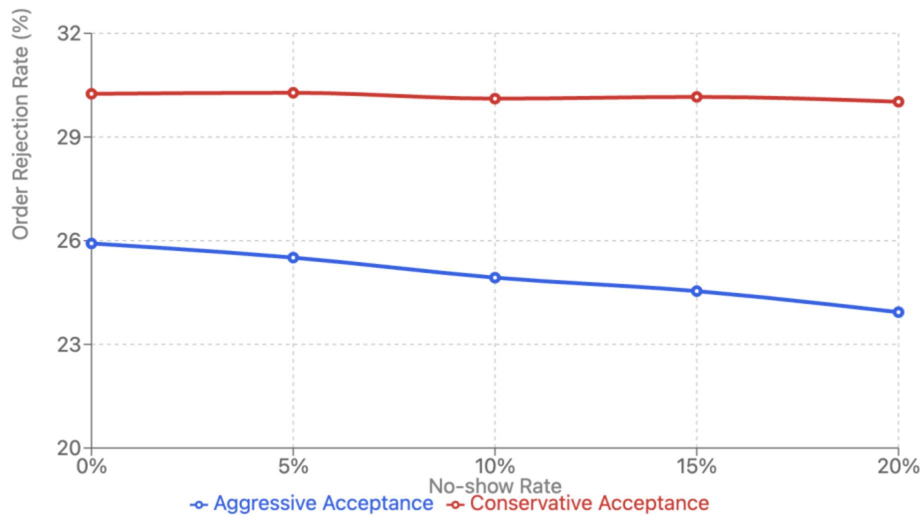


Figure 5.2.1.3: Change in Order Rejection Rate When No-show Rate Increases

5.3 Sensitivity Test of Overbooking Performance Across No-Show Levels

This section examines how overbooking strategies can address the capacity losses and inefficiencies identified in the previous analysis. By testing different overbooking rates (5%, 10%,15%, 20%) across each no-show scenario (5%, 10%,15%, 20%), the analysis evaluates the effectiveness of overbooking as a recovery mechanism. The focus is on determining whether overbooking can restore the capacity losses caused by no-shows and decrease the percentage of order rejections and at what operational cost in terms of increased trucking dependency.

Table 5.3.1: Conservative Acceptance Performance Across Overbooking Rates

	No Overbooking	**5% Rate**	**10% Rate**	**15% Rate**	**20% Rate**
5% No-Shows					
Barge Capacity Utilization	90.88%	91.78%	92.65%	93.52%	94.22%
Trucked TEU (Avg.)	285.30	444.45	657.35	905.60	1291.30
Rejection Rate	25.51%	22.9%	20.08%	18.53%	17.05%

10% No-Shows					
Barge Capacity Utilization	87.92%	89.03%	90.11%	90.93%	91.89%
Trucked TEU (Avg.)	212.45	300.05	485.35	602.85	860.85
Rejection Rate	24.93%	22.23%	19.06%	18.04%	16.67%
15% No-Shows					
Barge Capacity Utilization	84.26%	86.21%	87.87%	89.50%	90.52%
Trucked TEU (Avg.)	150.25	199.20	274.05	400.55	550.70
Rejection Rate	24.54%	21.76%	18.71%	17.76%	16.44%
20% No-Shows					
Barge Capacity Utilization	79.07%	81.24%	83.52%	86.67%	88.47%
Trucked TEU (Avg.)	112.20	146.30	200.95	260.25	346.86
Rejection Rate	23.93%	21.28%	18.29%	17.22%	15.57%

Table 5.3.2: Conservative Acceptance Performance Across Overbooking Rates

	No Overbooking	**5% Rate**	**10% Rate**	**15% Rate**	**20% Rate**
5% No-Shows					
Barge Capacity Utilization	86.42%	87.39%	88.32%	89.03%	89.66%
Trucked TEU (Avg.)	165.40	227.20	325.95	449.35	560.20
Rejection Rate	30.28%	27.63%	25.22%	22.78%	20.91%

10% No-Shows					
Barge Capacity Utilization	83.31%	85.38%	87.04%	88.09%	88.72%
Trucked TEU (Avg.)	100.80	160.75	228.10	275.20	360.85
Rejection Rate	30.11%	27.42%	25.26%	22.70%	20.72%
15% No-Shows					
Barge Capacity Utilization	79.28%	81.85%	84.31%	86.52%	87.79%
Trucked TEU (Avg.)	60.60	94.25	137.95	172.40	219.35
Rejection Rate	30.16%	27.04%	25.13%	22.49%	20.73%
20% No-Shows					
Barge Capacity Utilization	73.79%	77.01%	80.27%	82.76%	85.12%
Trucked TEU (Avg.)	39.30	51.65	72.50	99.95	120.30
Rejection Rate	30.02%	26.99%	25.06%	22.26%	20.24%

As seen in Figure 5.3.1, both overbooking strategies reveal trade-offs between capacity utilization and trucking requirements that vary in effectiveness depending on no-show rates. At lower no-show rates, overbooking produces disproportionately high trucking increases relative to capacity gains, while higher no-show rates yield more favorable returns for each overbooking increment. The comparative analysis between assignment strategies shows that while the aggressive strategy exhibits greater sensitivity to trucking volume increases when overbooking rates rise, both strategies demonstrate comparable capacity recovery potential.

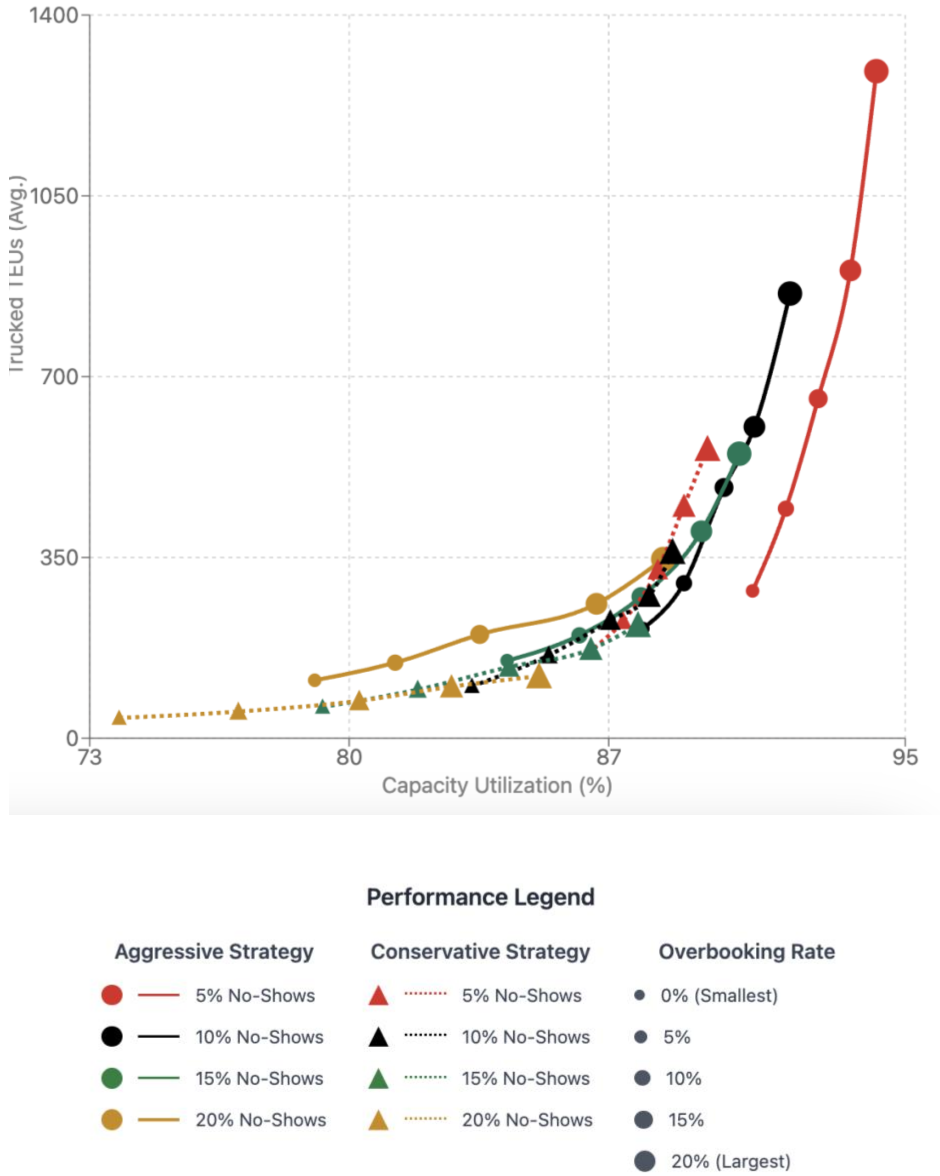


Figure 5.3.1.1: Comparison Graph Between Utilization and Trucking for Each No-Show and Overbooking Increment

Figure 5.3.1.2 and Figure 5.3.1.3 show the change in order rejection rate as we increment the overbooking rates and no-show rates. Rejection rates decrease as overbooking rates rise for both strategies across all no-show scenarios. As no-show rates increase in the aggressive strategy, we see a decrease in order rejection rates across all overbooking increments. However, in the conservative strategy we do not see significant change as the lines become more linear as no-show rate increments. The performance gap between strategies narrows at higher overbooking levels.

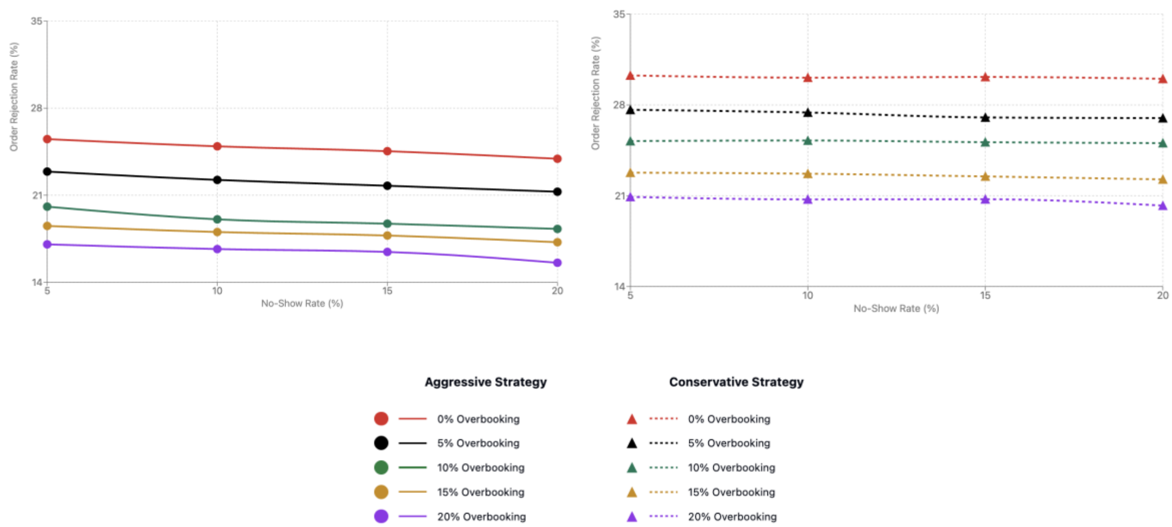


Figure 5.3.1.2 and Figure 5.3.1.3: Order Rejection Rate on Each No-show rate when Overbooking increments

5.4 Trade-off Analysis

This section aims to investigate the trade-off for overbooking while using different overbooking rates and strategies. Determining the exact break-even point for barges is a significant challenge, as it depends heavily on various operational factors including transportation distance, route complexity, and market conditions. We could not obtain a specific number for the break-even utilization from literature. However, from the industry dataset obtained, we observed that the 28 TEU capacity barge was utilized at least 50% on all transportation legs. This empirical observation forms the basis for using 50% as the break-even barge utilization point in this analysis.

The cost structure assumptions are derived from the Fazi et al. (2015) study as they use the same 28 TEU barge for their case study. In their study, a barge requires approximately 22 hours for a round trip, with an assumed operational cost of €80 per hour, resulting in a total barge trip cost of €1,760. In the case study it is estimated that €330 is required for a truck to complete a round trip, with trucks averaging 4.5 hours to cover the same distance, which aligns with trucking's inherent flexibility compared to barge transport. While these values cannot be confirmed with real-world data, they are consistent with the literature used in this study and provide sensible and tangible results for the trade-off analysis.

Table 5.4.1 shows the values used for costs to conduct the analysis.

Parameter	**Value**	**Source**
Barge cost	€1,760	(Fazi et al., 2015)
Truck cost per TEU	€330	(Fazi et al., 2015)

Break-even point for barge utilization	50%	Observed minimum utilization from industry dataset for the 28 TEU Barge

Table 5.4.1: Cost Assumptions for Analysis

The following tables present the financial outcomes of different overbooking strategies under varying no-show conditions. The analysis examines the profit of each rate and strategy to understand the trade-offs between aggressive and conservative booking approaches. Each table highlights the best strategy for each no-show scenario (marked in bold) and highlights the cell which provides the best overbooking rate and acceptance strategy combination for a no-show scenario.

Table 5.4.2: Aggressive Acceptance Net Profit (EUR)

No-Show Rate	No Overbooking	5% Rate	10% Rate	15% Rate	20% Rate
0% No-Shows	**€482,759**	N/A	N/A	N/A	N/A
5% No-Shows	**€481,441**	€441,594	€383,587	€313,914	€196,489
10% No-Shows	**€463,805**	€450,526	€404,583	€377,354	€305,731
15% No-Shows	€432,798	**€444,101**	€442,773	€423,979	€388,791
20% No-Shows	€372,280	€391,580	€405,648	**€430,431**	€427,194

Table 5.4.3: Conservative Acceptance Net Profit (EUR)

No-Show Rate	No Overbooking	5% Rate	10% Rate	15% Rate	20% Rate
0% No-Shows	**€454,981**	N/A	N/A	N/A	N/A
5% No-Shows	**€458,212**	€451,475	€431,982	€401,257	€373,547
10% No-Shows	€435,741	€445,103	**€446,250**	€445,491	€426,097
15% No-Shows	€392,264	€417,345	€437,561	€457,310	**€459,698**

20% No-Shows	€321,994	€363,256	€402,277	€428,277	**€454,791**

Table 5.4.3: Strategy Comparison (Aggressive-Conservative)

No-Show Rate	**No Overbooking**	**5% Rate**	**10% Rate**	**15% Rate**	**20% Rate**
0% No-Shows	+€27,778	N/A	N/A	N/A	N/A
5% No-Shows	+€23,229	*€-9,881*	*€-48,395*	*€-87,343*	*€-177,058*
10% No-Shows	+€28,064	€+5,423	*€-41,667*	*€-68,137*	*€-120,366*
15% No-Shows	+€40,534	€+26,755	€+5,212	*€-33,331*	*€-70,907*
20% No-Shows	+€50,286	€+28,324	€+3,371	€+2,154	*€-27,597*

Positive values = Aggressive strategy outperforms, Negative values = Conservative strategy outperforms

As no-show rates increase across the system, the effectiveness of overbooking strategies changes. With low no-show rates, both booking strategies perform best without any overbooking, indicating that the uncertainty on arrival time deviations off-sets the benefits of overbooking. However, as no-show rates rise, both strategies begin to profit more from overbooking. A clear threshold is seen where overbooking transitions from reducing profits, to improving them at 10% no-show rates at the conservative acceptance strategy, and at 15% no-show rates at the aggressive acceptance strategy. The aggressive strategy achieves higher peak profits under stable conditions but shows more variable performance as overbooking increases, while the conservative strategy trades outperforms the aggressive approach in high no-show rates.

Beyond profit considerations, we must also account for the broader business impact of rejecting customer orders. Order rejections carry hidden costs including lost future revenue, damaged customer relationships, and competitive disadvantage. To address this, the next trade-off analysis quantifies the question: "What is the opportunity cost of accepting additional orders to justify the expense of overbooking?" This approach enables decision-makers to evaluate overbooking strategies not just on immediate financial returns. The threshold values represent the minimum opportunity cost per rejected order that would make overbooking financially viable. The following results show the calculation of the acceptance opportunity cost threshold.

Table 5.4.4: Aggressive Acceptance, Acceptance Opportunity Cost Threshold

No-Show Rate	5% Rate	10% Rate	15% Rate	20% Rate
5% No-Shows	€636	€751	€1,000	€1,403
10% No-Shows	€205	€420	€523	€797
15% No-Shows	Profitable*	Profitable*	€54	€226
20% No-Shows	Profitable*	Profitable*	Profitable*	Profitable*

Table 5.4.5: Conservative Acceptance, Acceptance Opportunity Cost Threshold

No-Show Rate	5% Rate	10% Rate	15% Rate	20% Rate
5% No-Shows	€106	€216	€316	€376
10% No-Shows	Profitable*	Profitable*	Profitable*	€43
15% No-Shows	Profitable*	Profitable*	Profitable*	Profitable*
20% No-Shows	Profitable*	Profitable*	Profitable*	Profitable*

**Profitable = Overbooking increases both profit and reduces rejections*

Observed in tables 5.4.4 and 5.4.5, the aggressive strategy requires much higher opportunity cost thresholds to justify overbooking at lower no-show rates, indicating that overbooking is only economically rational when opportunity costs for orders are extremely high. The conservative strategy shows different threshold patterns, with much lower break-even costs required to justify overbooking. The threshold patterns demonstrate that strategy selection should account for the terminal's ability to quantify opportunity costs. Terminals with high customer values or strong competitive pressures may find overbooking justified at less profits. The analysis provides a quantitative framework for matching overbooking policies to both operational conditions and revenue management.

6. Discussion

6.1 Discussion of Results

Experimental results with different allocation strategies demonstrated that allocation strategy performance has a significant impact on the effectiveness of overbooking strategies. Maximum order count loading strategy consistently outperformed FCFS, largest orders first, and earliest due date strategies across all tested conditions, showing superior performance in both barge utilization and reduced trucking usage. This finding indicates that if a terminal believes it is performing poorly in allocation, it is important for the terminal to improve its allocation methods first before implementing overbooking, and to use a conservative acceptance strategy. The superior performance of maximum order count loading suggests that reducing the number of orders in the terminal queue creates operational flexibility that proves more valuable than other allocation priorities.

Two methods for accepting more orders were tested: the aggressive acceptance strategy and the conservative acceptance strategy. As discussed in section 4.2, the aggressive acceptance strategy allows orders to be reassigned into earlier departure slots with available capacity, provided that the order's estimated arrival time makes such allocation feasible. The conservative acceptance strategy is more selective, initially allocating each order only to its originally requested departure slot as determined by the order's due date. Both strategies were tested on different overbooking and no-show rates. At lower no-show rates, overbooking produces disproportionately high trucking increases relative to capacity gains, while higher no-show rates yield more favorable returns for each overbooking increment. The comparative analysis between assignment strategies shows that, while the aggressive strategy exhibits greater sensitivity to trucking volume increases when overbooking rates rise, both strategies demonstrate comparable capacity recovery potential. This demonstrates that if the operator believes uncertainty is very high, they can implement higher overbooking rates with less exposure to trucking risk, which makes the experimentation of overbooking decisions less risky in a terminal setting.

The trade-off analysis showed that different strategies perform better under different uncertainty conditions. The conservative strategy yielded more profits at higher no-show rates when combined with higher overbooking rates, while the aggressive strategy performed best at low no-show rates without requiring increased overbooking rates. In lower uncertainty conditions, instead of overbooking slots, terminals can accept orders to earlier feasible slots using the aggressive acceptance strategy to achieve better returns. With the aggressive acceptance strategy, until 15% no-show rate, no overbooking is still the best strategy. However, after 15% no-show levels, overbooking performs better than no overbooking. With the conservative acceptance strategy, at 5% no-show rate, no overbooking is the best performing strategy, while after 10%, overbooking becomes a viable strategy. Overbooking not being viable at 5% no-show rates on both strategies is most likely due to arrival time deviations causing more trucking when order materialization is high.

Analysis of the opportunity costs for accepting orders revealed that the economic viability of overbooking strategies depends on both the overbooking and no-show rates, and the terminal's ability to quantify opportunity costs of accepting additional orders. The aggressive acceptance strategy required much higher opportunity cost thresholds to justify overbooking at lower no-show rates. The conservative strategy showed different threshold patterns, with lower opportunity costs required to justify overbooking. At higher no-show rates, both strategies showed scenarios where overbooking increases both profit and reduces rejections, making it inherently profitable without requiring opportunity cost calculations. The opportunity cost thresholds calculation provides a framework for decision-makers to evaluate whether overbooking for lower profits is justified given their specific

6.2 Answering the Research Questions

6.2.1 Sub-Research Question 1

What are the main features of a booking system to manage orders and its dynamics in a barge transport system? What are the main trade-offs?

Sub research question 1 can be answered by the computational experiments in section 5 and the explanations in section 4. The main features of a booking system to manage orders and its dynamics in a barge transport system is the order acceptance and order allocation decisions. These two go hand in hand, as if the allocation strategy of the terminal is poor then this limits the performance of the implemented acceptance strategy as well. The dynamics of the problem are the no-show uncertainty, arrival time deviations and the different order characteristic parameters such as the due date, ETA, and TEU amount of the order.

The main trade-offs are between capacity utilization, order rejection rate and trucking. Depending on the costs that the terminals assign to these, they can use the framework for calculation and strategies for overbooking identified in this study.

6.2.2 Sub-Research Question 2

What methodology can better capture the dynamicity of the system with stochastic parameters?

Sub research question 2 can be answered by the literature study done in section 2, and section 4. Discrete event simulation is a methodology that can effectively capture the dynamicity of the system with stochastic parameters. The barge container transport system involves multiple interacting stochastic processes including random order arrivals, arrival time deviations, and no-show behavior that occur over time. These processes create temporal dependencies where earlier decisions influence the system state and capacity available for subsequent orders. Discrete event simulation enables the modeling of these interactions by allowing orders to progress through different stages of the system while uncertainties resolve progressively. The methodology can handle the sequential nature of booking decisions where operators must make accept/reject choices with incomplete information about future demand and order realization. Additionally, simulation allows for experimentation with different operational policies and strategies under varying uncertainty conditions without the computational constraints that analytical approaches face.

6.2.3 Sub-Research Question 3

Do overbooking strategies affect barge terminal performance under no-show, cancellation and arrival time deviation uncertainty?

Sub research question 3 can be answered by the findings in section 5. Overbooking strategies affect performance in a barge terminal, and it is highly dependent on no-show rates and arrival time deviations. The performance metrics identified are the capacity utilization of the barge, use of trucking, and the rejection rate of orders. The results demonstrate that overbooking effectiveness varies significantly based on the level of uncertainty present in the system. At low no-show rates, overbooking provides limited benefits and can result in disproportionately high trucking relative to capacity gains. However, as no-show rates increase, overbooking becomes increasingly effective at restoring capacity utilization that would otherwise be lost due to no-shows. Different strategies on the allocation of orders to barges also influences the terminal performance.

6.2.4 Main Research Question

How to develop a decision support system that supports understanding overbooking strategies and the management of no-shows and delays in an inland container transport system?

The main research question can be answered by integrating the findings from the three sub-research questions. Based on SRQ1, a decision support system must incorporate both order acceptance and allocation decision components while accounting for the key trade-offs between capacity utilization, order rejection rates, and trucking. The system needs to handle the dynamics of no-show uncertainty, arrival time deviations, and varying order characteristics.

From SRQ2, discrete event simulation provides an appropriate methodological foundation for such a decision support system, as it can effectively capture the stochastic and dynamic nature of barge container transport operations. The simulation approach enables experimentation with different strategies and policies while providing detailed system observation over extended periods.

From SRQ3, overbooking strategies significantly impact terminal performance, but their effectiveness depends highly on the uncertainty levels. Therefore, the decision support system must provide capability to evaluate different overbooking strategies under various no-show and delay scenarios to determine approaches for specific operational conditions.

6.3 Limitations

This study contains several limitations that affect the applicability of the findings. The simulation model assumes all containers generate the same revenue and treats all customers equally, while real operations involve different customer types with varying pricing and service requirements. The model assumes all containers go to the same destination, ignoring the routing constraints and network effects that exist in actual barge operations serving multiple destinations. The cost assumptions are based on literature rather than real world data. The study also does not consider the change in demand when an order is rejected, as it is possible that a rejected customer might be less likely to return. The study focuses on a single terminal and examines only specific overbooking rates and performance metrics, potentially missing other effective strategies or important operational factors. Moreover because of the entity limit of the student version of Arena, there were limitations on the level of sensitivity analysis that could be conducted.

However, despite these limitations, the study provides valuable insights into the trade-offs and decision-making processes in barge container transport overbooking. The simulation framework demonstrates the effectiveness of different strategies under varying uncertainty conditions and establishes a foundation for understanding capacity management in barge transportation.

6.4 Recommendations for Future Research

Future research can extend the model to include different customer types with varying characteristics such as customer priorities, and customer specific no-show behavior. This would enable more realistic overbooking strategies that account for customer differences. The model can be expanded to include multiple terminals and routes to understand how overbooking decisions affect network performance.

The integration of cost modeling into overbooking strategies represents an important step for practical implementation of overbooking. Future research could develop detailed cost structures that incorporate all relevant elements including barge costs, truck transport, specific container revenue, competitive positioning impacts, and other operational costs for a specific case study. This would enable precise economic impact of overbooking strategies tailored to specific operational contexts.

7. Conclusion

This research investigated the application of overbooking strategies in barge container transport to address capacity management challenges under no-show uncertainty and arrival time deviations. Through the development of a discrete-event simulation model and literature review, the study answers the main research question of how to develop a decision support system for understanding overbooking strategies and managing no-shows and delays in barge transport. The research identifies that booking systems in barge transport are characterized by two critical decision components: order acceptance and allocation strategies, which must be made sequentially under incomplete information while managing the dynamics of no-show uncertainty, arrival time deviations, and varying order characteristics. The main trade-offs involve balancing capacity utilization against order rejection rates and trucking, with the balance depending on the specific cost structure and operational context of each terminal. Discrete-event simulation proves to be an effective methodology for capturing the stochastic and dynamic nature of barge container transport systems, enabling experimentation with different strategies under varying uncertainty conditions without the computational complexity faced by analytical approaches.

The study demonstrates that overbooking strategies significantly affect barge terminal performance, with effectiveness highly dependent on the level of uncertainty present in the system. At low no-show rates, overbooking provides limited benefits and can result in disproportionately high trucking, while at higher no-show rates, overbooking becomes increasingly effective at restoring capacity utilization. Trade-off analysis between the different allocation strategies reveals that maximum order count loading consistently outperforms alternative allocation strategies, suggesting that better performance can be achieved through higher order processing. The trade-off analysis uses a framework that enables operators to evaluate the economic viability of overbooking based on their specific opportunity cost for accepting an order.

This research contributes to the container on barge literature by extending overbooking theory from traditional service industries to freight transportation contexts where service substitution rather than service denial characterizes capacity exceedance. The study provides the framework for evaluating overbooking strategies in barge container transport, addressing a gap in the literature on capacity management for barge transportation. Additionally it provides barge operators a framework to assess the viability of overbooking. While the study contains limitations related to model assumptions, data availability, and scope, it establishes the principles for overbooking in barge transport and provides a foundation for future research. Future research should focus on extending the model to incorporate customer heterogeneity, network effects, and cost structures, which would enhance the practical applicability of overbooking strategies and contribute to broader understanding of capacity management under uncertainty in barge transport.

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