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Forecasting Dock Door Congestion in Warehouse Logistics: An Integrated Forecast–Optimization Framework—Extended Abstract †

Vittorio Maniezzo [1,*], Livio Fenga [2] and Giacomo Ruscelli [3]

[1] Department of Computer Science, University of Bologna, 47521 Cesena, Italy
[2] Center for Simulation, Analytics and Modelling, University of Exeter Business School, Exeter EX4 4SB, UK; l.fenga@exeter.ac.uk
[3] Onit S.p.A., 47521 Cesena, Italy; giacomo.ruscelli@onit.it
* Correspondence: vittorio.maniezzo@unibo.it
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Abstract

Dock door congestion is an essential and persistent concern within the realm of outbound warehouse logistics. The inability to accommodate outbound vehicles at the loading docks, especially during peak hours, disrupts internal warehouse operations, leads to bottlenecks, and contributes to substantial additional costs and delays. This paper addresses the critical issue of dock door congestion by proposing an integrated forecast–optimization framework for its prediction and management. The framework uses advanced forecasting methods and optimization techniques to increase warehouse throughput, boost operational efficiency, and predict potential congestion events using historical and real-time data. It combines two proven methodologies, maximum entropy bootstrap (MEB) and ensemble learning via bagging, with scenario-based stochastic optimization. This hybrid approach significantly improves upon traditional models by capturing the complex, non-monotonic components and multi-seasonality inherent in warehouse throughput data. Through a detailed real-world case study, we demonstrate how the proposed approach can accurately predict the number of trucks that can be serviced within specific time windows. This information is crucial for making operational decisions, such as whether to expand the warehouse. The approach can be generalized beyond the specific case study and offers valuable insights for any logistics or supply chain operation requiring the integration of stochastic optimization with predictive modeling.

Keywords: warehouse logistics; data series forecast; maximum entropy bootstrap; stochastic programming; robust programming

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1. Introduction and Literature Review

Warehouse logistics plays a critical role in modern supply chains, particularly in the context of outbound logistics, where the timely and efficient loading of trucks is crucial for meeting customer demands and maintaining competitive advantage. One of the most pressing issues in warehouse operations is dock door congestion. This congestion arises when the number of incoming or outgoing trucks exceeds the available capacity of the dock doors, leading to delays, inefficiencies, and higher operational costs [1].

The problem of dock congestion is multifaceted, involving not only the number of handling units awaiting shipment but also the optimization of vehicle sequencing and

the assignment of specific bays to trucks, considering varying loading times, costs, and other operational constraints. These factors make the problem inherently complex and computationally challenging, leading to an NP-hard combinatorial optimization problem. In addition, the non-linearities and stochastic nature of warehouse operations further increase the complexity of the solution. Traditional allocation strategies often result in inefficiencies, poor utilization of available space, and missed opportunities to improve overall throughput.

In fact, traditionally, dock door congestion has been addressed through simple heuristic methods, such as first-come-first-served (FCFS) truck scheduling [2], which assigns bays to trucks as they arrive. However, these methods fail to account for the complexities of real-world warehouse environments, where multiple variables, such as truck availability, loading times, the volume of goods, and the sequencing of vehicles, contribute to congestion. Moreover, fluctuations in daily, weekly, and seasonal throughput make it difficult to predict when congestion might occur, and as a result, warehouse managers are often forced to make reactive decisions rather than proactive adjustments.

In response to these challenges, this paper presents an integrated forecasting and optimization framework that combines the strengths of maximum entropy bootstrap (MEB), bagging, and scenario-based stochastic optimization [3]. The goal is to create a reliable predictive model for dock door congestion and to provide a robust optimization method for managing bay assignments and truck scheduling.

Several approaches have been proposed in the literature to address the issue of dock door congestion. Early work focused on deterministic models of truck scheduling and bay allocation, which aimed to minimize delays and improve the throughput of the warehouse. However, these models often neglect the stochastic nature of real-world logistics operations, where demand and supply fluctuate over time.

Stochastic optimization methods have emerged as a viable solution to model the uncertainty inherent in logistics systems [4]. In particular, scenario-based optimization has been used in various areas of logistics, including supply, production, and distribution logistics [5,6]. This method generates multiple possible scenarios based on historical data or probabilistic models and then solves the optimization problem for each scenario. By considering multiple potential futures, scenario-based optimization provides a more reliable solution in uncertain environments.

In the context of warehouse logistics, MEB and bagging techniques have been increasingly adopted for predictive modeling. MEB is particularly suited for time series forecasting, as it generates resampled datasets that preserve the statistical properties of the original data, such as mean and variance, while introducing sufficient randomness to capture the underlying patterns. The bagging technique, which combines the outputs of multiple models trained on different bootstrap samples, further enhances the accuracy and robustness of the predictions.

While both MEB and bagging have been explored separately in various domains, their integration into a unified forecasting and optimization framework for warehouse logistics is a novel contribution of this paper. By coupling MEB with bagging, we can generate a diverse set of forecasted scenarios that inform the optimization process and guide bay assignment decisions.

2. Methodology

The integrated framework proposed in this study is composed of two key components: the forecasting module and the optimization module.

2.1. Forecasting Module: Maximum Entropy Bootstrap and Bagging

The first step in the framework is to forecast the number of handling units that will be loaded onto trucks in the near future. Given the historical data of handling unit volumes over the past two years, the forecasting model needs to account for multiple seasonal patterns, such as weekly fluctuations and long-term trends, which complicate the modeling process.

To address these complexities, we decompose the original time series into sub-series for each day of the week, creating shorter time series that exhibit more consistent patterns. These sub-series are then subjected to maximum entropy bootstrap (MEB), a method that maximizes the entropy of the bootstrapped distribution while adhering to constraints imposed by the observed data. MEB generates resampled datasets that preserve essential statistical properties of the original data, such as moments or quantiles, making it particularly effective for forecasting time series with irregular patterns [7,8].

Once the bootstrapped time series are generated, we apply bagging, an ensemble learning technique, to combine the outputs of multiple models trained on different bootstrap samples. Bagging improves the accuracy and stability of the forecast by reducing variance and mitigating the impact of outliers or noise in the data.

2.2. Optimization Module: Scenario-Based Stochastic Optimization

The forecasting module produces multiple forecasted series, each corresponding to a potential future scenario. These scenarios are then used as input to the optimization module, which addresses the problem of assigning dock bays to incoming trucks.

Given the limited number of available bays and the varying arrival times of trucks, the optimization problem is formulated as a stochastic version of an adaptation of the Berth Assignment Problem (BAP), a problem intensively studied in maritime logistics, where the objective is to assign a berth to incoming ships, given the berth capacities and the estimated arrival time of the ships. Our goal is to allocate trucks to available bay areas in a way that minimizes congestion, maximizes throughput, and ensures that trucks are loaded within the available time windows.

To model the uncertainty in the problem, we adopt a scenario-based optimization approach. Each forecasted series represents a potential future scenario, and we solve the optimization problem for each scenario. By considering multiple scenarios, we account for the variability in both truck arrival times and handling unit volumes. The final solution is based on the equally likely scenario assumption, which ensures that each scenario is treated with the same probability.

The optimization model seeks to maximize the utilization of available dock space while minimizing the time trucks spend waiting to be loaded. By considering both the forecasted truck volumes and the operational constraints of the warehouse, the optimization process provides a reliable indicator of potential congestion and helps guide decisions regarding warehouse space allocation.

2.3. Case Study: Warehouse Logistics Optimization

To demonstrate the effectiveness of the proposed framework, we conducted a case study using real-world data from a large warehouse that handles a high volume of outbound shipments. The data included a two-year history of daily handling unit volumes, truck arrival times, and loading times.

The case study involved forecasting the number of trucks that could be serviced in different time windows over the next three months. The forecast was based on the historical data, which exhibited significant fluctuations in throughput, with peaks on weekdays and lower volumes on weekends. The goal of the case study was to predict the likelihood of

congestion during peak periods and to determine whether additional warehouse space would be required to meet future demands.

Using the forecasting and optimization framework, we generated multiple forecasted scenarios based on the MEB–bagging combination and solved the scenario-based optimization problem for each scenario. The results revealed that, during certain time windows, the warehouse would reach full capacity, leading to potential congestion. Based on this prediction, the warehouse management team decided to expand their dock space to accommodate the anticipated increase in throughput.

The case study illustrates the practical applicability of the proposed framework, showing how it can be used to make informed decisions regarding warehouse space allocation and congestion management. Furthermore, the framework is not limited to this specific case but has general relevance for any logistics operation that requires effective forecasting and optimization of stochastic processes.

Figure 1 shows a sample output produced at the end of the pipeline of processes in the case of the dock door allocation. The case study is based on a large warehouse consisting of several internal areas. Time series of handling unit flows among the areas, specifically directed to the outbound staging areas, were available. The outbound flows were bootstrapped, as described in Section 2.1. After generating the bootstrapped time series, we applied bagging to combine the outputs of multiple models trained on different bootstrap samples, thus obtaining the desired forecasts.

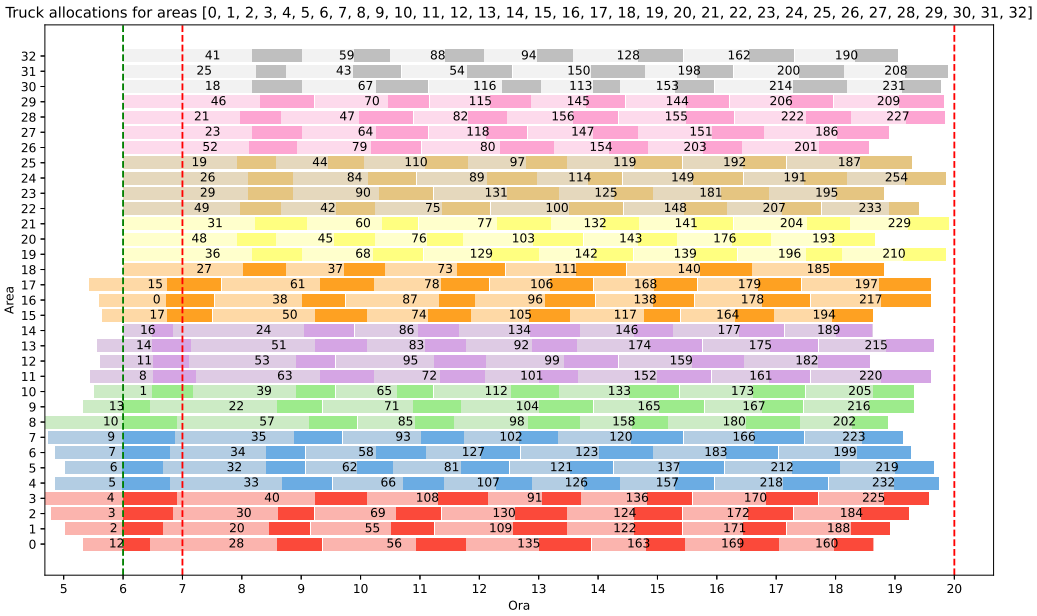


Figure 1. Case study example of final yard truck schedule.

The bootstrapped series were also used to generate different possible scenarios, according with the BESO approach [3]. These scenarios were chained in a single formulation that used an objective function based on the average cost of all scenarios, as in stochastic programming. This formulation also contained constraints based on the most limiting possible case, as in robust programming.

The overall formulation was a MILP, which was solved using a standard commercial solver. Figure 1 contains a graphical rendering of the final solution for a particularly challenging use setting.

3. Conclusions

This extended abstract refers to an innovative and integrated approach to forecasting and optimizing dock door congestion in warehouse logistics. By combining maximum entropy bootstrap, bagging, and scenario-based stochastic optimization, we propose a robust framework for predicting and managing congestion in outbound warehouse operations. A case study demonstrates the practical utility of the approach, highlighting its potential to improve warehouse throughput, reduce congestion, and guide strategic decisions such as warehouse expansion.

The proposed framework offers significant improvements over traditional methods by accounting for the complexity and uncertainty inherent in optimized future operations in general, and warehouse operations in this specific case. It provides a reliable tool for decision-making in logistics and supply chain management, particularly in the context of dynamic and fluctuating throughput. Future research could explore the integration of additional factors, such as transportation delays or inventory management, to further enhance the model's accuracy and applicability.

We are currently validating the case study results by applying the framework to an expanded set of dock door allocation problems with different characteristics. A full paper will report quantitative results both about the case study and the extended benchmark set.

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References

1. Tompkins, J.A.; White, J.A.; Bozer, Y.A.; Tanchoco, J.M.A. *Facilities Planning*, 4th ed.; John Wiley & Sons: Hoboken, NJ, USA, 2010.
2. Van Belle, J.; Valckenaers, P.; Van Oudheusden, D. Cross-docking: State of the art. *Omega* **2012**, *40*, 822–848. [CrossRef]
3. Fenga, L.; Maniezzo, V. Bootstrap Enhanced Scenario Optimization, a Case Study in Two-Echelon Logistics for Large-Scale Retail. In Proceedings of the EURO 2024 (The 33rd European Conference on Operational Research), Lyngby, Copenhagen, 30 June–3 July 2024.
4. Sethi, S.P.; Thompson, G.L. *Optimal Control Theory: Applications to Management Science and Economics*; Kluwer Academic Publishers: Dordrecht, The Netherlands, 2000.
5. Birge, J.R.; Louveaux, F. *Introduction to Stochastic Programming*, 2nd ed.; Springer Series in Operations Research and Financial Engineering; Springer: New York, NY, USA, 2011.
6. Santoso, T.; Ahmed, S.; Goetschalckx, M.; Shapiro, A. A stochastic programming approach for supply chain network design under uncertainty. *Eur. J. Oper. Res.* **2005**, *167*, 96–115. [CrossRef]
7. Vinod, H.D. Maximum Entropy Bootstrap: A New Technique for Problems in Statistics. *J. Stat. Plan. Inference* **1993**, *37*, 151–167.
8. Vinod, H.D.; Kourentzes, N. Maximum Entropy Bootstrap for Predictive Inference. *J. Forecast.* **2006**, *25*, 49–63.

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