Order picking planning with backorder optimization for customized products in an automated warehouse

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***Abstract*—Effective order picking planning is essential in automated warehousing, particularly for customized products where specific processing requirements create flow disparities. This issue is important in the studied textile distribution center, which must manage heterogeneous B2B and B2C flows under strict delivery deadlines. Operations are constrained not only by picking speed but by the limited capacity of downstream customization services, which can be easily saturated. To address these challenges, this paper proposes a Mixed-Integer Linear Programming (MILP) model designed to ensure synchronization between the automated picking zone and downstream flows. The main objective is to minimize backorders by aligning the upstream picking cadence with the capacity of the customization area. The model employs a multi-index formulation to handle product heterogeneity and process-specific lead times. Validated on real industrial data using CPLEX, the proposed approach surpasses current reactive heuristics, achieving a significant reduction in backorders while strictly respecting service-level agreements and maintaining smooth operational flows.**

***Index Terms*—Automated warehouse, Goods-to-Person system (GTP), Backorder minimization, Production planning, Omnichannel fulfillment**

I. Introduction

In the era of Industry 4.0, logistics is undergoing a transformation driven by the rapid expansion of e-commerce and the increasing demand for omnichannel fulfillment. To face these new challenges, modern distribution centers are transitioning towards "smart warehouses" powered by advanced automation technologies, such as Shuttle-based Storage and Retrieval Systems (SBS/RS) and Goods-to-Person (GTP) picking stations. These technologies promise to maximize throughput, reduce operational costs, and handle the growing complexity of order portfolios. However, while automation significantly enhances physical conditions, it shifts the operational bottleneck from manual labor to decision-making and synchronization.

A critical challenge in these environments arises from the simultaneous management of heterogeneous, particularly when Business-to-Business (B2B) and Business-to-Customer (B2C) operations coexist within the same facility. When B2B flows typically involve large, predictable volumes for store replenishment or specific value-added requirements, B2C flows are characterized by high fragmentation urgency. In a GTP system, these orders are completed from the same retrieval and picking resources. Without an optimized planning strategy, the high-speed capacity of the picking robots can easily overwhelm downstream processes, leading to congestion. This synchronization problem is particularly acute when downstream workshops - such as personalization or customization areas - have significantly lower capacities than the upstream picking zone.

The present study is motivated by these exact challenges observed in a real-world textile distribution center. In this facility, operators manage a dynamic portfolio of orders using a reactive, rule-based planning approach. Currently, waves of orders are released sequentially, prioritizing urgent deadlines without fully accounting for the cumulative load on downstream bottlenecks. Although intuitive, this lack of anticipation frequently leads to workloads imbalances: the picking zone feeds the personalization sector faster than it can process items, causing saturation or blocking the flow for other urgent orders. These inefficiencies result in the accumulation of backlogs, particularly for B2C shipments, and compromise the facility's ability to meet customer service levels.

To address these operational inefficiencies, this paper proposes a Mixed-Integer Linear Programming (MILP) model. Our model explicitly synchronizes the minimum throughput required in the automated picking zone with the capacity of the downstream customization area. By distinguishing between standardized and customized flows and incorporating process-specific deadlines, the model shifts short-term decision-making to a global anticipation. This study highlights how mathematical optimization can resolve strict physical constraints in the automated warehouse. The proposed approach was tested and validated using real industrial data over several specific periods of time from the partner facility. The optimization model, solved using IBM ILOG CPLEX, is compared against actual historical schedules to quantify improvements in terms of backorder and production. This will show the performance of our model over the current heuristic in use.

The remainder of this paper is structured as follows. Section II reviews the existing literature on production planning in an automated warehouse. Section III provides a detailed description of the industrial system and its specific constraints. Section IV presents the mathematical methodology and the MILP formulation. Section V reports and discusses the computational results and the comparative analysis. Finally, Section VI concludes the paper and outlines directions for future research.

II. Literature review

Warehouse operations are critical for supply chain performance. This section reviews the evolution from traditional picking to automated systems, emphasizing how advanced scheduling and planning are now the key drivers of performance in robotized environments.

A. From Traditional to Smart Warehousing

Order picking has traditionally been the most expensive activity in a warehouse. Early studies by Gu et al. [1] and De Koster et al. [2] estimate that it accounts for a significant portion of operational costs, primarily due to unproductive walking time in manual systems. However, the rise of e-commerce has drastically changed requirements. As described by Boysen et al. [3], warehouses must now cope with fragmented order profiles and extremely short delivery windows. This pressure led to the "Smart Warehouse" paradigm discussed by Zhen and Li [5], where real-time data enables dynamic decision-making rather than static management.

B. Automated Parts-to-Picker Systems

To increase speed and reduce reliance on manual labor, many companies are adopting Robotic Mobile Fulfillment Systems (RMFS). Azadeh et al. [4] and Jaghbeer et al. [6] describe these "Parts-to-picker" solutions in detail: instead of the operator walking to the shelf, autonomous robots bring the mobile storage racks directly to a fixed workstation. This technology offers huge benefits: it eliminates unproductive walking time and allows for much denser storage. However, it creates new management challenges. The performance of the system depends entirely on how well the robots are controlled. This technology offers huge benefits in terms of density and speed, but it requires highly sophisticated control logic and regular maintenance to function correctly. Vacher [14] demonstrated this complexity by developing specific optimization techniques for controlling flows within shuttle-based systems to maximize their internal throughput to fulfill the picking workstations. Similarly, Boysen et al. [11] showed that the sequencing of racks is critical to minimize robot travel and fully exploit the system's potential.

C. Improving Performance through Scheduling and Planning

Recent literature highlights that the true throughput of these systems is determined by the quality of the scheduling and planning algorithms. At the execution level, the sequence of tasks is critical. Boysen et al. [11] showed that optimizing the sequence of racks brought to the station can drastically reduce robot travel distance. Similarly, Zhao and Zhang [7] emphasized the importance of smart order allocation strategies to maximize robot utility, while Füßler and Boysen [9] analyzed processing times at the workstation to minimize operator idle time. However, planning must not ignore the human element; Kumar et al. [10] warn that pushing the system too hard can increase the operator's "perceived workload," leading to fatigue and errors.

Beyond individual tasks, the system must maintain a stable flow. D'Haen et al. [8] showed the necessity of integrated scheduling to handle dynamic order arrivals without disrupting operations. In parallel, Wang and Wang [12] proposed joint optimization methods to ensure workload balance across multiple stations, preventing local bottlenecks. Despite these improvements in local efficiency, a challenge remains in synchronizing this automated flow with downstream processes. Following the logic of Elsayed et al. [13], who focused on minimizing "earliness and tardiness," our paper applies a production planning model to synchronize the robotized picking with the limited capacity of the customization area, ensuring orders are processed exactly when needed.

In conclusion, while significant progress has been made in optimizing the internal efficiency of automated picking systems—focusing on task sequencing and horizontal workload balancing—a major gap remains. Current literature rarely addresses the synchronization between these high-speed automated upstream processes and capacity-constrained downstream operations. This study addresses this limitation by transposing production planning methodologies to the warehousing context. We propose a MILP model that globally coordinates the flow, ensuring that picking activities are not just fast, but synchronized with the customization bottleneck to minimize backorders.

III. Warehouse description

A. Global overview

The warehouse under study is a high-throughput omnichannel distribution center specializing in the textile industry, an environment characterized by extreme seasonality, rapid stock rotation, and strict service level agreements. Designed to process heterogeneous flows, the facility faces the dual challenge of managing massive replenishment volumes alongside vast e-commerce orders. The operational workflow begins with the storage phase, which relies on a hybrid architecture divided into two distinct subsystems to handle the diversity of Stock Keeping Units (SKUs). The first is an automated Miniload system (AS/RS) dedicated to high-density storage of standard cartons; this system ensures rapid retrieval speeds and optimal space utilization. Conversely, a conventional manual area is dedicated to oversized, fragile, or non-standard items that cannot be processed by the automated system. Despite their morphological differences, both systems feed a unified conveyor network that converges toward the preparation area.

Upon order release, items are retrieved and routed to the picking stations, where the facility must simultaneously manage two competing streams with divergent operational requirements. The first stream consists of B2B flows dedicated to store replenishment. These orders typically involve large volumes processed in waves to optimize picking density and generally follow a standard path directly to shipping. However, a significant portion of these items requires specific Value-Added Services (VAS), such as RFID labeling, anti-theft security tagging, or price ticketing, which introduces variable processing times. In parallel, the facility manages a B2C flow driven by e-commerce demand. Unlike the stable store flows, these orders are characterized by high volatility and low quantity per order line, involving the consolidation of individual items from mixed stock into customer-specific parcels. This flow is highly sensitive to lead times due to next-day delivery constraints and often requires specific customization or premium packaging before dispatch.

Ultimately, both flows converge at the expedition zone, where parcels are sorted by carrier and destination. The critical operational challenge lies in the synchronization of these heterogeneous streams. As they compete for shared resources—particularly the capacity-constrained downstream workshops responsible for customization and packing—uncoordinated releases from the high-speed storage zone frequently lead to congestion. This structural bottleneck necessitates a sophisticated planning approach to balance the upstream retrieval rate with the finite downstream processing capacity, ensuring that the high-speed automation does not overwhelm the manual finishing processes.

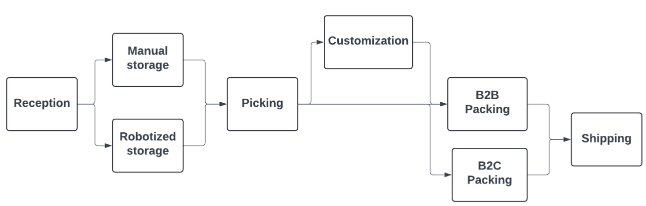

Fig. 1. Warehouse flow

B. Picking zone

The picking zone functions as a fully automated Goods-to-Person (GTP) system, structurally divided into two distinct sectors: storage and preparation.

The storage sector operates as a Shuttle-Based Storage and Retrieval System (SBS/RS), designed with the same high-density characteristics as a standard AS/RS. Autonomous shuttles, distributed across multiple levels and aisles, transport products horizontally to vertical lifts, which serve as the critical link between the storage tiers and the preparation level. To maximize efficiency, the system employs a strategic allocation policy where high-demand products are stored at the front of the racking to minimize retrieval times. The operational flow begins when a demand is formulated: a box exits the Miniload, travels to the SBS/RS, and is routed via conveyors to the specific GTP workstation.

Upon reaching the preparation sector, the box enters a buffer zone designed to sequence items and hold them temporarily until the corresponding target container is ready. The conveyor system then delivers the box to the picker, who fulfills the order according to instructions displayed on a tablet. For the process to be seamless, inbound flows (source products) and outbound flows (customer orders) must be perfectly synchronized to arrive simultaneously at the station. As illustrated in Fig. 2, this coordination is highly complex. If the planning of order releases ignores the real-time state of the system, discrepancies occur: boxes may arrive too early, saturating the limited buffer capacity, or too late, forcing the system to recirculate products unnecessarily. These synchronization failures lead to conveyor saturation and deadlocks that degrade the global throughput. Consequently, the system's performance relies less on the mechanical speed of the robots than on the intelligence of the planning strategy.

The following parts of the paper concentrate on the methodology for optimizing this planning. The objective is to orchestrate order releases to prevent saturation, ensuring a fluid synchronization between storage retrieval and workstation capacity.

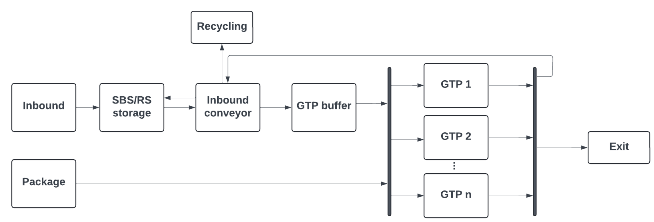

Fig. 2. Picking zone

C. Order planning process

The planning of production launches is organized around a wave-based process, designed to ensure timely fulfillment while maintaining a steady workload for the picking robots. The process is driven by the order portfolio, which is known in advance over a one or two-week horizon. To integrate real-time updates and new market insights, this file is updated twice daily, incorporating both customer orders and demand forecasts for e-commerce and store replenishment. This file consolidates all pending customer orders, specifying the reference, quantity, client priority, and shipping deadline. Consequently, while these values serve as a baseline for production projection, they remain inherently variable. The scheduling team typically operates within a rolling planning horizon, focusing primarily on the upcoming 24 to 48 hours to anticipate immediate production needs.

The decision-making process follows a heuristic where operators first identify and extract high-priority orders. These consist of B2C shipments and urgent B2B replenishment with imminent cut-off times, prioritizing them to mitigate the risk of late delivery penalties. Once these critical orders are grouped into a batch, operators utilize the remaining production capacity to process non-urgent orders. This secondary filling ensures that picking workstations remain supplied, thereby avoiding operator idle time.

A major complexity within this framework is the variability in preparation lead times. While standard picking orders typically flow to shipping within a few hours, orders requiring additional steps, such as B2C consolidation or value-added services, incur additional processing delays that extend the lead time. Currently, operators must mentally estimate these delays when building waves, a task that often leads to inefficiencies. The logic remains reactive and "picking-centric," where waves are released to maximize the picking rate without fully accounting for the downstream saturation. This lack of synchronization frequently results in a shift of the bottleneck, causing high-speed picking to flood the customization buffer, which leads to congestion and delayed shipments.

IV. Methodology

A. Problem analysis and modeling assumptions

The development of the proposed model is grounded in a detailed analysis of the planning process, conducted in collaboration with line managers. This study reveals that current inefficiencies stem largely from the specific characteristics of the footwear flow. Unlike standard textile items, footwear involves complex handling that requires significantly longer processing times at the workstations. Furthermore, the downstream customization zone is a highly manual process prone to bottlenecks; therefore, strict adherence to its capacity constraints is essential for optimal flow management.

Based on these observations, the mathematical formulation was designed to address three specific operational necessities. First, the model must explicitly distinguish the footwear family from standard flows rather than treating volume as a homogeneous block. Second, it is necessary to synchronize the minimum throughput required at the picking zone with the maximum capacity of the downstream customization workshop. Finally, unlike the current reactive rolling horizon, the model must optimize over the full planning window to anticipate peaks and smooth the workload.

B. Mathematical model development

To meet there requirements, the problem is formulated as a MILP model. The objective is to determine the optimal production quantities for each product family to minimize total backorders.

Product Types

- n: "normal" type products
- f: "footwear" type products
- np: "normal" type products requiring customization
- fp: "footwear" type products requiring customization
- b: B2C products
- rap: automatic replenishment products with customization
- rsp: automatic replenishment products without customization

Sets and Indices

- T: Set of production periods, indexed by t.
- K: Set of shipping periods, indexed by k.
- I: Set of product families, indexed by i.
- C: Set of capacities.

Parameters

Demand Parameters

- e_{ik}: Demand for product family i to be shipped in period k.

Capacities

- C_t: Production rate (throughput) in period t.
- CP_t: Customization capacity in period t.
- CF_t: Footwear processing capacity in period t.
- CFP_t: Capacity for customized footwear in period t.

Lead Time

- L_i: Production lead time for product family i.

Decision Variables

- $x_{itk} \geq 0$: Quantity to produce for product family i in period t for shipment in k.
- $B_{ik} \geq 0$: Backlog quantity for product family i at the end of period k.

Objective Function

$$\min Z = \sum_{k \in K} \sum_{i \in I} B_{ik} \tag{1}$$

Capacity Constraints

Production Rate

$$\sum_{k \in K} \sum_{i \in I} x_{itk} \geq C_t \quad \forall t \in T \tag{2}$$

Customization Processing Capacity

$$\sum_{k \in K} \sum_{i \in \{\text{np,fp,rap}\}} x_{itk} \leq CP_t \quad \forall t \in T \tag{3}$$

Footwear Processing Capacity

$$\sum_{k \in K} \sum_{i \in \{\text{f,fp}\}} x_{itk} \leq CF_t \quad \forall t \in T \tag{4}$$

Customized Footwear Processing Capacity

$$\sum_{k \in K} \sum_{i \in \{\text{fp}\}} x_{itk} \leq CFP_t \quad \forall t \in T \tag{5}$$

Flow Balance Constraints

Demand Satisfaction

$$\sum_{t=0}^{k-L_i} x_{itk} - B_{i,k-1} + B_{ik} \geq e_{ik} \quad \forall k \in K, \forall i \in I \tag{6}$$

Domain constraints

Non-negativity and Integrality

$$x_{itk}, B_{ik} \in \mathbb{N} \quad \forall i \in I, \forall t \in T, \forall k \in K \tag{7}$$

The model operates on a discrete time horizon where T denotes the set of production periods and K represents the set of shipping periods. the set of product families I is defined to capture the processing distinctiveness identified in the analysis, distinguishing between standard items (n, f) and personalized items (np, fp). Regarding parameters, e_{ik} represents the demand for the product i to be shipped in period k, while L_i denotes the specific production lead time. Capacity constraints are defined by C_t for the global picking throughput, and CP_t, CF_t, CFP_t for the customization, footwear and personalized footwear lines, respectively. The decision variables are the integer production quantity x_{itk} and the backorder B_{ik}.

The objective function minimizes the total accumulated backorders across all product families and shipping periods, reflecting the strategic goal of service level maximization (1)

The constraints strictly adhere to the identified operational topology. Constraint (2) enforces the global throughput target for the picking zone, aggregating all flows to ensure robot utilization.

Downstream bottlenecks are managed by specific capacity limits. Constraint (3) restricts the workload for the customization area, while Constraints (4 and 5) limit the footwear processing lines. Finally, flow consistency is ensured by Constraint (6) which dynamically links production to demand based on the product-specific lead time L_i.

V. Results

This section presents the results obtained from applying the proposed scheduling model to real operational data collected over two different periods of time: two weeks and one month. The primary objective of this analysis is to compare the optimized schedule generated by the model with the industrial schedule currently in use, to assess potential improvements in production flow and on-time order fulfillment. The study focuses on replicating real operational conditions as closely as possible, ensuring that the computational experiments reflect the actual constraints, resource capacities, and product mix of the production system.

A. Computational process

The validation framework was built upon a structured two-step approach to ensure both operational realism and data accuracy. The process began with an in-depth operational audit conducted directly in the warehouse. Sessions with scheduling managers and operators were essential to fully grasp the system's topology, identify the specific bottleneck in the customization flow, and formalize the critical constraints that govern daily production. This qualitative phase was a prerequisite to correctly defining the product families and validating the process-specific lead times used in the model.

Once the operational framework was established, the study moved to the data acquisition phase. Input data was derived directly from the order portfolio, the primary planning document used by operators, which consolidates demand signals transmitted by the commercial markets. To ensure robust testing, dataset samples were collected over multiple time horizons, covering various workload intensities and seasonal peaks. These datasets were then preprocessed to align with the mathematical structure of the MILP model, specifically by aggregating orders into product families and synchronizing deadlines with the model's discrete time indices. For the experimental validation, two distinct simulation horizons were defined to assess the model's stability: a short-term scenario spanning two weeks (10 working days) and a medium-term scenario covering one month (20 working days). To preserve industrial confidentiality while maintaining the structural integrity of the results, all quantitative data presented in this study have been normalized to a base 100 index. The complete dataset is available on this link. Finally, the model was implemented using IBM ILOG CPLEX. For both simulated horizons (the 2-week and 1-month scenarios), the model achieves computational efficiency with execution times of less than one second. The optimal results were then benchmarked against historical schedules derived from the same data sources, enabling a rigorous comparison between the proposed optimization approach and the reactive heuristic currently in use.

B. Performance Analysis and discussion

To evaluate the robustness of the proposed approach, the comparison was conducted over two distinct temporal horizons :

- **Scenario 1 (2 weeks)** : represents a typical operational cycle. The objective is to validate the model's behavior under normal conditions.
- **Scenario 2 (1 month)** : represents a medium-term test. This horizon evaluates the model's stability over time and its capacity to prevent backlog accumulation during demand peaks.

Table I summarizes the key performance indicators. Total production and total backlog - for both the industrial solution (Ind.) and optimized solution (Opt.) across these two scenarios.

TABLE I
COMPARISON OF TOTAL PRODUCTION AND BACKLOG (INDUSTRIAL VS. OPTIMIZED)

	Total Production		**Total Backlog**	
	2 weeks	1 month	2 weeks	1 month
Ind. Solution	1859	3584	699	2524
Opt. Solution	1906	3886	651	1225
Difference	**+3%**	**+8%**	**-3%**	**-51%**

In terms of total production, the optimization model consistently outperforms the industrial heuristic. Over the two-week horizon (Scenario 1), the model achieves a 3% increase in throughput. This gain becomes more pronounced over the one-month horizon, reaching 8%. This improvement is attributed to the model's ability to "fill the gaps" in production capacity. Unlike the manual heuristic, which tends to be conservative to avoid congestion, the MILP model utilizes the full available capacity of the picking and customization lines by sequencing orders to fit within the constraints. In addition, because the model runs in less than a second, it can be run iteratively throughout the day. It can be triggered whenever the order book is updated, ensuring that the production schedule remains aligned with actual changes.

The most significant impact of the optimization is observed in backlog management. While the reduction is moderate (-3%) over the first period, confirming that the model effectively handles standard flows, it becomes drastic over the one month, with a -51% reduction in total backlog. This difference highlights the weakness of the industrial method over a long period: manual scheduling tends to accumulate delays daily, which compound during peaks. In contrast, the MILP model anticipates these peaks by smoothing the workload across the entire planning window. By prioritizing orders with complex customization requirements earlier, thereby maintaining a fluid system and significantly improving the service level.

VI. Conclusion

This study addressed the complex problem of production scheduling in a Goods-to-Person distribution system characterized by heterogeneous product types, multi-stage processing requirements, and tight delivery deadlines. By developing a MILP Model, we proposed a rigorous framework capable of capturing the factors that govern day-to-day operations. The model successfully integrates multiple product categories, distinguishes between standard and customized flows, and explicitly accounts for capacity constraints across picking, personalization, and footwear processing areas. Furthermore, the formulation considers process-specific lead times, ensuring that the proposed schedules respect both the physical realities of the system and the temporal requirements of customer orders.

The computational study, conducted on real operational data covering multiple planning horizons, confirmed the practical relevance of the approach. The results highlighted a clear improvement in the optimized schedules compared to reference industrial practices. In particular, the optimization model consistently reduced the volume of backorders, improved the balance of daily capacity utilization, and led to smoother resource allocation across workstations. These findings suggest that even in the environments where production processes are highly standardized, mathematical optimization can uncover inefficiencies and deliver significant performance gains. Importantly, the model generated feasible solutions within industrially acceptable computational times, demonstrating its suitability for operational deployment.

Despite these encouraging results, several limitations must be acknowledged. First, the model assumes deterministic demand and processing times, whereas in practice, operational disturbances are frequent. Second, while the evaluation used real historical data, extending the experiments to include stochastic variability would further validate the robustness of the results.

These limitations pave the way for future research. A natural extension of this work is the design of a real-time decision-support interface. Such a system would continuously ingest updated data on orders and capacity availability to dynamically recompute schedules. By combining optimization techniques with intuitive visualizations, this tool would enhance both efficiency and operator trust. Additionally, integrating stochastic programming or robust optimization techniques could further strengthen the model's resilience to uncertainty in volatile environments.

In conclusion, this study demonstrates that advanced optimization approaches can significantly improve scheduling in complex distribution systems. By grounding the model in real industrial data and validating its performance against actual schedules, we contribute to closing the gap between theoretical research and practical industrial applications. This work represents a promising step toward achieving more agile, resilient, and operator-oriented production planning systems.

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