DOI: 10.2195/lj_proc_sonnemann_en_202510_01

Optimizing Picking Strategies in Luxury E-Commerce Logistics: A Simulation-Based Approach

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Optimizing order fulfillment is crucial for logistics centers, especially in e-commerce with luxury fashion, where dynamic conditions and strict customer expectations regarding speed, accuracy, and service significantly increase complexity. This study applies a three-phase simulation-based approach: First, the existing system is analyzed and modeled, then optimized picking strategies are implemented using heuristic methods, and finally their impact is evaluated through discrete event simulation. The results show measurable improvements with a productivity increase of up to 4 % and a 2 % improvement in service levels, highlighting the value of simulation-based optimization for increasing efficiency and service quality in luxury fashion logistics.

[Keywords: E-Commerce Logistics; Luxury Goods; Picking Optimization; Discrete-Event Simulation]

Die Optimierung der Auftragsabwicklung ist für Logistikzentren von entscheidender Bedeutung, insbesondere im E-Commerce mit Luxusmode, wo dynamische Bedingungen und strenge Kundenerwartungen hinsichtlich Geschwindigkeit, Genauigkeit und Service die Komplexität erheblich erhöhen. Diese Studie wendet einen dreiphasigen simulationsbasierten Ansatz an: Zunächst wird das bestehende System analysiert und modelliert, anschließend werden optimierte Kommissionierungsstrategien unter Verwendung heuristischer Methoden implementiert und schließlich werden deren Auswirkungen durch eine diskrete Ereignissimulation bewertet. Die Ergebnisse zeigen messbare Verbesserungen: Die Produktivität steigt um bis zu 4 %, das Servicelevel verbessert sich um 2 %. Damit wird deutlich, welchen Beitrag simulationsbasierte Ansätze zur Optimierung von Prozessen in der Luxusmode-Logistik leisten.

[Schlüsselwörter: E-Commerce-Logistik; Luxusgüter; Kommissionierungsoptimierung; Diskrete Ereignissimulation]

1 Introduction

E-commerce has experienced a strong upswing in recent years, including the luxury segment, which has increasingly adapted to digital requirements [1], [2]. Today's customers expect personalized services, high quality standards, and, above all, almost immediate delivery [3], [4], [5]. This places greater demands on logistics centers: efficient processes are necessary to avoid delays, errors, and losses in service levels.

In the luxury goods sector in particular, the high value of the goods requires additional care and quality assurance. At the same time, it is important to increase the picking performance and reduce costs. Digital twins and simulations offer new approaches for modeling complex processes realistically, identifying weak points, and testing improvements virtually.

The aim of this work is to develop an improved picking strategy in a person-to-good context for a reference logistics center in luxury e-commerce. The core is the implementation of an algorithm that uses resources more efficiently, shortens walking distances, and orchestrates order processing (prioritization, sequencing, resource allocation). This should shorten time to customer, increase process speed, reduce the error rate, and improve the service level. The measures developed will be evaluated using simulation and compared with the current situation. The approach leads to a practice-oriented solution that ensures high efficiency and customer satisfaction even with increasing order volumes.

After an overview of the state of the art in Chapter 2, including a literature review and identification of the addressed research gap with the research objective, Chapter 3 describes the modeling approach used. In particular, the analysis of the reference system is discussed. Chapter 4 explains the weaknesses of the current picking algorithm and the resulting improved picking strategies. Chapter 5 deals with the implementation and execution of the experiments, as well as the evaluation of the results of the simulation runs. This is followed by a discussion of the results in Chapter 6, before Chapter 7 summarizes the work and provides an outlook.

2 State of the Art

Order picking is a central component of logistics and can account for up to 50 % of warehouse costs [6]. It is carried out either according to the person-to-goods or goods-to-person principle and is increasingly supported by digital technologies such as pick-by-scanner, pick-by-voice or pick-by-light [7], [8]. Common strategies such as zone, batch, and wave picking offer different advantages in terms of route optimization and throughput time, but sometimes require complex warehouse management systems [9], [10].

Simulations, especially discrete event simulations, make it possible to test such picking strategies virtually and try out optimization measures without interfering with operations [11], [12]. Algorithmic optimization uses exact, heuristic, and increasingly AI-based methods that are particularly suitable for combinatorial problems such as route planning or order bundling [13], [14].

In the following, related works from the literature on the subject are presented.

2.1 Literature Review

The analyzed literature shows a variety of approaches for optimizing picking and delivery processes in a person-to-goods context. Gademann et al. examine order bundling in parallel aisles and develop a branch-and-bound algorithm combined with a 2-opt heuristic that reduces the throughput time of order waves [15]. Klumpp et al. apply data envelopment analysis with the free disposal hull approach in a food warehouse and show that the efficiency of manual pickers can be reliably measured [16]. Dynamic order arrivals are handled by D'Haen et al. using a large neighborhood search algorithm, which significantly improves efficiency and throughput time in a spare parts warehouse [17].

In the e-commerce context, Onal et al. examine fulfillment centers and optimize picking lists using mixed-integer programming and heuristic methods, reducing fulfillment time by up to 42% [18]. Pourahmadi et al. focus on delivery networks and apply robust optimization based on the Mulvey model, reducing costs by an average of 21.5 % [19]. In the food sector, Alrasheed et al. combine batch and zone picking in a hybrid model and achieve a 13.2 % increase in efficiency using genetic algorithms [20].

Other studies incorporate human factors: Gabellini et al. consider learning and fatigue effects and use a combination of genetic algorithms and machine learning to reduce picking times [21]. Gu et al. address same-day delivery scenarios with an integrated online batching and offline routing approach, supported by ant colony algorithms, and achieve significant reductions in processing time [22]. Raj et al. combine person-to-goods picking with stochastic queueing models to jointly optimize picking and delivery processes and increase delivery reliability [23]. Finally, Tao et al. develop a sustainable inventory strategy using Parallel Chicken Swarm Optimization that reduces costs and increases the service level to over 76% [24].

2.2 Research Gap and Goal

The studies show that significant efficiency gains, cost reductions, and service improvements can be achieved by using different optimization methods, from exact approaches to heuristic and metaheuristic methods to AI-based methods [15], [16], [17], [18], [19], [20], [21], [22], [23], [24]. However, the models are often industry-specific and their transferability to other contexts is limited. There are still gaps, particularly in the luxury segment, which is characterized by high item values, sensitive goods, and a low degree of automation with simple WMS systems. This is where the present work comes in, developing and evaluating practical and technically feasible optimization approaches for order picking in luxury logistics centers.

Based on the identified research gap, three key questions arise: First, it will be examined how a suitable picking strategy should be designed to make processes in luxury logistics centers with a low degree of automation more efficient and effective. Second, the specific requirements that a picking algorithm must meet in this context will be examined, particularly with regard to the heterogeneity and sensitivity of the items. Third, the study aims to examine the conditions under which a specially developed algorithm is able to reliably meet the high service requirements of the luxury segment in terms of speed, precision, and quality, while at the same time integrating seamlessly into existing systems.

3 Modeling Approach

This section presents the modeling approach that is the foundation of this work. First, the system analysis that was carried out and the subsequent data collection and preparation are discussed after the objectives of the approach have been defined. Subsequently, a mental abstraction model is constructed, which is then implemented in the *Plant Simulation* software (Version 2201). Finally, the verification and validation that were carried out are described, which checks the implemented model for correct replication of the real system.

3.1 Objectives

The objective of this work is to systematically analyze and optimize the picking process in the luxury segment of online retail. First, the relevant influencing factors are examined and the existing reference system is described in detail. Based on this, a special picking algorithm is developed that meets the high requirements of the luxury segment and improves the current state of affairs in the logistics center. Simulation experiments are then used to evaluate the efficiency and effectiveness of the algorithm in order to quantify its contribution to meeting service requirements. Finally, the findings are combined to design a holistic and optimized picking strategy for manual warehouses in the luxury segment.

3.2 SYSTEM ANALYSIS

This section analyzes the reference system. First, the system is described and the current picking process is detailed. This is followed by an analysis of the factors influencing the picking process.

3.2.1 SYSTEM DESCRIPTION

This work is based on a real reference warehouse belonging to one of the world's largest e-commerce companies for luxury fashion. Thanks to its strategic location and good connections to road, rail, and air transport, it is possible to deliver to some nearby customers on the same day. In addition to excellent customer support, the retailer offers personalized services such as a personal shopper for VIP customers.

The reference system is divided into three areas: goods reception, storage, and goods dispatch (see fig. 1). In the goods reception area, goods are checked, labeled, and prepared for storage; returns are handled in the same way. New items are also photographed and measured. In the storage area, goods are stored according to fixed strategies, with a distinction being made between lying goods (e.g., clothing, bags, shoes) and hanging goods (e.g., delicate textiles). The warehouse itself is structured into separate units (fire compartments) and four vertical levels.

The picking process combines zone and batch picking: pickers work in zones and pick items in standardized Euroboxes (also referred to as collection boxes in this document). The warehouse operates according to the "person-to-goods" picking principle, supported by a warehouse management system (WMS) with limited automation, although a conveyor belt transports the goods in collection boxes between areas. Single-item orders (SIO) are forwarded directly to gift wrapping, while multiple-item orders (MIO) are first consolidated. After a final quality check in the packaging department, the goods are shipped via various carriers.

3.2.2 ACTUAL PICKING PROCESS

According to the VDI guideline 3590 [25], the picking process is divided into three systems:

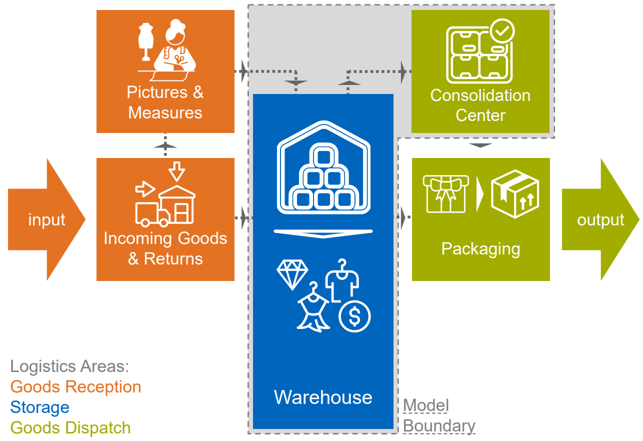

Figure 1: Material flow in the reference system

- **Material flow system**: Manual person-to-goods picking with collection boxes (2–4 Euroboxes). Storage compartments are up to 196 cm high; aids such as rolling stools are available. Transfer takes place at fixed conveyor belt stations.
- **Information system**: Control via WMS system with prioritization (e.g., express orders). The process is paperless and uses "pick-by-scanner." Each removal is confirmed by scan, and batches are formed by zone. Packaging requirements control the further flow of goods.
- **Organization system**: Warehouse divided into different zones, pickers are assigned manually via a dashboard. Standard orders are item-oriented, flash orders are order-oriented. MIO orders are consolidated in multiple stages across several zones.

3.2.3 CREATION OF A PICK RUN

When an order is received, the system checks the availability of the items and creates an entry in the picking reservation list for each item. The picking algorithm works through this list step by step: First, items from flash orders (across zones) are searched for. If any are available, the pick run is filled with these items up to the maximum run size or until the available flash items are exhausted. If there are no flash orders, the system searches for items in the picker's zone. The starting point is the highest-priority item in the zone (FIFO applies within the same priority level), which determines the destination of the pick run. Accordingly, only additional items that are assigned to the same destination can be included. This restriction does not apply to SIO orders, but it does apply to MIO orders due to subsequent consolidation. The process is repeated until no more suitable items are found, or the run size is reached. The algorithm then sorts the picking positions in ascending order by row and bin location. The picker scans an empty collection box and picks the items according to the specifications: scan the compartment, pick the item, confirm, and place it in the box. After the last item in the pick run has been completed, the collection box is placed at a transfer station and the pick run is ended. Special cases, such as missing items, are handled by specialized employees. Figure 2 shows the process schematically.

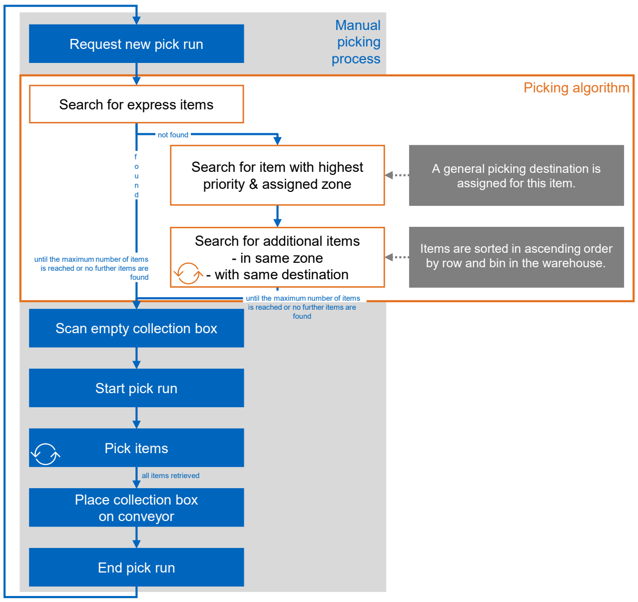

Figure 2: Process flow of a picking operation in the warehouse using the current picking algorithm

3.2.4 Influencing factors in the picking process

The picking process is influenced by a variety of factors, which are shown in the Ishikawa diagram (fig. 3). The customer group is particularly important, as it determines the priority of the incoming customer order. In addition to systemic rules, such as preferential processing of older orders (with the same priority level) or prioritization of items within MIO orders, storage conditions such as shelf layout, distances between picking units, and the exact position of items also influence the process.

In addition, item characteristics play a central role, e.g., size, packaging (shoe box, hanging goods), special categories such as returns, bestsellers, or oversized items. Added to this are external requirements such as delivery times, which are based on the carriers' pickup windows, as well as internal factors such as the available capacity in the logistics center. The latter is coordinated by the shift supervisor in order to optimally allocate personnel to warehousing, consolidation, gift wrapping, and final packaging.

Finally, the order characteristics themselves, such as the distinction between SIOs and MIOs, also have an impact on planning and organization. Taken together, these factors illustrate the complexity of the picking process and the need to take them into account appropriately in the algorithm.

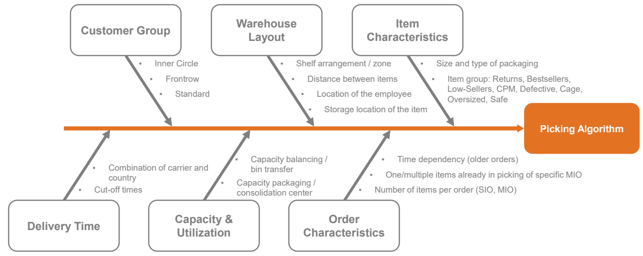

Figure 3: Ishikawa diagram of influencing factors in the picking process

3.3 Data processing

After the comprehensive system description and process recording, data processing follows. This step includes the collection and preparation of the data in order to create the system and the resulting model in the most complete and accurate way possible.

3.3.1 Data collection

During the on-site process assessment, the current picking process was examined in detail. This included analyzing order volumes, lead times, warehouse structures, and capacity utilization.

Using qualitative methods such as interviews and workshops with shop floor employees, WMS IT specialists, and managers, valuable insights into the processes and weaknesses were gathered. These were supplemented by observations and personal experiences with the process. Interviews were conducted partly online and partly directly in the work areas in order to gain authentic insights. These partial results were used not only to identify problem areas, but also to prepare the verification and validation work for the simulation model.

Building on this, quantitative methods were used: time measurements of individual process steps, the evaluation of specific WMS databases, and statistical analyses of historical process data. This enabled key figures such as average throughput times and capacity utilization to be determined.

3.3.2 Data preparation

The second step is data handling and preparation. First, the data was cleaned to check its completeness, quality, and consistency. Partially missing data were supplemented. It was divided into the following three categories: information about the system in general, functionality and process flows of the picking process, and quantified data.

A sample of five days was selected over a period of five months. Two basic data tables were collected: the picking reservation list (items “ready for picking”) and the list of booked picking entries (items “actually picked”). Only regular storage locations that follow the process defined above were taken into account. Special validation data sets were created for four days, as the fifth data set was incomplete in its picking reservation list.

Additional WMS data was also evaluated: An inventory revealed a median of 11 items per storage location. Analysis of the consolidation center showed an average processing time of 1.19 hours per order in a 6-month period. The adjusted lists of booked picking entries were used as the basis for creating fictitious orders (see section 3.6), from which the warehouse structure, article properties, order quantities, and customer segments were also derived.

3.3.3 PICKING TIMES

Furthermore, the model should determine the picking times stochastically. For this purpose, the standardized workflow time analysis (MTM) is used, which breaks down the process steps into basic movements (e.g., grasping, bringing, releasing) and specifies target times for them [26]. This allows theoretical times to be determined independently of individual working styles. Three main steps were recorded:

Step A Picking up the collection box
Step B Retrieving the order picking unit (including searching and picking)
Step C Depositing the collection box

Table 1: MTM times of the triangular distribution for the steps of the picking process

Process Step	Minimum Value a	Most Likely Value c	Maximum Value b
Step A	$21.84\,\mathrm{s}$	$27.30\,\mathrm{s}$	$32.75\,\mathrm{s}$
Step B	$18.92\,\mathrm{s}$	$43.61\,\mathrm{s}$	$79.11\,\mathrm{s}$
Step C	$9.02\,\mathrm{s}$	$11.28\,\mathrm{s}$	$13.53\,\mathrm{s}$

The time metrics derived from the official MTM data tables are available on the website of the *MTM Association e.V.* [26].

Comparison with actual time measurements showed a maximum deviation of $\pm 8\,\%$ and confirmed the reliability of the MTM times. A triangular distribution (minimum, most probable, and maximum values) was used for modeling, as no extensive historical data were available per pick run. The average number of items per storage location was taken into account in the search process, and the mean value was used conservatively. For regular steps such as door passages or climbing stairs, an equal distribution of the resulting MTM analysis times was used.

3.4 MODEL DEVELOPMENT

The modeling approach includes defining requirements, underlying assumptions, and building an abstract mental model. The abstract model is then implemented in *Plant Simulation*. Finally, the verification and validation work is explained.

3.4.1 REQUIREMENT DEFINITION AND MODEL ASSUMPTIONS

The requirements (R01 to R13) are divided into five categories: Among the **process requirements**, the model should be able to realistically map all recorded sub-steps of the picking process (R01). At the end of a pick run, pickers should deliver the collection box to the next conveyor belt delivery station (R02). Pick times, except for walking times, should have a newly randomized time that follows a suitable statistical distribution each time they occur (R03). The consolidation center should be able to be initialized with an adjustable start allocation (R04). In addition, this should be mapped using a simple table and not comprehensively modeled (R05). The dwell time of an order in the consolidation center should be adjustable and follow a suitable statistical distribution (R06). The category of **time requirements** includes throughput times, which should be measurable for each process step and pick run (R07). The following requirements are placed on the **simulation model**. The layout should be created using adjustable nodes (R08). No goods should be mapped; only the layout with paths and shelves. SKUs in *Plant Simulation*, as BE (movable elements), are not mapped to prevent the number of elements in the model in *Plant Simulation* from becoming too large (R09). Further requirements are placed on the **simulation runs**. Zone assignment should be flexible and adaptable (R10). Fictitious orders and thus order volumes should be randomly re-generated for each new experiment observation based on theoretical distributions of the recorded data points (R11). During a simulation, different seeds should be set to allow for fluctuations in the process flow (R12). For **validation** purposes, the simulation model should be compared with real data sets to assess the accuracy and significance of the model (R13).

To reduce system complexity, the following eight assumptions (A01 to A08) are made. These mainly relate to the resources and behavior of the model. Since the aisles in the warehouse are $1.20\,\mathrm{m}$ wide, it is assumed that a picker cannot turn around in the aisle, but must walk the entire length of the aisle (A01). Walking speed is also simplified and set to $1\,\mathrm{m/s}$ for all employees (A02). Each picker drops off the collection box at the nearest conveyor belt drop-off station (A03), and the number of pickers remains constant throughout the simulation (A04). In addition, there are no breaks, which means that the picking processes run continuously (A05). The packaging department can accept any collection box from a pick run, as performance is optimized for picking and sufficient buffer space and capacity are available at all times (A06). For simplicity, it is assumed that all items in the “Ready for picking” status are located exactly where they are needed in their storage location, so that no items are missing and no picking errors occur in the picking process (A07). The location position is automatically assigned as soon as the order is received in the system to ensure that the goods are handled after a shorter storage time (A08).

3.4.2 ABSTRACTION MODEL AND IMPLEMENTATION

Based on the performed process recordings, system analysis, warehouse structure, and defined requirements and assumptions, a mental model is first created, abstracted from the real system, which outlines the sub-functions for implementation. During layout creation, correct warehouse dimensions are taken into account, nodes are defined and connected via a matrix (paths, doors, stairs). Storage locations are assigned to the shelves by sensors in *Plant Simulation* so that the route algorithm already integrated in the software can be used. Picking zones are defined and assigned to the pickers. In the model, pickers are represented as vehicle objects as vehicle objects with attribute memory for the active picking list, important key figures for evaluation, active zone assignment, and time measurement. A list of items ready for picking is provided for the picking algorithm, which builds the backbone of the model. The functionality of the existing algorithm has already been described above in its current status. While processing an active picking list, each item position is targeted. As soon as the sensor modeled in *Plant Simulation* is triggered, the picker is stopped, and the item is removed. After completion of a pick run, the nearest conveyor belt delivery station is always approached, the collection box is delivered, and a new pick run is requested. The consolidation center is theoretically mapped using a data table. The size of this table (number of consolidation positions, i.e., maximum number of MIOs that can be completed simultaneously) is fixed and cannot be adjusted during a simulation run. In this way, the restrictions relevant to the picking algorithm are taken into account, but are processed methodically by means of time distribution and not, as in simulated picking, by means of moving elements. This simplifies the modeling effort and the throughput time of the experiments. Finally, various methods for recording key figures and parameterization functions are required to control and evaluate future simulation results. These can be represented as data tables, variables, or diagrams. With these preliminary considerations, the mental model can be implemented in *Plant Simulation*. The input parameters required for the experiments include:

- Maximum number of items per picking order
- Number of pickers
- Picking times
- Walking speed of pickers
- Initial fill level of consolidation
- Consolidation times
- Order structure
- Zone division

3.5 VERIFICATION AND VALIDATION

The verification and validation of the simulation model serve to ensure that the model realistically represents the actual system and delivers reliable results [27].

The verification of the simulation model was carried out iteratively. Each subfunction implemented in *Pant Simulation* was checked for technical, logical, and systemic errors. In addition to normal processes, extreme scenarios were also tested to ensure consistent results. Particular emphasis was placed on the correct formation of pick runs, the filling of consolidation centers, and compliance with the quantity structure. In addition, plausibility checks were integrated into the code so that only consistent data is recorded, and malfunctions, such as an overloaded consolidation center, automatically stop the simulation.

For validation, criteria were defined and reviewed in expert interviews. Employees at the reference logistics center evaluated process times, routes, logic, dependencies, and bottlenecks in particular. This confirmed that the model not only works correctly from a technical standpoint, but also meets the requirements of the work. The criteria include completeness, consistency, and accuracy (V01 to V05). Completeness means that all relevant process steps (V01), requirements, and assumptions (V02) are taken into account. Consistency requires a model sequence that is consistent and logically structured (V03). Accuracy is verified by comparing simulation results with real data. A t-test showed that the simulated picking times do not differ statistically significantly from the real ones (V04). All orders in the validation sets were processed within one working day (V05). Although there were larger deviations in two smaller data sets, these can be explained by the small amount of data in the individual data sets. In the more extensive data sets, the deviations were largely within the tolerance of $\pm 20\,\%$. Overall, $70\,\%$ of the comparison values were within this limit, meaning that the criterion was partially fulfilled. In summary, it can be concluded that the criteria for completeness and consistency were fully met, while the criteria for accuracy were largely fulfilled. The model thus achieved a conformity of around $94\,\%$ and can be considered sufficiently valid.

3.6 CREATION OF FICTIONAL ORDERS

As part of the process analysis, the theoretical distribution behind the order structure in the warehouse was analyzed and determined on a daily basis. This is recompiled for each experiment run so that the picking algorithms developed are not tailored to a specific order scenario, but rather their use can be evaluated in the context of possible scenarios. Before

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each simulation run, the order list is therefore regenerated in order to map different random scenarios and better quantify improvement measures. The basis for this is the picking performance of the pickers, which averages 30 picking units per hour, so that the number of items that can be processed daily can be calculated from the number of employees and the shift duration. Taking into account an average of 1.8 items per order, the theoretical number of orders is calculated. These orders are then divided between a mix of around 30 % MIO and 70 % SIO orders, with MIOs containing between 2 and a maximum of 20 items. The upper limit of 20 items reflects observed practice, as larger orders occur only as rare outliers and therefore do not represent the normal operating case. A backlog ratio of 59 % ensures that orders from previous days or from global time zones are realistically reflected. Priorities are assigned according to WMS data; 1 % of all orders are flash orders. The items are then randomly distributed to storage locations (on average 63 % lying goods, 37 % hanging goods). Finally, the shipping method and carrier are assigned, with flash orders automatically assigned to the same-day delivery service. These values were collected in the data collection during the process recording over a 6-month period using the median. The picking reservation list generated in this way forms the input for the picking algorithm.

4 Optimized picking strategies

This section deals with the design of the new picking strategy. The weak point analysis of the process recording is first completed and presented in the validated model. From this, potential improvements are derived in the form of new strategies, which are then implemented in the model.

4.1 Weak point analysis

During the analysis of the reference system, several weaknesses were identified, from which concrete potential for improvement in efficiency, flexibility, and customer focus can be derived.

A key problem lies in the inflexible zone allocation. The current allocation logic is based on a proportional calculation of the pickable items per zone and is updated manually in the WMS. If updates are not carried out regularly, imbalances in processing arise, which can lead to delays in MIOs and overload the consolidation center. Since the simulation model does not allow manual intervention, automatic employee changes at fixed intervals of 30 minutes were implemented as in the reference system based on expert interviews. The proportionally calculated distribution is rounded to whole persons and, in the event of deviations, compensated for by adjustments in the affected zones. To avoid unnecessary walking distances, an effort is also made to assign employees to the same zone as before, if possible.

Another weakness becomes apparent when item availability within the zones is low. As long as there are enough orders, the picking performance remains high, but once a certain tipping point is reached, utilization drops significantly because the pick runs can no longer be filled completely. This can be remedied by removing individual zones at a later point in time to create larger areas. The model examines whether zones spanning storage units or floors are more suitable, with the latter associated with longer walking distances.

In addition, the current picking algorithm does not take into account the cut-off times of the carriers. This means that even highly urgent orders can be processed late. To improve the service level, an additional sorting heuristic is introduced: dynamic cut-off priority. This complements the existing prioritization and ensures that time-critical orders regarding shipment are ready for pickup on time.

Finally, the picking process has weaknesses in route optimization. The routes of the pickers are not optimally coordinated with the end points of previous pick runs, which causes unnecessary walking time and distance. Dynamic route optimization based on the S-line principle is intended to ensure that pick runs are as efficient as possible and return trips are minimized.

4.2 Dynamic calculation of shipping priority

In order to further increase the service level, a new shipping priority is introduced in this work. By taking this dynamically calculated priority into account, orders in the process are prioritized more punctually to ensure that they are ready for shipment on time. The newly introduced shipping priority is calculated dynamically every ten minutes based on the cut-off times of the carriers and the time schedule of the simulated working day. Each order is assigned a variable priority number based on the time remaining until the next shipping deadline: Orders that need to be shipped soon are given a higher priority (mathematically low number) and should be processed first. The exact implementation of picking according to the additional shipping priority depends on the respective picking strategy and is explained in more detail hereinafter.

4.3 Strategy 1: Wave picking

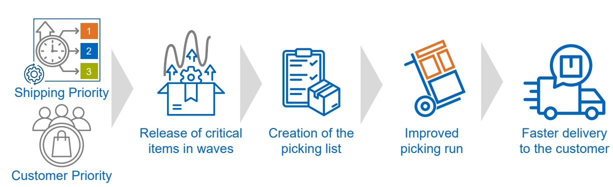

Figure 4: Simplified functionality of the wave picking strategy

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In wave picking, not every pickable item is released in the system immediately upon receipt. Instead, items are released systematically at intervals of 30 minutes, coordinated with the recalculation of employee zone assignments. These waves are calculated based on the occupied zone distribution and the priority of the items. As described above, pickers are assigned based on the number of the next important items in the respective zone. The number of items that could theoretically be picked within the time interval is then calculated for each occupied zone based on the expected picking performance. The quantity of these items is assigned to the zone, while also checking which items from previous waves have not yet been picked and are therefore still available. A simplified illustration of how this strategy works can be found in fig. 4.

Two heuristics support prioritization when releasing new items:

- The urgency with regard to the carrier's cut-off time (shipping priority): Items that are more urgent due to the scheduled pickup time are released preferentially to ensure that orders are ready for shipment on time (see section 4.2).
- Consideration of initial customer priority: This takes into account the customer's initial priority to ensure that orders are processed according to customer requirements without neglecting the overall urgency.

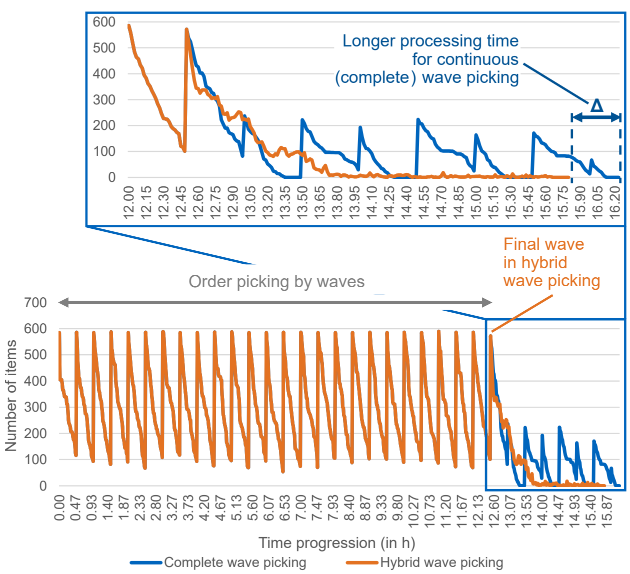

Figure 5: Release cycles for items ready for picking in the wave picking strategy over the entire working day

Figure 5 shows how wave picking structures the pickable items into distinct waves. Too long intervals between waves may lead to delays if only a small number of items are available. For this reason, an additional mechanism is used in this strategy as soon as there are too few items in the system (once the breakpoint is reached). In this case, wave picking is canceled to ensure a faster response time. This procedure ensures that orders are not held back when the order situation does not require it.

4.4 Strategy 2: Shipment-Prioritized Picking

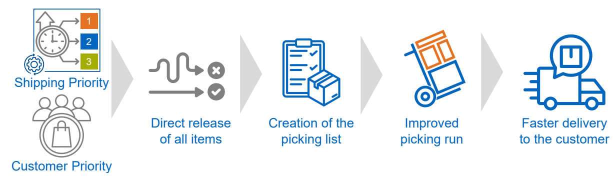

Figure 6: Simplified functioning of the shipping-priority picking strategy

The dynamic, shipping-priority picking strategy expands the classic logic of the existing picking system by flexibly adapting order prioritization to shipping time requirements. Instead of only considering the static priorities (mainly consisting of customer groups) of the orders, the priority assessment shown above is carried out, which is based on the shipping times of the respective carriers and their specific cut-off times. A simplified illustration of how this strategy works can be found in fig. 6.

For this purpose, each order is assigned a dynamic shipping priority level that takes into account the time remaining until the shipping deadline. The picking algorithm sorts the orders primarily according to this newly calculated shipping priority to ensure that time-critical orders are processed and prepared for shipping on time. Within this dynamic shipping priority, the original customer priority of the order, which was specified during order entry and reflects the importance of the customer, is then taken into account. This two-stage prioritization ensures that both time-critical and customer-relevant factors are included in order processing.

5 Implementation and Evaluation

This section describes the implementation and execution of the experiment. This is followed by an evaluation of the results.

5.1 Simulation Setup

First, the setup of the simulation will be discussed.

5.1.1 Initial Conditions and Parameterization

The simulation experiments are based on previously defined input parameters to ensure comparability between the individual scenarios. Important parameters include the number of pickers (30), the pick run sizes, i.e., the number of items per pick run (8 and 15), start fill levels, and number of positions in the consolidation center, picking times and walking speeds, and the update interval for employee zone assignment. This creates realistic conditions based on the process recordings and validation steps. Only individual parameters were varied in a targeted manner to investigate their influence. The number of pickers was set arbitrarily to 30; since the order volume scales accordingly, this parameter does not act as an influencing factor but rather serves as a fixed baseline across all experiments. The pick run sizes were chosen to cover the typical range observed in practice. Likewise, the start fill levels and the number of consolidation positions were defined to represent typical, valid operating conditions without simulating extreme cases.

5.1.2 DEFINITION OF THE EXPERIMENTS

The experiments were divided into three blocks: In the first block, the **preliminary investigations** required to determine the optimal update interval for zone assignment, the investigation of different pick run sizes (8, 10, 15, 20), and the analysis of different zone structures (the current zone division taken from the reference system and cross-floor or cross-unit zones) are carried out. The results of these preliminary investigations are then transferred to the two actual simulation studies. The **first simulation study** focuses on individual influence heuristics in the picking algorithm. The first study looks at efficiency gains through route optimization within a pick run and global zone cancellation once the minimum number of orders has been reached, also referred to as the breakpoint in this work. Furthermore, the combination of both approaches and the introduction of an additional heuristic that gives preference to spatially close items within a priority level will be investigated. The **second simulation study** will then be used to compare the developed strategies with the actual state of the system in terms of service level (effectiveness) and picking performance (efficiency).

5.1.3 KEY PERFORMANCE INDICATORS

The evaluation of the different strategies is based on two Key Performance Indicators (KPIs): the service level, also referred to as the on-time order fulfillment rate (effectiveness), and the overall picking performance (efficiency). In this context, efficiency refers to the optimal use of resources (e.g., working time per processed item), while effectiveness measures goal achievement—whether the customer experiences a reliable and timely delivery.

The first KPI measures effectiveness and reliability by ensuring that orders are shipped on time, thus reflecting the service level offered to the customer. The numerator indicates the number of orders that were actually completed within the transport company's cut-off time, while the denominator indicates the total number of orders that could have been shipped on time with the theoretical lead times:

$$\text{Service Level} = \frac{\text{Number of on-time orders}}{\text{Total feasible orders}} \cdot 100 \quad [\%] \tag{1}$$

The second KPI captures system efficiency and throughput, expressed as the number of items processed per picked hour as picking performance measure:

$$\text{Picking Performance} = \frac{\text{Total number of processed items}}{\text{Total employee working hours}} \left[\frac{\text{Items}}{\text{Hour}}\right] \tag{2}$$

5.1.4 NUMBER OF OBSERVATIONS REQUIRED

To ensure a statistically valid basis, an iterative approach was used to determine the sample size. Starting with five observations per experiment, the calculations showed that at least seven repetitions are necessary to maintain a confidence level of 95 % and to satisfy the condition $t \cdot \frac{s}{\sqrt{n}} \geq F$[1]. This ensures that the results are reliable. [11]

5.2 RESULTS

The following subsections explain and evaluate the results of the simulation runs.

5.2.1 RESULTS OF PRELIMINARY INVESTIGATIONS

The results of the preliminary investigations carried out are discussed below.

5.2.1.1 Optimal Update Intervall Short intervals (e.g., 10 minutes) enable dynamic adjustment and faster consolidation of multiple orders, but come at the expense of efficiency due to more frequent rescheduling. Longer intervals (45–60 minutes) ensure more even utilization and higher average picking performance, but result in slower order consolidation. The 30-minute interval proves to be a sensible compromise between stability and flexibility.

5.2.1.2 Influence of Pick Run Sizes Larger run sizes (15–20) increase the service level by up to 5 % and reduce the number of pick runs by around 6 %. However, the picking and run times per run increase proportionally. Values above 15 do not bring any significant additional benefits. For this reason, run sizes of 8 (short) and 15 (long) were selected for the main studies.

5.2.1.3 Analysis of the Zone Structure The usual zone division is more efficient for normal order volumes, as it reduces walking distances and improves resource utilization. Alternative structures (across floors or units) are slower but offer advantages when order volumes are lower, as fewer

[1] Where F the error bound of the confidence interval, t the t-value from the Student's t-distribution for the chosen confidence level of 95 % ($\alpha = 0.05$), s the standard deviation of the sample and n the sample size.

pick runs are required. In the model, the cross-unit variant proved to be slightly superior, which is why it was used in later scenarios.

5.2.2 Results of the First Simulation Study

The results of the first simulation study carried out are discussed below.

5.2.2.1 Overall Evaluation The elimination of zone divisions significantly reduced the number of pick runs ($-12.5\,\%$ to $-18.1\,\%$), but increased the average running time per run. Route optimization alone had only a minor effect, as many small runs occur at the end of the day anyway. Only the combination with other heuristics showed significant improvements.

5.2.2.2 Detailed Analysis of the First Shift Hours In the first eight shift hours, an order phase consisting of a sufficient number of pending orders and items ready to pick in the backlog, route optimization did result in a slight increase in the number of items processed ($0.7\,\%$ to $0.9\,\%$), but the overall effects remained minor. Only the additional heuristic, which gives preference to items located close to each other, brought about significant improvements. The picking performance increased by $4.5\,\%$ (for pick run size 8) and $3.8\,\%$ (for pick run size 15), with walking time per run reduced by $7.7\,\%$ (for pick run size 8) and by $5.1\,\%$ (for pick run size 15). This showed that proactive item selection when creating runs is more effective than retrospective optimization.

5.2.3 Results of the Second Simulation Study

In the second simulation study, the settings from the preliminary investigations and the results from the first simulation study were implemented in the previously developed picking strategies and compared with the actual state of the picking algorithm from the reference system. The wave picking achieved a significant improvement in service level of $12.2\,\%$ (for run size 8) and $7.7\,\%$ (for run size 15) compared to the actual algorithm, as orders are released in a way that is better aligned with the pick-up times. At the same time, however, the picking performance decreases by $11.9\,\%$ for run size 8 and $10.9\,\%$ for run size 15 compared to the pick run algorithm, as periodic release leads to fluctuating utilization. With shipping-priority picking, there would be a moderate increase in service levels of $2.8\,\%$ (for run size 8) and $2.0\,\%$ (for run size 15), but at the same time the picking performance would increase by $1.3\,\%$ (for run size 8) and $3.7\,\%$ (for run size 15) compared to the actual algorithm. This strategy therefore proves to be more balanced, as it takes into account both improved efficiency and on-time delivery.

5.3 Key Recommendations

The following conclusions can now be drawn from the results. For high-order volumes, larger run sizes (approx. 15 items/pick run) should be used, as this allows for optimized picking performance. For low-order volumes, the size of the pick runs is less relevant, but in order to better utilize pick resources, strict zone divisions should be eliminated or zones should be merged. Furthermore, the results show that a heuristic that favors nearby items reduces walking distances and significantly increases the picking performance. Shipping-priority picking improves on-time delivery without losing performance in picking and is preferable to the wave strategy or the current state of the picking algorithm of the reference system.

6 Discussion

This work contributes to the optimization of picking processes in luxury logistics centers and provides concrete, practical recommendations for action. Nevertheless, there are limitations that restrict transferability and completeness and offer starting points for future research.

The simulation model only maps the picking process of the system under consideration and does not take into account other areas, such as goods dispatching or goods reception. An extension could make the dependencies between these areas more transparent and allow for more comprehensive optimization. In addition, human behavior remains a key uncertainty factor: the efficiency of individual pickers varies and can strongly influence the results. Disruptions such as system failures or bottlenecks in the warehouse were also not taken into account, although they have a real impact on process performance.

Another aspect is the low level of automation in the warehouse examined. While the results are relevant for comparable luxury logistics centers, their transferability to more highly automated systems is limited. Similarly, the optimizations developed are limited to simple heuristics; more complex algorithms could achieve even better results in specialized environments.

Furthermore, the findings are tailored to the luxury segment, where service levels and product protection are particularly important. However, the basic principles, such as order bundling, route optimization, and flexible zone adjustment, are also relevant for other industries and show parallels to existing studies [15, 18, 20].

Some recommendations have already been presented to the reference center: adjustments to the picking algorithm are to be implemented in the near future, while others, such as the integration of cut-off times, will first be tested in pilot trials. Thus, the work not only offers theoretical approaches but also provides impetus for practical improvements in luxury goods logistics.

7 Summary and Outlook

This work examined the picking process in a luxury logistics center and developed optimization strategies for a largely manual environment with a simple WMS system. It was based on an event-discrete simulation model that was used to analyze weak points and test improvement measures. Two KPIs were used for evaluation: service level (effectiveness) and picking performance (efficiency).

The simulation results show clear potential: route optimization already during the creation of pick runs shortens runtimes and increases the picking performance by up to 3.8 %. A flexible, cross-zone structure proves advantageous for lower-order volumes, as resources are better utilized. The integration of cut-off times is particularly significant: Wave picking significantly increases the service level (by 7.7 %), but at the expense of efficiency. In contrast, shipment-priority picking combines both goals by improving the service level (2.0 %) and the picking performance (3.7 %) at the same time. The study thus provides practical recommendations on how luxury logistics centers can balance picking performance and service levels.

Several potential areas of future research have been identified. On the one hand, modern optimization algorithms and predictive analytics could further improve the process, for example, through dynamic adjustments in real time. Second, expanding the simulation model to a digital twin would make it possible to include additional areas and disruptive factors to map the entire process. The increased use of automation, from robot-assisted picking to hybrid systems, could also be investigated to test the transferability of the strategies to more technologically advanced environments. Finally, it would be worthwhile to validate the approaches developed in other luxury logistics centers and also in other industries with other specific requirements in greater depth.

Overall, the work shows that adaptive picking strategies can enable significant performance improvements even in less automated warehouses. Future research can build on these findings to make logistics processes in the luxury segment, and beyond, even more efficient and customer-centric.

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