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HYBRID ORDER PICKING STRATEGIES FOR FASHION E-COMMERCE WAREHOUSE SYSTEMS

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ABSTRACT

E-commerce has become an increasingly relevant business in Southeast Asia. Effective warehouse management in terms of order picking is a key competitive advantage in this industry. Fashion products are particularly difficult to efficiently manage in a warehouse as they have high demand variability, with a short shelf-life and very little replenishment. In this work, after a detailed analysis of demand and physical layout of the warehouse, we propose: (1) a new pick list generation algorithm considering aspects such as work balancing and picking time minimization, and (2) a family of picking strategies accounting for possible order configurations and warehouse layout. The main contribution of this work is in the development of hybrid order picking strategies: a combination of zone-based and order-based picking with batching. Simulation is used to assess the performance of these strategies. We have found that these hybrid strategies outperform FIFO order picking often employed in industry.

1 INTRODUCTION

The fast fashion e-commerce industry has been booming in recent years especially in Southeast Asia, with many players in the industry ranging from large corporations to small start-ups and online shops owned by individuals. In large fast fashion e-commerce corporations, stocks are kept in large warehouses. Such warehouses not only act as an inventory buffer in order to ensure availability but are, in fact, crucial to meet service levels in terms of delivery time. As such, the efficient management of such a warehouse - in terms of supply, order picking and location - represent a key competitive advantage to a company competing in this industry. Moreover, fast fashion products have unique characteristics which make them more challenging to manage efficiently in a warehouse. Their demand is highly variable and unpredictable, both in terms of volume and value, their short shelf-life makes obsolescence a vital concern, and they are seldom replenished where out-of-stock items are usually replaced with new collections instead of restocked.

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As a result of these characteristics, warehouse management becomes challenging due to the difficulty in identifying highly frequent or stable inventory, deciding on the inventory put-away (i.e. assignment of inventory to locations), and order picking strategy to generate pick lists for the pickers to fulfill the orders. In such a volatile and highly-variable environment, a single order picking strategy is unlikely to satisfy the demand profile faced by such an e-commerce company. After an initial analysis of the demand profiles and the physical layout of the warehouse, we realize that the warehouse operations and, especially, the picking process represent the most significant component in the warehouse operating costs. With the aim of improving the picking process, we propose an approach which relies on the characteristics of the orders faced by the company. Since the picking process is an operational issue, our algorithm needs to be implementable in a short time, thus hindering the possibility of using mathematical programming and traditional optimization techniques to assign picking jobs to the warehouse operators.

Therefore, in this paper, we propose (1) a new fast algorithm to generate pick lists which takes into consideration various aspects such as work balancing and pick time minimization, and (2) a family of picking strategies taking into account the possible order configurations as well as the physical warehouse layout. In order to assess and evaluate the performance of the various order picking strategies, we propose the use of a discrete-event simulation as a general approach which can easily be extended to more complicated and specialized warehouse layout.

2 WAREHOUSE OPERATIONS: A REVIEW

Warehouse operations and management as been a relevant research area for a considerable time and is still relevant today. Gu, Goetschalckx, and McGinnis (2007) and Gu, Goetschalckx, and McGinnis (2010) provide detailed reviews on warehouse operations including order picking. Order picking is the most expensive operations in a warehouse as it is very labor and time consuming (Frazelle 2001). The objective of the order picking system (OPS) is to maximize the service level (e.g. in terms of order lead time) subject to resource constraints, given the warehouse layout and inventory storage locations. Since the bulk of the OPS time is spent on traveling, minimizing item pick cycle time (i.e. item and order retrieval time) is an equivalent objective (de Koster, Le-Duc, and Roodbergen 2007). It has also been found that the throughput of the overall OPS is inversely proportional to the cycle time (Manzini, Gamberi, Persona, and Regattieri 2007). Hence the problem becomes providing the optimal wave size, batching, item-picker assignment and routing for these pickers to retrieve the assigned items such that the item cycle time is minimized.

While optimal routing is desirable, this may not be suitable in practice as some pickers might find the optimal routing illogical or counter-intuitive (Gademann and Velde 2005). Moreover, when there are multiple candidate locations for a single item, a multitude of complications arise in determining the optimal routing and that there are scare research done on this issue even though this scenario is often found in practice. With a more complex warehouse structure and inventory locations, routing heuristics such as S-shaped, return, mid-point, largest gap, and combined (hybrid) are more popular especially in practice where a solution has to be obtained quickly and that a satisfactory solution is sufficient. Note that many of these previous study assume a unit load. Moving forward, the rise of e-commerce poses a renewed challenge to optimize warehouse picking operations where less-than-unit-load picking (or even single-item picking) becomes very common. Since heuristics is preferred in practice, the routing used in this work is based on the nomenclature of the inventory locations, resulting in a routing which is similar to the return and S-shaped heuristics.

Order batching is often done to release a wave of orders to be picked. The batching problem in itself is a complex problem which can significantly impact the performance of the OPS. This batching creates a partition either between orders or between pickers/storage locations (otherwise known as zoning). The difficulty in optimizing the batches comes from the fact that the cycle time is not known until the batch has been created and the routing assigned (Gu, Goetschalckx, and McGinnis 2007). These batching problems are often solved with heuristics with a variation of order-closeness metric, with the objective of batching similar or close orders together (Elsayed and Unal 1989). The order proximity batching problem is studied by Gademann, Van Den Berg, and Van Der Hoff (2001), Hwang and Kim (2005), and de Koster, Van der Poort, and Wolters (1999). In terms of performance, Petersen, Aase, and Heiser (2004) compared various order picking strategies and found that batching often yields the lowest cycle time especially when the order sizes are small. de Koster, Van der Poort, and Wolters (1999) compared various seed and savings heuristics for manual warehouses and concluded that even a simple order batching method yields significant improvement from FIFO order picking and that the performance of these heuristics depends largely on the capacity of the carts utilized.

Simulation has often been used to optimize warehouse design and operations. A high-level manual order-picking warehouse design has been analysed through simulation by Altarazi, Ammouri, and Alzubi (2012). In terms of operations, simulation has been used to evaluate order-picking models solved with genetic algorithm (Chang, Liu, Liu, and Xin 2007). Yoo, Cho, and Yücesan (2010) employ nested partitioning and optimal computing budget allocation methods with simulation to optimize supply chain performance on a strategic level while reducing computational loads. Gagliardi, Renaud, and Ruiz (2007) developed a discrete-event simulation model to evaluate storage space strategies in a high-throughput warehouse. Similarly, Faria and Reis (2015) employed a discrete-event simulation model to evaluate various storage and routing strategies to improve order picking performance. Following these works, we have developed a discrete-event simulation model to evaluate the proposed hybrid picking strategies.

3 METHODOLOGY

We first analyzed the demand profile of the company and noticed that, in the scope of choosing the picking policy, it is important to understand how orders are characterized in terms of number of items and, in case of multi-item orders, how these are distributed throughout the warehouse.

Assuming a randomized put-away strategy, which is sensible for a fashion warehouse, we analyzed the warehouse density looking at the different zones (the zones referred to in this paper do not reflect the real warehouse). As a result of the randomized put-away strategy, SKUs may have several physical locations. Table 1 shows the distribution of the items in the warehouse. In particular, we can see that the majority of the orders are single item orders and therefore we should design picking strategies which improve the efficiency in fulfilling these orders. Nevertheless, a remarkable number of orders is multi-item and these form the largest picking volume in terms of units of items. Moreover, it looks clear how most of the orders are spread in different zones. Consequently, the picking has to consider an efficient way to manage multi-zone items. A possibility, as two of the strategies indeed propose, is to use a sorting station to consolidate orders from different zones, nevertheless, in this case we will need to control the maximum number of orders released for picking at any one time (called batch of incoming orders later on) in order to control the loading and waiting time at the sorting station.

Table 1: Orders Characterization.

Item Type	**%items**	**%orders**
Single Zone	6.182	5.995
Multi-Zone	76.781	50.99
Single Item	17.037	43.006

This work considers a manual picker-to-part order picking system where a picker collects a batch of orders instead of a single order or item as in single-command operations. We assume that a layout of the warehouse exists, along with the inventory locations, and that a list of orders is available and ready to be picked. The pick list generation procedure generates a *master pick list* which is the set of picking lists for single pickers. The pick list generation process is detailed in section 3.1. Four picking strategies are compared using a discrete-event simulation. A simple First-In-First-Out (FIFO) strategy acts as the base case as this the strategy commonly implemented in industry to simplify the order picking process. The four picking strategies are detailed in section 3.2. The overall proposed process is as such:

1. Batch incoming orders.
2. Group orders into three types: (1) multi-item single-zone, (2) multi-item multi-zone, and (3) single-item.
3. If the picking strategy is not the FIFO base case, generate order queues corresponding to the three order types.
4. Implement picking process and generate pick list based on the picking selected strategy.

3.1 Pick List Generation

In this section, we describe the pick list generation process through the phases of order batching, queue generation and order assignment, and finally picker routing and pick list generation.

Batch Creation Receives input of orders and generates the batches of orders. Simulation will be employed as a method to study the impact of batch size on performance and establish the optimal batch size. The batch size is a function of tote capacity, number of orders and system capacity (number of pickers, etc.) such that the batch size results in 3 hours' worth of picking activities. This is also known as the *pick wave*. The difficulty is that it is not known how to determine this batch size a priori.

Queue Generation Receives the orders, number of pickers, number of totes, totes capacity, and inventory locations. The output of this phase is the queue which associates the inventory location (UID) with the items in the orders. The criteria for the queue generation are as such: (1) ”Queue Dependency”: inventory in similar locations (zones, floor, etc.) are assigned to the same queue; (2) Order characteristics: express (high priority), single-item and multi-item orders are placed in separate queues; (3) ”Virtual Backlog”: items in locations are virtually reserved through the assignment process in order to prevent pickers from being directed to an eventually empty location. This process can be thought of as an order classification process which generates three types of order based on the three criteria above. The three types of queue generated are Type 1: multi-item single-zone, Type 2: multi-item multi-zone, and Type 3: single-item.

Inventory Reservation Procedure Locations containing the desired item are identified and the first location UID is assigned. Virtual reservation is done by decrementing the availability of the item in that location.

Pick List Generation Receives as input the picking strategy, queues generated, number of pickers and the tote capacity (which determines the maximum size of the pick list). The output is then the master pick lists which is the set of pick lists for individual pickers, complete with routing (items sequencing).

In essence, after order batching, the orders are grouped into queues based on their characteristics and the master pick list is generated by cutting each queue based on the suggested location UID (through the inventory reservation procedure) according to the picker capacity. Algorithm 1 details these procedures.

3.2 Picking Strategies

The picking strategy is incorporated into the pick list generation. We propose four different picking strategies. Strategy A represents the reference base case as it does not actually rely on any pick list generation algorithm but simply pick the orders in a FIFO manner.

Strategy A (Pure Order Picking) In this base case strategy, we adopt an “order-based” picking where orders are processed and picked sequentially in a FIFO manner, without any type of queue generation or order classification.

Algorithm 1 Queue and pick list generation algorithm.

<table>
<tr><th colspan="2">Queue Generation (Allocation)</th></tr>
<tr><td colspan="2">Identify item locations</td></tr>
<tr><td>Type 1 orders</td><td>Create list of multi-item single-zone orders. Each order reports all possible fulfilment zones.</td></tr>
<tr><td>Type 2 orders</td><td>Create list of multi-item multi-zone orders. Each order is characterized by an array of pairs of zones and items.</td></tr>
<tr><td>Type 3 orders</td><td>Create list of single-item orders and find zones fulfilling single-item orders.</td></tr>
<tr><th colspan="2">Pick List Generation (Assignment)</th></tr>
<tr><td>Type 1 orders</td><td>For each order in Type 1
   While(not all items assigned && zones not empty)
      If(item is available in zone)
         Inventory reservation procedure
      Else
         Eliminate zone and check next zone
      End If
   End While
   If(zone is empty)
      Add order to Type 2
   End If
End For</td></tr>
<tr><td>Type 2 orders</td><td>For each order in Type 2
   For each item in order
      Select zone with most number of items for the same order
      While(item not assigned)
         If(item available in zone)
            Inventory reservation procedure
         Else
            Eliminate zone and check next zone
         End If
      End While
   End For
End For</td></tr>
<tr><td>Type 3 orders</td><td>For each order in Type 3
   Select zone with lowest load
   If(item available in zone)
      Inventory reservation procedure
   Else
      Eliminate zone and check zone with next lowest load
   End If
End For</td></tr>
</table>

Strategy B (Hybrid Order Picking) In this strategy, each order is picked by a single picker and the pickers have to travel across zones to fulfill the orders and, as such, there is no sorting required after the picking. In literature, this is often identified as a pick-and-pass and sort-while-picking order picking.

- Type 3 orders: Single-item orders are separated into a special queue for fast processing.

- Type 1 orders: Multi-item orders which can be fulfilled in the same zone are grouped together under queues corresponding to a particular zone. A master pick list based on the tote capacity and the suggested picking route (item sequence) is generated. The location assignment and path generation is performed by Algorithm 1. Note that orders are not broken up into individual items (i.e. sorting happens on the tote itself) and completed orders are sent directly to the outbound.
- Type 2 orders: Multi-item orders which cannot be fulfilled in the same zone (hence multi-zone) are grouped into another queue. They are partially picked in a zone before moving on to subsequent zone(s) until completion.

Strategy C (Hybrid Zone Picking) In this strategy, orders in the batch is broken up into items which are located in the same zones such that each picker stays in a particular zone. At the end of the picking process, the picked items are sorted to the corresponding orders. In literature, this is often identified as a pick-then-sort order picking. The complication with this strategy is that there exists another sub-batch which controls the granularity of the sorting process. A larger sub-batch results in a higher pick density (hence potentially lower picking cycle time) but a longer consolidation and sorting time.

- Type 3 orders: Single-item orders are separated into a special queue for fast processing.
- Type 1 orders: Multi-item orders which can be fulfilled in the same zone are grouped together under queues corresponding to a particular zone. A master pick list based on the tote capacity and the suggested picking route (item sequence) is generated. The location assignment and path generation is performed by Algorithm 1. Note that orders are not broken up into individual items (i.e. sorting happens on the tote itself) and completed orders are sent directly to the outbound.
- Type 2 orders: Multi-item orders which cannot be fulfilled in the same zone (hence multi-zone) are batched into sub-batches of predefined size and broken up into individual items which are then grouped into their fulfillment zones. The queues generated correspond to the zones. The pickers stay in a particular zone during picking. These orders will be consolidated and then sorted after picking.

Strategy D (Pure Zone Picking) This strategy is similar to the hybrid zone picking but does not differentiate between multi-items orders which can be fulfilled in a single zone and those which can only be fulfilled by multiple zones. Sorting after picking is also required for this strategy.

- Type 3 orders: Single-item orders are separated into a special queue for fast processing.
- Type 1 and Type 2 orders: Multi-item orders are batched into sub-batches of predefined size and broken up into individual items which are then grouped into their fulfilment zones. The queues generated correspond to the zones. The pickers stay in a particular zone during picking. These orders will be consolidated and then sorted after picking.

4 SIMULATION MODEL

The simulation model employed is a discrete-event simulation based on the Object-Oriented Discrete-Event Simulation (subsequently referred to as "O2DES") framework, developed by one of the authors, written in C# on Microsoft Visual Studio IDE. In this framework, the simulation entities are partitioned into three major categories namely Dynamics, Events and Statics. Static elements have constant properties which describe the fixed physical warehouse layout. Dynamic elements have modifiable properties describing mutable entities such as pickers, SKUs, and picking lists. Finally, Events modify the states of the Dynamic entities and are executed sequentially according to a Future-Events List. This O2DES framework allows us to comply closely to the widely-accepted discrete-event simulation framework while exploiting object-oriented programming features such as inheritance and dynamic binding for flexibility.

The pick list generation module, which implements the proposed picking strategies, as well as the shortest-path routing module, based on Dijkstra's algorithm, are also integrated into the simulation model.

The pick list generation module takes in the orders and generates the batches and pick lists based on the selected strategy parameters. The routing module determines the travel time required based on the locations of the items in the pick list. These two modules combined result in routes which are similar to those generated with a return and S-shaped heuristics for order picking routing.

The discrete-event simulation model is used to evaluate and compare the various strategies. Firstly, actual demand data and inventory locations are obtained. Two weeks of demand data is used; this forms the source of stochasticity in the experiment. The physical layout of the warehouse is also translated into the simulation model; this physical layout is constant throughout all the experimental runs. For each set of demand data, the simulation is run using each of the picking strategies to obtain the desired output statistics (described in detail in Section 5). Parameters such as tote capacity, batch size, pickers, and sorting rate are subjected to a design of experiment as described in Section 5.2. Figure 1 illustrates the experiment flow.

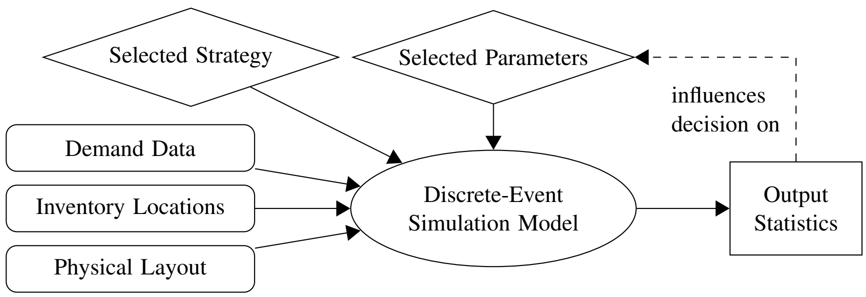

Figure 1: Simulation Experiment Flowchart.

5 FASHION WAREHOUSE CASE STUDY

ZALORA is one of the main e-commerce companies in Southeast Asia. A complexity for ZALORA is caused by the fact that the content of the customers' orders is particularly variable. As a consequence, as opposed to most of the warehouse in other sectors, it is difficult to identify fast-moving items and perform categorizations of the inventory using traditional ABC techniques. As a result, for the experiments, we consider a *randomized* inventory storage, i.e. SKUs are allocated to multiple and randomly positioned inventory locations. In the case constructed with the company, we consider a warehouse with 8 zones. The density per zone resulting from the random put-away is derived as the ratio between the number of items in a zone to the total number of items (in all zones). We took as a reference a specific warehouse and studied the order profile for two weeks. From this study, we were able to identify the profile in terms of single-item orders, multi-item orders and, within the multi-item orders, the single-zone and multi-zone orders. This information is very important for the allocation of operators to the different order types and also to establish the capacity of the different types of totes.

The simulation is constructed based on a real warehouse layout, inventory locations and demand data. The simulation model is validated against the real-world picking cycle time and pick list size based on the FIFO strategy. The warehouse layout evaluated consists of 725 rows, 68886 racks (i.e. possible storage locations), and 132378 items. The number of daily orders evaluated is in the range of 3000 and 6000 orders and the number of pickers available is as high as 150 operators. For confidentiality, these values do not reflect the actual values implemented in the company but are in the same order of magnitude. In essence, the stochasticity in this simulation comes from a sample of the real-world demand data as well as the real-world randomized inventory locations.

The objectives of the experimentation phase are presented in two stages:

1. Size the system capacity in terms of manpower required to complete the regular daily demand;
2. Given the manpower available, identify a good setting in terms of policy parameters. In particular, we are interested in:

- Capacity of the totes bringing items;
- Capacity of the carts bringing orders;
- Master Batch size, representing the number of orders the system processes simultaneously to perform the assignment to the operators in the warehouse (i.e., to form the pick lists). This parameter has a lower bound (degenerate, which is the number of operators) and an upper bound corresponding to the capacity given by the number of deployed operators and the capacity of the carts/totes. If the batch size is below the capacity in terms of totes, we will have idle operators which is something we need to avoid. Therefore, there is a strong correlation between the Master Batch Size and the capacities aforementioned;
- Sorting Rate: represents the number of items per time unit that a sorter is able to produce;
- Number of Sorters: represents the number of operators at the sorting station;
- Maximum Order Batch Size, which defines how many orders destined to the sorting station can be simultaneously put in the picking system. This parameter is important to control the waiting time at the sorting station and it is highly correlated to the number of sorting stations and the sorting rate.

When dealing with the second objective, we established with the company three main performance measures which are important to consider:

- Picking Cycle Time $[sec/item]$: represents the average time for an item to be picked. It is important to notice that the larger the capacity of the totes/carts, the larger will be the cycle time;
- Average Tote Utilization $[\frac{\text{average items per tote}}{\text{tote capacity}}\%]$: represents the ratio between the capacity of the tote and the number of items carried. This represents a good indicator of the work balance. Low saturation implies that some operators will be idle or finish ahead of time;
- Average Cart Utilization $[\frac{\text{average orders per cart}}{\text{cart capacity}}\%]$: this is the same as the previous indicator but for orders.

In the following section (5.1) we show the performance of the strategies with respect to the Stage 1 problem, i.e. the manpower sizing, while in the subsequent section (5.2) we use the input information related to the operators to perform a policy parameters optimization. Specifically, the second stage task was performed using Design of Experiment since the company was able to provide us with the possible values of the policy parameters due to technical and physical constraints over the parameters.

5.1 Manpower Allocation

Since labor cost constitute a significant portion of warehouse operating costs, we try to minimize the number of pickers for each of the strategies. The first issue that has to be solved for the allocation problem was the assignment of operators to each order type. The idea is to assign workers to the different order types based on the average total relative cycle cycle time required by each type with respect to the total average cycle time. In order to evaluate these average cycle times, we ran simulation by considering an over-sized system. The results are displayed in Table 2 below.

Considering the ratios in the last column of Table 2, we performed a simple enumeration over the total number of available operators according to the data provided by the company. Based on the data of 11 days of demand, we bootstrapped the data using an empirical discrete density in order to generate a statistically significant input. Under the advice of the company, we ensured that the allocated manpower is able to complete all the picking tasks for each day within 10 hours with a 95% probability. As suggested by the company, we started with 40 pickers and derived the following allocation shown in Table 3 below.

It is noteworthy that Strategy C and D, despite requiring a lower number of operators, necessitate sorting. As a result, at this point of the analysis we cannot conclude which strategy is superior considering the

Table 2: Average Picking Cycle Time Estimation.

Strategy	Order Type	Cycle time [min/item]	Cycle Time Multiplier $c_i/\sum_{i=1,\dots 3} c_i$
A	Order	1.127	1.000
B	Multi-Item Single Zone	0.874	0.293
	Multi-Item Multi Zone	1.008	0.338
	Single Item	1.101	0.369
C	Multi-Item Single Zone	0.874	0.293
	Multi-Item Multi Zone	0.583	0.195
	Single Item	1.095	0.367
D	Multi-Item	0.752	0.252
	Single Item	1.101	0.369

Table 3: Required Manpower.

Strategy	Order Type	# Workers
A	Order	26
B	Multi-Item Single Zone	2
	Multi-Item Multi Zone	17
	Single Item	4
C	Multi-Item Single Zone	1
	Multi-Item Multi Zone	15
	Single Item	4
D	Multi-Item	16
	Single	3

manpower requirements; only Strategy A appears to be dominated. In the next part of the experimentation, we will focus on this comparison by considering the remaining picking policy parameters in order to provide insights on dominance of the different strategies.

5.2 Strategy Comparison

Based on discussions with the company, we were able to identify a relatively small discrete set of possible feasible policy parametrization. Therefore, we constructed a Design of Experiment as depicted in Table 4 below (note that the values do not refer to the actual values implemented in the company). In the experimental runs, we collect the following output as Key Performance Indicators (KPIs):

- Cycle Time: for the example case, the company established a threshold for the cycle time for each item i, $c_i = 54$ $[sec/item]$;
- Average Tote Utilization: this indicator determines the productivity of the tote equipment and measures the efficiency of warehouse operations. This KPI is not applicable for Strategy A. For the company, the threshold average tote utilization should be at least 75%;
- Average Cart Utilization: this KPI determines the productivity of cart equipment. This KPI is not applicable for Strategy D. For this indicator, the optimal average cart utilization should be at least 90%.

The aforementioned design of experiment aims to determine the set of parameters for which the desired level of performance is achieved. In Table 5, the average results across all experimental conditions using a particular demand data for each strategy are reported. In particular, the "Satisfactory Performance Level" indicates the proportion (in terms of percentage) of tested experimental conditions in which a strategy is able to meet *all* the thresholds suggested by the company. We observe that the only strategy that meets all the requirements is **Strategy D**, under the settings with maximum item totes capacity 40 and maximum order batch size of 70.

Table 4: Testing Configurations (factors levels for a full factorial design).

Item Totes Capacity	Order Totes Capacity	Master Batch Size	Max Orders Batch Size	Sorting Rate	No. of Sorters
$(20,40)$	$(6,12)$	$(500,700)$	$(30,70)$	$(3,7)$	$(1,3)$

Table 5: Average Strategy Performance Over All Configurations.

Archived Percentage	Strategy A	Strategy B	Strategy C	Strategy D
Average Cycle Time [sec/item]	70	62.75	52.46	51.88
Average Tote Utilization	N.A.	92%	58%	58%
Average Cart Utilization	99.70%	86.80%	46.70%	N.A.
Satisfactory Performance Level	0%	0%	0%	12.5%

Although Strategy A performs the best in terms of cart utilization, it does not meet the requirement for average cycle time, which is around 70 seconds per item picked on average. For Strategy B, it does not meet requirement of the total cycle time, which is nearly 63 seconds per item picked on average. It is apparent how strategy A and B require a larger number of operators in order to reach the same performance of the other two strategies (considering also the operators at the sorting station). Therefore, at this phase of the experiment these two strategies are dominated by C and D. For Strategy C, it meets requirement for total cycle time with 52 seconds per item (still higher than that of Strategy D) but none of the simulation cases satisfies the requirement for cart utilization, which is only 47% on average.

Observing the effects analysis from the performed experiments, we found that:

- The cart (tote) capacity has an important impact over the system performance: a smaller capacity requires pickers to run more times to fulfill total orders picking, thus increasing the picking time. As a result, we should maximize the capacity provided that the picker can handle the cart in the same amount of time.
- The master-batch size is a key for the balance between picking and sorting. A very large batch size, will provide larger saturation, but results in longer waiting times at the sorting station. As a consequence, this size has to be set carefully.

Considering the results, after taking the desired KPIs and manpower allocation into consideration, Strategy D is the best strategy for the company based on this example scenario. In terms of the KPIs, Strategy D yields a significant reduction in average cycle time while not being absolutely disadvantaged in terms of tote utilization. As for manpower allocation, Strategy D requires less manpower to handle the same warehouse operations and thus reduces the related labor cost. Nevertheless, we need to consider that at this stage of development of the simulation model, we are considering the sorting process simply as a delay, i.e., the detailed sorting process is not modeled within the simulator. Nevertheless, sorting a large number of items, as strategy D requires, can be particularly problematic, due to the complexity for the operator to identify and match items. For this reason, strategy C should be considered since it lowers the number of items directed to sorting.

Another important aspect resides in the low saturation obtained both in strategy C and D. This result is due to the sorting station which represents the system bottleneck. Due to the presence of the order batch, the pickers cannot load to many items to avoid congestion at the sorting and this generates waiting times. Again, the efficiency of the sorting station is relevant for both strategies and we are currently in the process of designing a sorting process and the required technology.

6 CONCLUSION

This work contributes in the proposal of four innovative picking strategies, which were designed for an e-commerce company under the consideration that the main impact for the picking process resides in trying to pool together orders which are located in the same zone independently from the volume. The proposed approach has been rigorously evaluated using simulation, thus providing a tool to the company to evaluate the different strategies and we have found that the pure zone picking is the best.

From this work, we see that there is an indication that having a high picking density results in a higher picking performance. As such, future work is being performed to use learning techniques in order to maximize the inventory density by performing inventory put-away based on correlation between items instead of volume (differently from typical ABC classification).

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