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PICK ORDER ASSIGNMENT AND ORDER BATCHING STRATEGY FOR ROBOTIC MOBILE FULFILMENT SYSTEM WAREHOUSE

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ABSTRACT

This study aims to optimize the order fulfillment process in a Robotic Mobile Fulfilment System warehouse by improving the order batching and the pick order assignment in order-picking activities using a simulation approach. The order-to-station assignment considers the association between the new order and the in-progress order at the station instead of random assignment. The proposed model aims to maximize the total throughput, maximize the pile-on value, and minimize the required number of pods. The proposed model is compared with a baseline scenario. The result shows that the proposed model significantly decreases the number of required pods by 40 %, increases the pile-on by 60 %, and increases the throughput by 4 %. This result proves that the proposed strategy can improve the efficiency of the order-picking process by ensuring every order and/or batch of orders always goes to the picking station with the most similar order.

1 INTRODUCTION

During the recent decade, the online shopping trend has grown year by year, particularly during the pandemic. To fulfill a huge number of orders, the warehouse has a critical role in the whole supply chain, since all of the warehouse’s internal operations need to be conducted effectively and efficiently. The warehousing operations activities consist of several divisions, such as receiving and storing the product, order picking, replenishing, and shipping the order. The order-picking activities contribute about 55 % of the total cost of warehousing activity (Tompkins et al. 2010). Currently, many warehouses have already employed and developed an automatic parts-to-picker method (Li et al. 2022). Many companies are trying to invest in automation and robotic technologies that increase their company’s competitiveness (Zhiwen 2003). Automation in a warehouse might improve the order fulfillment process in a warehouse. One of the automation implementations in the order-picking process uses a Robotic Mobile Fulfillment System (RMFS) (Weidinger et al. 2018).

RMFS is an automated parts-to-picker system that uses an autonomous robot to carry the movable racks (pod) from the storage to the picking/replenishment station or vice versa (Merschformann et al. 2019). It utilizes an Automated Guided Vehicle (AGV) or Kiva robot to bring pods containing ordered items to the picking station to fulfill an order, bring the pods back to the storage for storing the pods, or bring them to the replenishment station for replenishing the SKU inside a pod (da Costa Barros and Nascimento 2021). The RMFS has developed in well-known companies like Amazon, Geek+, and Fetch Robotics (Yildirim et al. 2023). The use of RMFS is promising, because this system can help to increase the picking rates by reducing the picker walking time compared to the picker-to-parts system (Merschformann et al. 2019). Implementing RMFS also improves the order fulfillment speed by 50 % compared to traditional warehouses (Lamballais et al. 2017). However, several issues must be addressed by a company to implement RMFS: layout and facility (Li et al. 2021; Zhu and Li 2022), warehousing activities such as order assignment (Xie

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et al. 2021), product storage assignment (Yuan et al. 2021), pod storage allocation (Yuan et al. 2021), and robot routing problem (Cai et al. 2021). The total completed orders per unit of time (total throughput) usually is a measure for the efficiency of the warehouse. Therefore, optimization from all warehousing processes is needed to achieve higher throughput.

Pick Order Assignment (POA) is an activity to fulfill all orders in the warehouse, including the decision how to assign the order to a pod and a particular picking station. Fulfilling more orders with a lower number of robots or a lower number of pods to be picked is one of the crucial issues for optimizing the order-picking process in RMFS. The system needs an effective and efficient assignment model to pick more items from one pod. The pile-on value is a performance measure representing the average number of items picked from one pod. With a higher pile-on value, fewer pods are required to be delivered to the station. Order batching is used to process all orders effectively, where several orders are grouped in the same pick order to reduce the traveling time and order completion time.

This study focuses on the order-picking process or POA in the RMFS. The study aims to increase the total throughput by maximizing the pile-on and minimizing the number of pods needed to fulfill the order. This study applies order batching to the order assignment based on specific rules. The proposed strategy is evaluated using a simulation approach.

2 LITERATURE REVIEW

A robotic mobile fulfillment system is an automated parts-to-picker material handling system designed to fulfill e-commerce orders effectively. The system consists of pods, AGVs, and picking and replenishment stations. The process of RMFS starts when orders arrive in the system. After particular orders arrive, the system assigns each order to a specific picking station. Every picking station can fulfill several orders simultaneously, depending on the available capacity in each picking station. If an order arrives when there is no capacity available in the station, that order will be added to the order pool containing unassigned orders.

On the other hand, every pod stored in the warehouse can include multiple items depending on the item assignment and replenishment policy. Each pod only can serve or go to one station at a time. So, the system will search for possible pods containing the specific item for fulfilling current active orders in the picking station (Yang et al. 2021). In RMFS, order assignment and pod selection are crucial elements affecting the order-picking efficiency. The wrong decision for them may lead to the inefficiency of the order-picking process. Therefore, many studies have discussed this problem (Jaghbeer et al. 2020; Zhang et al. 2022).

The first decision that should be made in this system is to which station an order should be assigned. An operator or picker at a picking station can process several orders at once. If the on-progress orders have similar SKUs, the picker can fulfill more than one order at once time to save time. Therefore, assigning an order to the picking station also might influence the overall order fulfillment time. One key metric for measuring the efficiency of pick order assignment is pile-on, defined as the average number of SKUs collected from a storage pod during each visit to a picking station (Yang et al. 2021). Generally, a higher pile-on is preferable as it indicates that pickers can collect more units from each pod during their visits to a picking station, reducing the number of times pods need to be moved between picking stations and storage areas.

There are several approaches that previous studies have proposed. Xie et al. (2021) solve the pick order assignment problem with a mixed integer programming approach. Zhang et al. (2022) also represent the order-picking problem as mixed-integer non-linear programming and solve it using a variable neighborhood search algorithm. Teck et al. (2023) evaluate a decentral single-item auction mechanism, greedy look-ahead heuristic, regret-based task selection, and Lin-Kernighan-Helsgaun heuristics using a simulation approach to find the best order-picking mechanism. Despite various approaches that have been proposed, the decision in the order picking problem should be made based on the order data. Therefore, this study considers a data-driven approach to solve this problem and evaluates the proposed mechanism using simulation. Some previous studies in RMFS that are also based on a data-driven approach are included (Keung et al. 2021; Keung et al. 2022; Zhuang et al. 2022).

3 METHODOLOGY

3.1 System Process Flow

This study focuses on the order-picking process in the RMFS warehouse. In this system, a set of AGV robots are pickers bringing the products to the picking stations. An order triggers the picking process. When an order is received, the order picking system assigns the order to a picking station, determines pods that should be delivered to the designated picking station, and assign an available AGV robot to move the pod from the storage area to the picking station and back again to the storage area. Figure 1 illustrates the order-picking process in the RMFS.

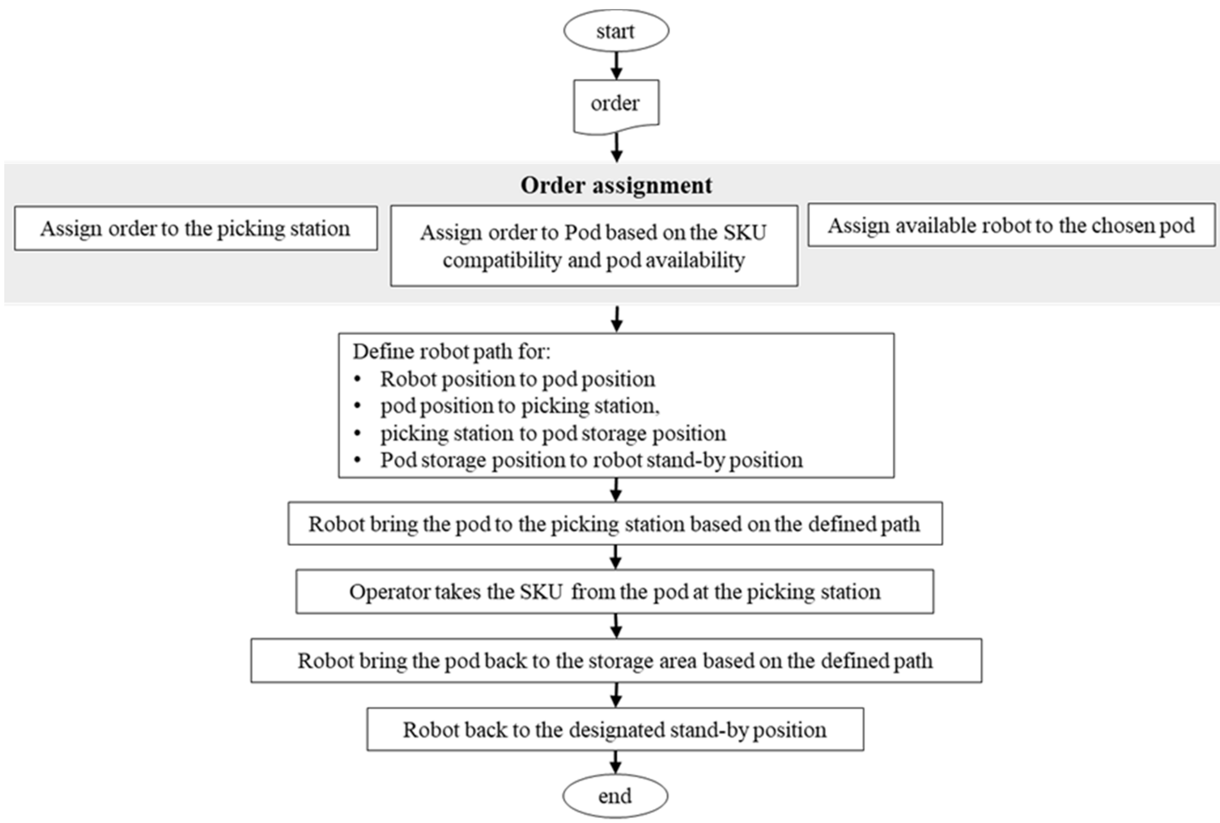

Figure 1: Order picking process in robotic mobile fulfillment system process flow.

The elements of the model in the RMFS are as follows:

- The input of the RMFS warehouse system is the order. The *order arrival* time and the list of SKUs in each order are the stochastic part of this system. In this simulation, the order arrival and list of SKUs in each order are generated based on a Poisson distribution.
- SKU-*to-pod assignment* means assigning and storing the SKUs inside different pods to maximize the pod's utility. This inventory strategy task involves dividing and classifying the SKUs based on the chosen rule. In this study, the inventory strategy applies the ABC rule classification to store the SKUs in the warehouse. The proportion of the number of units is 60 % class A, 25 % class B, and 15 % class C. The storage arrangement follows a mixed-storage sharing policy, so each pod has different SKUs and types.
- After orders have arrived in the system, an *order to pod assignment* is performed, assigning the orders to picking stations and generating a list of pods that can fulfill the order. A pod might satisfy

more than one order. In terms of assigning the order to the pod, the most pile-on rule is implemented in this system.

- After receiving orders, the system assigns the order to a specific picking station and generates a *pod sequence* to fulfill the orders. One pod can be assigned to fulfill more than one order. Likewise, one or more pods can complete one order. Regarding several pods needing to fulfill one order, the sequence of the selected pods indicates the pod priorities to be picked to fulfill the order.
- In the *robot to pod assignment*, AGVs will be allocated to the chosen pods based on proximity and earliest due date. Twice as many available AGVs are taken from the list of chosen pods and assigned to selected pods. However, the distance between the AGV and the chosen pod is computed using the Manhattan distance, and the Hungarian method is used to determine the assignment.
- The *robot routing* policy employs a simple routing with a traffic control policy as proposed in (Zhang et al. 2018) The traffic policy used is congestion and collision avoidance. This primary method in AGV routing allows for having a minimal route without path planning to reduce the calculation time.
- The *robot to workstation assignment* (picking/replenishment station) is determined by the minimal number of AGVs waiting in a line. It is related to how many AGVs need to be processed when the robot reaches the highway in the storage area before traveling to the picking station.
- After a pod finishes its task in the order picking or replenishment station, a *robot to storage assignment* has to performed to place it within the storage area in the nearest available empty location.
- After the pod finishes its task in a specific order-picking station, the system will check the pod inventory level. If the inventory level falls below the minimum inventory limit, it requires a *pod replenishment*. Then, the designated AGV will directly carry this pod to the replenishment station.

In the RMFS warehouse, the picking station has a given bin capacity. Each bin can only be used for one order. In this study, the system also utilizes an order batching system based on batching time. At every batching time, the orders in the order pool will be released and assigned to the picking station. This study improves the order batching process and order-to-pod scenarios for a more efficient order-picking process.

3.1.1 Order Batching and Order Assignment for the Proposed Model

In the proposed model, the order grouping model classifies orders into batches based on the similarity of SKU types, as measured using the Jaccard Index as shown in Equation (1), where J_{AB} is the similarity between order A and B, A is a set of SKU in order A, and B is a set of SKU in order B (Tan et al. 2013). After calculating the similarity of the orders, the model follows a clustering approach to group orders into batches, with the number of picking stations serving as the number of batches required.

$$J_{AB} = \frac{|A \cap B|}{|A \cup B|} \tag{1}$$

In the proposed model, the number of batches will be the same as the number of picking stations in the warehouse. All orders that arrive in the system during a specific period will be grouped based on their SKU's similarity to a picking station. The number of batches will be adjusted based on the number of idle picking stations at a given time, and the number of orders assigned to each batch will be adjusted based on the available capacity of the slot-picking stations. This approach represents the actual situation in the RMFS warehouse, where orders are immediately processed and exit the system after being picked. Additionally, this approach increases the system's utilisation by avoiding idle slots and allowing for continuous processing of orders rather than waiting for all orders to be completed before moving on to the next assignment. The proposed model allows the system to adjust the number of batches and the number of orders in each batch as needed.

The system starts when it receives an order and then checks if there is sufficient inventory for each order. If the order can be fulfilled with the current system inventory, the system can process the order for the assignment part. Otherwise, if there is an insufficient quantity of SKU in the pod for an order, the order will be kept in the order pool. Then, the system will identify which picking station is available for the new assignment, how many picking stations are free, and how much capacity is available for placing a new order assignment. Then, the system will identify the bin and station availability in the assignment process. Figure 2 gives the flowchart for the proposed model.

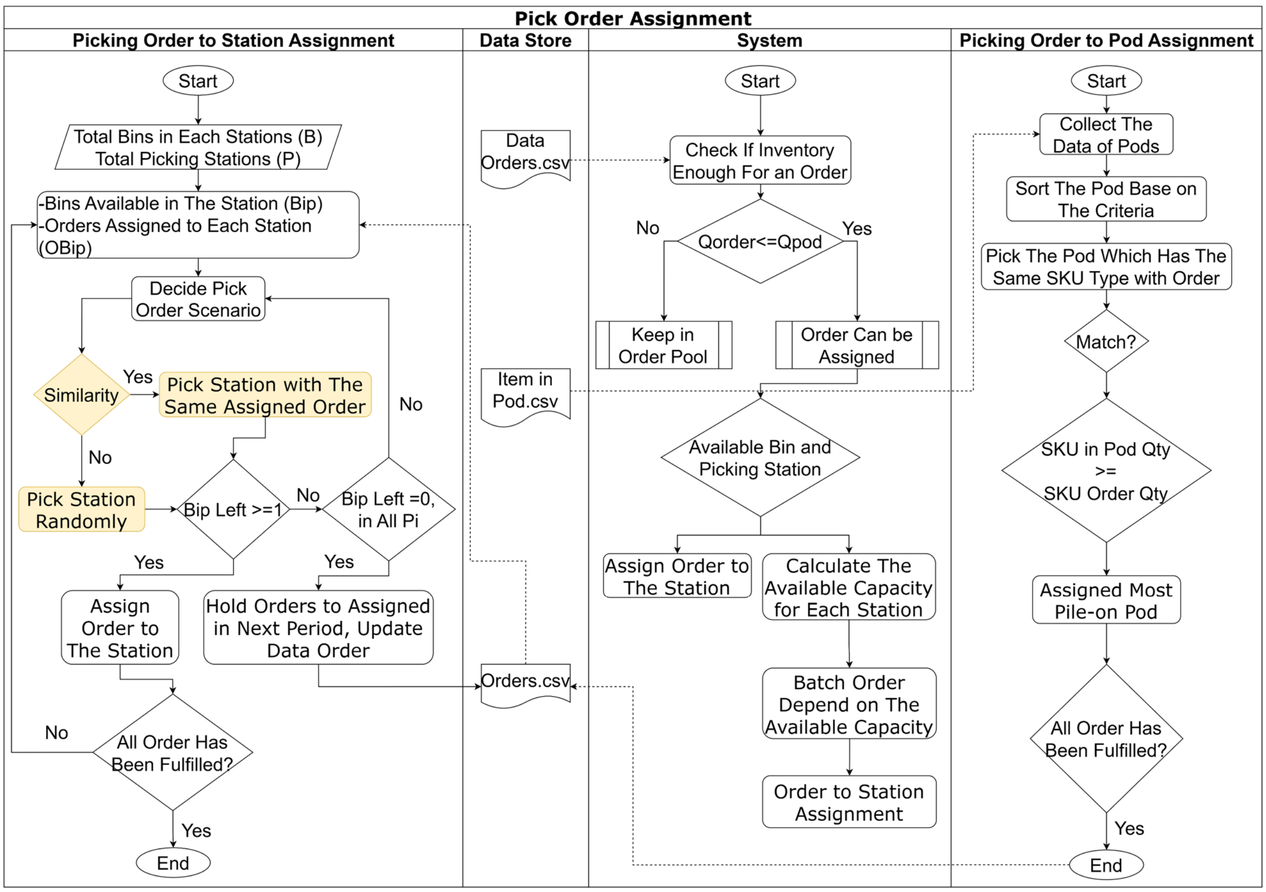

Figure 2: System flowchart for the proposed model.

3.1.2 Order Batching and Order Assignment for the Baseline Model

For the baseline model, the order batching will apply the random rule to allocate the order into the same batch. This random rule is used as a baseline for comparison with the proposed model that uses the similarity rule. The baseline model uses an arbitrary rule to assign the order to the designated picking station. Then, the system assigns the most pile-on pods to fulfill the order and deliver it to the designated picking station. Figure 3 defines the flowchart for the baseline model.

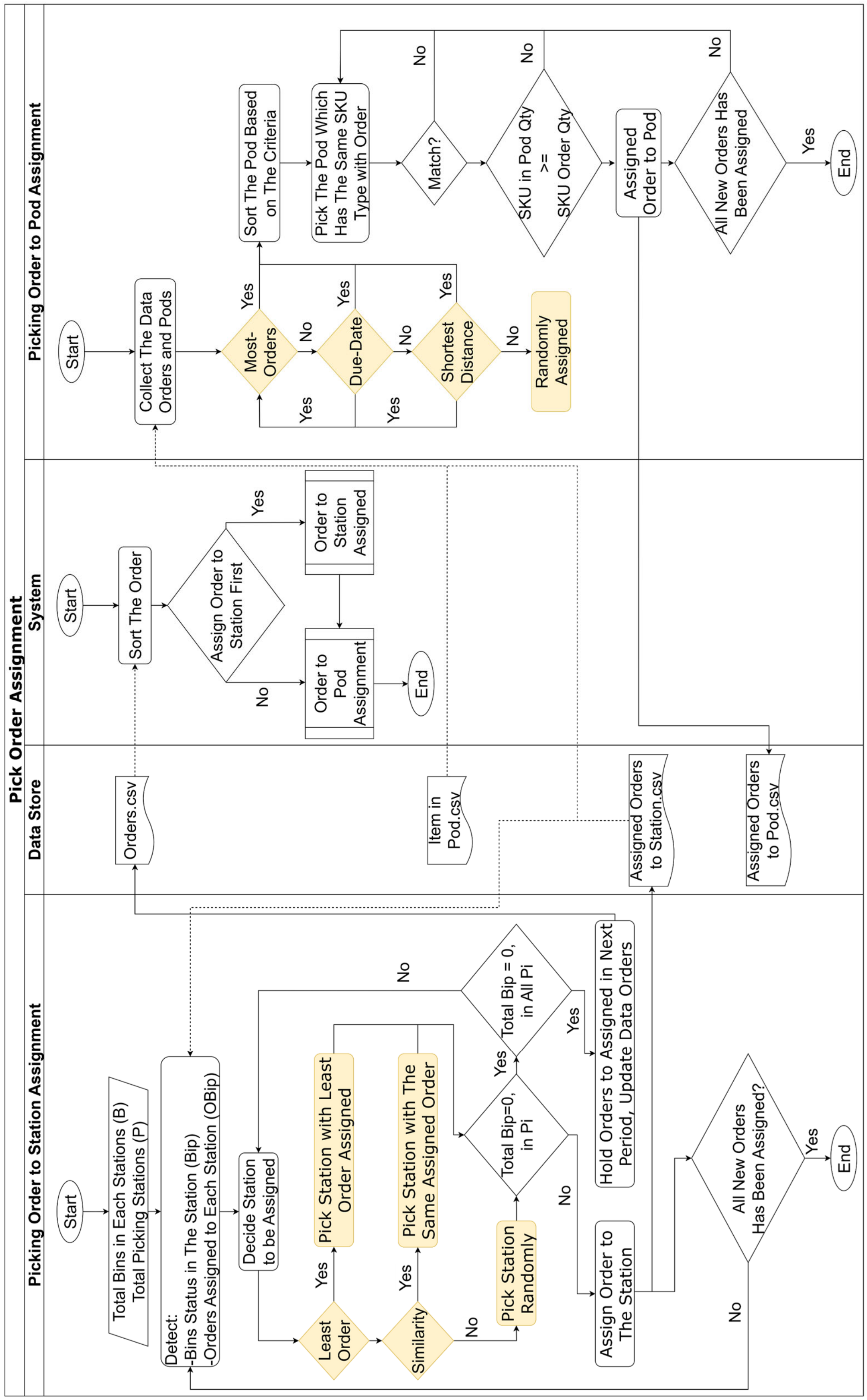

Figure 3: System flowchart for the baseline model.

3.2 Simulation Configuration

This study develops the simulation in NetLogo and Python. The main input in this simulation includes the warehouse layout, AGVs, pods, order, picking, and replenishment station configuration. Table 1 lists the parameters used in the simulation, while Figure 4 shows the simulation layout used in this study. The warehouse layout includes picking stations, a storage area, and replenishment stations. Picking stations with pickers and queue lines are at the top of the layout. There is a storage room holding pods carrying SKUs in the central part. A pod with a distinctive color indicates that it has been allocated to orders that an AGV will pick in the future. The vacant storage space with the blank square inside the pods means that the AGV might return the pod to that spot once it has been selected. An AGV can operate in a one-way aisle and go underneath the pod without direction. Within the aisle, the AGV can only move forward or stop. When it reaches a junction, it might turn towards the next aisle. Near the workstations, two-lane highways provide many routes to and from the workstations. According to their roles, there are two kinds of AGVs, which may be categorized as picking AGVs and replenishment AGVs. At the bottom of the layout, there are replenishment stations and queue tracks.

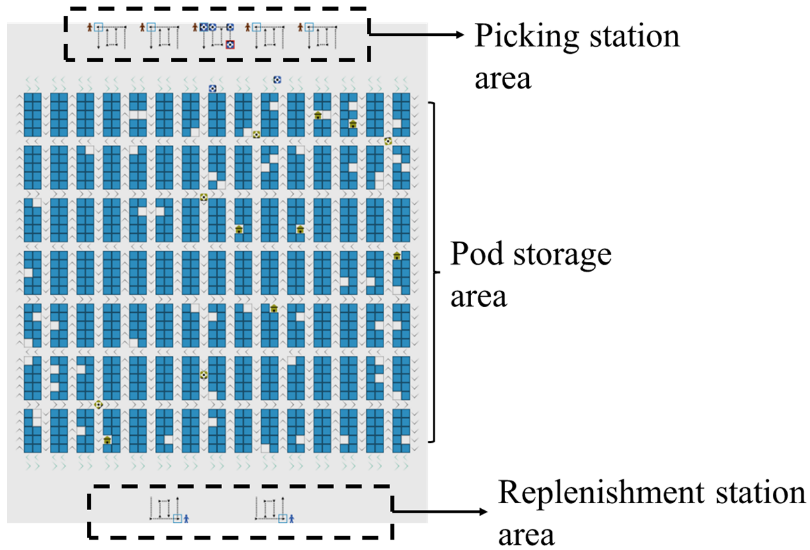

Figure 4: Simulation layout.

Table 1: Simulation parameter setting.

Parameter	Value
Inventory Area	1,050 locations
Inventory Capacity	999 pods
Empty Storage Area	51 locations
Pod Batch	2 x 5 blocks
Aisles	16 vertical aisles; 8 horizontal aisles
Stations	5 picking stations; 2 replenishment stations; 7 charging stations
Order Line	Multi-line orders
Initial Orders	100 orders
Capacity	100 units
SKU Distribution	Class A = 0-893 (10 %) SKUs; Class B = 894-3575 (30 %) SKUs; Class C = 3576-8938 (60 %) SKUs
SKUs/pod	20 SKUs (ABC mixed class storage policy)

Parameter	Value
Number of AGVs	50 AGVs
AGV Speed	1.5 m/s (load), 2 m/s (no load)
AGVAcceleration/Deceleration	1 m/s
Time to Lift and Store Pod	4 s
AGV to Pod Policy	Shortest pod
Queuing per Station	12 AGVs
Picking Time	10
Picking Policy	Random; similarity-based order batching and order assignment
Replication	30 replications for each scenario
Replenishment Time	20
Warehouse Inventory Level	60 %
Pod Inventory Level	90 %

3.3 Performance Analysis

The system performance evaluation involves comparing simulation results of different scenarios using a statistical test. Furthermore, a sensitivity analysis experiment with several parameter changes is conducted to examine the best scenario's robustness. In order to evaluate the performance of the warehouse simulation, this study uses several indicators to compare the impacts of different scenarios resulting from the simulation. The performance criteria used in this study are the pile-on value, the percentage of the number of pods transported in a specific period , and the throughput efficiency.

The *pile-on* (po) value is the average number of order items picked in one pod. It is calculated by the throughput rate (TR_t) and the number of picked pods (np_t) in period *t* (Equ. 2).

$$po = \frac{TR_t}{np_t} \tag{2}$$

As defined in (3), the *percentage of the number of pods transported in a specific period t* (P_{np}) is the number of pods picked (np_t) divided by the total number of pods (P).

$$P_{np} = \frac{np_t}{P} \; x \; 100 \tag{3}$$

The throughput efficiency at period t (TE_t) can be calculated by dividing the order rate (OR_t) and throughput rate (TR_t) in period *t,* as shown in (Equ. 4). The order rate is the total number of arriving orders in the system at period *t,* while the throughput shows how many orders can be fulfilled in period *t*. Based on this statement, the throughput efficiency represents how effectively the orders can be finished within the period *t*.

$$TE_t = \frac{TR_t}{OR_t} \tag{4}$$

This study aims to increase the total throughput by maximizing the pile-on and minimizing the total number of pods needed for fulfilling the order. The pile-on number represents a pod's levels of utility since a high pile-on value indicates that a pod can fill more SKUs in a single trip. The better the pile-on value, the more likely the order list can be fulfilled fast. Generally, the pile-on value is also related to the number of pods required to satisfy orders, because the larger the pile-on number, the fewer pods will be needed to finish the order list. As a result, there are fewer pods transported to the picking station and the AGVs do not have to move as much throughout the warehouse. Also, fewer pods delivered must optimize pod use to ensure warehouse throughput efficiency.

4 EXPERIMENTAL RESULTS

This study generates a dataset including the orders and pods for the simulation. There are 1,803 orders and 8,939 SKUs. The results in Table 2 show that the proposed model needs fewer pods to fulfill the order. The proposed model outperforms and is competitive compared with the baseline scenario. Using similarity-based order batching and the order assignment model can decrease the average number of pods needed by 40 %. These results are in line with the pods' utilization percentage, i.e., the number of pods needed divided by the total number of pods in the warehouse.

Furthermore, putting the order with the highest similarity into the same batch has proven to increase the pile-on value of the system, since it allows the simulation to achieve an almost 70 % better pile-on compared with the baseline scenario. The proposed model also sequences the order assignment to the station based on the similarity, with a higher chance of similar orders being processed concurrently. This strategy helped the system achieve a higher throughput of around 3 % by assigning similar orders concurrently within the batch and considering the active order in the picking station before assigning the batch. This order assignment strategy increases the possibility that every order or batch of orders goes to the picking station with the most similar order. It helps to maximize the pile-on, minimize the pod movement, and decrease the service time for each order fulfillment.

In addition, this study applies a statistical test to analyze the differences between the proposed and the baseline model. The normality test result using the Shapio-Wilk and Komogorov-Smirnov tests (Table 3) shows that most simulation results follow the normal distribution except for the throughput efficiency. Therefore, a mean comparison analysis for the percentage number of pods and pile-on is conducted using the Wilcoxon sum-ranked test, while the throughput efficiency uses the T-test. The results show that the proposed model significantly differs for all evaluation criteria from the baseline.

Table 2: Experiment result for the baseline (Base) and the proposed (Prop) model.

Metric	**Performance Measure**							
	Number of pods (np_t)		**% Number of pods (P_{np})**		**Throughput efficiency (TE_t)**		**Pile-on (po)**	
	Base	***Prop***	***Base***	***Prop***	***Base***	***Prop***	***Base***	***Prop***
Average	543	323.5	54.351	32.379	92.754	95.710	2.387	4.044
Standard deviation	6.074	23.238	0.609	2.325	1.438	1.385	0.023	0.443
Min	531	215	53.15	21.52	89.29	93.3	2.33	3.57
Max	558	349	55.86	34.93	94.76	99.28	2.44	6.2
Gap	**40.33 %**		**40.42 %**		**-3.19 %**		**-69.03 %**	

Table 3: Statistic test result (P-value).

Data	**Shapiro-Wilk**	**Kolmogorov-Smirnov**	**Levene-Test**
Percentage number of pods (baseline)	> 0.10	> 0.15	0.085
Percentage number of pods (proposed)	< 0.01	< 0.01	
Throughput efficiency (baseline)	> 0.10	> 0.15	0.021
Throughput efficiency (proposed)	0.09	0.128	
Pile-on (baseline)	> 0.10	< 0.01	0.077
Pile-on (proposed)	< 0.01	< 0.01	

This study conducts a further analysis to evaluate different parameter settings to the results. The sensitivity analysis is conducted for four different parameters: the number of picking stations, picking station capacity, batching time, and number of AGVs. The detailed results are listed in Table 4.

Table 4: Sensitivity analysis results comparison.

Parameter	**Value**	**Performance Measure**			
		Number of pods (np_t)	**% Number of pods (P_{np})**	**Throughput efficiency (TE_t)**	**Pile-on (po)**
Picking station	2	250	25.03	57.89	3.72
	3	295	29.53	69.38	3.64
	4	328	32.83	93.30	2.39
	5	543	32.43	95.93	4.01
	6	326	32.63	96.41	4.00
Station capacity	8	323	32.33	94.50	4.04
	12	332	33.23	93.30	3.90
	16	543	32.43	95.93	4.01
	20	326	32.63	94.26	3.98
	24	320	32.03	96.41	4.08
Batching time	5	324	32.43	95.93	4.01
	10	315	31.53	80.38	3.76
	15	240	24.02	48.09	3.75
	20	259	25.93	44.74	3.47
	25	225	22.52	33.73	3.34
Number of AGVs	25	323	32.33	96.89	4.02
	40	323	32.33	94.50	4.04
	50	324	32.43	95.93	4.01
	75	326	32.63	93.54	3.98
	100	317	31.73	84.21	3.83

Based on the results in Table 4, increasing the *number of picking stations* increases the percentage of throughput efficiency significantly. However, adding picking stations without significant improvement may increase investments and operational cost. Furthermore, the percentage of pods needed for all numbers of picking stations is not significantly different. In terms of the pile-on value, five picking stations achieve the highest pile-on.

A higher *picking station capacity* allows the station to process more orders concurrently and increase the total warehouse throughput. The results show that changing the station capacity affects the warehouse's performance. The throughput efficiency increase is aligned with the increase in picking station capacity. The highest station capacity achieves the highest pile-on.

Table 4 shows that shorter *batching times* can increase the order-picking efficiency in an RMFS warehouse. A longer batching time allows the system to gather more orders before assigning them to the picking station. However, a longer picking time might lead the picking station to idle longer.

A high *total number of AGVs* in the warehouse allows the system to undergo more tasks and finish more orders. However, a high total number of AGVs may cause traffic congestion. Table 4 shows that the throughput efficiency, pile-on value, and percentage number of pods needed with different numbers of AGVs have slight differences. The results show that the number of AGVs will increase the system's performance until a specific point. Behind this point, adding robots does not always have a positive impact. The management should critically assess adding AGVs in the warehouse, since higher AGVs lead to high investment, operational, and maintenance cost.

5 CONCLUSION

Order picking is a critical operation that significantly impacts the overall efficiency and productivity of the RMFS warehouse. Managing the order-picking assignment is one of the most challenging problems of implementing RMFS for the order-picking warehouse. POA is the decision problem related to assigning orders to the picking station. This study proposes a POA strategy and evaluates the proposed model using a simulation approach. The proposed model uses a similarity-based order batching rule to improve the system's performance. The order grouping rule uses the Jaccard index as a similarity measurement for assigning the most similar order in the same batch.

The simulation shows that the proposed model outperforms the baseline model. The similarity grouping and order assignment rule proposed in this study are competitive enough to capture the real warehouse with its dynamic environment. Based on the statistical test, it is 95 % proven that there is a significant difference between the baseline and the proposed model for all evaluation criteria. The simulation results also show that the proposed model could reduce the pods needed for fulfilling orders by around 40 %. Also, it can increase the throughput by around 4 % by maximizing the pile-on to almost 60 % higher than the baseline results.

Furthermore, the sensitivity results show that increasing the number of picking stations can increase the performance significantly. However, after a certain number of picking stations, the improvement might not be significant anymore. In this study, increasing the number of picking stations from three to four improves the performance significantly. Conversely, increasing the number of picking stations from four to five does not improve the performance significantly. Increasing the station capacity positively influences performance, because higher station capacities allow more orders to be processed concurrently. Besides, the number of batching times is sensitive to the system's performance. Finally, the number of AGVs increases the performance within a limit. Adding more of them might not affect the performance significantly, since the system has already reached convergence.

To enhance the analysis, further studies should consider batching the orders and considering the SKUs in pod affinity. Other evaluation criteria should be considered, e.g., the number of tasks or service level criteria, since the company also needs to maintain customer satisfaction to compete with other companies.

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