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Slotting Layout Optimization and Dynamic Scheduling Method for Smart Warehousing Systems

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Abstract. The development of e-commerce, smart manufacturing, and multi-channel logistics has changed the way warehouses operate from traditional static management of inventory to real-time decision-making. Many existing warehouse management systems focus on optimizing warehouse processes independently, such as assigning storage locations to stock-keeping units, replenishing inventory, and dispatching equipment. This can result in unnecessary long picking distances, uneven use of resources, and congestion in automated aisles. To help solve these issues, a method for developing an integrated slotting layout optimization and a system dynamic scheduling for smart warehouse systems is presented. The analysis of the test results shows that the proposed method reduces the expected picking distance, average order completion time, tardiness rates, and congestion in aisles while increasing the efficiency of using warehouse space and the level of reliability provided to customers.

Keywords: smart warehousing, slotting layout optimization, storage location assignment, dynamic scheduling, automated guided vehicle

1 Introduction

1.1 Research Background

Today's warehousing systems are experiencing a big change and moving away from being labor-oriented and instead, they are now moving toward being data-driven and assisted by automation [1]. As businesses continue to grow from E-commerce and Customized Manufacturing; this is driving the demand for Warehousing operations to be able to support small, often ordered, time-sensitive orders. The overall effective operating performance of a warehouse is based on the quantity of shelving, the number of workers, or the number of automated vehicles. However, additionally, the operating performance of today's Warehouse is dependent upon the way in which all storage locations are related structurally, inventory demand patterns, how picking routes are designed, how frequently replenishment orders are due, and the policies for dispatching equipment [2]. A smart warehouse can utilize SKU data, order streams, the total inventory state, the position of all equipment, as well as how congested aisleways are using warehouse management systems, bar code/radio frequency technology, IoT devices, and warehouse control systems. This data provides a means to minimize slotting layout and develop operational schedules in a closed-loop manner [3]. Nevertheless, many of the systems currently being used continue to use fixed-location storage, simple ABC classification methods, nearest-location put-away methods, and first-in/first-out dispatch methods. These methods are easy to implement; however, they cannot optimally reflect order co-occurrence, demand shift, space imbalance, and the relationship between layout and real-time scheduling. The process of slotting layout optimization establishes the optimal placement of Stock Keeping Units (SKUs) [4]. Dynamic scheduling determines when and what resource will execute an operational task. These two decision-

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making processes are strongly interrelated. When an SKU is placed at a distance from the pick station and is in high demand, dynamic scheduling will compensate for any travel burden created from that location [5]. Likewise, when an SKU is stored in a different location than those that are frequently co-picked, the total order-level picking distance will increase regardless of how popular or in demand each of those SKUs are by themselves [6]. Furthermore, if the dynamic scheduling does not account for the congestion of aisles or the replenishment of inventory, then making decisions based on local dispatching will cause delays throughout the system-level operation.

1.2 Research Motivation and Contributions

In this paper, the team presents an integrated approach to slotting and scheduling that combines strategic slotting layouts with dynamic operational scheduling, based on historical orders and SKU attributes, to generate a robust initial layout and use rolling-horizon methodologies to update scheduling decisions based on the real-time state of the system. When disturbances occur, such as urgent orders, AGV delays, temporary stockouts, or congestion, reinforcement learning will be employed to modify short-term decisions. The major contributions of this paper are outlined below: First, a correlation-aware slotting optimization model is developed to minimize the following criteria: picking distance, correlated item separation, space imbalance; relocation cost; and safety penalty [7]. Second, a rolling horizon scheduling model will develop an integrated view of task assignments, due dates for orders, resource capacity; replenishment precedence; aisle congestion; and workload balancing [8]. Third, a hybrid RHSSO algorithm is proposed to integrate the interpretability of mathematical programming; the search efficiencies of adaptive large neighborhood search algorithms; and the real-time adaptability of reinforcement learning [9]. Fourth, the team has developed a simulation-based evaluation framework to evaluate the performance of layouts, the performance of scheduling, and the sensitivity to demand intensity [10].

2 Smart Warehouse System and Slotting Problem

The smart warehousing system that will be investigated will have receiving docks, storage areas, picking workstations, packing areas, replenishment areas, and a material handling subsystem that utilizes an automated guided vehicle. Customer orders will arrive dynamically and the customer order can contain one or multiple stock keeping unit. Each stock keeping unit will have its own set of characteristics to include, but not be limited to, the following: demand frequency; co-occurrence relationships; volume; weight; turnover rate; and storage compatibility. Given that there is variability among storage locations, and since the bases on which warehouse layout decisions are made should not be the only parameters by which to make those decisions, the proposed smart warehousing framework has been segmented into four operational layers: data perception; decision modelling; execution-control. Accordingly, this study's primary decision factors include: stock keeping unit; storage location; customer order; automated guided vehicle/operational resources; picking station; travel distance; storage capacity; and normalized demand intensity.

2.1 Overall Configuration

In this research, the team will investigate smart warehouses that have receiving docks, storage areas, and several workstations (for allocation of inventory), packing areas (for preparing customer orders), replenishing areas (for returning inventory to the warehouse), and a robotic material handling subsystem (an Automated Guided Vehicle operation in a warehouse)). Customer orders are placed dynamically and may consist of several Stock Keeping Units (SKUs). Each SKU has unique demands defined by the frequency of demand, co-demand relationships, volume, weight, turnover rate, compatibility for storage, etc. Storage locations are finite in capacity, contain varying distances to pick-up stations, have different accessibility coefficients, and are assigned to different building zones. A smart warehouse has a four-layer operation: I) Data perception (to gather order, inventory, and equipment data), II) Decision modelling (convert operational data into variables for inventory location and rate of turnover), III) Optimisation algorithms (to generate a layout and schedule for order fulfilment), and IV) Execution-control feedback (to transmit the WMS/WCS decision back to the appropriate processes for re-optimisation) in Fig. 1.

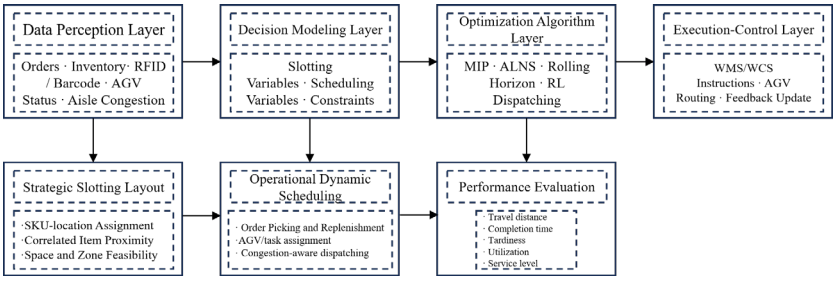


Fig. 1. Integrated framework of smart warehousing slotting and dynamic scheduling

2.2 Structural Parameters and Decision Factors

In smart warehousing practice, layout decisions should not be based only on demand frequency [11]. They should also account for item co-occurrence, storage capacity, compatibility, accessibility, replenishment frequency, and historical layout stability. Therefore, this study defines the main parameters shown in Table 1.

Table 1. Main parameters for smart warehouse slotting and scheduling

Symbol	Description
I	Set of SKUs
L	Set of storage locations, indexed
O	Set of customer orders
K	Set of AGVs or operational resources
P	Set of picking stations
d	Travel distance between location and picking station
Cap	Available capacity of storage location
a	Normalized demand intensity of SKU
ρ	Order co-occurrence coefficient between SKU and SKU
x	Binary slotting variable indicating whether the SKU is assigned to a location
y	Binary scheduling variable indicating whether a task is assigned to a resource in period

3 Research Methodology

Chapter describes the entire research design of this study: the creation of a research framework, development of research hypotheses, identification of research objects and associated data sources, the analytical procedure for each of the data types collected, defining the architecture of the system, and offering discussions of the limitations of the research. This research follows the research methodology used by the reference Journal of Computers article in that it does not describe all of the problems represented in terms of mathematical formulaic indicators [12]. Instead, this research constructs a procedural and hypothesis-based research framework in order to demonstrate how both smart warehouse slotting layout optimization and smart warehouse dynamic scheduling can work together to influence the operational efficiencies/performances of the warehouse in its entirety.

3.1 Research Framework and Hypotheses

The research study utilizes existing theories on warehouse management and logistics to analyze the relationships between multiple factors in order to develop a framework that incorporates all relevant elements [13]. The main relationships between the various factors include SKU demand frequency, item co-occurrence relationships, location accessibility of items, layout quality of the slotting system for each item, access to real-time data regarding those items, the ability to coordinate AGVs, the ability to use dynamic scheduling, and overall performance of warehouses. As part of the first phase of this research, warehouse operations were evaluated

based on many characteristics, including SKU turnover rates, the historical composition of orders, constraints from limited storage space, accessibility to picking locations, requirements for inventory replenishment, and the method used to dispatch AGVs [14]. Warehouse operations are not solely dependent on layout or execution; rather, their performance is derived from a combination of static and dynamic decisions or actions. This research builds upon traditional methods of assigning storage locations by including the importance of real-time data and AGV coordination as facilitating variables in the creation of an integrated framework [15]. The use of the four constructs examined in this study will provide insight into how the implementation of innovative technologies in smart warehousing systems can lead to better picking performance, less congestion, and improved order fulfillment. Fig. 2 shows the proposed research framework and illustrates the hypothesized relationships among the constructs.

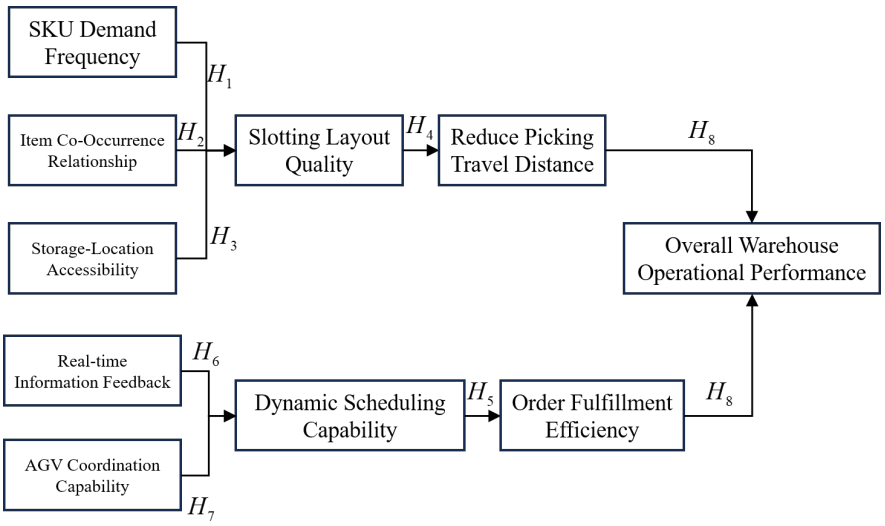


Fig. 2. Research framework and hypothesized relationships of smart warehouse slotting and dynamic scheduling

Based on the literature review and the operational logic of smart warehousing systems, this study proposes the following hypotheses:

H1: SKU demand frequency has a positive effect on slotting-layout efficiency.

H2: Item co-occurrence relationship has a positive effect on correlated-storage layout quality.

H3: Storage-location accessibility has a positive effect on picking-route efficiency.

H4: Slotting-layout quality has a positive effect on reducing total picking travel distance.

H5: Dynamic scheduling capability has a positive effect on order fulfillment efficiency.

H6: Real-time information feedback has a positive effect on scheduling adaptability.

H7: AGV coordination capability has a positive effect on reducing aisle congestion and resource imbalance.

H8: Integrated slotting layout and dynamic scheduling optimization has a positive effect on overall warehouse operational performance.

These hypotheses explain the core logic of this study. H1 to H4 focus on how SKU attributes and storage-location characteristics influence slotting layout quality and picking travel distance. H5 to H7 emphasize how real-time scheduling and AGV coordination affect order fulfillment and operational stability. H8 further integrates layout optimization and dynamic scheduling into a unified performance-improvement mechanism for smart warehousing systems. The above hypotheses are operationalized through the following measurement formulas without altering the original methodological logic:

$$DF_i = \frac{N_i}{\sum_{i=1}^{n} N_i} \tag{1}$$

Formula 1 measures how frequently a specific stock-keeping unit appears in historical orders. A higher value indicates that the item is ordered more frequently and should receive higher priority in slotting layout decisions.

$$TI_i = \frac{Q_i}{I_i} \tag{2}$$

Formula 2 evaluates the turnover intensity of a stock-keeping unit. It compares the outbound quantity of an item with its average inventory level. A higher value means that the item moves faster and requires more accessible storage placement.

$$CR_{ij} = \frac{N_{ij}}{\sqrt{N_i N_j}} \tag{3}$$

Formula 3 measures the strength of the relationship between two items that appear together in the same order. A higher value indicates that the two items are more likely to be picked together and should be stored close to each other.

$$LA_l = \frac{1}{1 + \alpha D_l + \beta H_l + \gamma C_l} \tag{4}$$

Formula 4 evaluates the accessibility of a storage location. It considers travel distance, shelf height, and aisle congestion. A higher value represents a more convenient and efficient storage location for picking operations.

$$x_{il} = \begin{Bmatrix} 1, if SKU i is assigned to location l \\ 0, otherwise \end{Bmatrix} \tag{5}$$

Formula 5 defines whether a stock-keeping unit is assigned to a specific storage location. It is used to describe the basic relationship between items and warehouse locations.

$$\sum_{i=1}^{n} V_i x_{il} \le C_{apl} \tag{6}$$

Formula 6 ensures that the total volume of items assigned to a storage location does not exceed the available capacity of that location. It prevents infeasible slotting decisions.

$$SLQ = \theta_1 \sum_{i=1}^{n} \sum_{l=1}^{m} DF_i LA_l x_{il} + \theta_2 \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{l=1}^{m} \sum_{r=1}^{m} \frac{CR_{ij} x_{il} x_{jr}}{1 + D_{lr}} \tag{7}$$

Formula 7 evaluates the overall quality of the slotting layout. It considers both the placement of high-demand items in accessible locations and the proximity of items that are frequently ordered together.

$$TPD = \sum_{o=1}^{O} \sum_{i \in S_o} \sum_{l=1}^{m} x_{il} D_{lp} \tag{8}$$

Formula 8 calculates the total travel distance required for order picking. A lower value indicates that the warehouse layout can reduce unnecessary movement and improve picking efficiency.

3.2 Research Objects and Data Sources

The object of research for this paper is a sample smart warehouse with storage racks; inbound docks; outbound picking and packing areas; replenishment channels; and AGV-based systems for material movement [16]. Core operational objects include SKUs, storage locations, customer orders, picking and replenishment tasks, AGV resources, and aisle nodes. These objects represent the fundamental decision space for slotting layout optimization and dynamic scheduling. The sources of data used in this study may be divided into 5 categories. 1) Historical order data are used to determine SKU demand frequency and co-occurrence patterns of items [17]. 2) SKU attribute data consists of item characteristics, such as size, weight, turnover rate, compatibility, and specific storage requirements. 3) Storage location data include characteristics such as zone type, shelf capacity, distance to picking stations, and levels of accessibility. 4) Real-time operational data includes inventory levels, order arrival times, positions of AGVs, and status of task execution and any potential congestion. 5) Simulation data was produced in a digital twin environment for measuring the performance of different layout and scheduling options under controlled situations.

3.3 Data Analysis Methods

Using a procedure-based approach to data analysis, this study investigates how slotting layout optimization relates to dynamic scheduling and ultimately warehouse operational performance. The analysis follows this five-step process:

Step 1: Data Preprocessing

Historical order records, SKU attributes, inventory logs, and location data are cleaned and standardized. Prior to analysis, any abnormal records, duplicate tasks, missing SKU information, or inconsistent location codes will be corrected or removed.

Step 2: Demand and Correlation Analysis

SKU turnover frequency is calculated to classify items into fast-moving, medium-moving, and slow-moving categories. In addition, item co-occurrence relationships are identified from multi-item orders to determine which SKUs need to be stored in close proximity to each other.

Step 3: Slotting Layout Evaluation

Storage locations are evaluated for accessibility, capacity, compatibility with other items, convenience for replenishment, and proximity to picking stations. The evaluation of the layout includes travel distance to pick items, adjacency of correlated items, space utilization, and degree of stability during relocation.

Step 4: Dynamic Scheduling Analysis

The dynamic scheduling system evaluates real-time order status, current inventory levels, AGV locations, task queues, and congestion in each decision window. The scheduling procedure will assign picking and replenishment tasks along with AGV resources in a continuous horizon manner according to the most recent current state.

Step 5: Comparing the Simulation-Based Approach:

The team will be comparing our proposed approach with previously accepted methods such as Random Storage, ABC Storage, First Come First Serve Scheduling, and Nearest AGV Scheduling for Vehicle Dispatch. The criteria for comparison will include the average time taken to complete an order, the percentage of tardy orders, the AGV utilization rate, the number of aisles blocked due to congestion, the total distance travelled by the AGVs, and the overall service level. The purpose of this analysis is to go beyond simply describing warehouse operations; it will link operational data with the testing of hypotheses. For instance, if the storage layout improves pick travel distances from established methods, the team may be able to support hypothesis 4 (H4). Similarly, if the rolling horizon-based scheduling method produces improved performance metrics for completing orders with T time between receipt of orders than the team will be able to support hypothesis 5 (H5). In summary, the proposed methodology creates a synergy of system design, simulation analysis, and a testable hypothesis-oriented framework in Fig. 3.

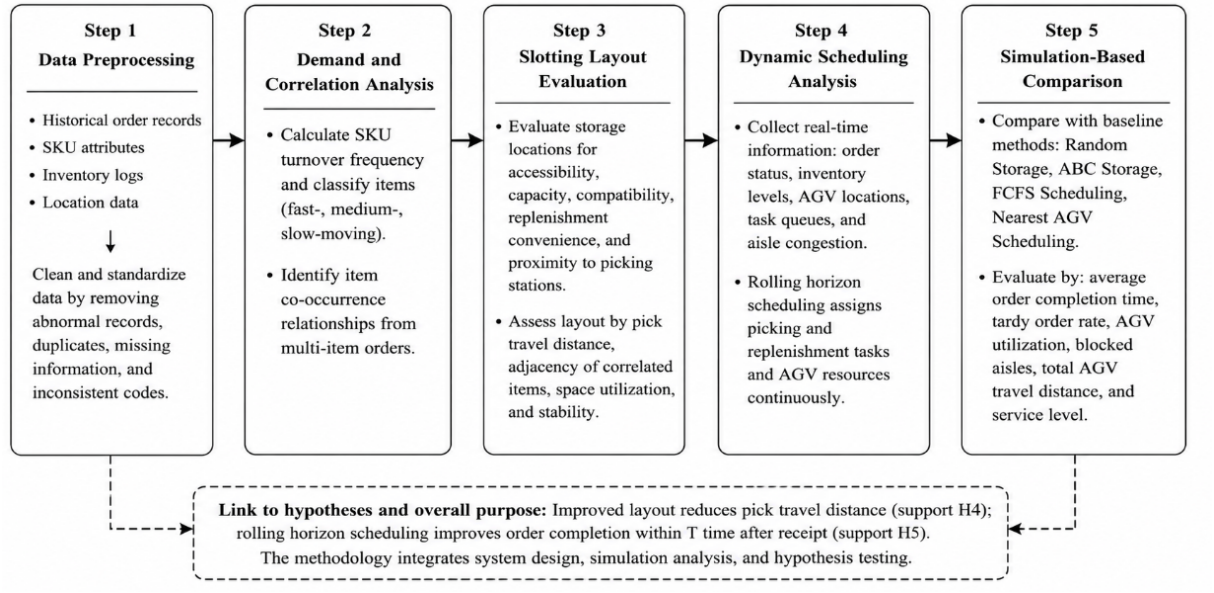


Fig. 3. Research framework for data-driven warehouse slotting optimization and dynamic scheduling

3.4 Research Limitations

This study has several limitations. First, the representative warehouse scenario cannot fully cover all industrial warehouse configurations, such as cold-chain warehouses, hazardous-material warehouses, and high-rise automated storage systems [18]. Second, when simulation data are used, the generated order structure and AGV operation rules may not fully reflect the complexity of real enterprise operations. Third, the proposed hypotheses are mainly verified through operational indicators rather than through human-subject survey data. Therefore, the interpretation of causal relationships should be combined with further empirical validation in real warehouse environments. Fourth, the proposed framework focuses on single-warehouse operation; cross-warehouse collaborative scheduling and supply-chain-level coordination are not included in the current scope. Moreover, the values assigned to some simulation parameters may affect the performance of the proposed framework since different values of such parameters as the number of AGVs, storage density, order arrival intensity, rolling horizon length, and reinforcement learning parameters may yield different results under other operational conditions. Although several simulation runs could reduce the effects of stochasticity, the model uncertainty and parameter values may remain the cause of uncertainty. For this reason, future studies should perform sensitivity analysis of the proposed framework to understand its performance with varying values of critical parameters. One more limitation is associated with the quality of operational information collected from warehouse operations. The framework assumes the availability of relatively accurate information on SKU demand, co-occurrence, inventory, AGV location, and aisle congestion.

3.5 Smart Warehousing System Architecture

Utilizing the research framework and operational assessment, this investigation develops a smart warehousing system architecture incorporating data perception, slotting layout optimization, dynamic scheduling, and execution feedback features. As depicted in the chart below, the operational sequence comprises the collection of data for orders, SKUs, inventories, locations, and pieces of equipment, which is subsequently processed within the warehouse management system (WMS) and submitted to the decision-support module. The smart warehousing system architecture consists of three primary functional modules:

1. Data Perception & Storage Management Module - This module provides a master SKU file with complete inventory information, active and inactive records for SKUs in the storage, and a complete inventory history for each SKU item located in the warehouse. The information maintained in this module supports the basis for

slotting and scheduling decisions made by the smart warehousing system.

2. Slotting Layout Optimization Module - By leveraging statistical techniques, this module reviews and evaluates multiple warehousing variables, such as the frequency that SKUs are sold, the co-occurrence of items, accessibility of a SKU location, the capacity restrictions for storing SKUs, and functional requirements, to determine the most efficient layout for SKUs in the warehouse and to provide for proper placement of those SKUs to minimize the distance traveled by an order picker when retrieving an SKU from storage.

3. Dynamic Scheduling & Execution Control Module - This module coordinates the scheduling of order picking, replenishment of inventory, dispatching of AGVs, sequencing of tasks, and controlling warehouse congestion by updating decisions on a rolling horizon as a result of real-time feedback from orders, inventories, and equipment.

4 Hybrid Optimization and Dispatching Method

The RHSSO algorithm is developed to solve the integrated problem of layout and scheduling in smart warehouses such that all factors, such as storage limitations, related items, Dispatchers, Operational changes. Because it would be computationally prohibitive to solve the entire optimization model at every decision point, RHSSO contains: 1) To provide an initial layout generation; 2) To use an adaptive large neighbourhood search; 3) To stick to a rolling horizon schedule; and 4) To use Reinforcement Learning to adjust Dispatching decisions. Initially, SKU abundance and co-occurrence are defined based upon the uses of historical orders, which creates a mixed integer programming model for the initial slotting layout.

$$minZ = w_1 D + w_2 C + w_3 B + w_4 R \tag{9}$$

Where D represents the total picking distance, C denotes the distance between correlated items, B indicates the degree of storage-space imbalance, and R represents the relocation cost. The parameters w are the corresponding objective weights. The initial layout is then improved upon based on a neighbourhood level assessment. Once the warehouse is in production, the rolling horizon schedule allows the continuous updating of Order Status, Inventory Levels, AGV Location, and Aisle Congestion; Executes part of the current schedule; and re-optimizes the remaining tasks based on real time information available from the first three. To increase adaptability, the Reinforcement Learning Agent adjusts the Dispatching decision by assigning AGVs to an order, changing the priority level of completing a task, delaying non-urgent replenishments, and selecting an alternative route. The reinforcement learning agent is rewarded more for completing a task with less distance travelled, less delay to completed task, less congestion, less energy used, and a lower risk of stockout. As a result, the contribution of the Reinforcement Learning Agent is to provide rapid adjustment for local adjustments, while the Warehouse Management System/Warehouse Control System, and rolling horizon schedule will maintain the operational feasibility of the warehouse.

4.1 RHSSO Algorithm

The comprehensive approach to the issue comprises binary decision-making variables, local capacities, non-linear correlational factors, and real-time scheduling [19].

$$\sum_{j=1}^{m} x_{ij} = 1 \tag{10}$$

$$\sum_{i=1}^{n} q_i x_{ij} \le Q_j \tag{11}$$

Where $x_{ij} = 1$ indicates that SKU i is assigned to storage location j. The parameter q_i represents the storage capacity required by SKU i, and Q_j denotes the available capacity of storage location j. Solving the entire model each time a decision is required would be a computationally intensive process; therefore, this study offers an

RHSSO, which is a hybrid approach consisting of generating an initial layout, adaptively improving using neighbourhood operations, rolling-horizon scheduling, and performing dispatch using reinforcement learning. Initially, the intensity of SKU demand, as well as their correlation to each other, were derived based on historical data, and then an initial mixed-integer-programming model was solved, producing a feasible slotting layout. Since many of the processing stages for large instances were performed, an adaptive large neighbourhood search was used to enhance the initial solution. Each iteration would remove a portion of the original layout, create a candidate layout, and evaluate the candidate layout against the current one. When a candidate layout is improved directly, it is accepted; however, if a candidate layout is only slightly improved and could help you move away from a local optimum, then you can hold on to that until an appropriate time to accept it.

$$P_{accept} = \begin{cases} 1 & \Delta Z \le 0 \\ \exp(-\dfrac{\Delta Z}{T}) & \Delta Z > 0 \end{cases} \tag{12}$$

Where ΔZ represents the difference between the objective values of the candidate solution and the current solution, and T denotes the current search temperature. An improved candidate is accepted directly, whereas a worse candidate may be accepted with a certain probability to avoid becoming trapped in a local optimum. Within the operational stage, rolling horizon scheduling continuously reviews the current state of the system, solves short-term scheduling using the current state of the system, implements one part of the scheduling plan:

$$\pi_t^* = \arg\min_{\pi=\Omega t} \sum_{\tau=t}^{t+H-1} C\tau(\pi) \tag{13}$$

Where π_t^* represents the optimal scheduling plan obtained at decision time t, H denotes the rolling-horizon length, The term $C\tau(\pi)$ represents the operational cost generated by scheduling plan π during period τ and re-evaluates remaining decisions based on feedback received from previous implementations (see Fig. 4).

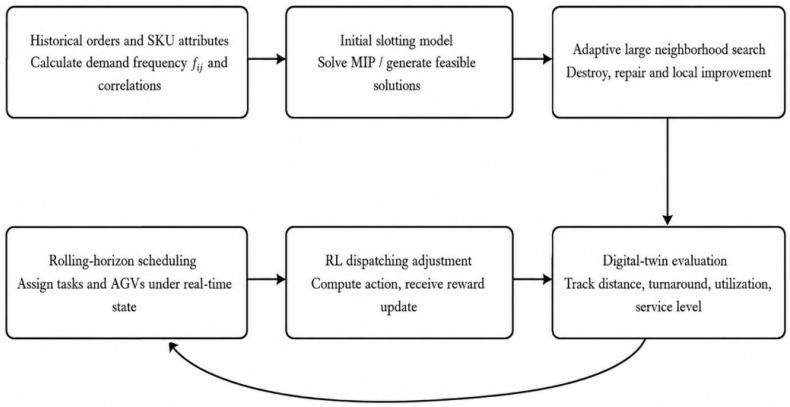


Fig. 4. Hybrid RHSSO algorithm for slotting layout and scheduling optimization

4.2 Reinforcement Learning-Based Dispatching Adjustment

In order to allow for maximum flexibility in adapting on-the-fly, the team have integrated an agent that uses reinforcement learning into the dispatching layer. The state that a reinforcement learning agent operates on is defined by the number of currently active orders, the position of the AGVs, the power remaining in the AGVs' batteries, the congestion state of each aisle, whether there are any inventory shortages, and the amount of work that each station has assigned to it. The action set for an agent operating using reinforcement learning typically includes assigning a job to a specific AGV, changing the job's execution priority, delaying the initiation of a

non-urgent replenishment job, or selecting an alternative route for the job. The reward designated for each action is provided for those actions that produce short travel distances, low delays, low congestion, low energy consumption, and low risk of stockouts. When the reinforcement learning agent observes a reward for an action, it updates its preferences for that action based on the reward and the next system state. Actions that consistently reduce delay and congestion will gradually receive greater preference, while actions that create increased waiting time, detours, and stockout risk will gradually lose their preference. As a result, paper provides a method by which an adjustment to dispatching can be described as a learning procedure through feedback, rather than through a derivation based upon a formula. The reinforcement learning component does not supersede the mathematics of optimization. However, the reinforcement learning component does provide a very fast local adjustment if the actual system is not located at the planned state. This design provides additional security for the implementation of adjusting dispatching because the critical constraints for the feasibility of adjusting dispatching are still maintained by the WMS/WCS and the rolling-horizon model.

5 Simulation Design and Evaluation Metrics

In this representative simulation example, an evaluation of the suggested method will be conducted on the smart warehouse with receiving docks, storage zones, 2 picking stations, a replenishment area and 12 AGVs. The warehouse contains 500 SKUs and 1200 storage spaces, an 8-hour planning time period, a 30-minute rolling time period and 30 independent simulation runs. There is a fluctuating order arrival timing pattern and each order includes realistic multi-item co-occurrence patterns. The proposed method is compared with random storage, ABC storage, correlation-based storage and rolling horizon scheduling. During the evaluation of the simulations, meant to provide information, data will be obtained on picking distance; order completion time; rate of tardiness; overall utilization; level of congestion; and overall service level achieved.

5.1 Experimental Setting

A representative simulation case is established to evaluate the proposed method. The warehouse contains receiving docks, storage zones, two picking stations, a replenishment area, and an AGV fleet. Customer orders are generated by a non-stationary arrival process. SKUs are divided into fast-moving, medium-moving, and slow-moving classes, and order co-occurrence is embedded to represent realistic multi-item orders. The parameter settings are shown in Table 2.

Table 2. Simulation parameters used in the representative case

Parameter	Value
Number of SKUs	500
Number of storage locations	1200
Number of picking stations	2
Number of AGVs	12
Planning horizon	8 h
Rolling-horizon length	30 min
Average order lines per order	3.6
Order arrival rate	0.6–1.4 times baseline
Simulation replications	30 independent runs

The proposed method is compared with four benchmarks: random storage with first-come-first-served scheduling, ABC storage with nearest-AGV dispatching, correlation-based storage with static scheduling, and rolling-horizon scheduling without slotting feedback.

5.2 Performance Indicators

Performance is measured from the perspectives of efficiency in traveling, order completion rate, usage of storage spaces, resource utilization, and stability of operations. There is no unique indicator to describe warehouse

performance because minimizing travel distance can cause congestion, whereas maximizing usage of AGVs can result in delays. Thus, there are several complementary indicators used. The first one is total expected picking distance, which determines the total traveling distance necessary to pick up the ordered products from storage locations. The measure describes the efficiency of the slotting plan and relations between storage locations, picking stations, and product demand. A smaller picking distance means that frequently required products and correlated ones are more efficiently placed in the warehouse. The average order completion time equals the average difference between the moment when the order arrives at the warehouse and its completion. The measure includes waiting time, transportation time, picking time, queuing time, and all other delays caused by congestion. The indicator provides an overview of responsiveness of warehouse operations. A smaller value shows that the warehouse is able to process customer orders faster. The tardiness rate is the rate of orders which are finished after the assigned due time. In contrast to average completion time, the indicator directly describes failures of warehouse performance. There is a possibility for the method to have moderate average completion time and yet lead to delays of urgent orders. Thus, the tardiness is used to evaluate the ability of the scheduling policy to protect time sensitive orders. Service level is a percentage of orders completed within their due-time requirements. Service level is strongly related to the tardiness but described from a positive perspective. High service level implies high delivery reliability and high operational stability in case of demand variations. The measure is especially important in the period of high demand when resource and space shortages can lead to quick deterioration of warehouse performance. Space-utilization indicator reflects how well the storage capacity is used throughout different warehouse zones. High utilization rate is not always desired if the goods are concentrated too much in a small area. In other words, both utilization and spatial imbalance should be taken into consideration. Balanced distribution helps to avoid local congestion and allows flexible replenishment. The second performance indicator is an AGV-utilization rate. It describes the percentage of operating time when vehicles are performing productive tasks. Too low utilization means underuse of equipment while too high utilization may mean the lack of equipment and insufficient recovery period. In other words, the goal is not to maximize the utilization rate but to keep it at a certain balanced level in order to ensure the high throughputs. Congestion frequency is another indicator that records how often the vehicles meet path conflicts, intersection queues or blocking in the area of storage or picking up places. It is necessary to estimate the efficiency of dispatching strategies that help to balance vehicle traffic. Low congestion frequency means more stable traveling times and more predictable order completion in Table 3.

Table 3. Warehouse operational performance indicators

Performance dimension	Indicator	Definition	Interpretation
Travel efficiency	Total expected picking distance	Total distance required to retrieve ordered products from their assigned storage locations	Reflects the efficiency of the slotting layout and the spatial relationship among product demand, storage locations, and picking stations
Order responsiveness	Average order completion time	Average time between order arrival and order completion, including waiting, transportation, picking, queuing, and congestion delays	Measures the overall responsiveness of warehouse operations
Delivery timeliness	Tardiness rate	Proportion of orders completed after their assigned due times	Measures the ability of the scheduling policy to prevent delayed orders, particularly urgent orders
Delivery reliability	Service level	Percentage of orders completed within their due-time requirements	Indicates delivery reliability and operational stability under changing demand conditions
Storage efficiency	Space-utilization rate	Proportion of available storage capacity used across warehouse zones	Reflects storage-capacity efficiency; it should be considered together with spatial imbalance to avoid excessive concentration
Resource utilization	AGV-utilization rate	Percentage of operating time during which AGVs perform productive tasks	Identifies equipment underuse or overload; excessively high utilization may indicate insufficient capacity
Traffic stability	Congestion frequency	Frequency of path conflicts, intersection queues, and blocking near storage or picking areas	Evaluates the effectiveness of vehicle dispatching and traffic-balancing strategies
Robustness	Replication variability	Variation in performance indicators across 30 independent simulation replications	Reflects the consistency and stability of the method under different order sequences

6 Results and Discussion

The proposed RHSSO approach has shown to be beneficial to both the slotting layout and dynamic scheduling performances. The results show that with regard to the slotting optimization, RHSSO has been able to reduce the normalized average expected picking distance by 62% when compared to random storage, ABC storage, and correlation-type storage. The optimality was achieved due to the ability to jointly consider the intensity of demand for an item the co-occurrence of items, space utilisation, and costs associated with relocation of the item from its current location to location for shipment when determining its optimal storage position. In addition, as demonstrated in the performance benefits associated with dynamic scheduling, RHSSO was able to reduce the average order completion time using rolling horizon scheduling from a FCFS basis of 42.6 minutes to 26.9 minutes, decrease the tardiness rate to an average of 5.1%, and reduce the frequency of congestion to 13 occurrences within each simulation horizon. Performance improvements were achieved through the optimisation of the location of items in the warehouse, the incremental decision-making regarding the placement of inventory, and the adjustment of local dispatchers with respect to instructions from customers based on their respective order arrival times. Sensitivity analysis indicated that, relative to the benchmark methods, RHSSO exhibits a greater robustness under a higher order arrival rate due to its ability to more effectively control travel distances, congestion, and workload balance. Therefore, from an engineering perspective, the finding suggests that warehouse layout and dynamic scheduling should be developed as a single integrated system. To implement the RHSSO methodologies, companies can first develop a demand correlation matrix based on historical order data, then periodically update their slotting plans as required, and lastly implement rolling horizon scheduling methodologies with local scheduling adjustments on a daily basis during their daily operations.

6.1 Slotting Layout Optimization Results

The slotting optimization results indicate that the proposed method achieves better layout quality than random storage, ABC storage, and simple correlation-based storage. As shown in Table 4 and Fig. 5, the proposed method reduces the normalized expected picking distance to 62%, while the ABC and correlation-based methods remain at 84% and 76%, respectively. This improvement results from the simultaneous consideration of demand intensity and item co-occurrence.

Table 4. Slotting layout performance comparison

Method	Expected picking distance	Correlation distance penalty	Space imbalance
Random storage	100	100	100
ABC Storage	84	91	88
Correlation-based storage	76	68	82
Proposed RHSSO slotting	62	55	66

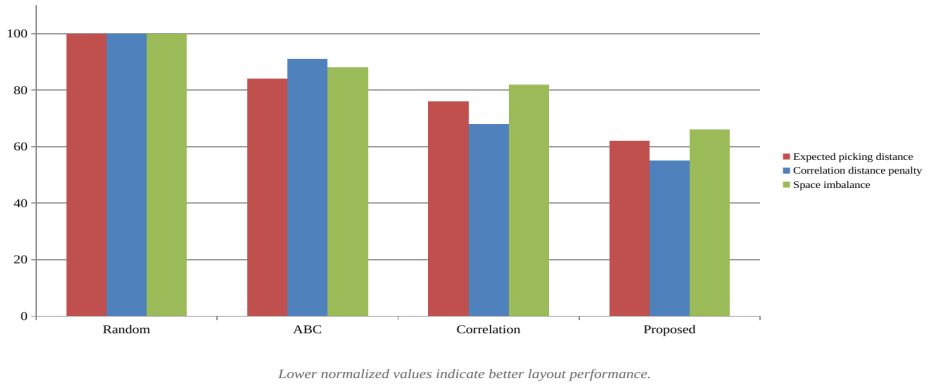


Fig. 5. Slotting performance comparison in the simulation case

The results reveal that ABC storage performs well in reducing single-item retrieval distance but is less effective in reducing the separation of co-picked items. Correlation-based storage improves item adjacency but may lead to space imbalance when demand intensity is ignored. The proposed method obtains a more balanced solution by optimizing picking distance, correlation distance, space utilization, and relocation cost in the same objective function. As seen from the Fig. 4 there is a comparison between the three storage systems and random storage which is normalized to 100 on all evaluation indicators. Lower values mean better performance as they reflect lower expected picking distances, correlation-distance penalties and space-imbalance. Expected picking distance becomes about 84 in ABC storage which confirms its superiority in keeping high-turnover products close to the most convenient picking location. At the same time, the correlation-distance penalty becomes relatively high, about 91, and space-imbalance index equals about 88. The fact means that the ABC classification considers only the item turnover or demand frequency and it does not sufficiently take into account the interrelations of the correlated items. In other words, high-turnover items are picked efficiently but the correlated items can be scattered in different places of storage. Correlation-based storage shows other results. There is a reduction in correlation-distance penalty to about 68 which means that there is a significant improvement comparing with random and ABC storage systems. It confirms that the joint positioning of co-picked items helps to decrease the movement distance for multi-item orders. Moreover, the expected picking-distance index is equal to 76. But the space-imbalance value is comparatively high, about 82. The fact means that the storage system based on correlations of items can lead to the concentration of strongly correlated products in some storage zones. Proposed method demonstrates the lowest values for all three indicators. Expected picking-distance index equals to 62 while the correlation-distance penalty and space-imbalance index equal to about 55 and 66, correspondingly. Relative to the random storage system, these values mean approximate reductions by 38%, 45% and 34%. It means that the combination of three factors – demand frequency, correlation of items and capacity of space-helps to make more coordinated storage than consideration of any factor separately. In particular, this way the accessibility of high-turnover items is kept while simultaneously the correlated items are clustered without concentration in some storage zones. It confirms the need for multi-objective optimization in assignment in warehouse. ABC storage system shows good results for individual-item retrieval while correlation-based storage supports multi-item orders. But each conventional system shows its weaknesses when it is used independently. Using several operational goals allows the proposed method to avoid the extremal solutions which are typical for the one-criterion systems and gives more realistic compromise between retrieval efficiency, adjacent items and use of space.

6.2 Dynamic Scheduling Results

The dynamic scheduling results are listed in Table 5 and illustrated in Fig. 6. Compared with first-come-first-served scheduling, the proposed method reduces the average order completion time from 42.6 min to 26.9 min. The tardiness rate decreases from 18.2% to 5.1%, and the congestion frequency decreases from 33 to 13 events per simulation horizon.

The improvements are mainly attributed to three mechanisms. First, the optimized layout reduces the physical travel burden before scheduling begins. Second, rolling-horizon scheduling updates decisions according to real-time order and inventory states. Third, reinforcement learning-based dispatching reduces local congestion by selecting more suitable task-resource combinations under disturbances. As seen from the Fig. 5, there are significant differences between the four scheduling approaches in terms of average completion time, tardiness, and congestion. The smaller values are better. The traditional FCFS strategy yields the highest values for all three measures, with average completion time being about 42.5, the tardiness being about 18 and the congestion frequency close to 33. FCFS is straightforward to implement but processes tasks in the order of their arrivals and does not take into account distances traveled, resources availability and new potential conflicts among AGVs. Therefore, vehicles can enter the same work areas several times, whereas urgent tasks receive insufficient attention. The nearest-AGV strategy makes use of geographical proximity between the task and the resource and, therefore, decreases the average completion time down to about 36. At the same time, tardiness and congestion frequency decrease to about 12.5 and 24 correspondingly. Thus, the result confirms the hypothesis that task execution efficiency can be increased by reducing empty travel distance and using available nearby resources. Nonetheless, the nearest-AGV approach employs local dispatching rule, which means that it will repeatedly allocate tasks to nearby vehicles located in high demand areas. This may create imbalances and lead to conflicts in the future. Rolling-horizon scheduling allows achieving additional improvements, with the average completion time being about 31.5, tardiness being about 8.5 and congestion frequency near 19. In contrast to

static dispatching techniques, the rolling-horizon approach continually updates the schedule in response to newly arriving orders and changes in the current state of the system. Therefore, the controller can take into account changes in inventory, delayed tasks and available AGVs better. Nevertheless, the quality of decisions made by the algorithm may also depend on the optimization model quality and time window size. The proposed approach yields the best results with average completion time equaling about 27 and tardiness and congestion frequency equaling about 5 and 13 correspondingly. In comparison with FCFS, this approach reduces completion time by about 36%, tardiness by about 72% and congestion frequency by about 61%. Therefore, the improvement can be explained by the fact that the proposed approach combines layout optimization, rolling-horizon rescheduling and reinforcement learning-based dispatching in a coordinated way. Layout optimization reduces travel burden initially, rolling-horizon rescheduling allows responding to dynamic conditions and learning-based dispatching finds good task-resource combinations.

Table 5. Dynamic scheduling performance comparison

Method	Avg. completion time	Tardiness rate	AGV utilization	Congestion frequency	Service level
FCFS scheduling	42.6 min	18.2%	72.4%	33	81.8%
Nearest-AGV rule	35.8 min	12.4%	78.1%	24	87.6%
Rolling-horizon scheduling	31.4 min	8.6%	82.7%	19	91.4%
Proposed RHSSO	26.9 min	5.1%	86.3%	13	94.9%

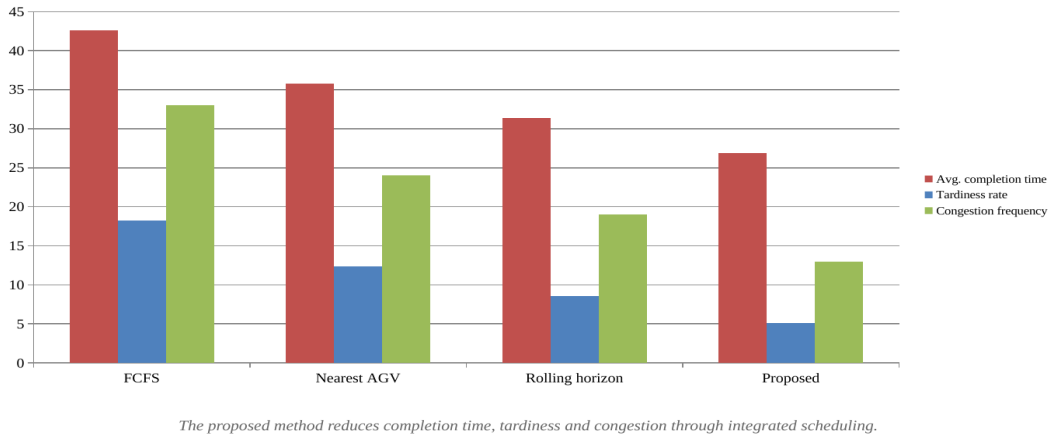


Fig. 6. Dynamic scheduling performance comparison

6.3 Sensitivity Analysis

Sensitivity analysis is conducted by changing the order-arrival rate from 0.6 to 1.4 times the baseline. As shown in Fig. 7, all methods show increased completion time under higher demand intensity. However, the growth rate of the proposed method is lower than that of the benchmarks. This indicates that the integrated layout and scheduling framework has better robustness under workload fluctuation.

When the arrival rate is low, the performance gap among methods is moderate because system resources are sufficient. When the arrival rate increases, poor slotting and myopic dispatching lead to rapid growth in congestion and tardiness. RHSSO maintains a lower average completion time because it jointly reduces travel distance, balances resource workload, and updates decisions in a rolling manner. As seen in Fig. 6, all four methods have larger average completion times when the arrival rate changes from 0.6 to 1.4. The reasons for this phenomenon are the increasing pressure of workload on transportation resources, storage location and shared travel paths. At the smallest rate of 0.6, all four methods have very close performances. Average completion times are about 19 for FCFS, 16 for the nearest-AGV strategy, 14 for rolling-horizon scheduling, and 12 for the

proposed RHSSO method. In this case, the number of idle vehicles and available paths is sufficient for absorbing most of the arriving tasks, therefore, the shortcomings of conventional scheduling rules are not fully revealed. As the arrival rate increases to 0.8 and 1.0, differences in performance become obvious. FCFS increases to about 27 and 43 as all tasks are allocated by the arrival order regardless of the location of vehicles and paths availability and workload balance. The nearest-AGV strategy performs better achieving values of 22 and 36 as the allocation based on the nearby location of vehicles eliminates part of empty travels. However, this strategy tends to allocate tasks to the same vehicles and travel zones creating workload imbalance and further congestion. The rolling-horizon scheduling restricts the average completion time to 19 and 31 as it continuously updates the task allocation according to updated information on the system. The proposed RHSSO method demonstrates the best results of approximately 16 and 27 as integration of slotting with dynamic rescheduling gives additional advantages compared with rescheduling only. At larger arrival rates, the superiority of RHSSO is especially apparent. The average completion times of FCFS, nearest AGV, rolling horizon, and RHSSO equal approximately 61, 51, 42, and 35 when the arrival rate reaches 1.2, and 84, 70, 58, and 47 when it is 1.4. Compared with FCFS, RHSSO decreases the completion time by 44% at the largest workload level. It also outperforms nearest-AGV and rolling-horizon scheduling by 33% and 19%, correspondingly. The growing gap in performance indicates that the proposed scheduling method is better suited for preventing the fast deterioration of the performance when the system approaches congestion. Due to the optimization of storage locations, related tasks need smaller distances to be traveled before the dispatching decision is made. Rolling updating enables the scheduler to react to the new orders and changes in vehicle state, and workload balancing prevents the overload of particular AGVs or routes.

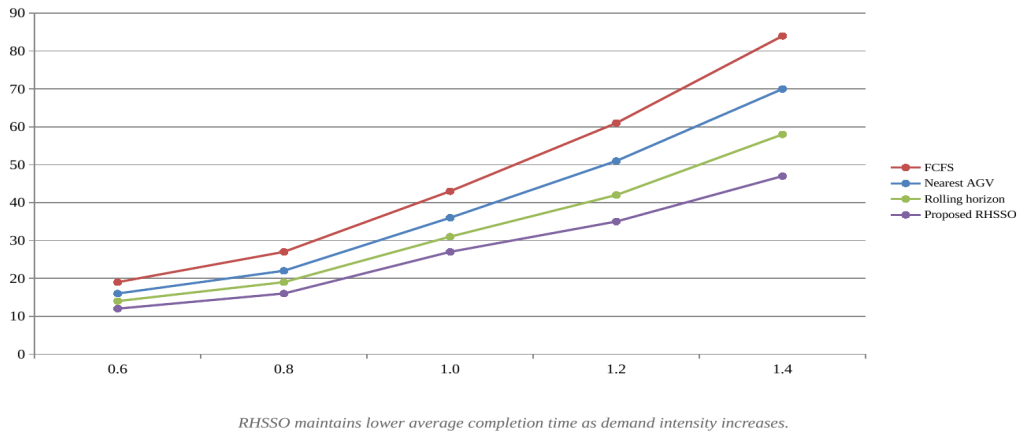


Fig. 7. Sensitivity analysis under different order-arrival rates

6.4 Engineering Implications

The hydraulic and electrical engineering aspects of the proposed method have many implications. The first implication is that the Warehouse Layout should be redesigned based on both the demands that are going to be generated and how items relate to each other. Pure ABC storage is no longer adequate in providing for all of the needs of warehouses with multiple item orders. This will create an increased likelihood of inventory shortages due to poor product placement. The second implication is that Dynamic Scheduling should not be separate from the layout of the warehouse. If the layout of the warehouse can be tweaked to reduce expected travel time, it will help the scheduling piece to allocate resources with less risk of congestion. The third implication relates to Rolling Horizons. A Rolling Horizon mechanism will assist in the WMS/WCS due to the Operational Stability effect. Reinforcement Learning should be used as an Agent-Dispatching adjustment rather than a black-box, unconstrained controller, to ensure that the operator has control over safety, capacity, and task precedence constraints. To implement the new method, enterprises will need to start by conducting an analysis of historical orders to build the demand-correlation matrix. The first run of the slotting plan can be performed at

a predetermined interval. Rolling Horizon will be performed during daily operations at either 15- or 30-minute intervals. If there is an urgent order or a disruption to the equipment, the Dispatching Agent will provide recommendations for local adjustments. Using layered implementation strategies will help ease the challenges associated with Digital Transformation while providing for incremental improvements in Warehouse Intelligence.

7 Conclusions

This research presents a comprehensive approach to optimizing slotting layouts and dynamic scheduling in smart warehouse environments by developing a multi-objective slotting model that considers demand, item co-occurrence, space utilization, relocation costs, and safety constraints; and then developing a dynamic scheduling model for coordinating picking, replenishment, putaway, and AGV dispatching using rolling-horizon decision logic. A hybrid RHSSO algorithm is proposed to solve this integrated challenge and combines mixed-integer programming, adaptive large neighborhood search, and reinforcement learning-based dispatching to arrive at an optimal solution. The simulation results demonstrate that the proposed methodology yields reduced normalized expected distance travelled by pickers during order fulfillment, shorter times for completing orders, fewer tardy shipments, and less congested warehouses than traditional slotting/dispatching methods; and results in greater service level stability with increased demand. The primary theoretical contribution is the integration of strategic slotting and operational scheduling models, while the primary practical contribution is a decision framework that can be implemented into Warehouse Management Systems/Warehouse Control Systems/and digital twin platforms.

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Design and Assembly of Intelligent Warehousing System in High Dynamic Production Environment.

References

[1] H. Min, Smart warehousing as a wave of the future, Logistics 7(2)(2023) 30.1-30.12. https://doi.org/10.3390/logistics7020030

[2] M. Živičnjak, K. Rogić, I. Bajor, Case-study analysis of warehouse process optimization, Transportation Research Procedia 64(2022) 215-223. https://doi.org/10.1016/j.trpro.2022.09.026

[3] J. Rios, D. Morillo-Torres, A. Olmedo, J. Coronado-Hernandez, G. Gatica, A faster optimal model slotting in rack positions with mono SKU pallet, Procedia Computer Science 203(2022) 588-593. https://doi.org/10.1016/j.procs.2022.07.084

[4] M.-F. Moghadam, K.-K. Damghani, V. Ghezavati, A.-R. Komijan, A Bi-level optimization method for integrated warehouse design, storage location assignment, and order picking, MethodsX 15(2025) 103595.1-103595.17. https://doi.org/10.1016/j.mex.2025.103595

[5] T. Lamballais, M. Merschformann, D. Roy, M.-B.-M. de Koster, K. Azadeh, L. Suhl, Dynamic policies for resource reallocation in a robotic mobile fulfillment system with time-varying demand, European Journal of Operational Research 300(3)(2022) 937-952. https://doi.org/10.1016/j.ejor.2021.09.001

[6] C. Wildt, F. Weidinger, N. Boysen, Picker routing in scattered storage warehouses: an evaluation of solution methods based on TSP transformations, OR Spectrum 47(2025) 35-66. https://doi.org/10.1007/s00291-024-00780-0

[7] P. Viveros, K. González, R. Mena, F. Kristjanpoller, J. Robledo, Slotting optimization model for a warehouse with divisible first-level accommodation locations, Applied Sciences 11(3)(2021) 936.1-936.30. https://doi.org/10.3390/app11030936

[8] Z.-K. Li, M.-G. Ierapetritou, Rolling horizon based planning and scheduling integration with production capacity consideration, Chemical Engineering Science 65(22)(2010) 5887-5900. https://doi.org/10.1016/j.ces.2010.08.010

[9] G. Hendel, Adaptive large neighborhood search for mixed integer programming, Mathematical Programming Computation 14(2022) 185-221. https://doi.org/10.1007/s12532-021-00209-7

[10] T. Mohanavelu, R. Krishnaswamy, V.-R. Mannepu, N.-M. Seshadri, O. McDermott, Dynamic layout optimisation through simulation: Enhancing machine utilisation for fluctuating demand, The International Journal of Advanced Manufacturing Technology 138(2025) 983-998.
https://doi.org/10.1007/s00170-025-15554-3

[11] J.-A. Bashatah, G.-R. Elnaggar, Enhancing warehouse picking efficiency through integrated allocation and routing policies: A case study towards sustainable and smart warehousing, Applied Sciences 15(20)(2025) 11186.1-11186.22.
https://doi.org/10.3390/app152011186

[12] K.-A. Sakyi, D. Musona, G. Mweshi, Research methods and methodology, Advances in Social Sciences Research Journal 7(3)(2020) 296-302.
https://doi.org/10.14738/assrj.73.7993

[13] K. Redżeb, Innovative methods in warehouse management: A comprehensive review, in: B. Alareeni, A. Hamdan (Eds.), Technology: Toward Business Sustainability, ICBT 2023, Lecture Notes in Networks and Systems 925(2024) 365-379.
https://doi.org/10.1007/978-3-031-54019-6_33

[14] N. Chen, Q.-L. Liu, Ž. Stević, M. Andrejić, V. Pajić, An integrated cost based approach for warehouse performance evaluation: A new multiphase model, Alexandria Engineering Journal 101(2024) 62-77.
https://doi.org/10.1016/j.aej.2024.05.063

[15] D. Winkelmann, F. Tolkmitt, M. Ulrich, M. Römer, Integrated storage assignment for an E-grocery fulfilment centre: Accounting for day-of-week demand patterns, Flexible Services and Manufacturing Journal 37(2025) 558-598.
https://doi.org/10.1007/s10696-024-09549-7

[16] M.-G. Khan, N.-U. Huda, U.-K.-U. Zaman, Smart warehouse management system: Architecture, real-time implementation and prototype design, Machines 10(2)(2022) 150.1-150.21.
https://doi.org/10.3390/machines10020150

[17] A. Sari, I. Butun, A security-centric warehouse management framework for mitigating product abuse and cybersecurity risks, Computers 15(6)(2026) 348.1-348.34.
https://doi.org/10.3390/computers15060348

[18] K. Ellithy, M. Salah, I.-S. Fahim, R. Shalaby, AGV and Industry 4.0 in warehouses: A comprehensive analysis of existing literature and an innovative framework for flexible automation, The International Journal of Advanced Manufacturing Technology 134(2024) 15-38.
https://doi.org/10.1007/s00170-024-14127-0

[19] M. Mollakazemiha, E. Bahrami Samani, A joint cognitive latent variable model for binary decision-making tasks and reaction time outcomes, Annals of Data Science 12(2025) 499-516.
https://doi.org/10.1007/s40745-024-00519-2