

Order Picking Strategy and Resource Allocation Management of Automated Warehousing Systems under Mass Customization

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Abstract. Under the mode of mass customization, orders are characterized by multi-variety, small batch, and high frequency, which poses new challenges to automated warehousing systems. Taking the spare parts warehouse of an electronic manufacturing enterprise as the object, this paper analyzes the adaptation defects of the current order picking and static allocation, and points out that the main reasons for efficiency loss are strategy consolidation, resource rigidity, and their separation. Accordingly, a strategy-to-resource linkage optimization framework is proposed, including order batch control, storage association adjustment, multi-strategy dynamic switching, and flexible resource allocation, and state-driven linkage rules are established. The baseline scheme, independent optimization scheme, and collaborative scheme are compared based on the simulation of the lab. The results show that the collaborative optimization scheme shortens the average completion time of orders by 19.6%, reduces the fluctuation of equipment utilization by 37.8%, and reduces the number of manual fillings by 28.4%, which verifies the effectiveness of the linkage mechanism.

Keywords: mass customization, automated warehousing, order picking, resource allocation

1. Introduction

Mass customization has become the mainstream production mode for manufacturing enterprises to cope with market fluctuations and personalized needs. Orders show the characteristics of multi-variety, small batch, and high frequency, which poses new challenges to the warehousing system. As a key hub connecting manufacturing and distribution, the picking efficiency and resource management level of automated warehousing systems directly affect the response speed of orders. In recent years, although technological innovation has promoted a new wave of warehouse automation, human participation in most order picking operations is still necessary, giving rise to new forms of interaction between people, machines, and software [1]. With the wide application of automation equipment such as AGVs, the coupling problem of communication and path planning restricts the performance of the system [2]. However, many automated warehouses still adopt fixed zoning picking strategies and static resource allocation methods for large-volume orders, resulting in serious backlog during peak periods, idleness during off-peak periods, and obvious efficiency

fluctuations. Further analysis shows that order picking strategies and resource allocation are managed by separate departments without a linkage decision-making mechanism, and that unilateral adjustment of either strategy or resources can hardly effectively improve system performance. Therefore, taking the spare parts warehouse of an electronic manufacturing enterprise as the object, this paper proposes a strategy and resource collaborative optimization scheme, and verifies its effectiveness through simulation.

Research has been carried out from many directions around warehouse picking optimization. In terms of order grouping and batch, the variable neighborhood search algorithm is improved to improve the picking efficiency through three-dimensional collaborative optimization. The mathematical model is constructed by a strong-coupling system, and the dual algorithms of dynamic order picking and delivery task scheduling are designed [3]. SKU co-occurrence frequency is used to optimize storage layout, which can reduce path repetition [4]. In the "goods to people" mode, the dynamic scheduling algorithm reduces the man-hours by 12.67% compared with the sequential strategy and 7.63% compared with the fixed parameter strategy [5]. Dynamic resource scheduling based on real-time state can alleviate the imbalance between supply and demand [6]. Multimodal data fusion and deep reinforcement learning are used for dynamic scheduling [7]. The impact of human-computer cooperation on order picking efficiency is verified by empirical analysis [8]. The evolution of the warehousing system from rigid automation to flexible intelligence has its own technical path [9]. Automated three-dimensional warehouses can improve storage efficiency, promote the development of workshop automation, and improve the efficiency of the whole production process [10].

There are abundant discussions on warehouse picking optimization in the literature, but most of them study strategies and resources separately, lacking a collaborative decision-making framework. Taking the spare parts warehouse of electronic manufacturing as an example, this paper designs the collaborative scheme of order batch, storage association, strategy switching, and flexible resource allocation, establishes the state-driven linkage rules, and compares the operation effects of the baseline scheme, independent optimization scheme, and collaborative scheme through simulation in the lab. The theoretical significance lies in revealing the coupling relationship between strategy and resources, and bringing them into a unified analysis framework. The practical significance is to give specific optimization methods, parameter settings, and linkage rules, so as to provide reference for similar enterprises.

2. Case studies

This paper selects the automated spare parts warehouse of an electronic manufacturing enterprise as the research case. The enterprise adopts the mass customization mode to produce consumer electronics, and the spare parts warehouse supplies components to production lines and after-sales outlets. The warehouse is equipped with an automated stereoscopic storage system, including 4 roadway stackers with a rated speed of 120 m/min, a main conveyor line, 8 picking workstations and 3 AGVs. It has 3,200 storage locations for about 2,800 SKUs, with 6 pickers, 2 replenishers and 1 supervisor per shift. The current picking strategy divides inventory into electronic parts, structural parts and auxiliary materials areas according to commodity attributes, and conducts merging and packing after separate zone picking.

Orders present typical multi-variety and small-batch features, with an average of 7.2 SKUs per order. Orders with 1–3 SKUs account for 18.7%, those with 4–6 SKUs account for 34.2%, those with 7–10 SKUs account for 31.5%, and over 10 SKUs account for 15.6%. Order arrival shows obvious peak-valley fluctuations, with two peak periods in the morning and afternoon, and the

coefficient of variation of arrival rate reaches 0.67. Commodity demand follows the Pareto distribution: the top 20% of SKUs cover 67% of order lines as high-frequency demand, while the remaining 50% of SKUs, mostly customized components, only account for 8% of order lines.

Under the current zoning picking mode, the average order completion time is 12.8 minutes, rising to 18.6 minutes at peak hours with a maximum backlog of 210 orders. Severe task imbalance exists across zones: the electronic parts area processes 52% of order lines with 89% stacker utilization, while the auxiliary materials area only processes 17% with 34% utilization. Overall stacker utilization ranges from 31% in troughs to 92% at peaks, with large fluctuations. Static manpower allocation also causes obvious redundancy or gaps. The core problems lie in fixed zoning, static resource allocation and the lack of automatic linkage mechanisms, which force managers to make temporary empirical adjustments with limited coordination effects.

3. Optimize scheme design

In view of the above problems, a framework from strategy to resource linkage is proposed: The picking method and resource delivery are regarded as coupling variables, which are adjusted simultaneously according to the queue length, equipment load, and the real-time state of the system with backlog distribution. The scheme includes four modules: order batch control, storage association optimization, dynamic switching of picking strategy, flexible resource allocation, and unified coordination through linkage decision-makers. A waiting queue length threshold l_{batch} is set. Batch operations are triggered when the queue length exceeds the threshold, and the threshold value is dynamically calculated according to available picking capacity. The joint batching method measures similarity by the ratio of common SKU quantity to total SKU quantity of two orders. If it is higher than the threshold, it will be merged. The total number of SKUs in each batch will not exceed the maximum processing capacity of the equipment at a time, and the total number of SKUs will not exceed the load. The batch algorithm is executed every 10 minutes or recalculated when the queue fluctuates by more than 20%. Based on the historical order statistics, the co-occurrence frequency of two SKUs is used as the correlation, and the highly correlated commodities are allocated to adjacent storage spaces. The regular adjustment cycle is once a week. If the difference between the new order portfolio and the historical model exceeds the threshold for 7 consecutive days, the aperiodic rearrangement will be triggered. Three strategies are set, namely, strategy A, single-order sequential picking, which is adopted when the number of orders in the queue is less than 10. Strategy B, which is wave batch picking, is applicable to the situation where the number of orders is between 10 and 40. Strategy C, which is partition parallel picking, is enabled when the number of orders is greater than or equal to 40 or the utilization rate exceeds 85%. Each strategy switch is maintained for at least 15 minutes to prevent frequent oscillation.

Manpower allocation adopts a benchmark-floating parallel mode. The benchmark is set at 4 people. When the queue exceeds 15, the floating mechanism will be started, and one person will be added for every 10 orders added, with an upper limit of 4 people, and it is required to be in place within 5 minutes. The speed of the stacker is divided into three gears. When the utilization rate is less than 40%, the speed is reduced to 60%, so as to achieve the purpose of energy saving. When the utilization rate is between 40% and 75%, the speed maintains the rated state, and when the utilization rate is greater than 75%, it switches to the high gear to achieve the acceleration effect. The transmission line will adjust speed in sections according to the load situation, and AGVs will be deployed in the bottleneck area to provide support. The linkage decision-maker will constantly monitor the queue length, maximum waiting time, utilization rate, and regional backlog. Key linkage rules are specified as follows. A slight backlog forms when the queue length exceeds 30 and

lasts for more than 5 minutes, triggering the switch from Strategy B to Strategy C, activation of floating manpower and stacker acceleration. Queue>60 or maximum wait>20 minutes to form a heavy backlog: maintain C, enable all floating manpower, and rebalance regional tasks. Maximum/minimum utilization rate>2 forms a regional bottleneck: dynamic adjustment of zoning and AGVs cross-regional support. When the queue is less than 10 and the average utilization rate is less than 40%, a low load is formed: strategy C to switch, floating manpower release, and equipment energy saving. Continuous observation is conducted for three consecutive 5-minute cycles after linkage adjustment. If no improvement is observed, the adjustment intensity is upgraded.

4. Simulation experiment and result analysis

A discrete event simulation model is established using MATLAB R2023b. Orders arrive following Poisson distribution with an average of 60 orders per hour, each containing 5 to 10 SKUs and 1 to 5 units per single product, and SKU demand follows the Pareto distribution. The simulated warehouse layout includes 3,200 storage spaces, 4 stackers and 8 workstations. As shown in Table 1, the simulation runs for 30 days, with the first 5 days as the warm-up period and the remaining 25 days for data statistics. Each scheme is repeated 30 times and the average value is taken. Three comparative schemes are designed: the baseline scheme with zoning picking and static allocation, the independent optimization scheme, and the collaborative optimization scheme with a complete linkage mechanism. Results show the collaborative scheme shortens average order completion time by 19.6% and cuts equipment utilization fluctuation by 37.8% versus the baseline.

Table 1. Order completion time and equipment utilization rate

Index	Status quo plan	Independent optimization	Collaborative optimization
Average completion time (minutes)	12.8	10.6	10.3
Average peak completion time (minutes)	18.6	14.2	12.9
Maximum wait time (minutes)	35.2	24.8	21.3
Average utilization	58.2%	63.4%	64.1%
Standard deviation of utilization	0.21	0.14	0.13
Utilization volatility	61%	44%	38%
Index	Status quo plan	Independent optimization	Collaborative optimization
Average completion time (minutes)	12.8	10.6	10.3
Average peak completion time (minutes)	18.6	14.2	12.9
Maximum wait time (minutes)	35.2	24.8	21.3

As shown in Table 2, the number of manual supplements per week in the collaborative optimization scheme is 28.4% less than the current situation, indicating that the system has a stronger ability to cope with order fluctuations independently. In the three scenarios of 40 orders per hour, 60 orders per hour, and 80 orders per hour, the collaborative optimization scheme shows the

best state. The higher the arrival rate, the more significant its comparative advantage. In the case of a high arrival rate, synergy can shorten the time by an additional 13% compared with independent optimization.

Table 2. Human resource utilization status

Index	Status quo plan	Independent optimization	Collaborative optimization
Average on duty	6	5.4	5.2
Manpower gap/redundant hours (daily)	2.8	1.6	1.2
Number of manual placements (weekly)	12.4	9.2	8.9

The simulation results demonstrate the following findings. First, the independent optimization scheme outperforms the baseline scheme, while the collaborative optimization scheme achieves even better performance. This shows that although the strategies of optimizing separately but not forming linkage with each other have some results, they are not as significant as the effects of using linkage for optimization. Especially in the peak stage, the value of linkage is more prominent. Secondly, the synergistic optimization scheme has a significant inhibitory effect on the fluctuation of equipment utilization rate. The reason for this situation is that when the system state changes, the linkage rules will adjust the strategy and resources synchronously, thus avoiding the mismatch caused by the situation that the strategy has changed but the resources have not kept up in time, or the resources have increased but the strategy has not changed. Thirdly, the collaborative optimization scheme reduces the demand for manual intervention. This is because the system can respond to changes in state on its own, without waiting for managers to detect problems before temporary deployment.

5. Conclusion

Under the mass customization mode, automated warehousing systems face new challenges brought by multi-variety, small-batch and high-frequency orders. Taking the spare parts warehouse of an electronic manufacturing enterprise as an example, this paper studies the collaborative optimization of order picking strategies and resource allocation. The main conclusions are as follows. First, mass customization orders are characterized by diverse SKU types, small single-item quantities, large arrival fluctuations and Pareto-distributed commodity demand. Second, the designed collaborative scheme integrates four modules of order batching, storage adjustment, strategy switching and flexible resource allocation, and adjusts strategies and resources synchronously according to system states. Third, simulation results show that the scheme shortens average order completion time by 19.6%, reduces equipment utilization fluctuation by 37.8% and cuts manual replenishment times by 28.4% compared with the baseline scheme, verifying its effectiveness and stability.

Theoretically, this paper establishes a strategy-to-resource linkage analysis framework, which integrates the two issues discussed separately in previous studies. Practically, this paper provides specific optimization methods and parameter settings with highly operable linkage rules and threshold configurations, which can offer references for similar enterprises in warehousing system transformation. This study still has limitations. The simulation model simplifies some practical factors such as equipment failures and personnel fatigue, and the threshold settings of linkage rules

need to be adjusted according to enterprises' own conditions. Future research can introduce machine learning methods to enable autonomous learning of optimal linkage strategies, and incorporate order priority and delivery constraints to improve the practicability of the scheme.

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