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Optimization of Storage Allocation of Mobile Racks Based on Demand Forecasts

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ABSTRACT

The complexity of a single multi-product order structure of retail e-commerce enterprises. There is a difficult situation of time-consuming step-by-step picking and a heavy load of rack handling. The product fails to take advantage of the flexibility of the mobile racks. Matching with the shelves according to the sales rules results in a long pick-and-walk distance. The general classification storage strategy in the warehouse makes it difficult to deal with fragmented picking. Given this, the optimization of the storage position of mobile racks in the warehouse of retail e-commerce enterprises is studied. A combination optimization model is established to minimize the length of the pick road. The first stage is the introduction of complex network abstraction of each commodity for the nodes to establish the correlation network, mining within the order of the commodity demand correlation for clustering; In the second stage, a subset of (1, N) Grey-Prediction model related factor series is used to distribute racks for the first stage of clustered commodity portfolio using single parent evolutionary genetic algorithm under elite strategy based on short-term sales prediction. The evaluation of the experimental data shows that compared to the current storage strategy of the enterprise, the optimized model yields a better-quality solution. Robustness perturbed by order size. At least a 2.85% reduction in pick length at large parameters. Rack handling is reduced by at least 5.62%. The result of a short distance and a small number of picks is realized.

INTRODUCTION

With the explosion of online shopping, building intelligent warehouse systems with Automated Guided Vehicle (AGV) and mobile racks to improve fulfillment speed has become the consensus. When the order arrives, the AGV interacts with the rack where the corresponding item is stored. Carry them together to the picking station where pickers pick out specific items in a fixed location. Breaking through the limitation of personnel shuttle through the roadway, greatly increased single-day shipments Chen et al. (2017).

According to the research data, order picking costs account for more than 60% of warehouse operating costs, picking operations account for 40% of the entire shipment process, and the walking phase accounts for 50% of the time spent in picking Li et al. (2013). At the same time, a variety of goods, small volume, and high shipment frequency are the features of retail e-commerce enterprises Wu et al. (2016), warehousing picking work is fragmented, add to that, the domestic online shopping platform prevalence of single package mail, full reduction, low price exchange and other promotional means led to a single multi-product order structure became the norm. One order average contains 7-8 items. Non-similar commodities account for about 40% Zhu et al. (2021). The AGV can only obtain 1-2 items in the order for single handling of the racks. The efficiency of the picking area is the key to the fulfillment speed. Affected by storage allocation, order batch, partition assignment, etc. And the decision of the storage assignment as the front of the process belongs to the strategic level will directly affect the fulfillment efficiency and logistics cost Hu et al. (2022). Wang et al. (2018). Hence, in a warehouse automation system, an important operation problem is to decide which product to put on which pod so that the robot movement distance can be reduced. If the reserve allocation strategy reflects the order portfolio, the number of individual order picks and path length will be significantly reduced.

Numerous studies have shown that the correlation between goods, the probability that they appear in the same order at the same time, makes it possible to improve the efficiency of picking through storage planning Chen et al. (2021), Guan et al. (2018). In addition, the frequency of selection of goods is affected by the heat of sale.

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There is a discrepancy in sales of closely related goods. Moving a small volume of goods through a combination of forms close to the picking center causes an imbalance in the turnover of the goods. High-volume goods need to be replenished individually and frequently. Increased workload outside the selection process to some extent. Therefore, this paper intends to study the optimization of storage assignment based on mobile racks in retail enterprise warehouses, pay attention to the correlation of commodity demand and the effect of change of sales volume on AGV picking road length, and propose a suitable storage allocation scheme for retail warehouses.

Literature View

In the research of automated warehouse storage location optimization, domestic and overseas scholars have conducted a great deal of explorations. Research has mainly been conducted through two categories: determine the storage distance between goods and distribute the storage area for each commodity.

For the first topic decide which items to place next to. In applications, the vast majority of businesses store items with similar properties close together Larson et al. (1997), Liu et al. (1999) presented a primal-dual type algorithm, which measures the similarity of non-homogeneous goods for storage allocation. There are various types of retail products in the intelligent warehouse, such as more than 10,000000 kinds of SKU stores in JD.com warehouses, products can be classified according to multiple standards, traditional similarity classification method is not applicable. A large number of scholars have proposed a correlation between commodities, which is influenced by commodity properties and purchasing preferences, and stable in the short term. Xiang et al. (2018) pioneered an integer planning model aimed at maximizing the correlation of goods on mobile racks. It has been shown that depending on commodity correlation to cluster for partitioning storage areas for commodity combinations reduces picking times by an average of 9% and up to 24%. Then, Li et al. (2022) designed a two-stage algorithm to solve the model by applying the commodity correlation to the replenishment scenarios when the initial rack state is not empty. Commodity similarity in the indicator system Lin et al. (2020), Wang et al. (2021), application scenarios, algorithm convergence rate Zhai et al. (2023), and other aspects of continuous improvement, has become an important basis for commodity clustering. Li et al. (2022) cluster items based on information contained in the order to be picked, based on the number of mobile racks, outbound frequency of items, and length for moving each rack. Use greedy ideas to group items after clustering to match items with racks.

Zhou et al. (2020) introduced the spectral clustering method, using commodity turnover and correlation as spectral clustering indicators to complete the assignment of goods. Given the characteristics of retail merchandise, single merchandise needs to be dispersed across multiple racks, and a one-bit storage model faces the key issue of multiple clustering of individual merchandise. Hu et al. (2022) focus on the optimization of one-product multi-bit storage based on mobile racks, prescribe the number of shelves that each item can store in advance, introduce complex networks for commodity clustering, abstract modelling of storage allocation, and output the most relevant scheme of goods inside racks.

For the second topic, based on random storage, ABC classified storage and closed open location storage, a large number of scholars refer to the historical outbound frequency to determine the storage of the goods Heskett et al. (1963), Li et al. (2013), Li et al. (2018), which place frequent outbound items in storage units near entrances or distribution centers. Heskett et al. (1963) proposed the COI (Cube-per-order Index), which divides the location by the frequency of goods in and out to minimize the cost of picking. Thonemann et al. (1998) optimization is achieved by considering the turnover of each category of goods based on a random distribution strategy. Yu et al. (2008) as the basis of dynamic storage distribution, Cai et al. (2009) relies solely on the commodity turnover rate to optimize the storage distribution strategy, and the get the approximate optimal solution by genetic algorithm. Yuan et al. (2020) make use of historical orders to determine the distribution of goods in the racks by reference to the frequency of commodity history in the second stage, enriching the structure of the study of the distribution strategy.

Due to the high flexibility of retail merchandise outgoing, warehousing, and shorter response times, storage of merchandise in warehouses requires more timely detection of the expected frequency of product outbound. Studies have demonstrated the effect of commodity correlation and turnover rate on picking efficiency, but most of them have more constraints Hu et al. (2022), inventory frequency and turnover rate and sales comparison lack dynamic mechanism Li et al. (2018), the number of reserves assumes strong subjectivity and other limitations Lin et al. (2020).

Therefore, this paper takes commodity correlation as the basis of storage assignment quantity, eliminates the assumption that goods can be stored in quantity, and forms a product combination that can meet the regular appearance of products in order. At the same time, to avoid the delay in the frequency and turnover of the library, combined with the characteristics of e-commerce, the short-term prediction of the factors influencing the change in sales volume is made. Add dynamic mechanisms to match goods to racks, align the location of the product with the trend of volume change, satisfy the picking needs, and at the same time, set the out-of-stock constraints, to some extent to ensure the scientific value of the target. Finally, the results of the optimization scheme are tested using mining data, and feasibility is tested.

Storage Allocation Optimization Model

Model Parameter Settings

Retail e-commerce enterprises are prevalent in multi-product orders, commodities appear as combinations, taking advantage of such commodity associations to cluster goods that appear in the same order at the same time, put the goods in combination on racks, and the probability and frequency of high-volume goods being picked time is high. The pick length can be reduced by being stored close to the picking station.

The problem is described as how to store items on racks so that AGV picking path length is minimized. To simplify the problem, make the following assumptions:

(1) Only one item can be stored at each storage level on the rack

(2) AGV moving speed is stable, the small difference in rack weight does not affect the picking speed

(3) Short-term stability of commodity types

(4) Commodity-Storage match relationship stabilizes during each cycle

(5) Assign AGVs in order of order, regardless of the combined selection of different orders

For subsequent expressions, define mathematical symbols in Table 1. To define the research scenario, the following definitions are made:

Table 1: Related parameters and their meanings.

Sets	**Definition**
l,L	represent items set
i,I	represent commodity groups set
k,K	represent orders set
Parameters	**Definition**
A_k	represent items set in k, i.e., $A_k \subset L$ and requires $A_k \neq \varnothing$ $k \in K$
De_{kl}	represent the demand for l in order k $k \in K$ $l \in A_k$
B_l	represent commodity groups that include l, i.e., $B_l \subset I$ and requires $B_l \neq \varnothing$ $l \in L$
C_l	represent a set of orders containing l, i.e., $C_l \subset K$ $l \in L$
d_j	represent moving distance from j to picking station $j \in J$
Cap_l	represent the capacity of individual racks $l \in L$
SU_i	represent commodity group i maximum number of commodity types that can be included, i.e., rack layers
S_{lq}	degree of correlation between l commodity q

Definition 1 Commodity Group. A commodity group is defined as $i=\langle SU_i, g_{il}\rangle$, one that represents most SU_i items included in i, g_{li} present i combined by the key item l.

Definition 2 Mobile Racks. A mobile rack is defined as $j=\langle t_{ji}, d_j\rangle$, a t_{ji} representation that j matches i, j is a stable position in the warehouse, and is the smallest unit of AGV handling. The distance from j to the picking station is d_j.

Definition 3 Picking Path. The picking path is defined as, which means that to complete the selection of all orders, the AGV moves from the first rack to the picking station to the last rack to the length of the picking station experience.

Definition 4 Optimization of Storage Assignment for Mobile Racks. Given L J, that the goal is to distribute l to j with certain rules, when k appears randomly in chronological order, the picking station is fixed, and the AGV is removed j from the picking station where A_k are stored, minimizing D (regardless of the length of the replenishment walk).

objective function：

$$min\,D=\sum_{k\in K}\sum_{l\in A_k}\sum_{j\in J} d_j y_{klj} \quad ,\forall l\in L,\ i\in B_l, j\in J \tag{1}$$

defining decision variables：

$$x_{ij}=\begin{cases}1, if\ i\ distribute\ to\ j\\ 0,\ else\end{cases}$$

$$y_{klj}=\begin{cases}1,\ l\ in\ k\ pick\ from\ j\\ 0,\ else\end{cases}$$

auxiliary variable：

$$z_{jl}=\begin{cases}1, l\ store\ in\ j\\ 0, else\end{cases}$$

The following constraints are met：

$$\sum_{j\in J} x_{ij}=1\ ,\ \forall i\in I \tag{2}$$

$$\sum_{i\in I} x_{ij}=1\ ,\ \forall l\in L \tag{3}$$

$$z_{jl}\ge x_{ij} \quad ,\forall l\in L, i\in B_l, j\in J \tag{4}$$

$$z_{jl}\le\sum_{i\in B_l} x_{ij} \quad ,\ \forall l\in L,\ j\in J \tag{5}$$

$$y_{klj}\ge z_{jl} \quad ,\forall k\in K, l\in A_k, j\in J \tag{6}$$

$$\sum_{j\in J} y_{klj}=1 \quad ,\forall k\in K, l\in A_k \tag{7}$$

$$\sum_{k\in C_l} De_{kl}\cdot y_{klj}\le z_{jl}\cdot Cap_l \quad ,\forall l\in L, \forall j\in J \tag{8}$$

$$x_{i,j}\in\{0,1\}\ \ \forall i\in I, j\in J \tag{9}$$

$$y_{k,l,j}\in\{0,1\}\ \ \forall k\in K,\ l\in A_k,\ j\in J \tag{10}$$

$$z_{j,l}\in\{0,1\}\ \ \forall l\in L,\ j\in J \tag{11}$$

The objective function (1) represents the minimum pick length, i.e., the length of the AGV moving the rack to the picking station Constraints (2), and (3) indicate that each combination must and can only occupy one rack. Constrained (4), (5) is an association constraint to indicate whether there is a commodity l on j, If there is no combination with l stored on j, is l not on j. Constraint (6) on behalf of the racks is not out of stock before the selection can be provided. (7) indicates each item in the order can only be picked from one rack. (8) indicates that each rack cannot take more than capacity, and out-of-stock cannot pick goods. Constraint (9) - (11) Value range constraints for variables.

Complexity analysis

The problem with the allocation of a single bit of storage is an NP-hard Li et al. (2016) problem, with exponential growth in the amount of space solved. One product multi-bit storage allocation problem, suppose there are items in the warehouse, which can be placed on up to racks, and most items can be stored on a rack and the number of racks in the warehouse is U, $U=\left[\dfrac{LR}{SU_i}\right]$.

The solution space is the largest when each item is evenly divided into racks. The calculus for the solution space element is:

$$|\Omega|=\frac{C_{RL}^{SU_i}\times C_{RL-SU_i}^{SU_i}\times\cdots\times C_{RL-(U-1)\,SU_i}^{RL-(U-1)\,SU_i}}{A_U^U} \tag{12}$$

$$=\frac{(RL)\,!}{U![RL-(U-1)\,SU_i]!\ \ SU_i!^{U-1}}$$

Theorem 1 When $L>1, R>1$ modelling (1)-(11)

Proof The number of racks in a warehouse is U' for each item only allowed to be distributed on a rack (clustered in a class) in the one-store distribution mode, $U'=\left[\frac{L}{SU_i}\right]$, the formula for calculating the number of solving space elements is:

$$|\Omega'|=\frac{C_L^{SU_i}\times C_{L-SU_i}^{SU_i}\times\cdots\times C_{L-(U'-1)SU_i}^{L-(U'-1)SU_i}}{A_{U'}^{U'}} \tag{15}$$

$$=\frac{L!}{U'![L-(U'-1)SU_i]!\ SU_i!^{U'-1}}$$

Comparing the space size of the solution can effectively reflect the complexity difference between the problem of the distribution of the one-bit reserve and the problem of the one-bit multi-bit storage allocation. The comparison is as follows:

$$\frac{|\Omega|}{|\Omega'|}=\frac{(RL)!\,U'!\ SU_i!^{U-U'}}{L!\ U!}\times\frac{[L-(U-1)SU_i]!}{[RL-(U'-1)SU_i]!}$$
(16)

$L-(U-1)SU_i$ in (14) represents several commodities stored on the U rack, and we can arrive at $1\le L-(U-1)SU_i\le SU_i$ $1\le RL-(U'-1)SU_i\le SU_i$. So, when the value of $L-(U-1)SU_i$ takes 1, $RL-(U'-1)SU_i$ takes SU_i, (14) gets the minimum.

$$\frac{|\Omega|}{|\Omega'|}\ge\frac{(RL)!\,U!\ SU_i!^{U-U'-1}}{L!\ U!}$$

Suppose $L=5$、$R=2$、$SU_i=5$, so we can find $|\Omega|\ge 30240|\Omega'|$, we can conclude that the problem of one-product multi-bit storage space distribution is much more complex than one-product storage space distribution. **Theorem 1** is proven. To reduce the decomposition space, the storage allocation problem will be completed in two steps.

Optimization Algorithm Design for Storage Allocation Problem

Phase I: Greed Algorithm Based on Core Commodity Clustering

The stage of commodity clustering, based on the historical order structure to determine the correlation of commodity demand, based on the building method of weighted association network Hu et al. (2022), presenting the clustering approach of "core goods" is proposed. Having changed the idea in previous literature of determining the number of racks in which goods are stored in advance. Instead, the number of storages allowed for each commodity is determined based on its association with other commodities, making the "one-bit" storage allocation result more in line with the commodity association law. The clustering steps are as follows:

1) Weights between items are calculated by the order-item association matrix. Equivalent to one or two phases of association network construction in literature [5], weighted means the probability or frequency of common occurrence of goods and others in order, weights goods selected as core goods, representing a large variety of goods associated with them and a high frequency of common ordering.

Describe the order matrix p as $p=p(l,q)_{K\times L}=p_1,p_2,p_3,\cdots,p_k$ the element p_{kl} of column L of the line l is expressed as:

$$p_{kl}=\begin{cases}1 & \textit{the k order contains l}\\ 0 & \textit{else}\end{cases} \tag{13}$$

Consumer orders for a retail e-commerce platform are shown in Table 2,

The corresponding matrix p is as follows

$$\boldsymbol{P}=\begin{pmatrix}1&1&0&0&0&1\\1&0&0&1&0&0\\0&0&0&1&1&0\\1&0&0&0&1&0\\0&1&1&1&0&0\\1&0&0&0&1&1\end{pmatrix}$$

Based on the matrix p, the association matrix $S=(s_{lq})_{L\times L}$ between goods is calculated by the formula (16). The larger the number, the higher the association, S as shown below.

$$s_{lq}=\begin{cases}0 & l=q\\ p_l^{\mathrm{T}}\cdot p_q & l\ne q\end{cases} \tag{14}$$

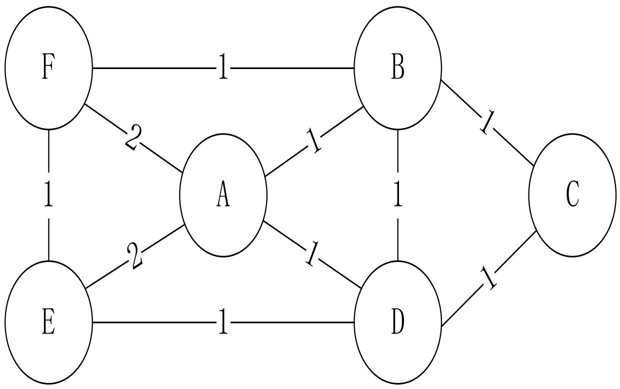
$$\boldsymbol{S}=\begin{pmatrix}0&1&0&1&2&2\\1&0&1&1&0&1\\0&1&0&1&0&0\\1&1&1&0&1&0\\2&0&0&1&0&1\\2&1&0&0&1&0\end{pmatrix}$$

Table 2: We can explain the construction of correlation networks by enumerating some simple order structures

order	commodity	order	commodity
1	A、B、F	4	A、E
2	A、D	5	B、C、D
3	D、E	6	A、E、F

Drawing on the second phase of association network construction in literature (5), the commodity association network is shown in Figure 1.

Fig 1: Commodity-related network



Node corresponding goods and the edge of the network represent an association between goods, and the number represents the degree of association. Based on calculating Boolean Matrix using formula (17). Calculating the degree of the node a_i using formula (18), which represents the number of connections between nodes,

as shown in Figure 2-a. Introducing the total weight of edge connections between nodes to indicate the frequency of association between goods, as shown in Figure 2-b. Finally, the weights of each node are calculated by introducing (19), the higher the value, the stronger the association between a product and others, the results are shown in Figure 2-c.

Fig 2: Weighting degree calculation.

(a) degree of the node (b) total weight of edge connections (c) weights of each node

	(a)	(b)	(c)
A	4	6	4.9
B	4	4	4
C	2	2	2
D	4	4	4
E	3	4	3.5
F	3	4	3.5

(a) represents the number of other nodes associated with a node, (b) indicates the number of times a node is associated with another node, we summarize (c) by (a) (b), indicating the weighted value.

Algorithm Pseudocode of clustering algorithm based on core commodities			
input	Initializing the Boolean Matrix B、S、L、SU_i、J		
output	list of product groups assigned		
	for	$i=1\to I$ do	
		based on B、S to calculate O, $O=\{o_1,o_2,\ldots,o_l,\ldots,o_q\ldots\}$	
		$o_l \leftarrow \max\{O\}$	
		$\{i\}\leftarrow o_l$ corresponding node l	
		$SU_i = SU_i - 1$	
		for	$q=1\to L$ do
			identify the nodes q、S that are most associated with the node l
			if the absolute values of l and q in the association matrix ≥0
			put q into the group i
			$q\leftarrow \max s_{lq}, q\in L$
			if $\max\lvert s_{lq}\rvert > 0$
		end	
		else	
			$\exists q'\in\{i\}, q'\neq l, s_{qq'}>0$ then
			$\{i\}\leftarrow max\, s_{qq'}$ corresponding node q
			$SU_i = SU_i - 1$
			end if
	if $SU_i<0$ then		
			$i\leftarrow\{i\}$
			end if
			remove the node l o_l from the $\{O\}$
			if $\lvert I\rvert<\lvert J\rvert$ then
			break
			end if
		end for	
		Assign I	
	end for		

$$\boldsymbol{B}=\begin{pmatrix}0&1&0&1&1&1\\1&0&1&1&0&1\\0&1&0&1&0&0\\1&1&1&0&1&0\\1&0&0&1&0&1\\1&1&0&0&1&0\end{pmatrix}$$

2）Core commodity clustering based on greed algorithm. The number of clusters is determined by the degree of correlation between the items in the order. The number of items in each combination is equal to the number of container layers, represents the number of types of goods remaining in the commodity group numbered, and represents the initial value of the number of clusters as 0. Combines goods based on greed algorithm, process pseudo-code as follows:

$$b_{lq}=\begin{cases}1 & s_{lq}>0\\0 & s_{lq}\le 0\end{cases} \tag{17}$$

$$a_l=\sum_{q=1}^{L}b_{lq} \tag{18}$$

$$o_l=\sqrt{a_l(\sum_{q=1}^{L}s_{lq})} \tag{19}$$

Theorem 1 When $L>>I$ The time complexity of the clustering algorithm based on core commodities is $O(L^4)$.

Proof There are two layers in the algorithm for cyclic nesting, external cycles are I times, so the complexity of the algorithm is $O(L^4)$, the maximum number of L runs. The 7th row is executed the most in the embedded loop, with $SU_i * L$ times, so the complexity of the algorithm is $O(IL^3SU_i)$. Since SU_i is less than or equal to the number of rack layers, that's the multiple of L/I, and $L>>I$. Therefore, the time complexity of the clustering algorithm based on core commodities is $O(L^4)$.

Phase II: Storage Allocation

Aggregate sales of each item in the group as combined sales value, so that the short-term expected high sales of goods in rack units were close to the picking station. The allocation of storage positions in the second phase is done in two steps: sales forecast and merchandise combination-rack matching.

Commodity Sales Forecasting Model

E-commerce retail enterprises with online sales channels as the mainstream.

Merchandise sales have the characteristics of strong randomness which are influenced by a variety of factors such as marketing activities. Eventually, sales are based on the platform as a carrier converted from views or favorites. A lot of literature proves that online indicators in the shopping platform can predict sales, such as: search guided views, merchandise views, favorites, etc. Zhang et al. (2021), Li et al. (2018), Huang et al. (2019), Kim et al. (2021). Searches increased by 10%, affecting weekly revenue by 7.4%. Through a data perspective analysis of the top 10 Tmall supermarket sales since 2020: sales peaked in November mostly and different product subpeak periods, which related to the random marketing time node of the product. Many elements of the e-commerce platform are consistent with the trend of volume fluctuations and show certain advances, such as the number of views, favorites, number of drive-thru views, the number of Tmall visitors, the number of views guided by search, the number of views guided by Juhuasuan, the number of Tmall views, the number of people guided by the search guide, the number of people guided by Juhuasuan.

After standardizing the above nine factors using the Range method, the dimension is reduced by grey correlation analysis. The results show that there are three factors with a sales correlation coefficient greater than 0.6, such as the number of Tmall views, the number of views guided by search, and the number of views guided by Juhuasuan. The grey prediction model can solve the problem of low historical data stock, low sequence integrity, and noise. (1, N) The grey-prediction model can be multi-factor dynamic, overall analysis Li et al. (2020), retail goods are relatively fast to update, with a multidimensional gray model more suitable. Modeling steps are as follows, at this time N = 4,

①Set the original non-negative feature data sequence t：

$$X_1=\left(x_1^{(0)}(1),x_1^{(0)}(2),\cdots,x_1^{(0)}(t)\right)$$

②Define a sequence of related factors：

$$X_w=\left(x_w^{(0)}(1),x_w^{(0)}(2),\cdots,x_w^{(0)}(t)\right),w=2,\cdots,N$$

A first-order cumulative generation of a sequence of related factors, which becomes a monotonous incremental sequence, expressed as:

$$X_w^{(1)}=\left\{x_w^{(1)}(v)\middle|x_w^{(1)}(v)=\sum_{h-1}^{j}x_w^{(0)}(h),v=1,2,\ldots,n\right\}$$

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The gray differential equation corresponding to the first-order cumulative sequence is:

$$\frac{dx_1^{(1)}(t)}{dt}+b_1x_1^{(1)}(t)=b_2x_2^{(1)}(t)+b_3x_3^{(1)}(t)+\cdots+b_Nx_N^{(1)}(t),t=1,2,\cdots,n \quad (20)$$

③calculate the nearest neighbor mean generation sequence $Z_1^{(1)}$ for $X_1^{(1)}$:

$$Z_1^{(1)}(h)=\frac{1}{2}\left(x_1^{(1)}(h)+x_1^{(1)}(h-1)\right),h=1,2,\cdots,t \quad (21)$$

$$x_1^{(0)}(h)+az_1^{(1)}(h)=\sum_{w=2}^{N}b_wx_w^{(1)}(h) \quad (22)$$

Parameter estimation using least squares method: $(a,b_2,b_3,\cdots,b_N)^T=(B^TB)^{-1}B^TY$. (23) represents its time response formula;

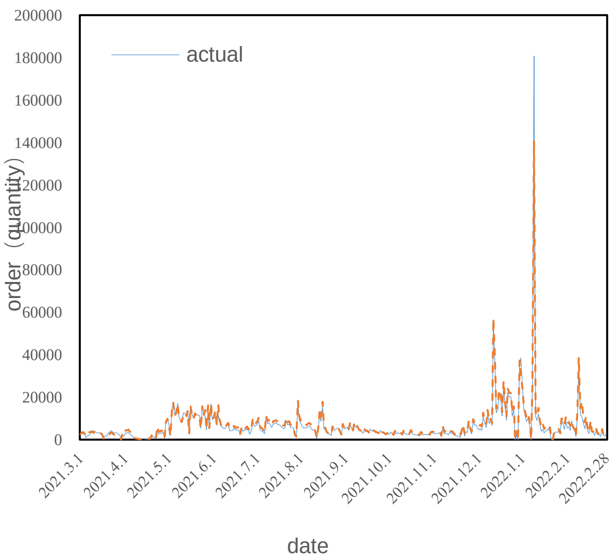
$$\hat{x}_1^{(1)}(h+1)=\left[x_1^{(0)}(1)-\frac{1}{a}\sum_{w=2}^{N}b_wx_w^{(1)}(h+1)\right]e^{-ak}+\frac{1}{a}\sum_{w=2}^{N}b_wx_w^{(1)}(h+1) \quad (23)$$

④the prediction value of the A $X_1^{(0)}$ series can be obtained by using the formula (24).

$$\hat{x}_1^{(0)}(h+1)=\hat{x}_1^{(1)}(h+1)-\hat{x}_1^{(1)}(h) \quad (23)$$

Selecting each of the 5 products randomly from the Tmall Platform protected area, food area, and daily necessities area. Collect sales data for the time dimension 2020.3.1-2021.3.1, and model training with 8:2 training sets and test sets. As shown in Figure 3,

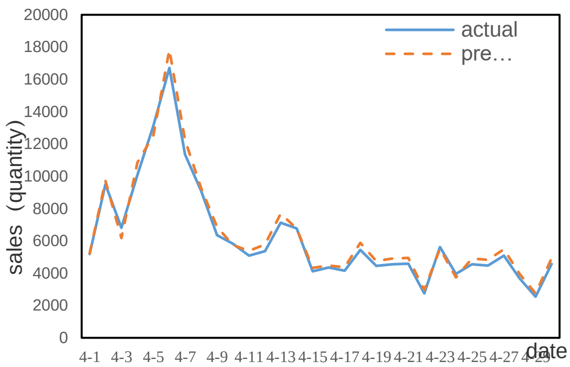
Fig 3: Grey prediction training set



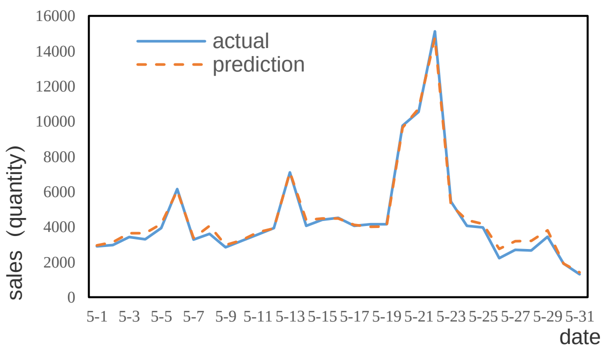
the product training effect with the greatest error between the forecast value and the actual value is given, and its forecast results for 2021.4.1-2021.6.1 are obtained as shown in Figure 4. The results show that grey forecasting has a good effect on commodity sales forecasting, and can accurately grasp the change of sales trend. Data stabilization stage prediction value and actual value deviation are small, in line with the expected accuracy, and can be used as a basis for the allocation of storage.

Fig.4: Grey prediction training results,

(a) data set 1



(b) data set 2



enter data for April to obtain a comparison between the predicted and actual values as shown in (a), and enter the data for May to compare the forecast value to the actual value as shown in (b)

Product Group - Storage Matching

To build a mathematical model of the storage allocation phase, a two-dimensional coordinate system is built with the picking station as the origin. $j(x_j,y_j)$ represents rack j at a position with abscissa x_j and ordinate y_j. The distance between the rack and the picking station can be expressed as $d_j=\sqrt{(x_j)^2+(y_j)^2}$.

The combined sales forecast F is equal to the accumulation of all merchandise sales forecast values in the group. The storage allocation function (25) represents the allocation of a cumulative high-volume product group to a rack that is close to the picking station and the design of a single-parent genetic algorithm (SPGA) to solve the problem.

$$min\sum_{i}^{I}\sum_{j}^{J}\sum_{l}F_i b_l x_{ij} d_j \quad (24)$$

Since the target form of integer programming is minimized, the target function is inverse to the fitness assignment, $fitness = \frac{1}{D}$

Output Optimal Individual

Descending individual order based on the fitness value determines whether the number of iterations is satisfied, and ends the calculation if satisfied. Select individual transfer (7) based on optimal save strategy, otherwise go to (5). Keep the fitness value in the top 10% of individuals based on the elitism-preserving strategy (maintain the best solution found over time before selection). The remaining individuals cross and mutate to generate new individuals.

Crossover、Variation

①on the basis of the crossover probability to allocate the proportion according to the fit value from the candidate, the individual is drawn to cross rows with the second point as the intersection point;

②Based on the probability of variation, individuals are drawn from the candidate to mutate with random points as the point of mutation.

(6) Calculate the fitness values of the new individuals and rank them in descending order. Leaving the top 10% of individuals to merge with (3) elites, and the remaining 90% into the next generation. Let the number of iterations $SE = SE + 1$, and go to (2).

Output Final Solution

The solution after iteration is the final solution, which represents the corresponding commodity group-storage match scheme and its target function value.

Experimental Validation and Analysis

To analyze the validity of the storage optimization model, the experiment of different parameters (order size, rack number, commodity type) was designed and carried out in two parts. After verifying the superiority of genetic algorithms, large-scale data experiments are conducted. The simulation experiment was done on a desktop computer with Win10 system, i5-6200U CPU, and 4GB of memory.

The solution of storage allocation modeling was realized by Python3.9.6 programming.

Small-Scale Parameter Mining Laboratory

A retail enterprise has a large online supermarket in China. In Shandong area A, the offline warehouse stores 260 goods for online distribution. 108 racks in the warehouse, each rack can store 5 layers of goods. A total of three pick tables are set at the entrance and exit, and 10 AGVs walk through the roadway at the entrance and exit. The current storage allocation strategy for A is to classify storage by commodity attributes, after that, according to the last cycle of product stock place a large stock of goods close to the pick center in the area in order. Training the Grey Prediction Model chronologically for daily product sales in the first to third quarters of 2020, before executing the storage allocation optimization model

Randomly intercepted 100 consecutive orders in Q4 2020 to form small-scale data for testing. Examples of partial order structure are Table 3, which contains the weighted results of 19 commodity nodes as shown in Table 4. 19 goods in the enterprise occupy 14 racks. Using 14 racks to implement this clustering method, the result is shown in Table 5. Assuming a storage allocation period of 15 days, therefore, the sales forecast value is cumulative 15 days of sales. The result of storage allocation is shown in Table 6. Filter 60 orders with the above items in the same cycle and test the remaining items, as shown in Table 6. When completing order 16, the AGV picks rack10 to offer 3 items instead of rack8 and rack1 to pick from the nearest pick table. And in order11 picking, because rack6 and rack14, which contain three goods at the same time, are larger distances from the pick table. The AGV is sorted twice in rack1 and rack8. The path length of the order as a whole is minimized. At the same time, rack10 was chosen because rack8 was not able to be picked due to the lack, and the most recent rack8 was unable to meet 3 kx picking requirements.

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Table 3: Examples of order structure excerpt

order sequence	order ID	commodity	order sequence	order ID	commodity
1	71101120	mb*2、cm、lw	11	71105016	gz、kx
2	71101121	zr、dl、mb	12	71105049	st
3	71101122	mb*2、yb	13	71105051	gg、yg
4	71101123	mb、mg	14	71105203	jr、gg
5	71101124	sz、mg	15	71105223	jz、cz
6	71101125	kx、sz、mg	16	71105231	cz*2
7	71101126	kx、sz	17	71105236	yg、gg、jr
8	71101127	yb*2	18	71105305	cz、jz
9	71101129	mg*2	19	71105359	cm、lw、gd
10	71105009	st、mg	20	71105366	mb、mg

Table 4: Weighting degree of points

commodity	weights	commodity	weights
cm	16.2	sz	7
mb	16	lw	5.5
gd	11.7	st	5.3
gz	9	cz	5
mg	8.4	jr	4.7
kx	8	dl	4
gg	3.5	gd	3
sp	2	lw	1
yb	1		

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Table 5: Clustering results with weighting

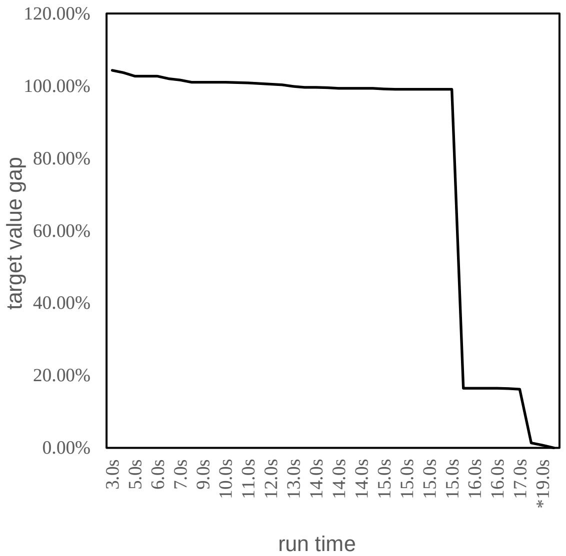
group No	rack	commodity group	distance	sales
1	4	cm-gz-mb-mg-zr	12	20689
2	5	mb-cm- mg-sr-sz	12	15975
3	14	gd-gz-lw-mb-zr	10	25892
4	6	gz-lw-mb-sz-zr	14	9891
5	10	mg-gz-kx- sr-sz	6	38406
6	8	kx-gz-mb-sz-zr	2	68957
7	11	sz-kx-mb-sr- zr	8	30694
8	1	lw-cm- mb-mg-sp	4	49057
9	9	st-mb-mg-sp- yb	4	50832
10	3	cz-gd-jz-mb-mg	8	28066
11	12	jr-cm- lw-mb-zr	12	19005
12	2	dl-mb-mg-yg-zr	6	39903
13	7	gg-dl- jr-lw-yg	14	10780
14	13	gd-gg-jr-st-yg	10	22764

Table 6: Order picking results

order	commodity	size	rack	distance	order	commodity	size	rack	distance
1	sz	1	8	2	11	lw	1	1	4
1	gz	1	8	2	12	zr	1	2	6
1	kx	1	8	2	12	dl	1	2	6
2	zr	1	2	6	12	mb	1	2	6
2	mg	1	2	6	13	mb	2	9	4
2	mb	1	2	6	13	yb	1	9	4
3	cm	1	1	4	14	mb	1	9	4
3	mg	1	1	4	14	mg	1	9	4
4	mb	3	8	2	15	sz	1	10	6
5	mb	1	1	4	15	mg	1	10	6
5	cm	1	1	4	16	kx	1	10	6
6	mg	1	9	4	16	sz	1	10	6
6	st	1	9	4	16	mg	1	10	6
7	mb	1	8	2	.	.	.	.	.
8	kx	3	10	6	.	.	.	.	.
9	sz	1	8	2	.	.	.	.	.
9	kx	1	8	2	58	kx	3	10	6
10	sz	1	8	2	59	sz	1	11	8
11	mb	2	1	4	59	kx	1	11	8
11	gz	1	8	2	60	sz	1	8	2

The difference between the target value and the optimal solution based on SPGA varies with the solving time. As shown in Figure 5,

Fig 5 Gap between result and optimal solution



the objective function achieved a local optimal solution at 3s. Drastic changes occur at 16s, with the target function value moving closer to the optimal solution. After local optimization is obtained again, global optimization is achieved at 19s. The validity of the genetic algorithm in small sample data was proved.

Large-Scale Cross-Month Order Mining

To validate the actual utility of sales forecasts in the allocation of storage, a group of one-week orders was collected online, and each group was drawn within four quarters in 2021. Order pooled with 4 groups for 28 days 1446,182 orders. The actual layout of racks in the warehouse is based on historical inventory, with high-frequency best-sellers placed close to the picking station for a 15-day refresh cycle. Select and test the enterprise strategy and the distribution strategy guided by the optimization model to compare the advantages and disadvantages of the strategy based on the target value and the total number of racks moved.

The results of the target value test are shown in Table 7. Available from the data in the table, enterprise orders fluctuate less daily, and the difference between quarters is large. Comparing the two storage strategies. In a few cases, the company's existing classification and distribution strategy based on commodity attributes can assist AGVs in achieving shorter pick path lengths, such as the performance of the AGV on the seventh day of the third group that is mainly related to the proportion of best-sellers in the order. When the storage cycle is updated, the product storage distribution results in the warehouse can respond to future demand. If the proportion of best-sellers in subsequent orders is high, and sales fluctuations are small in the short term.

Table 7: Comparison of results for groups

		one		**two**		**three**		**four**	
day	**Strategy**								
		current	**optimized**	**current**	**optimized**	**current**	**optimized**	**current**	**optimized**
1		41300	39009	99064	77997	699864	609853	106384	80043
2		51602	49049	127478	99759	689864	614329	105893	81953
3		69580	58960	136905	99994	795898	696403	137895	89533
4		68068	57096	128036	90789	784789	670736	169474	97964
5		50002	48098	108055	85784	1058328	957320	163679	94632
6		48000	46085	139988	136000	1353087	1295234	190742	99474
7		57609	49077	130908	126802	1068302	1072689	168690	86905

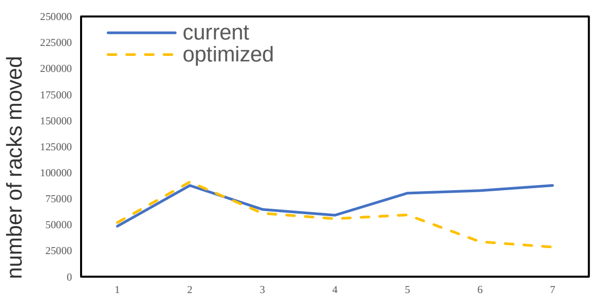
The strategy of simply considering the amount of outbound is to bring best-sellers close to the pick table so that they can reduce the length of pick. The optimized storage strategy takes demand dependency as a priority. Some of the best-sellers are assigned by clustering to a location further away from the picking station. In this case, the AGV picks a long walk, however, the difference from the outbound strategy is less than 1% and acceptable.

In most cases, the optimized strategy performs better in achieving fewer pick paths. With special exceptions, pick path lengths in the first group were reduced by at least 3.81% compared to existing strategies, and up to 16.12%; In the second group reduced by at least 2.85%, and up to 21.74%; In the third group reduced by at least 4.28%, up to 12.86%; In the fourth group reduced by at least 22.61%, up to 48.48%, and showed the most remarkable effect. With the increase of parameter scale, the optimized storage strategy is affected in terms of improving efficiency the third group is in a period of intensive promotion, the probability that the best-sellers are affected by the marketing strategy appears in the order increased, the best-sellers are not fully distributed on the racks that closer to the picking station, so the pick optimization results appear slightly unstable, but still keep the overall results optimistic. The robustness of the optimized storage model is proved.

The total number of times the daily order was processed is shown in Figure 6.

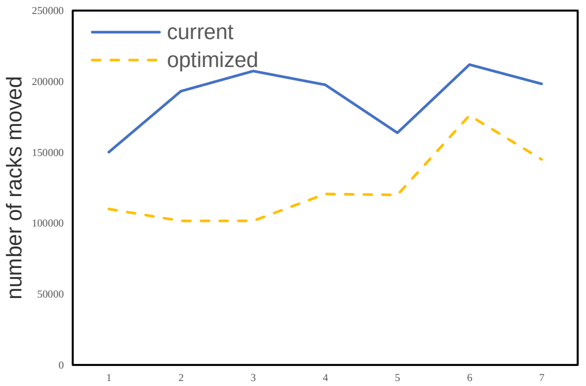
Fig 6: Racks moving times.

group one



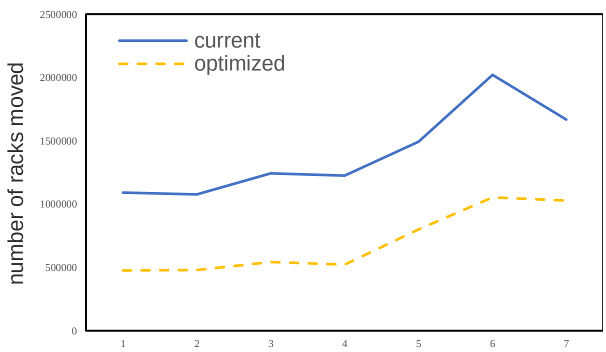
Except for the first and second days of the first group, the optimization strategy has achieved a significant reduction in the total number of racks handled by AGVs compared to the existing strategy. Illustrates that the results of the model guarantee the shortest target for the length of the pick path. When the racks where the goods are located have a smaller cumulative distance from the picking station, choose to move them separately.

group two

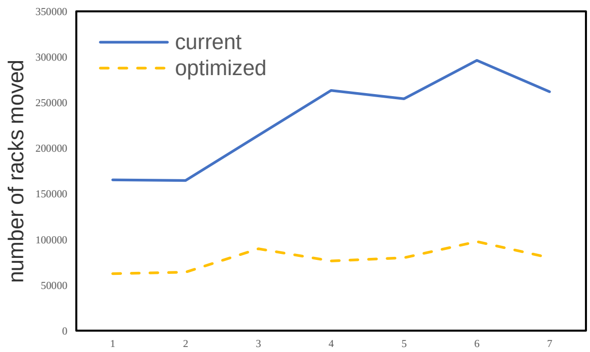


Rack handling was minimized by 5.62%, up to 70.96%. Appearing on the fourth day of the fourth set, which illustrates the complexity of the picking process, the optimization model demonstrates a high level of optimization. Indicating that considering the relevance of items can reduce AGV workload in the current enterprise.

group three



group four



Use data (a)、(b)、(c)、(d) which from different quarters to analyze the number of racks moved to complete orders under different allocation strategies or four sets of data.

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Conclusions

This paper discusses the optimization of mobile rack storage for retail e-commerce enterprises and constructs the storage allocation model to minimize the pick path length. Using a two-stage design, the first stage proposes a clustering method based on historical order, which is mainly based on core goods. In the second stage, the sales volume prediction of the commodities in the short term is carried out through (1, N) Grey-Prediction. The test results show that the model is suitable, the error is within an acceptable range and matches the commodity group with rack based on the total sales forecast value of the commodity group. The experimental results show that with the increase in order size, the optimization effect is obvious, which shows that the quality of the solution can be improved by considering the correlation between sales forecast and commodity. At the same time, to minimize the pick distance, taking into account the impact of the pick volume on the picking work, compensate for the situation that the same order of the same kind of goods ignored to be picked multiple times in the previous research, so that the optimization model is closer to the actual warehousing work. In contrast to the current storage allocation strategy, the storage assignment strategy of the optimization model guide outperformed the enterprise's current allocation strategy. Except in a few extreme cases, the length of the pick was reduced by at least 2.85%. In the interval between the days, storage distribution results in the warehouse and online sales situation synergistic effect well, the storage model can also be stabilized and optimized. Therefore, the results can provide an effective solution to the problem of intelligent warehouse optimization.

There are still shortcomings in the article, such as does not consider warehouse layout in depth. And layout optimization is the foremost problem of warehouse turnover, there is growing concern about the impact of AGV on walking length. We will explore the optimization of the storage space of mobile racks in a particular warehouse layout. Establish the corresponding picking distance model, longitudinal extension mobile rack storage allocation problem.

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