A study of order allocation in kiva-based order picking system

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Abstract As an essential component of any logistics network, distribution center plays an important role in realizing fast and reliable E-commerce logistics service. And order picking is an important process which will impact the distribution center's performance and logistics service quality directly. The kiva-based-order picking system is flexible, economical and efficient, the industry is keen to introduce this new solution to their E-commerce distribution center, but they found there are few theories to refer. This paper introduces a matrix-based clustering algorithm for order allocation in the kiva-based order picking system and verifies the algorithm efficiency by simulation example. The experimental model built based on a real practice case, and the Flexim software is used for the simulation study.

Keywords Kiva, Order picking system, Matrix-based clustering algorithm

1. Introduction

As an essential component of any logistics network, distribution center plays an important role in realizing fast and reliable E-commerce logistics service. The main activities in a distribution center include: receiving products from different suppliers, assigning products to the storage place, picking products according to the order information, consolidating orders which shared the same destination, and upload those combined orders for shipment. In this paper, we focus on the order picking process which will impact the distribution center's performance and logistics service quality directly(De Koster, Le-Duc, & Roodbergen, 2007; Gu, Goetschalckx, & McGinnis, 2007): 1) The errors made in order picking process would lead to bad customer experience and added logistics cost. 2) The productivity of order picking is a key constraint of the logistics service's efficiency.3) The reasonable schedule of the order picking process will connect the upstream and downstream transportation phases smoothly.

However, the efficient and accurate order picking process in E-commerce distribution center is a hard scenario. In general, an E-commerce distribution center must deal a huge number of customer orders with a large variety of SKUs every day. Because the number of E-commerce orders is enormous, and those small orders are placed by customer randomly with various requirements. De Koster(De Koster et al.) generated

the existed order picking method into two categories, the automatic machine method and the employing human method. And compared with the automatic machine method which is only used for valuable items and other special issues, the employing human method applied widely in industrial practice. In the order-picking method involved human, goods to man system and man to goods system are included. In the man to goods system, the operator walks through the distribution center's aisles with the orders' containers to pick the related items and put them into the appointed container. The man to goods system's cost is low, but, it cannot overcome the E-commerce logistics' challenges obviously. In the goods to man system, the operator is standing at a fixed depot, machines delivery the items to the depot for order picking. Those delivery machines include automated storage and retrieval system (AS/RS), modular vertical lift machines(VLM), or conveyors. The order picking accuracy and efficiency is improved in the goods to man system. However, it is costly and inflexible, and it always takes a long time to design and install(Zhou, Zhang, & Liu, 2015). These problems are well solved in the kiva-based order picking system(D'Andrea, 2012). The kiva system is a solution for automating storage search and retrieval instead of human workers. It mainly includes small fetch robots that fit underneath pods, mobile pods for storage, fixed order picking stations and control system(Flipse, 2011; Wulfraat, 2012). The main function of kiva is carrying the pods with appointed items to the order picking station.

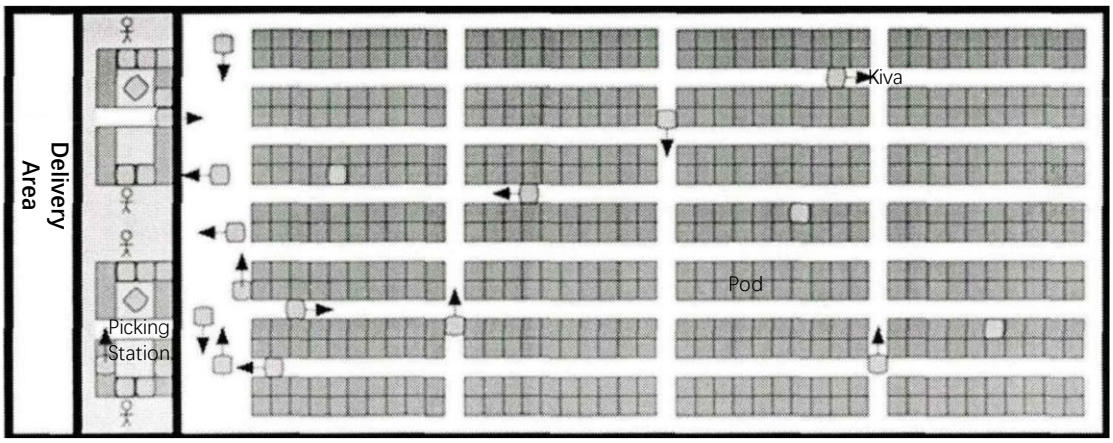
In the year 2014, Amazon started to use this new machine for delivering items in goods to man system, and it claimed about 20% operation expenses saved after applying this system(Wurman, D'Andrea, & Mountz, 2008). In another kiva's application case(Guizzo, 2008), the distribution center's productivity increased by a factor of two or more, while the number of order picking workers decreased from 75 to 25, the distribution center can fulfill 200,000 picks a day. The industry is keen to introduce this new solution to their E-commerce distribution center, but they found there are few theories to refer.

In this paper, we try to introduce a matrix-based clustering algorithm for order allocation in the kiva-based order picking system and verify the algorithm efficiency by simulation example. In section 2, we introduce the kiva-based order picking system in detail and design the simulation experimental. In section 3, we present a matrix-based clustering method to allocate order. In section 4, we discuss the simulation results and summarize the conclusions.

2. The Kiva-based Order Picking System Model

As shown in Figure 1, the kiva-based order picking system includes storage pods, kivas, picking stations and order picking workers at the picking station. When the system receives customer order, kivas delivery the storage pods with the correct items to the picking station, where the order picking worker remove the appointed items in the assigned order bin. When the order picking worker finished, the storage pod will be carried by kiva to an empty storage location.

Figure 1 Kiva-based Order Picking System Layout(Wurman et al., 2008)



The table 1 lists all the relevant parameters which are the union of the kiva-based order picking system, these parameters form what is called the KOPS(kiva order picking system model). The KOPSs as indicated by "-" in table 1 are static which means that they do not change with input date changes. The KOPSs as indicated by "#"are dynamic which means that they will change when input setting changes. The KOPSs as indicated by "*" are input setting parameters. A small set of KOPSs are chosen to form a performance indicator model. We choose the Distance per order (DO) to verify the order allocation's efficiency, because it is widely used in the literature as a primary objective while optimized the order picking system.

Table 1 List of parameters of KOPS

	KOPSs	Symbol	Factor Attribute
DC parameters	Layout	L	-
	Rank quantity	RQ	-
	Picking station quantity	SQ	-
	Order bin quantity per station	BQ	-
Kiva performance	Kiva quantity	KQ	-
	Kiva speed	KS	-
	Kiva capacity	KC	-
	Kiva accelerated speed	KAS	-
	Kiva route planning	R	#
Allocation Planning	Order Allocation	OA	*
	Storage Allocation	SA	#
	Rank Return Allocation	RA	#
	Task Allocation	TA	#
Order parameters	Order Size	O	-
	Number of products per order	an	*
	Kinds of product per order	ac	*
Item parameters	Total Category	tc	-
	Item Quantity	tn	-
KOPS Performance	Distance per order	DO	#

This simulation case is built based on one E-commerce logistics center, the layout of DC is similar with the Figure 1, and there are 533 ranks in the storage area, 4 order picking stations with 6 order bins for each station. Up to 50 kivas can be used at one

time, and its speed with full load is 1.2 m/s (1.5m/s without load), and its accelerated speed is 1.5m/s^2. The D star path finding algorithm is applied for kiva routing planning. The items ordered by the customer at high frequency are stored near the picking station. The order picking tasks assignment is based on the order priority which is set in the order allocation progress.

The KOPSs an, tc and ac are chosen to reflect the dispersity and complexity of customer orders, the simulation experimental design is shown in table2. And a total of 20 experimental groups are tested.

Table 2 Factors considered in the simulation experimental design

Factors	**Description**	**Levels**		
		1	**2**	**3**
an	Number of products per order	5	10	
tc	Total item category	50	200	
ac	Kinds of product per order	2	5	10

3. The Matrix-based clustering method

The Matrix-based clustering method was introduced to make efficient order allocation for goods to man system using AS/RS machine to deliver goods. This method was verified effective in the multiple-levels AGV order delivery system(Hu, 2016), but never been tested in the Kiva order picking system. And we make some improvement and adjustment to the method to get faster order allocation plan. Instead of pairwise comparison, we propose to find the core order which with most item types at first. The pseudocode program is shown as followed:

Assume that the order size O is n, and the total item category tc is m.

Step 1 Initialization

Input an n*m matrix[Orders], the value in the matrix[Orders] is 0 or 1, if the value in row i and column j is 0, it means that order i does not include the item j, while 1 presents that order i includes the item j.

```
Set e=BQ
station_sum=SQ
station=1        //Give initial value to the station
sque=1          //the order priority
sum:=n           //sum presents the unallocated order umber
```

Step 2 Find the Core order

```
while sum>e do
    max=0
    for i=1 to n
        if sum(orders[i])>max then
            max=sum(orders[i])
            core=orders[i]^T          // the order with most item types is core
```

```
multi=orders×core
```

Step 3 Choose the most similar order with core

```
for i=1 to e-1                //start to choose the most similar order with core
    max:=0
    for j := 1 to n
        if multi [j]>max then
            max:= multi [j]
            in:=j
    multi[in]:=-1             //Assigned -1 to selected order
    orders[in]:=-1
```

Step 4 Assign orders to stations

```
result[station][sque].append(in)
    station:=station+1
    if station>station_sum then
        sque:=sque+1
        station:=1
      sum:=sum-e
```

4. The simulation results and conclusions

The simulation results are showed in table 3 and Figure 2. The DOc presents the distance per order in the model that applied the matrix-based clustering algorithm for the order allocation, the DOr presents the distance per order in the model that allocated orders randomly to the order picking station. DOr-DOc and the improvement percentage presents the effectiveness of the algorithm.

Table 3 List of simulation results

Order		DOc (meter)	DOr (meter)	DOr-DOc (meter)	Improvement Percentage
tc50	ac2an5	169.904	176.9836	7.07962	4.00%
	ac2an10	168.9525	177.0481	8.095575	4.57%
	ac5an5	421.14	440.4572	19.3172	4.39%
	ac5an10	456.1425	478.3663	22.223775	4.65%
	ac10an10	468.772	482.8352	28.53416	5.91%
tc200	ac2an5	204.365	218.2455	12.10495	5.55%
	ac2an10	200.6695	216.6636	15.994085	7.38%
	ac5an5	552.127	550.3373	34.91731	6.34%
	ac5an10	510.551	549.5105	38.95953	7.09%
	ac10an10	529.8045	572.5066	42.702135	7.46%

Figure 2 The order picking system's improvement results

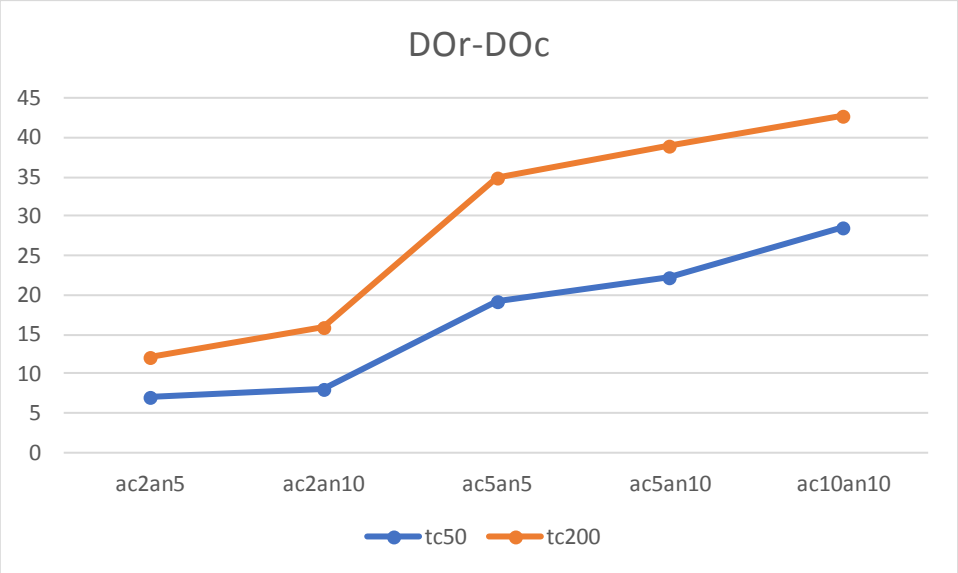


Table 1 summarizes the general insights into the performances of the two order allocation strategies: the strategy applying the matrix-based clustering algorithm performed better than the random order allocation strategy. But the figure 2 and the improvement percentage showed in table 3 indicates that the improvement is not obvious while the item category per order(ac) and the item number per order(an) is small. And the performance indicator is more sensitive to the value of ac than the value of an. And the total item category(tc) in the order batch also has an obvious influence on the performance improvement, the performance improvement is more remarkable when the value of tc is larger. In general, the matrix-based clustering algorithm improves the kiva-based order picking system's performance, especially when the system handling complexity order batch which the value of ac, tc and an is large.

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