Advances in Computer Science Research, volume 87
3rd International Conference on Mechatronics Engineering and Information Technology (ICMEIT 2019)

Research of Order Batching Variable Neighborhood Search Algorithm based on Saving Mileage

Zeping Pei, Zhuan Wang [a] and Yiwen Yang

School of Mechanical Engineering, University of Science and Technology Beijing, Beijing 100083, China.

[a]wangzhuan@ustb.edu.cn

Abstract. Basing on a picker-to-parts batch picking system of full container load, an order batching model takes picking equipment and commodity packaging volume into consideration is constructed, the objective of the model is to maximize the saving mileage. To solve the model, an order batching variable neighborhood search algorithm is proposed. With the data from a specific logistic center, a simulation experiment has been carried out. The results show that, the performance of VNS-Deco is superior to FCFS, SBBM and S&U-Deco under 4 different order pool situations, the total picking mileage optimized by VNS-Deco is reduced by 13.2%, 3.3% and 1.6% compared with FCFS, SBBM and S&U-Deco.

Keywords: order batching; mileage saving; routing optimization; variable neighborhood search algorithm.

1. Introduction

With the development of e-commerce market, the production mode of the enterprise and the characteristics of customer orders have changed, and improving the efficiency of picking operations in the distribution center has become a breakthrough point for more enterprises to seek. Picker-to-parts batch picking is one of the main picking operations in the distribution center. Orders for e-commerce are generally split and small orders. Thus, batch picking is often used, which includes two strategies: pick-while-sort and pick-and-sort. Therefore, how to merge orders to minimize the picking distance, then increase picking efficiency becomes a key issue for picker-to-parts batch picking.

Sebastian Henn et al. in [1] consider that the major issue of picker-to-parts batch picking systems is the consolidation and transformation of orders into, namely order batching. Lenoble Nicolas et al. in [2] propose that how to regroup orders into batches before the phase of collect is an effective method for order picking efficiency. In recent years, studies on order batching strategy has generally focused on solving problems with different ways. Such as queuing theory, seed algorithm, genetic algorithm, particle swarm optimization and so on.

With the idea of queuing theory, Cathy H.Y. Lam et al. use the fuzzy logic method in [3] to set the priority of the order in the picking system and then the order is combined. The experimental results show that the picking task sequence generated by the calculation method proposed in the paper reduces the walking distance of the picking persons. Xiaowei Jiang et al. in [4] use a modified seed algorithm to solve the order batching and sequencing problem with limited buffers. Sören Koch et al. in [5] solve the order batching model with grouping genetic algorithm combining with the process of local search. Marek Matusiak et al. in [6] introduce a joint order-batching and pick routing method which consists of optimal A*-algorithm and simulated annealing algorithm to solve the combined precedence-constrained order-batching and routing problem. Soondo Hong et al. in [7] propose a solving method of order batching for the wide lane physical model, considering the ergodic picking path. The results show that the total distance after the method is reduced by 9.9% compared with the single picking. Based on a Manhattan picking path strategy, Chun-Cheng Lin et al. use the particle swarm optimization algorithm in [8] to overcome the problem that the Manhattan route cannot cross the shelf in the case of order picking, and solve the order batch problem. André Scholz et al. in [9] develop a method of considering all sub-problems for the first time and propose a variable neighborhood descent (VND) algorithm. A two-stage variable domain search method is proposed to solve the order batch model by Borja Menéndez et al. in [10], and this method can find a better near optimal solution and some retained sub-optimal solution. Zhuan Wang et al. in [11] take picking equipment and commodity packaging volume as considerations and maximizing the picking mileage as optimization goal. They propose an order batching heuristic algorithm which reduces total picking distance obviously.

Order batching optimization is an NP-hard problem, large-scale such problems are difficult to solve with accurate solution methods; traditional heuristic seed or conservation algorithms are likely to fall into local extremum. Therefore, on the basis of order batching algorithm based on heuristic picking route for saving mileage presented by the author in [11], this paper takes picking equipment and commodity volume into comprehensive consideration and propose an order batching variable neighborhood search algorithm based on saving mileage namely VNS-Deco which aims at maximize the mileage saving and combines with heuristic routing strategy. At last, we compare VNS-Deco proposed in this paper with First Come First Service (hereinafter referred to as FCFS), Similarity Based Batching Method (hereinafter referred to as SBBM) and order batching algorithm based on heuristic picking route namely S&U-Deco proposed in [11].

2. Order Batching Model based on Saving Mileage

2.1 Problem Description

This paper takes the picker-to-parts picking system of full container load as the research object which adopts P-C storage and transportation mode, and the layout of the picking area is shown in Fig.1. For this picker-to-parts picking system which the variety and reserves of each cargo storage, the volume of individual packaging for each commodity and the capacity of the picking equipment is known, the current order pool data is known, how to divide the order pool into several batches (each batch is a picking task) so that the order picking route after batching can save the largest mileage compared to the single picking route. For example, the picking mileage before the combination of order 1 and 2 is d_1 and d_2 respectively while the result after combination is d_{12}. The goal of solving this problem is to maximize the saving mileage $d_{save} = d_1 + d_2 - d_{12}$ after the order is combined.

The rest of the model assumptions are the same as the model assumptions proposed by the author in [11].

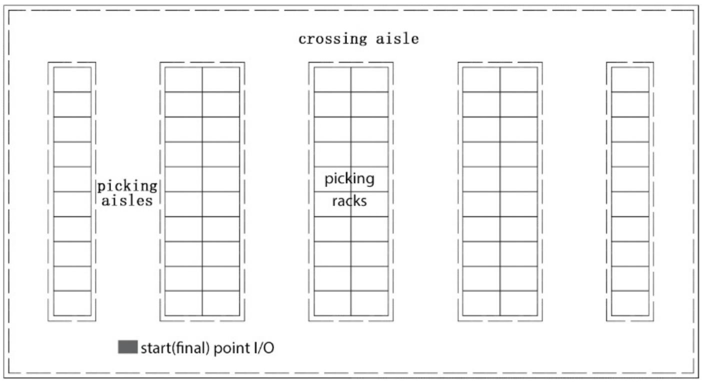

Fig. 1 layout of picker-to-parts picking system

2.2 Mathematical Model

In this section, we establish an order batching model based on saving mileage taking the volume of individual commodity packaging into consideration, and define the variables and constants in the model as follows:

I: set of orders;

B: set of batched;

N: set of commodity items;

V_{max}: the maximum allowed capacity for each picking equipment;

q_{in}: quantity of item n included in order $i \in I$;

c_n: number of stacks of item $n \in N$;

S_b: total saving mileage of batch $b \in B$;
Let X_b be a binary variable:

$$X_b = \begin{cases} 1, \text{if batch } b \text{ is selected} \\ 0, \text{if batch } b\ is\ not\ selected \end{cases}$$

Y_{ib} be a binary variable:

$$Y_{ib} = \begin{cases} 1, \text{if order } i \text{ is included in batch } b \\ 0, \text{if order } i \text{ is not included in batch } b \end{cases}$$

We denote with $\mathcal{B}$ as the set of all feasible batches, i.e., those where the capacity constraint is not violated. We also denote with $N_1(\mathcal{B})$ as the set of solutions in the k-th neighborhood of $\mathcal{B}$, $k=1,2$.
This problem can be formulated as follows:
Maximize:

$$Z = \sum_{b \in \mathrm{B}} S_b \,.\, X_b \tag{1}$$

Subject to:

$$\sum_{i=1}^{n} \left(Y_{ib} . \sum_{n \in N} \frac{q_{in}}{c_n} \right) \leq V_{max} \,, for\ \ b \in \mathrm{B} \tag{2}$$

$$\sum_{b \in \mathrm{B}} Y_{ib} . X_b = 1 \,, for\ \ i \in I \tag{3}$$

The objective function (1) indicates that the sum of the saving mileage is the largest after the order batching. (2) constrains the load volume of picking equipment, indicating that the total volume of each commodity batch does not exceed the max load volume of picking equipment. (3) means that an order can only be assigned to one batch task. The solution of this model is vector $Y_b = (Y_{1b}, Y_{2b}, Y_{3b}, \ldots)$, namely composition of batch b.

3. Order Batching Variable Neighborhood Search Algorithm

3.1 Initial Solution Generation Strategy

Taking into account the simplicity of generating the initial solution, while at the same time striving to ensure its feasibility and randomness, this section generates an initial feasible solution based on the strategy of each order for a picking batch. The initial feasible solution is a collection of pick orders consisting of $\mathcal{B}_j$, and each picking task list $\mathcal{B}_j$ corresponds to the picking task walking mileage $Dis(\mathcal{B}_j)$.

3.2 Local Search Algorithm

In this algorithm flow, the local search process is performed in the first neighborhood $N_1 = \{M_1\}$, mainly including neighborhood movement M_1: an order is moved from one batch to another batch. In the local search algorithm under the neighborhood movement, the initial feasible solution will change: $\mathcal{B} \rightarrow N_1(\mathcal{B})$. Each time the neighborhood movement ends, the mileage saved value of the new batch picking list is calculated until the saving mileage value reaches the maximum.

3.3 Neighborhood Structure

Combining the characteristics of the mathematical model of picker-to-parts order batching, this paper proposes several neighborhood movements that are applicable to the order batch problem, which is mainly reflected in the operations of orders of the picking task lists held by the single or different pickers with the condition of meeting the capacity constraints of the picking equipment:
N_1^{batch}: move an order to a different batch of the same picker;

N_2^{batch}: move an order to a different picker;
N_3^{batch}: exchange two orders of the same picker;
N_4^{batch}: exchange two orders of different pickers.

3.4 Shaking Procedure

This section presents a neighborhood shaking procedure for the picker-to-parts order batch picking problem, see Fig. 2. This variable neighborhood procedure includes two neighborhoods: N_1, N_2. Movement M_1 generates neighborhood N_1. M_2 and M_3 generate N_2:

M_1: move an order to a different batch;
M_2: move two orders to a different batch;
M_3: move two orders to two different batches.

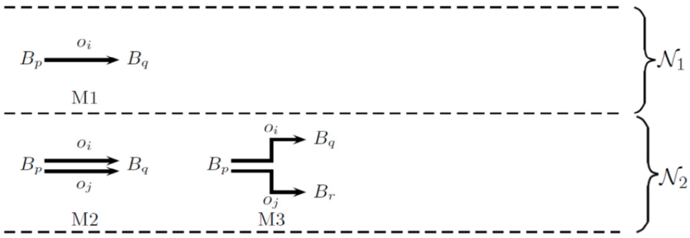

Fig.2 neighborhood movements of order batching variable neighborhood search algorithm

3.5 Implementation of Variable Neighborhood Search Algorithm

Based on the design of the above-mentioned neighborhood movements and initial feasible solution, the implementation process of the order batching variable neighborhood search algorithm is as follows and flow chart is shown in Fig. 3:

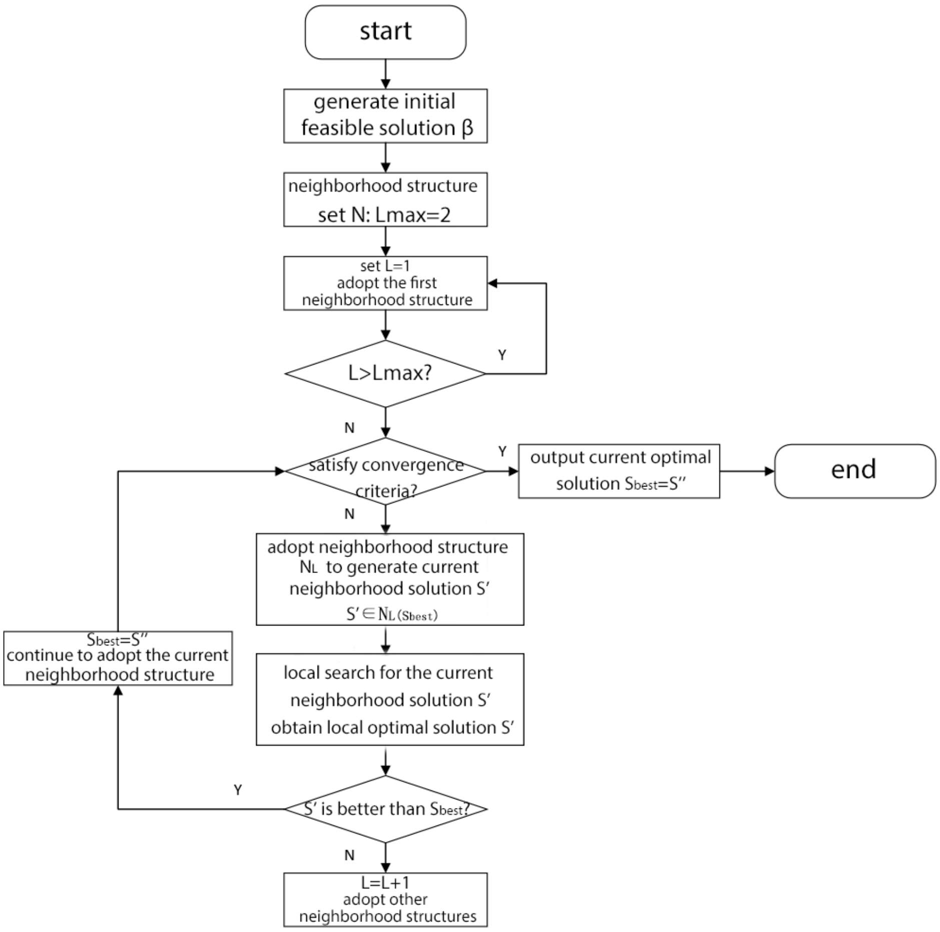

Fig.3 implementation process of the order batching variable neighborhood search algorithm

Step1. Generate an initial feasible solution $\mathcal{B}$ with a strategy that one order generates one picking order, and set $Dis(\mathcal{B})$ as the corresponding picking distance.

Step2. Execute the neighborhood $N_1 = \{M_1\}$, set $\mathcal{B} \to N_1(\mathcal{B})$, where $N_1(\mathcal{B})$ is the set of solutions generated by executing neighborhood movement performed by initial feasible solution $\mathcal{B}$. Then we can get a set of savings distances based on the original solution optimization:

$$\mathrm{S} = \{s_i = Dis(\mathcal{B}_i) - Dis(\mathcal{B}) | \mathcal{B}_i \in N_1(\mathcal{B})\}$$

We find the largest saving mileage s^* based on initial solution $\mathcal{B}$ under greedy algorithm:

$$s^* = max(S')$$

Where $S' = \{s_i > 0 | s_i \in S\}$ is a combination of all positive savings mileage based on the initial solution optimization, and $S' \subset S$.

At this time, batch B^* is an optimal solution generated by neighborhood movement N_1 and we update initial solution $\mathcal{B}$ to B^*.

Step3. Repeat Step2 until $S' = \emptyset$ and go to Step 4.

Step4. Execute the neighborhood $N_2 = \{M_2, M_3\}$, set $\mathcal{B} \to N_2(\mathcal{B})$, where $N_2(\mathcal{B})$ is the set of solutions generated by excuting neighborhood movement N_2 performed by initial feasible solution $\mathcal{B}$. Then we can get a set of savings distances based on the original solution optimization:

$$\mathrm{S} = \{s_i = Dis(\mathcal{B}_i) - Dis(\mathcal{B}) | \mathcal{B}_i \in N_2(\mathcal{B})\}$$

We find the largest saving mileage s^* based on initial solution $\mathcal{B}$ under greedy algorithm:

$$s^* = max(S')$$

Where $S' = \{s_i > 0 | s_i \in S\}$ is a combination of all positive savings mileage based on the initial solution optimization, and $S' \subset S$.

At this time, batch $B^*$is an optimal solution generated by neighborhood movement N_2 and we update initial solution $\mathcal{B}$ to B^*.

Step5. Repeat Step2 until $S' = \emptyset$, then the solution $\mathcal{B}$ is the approximate optimal solution we get.

4. Empirical Analysis and Effect Evaluation

In order to verify the effectiveness of the order batching algorithm based on variable neighborhood, an empirical experiment based on MATLAB has been carried out with the data from a specific logistic center. In this section, we set up 3 control groups to evaluate the effect of the algorithm.

4.1 Experiment Design

The physical model, picking area parameters, and order pool parameters carried out in the experiment are consistent with the experimental parameters given by the author in [11]. This paper designs four different order pools (100 orders, 150 orders, 200 orders, 250 orders) for simulation.

In order to measure the performance of each order batching method, the total picking mileage S and the average picking mileage S_k are used to evaluate. The total picking mileage S is the total distance traveled by all the picking tasks; the average walking distance S_k is the distance traveled by each picking task list, including the total distance of picking and the number of picking orders. S_k is a good measure of the work intensity of the order batching.

Three control groups, FCFS, SBBM and S&U-Deco, were set up to compare the output of the VNS-Deco with the control output. Settings S&U-Deco as a control group is order to analyze the effect of order batching using the VNS-Deco algorithm under the same path strategy.

4.2 Experiment Results

The results of the quantity of picking orders obtained by different methods under different order pool situations are shown in Table 1. It can be seen that difference among different results is small and there is no large fluctuation. According to the analysis, the quantity of picking orders K is most affected by the loading volume of the picking equipment, and is little affected by other factors. Therefore, K is only used to calculate the average walking distance S_k.

Table 1. Quantity of picking orders under different order pool situations

	Result	Unit	E1	E2	E3	E4
FCFS	K	piece	15	21	30	37
SBBM			16	23	33	40
S&U-Deco			15	22	30	38
VNS-Deco			15	22	30	38
	Average		15.3	22.0	30.8	38.3
	Variance		0.2	0.5	1.7	1.2

The total picking mileage and average picking mileage output of different batching methods are shown in Table 2. Under the different order pool situations, the total picking mileage under the VNS-Deco is the shortest. Although the total picking mileage obtained by VNS-Deco, S&U-Deco and SBBM is not much different when the order size is small, the effectiveness of the VNS-Deco becomes more and more obvious as the scale of order pool increases: when there are 250 pieces of orders, $S^{VNS\text{-}Deco}$=1811m, $S^{S\&U\text{-}Deco}$=1983m, S^{SBBM}=2206m.

Table 2. S and S_k under different order pool situations

Method	Evaluating indicator	Unit	E1	E2	E3	E4
FCFS	S^{FCFS}	m	1323	1879	2684	3302
	S_k^{FCFS}	m/piece	88.2	89.5	89.5	89.2
SBBM	S^{SBBM}	m	891	1288	1801	2206
	S_k^{SBBM}	m/piece	55.7	56.0	54.6	55.2
S&U-Deco	$S^{S\&U\text{-}Deco}$	m	808	1205	1633	1983
	$S_k^{S\&U\text{-}Deco}$	m/piece	53.9	54.8	54.4	52.2
VNS - Deco	$S^{VNS\text{-}Deco}$	m	790	1087	1429	1811
	$S_k^{VNS\text{-}Deco}$	m/piece	52.7	49.4	47.6	47.7

The saving rate of the total picking mileage under each algorithm is shown in Table 3. When the order pool scale is 250, the VNS-Deco shortens the total picking mileage by 83.3% compared to the single picking. VNS-Deco saves 1.6%, 3.6%, and 13.8% more than S&U-Deco, SBBM, and FCFS, respectively. It can be inferred from the curve trend in Fig. 4 that as the scale of order pool increases, the VNS-Deco saves more mileage.

Table 3. Saving rate of the total picking mileage under each algorithm

	E1	E2	E3	E4	Average
FCFS	68.9%	71.7%	69.5%	69.5%	69.90%
SBBM	79.1%	80.6%	79.6%	79.7%	79.75%
S&U-Deco	81.0%	81.9%	81.5%	81.7%	81.53%
VNS-Deco	81.4%	83.7%	83.8%	83.3%	83.05%

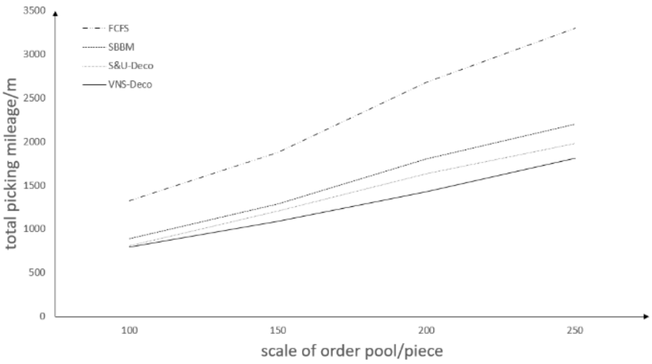

Fig. 4 Comparison of total picking mileage under four methods

Fig. 5 is a comparison chart of the average picking mileage under the four algorithms. The experimental results show that the performance of VNS-Deco is better than FCFS, SBBM and S&U-Deco under each scale of order pool. S_k includes two dimensions of total picking mileage and quantity of picking orders, which can better evaluate the effectiveness of the algorithm. Therefore, the VNS-Deco proposed in this paper has better batching optimization effect under each order scale. The larger the order scale, the more obvious the optimization effect.

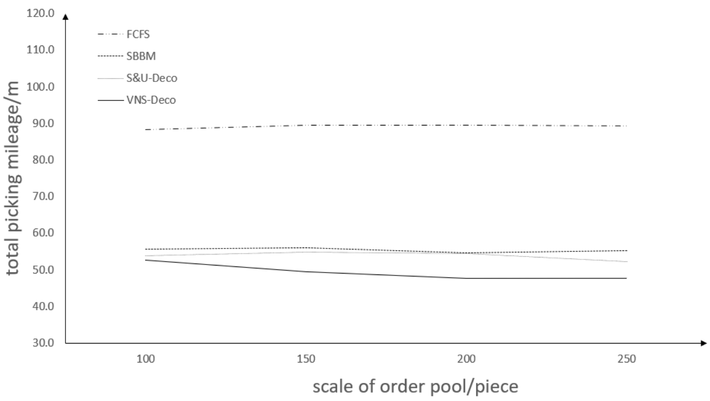

Fig. 5 Comparison of average picking mileage under four methods

4.3 Conclusion

Through empirical analysis, the following conclusion are obtained:

The total picking mileage S obtained under the VNS-Deco algorithm is the shortest, and as the quantity of orders increases, the optimization effect becomes more apparent;

The average picking mileage S_k obtained under the VNS-Deco algorithm is the shortest, and pickers will complete the picking task generated by VNS-Deco more quickly;

The VNS-Deco algorithm has the best performance and can save an average of 83.05% picking mileage under four different order pool situations. In contrast, FCFS, SBBM, and S&U-Deco algorithms can only save an average of 69.9%, 79.75%, and 81.53% of total picking mileage, respectively.

5. Summary

In this paper, maximizing the saving mileage of batch picking is the goal of optimization and principle of order consolidation, and we propose an order batching variable neighborhood search algorithm based on saving mileage namely VNS-Deco. Using the MATLAB simulation platform, simulation experiments were carried out on FCFS, SBBM, S&U-Deco and VNS-Deco under 4 different order pool situations. The experimental results show that the VNS-Deco is effective in saving picking mileage under different scales of order pools: the VNS-Deco can save an average of 83.05% picking mileage.

References

[1]. Sebastian Henn, Verena Schmid, Metaheuristics for order batching and sequencing in manual order picking systems, Computers & Industrial Engineering, Volume 66, Issue 2,2013, Pages 338-351, ISSN 0360-8352.

[2]. Lenoble Nicolas, Frein Yannick, Hammami Ramzi, Optimization of order batching in a picking system with Carousels, IFAC-PapersOnLine, Volume 50, Issue 1,2017, Pages 1106-1113, ISSN 2405-8963.

[3]. Cathy H.Y. Lam, K.L. Choy, G.T.S. Ho & C.K.M. Lee.An order-picking operations system for managing the batching activities in a warehouse [J]. International Journal of Systems Science, 2014, 45(6): 1283-1295.

[4]. Xiaowei Jiang, Yaxian Zhou, Yuankai Zhang, Lijun Sun, Xiangpei Hu, Order batching and sequencing problem under the pick-and-sort strategy in online supermarkets, Procedia Computer Science, Volume 126, 2018, Pages 1985-1993, ISSN 1877-0509.

[5]. Sören Koch, Gerhard Wäscher. A grouping genetic algorithm for the Order Batching Problem in distribution warehouses [J]. Journal of Business Economics, 2016, 86(1–2):131–153.

[6]. Marek Matusiak, René de Koster, Leo Kroon, Jari Saarinen, A fast simulated annealing method for batching precedence-constrained customer orders in a warehouse, European Journal of Operational Research, Volume 236, Issue 3, 2014, Pages 968-977, ISSN 0377-2217.

[7]. S Hong, Y Kim. A route-selecting order batching model with the S-shape routes in a parallel-aisle order picking system [J]. European Journal of Operational Research, 2017, 257(1):185-196.

[8]. Chun-Cheng Lin, Jia-Rong Kang, Chung-Chih Hou, Chen-Yang Cheng, Joint order batching and picker Manhattan routing problem, Computers & Industrial Engineering, Volume 95, 2016, Pages 164-174, ISSN 0360-8352.

[9]. André Scholz, Daniel Schubert, Gerhard Wäscher, Order picking with multiple pickers and due dates – Simultaneous solution of Order Batching, Batch Assignment and Sequencing, and Picker Routing Problems, European Journal of Operational Research, Volume 263, Issue 2, 2017, Pages 461-478, ISSN 0377-2217.

[10]. Borja Menéndez, Eduardo G. Pardo, Antonio Alonso-Ayuso, Elisenda Molina, Abraham Duarte. Variable Neighborhood Search strategies for the Order Batching Problem [J]. Computers & Operations Research, 2017, 78: 500-512.

[11]. WANG Zhuan, PEI Zeping. An order batching algorithm based on heuristic picking route for saving mileage. [J]. Computer Engineering and Applications,2018,54(23):203-209+222.