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A Solution of Freshness Constraint Order Batching Problem for Fresh Food E-Commerce

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Abstract. Influenced by the Covid-19 pandemic, fresh food e-commerce market in China developed quickly. Efficient solution for Order Batch Problem (OBP) could achieve efficient batching operation and then reduce costs and control risks. However, the OBP model proposed by the previous researches did not consider the characteristics of fresh food products such as the less demand of orders, the large variety of products, perishability of products and etc. Therefore, this paper proposed a model of OBP with freshness constraint of perishable food products, and proposed a two-stage heuristic algorithm to solve the target problem of the model. Our solution could improve the efficiency of the sorting process while ensuring the freshness of food products.

Keywords. Genetic Algorithm, Ant Colony Optimization, Order Batching Problem, Fresh Food E-commerce

1. Introduction

Influenced by the Covid-19 pandemic, fresh food e-commerce market in China developed quickly. In 2020, fresh food e-commerce market reached 458.49 trillion yuan, increasing by 64% compared to 2019. Sorting process is important in e-commerce, because it affects logistics efficiency and service quality. Previous researches have focused on Order Batch Problem (OBP) to achieve efficient batching operation and then reduce costs and control risks [1]. However, since traditional e-commerce mostly sales the products with long shelf life, traditional OBP normally considers the facts of storage locations, aisles and picking vehicles. Therefore, this paper proposed an OBP that considers freshness of perishable food products, intended to improve the efficiency of the sorting process and reduce the cost of fresh food e-commerce.

Inspired by the idea that the sorting process of a distribution center can be considered as an assembly line that includes picking, collecting, and packing [2]. This paper firstly constructed a two-level model with the goal of reducing the idle time for the sorting process. A concept of freshness was introduced as a constraint to ensure that all products were in good condition when loading. Secondly, it proposed a two-stage heuristic algorithm in accord with two sub-processes based on an elitism Genetic Algorithm

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(e-GA) and an improved Ant Colony Optimization (ACO) to solve the target problem of the model. Lastly, the effectiveness of the algorithm was validated by simulated data. The results indicate that the method proposed in this study can improve the efficiency of the sorting process while ensuring the freshness of food products.

2. Procedures of Sorting in Parallel Partition Mode

Constrained by storage conditions and relevance, perishable products are stored in different areas separately in distribution centers. For large storage center with a great many of product categories, a parallel partition mode could improve the efficiency of sorting, which includes parallel picking, collecting and inspecting, packing and loading. Figure 1 shows the example flows of batches A, B, and C during sorting process.

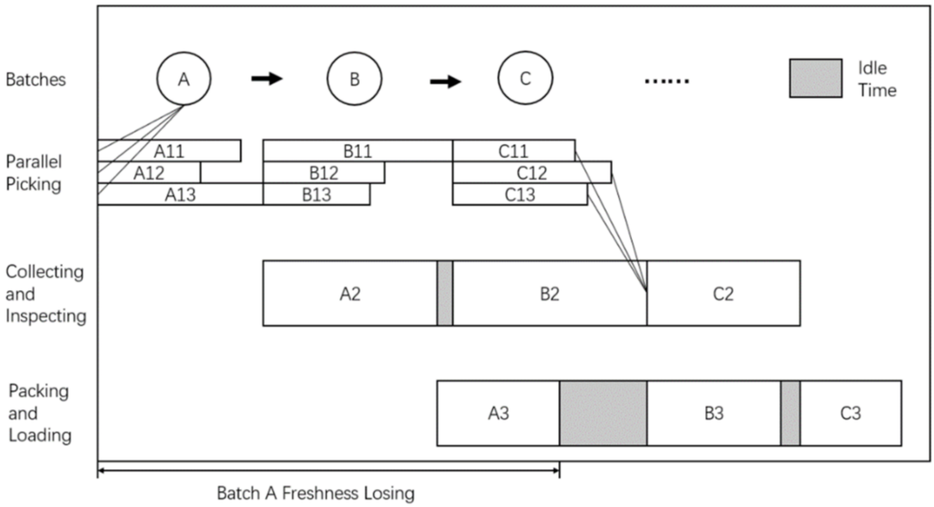

Figure 1. The flows of batches A, B, and C during sorting process under parallel partition mode

3. Model Description

3.1. Problem Description

The study focused on the sorting process of perishable products in a single warehouse. The different kinds of fresh products stored in different regions in the warehouse, and sorted in parallel between regions. Each order has random demand for different kinds of products with different shelf lives. And different orders composed as batch, which would be dispatched by a fleet of cold chain vehicles according to the shipping capacity. Obviously, the larger batch size could cause longer process and increase the freshness loses. On the one hand, considering of the economies of scale, each batch should be as large as possible. On the other hand, the size of batches should be limited by the constraint of freshness. Therefore, a suitable number of orders per batch should be achieved. The order batching and sequencing are determined to minimize the idle time between procedures.

3.2. Assumption

(1) The probability distribution of demand for all goods is in accordance;
(2) Any order is not allowed to be split into different batches;
(3) Picking for the next batch can only begin after the picking for current batch in all regions has been finished;
(4) After the order set is determined, new orders are not allowed to be inserted (Urgent orders are not considered);
(5) The freshness of the goods decays constantly from the beginning of sorting, and the minimum freshness must be met at the time of loading;
(6) Shelf lives of products in different areas are different, but in same area are the same.

The table 1 shows the symbols to be used later and their meanings.

Table 1. Symbol description

Sets			
N	Orders set in a certain period, $\{1,2,\dots,n\}$	i	Order $i \in N$
M	Batches set, $\{1,2,\dots,m\}$	j	Batch $j \in M$
O	Sequence of the batches, $\{1,2,\dots,m\}$	k	Position of batch $k \in O$
D	Picking areas, $\{1,2,\dots,d_{max}\}$	p	Procedure $p \in P$
P	Procedures, {1 = Picking, 2 = Collecting, 3 = Packing}	d	Location of good $d \in D$
S_j^D	Number of picking areas batch j involves	S_j^N	Number of orders batch j involves
Constants			
Q_{id}	The number of SKUs of order i in area d	t_1	Picking time for an SKU
Q_i	The number of SKUs in order i	t_2	Time constant for collecting
T_d	Shelf life of goods in area d	t_3	Time constant for packing
g_d	Minimum freshness of goods in area d	t_0	Set time for each batch of orders
Variables			
S	The maximum number of orders per batch	t_{jd}^1	Picking time of batch j in area d
A_{jd}	When batch j contains goods in area d, $A_{jd}=1$, otherwise $A_{jd}=0$	t_j^p	Operation time of the batch j in procedure p
I_k^p	Initial time of the kth batch in procedure p		
F_k^p	Finish time of the kth batch in procedure p		
Decision Variables			
x_{ij}	When order i is in batch j, $x_{ij}=1$, otherwise $x_{ij}=0$, $i \in N, j \in M$		
y_{jk}	When batch j is at the kth, $y_{jk}=1$, otherwise $y_{jk}=1$, $i \in N, k \in O$		

3.3. Variable Calculations

Eq. (1) corresponds to whether the batch contains goods in certain picking area; Eq. (2) simplifying the solution of the picking time in each region; Eq. (3) indicates the picking time of the batch order is the longest one of each area; Eq. (4) calculates the time of collecting and inspecting; Eq. (5) calculates the time of packing and loading; In eq. (6), $\theta(t)$ is the freshness of the goods, t is an independent variable about time, T is shelf life of goods.

$$A_{jd} = \begin{cases} 0, & \sum_i x_{ij} \cdot Q_{id} = 0 \\ 1, & else \end{cases} \tag{1}$$

$$t_{jd}^1 = t_0 + t_1 \cdot \sum_i x_{ij} \cdot Q_{id} \tag{2}$$

$$t_j^1 = max\{t_{jd}^1 | d \in D\} \tag{3}$$

$$t_j^2 = t_2\left(\sum_i x_{ij} \cdot Q_i + \frac{1}{5}S_j^P\right) \tag{4}$$

$$t_j^3 = t_3\left(\sum_i x_{ij} \cdot Q_i + \frac{1}{5}S_j^N\right) \tag{5}$$

$$\theta(t) = 1 - \frac{t}{T}, \quad 0 \le t \le T \tag{6}$$

Eq. (7) and (8) calculate the maximum order quantity per batch. Eq. (7) indicates that the maximum order quantity needs to meet the minimum freshness.$t(S)$ indicates the estimated operation time for single batch with largest order quantity. Eq. (8) uses the probability distribution of the Q_{id} and the operation time of the three procedures to estimate the maximum number of orders per batch, and obtains the quantity of the order batch $m = \left\lceil \frac{n}{S} \right\rceil$. λ is the expectation of Q_{id}. α is a prediction factor$(1 < \alpha < 2)$.

$$1 - \frac{t(S)}{T_d} \ge g_d, \ \forall d \tag{7}$$

$$\begin{aligned} t(S) = (t_0 + \alpha \cdot S \cdot \lambda \cdot t_1) + t_2\left(\alpha \cdot S \cdot \lambda \cdot d_{max} + \frac{1}{5}d_{max}\right) \\ + t_3\left(\alpha \cdot S \cdot \lambda \cdot d_{max} + \frac{1}{5}S\right) \end{aligned} \tag{8}$$

Eq. (9) and (10) calculate the end and start times of the procedure p of the kth batch.

$$F_k^p = I_k^p + \sum_j t_j^p \cdot y_{jk}, \quad \forall k, p \tag{9}$$

$$I_k^p = \begin{cases} 0, & k = 1, p = 1 \\ F_{k-1}^p, & k \ge 2, p = 1 \\ F_k^{p-1}, & k = 1, p \ge 2 \\ max\{F_{k-1}^p, F_k^{p-1}\}, & k \ge 2, p \ge 2 \end{cases}, \quad \forall k, p \tag{10}$$

3.4. Two-level Programming Model

(1) Upper model:

$$min \sum_j \sum_d \left| \sum_i x_{ij} \cdot Q_{id} - \frac{1}{m} \sum_i Q_{id} \right| \tag{11}$$

$$s.t. \ \sum_j x_{ij} = 1, \quad \forall i \tag{12}$$

$$\sum_i x_{ij} \le S, \quad \forall j \tag{13}$$

$$1 - \frac{t_j^1 + t_j^2 + t_j^3}{T_d} \ge g_d, \quad \forall j, d \tag{14}$$

$$x_{ij} \in \{0,1\}, \quad \forall i, j \tag{15}$$

(2) Lower model:

$$min \sum_{p=1}^{3} \sum_{k=1}^{m} I_k^p - F_{k-1}^p \tag{16}$$

$$s.t. \ \sum_k y_{jk} = 1, \quad \forall j \tag{17}$$

$$\sum_j y_{jk} = 1, \quad \forall k \tag{18}$$

$$1 - \frac{F_k^3 - I_k^1}{T_d} \ge g_d \cdot A_{jd}, \quad \forall k, d \tag{19}$$

$$y_{jk} \in \{0,1\}, \quad \forall j,k \tag{20}$$

The objective function (11) of the upper model keeps balance of the load of each picking area in each batch to ensure the balance of scale between each batch, thereby reducing the idle time caused by excessive load differences. Constraint (12) represents that any order cannot be split; Constraint (13) means that the scale of each batch cannot exceed the maximum number of orders; Eq. (14) represents the constraint of the lowest freshness; Constraint (15) represents the range of values of the decision variable x_{ij}.

In the objective function (16) of the lower model, the total idle time of the sorting process of all batches is minimized. Constraints (17) and (18) ensure the uniqueness of the sequence of all batches. Constraint (19) means that the minimum freshness must be met when goods leave the warehouse; Constraint (20) represents the range of values of the decision variable y_{jk}.

4. Algorithm of Solution

In the two-stage heuristic algorithm [3] proposed in this study, the e-GA is used to solve the OBP for the upper model (figure 2a), the improved ACO is used to solve the batch sorting problem for the lower model (figure 2b).

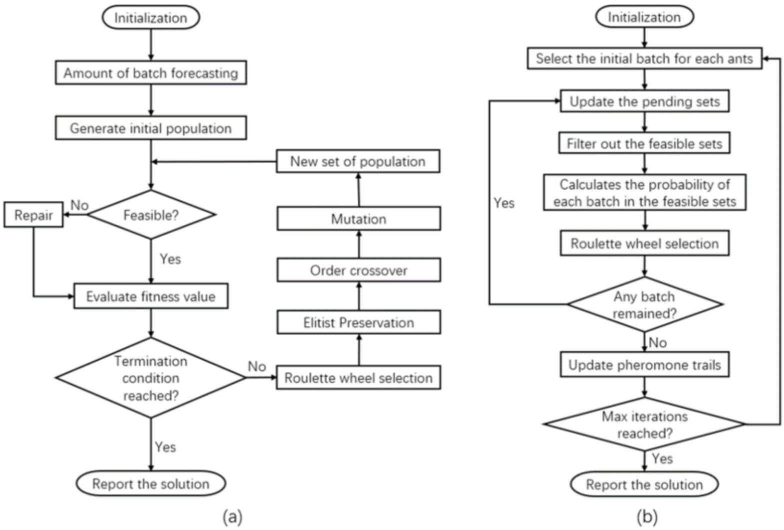

Figure 2. Flowchart of the two-stage heuristic algorithm proposed. (a) The e-GA for the upper model. (b)The improved ACO for the lower model

4.1. The e-GA for Order Batching

In order to cope with the two main problems in GA: slow convergence speed, and lack of effective processing strategies for constraints [4]. We adopted the elitist preservation strategy in GA. Two individuals with the highest fitness in the previous population are chosen to replace two individuals with the lowest fitness in the subsequent population. Moreover, binary encoding is used to transform the solution into the search space of the algorithm. With the help of the penalty function, the constraint problem is transformed into an unconstrained problem. The algorithm uses a proportional fitness value to measure the adaptability of chromosomes (see Eq. (21)). F_i correspond to the objective function values. The roulette method is used to select the individuals for crossover, mutation and preservation based on the probability of the individual's fitness (see Eq. (22)). In the stage of crossover, the strategy is shown as figure 3. We first select two intersections on two parent chromosomes randomly. The locations of the orders between the intersections are then exchanged. There are two strategies for mutation, selecting two batches A and B randomly in an individual, (i) if the number of orders in A is equal to B, the position of an order in each other will be exchanged; (ii) If the number of orders in A is greater than B, one of the orders will be transferred from A to B. Children meet the constraints will be retained, or be fixed by local search. Through this manner overall fitness of the offspring could be improved.

$$fitness_i = \frac{1}{(F_i/\sum_i F_i)} \tag{21}$$

$$P_i = \frac{fitness_i}{\sum_i fitness_i} \tag{22}$$

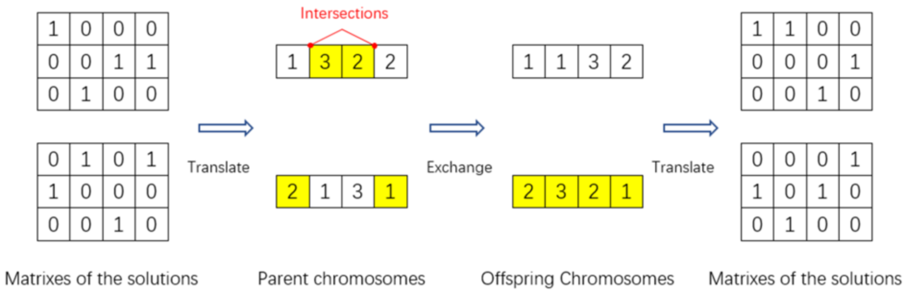

Figure 3. Strategy of double-intersections crossover

4.2. The Improved ACO for Batch Sorting

We proposed an improved ACO. Before the ant selects the next batch, a feasible set was created by calculating whether each batch in the candidate set can meet the constraint of freshness according to Eq. (19). Eq. (23) calculates the probability of each batch in the feasible set being the subsequent. The subsequent batch is determined using the roulette wheel selection. The calculation of the heuristic term takes the fluency between the current batch and the candidate batch into account. From figure 1, the smaller the difference in the time between the adjacent procedures correspond to batch A and B is, the shorter the waiting time between two batches is, and the better the fluency between A and B is. The calculation of the heuristic term is as in Eq. (24). The pheromones will be updated once after an iteration of all batches (see Eq. (25)).

$$p_{ij}^k = \frac{{\tau_{ij}}^{\alpha} \cdot {\eta_{ij}}^{\beta}}{\sum_{k \in allowed} {\tau_{ik}}^{\alpha} \cdot {\eta_{ik}}^{\beta}}, \quad j \in allowed \tag{23}$$

$$\eta_{ij} = \frac{1}{\left|t_i^2 - t_j^1\right| + \left|t_i^3 - t_j^2\right|} \tag{24}$$

$$\tau_{ij}(t+1) = (1-\rho) \cdot \tau_{ij}(t) + \sum_{k=1}^{K} \Delta\tau_{ij}^k \tag{25}$$

$$\Delta\tau_{ij}^k = \begin{cases} Q/T_k, & The\ \ ant\ k\ passed\ through\ route\ ij; \\ 0, & The\ \ ant\ k\ did\ not\ pass\ through\ route\ ij. \end{cases} \tag{26}$$

τ_{ij} represents the pheromone on route ij. η_{ij} is the heuristic term. α and β are the pheromone factor and the heuristic factor. $allowed$ is the feasible set. k is the number of the ant. ρ is a pheromone volatile factor. $\Delta\tau_{ij}^{k}$ is the total pheromone left by the ant k on route ij (see Eq. (26)). Q is a pheromone constant. T_k represents the cumulative idle time of the ant k.

5. Experiments and Results

This paper took five different scales of experiments from 100 to 1000 order, the data of different fresh food demand is stimulated by following the Poisson distribution [5] of $\lambda = 1.5$. Referring to the actual warehouse layout, the number of picking areas was set to 3. The specific parameters of the experiment are shown in table 2.

Table 2. Parameters of the distribution center

Parameter	Value
n	100,300,500,750,1000
d_{max}	3
Q_{id}	Follows the Poisson distribution of $\lambda = 1.5$
t_0	5
t_1	4
t_2	0.9
t_3	1.3
α	1.2
T_d	$\{d = 1,2,3 \vert 600,650,700\}$
g_d	$\{d = 1,2,3 \vert 0.20,0.35,0.30\}$

The parameters of algorithms for different scales are shown in table 3. The population size and the number of ants should take convergence velocity and randomness into account [1].

Table 3. Parameters set

n	Population size	Generations of GA	Number of ants	Iterations of ACO
100	100	13	8	5
300	100	15	21	10
500	200	25	36	100
750	350	35	53	130
1000	500	35	70	140

In this paper, rest of the parameters of the ACO were set as follows: $\alpha = 1,\ \beta = 4.5,\ \rho = 0.2, Q = 100$.

This study set a horizontal and vertical comparison between the sorting mode based on the two-stage heuristic algorithm and the traditional first come first serve (FCFS) rule at different scales, as shown in table 4. The analysis shows that the proposed method can reduce the idle time by 4.245% to 30.77%, which proves that the proposed model has certain feasibility and superiority. As the number of orders increasing from 100 to 1000, the improvement shows a trend of rising first and then decreasing, indicating that there is an optimal number of orders to make the effect of the proposed method reach the best.

Table 4. Comparison of results for the proposed method and FCFS

n	The proposed method	FCFS	Reduction (%)
100	250.04	269.58	7.25%
300	878.20	1268.60	30.77%
500	1648.48	1959.08	15.85%
750	2806.16	3122.69	10.14%
1000	3688.98	3852.14	4.24%

6. Conclusion

Base on the growing demand of market for fresh food products, we aimed to propose a strategy that improves the efficiency of OBP in fresh food e-commerce. Our study analyzed the sorting process of fresh goods in parallel partition mode in a distribution center, and model an OBP that considered freshness. Then, we proposed a two-stage heuristic algorithm, which used the e-GA and the improved ACO to solve the order batching problem and the batch sorting problem. The model was validated by stimulated data and showed the superiority over FCFS, which exhibited that our solution could increase the operational efficiency of sorting process and preserve the freshness of food, and then reduce the cost of fresh food e-commerce.

Acknowledgments

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