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The Multi-objective Optimization for Perishable Food Distribution Route Considering Temporal-spatial Distance

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Abstract

For perishable food products, customer satisfaction mainly reflects on the freshness. Due to the highly value lost in the distribution process, the complexity of perishable food vehicle routing problem increases. So it is important to design an effective distribution route that can minimize the total costs and maximize the freshness state of the delivered products. We propose a multi-objective vehicle routing problem with time windows dealing with Perishability (MO-VRPTW-P). A two-phase heuristic algorithm based on Pareto variable neighborhood search-genetic algorithm considering temporal-spatial distance (STVNS-GA) is applied to solve the problem. Several numerical examples are presented. The results illustrate that the algorithm is effective and efficient.

Keywords: perishable food distribution; freshness, MO-VRPTW-P; temporal-spatial distance; VNS; genetic algorithm

1. Introduction

The perishable food products distribution can be abstracted as vehicle routing problem (VRP) [1].It has long been recognized that managing perishable food is a difficult problem, such as vegetables, milk, meat, flowers distribution. For perishable food products, customer satisfaction mainly reflect on the freshness. Perishable products usually have a short life cycle and deteriorate rapidly, the value or quality of perishable food products will decrease rapidly once

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they are produced and will keep decaying when being delivered. The life of perishable food depends on the time. Thus, timely delivery perishable food not only significantly affects the delivery operator's cost, but also the satisfaction of customers. Furthermore, with fresh e-commerce develops rapidly in recent years such as Alibaba, JD, Amazon, Local harvest, and so on, the orders characteristics tend to be smaller lot-size and higher frequency, which increase the complexity of the distribution [2]. A well-designed delivery method must be made so that supplier can ensure the freshest products in a cost-effective way. So effective solution and algorithm are necessary to improve the work efficiency in the perishable food distribution process.

In the paper, we present a multi-objective vehicle routing problem with time windows dealing with Perishability (MO-VRPTW-P). In our work, we propose a framework to minimize the total costs and maximize the freshness state of the delivered products. Thus, company can reduce costs and achieve higher level of the customer satisfaction in freshness aspect. We design a two-phase variable neighborhood search-genetic heuristic algorithm considering temporal-spatial distance (STVNS-GA) based on Pareto to solve this multi-objective problem. In the first stage, we use K-means clustering methods that considering spatial-temporal (ST) distance to obtain the initial solution. In the second stage, we apply the variable neighborhood search (VNS) and genetic algorithm based on Pareto method to optimize the distribution route. We select the better non-determined solutions of each generation by adopting the crowding distance strategy and put them into the external-archive.

The remainder of this paper is organized as follows. Section 2 contains literature review of perishable food distribution problem. We establish an optimization model to minimize the total costs and maximize the freshness of the products in Section 3. The solution of the model and the suitable algorithm are presented in Section 4. In Section 5, the results obtained from the computational experiments are shown. Finally, we conclude the paper in Section 6 by providing several topics for further research.

2. Literature review

The well-known vehicle routing problem with time windows (VRPTW) has been discussed deeply. However, few papers consider VRPTW for perishable goods in recent years.

Some literatures concentrated on perishable food products distribution problems without explicitly taking the losing of freshness into account as time go on. The work of Tarantilis and Kiranoudis[3] solved a heterogeneous fixed-fleet to find a vehicle operation schedule for fresh milk. A threshold-acceptance-based algorithm was developed that aimed to satisfy the needs of a company. Zhang et al.[4] presented a tabu search algorithm that optimizing the structure of cold chains distribution system. Faulin et al.[5] presented a hybrid algorithm that combination heuristics and exact algorithms to find a solution to VRP with constrains.

In concerning the freshness explicitly, Chen et al.[6] proposed a nonlinear mathematical model to consider production scheduling and vehicle routing with time windows for perishable food products, and the model is solved by Neder-Mead method and heuristic algorithm. Naso et al.[7] considered the perishable materials problem of scheduling and distribution. They proposed a strategy that combines genetic algorithms and schedule construction heuristics for job scheduling and truck routing. Osvald and Stirn[8] extended a heuristic algorithm to solve the distributing fresh vegetables in which perishability represents a critical factor. Hsu et al.[9] considered the randomness of the perishable food delivery process and presented a stochastic VRPTW model to obtain optimal delivery routes. The problem is solved by a heuristic procedure.

Recently, Hasani et al.[10] designed a closed-loop supply chain for perishable goods. Commercial optimization software LINGO was applied to derive a solution to be mathematical model. Amorim et al.[11] considered the issue of lot sizing versus batching in the production and distribution planning of perishable goods. Govindan et al.[12] suggested a two-echelon multiple-vehicle location-routing problem for supply chain network of perishable food and a multi-objective optimization model for perishable food supply chain network was developed. Song et al.[13] proposed a nonlinear model and a heuristic algorithm to generate efficient vehicle routings with the objective of maximizing the customer satisfaction in freshness aspect.

However, few research focus on the effective algorithm to solve the perishable food products multi-objective that minimization the distribution costs and maximization the freshness concerning on the freshness explicitly. In our work, we design a two-phase heuristic algorithm which based on Pareto variable neighborhood search-genetic algorithm.

3. Problem statement and Mathematical model

3.1. Problem statement

Real perishable food distribution network is a complex system, which including the distribution in different parts with distribution center and many customers. We propose the MO-VRPTW-P that considering time-sensitive spoilage rates of perishable food products. The first objective minimizes the total costs, which contains fixed costs, transportation costs, penalty costs and damaged costs. The second objective maximizes the average freshness of the deteriorating products remaining life. We assume that distribution system includes a farm depot as a distribution center and multiple customers. Meanwhile the demand and time window of the customers are known. These perishable products need to be sent to customers, which may have different time window requirements. Any vehicle that arrives early has to wait until the beginning of the time window. Any vehicle that arrives late will incur a penalty. The value of perishable food products will decay once distribution begin. All the products remaining life meet the demand of customers. In order to describe the damaged costs and characteristic of perishable products, this article will consult the definition from the literature[14] to cite the freshness factor. The perishable food quality rapidly decreases with the transportation time t_i. $\theta(t_i)=1-t_i^2/T^2$, T indicates the life cycle of perishable products, $0 \le t_i \le T$.

The changing loss ratio of food: $\varphi(t_i)=e^{\frac{\ln 2}{T}t_i}-1$. The freshness factor: $\beta(t_i)=1-\varphi(t_i)=2-e^{\frac{\ln 2}{T}t_i}$, $\beta(t)\in[0,1]$.

To formulate the mathematical model, the assumptions are as follows:

1. The customer orders can't be split.
2. The distribution center has enough ability to complete all distribution tasks.
3. All vehicles leave and return to the distribution center.
4. We only consider the service time regardless of loading and unloading time.
5. The loss of the perishable products quality as a linear function of time during the process of distribution.
6. The travel path between the customers depends on time.
7. Soft time windows for all customers.
8. The damaged costs are equal to the product of loss ratio and quantity of perishable food.

3.2. Mathematical model

The following notations are used to formulate the problem considered in this paper.

Parameters:

N : A set of nodes, $N\{n \| n=1,2......,\|N\|\}$;	c_k : The unit transportation cost of the vehicle k ;
K : A set of vehicles, $K\{k \| k=1,2......\|K\|\}$;	t_{ij} : The transportation time between node i and j ;
(i,j) : Arcs;	d_{ij} : The distance between node i and node j ;
$[e_i,l_i]$: The time window of customer i ;	q_i : The demand of the customer i ;
t_{oki} :The time of vehicle k arriving at customer i ;	β : The minimum level that the customer can accept;
Q : The vehicle maximum capacity;	f_k : The fixed costs of the vehicle k ;
s_i : The service time in customer i ;	v : The speed of vehicle k ;
$\beta(t_i)$: Freshness of products delivered to customer i ;	w_2 : Weighting coefficient of penalty waited cost;
w_2 : Weighting coefficient of penalty delayed cost;	w_3 : Weighting coefficient of damaged cost;

Decision variables:

x_{ij}^k : binary that takes the value 1 if arc (i,j) belongs to the route of vehicle k ;
y_i^k : binary that takes the value 1 if customer i is assigned to vehicle k ;

The mathematical model is:

$$Min\ Z_1 = \sum_{(i,j,k)} x_{ij}^k t_{ij} c_k + \sum_{(i=0,j,k)} x_{ij}^k f_k + w_1 \sum_{(i,j,k)} x_{ij}^k \max(e_i - t_{oki}, 0) + w_2 \sum_{(i,j,k)} x_{ij}^k \max(t_{oki} - l_i, 0) + w_3 \sum_{(i,j,k)} \varphi(t_i) q_i x_{ij}^k \quad (1)$$

$$Max\ \ Z_2 = \frac{\sum_{i=0}^{N} \beta(t_i) \cdot q_i}{\sum_{i=0}^{N} q_i} \quad (2)$$

$$\sum_{i=1}^{N} y_i^k q_i \le Q^k \quad \forall k \in K \quad (3)$$

$$\sum_{i \in N} x_{ij}^k = \sum_{i \in N} x_{ji}^k \quad \forall j \in N, k \in K \quad (4)$$

$$\sum_{k=1}^{K} \sum_{i=1}^{N} x_{i0k} = \sum_{k=1}^{K} \sum_{j=1}^{N} x_{0jk} = 1 \quad \forall i \in N, j \in N, k \in K \quad (5)$$

$$t_{oki} = t_{ok(i-1)} + s_{i-1} + t_{i(i-1)} \quad \forall i \in N \quad (6)$$

$$\beta(t_i) \ge \beta \quad \forall i \in N \quad (7)$$

$$x_{ij}^k (1 - x_{ij}^k) = 0 \quad \forall i \in N, j \in N, k \in K \quad (8)$$

$$y_i^k (1 - y_i^k) = 0 \quad \forall i \in N, k \in K \quad (9)$$

Where the objective function (1) minimizes total costs, which are composed of fixed cost, transportation cost, penalty costs and damaged costs; The objective function (2) maximizes the average freshness. Constrain (3) represents that the demand on one route cannot exceed vehicle maximum capacity; Constrain (4) is flow conservation constrain that describe the individual route; Constrain (5) states that each vehicle should leave and return to distribution center; Constrain (6) defines that the vehicle k arrival time at customer i; Constrain (7) ensures the lowest level of freshness that customer can accept; Constrain (8) represents that vehicle k travel from customer i to j; Constrain (9) represents vehicle k serves customer i.

4. A two-phase Solution of the Model

The MO-VRPTW-P optimization is a NP-hard problem. Multiple objectives usually need to be optimized at the same time. In the combination optimization problem, Genetic algorithm (GA) is an efficient global optimal algorithm and variable neighborhood search (VNS) is an efficient local search algorithm. In the paper, we combine the improved GA with the VNS, and then applied the hybrid algorithm to solve the multi-objective problem. We design a two-phase heuristic algorithm (STVNS-GA) based on Pareto method. In the first stage, we use the K-means method cluster the nodes to obtain the initial solution considering spatial-temporal (ST) distance. In the second stage, we adopt the Variable neighborhood search (VNS) and genetic algorithm to optimize the distribution route. We select the better non-dominated solutions of every generation by adopting the crowding distance and put them into the external archive.

4.1. Generate initial solution in the first stage

A. Temporal-spatial distance

Refined fresh food distribution task has obvious space and time characteristics. In the process of delivery, each fresh food order has a corresponding distribution object, delivered quantity and time window. Considering orders of Temporal-spatial Distance may solve the problem effectively than just considering the distance. This article will consult the definition Temporal-spatial Distance from the literature[15] to cluster orders, and then structure the initial solution.

D_{ij}^{ST} is the Temporal-spatial distance between orders. D_{ij}^{S} is the Euclidian distance between customer i and j, t_{ij} is the corresponding transportation time. This paper uses the running time of the distribution points to replace the Euclidean distance for the sake of closing to the actual transport conditions, which means $D_{ij}^{S} = t_{ij}$. $\alpha_1 + \alpha_2 = 1$.

$$D_{ij}^{ST} = \alpha_1 \left(\frac{D_{ij}^{S} - \min\limits_{\substack{m,n\in C\\ m\neq n}}(D_{mn}^{S})}{\max\limits_{\substack{m,n\in C\\ m\neq n}}(D_{mn}^{S}) - \min\limits_{m,n\in C}(D_{mn}^{S})} \right) + \alpha_2 \left(\frac{D_{ij}^{T} - \min\limits_{m,n\in C}(D_{mn}^{T})}{\max\limits_{\substack{m,n\in C\\ m\neq n}}(D_{mn}^{T}) - \min\limits_{\substack{m,n\in C\\ m\neq n}}(D_{mn}^{T})} \right) \quad \forall i,j \in C \tag{10}$$

$[a,b]$ and $[c,d]$ is the time window of customer i and j, the specific arrival time at customer j is $t' \in (a',b')$, $a' = a + s_i + t_{ij}$, $b' = b + s_i + t_{ij}$, A is the max window width of order, k_1, k_2, k_3 are parameters related to time. Denote $Sav_{ij}(t')$ to be the saved time when vehicle arrives at customer j at the moment t'.

$$Sav_{ij}(t') = \begin{cases} k_2 t' + k_1 d - (k_1 + k_2)c & t' < c \\ -k_1 t' + k_1 d & c \le t' \le d \\ -k_3 t' + k_3 d & t' > d \end{cases} \tag{11}$$

The greater the $Sav_{ij}(t')$ is, the smaller spatial distance is between i and j, the easier is to go from i to j.

$$D_{ij}^{T}(t') = k_1 A - Sav_{ij}(t') \qquad t' \in (a',b') \tag{12}$$

We take the maximum of the two as temporal distance.

$$D_{ij}^{T} = \max(\overline{D_{ij}^{T}}, \overline{D_{ji}^{T}}) \tag{13}$$

And we denote $\overline{D_{ij}^{T}}$ as shows:

$$\begin{aligned} \overline{D_{ij}^{T}} &= \int_{a'}^{b'} D_{ij}^{T}(t')dt' \big/ (b' - a') \\ &= k_1 A - \int_{\min(a',c)}^{\min(b',c)} (k_2 t' + k_1 d - (k_1 + k_2)c)dt' + \int_{\min(\max(a',c),d)}^{\max(\min(b',d),c)} (-k_1 t' + k_1 d)dt' \\ &\quad + \int_{\max(a',d)}^{\min(b',d)} (-k_3 t' + k_3 d)dt' \big/ (b' - a') \end{aligned} \tag{14}$$

B. Order clustering based on K-means

The orders are divided into k clusters, and the clustering center $(z_1, z_{2.}, \cdots, z_k)$ of each cluster z_i is o_i. Define the clustering objective function as follows, namely in all clustering clusters, minimizing the sum of the rest of the order's temporal-spatial distance to the center. The number of clusters is the needed vehicles. Temporal-spatial distance of distribution order is D_{ij}^{ST}

$$\min F = \sum_{i,j\in z_i/o_i}^{k} \sum D_{ioj}^{ST} \tag{15}$$

$k = \max \sum q_i / Q_{\max}$, $\sum q_i$ represents the total demand of the largest distribution order, $Q_{\max}$ is corresponding to the maximum available capacity. So the clustering process:

Step1: Determine the cluster number k, select the initial customer k as the cluster center.

Step2: Determine the temporal-spatial distance $\left[D_{ij}^{ST}\right]$ of each customer point with the k cluster center according to the function.

Step3: To the customer that is not the cluster center, select the smallest temporal-spatial distance cluster center from Step2, then put this customer point into this cluster center.

Step4: Get the k cluster centers from Step3, then recalculate each cluster center.

Step5: Judge the convergence of the cluster center, if convergence, output the k cluster centers, otherwise, return Step2, recalculate k cluster centers temporal-spatial distance $\left[D_{ij}^{ST}\right]$ with each customer, then repeat calculation, until convergence.

C. Construct initial solution

After the completion of the cluster division, then make vehicles capacity as constraint conditions to improve the orders assigned based on the nearby principle. Orders that violate constraints are reassigned. $J(J<k)$ is the number of on-line reassigned, k is the number of vehicles. The following operations are performed on each cluster:

Step1: Select the order that nearest depot distribution, then assign to the available vehicles, namely $k=1$;

Step2: To vehicle load conditions, assign the remaining orders according to the ascending temporal-spatial distance, once the load constraint is violated by an order, turn to Step3;

Step3: Select nearest the order from k clusters, and judge whether each cluster meets the requirements of the order according to ascending temporal-spatial distance, if feasible, reassign the order and $k=k+1$, otherwise, let the order assigned to a new cluster.

Step4: Checking whether there is no assignment clustering, then stop and output results, otherwise switch to Step2.

4.2. Optimization solution based on VNS-GA in the second stage

Genetic algorithm (GA) is an efficient global optimal algorithm and variable neighborhood search (VNS) is an efficient local search algorithm. In the paper, we combine the improved a variable neighborhood search and genetic algorithm based on Pareto method to solve the multi-objective problem. We select the better non-dominated solutions of every generation by adopting the crowding distance and put them into the external archive.

A. Chromosome coding

Coding method use real number coding, each chromosome represents a possible order delivery sequence. Each demand point is used as a gene, which has the relevant information, including the position coordinates, the demand, the earliest and latest service time and so on. The gene sequence $(G_1, G_2, \cdots, G_k)$ is a full array of all orders. G_k is a separate distribution path.

B. Generate the initial population

Select nearest depot distribution order and assign to the available vehicles, insure the quality of the initial solution and speed up the convergence rate of the algorithm.

C. Pareto ranking

In order to improve the search efficiency of algorithm, we apply the external archive to keep the process of evolution. The Pareto operation steps are as follows:

Step1: In the initial state, set the non-dominated solutions ($NDSet$) empty.

Step2: Put an individual X from the population into the $NDSet$.

Step3: Select the next individual Y, compare the individual in the $NDSet$ in turn, remove the individual that dominated by the population. If the individual not be dominated by $NDSet$, put the individual into $NDSet$, then, go to the next population.

At the same time in order to ensure $NDSet$ with high dispersion, set an upper bound M of to the number of individuals in the $NDSet$. If the number does not reach the upper bound M in the phase of Pareto optimal solution, put all Pareto optimal solutions into the external archive, otherwise, select M individuals from $NDSet$, then put into the external archive.

Considering the crowed distance[16] in the selection process. The crowed distance $L[i]dis$ is the same level adjacent individual distance in each target. The larger individual crowed distance is, the smaller the solution space density is, the larger solution probability is, the larger participate in reproduction and evolution opportunity is. Set individual i objective function (1) $Obj_1(i)$, objective function (2) $Obj_2(i)$. The crowed distance $L[i]dis$ is the sum of width of a rectangle.

$$L[i]dis = (L[i+1].Obj_1(i) - L[i-1].Obj_1(i)) + (L[i+1].Obj_2(i) - L[i-1].Obj_2(i)) \tag{16}$$

D. Fitness function

The fitness function is formulated as follows: calculate the chromosome i the value of Obj_1 is $Obj_1(i)$, the Obj_2 value is $Obj_2(i)$; Calculate the value of all population chromosomes Obj_1 and Obj_2 , rank them from smallest to largest. Suppose the number of permutations $Obj_1(i)$ is $R_1(i)$ in its population, so $f_1(i)$ is the chromosome i fitness value of the objective function (1). $R_2(i)$ is $Obj_2(i)$ the sequence number, $f_2(i)$ is the chromosome i fitness value of the objective function (2). After sorting chromosome, the individual fitness of the two targets is calculated and the overall fitness of each chromosome is calculated[17-18].

$$f_j(i) = \begin{cases} (N - R_j(i))^2 & R_j(i) > 1 \\ kN^2 & R_j(i) = 1 \end{cases} \qquad f(i) = f_1(i) + f_2(i) \tag{17}$$

$f_j(i)$ represents the chromosome i towards j th objective function fitness, $f(i)$ represents the overall fitness of the chromosome i , N represents the total number of chromosomes, that is, the size of the population, $R_j(i)$ represents ranking of j th objective functions for chromosome i . $K \in [1,2]$.

E. Crossover and mutation operation

Individual selection uses tournament and random methods. Crossover probability and mutation probability apply the adaptive method. The calculation formulas are as follows:

$$P_c = \begin{cases} \dfrac{p_c(f_{\max} - \max(f(i_1), f(i_2)))}{(f_{\max} - f_{avg})} & \max(f(i_1), f(i_2)) \ge f_{avg} \\ p_c & \max(f(i_1), f(i_2)) < f_{avg} \end{cases} \qquad P_m = \begin{cases} \dfrac{p_m(f_{\max} - f(i))}{(f_{\max} - f_{avg})} & f(i) \ge f_{avg} \\ p_m & f(i) < f_{avg} \end{cases} \tag{18}$$

P_c represents cross fitness function; p_c represents crossover probability; P_m represents the variation fitness function ; p_m represents mutation rates ; $f_{\max}$ represents the maximum fitness value of population ; f_{avg} represents the average fitness value of population.

F. Neighborhood structure

The neighborhood structures are composed of inverse operation, insert operation and swap operation.

1）Inverse operation: Randomly generate two variation points, contrarily put the two genes nodes into the original gene string orders. 2）Insert operation: Randomly select a gene point, randomly insert this gene into other point of the chromosome. 3）Swap operation: Randomly exchange the positions of the two genes in chromosome.

4.3. The algorithm process

Step 1: Determine the population size and the maximum number iterations, then generate initial population.

Step 2: Rank the population according to the non-dominated solutions, find the current population Pareto solutions, apply the crowded distance and tournament strategy update the external archive.

Step 3: Judge the algorithm whether meet the termination criterion, if meet, return to the optimal solution, otherwise, go to Step 4.

Step 4: In the crossover operation, randomly select one ways, until the new individual equal to the population.

1）Randomly select an individual from the external archives, select an individual using the championships method choice, then cross the new individual.

2）Select two individuals from the current population based on the tournament, then cross the new individual.

Step 5: Mutation operation, replace the current individual with mutation individual.

Step 6: To each individual, use the neighborhood structures search, then, obtain the optimal solution of each individual, update the current individual with the optimal solution.

Step 7: Go to Step 2.

5. Computational results

5.1. Data description

Experiments are proposed in this part to prove the effectiveness and feasibility of the algorithm. The program is implemented in Matlab and run on a computer with 2.4 GHz Intel Core 2 Duo CPU, 2 GB of RAM and Windows 7. The parameters of the experiments are shown in Table 1.We apply Solomon data to test. We define the parameters $w_1 = 10$, $w_2 = 10$, $w_3 = 20$, $\beta = 0.75$. The detailed parameters are as follows:

Table 1. Parameters of the experiments

Parameter	Value
The vehicle speed(km/h)	30
The lifetime of the product(h)	12
fixed cost per vehicle (RMB)	50
The transportation cost per kilometer(RMB/km)	0.5
Each customer service time(minute)	5
The vehicle capacity(kg)	50

5.2. Effectiveness of considering temporal-spatial distance

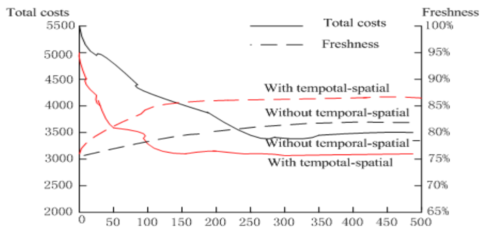
As it can be seen from Table 2, Obj_1 excellent ratio could reach 7.25% on average and Obj_2 optional ratio could achieve 5.8% on average with fewer vehicles. The advantages of temporal-spatial clustering significantly enhance especially with the growing number of customers. For example R4, the value of Obj_1 is 3300.44 and the value of Obj_2 is 80.7% with 33 vehicles in the condition of considering space distance method. But with the temporal-spatial distance clustering, the value Obj_1 is 2966.11 and value Obj_2 is 87.8% with 28 vehicles.

Table 2. Computation temporal-spatial results

Case(The number of customer)	Considering space distance			Considering temporal-spatial distance			Obj_1 ratio	Obj_2 ratio
	Numbers	Obj_1	Obj_2	Numbers	Obj_1	Obj_2		
R1(25)	6	752.73	79.3%	6	735.79	81.9%	2.25%	3.27%
R2(50)	16	1633.34	79.5%	14	1507.41	82.7%	7.71%	4.23%
R3(75)	23	2463.70	79.1%	21	2244.68	84.6%	8.89%	6.89%
R4(100)	33	3300.44	80.7%	28	2966.11	87.8%	10.13%	8.81%

In order to further validate the effectiveness of temporal spatial distance in the multi-objective distribution problems, For R(4), we compare the objective value and iterations of those two algorithms, which shown in Figure1.

Figure 1. Iterations results comparison



Result shows that in the initial stage, the convergence speed of the algorithm is fast, especially with the temporal-spatial clustering, the value decreased dramatically, when iterations reach 200, the convergence rate of the two algorithms are space. The algorithm without temporal spatial also constantly update the optimal solution, but because of the initial solution space is large, thus the convergence speed is slow, the whole solving performance significantly inferior to STVNS-GA algorithm in the process of iteration process.

5.3. *Effectiveness of STVNS-GA*

For better analysis the effectives of proposed variable neighborhood search-genetic algorithm that considering temporal-spatial distance (STVNS-GA), we compare the genetic algorithm (T-GA) that without using the variable neighborhood, then respectively compare the two different algorithm of costs and freshness, record the run time in different orders environment.

Table 3. Computation results

Case(The number of customer)	T-GA				STVNS-GA				Obj_1 ratio	Obj_2 ratio
	Numbers	Obj_1	Obj_2	Time s	Numbers	Obj_1	Obj_2	Time s		
R1(25)	6	793.27	78.9%	30.31	6	735.79	81.9%	20.83	7.25%	3.84%
R2(50)	17	1670.45	78.6%	48.14	14	1507.41	82.7%	35.18	9.76%	5.13%
R3(75)	25	2609.59	78.9%	64.73	21	2244.68	84.6%	43.29	13.83%	7.19%
R4(100)	34	3504.38	80.1%	90.42	28	2966.11	87.8%	60.38	15.36%	9.69%

It can be seen from the experimental results:

In small order environment R1, STVNS-GA distribution costs are 735.79 and the freshness is 81.9%, while the T-GA distribution costs are 793.27 and the freshness is 78.9%. We can see that the cost and fresh degree respectively improve 7.25% and 3.84%;

In moderate order environment R3, the STVNS-GA distribution costs are 2244.68 and the freshness is 84.6%. The T-GA costs are 2609.59 and the freshness is 78.9%. Compared to the costs and fresh degree, the STVNS-GA respectively improve 13.83% and 7.19%;

In mass volume R4, the STVNS-GA distribution costs are 2966.11, the T-GA costs are 3504.38. Compared to the cost and fresh degree respectively improve 15.36% and 9.69%;

The result shows that the distribution costs and freshness greatly improved. In three different orders, the distribution costs increase to 15.36%, and the highest freshness improvement rate is 9.69%. Genetic algorithm (GA) is an efficient global optimal algorithm and variable neighborhood search (VNS) is an efficient local search algorithm. We combine the improved heuristic algorithm. The results illustrate the effective and efficient of the proposed algorithm. It also shows that the algorithm is more beneficial to improve the quality of multi-objective solutions in the large quantity orders environment.

In order to show the performance of the algorithm more clearly, For R(4), we record 10 times computation results.

Table 4. Computational process of the Hybrid genetic algorithm

Case	1	2	3	4	5	6	7	8	9	10	Aver
Obj_1	3068	2997	2893	2944	3015	2948	2962	3092	2974	3159	3002.5
Transport	1504	1411	1327	1343	1438	1327	1328	1521	1391	1454	1397.7
Fixed	1350	1400	1350	1400	1350	1400	1400	1350	1350	1400	1375
Delay	128	105	110	107	124	126	103	124	128	124	131.2
Damage	86	91	106	94	103	95	131	97	105	81	98.9
Number	27	28	27	28	27	28	28	27	27	28	28
Obj_2	87%	88%	81%	89%	82%	86%	79%	89%	84%	91%	85.6%
Time/s	65	53	57	79	68	51	71	63	65	57	69.1

It can be seen from Table 4 that quality of the solution is very high in 10 times the solving process. The computation time is 69.1s. Especially the general search algorithm cannot achieve the target within 100 seconds time. The improve hybrid algorithm is robust, and it can converge to a better solution in a relative short period time.

6. Conclusion

We establish an optimization model to minimize the distribution costs and maximize the freshness of perishable products, then use a two-phase algorithm that considering temporal-spatial distance (STVNS-GA) to solve this multi-objective problem. Genetic algorithm is an efficient global algorithm and variable neighborhood search is an efficient local search algorithm. We combine the improved variable neighborhood search-genetic algorithm. Several numerical examples are presented to demonstrate the effective and efficient of proposed algorithm. The example results show that the STVNS-GA can greatly improve solutions quality and speed up the convergence of algorithm.

It is worth nothing that some places need to be improved, for example, the interference management in the process of perishable food products multi-objective distribution will be focused on in the next step. In addition, it is necessary to further research on freshness with monitoring system in distribution routing optimization problem.

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