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Multi-objective optimization for delivering perishable products with mixed time windows

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A B S T R A C T

Perishable products generally have a short shelf life, and the freshness often depends on the postharvest time. The freshness of perishable products can ensure better customer satisfaction. Owing to the deterioration of perishable goods, the complexity of the corresponding vehicle routing problem (VRP) increases, because time delay will lead to serious costs. In this study, we are concerned with not only time-sensitive spoilage rates with mixed time windows, but also the delay costs in delivering perishable products. This study proposes a multi-objective VRP optimization model with mixed time windows and perishability (MO-VRPMTW-P) to minimize the distribution costs and maximize the freshness of perishable products. Then, in view of the fresh products orders space and time characteristics, we propose a heuristic algorithm (ST-VNSGA) composed of a variable neighbourhood search (VNS) method and a genetic algorithm (GA) considering the spatio-temporal (ST) distance to solve the complex multi-objective problem. The solution algorithms are evaluated through a series of experiments. We illustrate the performance and efficiency comparisons of ST-VNSGA with the method without spatio-temporal strategy algorithm and NSGA-II algorithm. It is demonstrated that the proposed ST-VNSGA algorithm can lead to a substantial decrease in the computation time and major improvements in solutions quality, thus revealing the efficiency of considering the spatio-temporal strategy with mixed time windows.

A R T I C L E I N F O

Keywords:
Perishable products distribution;
Multi-objective optimization;
Mixed time windows;
Freshness;
Heuristic algorithm;
Spatio-temporal distance

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1. Introduction

The distribution of perishable products can be abstracted as a vehicle routing problem (VRP) [1]. It has been recognized that managing perishable products distribution, such as the distribution of vegetables, milk, meat, and flowers, is a difficult problem [2]. Perishable products generally have a short lifecycle, and the value or quality of perishable products decreases rapidly once they are produced, they will continue to decay while being delivered [3]. The life of perishable products depends on time. However, perishable products freshness affects customer satisfaction [4]. Owing to deterioration of perishable goods, distributors are increasingly adopting delivery strategies to fulfil their orders. Timely delivery of perishable food affects not only the delivery operator's cost [5], but also the satisfaction of customers. Furthermore, with the recent rapid development in fresh e-commerce, the characteristics of orders tend to be of smaller lot-size and higher frequency, which has increased the complexity of distribution problems.

However, traditional production scheduling focuses on minimizing the transportation cost of perishable goods without explicitly considering the time-sensitive freshness of perishable products and the serious delay costs in mixed time windows [6-9]. In particular, in fresh e-commerce, the delivery of perishable products is different from traditional transportation, and creates new challenges. In the literature concerned explicitly with freshness, Chen *et al.* [10] proposed a nonlinear mathematical model to consider VRP with time windows (VRPTW) for perishable food products. The objective of this model was to maximize the expected total profit of the supplier. Osvald and Stirn [11] formulated a VRPTW with time-dependent travel-times (VRPTWTD). The model considered the impact of perishability as part of the overall distribution costs. Hsu *et al.* [12] focused on the randomness of the perishable food delivery process and presented a stochastic VRPTW model to obtain optimal delivery routes. These papers mainly considered the impact of perishability affects the overall distribution costs, however, they didn't take into account customer satisfaction with regard to freshness.

Some scholars [13-19] researched perishable products from the supply chain network perspective. For example, Amorim *et al.* [15] explored a multi-objective framework that integrated production and distribution perishable goods planning problems. However, most studies have concentrated on conventional VRPs, paying little attention to designing an effective method combined with time-sensitive freshness and delay costs for the multi-objective perishable good distribution problem. Meanwhile, different fresh delivery orders have specific space and time characteristics. It is therefore critical to design an effective and efficient delivery method so that the supplier can ensure the freshest products are delivered in a cost-effective and timely manner.

In this study, we both consider vehicle time-dependent travel and perishable products freshness under mixed time window constraints, where freshness has a minimum level that the customer can accept. We establish a multi-objective VRP optimization model with mixed time windows and perishability (MO-VRPMTW-P) to minimize the distribution costs and maximize the freshness of perishable products. We consider the time-sensitive freshness of perishable products, and the high serious delay cost in mixed time windows. Thus, a company can reduce costs and achieve a higher level of customer satisfaction with regard to freshness. Previous algorithms mainly considered the customer spatial location relationships, but did not take time and space characteristics constraints into account. Then, considering the obvious space and time characteristics of the fresh food distribution task, we design a heuristic algorithm (ST-VNSGA) composed of a local variable neighbourhood search algorithm (VNS) and a global genetic algorithm (GA) that considers spatio-temporal distance to solve this multi-objective problem, hence, provide the decision maker with a whole set of equally efficient solutions.

The remainder of this paper is organized as follows. In Section 2, we establish an optimization model to minimize the total costs and maximize the freshness of the products with mixed time windows. The solution of the model and a suitable algorithm are presented in Section 3. In Section 4, several examples are tested to verify the effectiveness and efficiency of the proposed model and algorithms for MO-VRPMTW-P. Finally, the paper concludes with a summary and an outlook on further research topics in Section 5.

2. Problem statement and mathematical model

2.1 Problem statement

A perishable product distribution network is a complex system that presents many challenges. We propose a mathematical model the MO-VRPMTW-P that considers the time-sensitive spoilage rates of perishable products, aiming at achieving the following objectives:

- Minimum total costs, which contain fixed costs, transportation costs, damage costs and penalty costs;
- Maximum the freshness of perishable products.

We assume that the distribution system includes a distribution centre and multiple customers. All vehicles must leave and return to the distribution centre. The distribution centre has sufficient capacity to complete all tasks. The transportation costs between the customers depend on travel distance. Each vehicle can travel at most one route per time period. Each customer can be served by only one vehicle. The demand and time window of the customers are known. These perishable products need to be sent to customers. If not, this usually means higher costs for the operator, who must pay a penalty for the loss. We consider only the transit time, ignoring loading and unloading time. Each vehicle has a capacity constraint.

2.2 Mathematical model

The optimization model for the MO-VRPMTW-P is presented to analysis the proposed problem. The parameters and variables of the models are defined in Table 1. Table 2 shows the list of abbreviations.

Table 1 The parameters and variables of the models

Parameters	Explanation of the parameters
N	A set of customer notes, $N = \{n \mid n = 1,2,\dots,\lvert N\rvert\}$ represents customers
N^+	A set of depot and customer notes, $N^+ = \{n \mid n = 1,2,\dots,\lvert N\rvert\}$, $n = 0$ represents depot
K	A set of vehicles, $K = \{k \mid k = 1,2,\dots,\lvert K\rvert\}$
$[e_i, l_i]$	e_i and l_i are the starting and ending time of the time window at customer *i*, respectively, $i \in N$
Q	The maximum capacity of the vehicle
d_{ij}	The distance between node i and node j, $i, j \in N^+$, $i \neq j$
q_i	The demand of the customer i that vehicle k service, $i \in N$
r_0	The minimum freshness level that the customer can accept
T	The life cycle of perishable products
v	The speed of vehicle k
f	The unit fixed costs of the vehicle
c_0	The average cost of travelling
y_{ik}	Binary that takes the value 1 if customer i is assigned to vehicle k
t_{ij}	The transportation time between node i and node j, $i, j \in N^+$, $i \neq j$
t_{ik}	The time vehicle k arrives at customer i, $i \in N$
$r(t_{ik})$	The perishable product freshness level when customer i is serviced by vehicle k
x_{ijk}	Binary that takes the value 1 if vehicle k transports between node i and node j. $i, j = 1,2,\dots,n$

Table 2 The list of abbreviations

Abbreviation	Full names
MO-VRPMTW-P	A multi-objective VRP optimization model with mixed time windows and perishability
ST-VNSGA	A heuristic algorithm composed of a local variable neighbourhood search algorithm and a global genetic algorithm that considers spatio-temporal distance
VNSGA	A heuristic algorithm composed of a local variable neighbourhood search algorithm and a global genetic algorithm
ST-NSGA-II	A heuristic algorithm that NSGA-II algorithm considers spatio-temporal distance

Analysis of objective functions

The total costs Z_1 are composed of fixed costs C_1, transportation costs C_2, damage costs C_3, and penalty costs P. To describe the characteristics of perishable products, we cite the freshness factor from the literature [20]. The objectives specific expressions are described as follows:

- Fixed costs and transportation costs

The vehicle fixed costs C_1 generally include the depreciation costs, maintenance costs, and so on. Transportation costs C_2 depend on the distance vehicle travelled. They are expressed as below:

$$C_1 = \sum_{j \in N \setminus \{0\}} \sum_{k \in K} f x_{0jk} \tag{1}$$

$$C_2 = \sum_{(i,j) \in E} c_0 d_{ij} \sum_{k \in K} x_{ijk} \tag{2}$$

- Damage costs

The loss of quality in the transportation of the perishable products is a significant cost for companies. The product quality decay influences network designs [21-22]. We select perishable milk as the main study object. The goods have specific time storage characteristics. The rate of corruption is mainly exponential with time [20, 23-25], $r = e^{-\phi t}$, where r is the freshness of perishable product quality, and ϕ is the shrinkage factor, which is related to the type of goods. If the goods are sensitive to time, the value is relatively small; otherwise, the value is large. The exponential damage percentage changes over time.

Thus, the perishable product damage costs can be expressed as:

$$C_3 = w \sum_{i \in N} \sum_{k \in K} q_{ik}(1 - r(t_{ik}))\, y_{ik} \tag{3}$$

w represents the unit value of the perishable products. $r(t_{ik})$ is the freshness of customer i, the calculation expressions are: $r(t_i) = e^{-\phi(t_{ik} - t_{0k})}$. t_{0k} is the start time of vehicle k from the distribution centre, $k = 1,2, \dots, |K|$.

- Mixed time window penalty costs

To improve the quality of distribution services, customers require the distributor arrives within specified time windows; if not, they need to pay the corresponding wait or delay costs. The quality of fresh goods is sensitive to time. Any vehicle that arrives early has to wait until the beginning of the time windows. Any vehicle that arrives late will incur a penalty, and the delay costs of damaged goods are serious. Therefore, this study uses mixed time windows to measure fresh good distribution penalty costs. Thus, the penalty function can be shown in the formula:

$$P_i(t_{ik}) = \begin{cases} \alpha q_{ik}(t_{ik} - LT_i) & T_{ie} < t_{ik} < ET_i \\ 0 & ET_i < t_{ik} < LT_i \\ q_{ik}(t_{ik} - LT_i)^{\beta} & LT_i < t_{ik} < T_{il} \\ q_{ik} & T_{ie} > t_{ik}\ , t_{ik} > L_i \end{cases} \tag{4}$$

$P_i(t_{ik})$ represents penalty costs if vehicle k transgresses the time window of customer i. The lower bound T_{ie} represents the earliest arrival time that a customer can endure when a service starts earlier than ET_i. Similarly, the upper bound T_{il} represents the latest arrival time that the customer can endure when the service starts later than LT_i. Here, α represents the penalty coefficient that is within the actual time but earlier than the optimal satisfactory time and β represents the penalty coefficient that is within the actual time but later than the optimal satisfactory time. $\alpha > 1, \beta > 1$. The corresponding penalty function is shown in Fig.1.

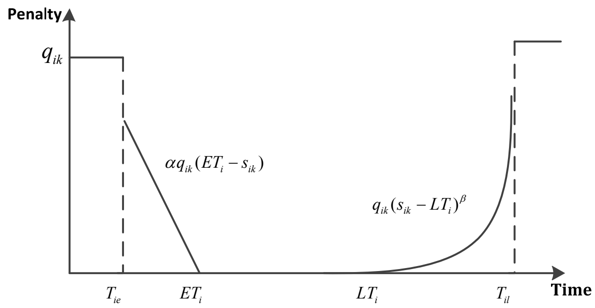

Fig. 1 Relationship between arrival time, time-windows and penalty cost

- Average freshness

The products average freshness is related to the quality and freshness factor. Thus, the average freshness is defined as:

$$Z_2 = \sum_{i \in N} \sum_{k \in K} q_{ik} r(t_{ik}) y_{ik} \Big/ \sum_{i=0}^{N} q_{ik} \tag{5}$$

Then, the mathematical model MO-VRPMTW-P can be given as follows. Objective functions:

$$maxZ_1 = \sum_{j\in N\backslash\{0\}}\sum_{k\in K} f x_{0jk} + \sum_{(i,j)\in E} c_0 d_{ij} \sum_{k\in K} x_{ijk} + w\sum_{i\in N}\sum_{k\in K} q_{ik}\left(1 - e^{-\phi(t_{ik}-t_{0k})}\right) y_{ik} + \sum_{(i\in N)} P_i(t_{ik}) \tag{6}$$

$$minZ_2 = \sum_{i\in N}\sum_{k\in K} q_{ik} e^{-\phi(t_{ik}-t_{0k})} y_{ik} \Big/ \sum_{i=0}^{N} q_{ik} \tag{7}$$

Constraint conditions:

$$\sum_{j\in N}\sum_{k\in K} x_{0jk} \le K \tag{8}$$

$$\sum_{j\in N} x_{0jk} = \sum_{j\in N} x_{j0k} \le 1, \quad \forall k \in K \tag{9}$$

$$\sum_{i\in N^+}\sum_{j\in N^+} x_{ijk}\, q_i \le Q, \quad \forall k \in K \tag{10}$$

$$\sum_{i\in N^+}\sum_{k\in K} x_{ijk} = 1, \quad \forall j \in N \tag{11}$$

$$\sum_{i\in N^+}\sum_{k\in K} x_{jik} = 1, \quad \forall j \in N \tag{12}$$

$$r(t_{ik}) = e^{-\phi(t_{ik}-t_{0k})}, \quad \forall i \in N, k \in K \tag{13}$$

$$r(t_{ik}) \ge r_0, \quad \forall i \in N \tag{14}$$

$$t_{jk} = (t_{ik} + d_{ij}/v_0)x_{ijk}, \;\; \forall i,j \in N^+, k \in K \tag{15}$$

$$x_{ijk} \in \{0,1\}, \;\; i,j \in N^+, k \in K \tag{16}$$

In the first objective function Eq. 6, total costs are minimized, namely: the fixed costs, transportation costs, damage costs, and penalty costs. In the second objective function Eq. 7, the average remaining freshness of products to be delivered is maximized. Eq. 8 is the number of vehicles constraint. Eq. 9 states that each vehicle should leave and return to distribution centre. Eq. 10 is a vehicle capacity constraint. Eqs. 11 and 12 represent that each customer should be serviced, and each can only be serviced once time. Specially, Eq.13 defines freshness function of the perishable products, and Eq. 14 ensures the lowest level of freshness that the customer can accept. Eq.15 defines the time that vehicle k takes from leaving customer i to arrival at customer j. Eq. 16 represents that vehicle k serves customer i before customer j.

3. Used methods

The MO-VRPMTW-P problem is an NP-hard problem. Multiple objectives need to be optimized at the same time. In the combination optimization problem, GA is an efficient global optimal algorithm and VNS is an efficient local search algorithm. In this work, we combine the improved GA with the VNS algorithm. Traditional algorithms mainly consider the customer spatial location relationship; however, they rarely take orders the time and space characteristic constraints of orders into consideration. Since the orders have obvious ST characteristics, we use the k-means method to cluster the nodes to obtain the initial solution considering the ST strategy in the first stage. Then, in the second stage, we adopt VNSGA to optimize the distribution route.

3.1 Generate initial solution

Calculating spatio-temporal distance

In the process of delivery, each perishable order has a corresponding demand. Considering orders with spatio-temporal distance may solve the problem more effectively than just considering the distance. So, we use the definition of ST distance from the literature [26] to cluster orders.

Use D_{ij}^{ST} to denote the ST distance. D_{ij}^{S}, D_{ij}^{T} represent the Euclidean distance and temporal distance between customer i and j, respectively. The transportation time of the points is related to the Euclidean distance, which means $D_{ij}^{S} = t_{ij}$. Here, $[a, b]$ and $[c, d]$ are the time windows of customer i and j, the specific arrival time at customer j is $t' \in (a', b')$, $a' = \mathrm{a} + t_{ij}$, $b' = \mathrm{b} + t_{ij}$. Use $Sav_{ij}(t')$ to denote the saved time when vehicle arrives at customer j at the moment t'. Here, A is the maximum window, and K_1, K_2, K_3 are parameters related to time.

$$Sav_{ij}(t') = \begin{cases} k_2 t' + k_1 d - (k_1 + k_2)c & t' < c \\ -k_1 t' + k_1 d & c \le t' \le d \\ -k_3 t' + k_3 d & t' > d \end{cases} \tag{17}$$

A greater $Sav_{ij}(t')$ means a smaller spatial distance. $D_{ij}^{T}(t')$ is defined as:

$$D_{ij}^{T}(t') = k_1 A - Sav_{ij}(t') \quad t' \in (a', b') \tag{18}$$

Temporal distance $\overline{D_{ij}}$ is defined as:

$$\begin{aligned} \overline{D_{ij}^{T}} = \int_{a'}^{b'} & D_{ij}^{T}(t')dt'/(b' - a') \\ & = k_1 A \\ & - \int_{\min(a',c)}^{\min(b',c)} (k_2 t' + k_1 d - (k_1 + k_2)c)dt' \\ & + \int_{\min(\max(a',c),d)}^{\max(\min(b',d),c)} (-k_1 t' + k_1 d)dt' \\ & + \int_{\min(a',d)}^{\min(b',d)} (k_3 t' + k_3 d)dt'/(b' - a') \end{aligned} \tag{19}$$

We take the maximum distance as the temporal distance.

$$D_{ij}^{T} = \max(\overline{D_{ij}^{T}}, \overline{D_{ji}^{T}}) \tag{20}$$

The ST distance D_{ij}^{ST} is related to D_{ij}^{S} and D_{ij}^{T}. α_1 , α_2 are the D_{ij}^{S} and D_{ij}^{T} weight coefficients, respectively. $\alpha_1 + \alpha_2 = 1$. The ST distance can be expressed as follow:

$$D_{ij}^{ST} = \alpha_1 \left(\frac{D_{ij}^{S} - \min\limits_{m,n \in C, m \ne n} (D_{mn}^{S})}{\max\limits_{m,n \in C, m \ne n} (D_{mn}^{S}) - \min\limits_{m,n \in C} (D_{mn}^{S})} \right) + \alpha_2 \left(\frac{D_{ij}^{T} - \min\limits_{m,n \in C} (D_{mn}^{T})}{\max\limits_{m,n \in C, m \ne n} (D_{mn}^{T}) - \min\limits_{m,n \in C} (D_{mn}^{T})} \right) \tag{21}$$

Construct initial solution

After the calculation of the ST distance, we apply k-means method to cluster the orders and construct initial solution. Here, k is the number of vehicles. The orders are divided into k clusters, and the clustering centre $z_i(z_1, z_2, \ldots z_k)$ of each cluster is o_i. The cluster k is defined as follow:

$$Min \sum_{j=1}^{k} \sum_{i \in z_i / \{o_i\}} D_{io_j}^{ST} \tag{22}$$

$k = max \sum_{i \in N} d_i / Q$. $\sum d_i$ represents the total demand of the largest distribution order, and $\mathrm{D}(\mathrm{i}, o_j)$ represents the distance of the sub-order i to the cluster centre z_i.

3.2 Optimization solution based on VNSGA

We combine the improved GA and the VNS to solve the multi-objective problem. Owing to the different mechanisms used in population search and local search, we use two different fitness functions in the selection operations. We apply non-dominance ranking and crowding distance sorting in the NSGA-II method as a global strategy and adopt an external archive to maintain the process of evolution. Then, VNS realizes the dynamic search. The flow chart is shown in Fig. 2.

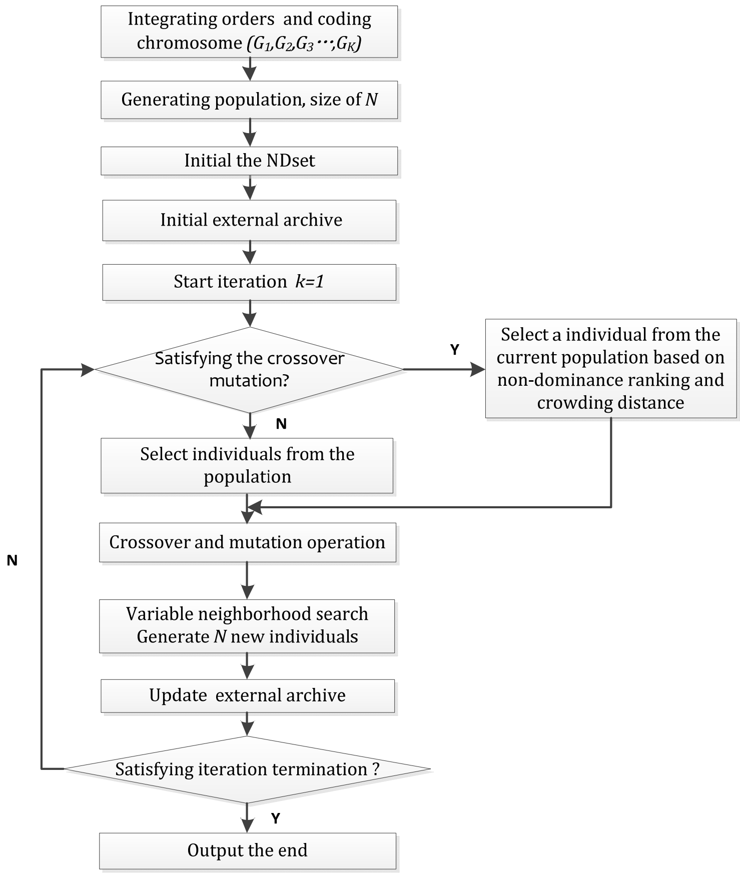

Fig. 2 Flowchart of the solution algorithm

Fitness function

We adopt two different fitness functions in population and local search operation selection.

First, in the population selection operation, we propose the ranking and crowding degree method based on the Pareto dominance. $fit_1(x)$ is the population selection fitness. Use $rank(x)$ to denote the relationship of Pareto dominance, $rank(x) < rank(y)$ indicates that x dominates y. The crowding distance is $Crowding - distance(x)$. The first keyword is ascending in a particular order and the second key sort is descending according to the crowding distance.

$$fit_1(x) = (rank(x), Crowding - distane(x)) \tag{23}$$

Second, in the local search selection operation, we select a better solution from the neighbourhood. $S(x)$ is the number of solutions x dominated. $W(x)$ is the number of solutions x dominate in storage pool. $fit_2(x)$ is the local search selection operation fitness.

$$fit_2(x) = \frac{1 + S(x)}{1 + W(x)} \tag{24}$$

4. Results and discussion

4.1 Data description

In this section, we use numerical experiments to demonstrate the efficiency and advantages of applying our heuristic algorithm. We adopt the instances developed by Solomon for VRPTW. Six different instance types are considered: R1, R2, C1, C2, RC1, and RC2.

Suppose the distributed perishable product is milk. Set the shrinkage factor as $\phi = 1/200$. $\alpha = 1.5$, $\beta = 1.5$, $\alpha_1 = 0.5$, $\alpha_2 = 0.5$. These experiments were performed on a personal computer with Intel® CoreTM i5-4460 CPU at 2.40 GHz and 8.00 GB of RAM. The computation run time unit is seconds. The stopping criterion is set to $Max_t = 300$. The parameters are listed in Table 3.

Table 3 Parameters of the experiments.

Parameter	Meaning	Value
v	The speed of the vehicle (km/h)	30
T	The lifecycle of the perishable product (h)	24
f	The unit fixed costs per of the vehicle (yuan)	50
Q	The maximum capacity of the vehicle (kg)	300
c_0	The average cost of travelling (yuan/km)	2.5
r_0	The minimum freshness level that the customer can accept	0.75
w	The unit value of the perishable products(yuan/kg)	30
K	A set of vehicles	50

4.2 Effectiveness of considering spatio-temporal distance

Consider the time and space characteristics of the order, we propose a method based on the spatio-temporal metrics to verify the strategy of spatio-temporal distance. We define the method that considers the customer spatio-temporal location relationship as ST-VNSGA and the method that does not consider the customer spatial location as VNSGA. Comparison results between ST-VNSGA and VNSGA are given in Table 4.

Table 4 Comparison results between ST-VNSGA and VNSGA

Case	ST-VNSGA			VNSGA			Gap		
	Time (s)	Cost (yuan)	Freshness (%)	Time (s)	Cost (yuan)	Freshness (%)	Time (%)	Cost (%)	Freshness (%)
R101_25	43	771.58	93.4	73	791.24	92.1	41.10	2.48	1.41
R101_50	79	1403.31	91.7	144	1449.73	88.6	45.14	3.20	3.50
R101_100	127	2649.43	88.1	278	2784.37	85.7	54.31	4.84	2.80
C101_25	22	185.36	94.5	26	191.11	92.9	15.38	3.00	1.72
C101_50	44	367.98	92.8	54	379.45	91.7	18.52	3.02	1.20
C101_100	79	730.91	92.3	99	758.69	90.0	20.2	3.66	2.56
RC101_25	29	799.72	93.3	49	819.43	91.6	40.82	2.41	1.86
RC101_50	52	1360.98	91.4	94	1398.21	89.0	44.68	2.66	2.70
RC101_100	91	2556.67	87.5	189	2678.85	84.9	51.85	4.56	3.06

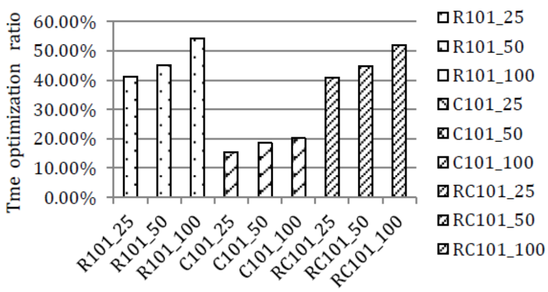

Fig. 3 Time optimization rate with the spatio-temporal strategy

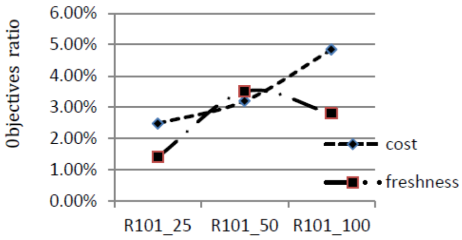

Fig. 4 R class case objectives ratio

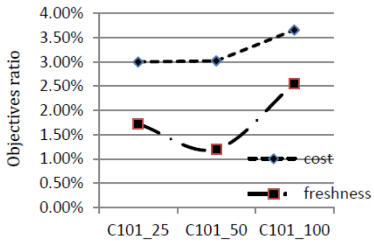

Fig. 5 C class case objectives ratio

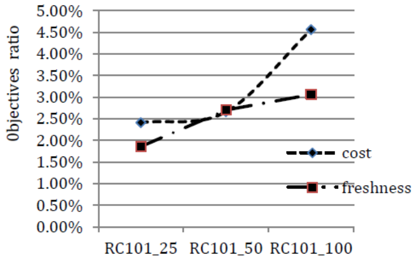

Fig. 6 RC class case objectives ratio

Table 4 lists the computation results of ST-VNSGA and VNSGA with regard to run time, cost and freshness, as well as the optimization gap. Fig. 3 displays the optimization rate of the run time with regard to R, C, and RC classes. As can be seen from Table 4, ST-VNSGA can obtain a better solution in less time compared to VNSGA. For example, the ST-VNSGA run times of R101_25, R101_50, and R101_100 are 43, 79, and 127, respectively. The VNSGA run times are 73, 144, and 278, and the improvement rates of run time are 41.10 %, 45.14 %, and 54.31 %, respectively. The ST strategy can add the customer to the path where the distance is as close to the customer as possible. Thus, the ST strategy can both effectively reduce the search scope and reach a better solution faster.

Fig. 4 shows R class optimization rate in cost and freshness. Similarly, Fig. 5, Fig. 6 show the results for the C class and RC class, respectively. Conclude from Table 4 and Figs. 4–6 , the cost and freshness of ST-VNSGA-P are also optimized to some extent; for example, the cost of R101_100 reduces to 4.84 % and the freshness of RC101_100 increases to 3.06 %, which proves that the considered spatio-temporal approach has certain guiding significance.

At the same time, Table 4 and Fig. 3 indicate that the proposed algorithm run time is reduced greatly compared to VNSGA, especially in R and RC problems, where the run time is reduced by more than 50 %. R class problem optimization rates are 41.10 %, 45.14 %, and 54.31 %, RC class problem optimization rates are 40.82 %, 44.68 %, and 51.85 %, respectively. The customer points in C class almost appear as an aggregated distribution. The improvement in spatio-temporal distance is not obvious. However, the points in R and RC class randomly spread, so the efficiency of ST-VNSGA solution significantly improved. Thus, the strategy proposed in this study is more suitable for the optimization of the disperse region.

Meanwhile, we can see from Fig. 3 that considering spatio-temporal distance has good potential in solving large-scale VRPs. For example, RC class problem run time optimization rates are 40.82 %, 44.68 %, and 51.85 %, all successively increasing. Therefore, the ST strategy optimizes obviously effect on large-scale VRPs.

To validate the ST strategy optimization effect on the fresh product distribution model and algorithm, we compared without ST strategy (VNSGA) with ST-VNSGA in different order environments. Six numerical examples were created for testing. The impact of the ST strategy on run time and objective values is listed in Table 5.

As indicated by Table 5, comparing the run time rate R101_100 (54.31 %) with R201_100 (46.15 %), C101_100 (20.2 %) with C201_100 (15.46 %), and RC101_100 (51.85 %) with RC201_100 (42.15 %), ST-VNSGA excels VNSGA algorithm in run time optimization, especially with the narrow time windows. In VNSGA, clustering and optimization proceed at the same time. ST-VNSGA optimizes the procedure after clusters. The strict time window constraint interferences the progress clustering. The larger time windows are, the constraints are smaller.

Table 5 Comparison results of different orders environment

Case	ST-VNSGA			VNSGA			Gap		
	Time (s)	Cost (yuan)	Freshness (%)	Time (s)	Cost (yuan)	Freshness (%)	Time (%)	Cost (%)	Freshness (%)
R101_100	127	2649.43	88.1	278	2784.37	85.7	54.31	4.84	2.80
R201_100	161	1756.43	85.8	299	1802.98	83.1	46.15	2.58	3.25
C101_100	79	730.91	92.3	99	758.69	90.0	20.2	3.66	2.56
C201_100	82	368.84	90.1	97	380.16	88.8	15.46	2.98	1.46
RC101_100	91	2556.67	87.5	189	2678.85	84.9	51.85	4.56	3.06
RC201_100	199	1794.49	84.1	344	1934.89	80.5	42.15	7.26	4.47

We conclude that time windows have a major impact on the delivered perishable products; moreover, the cost and freshness of ST-VNSGA increase at different rates; for example, the cost of R201_100 decreases by 7.26 % at most, and the freshness of RC201_100 increases by 4.47 %.

4.3 Effectiveness of ST-VNSGA

For a better analysis of the effectiveness of the proposed heuristic algorithm combined GA and VNS, we compare the NSGA-II algorithm (ST-NSGA-II) with ST-VNSGA. Comparison results between ST-VNSGA and ST-NSGA-II are provided in Table 6.

Table 6 Comparison results between ST-VNSGA and ST-NSGA-II

Case	ST-VNSGA			VNSGA			Gap		
	Time (s)	Cost (yuan)	Freshness (%)	Time (s)	Cost (yuan)	Freshness (%)	Time (%)	Cost (%)	Freshness (%)
R101_25	43	771.58	93.4	38	789.35	91.9	13.16	2.25	1.63
R101_50	79	1403.31	91.7	69	1427.97	88.9	14.49	1.7	3.15
R101_100	127	2649.43	88.1	98	2801.66	86.3	29.59	5.43	2.09
C101_25	22	185.36	94.5	19	189.26	93.8	15.79	2.06	0.75
C101_50	44	367.98	92.8	37	383.81	90.1	18.91	4.12	3.00
C101_100	79	730.91	92.3	65	762.49	88.9	21.54	4.14	3.82
RC101_25	29	799.72	93.3	23	811.18	90.1	26.09	1.41	3.55
RC101_50	52	1360.98	91.4	43	1451.15	87.4	20.93	6.21	4.58
RC101_100	91	2556.67	87.5	72	2720.21	83.1	26.39	6.01	5.29

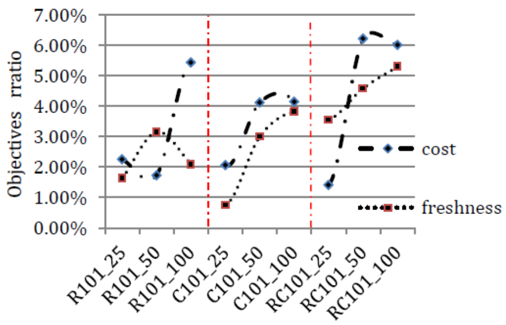

Fig. 7 Objective ratio between ST-VNSGA and ST-NSGA-II under different order environments

We can further derive the validity of ST-VNSGA in Table 6. Result shows that for the run time in R, C, and RC classes, ST-VNSGA takes on an increasing format, for example, R101_25 (13.16 %), R101_50 (14.49 %), and R101_100 (29.59 %). Because the VNS algorithm needs to search mass neighbourhood structures, which increases the run time dramatically, and the ranking based on Pareto dominance further increases the operation time. However, we can see that ST-VNSGA ameliorates the quality of satisfactory solutions; for example, the cost optimal rate of RC101_100 is 6.01 %, the freshness optimal rate of RC101_100 is 5.29 %, indicating that the local search strategy has excellent optimization in seeking the best solution. ST-VNSGA has an advantage in solving multiple objectives, which shows that the proposed algorithm is effective and efficient.

The objective value improves between ST-VNSGA and ST-NSGA-II with regard to cost and freshness, as shown in Fig. 7. In terms of the algorithm solving efficiency, the ST-VNSGA has a significant advantage, especially with the growing number of customers.

4.4 Contrastive analysis of results

According to the contrastive analysis of optimization results, we have found several findings:

- Compared with the method using spatial clustering, the strategy that considers the spatio-temporal distance distribution can achieve better solutions in a shorter period of time, especially in the medium or large-scale distribution problem where it can reach 54.31 % (Table 4, R101_100). This also shows that the algorithm has good potential in solving large-scale VRPs. The strategy proposed in this paper, ST-VNSGA, has obvious advantages for dispersed customer distributions. The results also provide effective decision support to solve the fresh distribution practical problem.
- In fresh product distribution, the heuristic algorithm calculation run time with narrow time window constraints is better than the algorithm based on spatial distance in accordance with the actual needs of customers. In addition, it can save the cost of logistics and improve the service with regard to freshness to a certain extent.
- From the results (Table 6), we can see that ST-VNSGA ameliorates the quality of satisfactory solutions, has excellent optimization in seeking the best solution, and has advantages in solving the multiple objectives, especially with the growing number of customers, with regard to cost and freshness, which show that ST-VNSGA is effective and efficient.

5. Conclusion

In this study, we established the MO-VRPMTW-P model to minimize the distribution costs and maximize the freshness of perishable products. We considered the time-sensitive freshness of perishable products and the high cost of delay in mixed time windows. Then, in view of the fresh product order space and time characteristics, we designed a heuristic algorithm that considers spatio-temporal distance (ST-VNSGA) to solve the fresh product distribution problem. Several numerical examples were presented to demonstrate the effectiveness and efficiency of the proposed algorithm. It was demonstrated that these algorithms can lead to a substantial decrease in run time and major improvements in solution quality, which reveals the importance of considering a spatio-temporal strategy with mixed time windows.

It is worth noting that some areas require improvement; for example, we will focus on interference management in the process of perishable product distribution in the next step.

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