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RESEARCH ON PERISHABLE FOOD PRODUCTS DISTRIBUTION OPTIMIZATION BASED ON FRESHNESS

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Abstract. *For perishable food products, customer satisfaction mainly reflects on the freshness. Due to the high value lost in the distribution process, the complexity of perishable food vehicle routing problem increases. We propose a vehicle routing problem with time windows dealing with perishability (VRPTW-P) based on the tangible distribution costs and the intangible freshness of the delivered products. A hybrid genetic algorithm is applied to solving the problem. Finally, experimental studies are proposed to evaluate this model and algorithm in different orders case. The results illustrate that this model is feasible and effective.*
Keywords: Perishable food, Freshness, Vehicle routing problem, Hybrid genetic algorithm

1. **Introduction.** It has long been recognized that managing perishable food is a difficult problem, such as milk, vegetables and meat distribution. Perishable products usually have a short life cycle and deteriorate rapidly, the value or quality of perishable food products will decrease rapidly once they are produced and will keep decaying when being delivered. In other words, the life of perishable food products depends on the time. Thus, timely delivery of perishable food not only significantly affects the delivery operator's costs, but also the satisfaction of customers. Highly perishable products have an important role in the distribution decision-making process, particularly in the vehicle routing planning task. In the paper, the perishable food products distribution problem is formulated as the vehicle routing problem with time windows dealing with perishability (VRPTW-P).

The well-known vehicle routing problem with time windows (VRPTW) has been discussed deeply. However, few papers consider VRPTW for perishable food distribution in recent years. Some literature concentrated on perishable food products distribution problems without explicitly taking the losing freshness into account as time goes on [1,2]. In concerning the freshness explicitly, Chen et al. [3] proposed a nonlinear mathematical model to consider production scheduling and vehicle routing for perishable food products, which maximizes the expected total profit of the supplier. Osvald and Stirn [4] extended a heuristic algorithm for the distribution of fresh vegetables in which the perishability represents a critical factor. Hsu et al. [5] considered the randomness of the perishable products delivery process and presented a stochastic VRPTW model to obtain optimal delivery routes, loads, fleet dispatching and departure times. Recently, Amorim and Almada-Lobo [6] proposed a model that decouples the minimization of the distribution costs from the maximization of the freshness of the products. However, the relationship between distribution costs and freshness has not been studied yet. In our work, we propose a new framework, hence, giving the decision maker a whole set of efficient solutions between the supply chain optimization and the service aspect related to freshness. We apply the hybrid genetic algorithm, performance matrix based on ranking and optimal preservation strategy to solving this problem.

The paper is organized as follows. In Section 2, we establish an optimization model to minimize the total costs based on the perishable products freshness. The solution of the model and suitable algorithm are presented in Section 3. The results obtained from the computational experiments are shown in Section 4. Finally, we conclude the paper in Section 5 by providing several topics for further research.

2. **Mathematical Formulation.** We elaborate a vehicle routing problem with time windows dealing with perishability (VRPTW-P) that considers time-sensitive spoilage rates of perishable food products. The first objective minimizes the total costs, which contain fixed costs, transportation costs, penalty costs and damaged costs. The second objective maximizes the average freshness of the deteriorating products remaining shelf-life. We assume that the freshness of the products is at the maximum level when the vehicles leave the depot. The value of perishable food products will decay once distribution begins.

In order to describe the characteristic of perishable products, this article will consult the definition from [7] to cite the freshness factor that the products quality rapidly decreases with the transportation time t_i. $\theta(t_i) = 1 - t_i^2/T^2$, T presents the effective life cycle, $0 \le t_i \le T$. We construct a changing coefficient loss ratio of the perishable food products, and $\varphi(t_i) = e^{\frac{\ln 2}{T} t_i} - 1$. The freshness factor related to the transportation time can be represented as $\beta(t_i) = 1 - \varphi(t_i) = 2 - e^{\frac{\ln 2}{T} t_i}$, $\beta(t) \in [0, 1]$.

The following notations are used to formulate the problem in this paper. N: The set of all customer nodes. K: A collection of vehicles. Q^k: The maximum capacity of the vehicle k. $[e_i, l_i]$: The time window of customer i. t_{oki}: The arriving time at customer i of vehicle k. s_i: The service time of customer i. v: The speed of vehicle k. t_{ij}: The travel time from customer i to customer j, and $t_{ij} = t_{ji}$. q_i: The demand of the customer i. $\beta(t_i)$: The freshness level of the perishable products. β: The minimum level that the customer can accept. c_k: The unit transportation cost of the vehicle k. f_k: The fixed costs of the vehicle k.

Decision variables:

x_{ij}^k: binary that takes the value 1 if arc(i, j) belongs to the vehicle k.

y_i^k: binary that takes the value 1 if customer i is assigned to vehicle k.

Then the VRPTW-P can be modeled as follows:

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

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

$$\sum_{i \in N} x_{ij}^k = \sum_{i \in N} x_{ji}^k \quad \forall j \in N, \quad k \in K \tag{3}$$

$$\sum_{k=1}^{K}\sum_{i=1}^{N} x_{i0k} = \sum_{k=1}^{K}\sum_{j=1}^{N} x_{0jk} = 1 \quad \forall i \in N,\ j \in N,\ k \in K \tag{4}$$

$$t_{oki} = t_{ok(i-1)} + s_{i-1} + t_{i(i-1)} \quad \forall i \in N \tag{5}$$

$$\beta(t_i) \geq \beta \quad \forall i \in N \tag{6}$$

$$\sum_{i=1}^{N} y_i^k q_i \leq Q^k \quad \forall k \in K \tag{7}$$

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

$$y_i^k \left(1 - y_i^k\right) = 0 \quad \forall i \in N,\ k \in K \tag{9}$$

$$\sum_{i,j \in s*s}^{N} x_{ij}^k \leq |S| - 1 \quad S \in \{1, 2, \ldots, N\}, \quad \forall k \in K \tag{10}$$

Equation (1) represents the objective function, namely minimizing total costs. Equation (2) represents the objective function that maximizes the average freshness; Equation (3) is flow conservation constraint that describes the individual routes; Equation (4) states that each vehicle should leave and return to distribution center; Equation (5) defines the arrival time at the vehicle k of customer i; Equation (6) ensures the lowest level of freshness that customers can accept; Equation (7) represents that the demand on one route cannot exceed the vehicle maximum capacity; Equation (8) represents that vehicle k travels from customer i to customer j; Equation (9) represents that vehicle k serves customer i; Equation (10) is used to eliminate the loop for one route.

3. Hybrid Genetic Algorithm.

As we all know, the VRPTW-P is an NP-hard problem [8]. We propose an improved hybrid genetic algorithm to solve this problem. We define the individual fitness function on account of the expression matrix. Referring to others' ideas, we rank the objective functions values of different chromosomes, and apply a probability function based on the individual adaptability crossover and mutation, as well as optimal preservation strategy.

3.1. Encoding mechanism.

In this work, we use the real coding method. The gene sequence is $(G_1, G_2, G_3, \ldots, G_K)$. Each gene is composed of vehicle-number (Vehicle-Num), service order value (Service-Value), and service start time s_i.

3.2. Encoding.

Step 1: Initialize an empty new route. Insert one gene of the chromosome into the new route randomly. Step 2: Evaluate the capacities, distribution time and freshness of the new route. Step 3: If the capacities are full, the distribution time or freshness cannot meet the constraints, then construct one route and initialize another new route. Else go back to Step 1, and delete the gene from the chromosome. Step 4: If there are no genes in the chromosome, then stop.

3.3. Constructing the initial population.

Select the first customer according to the seed rules. The rules of the seed customer are as follows: 1) Rule1: The farthest point from the distribution center; 2) Rule2: The narrowest time window of the customer point.

3.4. Algorithmic framework of the genetic operation.

Step 1: Randomly generate population n.

Step 2: Calculate the fitness of each chromosome in the population. This optimal must make sure the lower bound of the vehicles. Repeat the following steps until a feasible solution has been created.

Step 3: Repeat the following steps until n offspring have been created:

Step 3.1: Select a parent chromosome from the current population, and the probability of selection depends on the fitness function;

Step 3.2: With probability p_c, we use the corresponding crossover operation at a randomly chosen point to form two generations;

Step 3.3: Mutate the two generations with probability p_m, and place the resulting chromosomes in the new population.

Step 4: Replace the current population with the new population.

Step 5: Go to Step 2.

3.5. **The individual fitness function.** Set objective function (1) Obj_1 and function (2) Obj_2. Calculate all chromosomes and rank them from the smallest to the largest [9,10]. Suppose the number of permutations $Obj_1(i)$ is $R_1(i)$, so $f_1(i)$ is the chromosome i fitness value of Obj_1. The definition Obj_2, $R_2(i)$ and $f_2(i)$ are the same as the above. The chromosome i towards the jth fitness function is $f_j(i)$, and $f(i)$ represents the overall fitness of the chromosome i. $R_j(i)$ represents the jth objective function ranking of chromosome i. $k \in [1, 2]$.

$$f_j(i) = \begin{cases} (N - R_j(i))^2 & R_j(i) > 1 \\ kN^2 & R_j(i) = 1 \end{cases} \quad i = 1, 2, \ldots, N; \; j = 1, 2 \quad f(i) = f_1(i) + f_2(i)$$

3.6. **Crossover and mutation probability of adaptive function.** P_c, P_m represent the fitness function crossover and mutation respectively; p_c, p_m represent crossover and mutation probability rates; $f_{\max}$ represents the maximum fitness value; f_{avg} represents the average fitness value; the calculations are as follows:

$$P_c = \begin{cases} \dfrac{p_c\,(f_{\max} - \max(f(i_1), f(i_2)))}{(f_{\max} - f_{avg})} & \max\,(f(i_1), f(i_2)) \geq f_{avg} \\ p_c & \max(f(i_1), f(i_2)) < f_{avg} \end{cases}$$

$$P_m = \begin{cases} \dfrac{p_m\,(f_{\max} - f(i))}{(f_{\max} - f_{avg})} & f(i) \geq f_{avg} \\ p_m & f(i) < f_{avg} \end{cases}$$

4. **Numerical Experiments.** 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. We apply Solomon [11] data to test. We define the parameters $w_1 = 10$, $w_2 = 10$, $w_3 = 20$, $\beta = 0.65$. The detailed parameters are shown as Table 1.

Table 1. Parameters of the experiments

Parameter	Value
The vehicle speed (km/h)	30
The lifetime of the product (h)	12
Per vehicle fixed cost ($)	50
Transportation cost per distance ($/km)	0.5
The customer service time (minute)	5
The vehicle capacity (kg)	50

In order to analyze the effectiveness of the proposed model algorithm (D-GA), we compare the single-objective (S-GA) that only considers distribution costs under the premise of meeting the requirement freshness. The comparison results are shown in Table 2.

In small order environment R(1), D-GA distribution costs are 822.71 and S-GA distribution costs are 797.27. We can see that the improvement ratio of Obj_1 is -3.16%, while the freshness improvement ratio is 7.94%. In mass volume R(4) D-GA distribution costs are 2902.13 and S-GA costs are 2846.06. The costs of D-GA increase 1.97%, but the freshness improves 11.68%. It can be seen that the total costs of distribution and the perishable products freshness level are two contradictory goals. The increase of the

Table 2. Comparison of different policies results

Case (orders)	D-GA			S-GA			Obj_1 ratio	Obj_2 ratio
	Num	Obj_1	Obj_2	Num	Obj_1	Obj_2		
R1(25)	8	822.71	92.3%	8	797.27	85.5%	−3.16%	7.94%
R2(50)	14	1507.41	89.9%	14	1469.53	83.1%	−2.58%	8.21%
R3(75)	21	2234.68	87.2%	21	2182.52	79.7%	−2.39%	9.43%
R4(100)	27	2902.13	85.9%	27	2846.06	76.9%	−1.97%	11.68%

Table 3. Computational process of the hybrid genetic algorithm

Case	1	2	3	4	5	6	7	8	9	10	Aver
Obj_1	3128	2967	2823	2834	2914	2948	2862	2792	2904	2849	2902
Transport	1564	1371	1267	1243	1338	1337	1228	1221	1331	1254	1315
Fixed	1350	1400	1350	1400	1350	1400	1400	1350	1350	1400	1375
Delay	126	105	110	107	134	116	103	124	128	114	1166
Damage	88	91	96	84	93	95	131	97	95	81	95.1
Number	27	28	27	28	27	28	28	27	27	28	28
Obj_2	87%	88%	81%	89%	82%	85%	79%	84%	84%	94%	85%
Time/s	121	126	103	113	141	98	124	125	123	138	121.2

freshness is much higher than the increase of the distribution costs. It also shows that the model is more beneficial to improve the freshness in the large orders environment.

In order to verify the efficiency of hybrid genetic algorithm, we record the R4(100) computation process. The detailed results are shown in Table 3.

It can be seen from Table 3 that the Obj_1 average costs are 2902 and the Obj_2 average freshness is 85%. The computation time is 121.2s, so it can converge to a better solution in a relatively short period time.

5. **Conclusions.** We establish an optimization model to minimize the distribution total costs based on the intangible value freshness of perishable products, and then construct a genetic algorithm to solve this problem. Research shows that: 1) the total costs of distribution and the perishable products freshness level are two contradictory goals; 2) the increase of the freshness is much higher than the increase of the distribution costs; 3) in large volume orders, the validity that considers freshness is more obvious. In conclusion, this paper gains higher customer satisfaction at the expense of smaller costs. In addition, the operator may sacrifice some costs in short term, but the operator can have a stable relationship with customers and keep the sustainable development from a long-term strategic perspective.

It is worth noting that the computational complexity dramatically increases in the large scale of problem. In addition, it is necessary to further research freshness with real-time RFID monitoring [12] in distribution routing optimization problem.

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