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Vehicle routing optimization with multiple fuzzy time windows based on improved wolf pack algorithm

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A B S T R A C T

The vehicle routing problem with multiple fuzzy time windows is investigated in this paper. The dynamic change of traffic flow and the fuzzy time window of customers are considered. A multi fuzzy time window vehicle routing model based on time-varying traffic flow is proposed, and the objective function is to minimize the total cost of distribution and maximize customer satisfaction. According to the basic principle of wolf pack algorithm, in order to promote the exchange of information between the artificial wolves, improve the wolves' grasp of the global information and enhance the exploring ability of wolves, a drift operator and wave operator were introduced into scouting behaviors and summing behaviors. An adaptive dynamic adjustment factor strategy was proposed for beleaguering behaviors, the exploitation ability of the algorithm strengthened constantly. Thus the convergence rate of algorithm was enhanced. We further do simulation on an example, and compare the results obtained by wolf pack algorithm and ant genetic algorithm. The results show that use improved wolf pack algorithm to solve vehicle routing problem with multiple fuzzy time windows has the advantages of small number of iterations and high efficiency, it can converge to the global optimal solution in a short time. The improved wolf pack algorithm is an efficient algorithm for solving vehicle routing problem with multiple fuzzy time windows.

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A R T I C L E I N F O

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1. Introduction

With the development of the times, more and more attention has been paid to logistics, which has become one of the most important competitive fields. Whether the logistics distribution scheme is reasonable or not directly affects the enterprise's cost, service quality, efficiency and comprehensive competitiveness. In this paper, through the study of vehicle routing problem, choose a reasonable vehicle delivery path, in order to achieve the enterprise's distribution costs at least, customer satisfaction is the biggest, improve the enterprise's comprehensive competitiveness.

Dantzig and Ramser proposed vehicle routing problem in 1959 [1]. Many scholars have studied its optimization, and obtained rich research results in the fields of transportation [2], logistics [3], interference management [4].

The vehicle routing problem with time windows (VRPMTW) is generated in the traditional vehicle routing problem considering the time window requirements of customers. Most of the researches focus on hard time windows, soft time windows and fuzzy time windows, Cordeau (2001), Qureshi (2009), Hong (2012), He (2013), Meng Xianghu (2014) gave the methods for solving such problems: dynamic programming algorithm, branch and bound method, improved large neighbourhood search algorithm, column generation algorithm and quantum ant colony algorithm [5-9]. On the basis of the above research results, in the distribution of fresh agricultural products, Shao (2015) *et al.* reflected the customer satisfaction by fuzzy membership function which is represented by the time window [10]. Li (2015) *et al.* researched the vehicle routing problem with multiple time windows, considered multiple hard time windows and the capacity of the distribution vehicle, designed a intelligent water drop algorithm to solve the problem [11]. In the study of fuzzy time windows, Yan (2016) *et al.* dealt with the multiple time windows as fuzzy variables, applied particle swarm optimization (PSO) algorithm solve the vehicle routing problem with multiple fuzzy time windows, compared with the VRPMTW model, the model is more close to the needs of customers in real life [12].

Vehicle routing problem based on time varying traffic flow is that when formulate vehicle distribution routes, based on the constraints of the basic transportation scheduling to consider the changing road traffic flow. In the classical research results, the vehicle speed is assumed to be a constant value, but in real life, vehicles are affected by changing traffic flow, and the driving speed is not constant. Van Woensel (2008) *et al.* solved the vehicle routing problem with dynamic traffic time considering potential traffic congestion, considered the traffic jam can shorten the total travel time in the optimization process effectively, optimized the departure time of the vehicle [13]. Kritzinger (2012) *et al.* considered the traffic information in real life into the vehicle routing problem, used the Dijkstra algorithm and a variable neighbourhood search algorithm to solve the problem [14]. Kok (2012) *et al.* considered the influence of traffic jam in vehicle routing, respond to the actual situation of traffic congestion in the speed model [15]. Li (2012) *et al.* proposed a method of cross-time processing, which can deduce the corresponding vehicle travel time directly [16].

Vehicle routing problem with time window in time-varying traffic flow considered the two constraints of customer time window and time-varying traffic flow at the same time, closer to real life, and some achievements have been made in the optimization of cold chain transportation and transportation of dangerous chemicals. Tagmouti (2007), Woensel (2008) *et al.*, Donati (2008) *et al.*, Zhu (2014) and Lin (2014) gave the algorithm column for solving the problem is that generation algorithm, queuing theory, multi ant colony system and tabu search algorithm [17-19]. Xiang (2008) *et al.* researched the scheduled delivery service problem under time-varying constraints [20]. Shi (2013) *et al.* analyzed the travel time based on time-varying characteristics of distribution roads, designed the satisfaction function according to the service time window [21]. Zhu (2016) *et al.* took transportation time and risk as multiple objectives, considered the time-varying transportation time and risk, the service time window constraint of the road node, the mathematical model of the problem is established, designed ant colony algorithm to solve it [22].

In summary, scholars at home and abroad have a deep research on vehicle routing problem with traffic flow and time window constraints, it was also a very useful attempt, the theory, model and algorithm have achieved abundant results. However, the vehicle speed is affected by the dynamic traffic flow in real life, and customers usually have multiple fuzzy time windows, therefore, the study of vehicle routing problem with multiple fuzzy time windows based on time-varying traffic flow is more in line with the actual situation, and the problem has not been studied at present. This paper aims at the dynamic changes of traffic flow in real life and customer acceptance of the delivery service period is not unique, a vehicle routing model with multiple fuzzy time windows based on time-varying traffic flow is constructed, design an improved wolf pack algorithm to solve the problem.

2. Problem description and definition of the model

This paper takes into account the different speed during different time periods in delivery process, deal multiple time windows with fuzzy, establish the membership function of service start time to quantify customer satisfaction, and the objective is to minimize total delivery cost and maximize customer satisfaction, construct a vehicle routing model with multiple fuzzy time windows based on time-varying traffic flow.

2.1 Problem description

A vehicle routing problem with multiple fuzzy time windows based on time-varying traffic flow is described as: a distribution center has m cars and serve n clients, customer i has W_i fuzzy time windows; the coordinates, requirement of n clients and the capacity of m cars are known, vehicles of the same type will start from the distribution center, select a time window for the customer's delivery service, return to the distribution center after all delivery tasks have been completed; the distribution center has sufficient stock, not to consider the shortage situation; at different times of the day, the corresponding driving speed is also different; the fixed cost per vehicle and the cost of travelling per unit distance are known throughout the delivery schedule; the time to service each customer point is known; the total travel distance (time) of each vehicle is within the limits, and the path is rationally planned to obtain the optimal objective function.

2.2 Model definition

$G = (L, A)$: represents the relation between the location of the distribution center and the point of delivery, the path and the spatial temporal distance between each other;
$A = \{a_{i,j} | i \neq j \wedge i, j \in L\}$: represents the route between two delivery points or distribution points and distribution centers;
$L = \{1,2, \dots, n\}$: represents customer set for distribution;
$K = \{1,2, \dots, m\}$: represents distribution vehicle set;
Q_k: represents capacity of vehicle k;
$d_{i,j}$: represents distance from point i to point j;
D_k: represents the total distance (time) value of the vehicle k during the distribution process;
c: represents the fixed cost of delivering a vehicle;
$c_{i,j}$: represents the cost of delivery per unit distance;
t_i: represents the time when the vehicle started serving customer i;
s_i: represents the time of service client i;
t_{ij}: represents the time from customer i to customer j;
q_i: represents the requirements of customer i;
W_i: represents the number of time windows for client i;
$[a_i^\alpha, b_i^\alpha]$: represents that the customer i expects to be served at the α time window, a_i^α represents the earliest service time to start, b_i^α represents the latest service time;
$[E_i^\alpha, L_i^\alpha]$: represents the α fuzzy time window that the client has, E_i^α represents the earliest service time that can be tolerated, L_i^α represents the latest service time that the customer i can tolerate. Introducing decision variables.

$$x_{ijk} = \begin{cases} 1, \text{vehicle } k \text{ access } i \text{ from } j \\ 0, else \end{cases}$$
$$y_i^\alpha = \begin{cases} 1, \text{service the } \alpha \text{ window of the client } i \\ 0, \text{else} \end{cases} \tag{1}$$

In this paper, we use trapezoidal fuzzy time window from literature [12], the satisfaction of customer i is defined by the service start time membership function, $\mu_i(t_i)$ as shown in Eq. 2.

$$\mu_i = \begin{cases} 0, & t_i < E_i^\alpha \\ (t_i - E_i^\alpha)/(a_i^\alpha - E_i^\alpha), & E_i^\alpha < t_i < a_i^\alpha \\ 1, & a_i < t_i < b_i \\ (L_i^\alpha - t_i)/(L_i^\alpha - b_i^\alpha), & b_i^\alpha < t_i < L_i^\alpha \\ 0, & t_i > L_i^\alpha \end{cases} \tag{2}$$

The characteristics of traffic flow are expressed by driving speed, the road traffic flow corresponding to the day is divided into three sections: congestion time, general time and unblocked time, the vehicle speed distribution function is as follows:

$$f\big(v(t)\big)=\begin{cases}\dfrac{1}{\sqrt{2\pi}v(t)\sigma}e^{\frac{(\ln v(t)-\mu)^2}{2\sigma^2}}, v\in[v_{min},v_{max}], t\epsilon tw_1\\ \dfrac{1}{\sqrt{2\pi}\sigma}e^{\frac{(v(t)-\mu)^2}{2\sigma^2}}, v\in[v_{min},v_{max}], t\in tw_2, tw_3\end{cases} \tag{3}$$

$$\mu=\begin{cases}\lambda_1, t\in tw_1\\ \lambda_2, t\in tw_2\\ \lambda_3, t\in tw_3\end{cases}, \sigma_v=\begin{cases}\sigma_{v1}, t\in tw_1\\ \sigma_{v2}, t\in tw_2\\ \sigma_{v3}, t\in tw_3\end{cases} \tag{4}$$

Symbols tw_1, tw_2, tw_3 represent three time periods: unblocked time section, general time section and congestion time section, λ_1, λ_2, λ_3 represent the speed expectations of the vehicle in these three time periods, σ_{v1}, σ_{v2}, σ_{v3} represent the standard deviation of speed in these three time periods.

When the vehicle speed is in the unblocked period, it obeys the logarithmic distribution:

$$\ln v(t)\sim N(\mu,\sigma^2)$$

$$E\big(v(t)\big)=\lambda_1 e^{(\mu+\frac{\sigma^2}{2})},\ \ var\big(v(t)\big)=\sigma_{v1}=(e^{2\mu+\sigma^2})(e^{\sigma^2}-1) \tag{5}$$

When the vehicle speed is in the normal time period and the peak time period, it obeys normal distribution, that is $v(t)\sim N(\mu,\sigma^2)$, so that:

$$E\big(v(t)\big)=\mu, var\big(v(t)\big)=\sigma \tag{6}$$

Vehicle routing model with multiple fuzzy time windows based on time varying traffic flow:

Objective functions:

$$maxZ_1=\frac{1}{n}\sum_{i\in N}\mu_i(t_i) \tag{7}$$

$$minZ_2=C+\sum_{m=1}^{M}\sum_{i=0}^{N}\sum_{j=0}^{N}c_{ij}\cdot x_{ijk} \tag{8}$$

Constraint conditions:

$$\sum_{i=1}^{n}\left(q_i\sum_{j=0}^{n}x_{ijk}\right)\le Q_k, \forall k\in K \tag{9}$$

$$\sum_{i=0}^{n}\sum_{j=1}^{n+1}d_{ij}x_{ijk}\le D_k \tag{10}$$

$$\sum_{i=1}^{n}\sum_{k=1}^{m}x_{ijk}=1, \forall j\in L \tag{11}$$

$$\sum_{i,j\in S\times S}x_{ijk}\le|S|-1, S\subseteq L; \forall k\in K \tag{12}$$

$$L_i^{\alpha}\le E_i^{\alpha+1}, \forall i\subseteq L; \alpha\in\{1,2,\dots,W_i-1\} \tag{13}$$

$$t_j \geq max\left\{\sum_{\alpha=1}^{w_i} y_i^\alpha E_i^\alpha, (t_i + s_i + t_{ij})x_{ijk}\right\}, \forall i, j \in L; \forall k \in K \tag{14}$$

$$t_j \leq \sum_{\alpha=1}^{w_i} y_j^\alpha L_j^\alpha, \forall j \in L \tag{15}$$

$$\sum_{\alpha=1}^{W_i} y_i^\alpha = 1, \forall i \in L \tag{16}$$

$$\ln v(t) \sim N\left(\overline{v(t)}, \sigma_v\right), t \in tw_1$$

$$\mathrm{v(t)\sim N}\left(\overline{v(t)}, \sigma_v\right), \mathrm{t} \in \mathrm{t}w_2, tw_3$$

$$\overline{v(t)} = \begin{cases}\lambda_1, tw_1 \\ \lambda_2, tw_2 \\ \lambda_3, tw_3\end{cases}, \sigma_v = \begin{cases}\sigma_{v1}, tw_1 \\ \sigma_{v2}, tw_2 \\ \sigma_{v3}, tw_3\end{cases}$$

$$t_{ij} = \frac{s_{ij}}{v(t)}, i \in [0, N + M], j \in [0, N + M] \tag{17}$$

$$x_{ijk} = 0 \text{ or } 1, \forall i, j, k \tag{18}$$

$$y_i^\alpha = 0 \text{ or } 1, \forall i \in L; \alpha \in \{1,2, \ldots, W_i\} \tag{19}$$

Function (Eq. 7) is maximize average customer satisfaction; function (Eq. 8) is minimum distribution cost. Constraint condition (Eq. 9) ensure that each vehicle does not exceed the maximum load capacity. Constraint condition (Eq. 10) represents the total travel distance (time) of any distribution vehicle is within the limit. Constraint condition (Eq. 11) ensure that each customer is only served by one car. Constraint condition (Eq. 12) represents a cancellation loop. Constraint condition (Eq. 13) represents the travel time from the customer point $\boldsymbol{i}$ to the customer point j is related to the distribution of traffic flow on the road, and the delivery time is affected by vehicle speed. Constraint conditions (Eq. 14) and (Eq. 15) represent customers are served within the time window. Constraint condition (Eq. 16) represents that each client is only served at one of the time windows. Constraint condition (Eq. 17) represents that a mathematical expectation that corresponds to the speed of the vehicle at different times of the day. Constraint conditions (Eq. 18) and (Eq. 19) represent the range of variables.

3. Improved wolf swarm algorithm

Wolf Colony Algorithm (WCA) is a new intelligent optimization algorithm proposed in 2011, as soon as the algorithm was put forward, it attracted the attention of scholars at home and abroad. Wu Husheng (2013) *et al*. proposed Wolf Pack Algorithm (WPA) based on the characteristics of cooperative hunting of wolves, which is different from WCA algorithm [23]. After several years of research and exploration, the WPA has been applied to the TSP problem, vehicle routing problem and other fields successfully [24, 25].

3.1 Migration modes with drift operators and wave operators

In order to strengthen the information interaction between wolves, this paper adds the drift operator and wave operator to search the whole search space comprehensively, such as Eq. 20:

$$v_{i,d} = x_{i,d} + \varphi_{i,d}\left(x_{i,d} - x_{k,d}\right) + \phi_{i,d}(x_{g,d} - x_{k,d}) \tag{20}$$

$\phi_{i,d}$ is random number within the interval [0,1], $\varphi_{i,d}$ is random number within the interval [−1,1], $x_{g,d}$ represents optimum solution in explore wolf's individual history, $\phi_{i,d}$ is drift coefficient, $(x_{g,d} - x_{i,d})$ is drift direction, $\varphi_{i,d}(x_{i,d} - x_{k,d})$ is fluctuation term, $\varphi_{i,d}$ is fluctuation coefficient.

3.2 Summoning behavior with drift operators and wave operators

In order to improve the ability of information interaction in the process of fierce wolf raid, in this paper, the wolf executes each round of search, and then search again with formula (21). Select the strongest scent of prey and advance in the direction of the smell concentration in the current position, update fierce wolf position, select the maximum smell concentration wolf as leader wolf.

3.3 Self-adaption dynamic adjustment factor strategy

The siege behavior requires the fierce wolf to have stronger local searching ability, in order to enhance exploit capacity of fierce wolf, this paper introduce the adaptive adjustment factor strategy, as shown in Eqs. 21 to 24.

$$v_{ij} = t_1 \cdot x_{ij} + t_2 \cdot \varphi_{ij}(x_{ij} - x_{kj}) \tag{21}$$

$$\varphi_{ij} = (rand - 0.5) \cdot 2 \tag{22}$$

$$t_1 = m(w_2 - \left(\frac{iter}{max\ cycle}\right)^{\alpha} (w_2 - w_1)) \tag{23}$$

$$t_2 = m(w_4 - \left(\frac{iter}{max\ cycle}\right)^{\beta} (w_4 - w_3)) \tag{24}$$

t_1 represents memory factor, is the record of the historical position of the proportion, the greater the value, the better the global optimization ability, the change is shown in Eq. 23; t_2 represents relationship factors of information sharing between food sources and adjacent food sources, its change is shown in Eq. 24.

In formula, w_1, w_2, w_3, w_4 is constants, simultaneous satisfaction $w_2 > w_1, w_4 > w_3$, and its range of value is in the range [0.1,1.5]. t_1 is reduced from w_2 to w_1, is from the global search gradually refined to local search, α usually less than 1, but the numerical value is too small is not conducive to global convergence, so the range of numerical value is in [0.6,1]. t_2 is reduced from w_3 to w_4, usually, $\beta > 1$, but the fierce wolf can easily cross the global optimal solution when the numerical value is too large, so the range of numerical value is in [1,1.3]. m is a constant, it is based on the comparison between the food source and the food source in the neighborhood, when the neighborhood food source position is better than the current food source, the neighborhood tends to search and share information, value $m = 1.5$, otherwise m = 0.6.

3.4 Algorithm flow

The improved WPA solves the flow chart of the multi time vehicle path model based on time varying traffic flow, as shown in Fig 1.

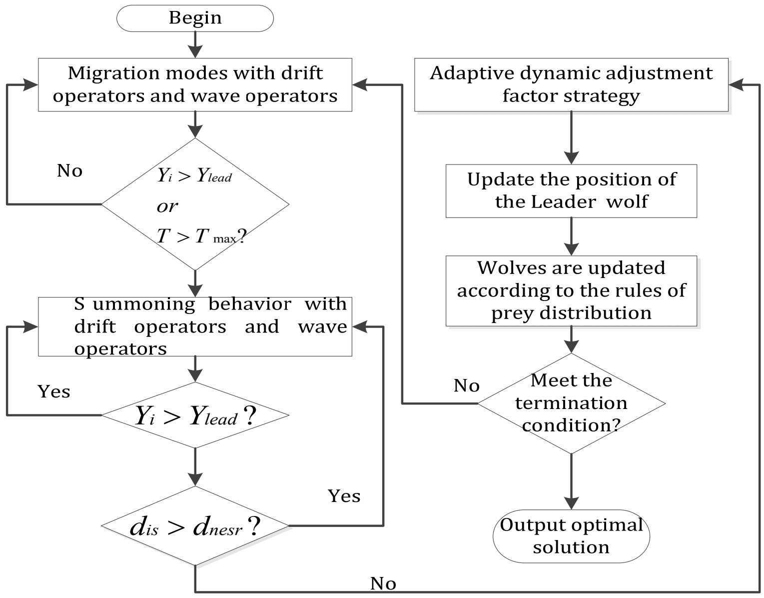

Fig 1 algorithm flow chart

4. Results and discussion

Multiple fuzzy time windows vehicle routing problem for time-varying traffic flow, considers the time-varying traffic flow and fuzzy time windows at the same time. At present, there is no common standard test data internationally, referring to the literature [11], the simulation data are designed as follows. A distribution center services for 20 clients, each client has 2 time windows, the distribution center has N delivery vehicles, it's a single model, the maximum capacity of each car is 45 t, the delivery cost of the distribution vehicle is 6 yuan per kilometer, the fixed cost of each car is 150 yuan, customer coordinates, customer requirements, service times, and time windows are shown in Table 1. It is assumed that the delivery vehicle will work from 7:00 to 20:00 a day, affected by traffic flow at different times, the corresponding distribution vehicles have different running speeds, based on the actual situation to do the relevant design, as shown in Table 2.

Table 1 Customer information

Customer	q_i	s_i	Coordinate	E_i^1	a_i^1	b_i^1	L_i^1	E_i^2	a_i^2	b_i^2	L_i^2
1	2	0.2	(1,5)	23.0	0.0	1.0	3.0	2.7	4.0	5.0	6.6
2	3	0.2	(22,10)	22.5	0.5	1.5	2.0	2.4	3.0	4.0	5.6
3	4	0.3	(12,20)	22.5	0.5	2.0	2.2	2.6	3.0	4.0	5.6
4	3	0.2	(6,28)	23.0	0.5	1.5	2.5	2.2	3.0	4.0	5.6
5	5	0.3	(10,2)	22.5	0.0	1.0	2.4	2.2	3.0	4.0	5.6
6	7	0.4	(8,15)	22.5	0.5	1.0	1.4	1.4	2.0	3.0	4.6
7	6	0.4	(-10,20)	22.5	0.5	1.5	1.5	2.0	2.5	3.5	5.1
8	4	0.3	(-15,6)	22.5	0.5	2.0	2.0	2.4	3.0	4.0	5.6
9	6	0.4	(-18,25)	22.5	0.5	1.5	1.8	1.8	2.0	3.0	4.6
10	6	0.4	(-22,5)	23.0	0.5	1.0	1.4	1.4	2.0	4.0	5.6
11	7	0.4	(-15,-5)	23.0	0.5	1.5	2.5	2.4	3.0	4.0	5.6
12	10	0.5	(-17,-12)	23.0	0.5	1.0	1.8	1.7	3.0	4.0	5.6
13	5	0.3	(-10,-25)	22.5	0.5	1.0	1.5	1.4	1.5	3.0	4.6
14	7	0.4	(-5,-15)	23.0	0.5	1.0	1.5	1.4	2.0	3.0	4.6
15	11	0.5	(2,-35)	23.5	1.0	3.0	3.5	3.6	4.0	5.0	6.6
16	12	0.5	(3,-15)	23.5	0.5	1.5	2.5	2.2	3.0	4.0	5.6
17	4	0.3	(5,-10)	22.5	0.0	1.0	2.5	2.6	4.0	5.0	6.6
18	5	0.3	(12,-35)	23.0	0.5	1.5	1.8	1.9	2.0	4.0	5.6
19	10	0.5	(23,-20)	23.6	1.0	2.0	2.3	2.4	3.0	5.0	6.6
20	12	0.5	(16,-12)	23.0	0.5	1.0	2.0	2.1	3.0	5.0	6.6

Table 2 Vehicle speed

Congestion situation	Specific time	Running speed
Expedite time	7:00-7:20 19:00-20:00	55
General time	9:00-12:00 13:00-17:00	45
Congestion time	7:20-9:00 12:00-13:00 17:00-19:00	35

Authors through a large number of experiments to verify that α (i.e., exploring wolf scaling factor) and β (i.e., update scaling factor) in WPA not as sensitive as other intelligent algorithms, random selection is only required within the bounds; ω (the distance determination factor) is an important parameter to control the artificial wolf from the raid state to siege behavior, with the increase of ω, determine the distance decreases, the artificial fierce wolf into siege behavior in the distance near the position of the leader wolf, improve the convergence speed of the algorithm, reduce iterations, but the value of ω is too large, the artificial wolf is difficult to move into the siege, which leads to an increase in iterations; S (the step size factor) shows the fine degree of searching the optimal solution for the wolf in the solution space, with the increase of S, the search precision is increased, and the average iteration number of the algorithm is also increased, if the S exceeds a certain range, the convergence accuracy of the algorithm will decrease and the optimization results will be poor.

According to references [23-26], this paper sets up the running parameters of the improved WPA: experimental setting maximum iterations is 100, maximum number of trips is 15, initial wolf size is 200, $\alpha = 4, \beta = 6, S = 22$; the average level of satisfaction is set to 0.75, the optimal experimental results obtained by the improved wolf pack algorithm are shown in Table 3, the optimal experimental result path is shown in Fig 2.

For further analysis the improved WPA, the calculation results are compared with the results of genetic algorithm, the selected algorithm parameters are as follows: population size is 30, crossover rate is 0.6, mutation rate is 0.05. Each algorithm is calculated with the same constraints and computer configuration, run 100 times separately.

Table 3 Optimal experimental results

Vehicle	Route	Travel distance (km)	Customer satisfaction	Loading capacity (t)	Distribution cost (yuan)
1	0-17-16-14-13-12-0	71.32	0.75	38	577.92
2	0-7-9-10-8-11-0	86.07	0.77	29	666.42
3	0-20-19-18-15-0	94.29	0.76	38	715.74
4	0-5-2-6-3-4-1-0	84.53	0.78	24	657.18

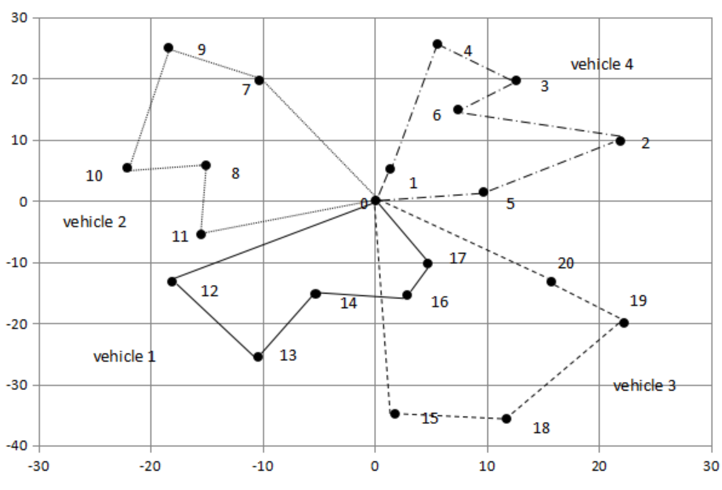

Fig 2 Optimal experimental result path chart

The experimental comparison results are shown in Table 4, the improved WPA has the best path, the shorter total travel distance and the lower total distribution cost, average customer satisfaction is higher; The Table 4 shows that the improved WPA does not increase the computational time on the basis of performance improvement, and is an efficient improved wolf swarm algorithm.

The convergence of the optimal solution is shown in Fig 3. These results show that the improved WPA has the advantages of small number of iterations and high efficiency. It can converge to the global optimal solution in a short period of time.

Table 4 Experimental results of improved WPA and genetic algorithm

Algorithm	Vehicle route	Total travel distance (km)	Total distribution cost (yuan)	Average customer satisfaction	Average computational time (s)
Improved WPA	0-17-16-14-13-12-0 0-7-9-10-8-11-0 0-20-19-18-15-0 0-5-2-6-3-4-1-0	336.21	2617.26	0.77	10.39
Genetic algorithm	0-8-10-11-12-0 0-1-5-2-6-3-4-7-9-0 0-20-19-18-15-0 0-17-16-13-14-0	343.033	2658.17	0.76	11.87

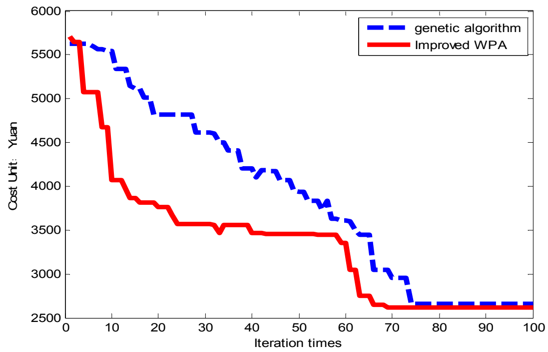

Fig 3 Convergence of the optimal solution

5. Conclusion

This paper considers the time-varying speed in real life and the fuzzy time window of customers, a vehicle routing model with multiple fuzzy time windows based on time-varying traffic flow is constructed. The drift operator and wave operator are introduced in the migration and wave operators, in order to enhance the exploit capacity of the wolf, an adaptive dynamic adjustment factor is introduced, design an improved WPA and give the algorithm steps. Through simulation analysis, the improved wolf pack algorithm is compared with genetic algorithm, it shows that the algorithm can obtain the optimal solution, and the efficiency of the solution has been improved, can reduce the total distance travelled more effectively, reduce distribution costs and improve customer satisfaction.

Therefore, the improved WPA increase exchanges of information between the artificial wolf, enhance the wolves grasp of global information, the exploration ability and exploitation ability. WPA is a swarm intelligence optimization algorithm to solve multi fuzzy vehicle routing problem with time window. WPA is a new swarm intelligence algorithm. How to combine the WPA with other intelligent algorithms to solve the problem more efficiently is the next step.

Meanwhile, the uncertainties faced in reality are even more complex, for example, changes in customer demand, sudden vehicle failure, customer cancellations, changes in customer's time window, bad weather, etc. In the future, such extensions can study in depth.

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References

[1] Dantzig, G.B., Ramser, J.H. (1959). The truck dispatching problem, *Management Science*, Vol. 6, No. 1, 80-91, doi: 10.1287/mnsc.6.1.80.

[2] Lu, X.C., Chen, Q.B., Zhang, Z.J. (2014). The electric vehicle routing optimizing algorithm and the charging stations' layout analysis in Beijing, *International Journal of Simulation Modelling*, Vol. 13, No. 1, 116-127, doi: 10.2507/IJSIMM13(1)CO4.

[3] Cao, Q.-K., Liu, X.-Y., Ren, X.-Y. (2015). Vehicle scheduling problem based on plant growth simulation algorithm, *Systems Engineering – Theory & Practice*, Vol. 35, No. 6, 1449-1456, doi: 123.57.41.99/jweb_xtgcllysj/CN/10.12011/1000-6788(2015)6-1449.

[4] Wang, X., Ruan, J., Sun, Z., Cao, H. (2013). Disruption recovery model for vehicle routing problem with backhaul, *Journal of Systems Engineering*, Vol. 28, No. 5, 608-616.

[5] Cordeau, J.-F., Laporte, G., Mercier, A. (2001). A unified tabu search heuristics for vehicle routing problems with time windows, *Journal of the Operational Research Society*, Vol. 52, No. 8, 928-936, doi: 10.1057/palgrave.jors.2601163.

[6] Qureshi, A.G., Taniguchi, E., Yamada, T. (2009). An exact solution approach for vehicle routing and scheduling problems with soft time windows, *Transportation Research Part E: Logistics & Transportation Review*, Vol. 45, No. 6, 960-977, doi: org/10.1016/j.tre.2009.04.007.

[7] Hong, L. (2012). An improved LNS algorithm for real-time vehicle routing problem with time windows, Computers & Operations Research, Vol. 39, No. 2, 151-163, doi: org/10.1016/j.cor.2011.03.006.

[8] He, X.-F., Ma, L. (2013). Quantum-inspired ant colony algorithm for vehicle routing problem with time windows, *Systems Engineering – Theory & Practice*, Vol. 33, No. 5, 1255-1261, doi: 10.3969/j.issn.1000-6788.2013.05.021.

[9] Meng, X.-H., Hu, R., Qian, B. (2014). Effective hybrid population-based incremental learning algorithm for vehicle routing problem with time windows, *Systems Engineering – Theory & Practice*, Vol. 34, No. 10, 2701-2709, doi: 10.12011/1000-6788(2014)10-2701.

[10] Shao, J.-P., Cao, Q., Shen, M., Sun, Y. (2015). Research on multi-objective optimization for fresh agricultural products VRP problem, *Industrial Engineering and Management*, Vol. 20, No. 1, 122-127, doi: 10.3969/j.issn.1007-5429.2015.01.019.

[11] Li, Z.P., Zhao, F., Liu, H.D. (2015). Intelligent water drops algorithm for vehicle routing problem with multiple time windows, *Operations Research and Management Science*, Vol. 24, No. 6, 1-10.

[12] Yan, F., Wang, Y. (2016). Modeling and solution of vehicle routing problem with multiple fuzzy time windows, *Journal of Transportation Systems Engineering and Information Technology*, Vol. 16, No. 6, 182-188, doi: 10.3969/j.issn.1009-6744.2016.06.028.

[13] Van Woensel, T., Kerbache, L., Peremans, H., Vandaele, N. (2008). Vehicle routing with dynamic travel times: A queueing approach, *European Journal of Operational Research*, Vol. 186, No. 3, 990-1007, doi: 10.1016/j.ejor.2007.03.012.

[14] Kritzinger, S., Doerner, K.F., Hartl, R.F., Kiechle, G.Ÿ., Stadler, H., Manohar, S.S. (2012). *Using traffic information for time-dependent vehicle routing*, Procedia – Social and Behavioral Sciences, Vol. 39, 217-229, doi: 10.1016/j.sbspro.2012.03.103.

[15] Kok, A.L., Hans, E.W., Schutten, J.M.J. (2012). Vehicle routing under time-dependent travel times: The impact of congestion avoidance, *Computers & Operations Research*, Vol. 39, No. 5, 910-918, doi: 10.1016/j.cor.2011. 05.027.

[16] Li, Y., Li, J., Gao, Z. (2012). Dynamic programming heuristics for solving time dependent vehicle routing problem, *Systems Engineering – Theory & Practice*, Vol. 32, No. 8, 1712-1718, doi: 10.3969/j.issn.1000-6788.2012.08.010.

[17] Tagmouti, M., Gendreau, M., Potvin, J.-Y. (2007). Arc routing problems with time-dependent service costs, *European Journal of Operational Research*, Vol. 181, No. 1, 30-39, doi: 10.1016/j.ejor.2006.06.028.

[18] Van Woensel, T., Kerbache, L., Peremans, H., Vandaele, N. (2008). Vehicle routing with dynamic travel times: a queueing approach, *European Journal of Operational Research*, Vol. 186, No. 3, 990-1007, doi: 10.1016/j.ejor.2007.03.012.

[19] Donati, A.V., Montemanni, R., Casagrande, N., Rizzoli, A.E., Gambardella, L.M. (2008). Time dependent vehicle routing problem with a multi ant colony system, *European Journal of Operational Research*, Vol. 185, No. 3, 1174-1191, doi: 10.1016/j.ejor.2006.06.047.

[20] Xiang, Z., Chu, C., Chen, H. (2008). The study of a dynamic dial-a-ride problem under time-dependent and stochastic environments, *European Journal of Operational Research*, Vol. 185, No. 2, 534-551, doi: 10.1016/j.ejor.2007.01.007.

[21] Shi, Z., Fu, Z. (2013). Distribution location routing optimization problem of food cold chain with time window in time varying network, *Application Research of Computers*, Vol. 30, No. 1, 183-188, doi: 10.3969/j.issn.1001-3695.2013.01.047.

[22] Zhu, T., Wang, X.L., Zhao, L.J. (2016). Path selection of hazardous materials road transportation with time window and multi-objectives, *Industrial Engineering Journal*, Vol. 19, No. 2, 62-67, doi: 10.3969/j.issn.1007-7375.2016.02.010.
[23] Wu, H.S., Zhang, F.M., Wu, L.S. (2013). New swarm intelligence algorithm-wolf pack algorithm, *Systems Engineering and Electronics*, Vol. 35, No. 11, 2430-2438.
[24] Wu, H.-S., Zhang, F.-M., Li, H., Liang, X.-L. (2015). Discrete wolf pack algorithm for traveling salesman problem, *Control and Decision*, Vol. 30, No. 10, 1861-1867, doi: 10.13195/j.kzyjc.2014.1055.
[25] Ye, Y., Zhang, H.Z. (2017). Wolf pack algorithm for multi-depot vehicle routing problem, *Application Research of Computers*, Vol. 34, No. 9, 2590-2593.
[26] Li, G., Wei, Z., Xu, L. (2015). Wolf pack algorithm based on modified search strategy, *Journal of Computer Applications*, Vol. 35, No. 6, 1633-1636, doi: 10.11772/j.issn.1001-9081.2015.06.1633.