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A Vehicle Routing Problem Model With Multiple Fuzzy Windows Based on Time-Varying Traffic Flow

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ABSTRACT In actual distribution process, the traffic flow varies with time, and each consumer has multiple fuzzy windows. To minimize the total distribution cost and mean consumer dissatisfaction, this paper sets up a vehicle routing problem (VRP) model with multiple fuzzy time windows, based on time-varying traffic flow. In addition, the Ito algorithm was improved based on time-varying traffic flow. The model and algorithm were verified through example simulation, in comparison with ant colony optimization (ACO). During the simulation, the improved Ito algorithm effectively reduced the distribution cost and consumer dissatisfaction, and outperformed the ACO in solving efficiency and solution quality. The results fully demonstrate the feasibility and effectiveness of the proposed algorithm. The research findings provide a desirable solution to VRPs with multiple fuzzy windows and time-varying traffic flow in the real world.

INDEX TERMS Time-varying traffic flow, multiple fuzzy time windows, Ito algorithm, vehicle routing problem (VRP), consumer satisfaction.

I. INTRODUCTION

The booming economy in China is accompanied by the rise of the logistics industry. The logistics cost has become a major concern among profit-seeking enterprises. In addition to cost saving, a rational logistic distribution plan should also enhance consumer satisfaction, service efficiency, and boost the overall competitiveness of enterprises.

Focusing on vehicle routing problem (VRP), this paper attempts to minimize total distribution cost and maximize mean consumer satisfaction by rationalizing the distribution routes of vehicles, with the aim to promote service efficiency and bolster the overall competitiveness of enterprises.

Since its proposal by Dantzig and Ramser in 1959 [1], the VRP has always been a research hotspot. Considering the delivery time required by consumers, many scholars probed into the VRP with time windows (VRPTW), including hard time window, soft time window and fuzzy time window. For example, Li and Qin [2], Nguyen *et al.* [3], Tan *et al.* [4], Osaba *et al.* [5], Qiu *et al.* [6] and Song [7] solved the VRPTW with improved ant colony optimization (ACO) [8], tabu search, heuristic algorithm [9], discrete bat algorithm (DBA), branch-and-cut algorithm, and improved genetic algorithm (GA) [10], respectively.

Drawing on the above research, Ge and Zhu [11] explored the VRP of electric vehicles with soft time window. Beheshti and Hejazi [12] investigated the VRP with soft time window, and proposed a hybrid column generation-metaheuristic approach that can efficiently solve the problem. Based on consumer satisfaction and vehicle transport cost, Sun and Ma [13] constructed a multi-objective VRP with fuzzy time window, and solved the problem with hybrid bat algorithm. In the light of consumer demand in actual distribution, Yan and Wang [14] studied the VRP with multiple fuzzy time windows, solved the problem with particle swarm optimization (PSO), and verified the cost effectiveness of the solution.

In real-world scenarios, traffic congestion is common in the distribution process, which suppresses the distribution efficiency. Therefore, the traffic flow has been introduced to the VRP at home and abroad. Considering the impact of congestion on travel time, Mancini [15] established a VRP model constrained by traffic congestion, and solved the model in an accurate and effective manner, using a self-developed multi-stage heuristic algorithm. Incorporating route flexibility to the VRP, Huang *et al.* [16] created and solved a time-dependent VRP with path flexibility. Hiermann *et al.* [17] tackled the time-varying mix VRP of electric vehicles, and

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put forward a hybrid heuristic algorithm to solve the problem accurately and effectively. In the context of the Internet of vehicles (IoV), Qin *et al.* [18] improved the autopilot car-following model, and enhanced the stability of front and rear cars in the model by analyzing the stability domain of mixed traffic flow. Cruzlt and Woensel [19] explored deep into the finite queueing model, and enumerated the advantages of generalized expansion method in evaluating the finite queueing network.

The realistic modelling of actual distribution should consider both the time window required by consumers and the time-varying traffic flow. Many Chinese and foreign scholars have included the two factors into the VRP. Foreign scholars like Tagmouti *et al.* [20], Akdogan *et al.* [21] and Alinaghian and Naderipour [22] solved the VRP models containing the two factors by variable neighborhood descent heuristic, approximate queuing model, and improved Gaussian firefly algorithm, respectively. Wu and Ma [23] adopted a hybrid GA to solve the integrated production and distribution of perishable food with time window and time-varying network. Okulewicz and Mańdziuk [24] solved the dynamic VRP with the aid of the PSO. Targeting multi-objective VRP, Lou [25] designed a multi-objective scalar model to minimize the number of vehicles, the total travel distance and consumer dissatisfaction, and solved the model with simulated annealing (SA) algorithm. Cai *et al.* [26] verified the suitability of adaptive ACO to low-cost distribution. To minimize time-varying travel time and risk, Zhu *et al.* [27] created a bi-objective VRP model with time window, and designed an ACO to solve the established model.

To sum up, scholars at home and abroad have examined the VRPs with time window and/or traffic flow. However, there is not enough research into VRPs with time-varying traffic flow or multiple time windows of a single consumer, both of which are common in the real-world. To make up for the gap, this paper sets up a VRP model with time-varying traffic flow and multiple fuzzy time windows, and improved the Ito algorithm based on time-varying traffic flow to solve the problem.

II. PROBLEM DESCRIPTION

This paper establishes a membership function for the time that a vehicle arrives at a consumer (i.e. service start time), in the light of the multiple fuzzy time windows required by the consumer and the time-varying travel speed. Considering consumer satisfaction, a bi-objective function was constructed to minimize the total distribution cost and mean consumer dissatisfaction. Next, a VRP model with multiple fuzzy time windows was set up based on time-varying traffic flow.

Based on time-varying traffic flow, the VRP with multiple fuzzy time windows can be described as the minimizing the total distribution cost and mean consumer dissatisfaction under the following hypotheses: there is one distribution center that serves n consumers, each of whom has Wi fuzzy time windows; the coordinates and demand of each consumer and the load capacity of each vehicle are known in advance; each vehicle leaves from the distribution center, delivers goods to each consumer within one of the fuzzy time windows, and returns to the distribution center after completing all delivery tasks; there is no shortage of any goods at the distribution center; the traffic speed satisfies mathematical expectation in each period of the day; the fixed cost and travel cost per unit distance of each vehicle are known in advance; the service time at each consumer is known in advance; the total travel distance (time) of each vehicle falls in a preset range.

III. MODEL CONSTRUCTION

The path network of the distribution center and consumers can be illustrated by a directed graph $G = (L, A)$, where $L = \{1, 2, \ldots, n\}$ is the set of consumers, and $A = \{ai, j | i \neq j \Lambda i, j \in L\}$ is the set of the paths between two consumers and those between a consumer and the distribution center. The distance and travel time between consumers i and j are denoted as d_{ij} and t_{ij}, respectively.

For consumer i, the demand is denoted as q_i; the number of time windows is denoted as W_i; the expected time window α to be served is denoted as $\left[a_i^\alpha , b_i^\alpha\right]$, where a_i^α and b_i^α are the earliest and latest service start times, respectively; the fuzzy time window α is denoted as $\left[E_i^\alpha , L_i^\alpha\right]$, where E_i^α and L_i^α are the earliest and latest tolerable service start times, respectively.

Let $K = \{1, 2, \ldots, m\}$ be the set of vehicles. For vehicle k, the load capacity is denoted as Q_k; the maximum total travel distance (time) is denoted as D_k; the fixed cost and the travel cost per unit distance are denoted as c and c_{ij}, respectively; the service start time at consumer i is denoted as t_i; the service time at consumer i is denoted as S_i.

Then, two decision variables can be introduced:

$$xijk = \begin{cases} 1, & vehicle\ k\ travels\ to\ consumer\ j \\ 0, & others \end{cases}$$

$$y_i^\alpha = \begin{cases} 1, & vehicle\ k\ serves\ consumer\ i\ at\ time\ window\ \alpha \\ 0, & others \end{cases}$$

Using the trapezoidal fuzzy time window [10], the membership function of service start time $\mu_i(t_i)$ can be defined as the satisfaction of consumer i:

$$\mu i = \begin{cases} 0, & ti < L_i^\alpha \\ (\mathrm{t}_i - E_i^\alpha)/(a_i^\alpha - E_i^\alpha), & E_i^\alpha < t_i < a_i^\alpha \\ 1, & a_i < t_i < b_i \\ (L_i^\alpha - t_i)/(L_i^\alpha - b_i^\alpha), & b_i^\alpha < t_i < L_i^\alpha \\ 0, & \mathrm{t}_i < L_i^\alpha \end{cases} \tag{1}$$

The travel speed is a feature of the traffic flow. Considering the features of traffic flow, each day was divided into three periods: smooth period tw_1, general period tw_2 and congestion period tw_3. The travel speed distribution can be described as [27]:

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

where, $\mu = \begin{cases} \lambda_1, t \in tw_1 \\ \lambda_2, t \in tw_2 \\ \lambda_3, t \in tw_3 \end{cases}$; $\sigma v = \begin{cases} \sigma v_1, t \in tw_1 \\ \sigma v_2, t \in tw_2 \\ \sigma v_3, t \in tw_3 \end{cases}$; λ_1, λ_2 and λ_3 are the expected travel speeds in smooth period, general period and congestion period, respectively; σ_{v1}, σ_{v2} and σ_{v3} are the standard deviations of travel speed in smooth period, general period and congestion period, respectively.

In the smooth period, the trajectory of a vehicle obeys the logarithmic distribution:

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

In this case, $E(v(t)) = \lambda 1 e^{(\mu + \frac{\sigma^2}{2})}$ and, $var(v(t)) = \sigma v1 = (e^{(2\mu+\sigma^2)})(e^{\sigma^2} - 1)$.

In the general period or congestion period, the trajectory of a vehicle obeys the normal distribution:

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

In this case, $E(v(t)) = \mu$ and, $var(v(t)) = \sigma$.

Based on time-varying traffic flow, the VRP model with multiple fuzzy time windows can be established as:

$$f(x) = \max Z_1 = \frac{1}{n} \sum_{i \in N} \mu_i(t_i) \tag{3}$$

$$\min Z_2 = C + \sum_{m=1}^{M} \sum_{i=0}^{N} \sum_{j=0}^{N} c_{ij} \cdot x_{ijk} \tag{4}$$

$$s.t. \sum_{i=1}^{n} (q_i \sum_{j=0}^{n} x_{ijk}) \leq Q_k, \quad \forall k \in K \tag{5}$$

$$\sum_{i=0}^{n} \sum_{j=1}^{n+1} d_{ij} x_{ijk} \leq D_k \tag{6}$$

$$\sum_{i=1}^{n} \sum_{k=1}^{m} x_{ijk} = 1, \quad \forall j \in L \tag{7}$$

$$\sum_{i,j \in S \times S} x_{ijk} \leq |S| - 1, S \subseteq L; \quad \forall k \in K \tag{8}$$

$$L_i^{\alpha} \leq E_i^{\alpha+1}, \forall i \in L; \alpha \in \{1, 2, \ldots, W_i - 1\} \tag{9}$$

$$tj \geq \max \left\{ \sum_{\alpha=1}^{W_i} y_i^{\alpha} E_i^{\alpha}, (t_i + s_i + t_{ij}) x_{ijk} \right\}, \quad \forall i, j \in L; \forall k \in K \tag{10}$$

$$tj \leq \sum_{\alpha=1}^{W_i} y_j^{\alpha} L_j^{\alpha}, \quad \forall j \in L \tag{11}$$

$$\sum_{\alpha=1}^{W_i} y_i^{\alpha} = 1, \quad \forall i \in L \tag{12}$$

$$\begin{aligned} &\ln v(t) \sim N(\bar{v}(t), \sigma v), \quad t \in tw_1 \\ &v(t) \sim N(\bar{v}(t), \sigma v), \quad t \in tw_2, tw_3 \\ &\bar{v}(t) = \begin{cases} \lambda_1, tw_1 \\ \lambda_2, tw_2 \\ \lambda_3, tw_3 \end{cases} \quad \sigma v = \begin{cases} \sigma_v 1, tw_1 \\ \sigma_v 2, tw_2 \\ \sigma_v 3, tw_3 \end{cases} \\ &t_{ij} = s_{ij}/v(t) \quad i \in [0, N+M],\ j \in [0, N+M] \end{aligned} \tag{13}$$

$$x_{ijk} = 0 \text{ or } 1, \quad \forall i, j, k \tag{14}$$

$$y_i^{\alpha} = 0 \text{ or } 1, \quad \forall i \in L;\ \alpha \in \{1, 2, \ldots, Wi\} \tag{15}$$

Formula (3) aims to maximize the mean consumer satisfaction; formula (4) aims to minimize the total distribution cost; formula (5) ensures that no vehicle surpasses its load capacity; formula (6) controls the total travel distance (time) within the preset range; formula (7) guarantees that each consumer is served by only one vehicle; formula (8) eliminates sub-loops; formula (9) specifies the chronological order of the multiple time windows of each consumer; formulas (10) and (11) regulates that each consumer is served within a time window; formula (13) shows the expected travel speed of a vehicle in each period of the day; formulas (14) and (15) provide the intervals of different variables.

IV. IMPROVED ITO ALGORITHM

The Ito algorithm [28] provides a good solution to combinatorial optimization problems. Over the years, this algorithm has been improved by many scholars. For example, Hua and Yu [29], Yin and Yu [30] and Man *et al.* [31] improved the Ito algorithm with the constraints like load capacity and soft time window, and applied the improved version to solve the VRP. To avoid the local optimum trap, this paper introduces the Cauchy mutation to improve the Ito algorithm, aiming to solve the established VRP model.

A. IMPROVEMENT OF PATH SELECTION STRATEGY

From the global perspective, the influence of the current consumer on the next consumer was added to the path selection strategy. The minimum total distance between the two consumers was calculated to improve the formula $\eta(i,j) = 1/d_{ij}$:

$$\eta ij = 1/\min[dis(i,j) + dis(j,g)] \tag{16}$$

where, $dis(i,j)$ and $dis(j,g)$ are the distances between nodes i and j, and between nodes j and g. The improved path selection strategy can be expressed (17), as shown at the bottom of the next page, where, $\tau(i,j)$ is the weight of the path between nodes i and j; α is the influence of path weight on the selection of consumers; β is the influence of distance heuristic factor on the selection of consumers; *tabum* is the tabu table containing all the served consumers; l is the set of unserved consumers.

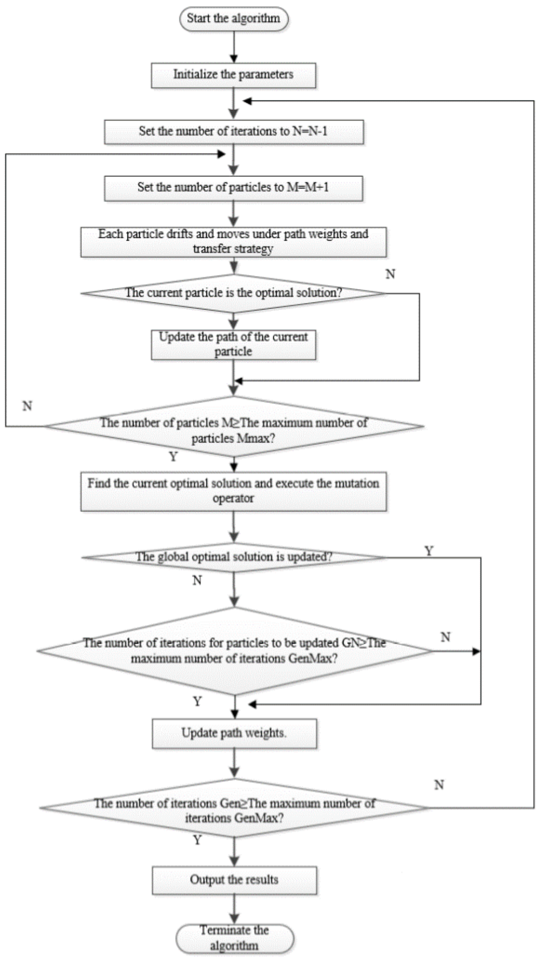

FIGURE 1. The flow of the improved Ito algorithm.

B. IMPROVEMENT OF PATH WEIGHT UPDATE STRATEGY

The path weight can be updated by:

$$\tau(i,j)=\begin{cases}2-\rho, & if\ e(i,j)\in\sigma\cap e(i,j)\in\sigma' \\ 1+\rho+\mu, & if\ e(i,j)\in\sigma' \\ 1+\mu, & if\ e(i,j)\in\sigma \\ \rho+\mu, & \text{else}\end{cases}\tag{18}$$

where, ρ is the strength of the wave operator; σ' is the current optimal path; σ is the current path; μ is the strength of the drift operator; $e(i,j)$ is the path between consumers i and j.

C. CAUCHY MUTATION

The Ito algorithm is prone to the local optimum trap. To solve the problem, the Cauchy mutation was introduced. The

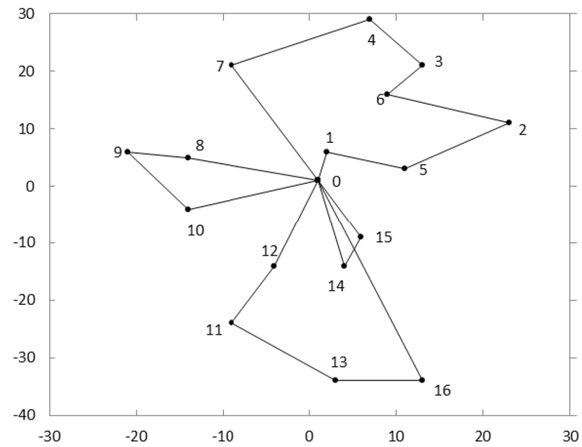

FIGURE 2. Optimal route obtained by simulation.

mutation strategy can be expressed as:

$$x_{best}=x_{best}+\varphi(k)\cdot C(1)\tag{19}$$

$$\varphi(k+1)=\varphi(k)\exp(t'\cdot C(0,1))\tag{20}$$

$$t'=1/\sqrt{2\sqrt{n}}\tag{21}$$

where, x_{best} is the current optimal solution; C(1) is a random number under standard Cauchy distribution at $t=1$; k is the current number of iterations; n is the maximum number of iterations.

D. ALGORITHM FLOW

The flow of the improved Ito algorithm is explained in Figure 1.

V. SIMULATION AND RESULT ANALYSIS

To verify its effectiveness, the proposed model and algorithm were simulated with a real example. In the example, there is a distribution center A serving 16 consumers nearby with M identical vehicles (maximum load capacity: 40t; distribution cost: RMB 5 yuan/km; fixed cost: RMB 100 yuan/vehicle). The coordinates, demand, service time and time windows of each consumer are listed in Table 1. It is assumed that each vehicle operates from 7:00 to 20:00 each day, and travels at different speeds in different periods. The travel speeds were designed realistically (Table 2).

The parameters of improved Ito algorithm were configured as follows: the number of particles K = 50; path weight $\tau(i,j)=1$; influence of path weight $\alpha=5$; influence of distance $\beta=3$; initial particle radius $r=0$; initial ambient temperature $itmp=8000$; annealing speed $aspeed=0.95$; mean consumer satisfaction = 0.75. Using the improved Ito

$$p^m(i,j)=\begin{cases}\dfrac{[\tau(i,j)]^\alpha\left\{1/\min[dis(i,j)+dis(j,g)]\right\}^\beta}{\sum\limits_{l\notin tabum}[\tau(i,l)]^\alpha\left\{1/\min[dis(i,j)+dis(j,g)]\right\}^\beta}, & i\in tabum\cap j\notin tabum \\ 0, & else\end{cases}\tag{17}$$

TABLE 1. Information of consumers.

Consumer	di	si	Coordinates	E_i^1	a_i^1	b_i^1	L_i^1	E_i^2	a_i^2	b_i^2	L_i^2
0	0	0	(1, 1)	-	-	-	-	-	-	-	-
1	2	0.2	(2, 6)	22:30	0:00	1:00	2:30	2:36	4:00	5:00	6:30
2	3	0.2	(23, 11)	23:00	0:30	1:30	2:12	2:18	3:0	4:00	5:30
3	4	0.3	(13, 21)	23:00	0:30	2:00	2:24	2:30	3:00	4:00	5:30
4	3	0.2	(7, 29)	23:00	0:30	1:30	2:00	2:06	3:00	4;00	5:30
5	5	0.3	(11, 3)	22:30	0:00	1:00	2:00	2:06	3:00	4:00	5:30
6	7	0.4	(9, 16)	23:00	0:30	1:00	1:12	1:18	2:00	3:00	4:30
7	6	0.4	(-9, 21)	23:00	0:30	1:30	1:48	1:54	2:30	3:30	5:00
8	4	0.3	(-14, 5)	23:00	0:30	2:00	2:12	2:18	3:00	4:00	5:30
9	6	0.4	(-21, 6)	23:00	0:30	1:00	1:12	1:18	2:00	4:00	5:30
10	7	0.4	(-14, -4)	23:00	0:30	1:30	2:12	2:18	3:00	4:00	5:30
11	5	0.3	(-9, -24)	23:00	0:30	1:00	1:12	1:18	1:30	3:00	4:30
12	7	0.4	(-4, -14)	23:00	0:30	1:00	1:12	1:18	2:00	3:00	4:30
13	11	0.5	(3, -34)	23:30	1:00	3:00	3:24	3:30	4:00	5:00	6:30
14	12	0.5	(4, -14)	23:00	0:30	1:30	2:00	2:06	3:00	4:00	5:30
15	4	0.3	(6, -9)	22:30	0:00	1:00	2:24	2:30	4:00	5:00	6:30
16	5	0.3	(13, -34)	23.0	0.5	1.5	1.7	1.8	2.0	4:00	5:30

TABLE 2. Travel speeds of vehicles.

Period	Time slots	Travel speed
Congestion period	7:30-9:00 11:30-13:00 17:00-19:00	30
General period	9:00-11:30 13:00-17:00	40
Smooth period	7:00-7:30 19:00-20:00	50

TABLE 3. The optimal results.

Vehicle	Route	Travel distance/km	Mean consumer satisfaction	Total distribution cost
1	0-8-9-10-0	51.17	0.83	355.85
2	0-12-11-13-16-0	89.61	0.81	548.05
3	0-1-5-2-6-3-4-7-0	100.53	0.82	602.65
4	0-14-15-0	31.86	0.81	259.32

TABLE 4. Comparison between the results of the improved Ito algorithm and the ACO.

Algorithm	Route	Total travel distance	Total distribution cost	Mean consumer satisfaction
Improved Ito algorithm	0-8-9-10-0 0-12-11-13-16-0 0-1-5-2-6-3-4-7-0 0-14-15-0	273.17	1765.87	0.82
ACO	0-7-8-9-10-0 0-12-11-13-16-0 0-1-5-2-6-3-4-0 0-14-15-0	303.01	1915.05	0.76

algorithm, the optimal results are listed in Table 3, and the optimal route is shown in Figure 2.

Furthermore, the results of the improved Ito algorithm were compared with those of the ACO (Table 4). The ACO

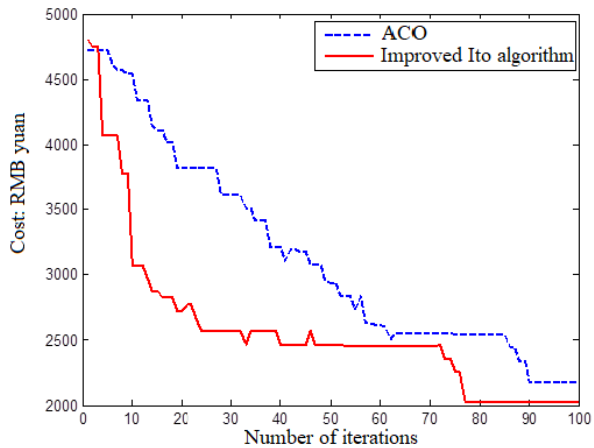

FIGURE 3. Convergence to the optimal solution.

parameters were set as follows: the number of ants $m_1 = 50$; influence of pheromone concentration $\alpha_1 = 5$; influence of intermodal distance $\beta_1 = 3$; scope of pheromone concentration $\tau_{\max} = 10$ and $\tau_{\min} = 0.01$; pheromone volatilization rate $\lambda_1 = 0.05$.

As shown in Table 4, the optimal route obtained by the improved Ito algorithm had the shorter total travel distance, the lower total distribution cost, and the higher mean consumer satisfaction.

Judging by the convergence to the optimal solution (Figure 3), the improved Ito algorithm converged to the global optimal solution in a short time within a few number iterations, an evidence of the high efficiency of the algorithm.

VI. CONCLUSION

In actual distribution process, the travel speed of vehicles varies with time, and each consumer requires several fuzzy time windows. This paper creates a VRP model with multiple fuzzy time windows, based on time-varying traffic flow. Besides, the Ito algorithm was improved drawing on the strategies for path weight update and path selection. The

Cauchy mutation was introduced to enhance the algorithm's resistance to the local optimum trap. Through the simulation of an actual VRP, the improved Ito algorithm was proved as capable of outputting a high-quality distribution plan, with minimal total travel distance and total distribution cost. The results demonstrate the effectiveness and feasibility of the improved Ito algorithm.

This paper mainly optimizes the distribution route to consumers, in the light of the time-varying feature of traffic flow. The future research will consider even more uncertain factors in actual distribution in the VRP, including bad weather, road congestion, vehicle failure and changing time windows of consumers.

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