Multi-Objective Distribution Model and Algorithm for Online Shopping Express Logistics

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***Abstract*— The multi-objective distribution problem with time windows for online shopping express logistics (OSEDP) is an extension of the vehicle routing problem with time windows (VRPTW). In additional to the time windows, we also take the customers' satisfaction degree (CSD), the cost, and both integrated conditions into consideration. To solve this problem, we design a modified particle swarm optimization algorithm (PSO) which can enhance the quality of the particle evolution and the speed of the original algorithm. This algorithm begins with random solutions, uses the fitness degree as the evaluation function, and searches for optimal solution by the iterative steps. The simulation experimental results also show that the proposed model and algorithm are efficient and effective for online shopping express logistics distribution problem.**

***Index Terms*—customers' satisfaction degree, time windows, penalty function, particle swarm algorithm**

I. Introduction

As the rapid development of Network Communication Technology (NCT) in the 21st century, the Electronic Business (E-Business) has become a new driving force for the economic growth. It also contributes to the rapid development of online shopping by adjusting the economic structure, transforming the model of traditional business and combining the traditional industry with the modern one. As the data shows, the population of online shoppers in China is more than that of American online shoppers, 193million for the former and 170million for the latter. Besides, the percentage of the Internet users has risen from 28% to 36% during 2009 to 2011, which is even expected to exceed 47% in 2015. Additionally, the express logistics industry has been an increasingly crucial part in our lives. According to the statistics, the income of the express companies on a national scale has increased dramatically between 2011 to 2012 from 7.58 billion to 10.60 billion, as well as the annual delivery has increased from 3670 million to 5700 million over the period.

However, the development of our express logistics industry can't keep pace with the development of the Business-to-Business (B2B) business and Business-to-Customer (B2C) business. Lack of experience, resources and funds has put the express logistics industry into a dilemma which is already at a full capacity. Therefore, the logistics service is faced with new challenges. Firstly, the scale of customers has been enlarged, resulting in a more difficult NP-hard problem. Secondly, the customers have requirements of time windows, including both the basic time window and the expected time window. Thirdly, it is essential to focus on prompting the service standard in an increasingly competitive express logistic industry market. Thus, the multi-objective distribution problem with time windows (online shopping express distribution problem, OSEDP) which is the extension of the VRPTW by considering the customers' satisfaction degree(CSD), the cost, and both integrated condition is worthy of studying. Also, we design a modified particle swarm optimization algorithm (PSO) to solve this problem.

II. Literature Review

The vehicle routing problem with time windows (VRPTW) is an extension of the vehicle routing problem (VRP) proposed by Dantzing and Ramser in 1959. Since the VRPTW is an NP-hard problem, a lot of scholars have proposed various heuristic algorithms to solve it, including Simulated Annealing (SA) Algorithm, tabu Search (TS) Algorithm, Genetic Algorithm (GA), and so on. Here are some related literatures.

Ref. [6] studies VRPTW under the time-varying condition, considers describing the vehicle velocity as time-varying piecewise function, and solves the problem with the Simulated Annealing method. Ref. [7] adopts an adaptive parallel way, considers the distance, the approximation of time limit, and the waiting time, and

doi:10.4304/jcp.8.10.2558-2564

designs the construction heuristic algorithm. Ref. [8] designs a two-phase hybrid metaheuristic which combines the modified saving algorithm with the tabu search algorithm to solve the VRPTW problem on a scale of 100-1000 customer points, aiming at the minimum working vehicles and line lengths. Ref. [9] solves the OSEDP problem with the modified multi-objective evolutionary algorithm, in the consideration of the minimum working vehicles, run time, and line lengths. Ref. [10] designs a two-phase hybrid metaheuristic which combines the guided local search (GLS) with the evolutionary algorithms (EA) to solve the VRPTW problem on a large scale. Ref. [11] studies the open vehicle routing problem with single and mixed fleet strategy. Ref. [12] proposed an efficient intelligent optimized algorithm to solve the dynamic VRP. Ref. [13] studies the urban delivery distribution routing optimizing key technologies based on Web GIS. Ref. [14] and Ref.[15] studies the dynamic routing problems and proposed several effective algorithms.

III. MATHMATICAL MODEL

A. Prolbem Description

The multi-objective distribution problem of the online shopping express logistics, which is based on the customers' satisfaction degree, can be described as follows. The distribution center (DC) will dispatch a set of vehicles to serve the customers from DC to DC. The problem is to find the optimum route for the vehicles to reduce the total cost while still ensuring a high customers' satisfaction degree by taking the demands and time windows of customers into consideration. An example of online shopping express distribution problem is shown in Fig. 1.

B. Problem Assumptions

According to the problem description, we make the following assumptions:

(1) DC: All of the vehicles should start from and return to the same DC;

(2) The uniqueness of accessibility: Each customer must be visited once and only once;

(3) The carriage capacity: The carriage capacity of the vehicle should be able to meet the total demands of customers along each line.

(4) Time windows: Each customer has a basic time windows and an expected time windows, with the former containing the latter. The customers' service is expected to be provided in the expected time window. Otherwise we will bear a loss on the cost. From a practical point of view, it is a soft time window problem, and we shall use a function to handle it.

C. Parameters and Notations

$G=(V,E)$: Distribution network;

V : Set of nodes of node V_i,

$V=\{0,1,\cdots,n\}$ $V_i=\begin{cases}0, & \text{the DC}\\ 1,\ldots,n, & \text{the nodes of customers}\end{cases}$;

E: Set of arc. $E=\{(i,j)\mid i,j\in V, i\neq j\}$;

c_{ij} : The travelled distance of arc (i,j);

t_{ij} : The travelled time of arc (i,j);

t_i : The point in time of the vehicle arrives at the Customer i;

K: Set of vehicles, $K=\{1,2,\cdots,m\}$, m is the demand quantity of vehicles;

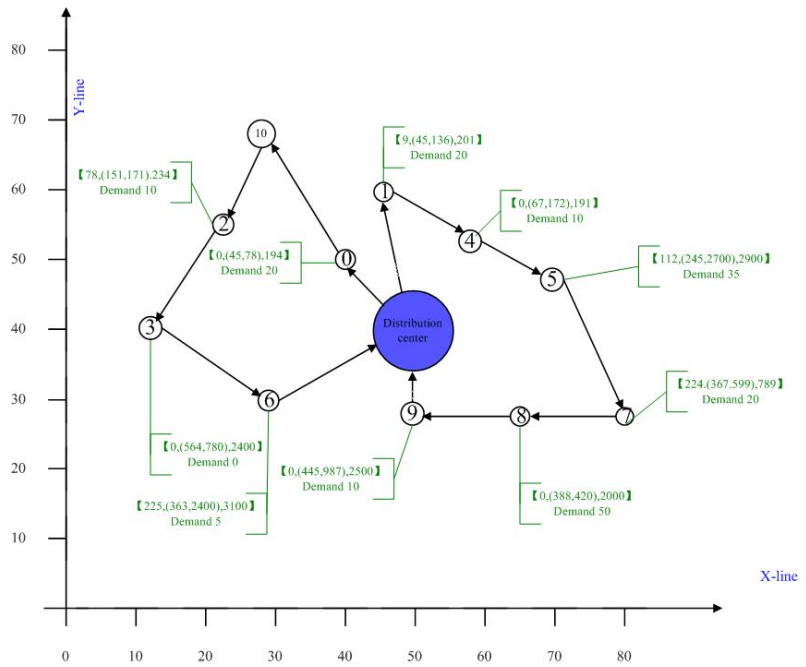

Figure 1. An example of online shopping express distribution problem, OSEDP.

Q: The carrying capacity;

$[e_i, l_i]$: The expected time window of Customer i;

$[E_i, L_i]$: The basic time window of Customer i;

q_i: The demanded quantity of Customer i, $q_0 = 0$;

x_{ijk}: The number of times of the Vehicle k will visit the arc (i, j).

$x_{ijk} = \{0,1\}$, $x_{ijk} = \begin{cases} 0, & \text{visited} \\ 1, & \text{non-visited} \end{cases}$

D. Customers' Satisfaction Degree

The Customers' Satisfaction Degree (CSD) is measured to describe the service performance of the logistics enterprises. This paper describes it as a number between [0,1], where 0 means the customer is not satisfied with the service totally while 1 means the opposite. In addition, we set the basic time window of Customer i as $[E_i, L_i]$ and the expected time window of Customer i as $[e_i, l_i]$. Then, $[e_i, l_i] \subset [E_i, L_i]$. If the customer is served in the expected time window, the CSD of the customer SI =1. If the customer gets the service in the basic time window, the CSD will rise with the reduction of the deflection of the expected time window. We define the CSD of the Customer i as shown in Figure 2:

$$SI(t_i) = \begin{cases} 0 & t_i \in (0, E_i) \cup (L_i, \infty) \\ (t_i - E_i)/(e_i - E_i) & t_i \in (E_i, e_i) \\ 1 & t_i \in (E_i, e_i) \\ (L_i - t_i)/(L_i - l_i) & t_i \in (l_i, L_i) \end{cases} \quad (1)$$

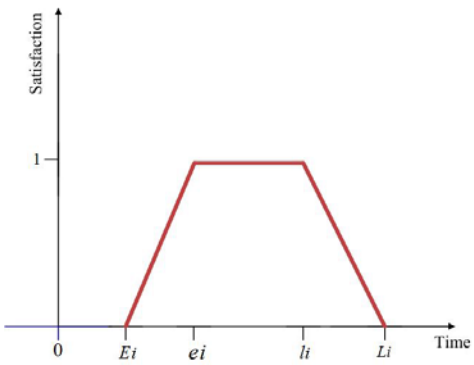

Figure 2: The satisfaction degree of Customer i

E. Penalty Function

If the vehicle arrives in $[e_i, l_i]$, the SI will be the highest and the waiting cost will be zero. If the vehicle arrives before $[e_i, l_i]$, the SI is great but the opportunity cost of waiting will not be zero. If the vehicle arrived after $[e_i, l_i]$, the SI will reduce but the waiting cost will be zero. Therefore, in our model, we use a penalty function to handle these problems. The function $p_i(t_i)$ can be designed as follows:

$$p_i(t_i) = c_1 \sum_{i \in n} \max[(e_i - t_i), 0] + c_2 \sum_{i \in n} \max[(t_i - l_i), 0] \quad (2)$$

where, t_i is independent variable, the point of time when the vehicle arrives at customer i; c_1 is the proportion of the cost of waiting in the penalty function; c_2 represents the proportion of the cost of CSD reduction in the penalty function.

The penalty function is shown in Figure 3.

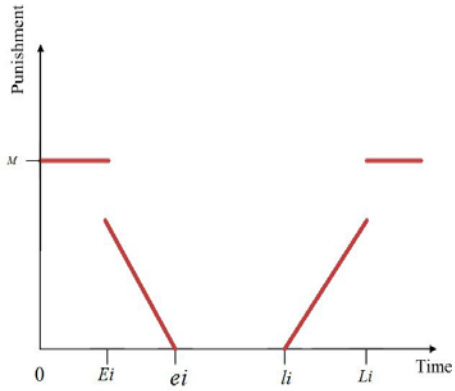

Figure 3: The penalty function of customer i

F. Mathematical Model

We establish the OSEDP model as follows:

$$\max z_1 = \sum_{i=1}^{n} SI(t_i) \quad (3)$$

$$\min z_2 = \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} c_{ij} x_{ijk} \quad (4)$$

$$\min z_3 = \sum_{i=1}^{n} p_i(t_i) \quad (5)$$

$$s.t. \quad \sum_{k \in K} \sum_{j \in C} x_{ijk} = 1, \forall i \in c \quad (6)$$

$$\sum_{i \in V} q_i \sum_{j \in V} x_{ijk} \le Q, \forall k \in K \quad (7)$$

$$\sum_{j \in V} x_{0ik} = 1, \forall k \in K \quad (8)$$

$$\sum_{i \in V} x_{ihk} - \sum_{j \in V} x_{hjk} = 0, \forall h \in V, \forall k \in K \quad (9)$$

$$\sum_{i \in V} x_{i0k} = 1, \forall k \in K \quad (10)$$

$$\sum_{k \in K} \sum_{i \in V \setminus \{0\}} x_{i0k} = \sum_{k \in K} \sum_{j \in V \setminus \{0\}} x_{0jk} = m \quad (11)$$

$$t_i + t_{ij} = t_j, \forall i, j \in V \quad (12)$$

$$t_i \in [E_i, L_i], \quad \forall i \in V \quad (13)$$

where (3) is the objective function of the highest SI; (4) is the objective function of the shortest route; (5) is the objective function of the minimum penalty function of equation (2); Constraint (6) guarantee each customer must be visited once; Constraint (7) means the vehicles do not overload; Constraints (8),(9) and (10) ensure that

each vehicle sets out from 0 and returns to 0 among the unrepeatable customers. Constraint (11) guarantee that the quantities of the vehicle go in and out the DC are equal, which values m; Constraint (12) represents that i is the accumulation of the time; Constraint (13) means that the point of time when the vehicle arrives at Customer i must be in $[E_i, L_i]$;

IV. The Algorithm

A. The Ideas of Algorithm

The particle swarm optimization (PSO) algorithm is a relatively recent bio-inspired approach to solve combinatorial optimization problems in continual multi-dimensional parameter space, which emulates the social behavior of animals such as insects swarming, birds flocking, and fish schooling where these swarms search for food in a collaborative manner. PSO has limited number of parameters to adjust, which makes it particularly easy to implement. Furthermore, our research results also have demonstrated its efficiency, versatility and robustness in solving the VRPTW.

PSO involves a swarm of particles that represent the potential solutions to the problem. Each particle embeds the relevant information regarding the design variables and associated fitness providing an indication of its performance in the objective space. Each particle flies through the search space and updates its position based on the best position visited by the particle itself (local best) and by the best among the neighbors of the particle (global best).The fitness function is as follows:

$$fitness = \lambda_0 \sum_{i=1}^{n} SI(t_i) - \lambda_1 \sum_{k\in K}\sum_{i\in V}\sum_{j\in V} c_{ij} x_{ijk} - \lambda_2 \sum_{i=1}^{n} p_i(t_i) \quad (14)$$

where $\lambda_0, \lambda_1, \lambda_2$ are the proportion coefficients. The biggest $fitness$ of each particle will be kept.

The particle will update itself through the two principles as follows:

(1) Keep its inertia during the flight;

(2) Update on its position is based on the best position visited by the particle itself (local best) and by the best among the neighbors of the particle (global best).

B. The Detail Steps of Algorithm

The detail steps of the proposed particle swarm algorithm are described as follows:

Step 1: Initialization

Step 1.1.: Divide the particle swarm into some overlapping adjacent ones.

Step 1.2.: The dimension of each particle's position vector x_v is a random integer between 1 and m (m vehicles), and the dimension of x_r is a random real number between 1 and n (n customers).

Step 1.3.: The dimension of each speed vector V_V is a random integer ranging in [-(m-1), (m-1)] (m vehicles), and the dimension of V_r is a random real number ranging in [-(k-1), (k-1)].

Step 1.4.: Evaluate all of the particles with the fitness function.

Step 1.5.: Set the initial evaluation as the individual optimum solution P_i, and find the optimum solution P_l in every particle swarm and the optimum solution P_g for the whole swarms.

Step 2: Repeat the steps as follows until it satisfies the termination condition or it reaches the maximum times of iteration.

Step. 2.1.: Calculate the V_V, V_r, X_v, X_r for each particle. And we round the X_v up to the next integer. If the V or X goes over range, then set the value as its boundary.

Step 2.2.: Evaluate all of the particles with the fitness function.

Step 2.3.: If the current evaluation is better than the former best evaluation, then set the current one as the best evaluation and the current position as the best position P_i

Step 2.4.: Find the optimum solution for current adjacent particle swarm and the optimum solution for the whole swarms. If they are better than the previous optimum solution, then update P_l and P_g.

C. Time Complexity Analysis of Algorithm

According to the steps of the algorithm, we can see that when the travel time and label of the node is a scalar, the time complexity in worst case is $O(|V|^2|E|)$. As each label is generated when the length of time series is T, the total computational time is $O(|V|^2|E|T)$.

The above analysis indicates that our algorithm is a polynomial algorithm, and can meet the real-time applications.

V. Numerical Example

A. The Computer Simulation

In order to verify the validity and the feasibility of the model described in this paper, we use the most commonly accepted benchmark data for the OSEDP. The data are illustrated as follows.

Firstly, we assume that there is an express logistics enterprise delivering goods to the customers, a logistics distribution center numbered 0, seven customers numbered 1 to 7 with their own basic time windows, expected time windows, coordinates, and demands. All above-mentioned parameters are assumed as we list in Table 1. Then, we assign the distances between i, j (Euclid Distance) and the parameters of particle swarm optimization as we show in Table 2 and Table 4. In addition, the logistics distribution center has three cars (m=3), each car's transportation volume is 1 (Q=1). Next, the time between two customers is proportional to the relative distance, so we assign 50 to the speed, convert

the time, and multiply the time by 60 to get the running time (t_{ij}) between the two customers i, j. Table 3 shows the results. Finally, we convert the algorithm into codes by the MATLAB R2008b，and run it ten times，Table 5 shows the results.

TABLE I
EACH CUSTOMER'S BASIC TIME WINDOW, DESIRED TIME WINDOW, COORDINATES, DEMAND

Customer's number	0	1	2	3	4	5	6	7
$[e_i, l_i]$	(0,0)	(50,100)	(51,101)	(52,102)	(53,103)	(54,104)	(55,105)	(56,106)
$[E_i, L_i]$	(0,0)	(1,400)	(2,401)	(3,402)	(4,403)	(5,404)	(6,405)	(7,406)
Coordinates	(18,54)	(22,60)	(58,69)	(71,71)	(83,46)	(91,38)	(24,42)	(18,40)
Demand	0	0.35	0.14	0.28	0.33	0.21	0.41	0.57

TABLE II
THE DISTANCE BETWEEN i, j

Distance	0	1	2	3	4	5	6	7
0	0	7.2111	42.72	55.66	65.49	74.733	13.416	14
1	7.2111	0	37.108	50.22	62.586	72.422	18.111	20.396
2	42.72	37.108	0	13.153	33.971	45.277	43.417	49.406
3	55.66	50.22	13.153	0	27.731	38.588	55.227	61.4
4	65.49	62.586	33.971	27.731	0	11.314	59.135	65.276
5	74.733	72.422	45.277	38.588	11.314	0	67.119	73.027
6	13.416	18.111	43.417	55.227	59.135	67.119	0	6.3246
7	14	20.396	49.406	61.4	65.276	73.027	6.3246	0

TABLE III
THE RUNNING TIME (t_{ij}) BETWEEN THE TWO CUSTOMERS i, j

Time	0	1	2	3	4	5	6	7
0	0	6.00	35.60	46.38	54.55	62.28	11.18	11.67
1	6.00	0	30.92	41.85	52.13	60.35	15.09	17.00
2	35.60	30.92	0	10.96	28.30	37.73	36.18	41.16
3	46.38	41.85	10.96	0	23.11	32.16	46.02	51.15
4	54.55	52.13	28.30	23.11	0	9.43	49.26	54.39
5	62.28	60.35	37.73	32.16	9.43	0	55.93	60.85
6	11.18	15.09	36.18	46.02	49.26	55.93	0	5.27
7	11.67	17.00	41.16	51．15	54.39	60.85	5.27	0

TABLE IV
PARAMETERS OF PARTICLE SWARM OPTIMIZATION

Weighing coefficient	Learning factor	The maximum number of iteration	The dimension of the search space	The number of initial population
w=0.7298	$c_1 = c_2 = 1.4962$	MaxDT=50	D=7	N=40

Notation: Fitness function's parameters: $\lambda_0 = 100, \lambda_1 = 0.1, \lambda_2 = 0.1$; Punishment function's parameters: $c_1 = c_2 = 1$.

TABLE V
THE EXPERIMENTAL RESULTS

	Fitness value	The vehicle path	The average running time	The success rate
$fitness = \max z_1$ （The maximum satisfaction）	6.16	Vehicle 1: 0—6—0 Vehicle 2: 0—2—0 Vehicle 3; 0—4—7—3—5—1—0	35.6s	80%
$fitness = \min z_2$ （The minimum path）	217.81	Vehicle 1: 0—7—6—0 Vehicle 2: 0—1—0 Vehicle 3: 0—2—3—4—5—0	19.7s	100%
$fitness = \min z_3$ （The minimum punishment function）	113.12	Vehicle 1: 0—5—0 Vehicle 2: 0—3—1—0 Vehicle 3; 0—4—7—2—6—0	22.3s	100%
$fitness = \max \lambda_0 * z_1 - \lambda_1 * z_2 - \lambda_2 * z_3$ (Overall satisfaction and cost considerations)	1579.8	Vehicle 1: 0—2—3—0 Vehicle 2： 0—6—0 Vehicle 3： 0—4—7—5—1—0	67.2s	70%

B. Experimental Analysis

The classical VRP only considers the shortest distance as the single target, which has a limit in reflecting the requirements of real time windows and CSD. Comparing to it, the VRPTW, an extension to the VPR, is more practical. Thus, we propose a multi-objective distribution model and algorithm for Online shopping express logistics which can practically solve the OSEDP.

Comparing to standard particle swarm optimization algorithm, our algorithm is a new modified PSO algorithm. In our algorithm, we turn the waiting time into cost by using the penalty function to promote the objective function. This algorithm not only partly adopts the method of PSO, but also promotes Standard PSO from the particle evolution and the multi-swarms. In addition, each particle flies through the search space to keep the diversity of particle swarms, which can also enhance the ability of global search. Furthermore, an appropriate particle evolution can overcome the particular drawbacks of lack of local search ability and premature convergence to enhance the stability of the algorithm. The success rate of the algorithm can reach over 80%.

Our algorithm provides a practical strategy to solve nonlinear equations, because it has some advantages as follows:

1. High accuracy;
2. Fast convergence rate;
3. Some algorithms are allergic to initial value, and some need derivable function. However, our algorithm can get over both of them.;
4. It can solve complicated nonlinear equations fast;
5. Effective and feasible. Data simulation indicates that our algorithm is effective and feasible.

V. CONCLUSION

In this paper, we propose a multi-objective distribution model and algorithm for online shopping express logistics. The proposed algorithm is a modified particle swarm optimization (PSO) algorithm. In our study, we address the time windows problem and the Customer Satisfaction Degree (CSD) by a penalty function and a segmented function SI , use the fitness degree as the evaluation

function, and figure out the optimum solutions. Our research is based on seven customer points, one center warehouse and three cars. As the research results show, using the improved PSO algorithm to tackle multi-objective distribution problem for online express logistics which is based on the CSD has practical significance.

For future work, we can further study whether our algorithm can be combined with other algorithms to improve the scalability of the algorithm.

ACKNOWLEDGMENT

The authors wish to thank the reviewers for their valuable comments. This work was supported in part by the Contemporary Business and Trade Research Center of Zhejiang Gongshang University which is the Key Research Institute of Social Sciences and Humanities Ministry of Education (Grant No.12JDSM16YB), Humanities and Social Sciences Foundation of Ministry of Education of China (Grant No. 12YJC630091), Zhejiang Provincial Natural Science Foundation of China (Grant No. LQ12G02007), the National Natural Science Foundation of China (Grant No.71171178), and Zhejiang Provincial Commonweal Technology Applied Research Projects of China (Grant No.2011C23076).

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