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No-load Backhaul Ratio Reduction by Interactive Routing for Small Goods Delivery with Time Window Constraints

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***Abstract*—In 2016, owing to the growth in e-commerce, over 31 billion of goods have been delivered in Mainland China which is more than 50% volume in 2015. The rapid growth of delivery volume introduces a big challenge to logistics researches. Existing researches focus on single trip routing problems which delivers goods to multiple customers in a single trip and backhauling to the distribution center with no-load. With the huge volume of delivery with time window constraints in every day, multiple backhauling with no-load is time-consuming and greatly increases the transportation cost. So, in this work, we propose an interactive routing model using a mobile storage house to meet delivery vehicles dynamically to reduce the cost of backhauling with no-load under time window constraints. Experimental results show that the proposed method effectively reduces the transportation cost in all cases and enhances customer satisfactory in many cases.**

Keywords*—interactive routing model, time window constraint, mobile storehouse.

I. Introduction

The Vehicle Routing Problem (VRP) is one of the key research problems in logistics and supply chain management due to its pervasive applications. However, the volume of goods deliveries increases rapidly and the traffic jam has become a serious issue in goods deliveries. Therefore, increasing either or both the number of trucks and the capacity of trucks cannot solve the problem practically. In contrast, they may make the transportation jam more serious. Instead, there are many trials or implementations on using small vehicles or drones to deliver goods, e.g. the Unmanned Aerial Vehicle (UAV) of Amazonas [1] and electric-bicycles in Mainland China. The major limitation of them is the multiple backhauling with no-load between customers and depots. In this work, with the time window constraints and the high dense of demands, we propose an interactive routing model using mobile depots to reduce the cost generated by multiple backhauling of small vehicles. The interactive routing model generates optimal routes for both mobile depots (e.g. high capacity trucks) and small vehicles (e.g. electric-bicycles and UAVs). The idea is motivated by the operations of aircrafts and aircraft carriers.

This new idea makes the routing problem different from the multi-vehicle routing problem with time window (m-VRPTW) problem as follows:

1. A truck can transfer goods to electric-bicycles outside the depot, such that they can meet and transfer at anywhere and anytime.

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2. Each delivery task can only be served by either a single truck or a combination of a truck and an electric bicycle.
3. A customer can only be served by one vehicle within its time window, but it can have at most two vehicles in each customer's route.

The paper is structured as follows: In Section 2, related works of both the VRP and the VRP with Time Window constraint (VRPTW) are briefly reviewed. The interactive routing model for VRPTW is proposed in Section 3. The analysis of the proposed model is provided in Section 4. We conclude this work in Section 5.

II. RELATED WORKS

To overcome backhauling problems, current studies focus on routing algorithms based on multi-round-trip models. Trucks start their deliveries to customers with a full load from a depot and return to the depot with no-load repeatedly until all customers are served.

The VRP has several variants with different constraints, e.g. the capacitated VRP (CVRP) and the VRPTW. Many efficient meta-heuristic algorithms are proposed for the VRPTW. For example, the Tabu search algorithm [2] and the Smoothed Dynamic Tabu Search Embedded GRASP for m-VRPTW [3]. A Deterministic Annealing approach [4] is proposed to avoid repetition of search processes and poor local optima for VRPTW problems. It can be modified to accommodate various capacity constraints and is robust to uncertainties in customer service schedules or locations. However, it cannot incorporate distance functions to the time window directly. The hybrid genetic algorithm [5] outperforms other methods in searching for the optimal solution in terms of the number of vehicles. The improved hybrid genetic algorithm [6] can be applied to optimize multi-depots VRPTW. The genetic algorithm has also been applied for multi-vehicle and multi-depots pickup and delivery problem with time windows (m-MDPDPTW) [7]. An improved approach combining the geographical information system and the parallel genetic algorithm [8] is proposed for the multi-vehicle routing problem with time window (MVRTW). The beam search with an improved compromise and automated knowledge elicitation [9] is applied to improve its application scenarios in VRPs. It also considers a series of additional side-constraints and provides a reasonable routing in dynamic environments. Moreover, to investigate the conflicting (or not) nature of various objectives in the VRPTW, an open source generator for VRPTW problem instances is made available to the research community [10].

When a large number of customers need to be served, existing methods either divide them into several regions for multi-round-trip deliveries or serve all of them directly using a single round trip. In this work, we treat multi-round-trip as a repetition of single round trip and break the limitation of multi-round-trip to improve the routing efficiency and route vehicles interactively.

III. INTERACTIVE ROUTING MODEL FOR VRPTW

The VRPTW problem is defined as follows formally. There is an undirected graph $G(V, W, E)$ where $V=\{v_0, v_1,\ldots,v_n\}$, $W = \{w_0, w_1, \ldots, w_m\}$, and $E = \{(v_i, v_j) : i\neq j,\ 0 \leq i, j \leq n\ \}$. w_i represents the depot which is also the parking area for trucks and electric bicycles. v_i represents a customer with demand d_i. Time window constraints are represented by (p_i, q_i) for all $1 \leq i \leq n$, where p_i and q_i represents denote the earliest and the latest allowed time to start their work, q_i represents the latest allowed time to start their work respectively. In addition, we assign a travel speed to every vehicle, such that the transportation time can be computed automatically. Moreover, there are h small delivers (such as electric bicycles or UAVs) with the capacity of C. The objective is to maximize the customer's customer satisfaction function and minimize the cost of delivery simultaneously.

The objective function is built using both the customer satisfaction function and the transportation cost to build our objective function for a better modeling to the profits. The customer's objective function considers the following factors:

1, the customer with a shorter time window will have a larger endurance for the service quality. Namely, even this model cannot serve the customer with a shorter time window within their required time window, the customer will still keep a high satisfaction, vice versa.

2, when we serve the customer that have a short time window in his requirements, they will have a larger satisfaction, vice versa.

Constraints of our problem are as follows:

1, for each electric bicycle, it must start and end at the depot w_m.

2, the total demand among all served customs in one route cannot exceed the capacity of an electric bicycle.

3, vehicles can achieve reach to the customers earlier than the required time windows and wait but they cannot arrive to the customers later than the required time windows.

So if we define the S_i to be the reaching time of the customer v_i and $U(S_i)$ to be the satisfaction function, then

$$U(S_i) = \begin{cases} \frac{1}{T}\left[\frac{S_i - O_i}{P_i - O_i}\right]^{\frac{T}{(l/2)}} & S_i \in [O_i, P_i) \\ \frac{1}{T} & S_i \in [P_i, Q_i] \\ \frac{1}{T}\left[\frac{R_i - S_i}{R_i - Q_i}\right]^{\frac{T}{(l/2)}} & S_i \in (Q_i, R_i] \\ 0 & S_i \notin [O_i, R_i] \end{cases} \quad (1)$$

where $T_i = Q_i - P_i$, $O_i = P_i - \lceil 0.1\,T \rceil$, and $R_i = Q_i + \lceil 0.1T \rceil$. The term $(0.1\,T)$ restricts the model not to serve a customer $0.1T$ later than the required time window. If the delivery reaches the customer at time outside the time window, $U(S_i)$ =0. Therefore, the model will keep a fuzzy time window within $0.1T$ more time slots.

The exponent of the objective function is $2*T/l$ which is the time sensitivity of customer. We divide the whole working time into l parts and each part is called a time slot. Namely, we discretize the time in one day into l time slots and the average length of time window is $l/2$ time slots. The average length is the dividing line between a long time window and a short time window. We also define that the base number belongs to (0, 1). When the required time window is larger than the average length, the exponent is bigger than 1, the $U(S_i)$ is an upwards parabola. In the opposite, if the time slot is shorter than the average length, then the exponent is smaller than 1, the parabola of $U(S_i)$ is downwards. These match the considering factor 1 of the model.

Considering the factor 2, the piecewise function is multiplied by $1/T$ which ensures customers having a short time window will have a larger satisfaction when they are served.

The transportation cost is defined as follows:

$$\text{Cost} = \sum_{i,j \in p} d_{ij} e \quad (2)$$

where $e = \begin{cases} e_d & \text{the cost rate of electric bicycles} \\ e_t & \text{the cost rate of trucks} \end{cases}$

and $d_{i,j} = \text{the distance of between } v_i \text{ and } v_j$.

Therefore, the objective function is defined as follows:

$$\text{Max profit} = \sum_{i \in [1,n]} \frac{10000U(S_i)}{Cost} \quad (3)$$

The multiple of 10000 is to make the $U(S_i)$ to have similar magnitude with the *Cost*.

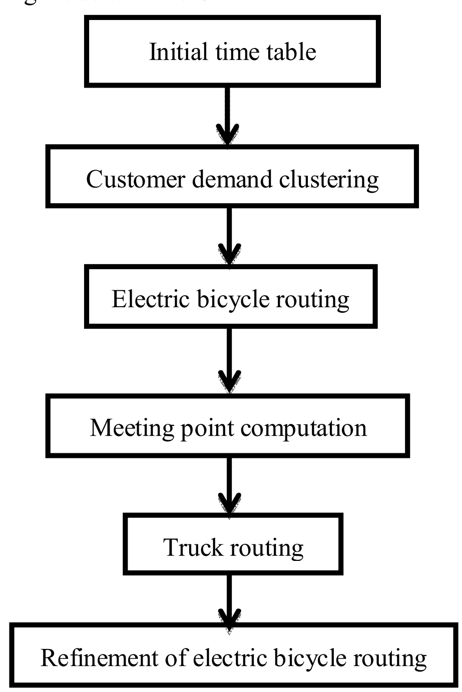

Fig. 1. Procedures of the interactive routing model.

The depth-limited tree search is used to optimize routes based on the proposed model. Procedures of the interactive routing model are shown in Figure 1.

A. *Initial time table*

In the proposed model, every order consists of coordinates of the customer, demands, time window, and service time. Service time is the time that the deliver spent to contact with the customer. The information about time window refer to the earliest start time (p_i) and the latest start time (q_i), i.e. the goods should arrives the customer between p_i and q_i. Based on the information of time window, we discretize the time format into time slots for trucks and electric bicycles. Then, the set of time windows of all customers is called the time table. In the time table, a row represents a time slot while each order is stored in a column. Blank columns are added to represent vehicle routing without delivery order. Such that, routing model uses the time table to schedule routs for trucks and electric bicycles. Additionally, an assistant matrix is also initialized to monitor capacities of vehicles and a state record matrix to track on every order in every step.

B. *Customer demand clustering*

Before routing, customers are clustered to extract their relationship with depots. The k-means clustering is used in this work and the number of clusters equals to the number of depots available. Customers in the same cluster are assigned to the nearest depot and they are served by electric bicycles in this depot. In cases that customers cannot be served by electric bicycles in the corresponding depot owing to different reasons, e.g. too far away from depot or insufficient electrics bicycles, they will be served by trucks.

C. *Small deliver routing*

The depth-limited search algorithm with 2-layer depth limitation is used to find the optimal routes and the heuristic function being used for scoring each slot in the time table is as follows:

$$B_{i,j,t} = \frac{10000 U_i(t)/C_{i,j}}{\sum_k (10000 U_k(t)/C_{k,j})} \tag{4}$$

where $B_{i,j,t}$, $U_i(t)$, and $C_{i,j} = d_{ij}e$ denote the profit of serving order i from order j at time t, the satisfaction of customer i when he is served at time t, the transportation cost from order j to order i. $k = 1,2,\dots,i-1,i+1,\dots,z$ where z is the number of unvisited orders in the same time grid as i. In each iteration, the current location of the vehicle is equal to the coordinate of the last served customer. $\sum_k(10000U_k(t)/C_{k,j})$ indicates the opportunity cost when we choose to serve customer i instead of other customers.

Scores for other slots within the depth limitation are computed and then a search tree is built based on these scores. The customer yielding the largest combination score will be put into the time slot t in the initial route. Other customers in the same combination will not be put into the initial route. By iterations, the model obtains the initial route of electric bicycles.

The model applies pruning to the combination computations to reduce the computational costs of depth-limited search. With the current coordinate, orders located too far away from the current order will be pruned because serving this customer is not cost-effective.

D. *Meeting point computation*

Meeting point is the location where a truck transfers its load to electric bicycles. So, when a meeting point is created, orders transferred from the truck to electric bicycles will be moved from the time table of trucks to the time table of electric bicycles. The meeting point will be inserted in the time slot of first following order of truck. This means that the time window of meeting point is same as the time window of the first following order of the truck. Multiple meeting points can be created to reload bicycles.

Orders between two meeting points of the same vehicle or between a meeting point and the termination in the time table are corresponding orders of the previous meeting point. These orders are transferred from the truck to an electric bicycle at the previous meeting point.

A meeting point is created for an electric bicycle when it has no more goods to deliver while there are orders not yet been visited in later time slots.

E. *Truck routing*

In this step, meeting points are created and therefore the route of a truck can be created according to those meeting points. However, meeting points are possibly not chosen with their corresponding time windows if they either yield a low score or located too far away. The score of a meeting point is computed by the sum of its corresponding orders' scores plus certain weights to encourage the meeting point to be chosen.

When meeting points are not chosen, their corresponding orders would not be served. This will reduce the satisfaction of customers. However, according to the heuristic function, a meeting point will not be selected if it is cost ineffective or orders or vehicles are too far away to serve this meeting point. If these orders are not served, they are moved from the initial route of electric bicycles back to the time table of the truck. The corresponding meeting point and $P_{i,j,t}$ of corresponding orders in the time table of the truck are deleted.

F. *Refinement of small deliver routing*

After routes of trucks and meeting points are fixed, the final routes of electric bicycles are obtained based on their initial routes and selected meeting points. In this paper, orders being sent back to trucks are served by trucks directly because the cost of calculating another meeting point to fit in truck's route is large in the VRPTW. In our future works, we will find an effective and efficient way to iteratively update the routes of both trucks and electric bicycles to further optimize the overall performance.

IV. EXPERIMENTAL ANALYSIS

The well-recognized Solomon dataset [11] is used to test the efficiency of the proposed method for VRPTW problems. The dataset consists of 56 test cases with 100 to 200 customer records in each case. Test cases are divided into 3 types: C, R, and RC types. C type means that the distribution of geographical coordinates of customers are clustered, R types means the distribution of customers is uniform, and RC type is a mix of C and R types. Each customer record has an index number, a pair of geographical coordinates, a customer demand, and a time window with a start time and a due time. Moreover, the Solomon dataset also specifies the depot, the maximum quantity, and capacities of vehicles. In our experiments, C101, C102, C103, R101, R102, R103, RC101, R102, and RC103 are used as testing cases and each of them consists of 100 customers. Velocity of vehicles is set to be 1km/min. Units of the time and coordinate are minute and kilometer, respectively. To force vehicles to perform multiple round trips between customers and depot, maximum capacities of small deliver (electric bicycles) and truck are 50 and 400 units, respectively. In this experiment, 2 electric bicycles and 1 truck are used.

For comparison, an experiment using 3 electric bicycles without any truck is carried out to simulate the scenario that traditional routing model requiring multiple no-load backhauling. Both methods use depth-limited search with limitation of 2 layers.

Tables I and II show that the proposed model serves more customers within the time limit and obtains higher customer satisfaction scores for clustered customers. In contrast, the proposed method yields a worse performance on uniform distributed customers. Although the number of served customers and customer satisfaction are lower than the traditional multiple round trip in some datasets with uniform customers, the proposed model yields a great reduction on transportation costs in all datasets as shown in Table III. In the proposed method, electric bicycles only need to go to the meeting point to reload without the need of returning to the depot with a long distance no-load backhauling. Therefore, the proposed method is more efficient and yields much small transportation costs. Given the fact that the customer satisfaction is only one of components of the objective function of the proposed method, the performance in this aspect cannot be guaranteed to be optimal. Finally, Table IV shows the proposed method yields high values in objective function

TABLE Ⅰ. CUSTOMER SATISFACTION

customer satisfaction									
dataset	C101	C102	C103	R101	R102	R103	RC101	RC102	RC103
Proposed Method	**25.49**	**16.16**	**15.33**	**19.95**	14.6	7.86	11.46	8.17	6.5
Traditional Multiple No-load Round Trip	19	13.83	11.5	18.96	**14.97**	**9.37**	**13.13**	**9.42**	**6.95**

TABLE Ⅱ. THE NUMBER OF SERVED CUSTOMER

the number of served customer									
dataset	C101	C102	C103	R101	R102	R103	RC101	RC102	RC103
Proposed Method	**32**	**31**	**36**	**28**	**36**	30	24	28	**32**
Traditional Multiple No-load Round Trip	25	26	28	27	31	**33**	**27**	**29**	30

TABLE Ⅲ. TRANSPORTATION COST

Transportation cost									
dataset	C101	C102	C103	R101	R102	R103	RC101	RC102	RC103
Proposed Method	**91674.05**	**75824.03**	**99644.53**	**95648.54**	**87056.16**	**81036.81**	**90435.28**	**103244.53**	**91419.74**
Traditional Multiple No-load Round Trip	117709.32	79491.95	77695.45	108389.47	105859.48	127064.58	114710.26	138657.35	119869.68

TABLE Ⅳ. OBJECTIVE FUNCTION VALUE

objective function value									
dataset	C101	C102	C103	R101	R102	R103	RC101	RC102	RC103
Proposed Method	**9.62**	**7.21**	**3.65**	**4.16**	**3.24**	**3**	**3.42**	**1.58**	**1.97**
Traditional Multiple No-load Round Trip	0.97	1.74	1.48	1.75	1.41	0.74	1.14	0.68	0.58

which considers both the customers' satisfaction and the transportation cost. Overall, the proposed method is more efficient in comparison with the traditional method using multiple no-load backhauling.

V. CONCLUSION

An interactive routing model is proposed in this work to allow small delivers (electric bicycles) to reload in meeting points with trucks instead of a fixed depot. Experimental results show that the proposed method yields a much lower transportation cost in comparison with traditional routing method requiring small delivers to backhaul to depot with no-load for a long distance.

One of our important future works is to improve the efficiency of the interactive routing model. Further studies on more realistic scenarios and constraints are needed before the proposed method can be applied to real world routing for express companies.

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