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FUZZY CREDIBILITY APPROACH TO THE FUZZY FLEXIBLE DELIVERY AND PICKUP PROBLEM WITH TIME WINDOWS

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Abstract

As the reverse logistics and the closed loop supply chain networks have been adopted by enterprises, the delivery and pickup problems with time windows have much attention and have been studied extensively. After investigating their uncertainty properties and complexities in finding solutions, this study, based on the Fuzzy Credibility Theory, proposes a Chance Constrained Programming (CCP) model to describe a Fuzzy Flexible Delivery and Pickup

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Problem with Time Windows (FFDPPTW). In the meantime, a Coevolutionary Algorithm is implemented to obtain near optimal solutions in an acceptable computational time. Some test problems are generated by revising the well-known Solomon's benchmarks which are originally used for the vehicle routing problem with time windows. The results show the coevolutionary algorithm is not only accurate but more efficient. Further comparison between different confidence levels shows that the higher the confidence level is required, the larger the cost is paid; this facilitates the decision support based on the decision maker's preference.

1. Introduction

Due to the awareness of the environmental protection, how to reduce the utilization of the materials by reusing and remanufacturing the used products has been a critical issue for an enterprise. This induces the concept of the green supply chain management and has led to a problem of the closed loop supply chain management (Wang and Hsu [30]). A state of the art survey of reverse and closed supply chains can be found in Ilgin and Gupta [12]. Within a closed loop supply chain, the logistics between the distribution/collection center and the customers is the most complicated part because it is related to a bi-directional logistics regarding delivery and pickup activities. It has been shown that incorporating reverse logistics with conventional forward-only logistics to form bi-directional logistics can significantly reduce the cost of returned merchandise, improve customer satisfaction, and increase the profit of enterprises. The bi-directional logistics problem has been referred to as delivery and pickup problem (DPP) in literature.

The DPP has been widely applied. For example, it is frequently encountered in the distribution system of grocery store chains. Each grocery store may have a demand for both delivery (cf. fresh food or soft drinks) and pickup (cf. outdated items or empty bottles). The foundry industry is another example studied by Dethloff [8]. Collection of used sand and delivery of purified reusable sand at the same customer location are carried out. For more realistic applications, this paper further investigates a more general situation, called the Fuzzy Flexible Delivery and Pickup Problem with Time Windows (FFDPPTW).

This paper is organized as follows: Section 2 reviews the literature related to the issues in interest. Section 3 briefly introduces some basic concepts in Fuzzy Measure Theory. Section 4 first defines the FFDPPTW and then develops a Chance Constrained Programming model for it. Section 5 provides the computational results of an effective and efficient coevolutionary algorithm with the evaluation on the accuracy and the efficiency. Finally, the conclusions are drawn in Section 6.

2. Literature Review

The delivery and pickup problem (DPP) was developed from the vehicle routing problem (VRP). The VRP originally focused on how to dispatch a group of vehicles to serve a group of customers with a given demand when the minimum operational cost is desired. In the delivery and pickup problems (DPP), vehicles are required not only to deliver goods to customers but also to pick some goods up at customer locations. It can be regarded as that two types of customers are served from a single depot by a fleet of vehicles. The first type of customers is known as “linehaul” customers, who require deliveries of their goods to the specific locations. The second type is known as “backhaul” customers, who require pickups from their specific locations. A survey of the DPP can be referred to Parragh et al. [22].

There are three main strategies for the DPP: (1) delivery-first, pickup-second; (2) mixed deliveries and pickups; and (3) simultaneous deliveries and pickups.

Delivery-first, pickup-second strategy: vehicles can only pickup goods after they have finished delivering their entire load (e.g., Ropke and Pisinger [24]). One reason for this is that it may be difficult to rearrange delivery and pickup goods on the vehicles. Such an assumption makes the implementation issue easier because accepting pickups before finishing all deliveries results in a fluctuating load. This may cause the vehicle to be overloaded during its trip (even if the total delivery and the total pickup loads are not above the vehicle capacity), resulting in an infeasible vehicle tour.

Mixed deliveries and pickups strategy: linehauls and backhauls can occur in any sequence on a vehicle route (Wade and Salhi [27], Nagy and Salhi [19], Crispim and Brandao [7] and Tütüncüa et al. [26]). This strategy releases the constraints that pickups are only accepted after finishing all deliveries. When there are no difficulties in rearranging the load on the vehicle, this strategy is more attractive to backhaul customers and enterprises. The satisfaction of backhaul customers can be higher since they can be served earlier. Moreover, the enterprises can save the transportation cost since the sequence of deliveries and pickups can be arranged in a more economical way.

Simultaneous pickups and deliveries: simultaneously performing delivery and pickup services with a single stop for each customer. In some applications, customers can have both a delivery and a pickup demand. They may not accept to be serviced separately for the delivery and pickup they require because handling effort is caused by both activities. In this situation, simultaneous pickups and deliveries is the only choice, see Min [17] and Dethloff [8].

Referring to these service strategies, the DPP is divided into three categories: the vehicle routing problem with backhauls (VRPB), the mixed vehicle routing problem with backhaul (MVRPB), and the simultaneous delivery and pickup problem (SDPP). In some literature, the SDPP was called the *vehicle routing problem* with simultaneous delivery and pickup (VRPSDP), see Min [17] and Dethloff [8].

In order to provide more satisfactory services, nowadays, enterprises have allowed customers to request their goods being delivered or picked up within specific time windows. Such consideration extends the aforementioned problems into VRPB and Time Windows (VRPBTW), MVRPB and Time Windows (MVRPBTW), and SDPP with Time Windows

(SDPPTW), respectively. Since such extension increases the complexity of the problems, therefore researchers have devoted to developing efficient algorithms for finding good feasible solutions. For instance, Kontoravdis and Bard [13] developed a greedy randomized adaptive search procedure to solve the MVRPBTW. Zhong and Cole [33] developed a guided local search heuristic to solve both the VRPBTW and the MVRPBTW. Angelelli and Mansini [1] developed a branch and price algorithm for the small-scale SDPPTW. Wang and Chen [28] developed a coevolutionary algorithm for the SDPPTW.

Based on the advantage of flexible delivery and pickup with MVRPBTW, further improvement on reducing the operation cost has been carried out. One issue is how to reduce the accessing time when a simultaneous delivery and pickup at the same customer location occurs. Dethloff [8], Chen and Wu [6], and Montané and Galvao [18] have suggested that the accessing time can be reduced by performing a simultaneous delivery and pickup. This possibility was adopted and evaluated by Wang and Chen [29], of which a new model was developed to realize time saving from simultaneously performing delivery and pickup while the flexibility of mixing pickup and delivery operations is remained. This kind of problems was called the flexible delivery and pickup problem with time windows (FDPPTW). A detailed review of these delivery and pickup problems with time windows can be found in Chen and Wang [5].

The models used in aforementioned problems were all deterministic models; all the factors involved in the models must be known exactly. Unfortunately, real world is often uncertain. There are cases that the imprecision/uncertainty concerning demand, service time, and traveling time must be taken into account. Fuzzy set theory has provided efficient and meaningful concepts and methodologies to formulate and solve mathematical programming and decision making problems of real world (Dong and Kitaoka [9]). Fuzzy approaches have been applied to solve some fuzzy vehicle routing problems.

Xu et al. [31] considered a VRP with soft time windows and fuzzy demand. The problem was formulated as a two stages resource model. The theory of possibility and necessity is applied in the capacity constraint and a genetic algorithm was proposed to solve the problem. Maekly et al. [16] proposed a fuzzy random vehicle routing problem whose demands were assumed to be fuzzy random variables. They used the concept of the chance constrained programming (CCP) model to formulate the problem and proposed a tabu search method to solve it. Brito et al. [2] considered the vehicle routing problem with time windows where traveling times were fuzzy numbers. The weighted possibility and necessity measure of fuzzy relations was used to specify a confidence level at which it was desired that the arrival time to reach each customer fell into their time windows. They proposed and analyzed a solution procedure consisting in hybridizing a variable neighborhood search and a greedy randomized adaptive search procedure for the corresponding optimization problem. Cao and Lai [3] considered the vehicle routing problem with fuzzy demands. They proposed a chance constrained programming (CCP) model based on credibility theory for the problem. Then, a hybrid intelligent algorithm integrating stochastic simulation and differential evolution algorithms was developed to solve the problem. Peng and Qian [23] coped with the vehicle routing problem with fuzzy demands. To formulate the problem, they used a chance constrained programming (CCP) model, of which the credibility was used to evaluate the chance. Then, a particle swarm optimization algorithm was developed for finding the solution. Cao and Lai [4] addressed the open vehicle routing problem with fuzzy demands. In this problem, a vehicle was not required to return to the distribution depot after serving the last customer on its route. Again, a fuzzy chance constrained programming (CCP) model was designed based on the fuzzy credibility theory to formulate the problem; for solving the problem, stochastic simulation and an improved differential evolution algorithm were integrated into a hybrid intelligent algorithm.

One can see that chance constrained programming (CCP) model was frequently used to formulate a variety of fuzzy vehicle routing problems.

Through this model, a decision maker can choose a confidence level to plan or determine the best alternative after comparing different planning results under different confidence levels. Therefore, the decision maker not only can take part in the decision process; but also can evaluate the results with confidence.

In this paper, we propose a fuzzy flexible delivery and pickup problem with time windows (FFDPPTW). The deterministic case of the FFDPPTW, the FDPPTW, is NP-hard (Wang and Chen [29]). The FDPPTW is polynomial time reducible to the FFDPPTW by setting all lower bounds and upper bounds of fuzzy numbers equal to their medians; therefore the FFDPPTW is also NP-hard. To facilitate the development of solution procedure, the FFDPPTW is formulated into a chance constrained programming (CCP) model based on the fuzzy credibility theory. A coevolutionary algorithm is then implemented for solving it.

3. Fuzzy Credibility Measure Theory

In this section, some basic concepts in fuzzy measure theory are introduced briefly. First, the axioms of possibility measure theory proposed by Liu [14] are introduced. These axioms form the basis of Credibility Measure Theory. In order to deal with fuzziness, Zadeh [32] suggested a possibility measure and Nahmias [20] proposed the related axioms to characterize the concept. They are briefly introduced below:

Let Θ be a nonempty set, and let $P(\Theta)$ be the power set of Θ. Each element in $P(\Theta)$ is called an *event*, and $\varnothing$ is an empty set. In order to present an axiomatic definition of possibility, it is necessary to assign a number $Pos\{A\}$ to each event A, which indicates the possibility that A will occur (Nahmias [20]).

Axiom 1 (Normality Axiom)**.** $Pos\{\Theta\} = 1.$

Axiom 2 (Nonnegativity Axiom)**.** $Pos\{\varnothing\} = 0.$

Axiom 3 (Maximality Axiom)**.** For every sequence of events $\{A_i\}$, we have

$$Pos\left\{\bigcup_{i=1}^{\infty} A_i\right\} = \bigvee_{i=1}^{\infty} Pos\{A_i\}. \tag{1}$$

Unfortunately, possibility measure does not obey the law of truth conservation and is inconsistent with the law of excluded middle and the law of contradiction. In order to overcome the shortage of possibility measure, Liu and Liu [15] presented a credibility measure which is a combination of possibility measure and necessity measure. Let A^c be the complementary of event *A*.

Definition 4 (Dubois [10])**.** For every event *A*, the necessity of event *A* is defined as

$$Nec\{A\} = 1 - Pos\{A^c\}. \tag{2}$$

Definition 5 (Liu and Liu [15])**.** For every event *A*, the credibility of event *A* is defined as

$$Cr\{A\} = \frac{1}{2}\left(Pos\{A\} + Nec\{A\}\right) = \frac{1}{2}\left(Pos\{A\} + 1 - Pos\{A^c\}\right). \tag{3}$$

Credibility measure obeys the law of truth conservation and is consistent with the law of excluded middle and the law of contradiction. Obviously, a fuzzy event may not hold even though its possibility approaches 1 and such an event may hold even though its necessity is 0. However, a fuzzy event must hold if its credibility is 1, and it must fail if its credibility is 0. The credibility measure is self-dual, and in the theory of fuzzy subsets, the law of credibility plays a role similar to that played by the law of probability in measurement theory for ordinary sets.

Now let us consider a triangular fuzzy variable $\tilde{p} = (p_1, p_2, p_3)$ as the pickup demand of a given customer such that $\tilde{p}$ is described by its left boundary p_1 and its right boundary p_3. Thus, a dispatcher or analyst studying such a problem can subjectively estimate that a customer's pickup demand will not be less than p_1 or greater than p_3, based on his/her experience, intuition and/or available data. The value of p_2 corresponds to a grade of membership of 1, which can also be determined by a subjective estimate. Assume the capacity of the vehicle is q. Based on above definitions of possibility, necessity, and credibility, we can derive:

$$Pos\{\tilde{p} \le q\} = \begin{cases} 1, & \text{if } q \ge p_2, \\ \dfrac{q - p_1}{p_2 - p_1}, & \text{if } p_1 \le q \le p_2, \\ 0, & \text{if } q \le p_1, \end{cases} \tag{4}$$

$$Nec\{\tilde{p} \le q\} = \begin{cases} 1, & \text{if } q \ge p_3, \\ \dfrac{q - p_2}{p_3 - p_2}, & \text{if } p_2 \le q \le p_3, \\ 0, & \text{if } q \le p_2, \end{cases} \tag{5}$$

$$Cr\{\tilde{p} \le q\} = \begin{cases} 1, & \text{if } q \ge p_3, \\ \dfrac{q + p_3 - 2p_2}{2(p_3 - p_2)}, & \text{if } p_2 \le q \le p_3, \\ \dfrac{q - p_1}{2(p_2 - p_1)}, & \text{if } p_1 \le q \le p_2, \\ 0, & \text{if } q \le p_2. \end{cases} \tag{6}$$

If the decision maker would like to have a vehicle routing plan with confidence level, Cr^*, that the vehicle can pickup the demand, then we can model this situation as the following constraint:

$$Cr\{\tilde{p} < q\} \ge Cr^*. \tag{7}$$

Constraint (7) is a simple example illustrating how the chance of accomplishing a pickup job can be expressed in a Chance Constrained Programming model where the chances are evaluated by the credibility measure.

4. Problem Formulation

The fuzzy flexible delivery and pickup problem with time windows (FFDPPTW) can be stated as below:

A set of customers, each requires a delivery and/or a pickup of certain quantities within specific time window(s), must be served by a fleet of capacitated vehicles stationed at a distribution center (DC). The pickup demands, the service times, and the traveling times are uncertain. The FFDPPTW is thus to search for the most economic route for each vehicle with the minimum operational cost under a specific confidence level.

For each service (either delivery or pickup) required by any customer, one vehicle will be assigned exactly once. If both services are required by one customer, then he/she can request different or the same time windows for delivery and pickup.

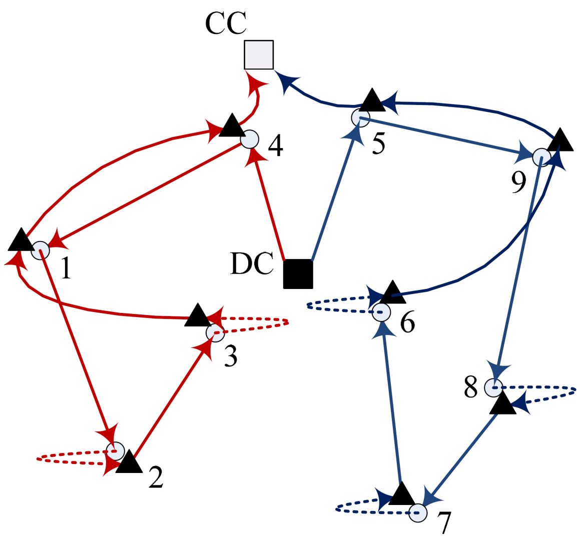

Figure 1. The infrastructure of the delivery and pickup network.

In a common application of the FFDPPTW to a network with recycling task, for illustration, all vehicles may return to a collection center (CC) to unload the recycled stuff. The infrastructure of the system can be seen in Figure 1. The black and the white squares indicate the distribution center (DC) and the collection center (CC), respectively. The white circles and black triangles indicate linehaul and backhaul customers correspondingly. The solid arrows indicate the movements. A driver will not need to re-access to a customer if he/she picks up stuff right after delivers goods. Therefore, we use a dot arrow to describe that the pickup service for a customer is performed right after the delivery service. Figure 1 shows that there are five customers (2, 3, 6, 7, and 8) who are served delivery and pickup simultaneously; and the other four customers are served delivery earlier than the pickups.

The FFDPPTW has two objectives involved in the aggregated cost: minimizing the number of vehicles and minimizing the total traveling distance. Trade-off between these two kinds of costs is needed to be considered. Refer to the mathematical models used in Wang and Chen [28] and Wang and Chen [29], the model formulation of the FFDPPTW is developed as follow.

Based on the principle of a VRP problem, one customer is visited exactly once by one vehicle for one service. A pseudo customer should be introduced for separating two services required by one customer. Assume there are n customers, each is indicated by customer i, $i = 1, ..., n$. When modeling, $2n$ customers are generated with n new customer i, $i = 1, ..., n$, each demanding only a delivery service, and n new customer $n + i$, $i = 1, ..., n$, each demanding only a pickup service. Assume there are m vehicles. The flexible delivery and pickup problem with time windows is then formulated into a fuzzy chance constrained programming model denoted by Model FFDPPTW as below where $k = 2n + 1$ denote the collection center (CC).

Notations

Sets

J_D	Set of all delivery customers, $J_D = \{j \mid j = 1, ..., n\}$
J_P	Set of all pickup customers, $J_P = \{j \mid j = n + 1, ..., 2n\}$
J	Set of all customers, $J = J_D \cup J_P = \{j \mid j = 1, ..., 2n\}$
J_0	Set of all customers plus DC, $J_0 = \{0\} \cup J$

J_k Set of all customers plus CC, $J_k = J \cup \{k\}$

V Set of all vehicles, $V = \{v \mid v = v_1, ..., v_m\}$

Coefficients

q_v Capacity of vehicle v, $q_v \in \boldsymbol{R}^+$

g_v Dispatching cost of vehicle v, $g_v \in \boldsymbol{R}^+$

c_{ij} Distance between nodes $i \in J_0$, $j \in J_k$; $i \neq j$, $c_{ij} \in \boldsymbol{R}^+$

$\tilde{t}_{ij}$ Traveling time between nodes $i \in J_0$, $j \in J_k (i \neq j)$, $\tilde{t}_{ij}$ is a fuzzy number

d_j Delivery demand of customer $j \in J$, $d_j \in \boldsymbol{R}^+$

$\tilde{p}_j$ Pickup demand of customer $j \in J$, $\tilde{p}_j$ is a fuzzy number

$\tilde{s}_j$ Service time of customer $j \in J$, $\tilde{s}_j$ is a fuzzy number

r_j Accessing time reduction if the delivery and pickup services of customer j are performed simultaneously, $j \in J_D$, $r_j \in \boldsymbol{R}^+$

a_j Earliest service starting time of customer $j \in J$, $a_j \in \boldsymbol{R}^+$

b_j Latest service starting time of the time window of customer $j \in J$, $b_j \in \boldsymbol{R}^+$

a_0 Earliest departure time of any vehicle from DC, $a_0 \in \boldsymbol{R}^+$

b_k Latest arrival time that a vehicle must return to CC, $b_k \in \boldsymbol{R}^+$

Cr^* Credibility confidence level that constraints would not be violated

M An arbitrary large constant

α A parameter indicating the trade-off between dispatching cost and traveling cost, $\alpha \in [0, 1]$

Decision Variables

x_{ijv} Traveling variable of a vehicle $v \in V$, $x_{ijv} \in \{0, 1\}$; if vehicle v travels directly from node $i \in J_0$ to node $j \in J_k$, $x_{ijv} = 1$; otherwise $x_{ijv} = 0$

Auxiliary Variables

L_{0v} Load of vehicle $v \in V$ when leaving DC, $L_{0v} \in \boldsymbol{R}^+$

$\tilde{L}_j$ Remaining load of a vehicle after having served customer $j \in J$, $\tilde{L}_j$ is a fuzzy variable

$\tilde{T}_j$ Time to begin service at customer $j \in J$, $\tilde{T}_j$ is a fuzzy variable

T_{0v} Departure time of vehicle $v \in V$ from DC, $T_{0v} \in \boldsymbol{R}^+$

$\tilde{T}_{kv}$ Arrival time of vehicle $v \in V$ to CC, $\tilde{T}_{kv}$ is a fuzzy variable

Model FFDPPTW

$$\text{Minimize } z = \alpha \sum_{v \in V} \sum_{j \in J} g_v x_{ojv} + (1 - \alpha) \sum_{i \in J_0} \sum_{j \in J_k} \sum_{v \in V} c_{ij} x_{ijv}, \tag{8}$$

subject to

$$\sum_{i \in J_0} \sum_{v \in V} x_{ijv} = 1, \quad \forall j \in J, \tag{9}$$

$$\sum_{i \in J_0} x_{ihv} = \sum_{i \in J_k} x_{hjv}, \quad \forall h \in J, \forall v \in V, \tag{10}$$

$$\sum_{j \in J} x_{0jv} = \sum_{i \in J} x_{ikv}, \quad \forall v \in V, \tag{11}$$

$$\sum_{j \in J} x_{0jv} \le 1, \quad \forall v \in V, \tag{12}$$

$$L_{0v} = \sum_{i \in J_0} \sum_{j \in J} d_j x_{ijv}, \quad \forall v \in V, \tag{13}$$

$$\tilde{L}_j \ge L_{0v} - d_j + \tilde{p}_j - M(1 - x_{0jv}), \quad \forall j \in J, \forall v \in V, \tag{14}$$

$$\tilde{L}_j \ge \tilde{L}_i - d_j + \tilde{p}_j - M\left(1 - \sum_{v \in V} x_{ijv}\right), \quad \forall i \in J, \forall j \in J, \tag{15}$$

$$L_{0v} \le q_v, \quad \forall v \in V, \tag{16}$$

$$Cr\left\{\tilde{L}_j \le q_v + M\left(1 - \sum_{i \in J_0} x_{ijv}\right)\right\} \ge Cr^*, \quad \forall j \in J, \forall v \in V, \tag{17}$$

$$\tilde{T}_j \ge T_{0v} + \tilde{t}_{0j} - M(1 - x_{0jv}), \quad \forall j \in J, \forall v \in V, \tag{18}$$

$$\tilde{T}_j \ge \tilde{T}_i + \tilde{s}_i + \tilde{t}_{ij} - M\left(1 - \sum_{v \in V} x_{ijv}\right), \quad \forall i \in J, \forall j \in J - \{n + i\}, \tag{19}$$

$$\tilde{T}_{n+i} \ge \tilde{T}_i + \tilde{s}_i - r_i + \tilde{t}_{i(n+i)} - M\left(1 - \sum_{v \in V} x_{i(n+i)v}\right), \quad \forall i \in J_D, \tag{20}$$

$$\tilde{T}_{kv} \ge \tilde{T}_i + \tilde{s}_i + \tilde{t}_{ik} - M(1 - x_{ikv}), \quad \forall i \in J, \forall v \in V, \tag{21}$$

$$a_0 \le T_{0v}, \quad \forall v \in V, \tag{22}$$

$$a_j \le \tilde{T}_j, \quad \forall j \in J, \tag{23}$$

$$Cr\{\tilde{T}_j \leq b_j\} \geq Cr^*, \quad \forall j \in J, \tag{24}$$

$$Cr\{\tilde{T}_{kv} \leq b_k\} \geq Cr^*, \quad \forall v \in V, \tag{25}$$

$$x_{ijv} \in \{0, 1\}, \quad \forall i \in J_0, \forall j \in J_k, \forall v \in V. \tag{26}$$

Objective function (8) is to minimize the total cost, which includes the total dispatching cost and the total traveling cost. Since these costs are compensated to each other, the trade-off parameter, $\alpha \in [0, 1]$, is employed to adjust for different decision criteria. This trade-off parameter α is determined by the decision maker. The most commonly considered objective functions are to minimize the number of vehicles and to minimize the total distance. In general, minimizing the number of vehicles is the primary objective, whereas minimizing the total distance is the secondary. This can be achieved by setting α close to 1, i.e., $\alpha \to 1$. Constraint (9) ensures that each customer will be visited exactly once by a vehicle. Constraints (10) and (11) ensure the flow conservation 'for each customer *h*' and 'between the distribution center and the collection center,' respectively. Constraint (12) ensures each vehicle is at most assigned to a route.

Constraints (13)-(17) describe the vehicle loading along a route. While equation (13) shows the initial load of each vehicle, constraint (14) calculates the vehicle load of each vehicle after finishing the service to its first customer. If the first customer of vehicle *v* is customer *j*, which denotes by $x_{0jv} = 1$, then

$$\tilde{L}_j = L_{0v} - d_j + \tilde{p}_j. \tag{27}$$

This implication can be stated as below:

$$x_{0jv} = 1 \Rightarrow \tilde{L}_j = L_{0v} - d_j + \tilde{p}_j. \tag{28}$$

Implication (27) can be remodeled as the following constraint:

$$\tilde{L}_j = L_{0v} - d_j + \tilde{p}_j + y_{0jv}(1 - x_{0jv}), \tag{29}$$

where y_{0jv} is an auxiliary variable, $y_{0jv} \in \boldsymbol{R}$. When $x_{0jv} = 0$, $\tilde{L}_j$ is not necessarily equal to $L_{0v} - d_j + \tilde{p}_j$ since y_{0jv} could be any real number; when $x_{0jv} = 1$, $\tilde{L}_j$ must be equal to $L_{0v} - d_j + \tilde{p}_j$. However, this constraint is not linear. In order to get a linear constraint, implication (27) is revised as below:

$$x_{0jv} = 1 \Rightarrow \tilde{L}_j \geq L_{0v} - d_j + \tilde{p}_j. \tag{30}$$

Although the consequence in implication (30) is an inequality not equation (27), it still preserves the meaning of capacity constraint. Thus, implication (30) can be remodeled into constraint (14) which is linear. This modeling technique also applies to the formation of constraints (15) and (17)-(21).

Constraint (15) calculates the ‘en route’ vehicle loads. If any vehicle delivers the commodity from customer *i* to customer *j*, which denotes by $\sum_{v \in V} x_{ijv} = 1$, then

$$\tilde{L}_j = \tilde{L}_i - d_j + \tilde{p}_j. \tag{31}$$

By the technique mentioned above, the implication with equation (31) can be rewritten as constraint (15). Constraint (16) ensures that the initial load of each vehicle is below the vehicle capacity. Constraint (17) ensures the ‘en route’ vehicle loads are below the vehicle capacity with a confidence level. The constraint to describe that the ‘en route’ vehicle loads are below the vehicle capacity should be like constraint (32):

$$\tilde{L}_j \leq q_v + M\left(1 - \sum_{i \in J_0} x_{ijv}\right), \quad \forall j \in J, \forall v \in V. \tag{32}$$

Assume that the decision maker specifies that he/she would like to have a credibility confidence level, Cr^*, that the vehicle can pickup the demand without exceeding the capacity of the vehicle. We then can adopt the concept of the chance programming model mentioned in Section 3 to remodel constraint (32) as constraint (17) based on the structure of constrain (7).

Hence, according to the credibility confidence level which the decision maker specifies and the credibility that the next customer’s demand does not exceed the vehicle capacity, a decision is made regarding whether to send the vehicle to the next customer or to return it to the depot. In this study, this decision is made as follows: if $Cr \geq Cr^{*}$ holds, then the vehicle is sent to the next customer; otherwise, the vehicle is returned to the depot.

The traveling and service time along a route is described in constraints (18)-(21). Constraints (18)-(21) establish the relationship between the vehicle arrival time to a customer and its immediate predecessor; they are remodeled from the following implications:

$$x_{0jv} = 1 \Rightarrow \tilde{T}_j \geq T_{0v} + \tilde{t}_{0j}, \tag{33}$$

$$\sum_{v \in V} x_{ijv} = 1,\ j \neq n+i \Rightarrow \tilde{T}_j \geq \tilde{T}_i + \tilde{s}_i + \tilde{t}_{ij}, \tag{34}$$

$$\sum_{v \in V} x_{i(n+i)v} = 1 \Rightarrow \tilde{T}_{n+i} \geq \tilde{T}_i + \tilde{s}_i - r_i + \tilde{t}_{i(n+i)}, \tag{35}$$

$$x_{ikv} = 1 \Rightarrow \tilde{T}_{kv} \geq \tilde{T}_i + s_i + \tilde{t}_{ik}. \tag{36}$$

Constraint (22) ensures that each vehicle never departs from the distribution center before it opens. Constraint (23) ensures that customers are only served after the earliest service time points they specify. Constraints (24) and (25) are remodeled from the following constraints:

$$\sum_{v \in V} x_{i(n+i)v} = 1 \Rightarrow \tilde{T}_{n+i} \geq \tilde{T}_i + \tilde{s}_i - r_i + \tilde{t}_{i(n+i)}, \tag{37}$$

$$x_{ikv} = 1 \Rightarrow \tilde{T}_{kv} \geq \tilde{T}_i + s_i + \tilde{t}_{ik}. \tag{38}$$

Constraint (37) aims to emphasize that drivers should serve customers no later than the latest service time points. Constraint (38) aims to emphasize that each vehicle should enter the collection center no later than the scheduled closed time. By the similar technique of constrain (7) mentioned in

Section 3, constraints (37) and (38) are remodeled into constraints (24) and (25). Finally, constraint (26) is the binary constraint.

This model contains $4n + m$ fuzzy variables, $4n^2m + 4nm + m$ binary variables, and $2m$ real number variables. This model contains $8n^2 + 8nm + 4n + m$ fuzzy constraints and $2nm + n + 5m$ crisp constraints.

5. Computational Experiments

Since there have not been any studies with testing problems which were dedicated to the FFDPPTW, for evaluation, this study generates some FFDPPTW test problems which are revised from Wang and Chen's FDPPTW test problems (Wang and Chen [29]). Wang and Chen's FDPPTW test problems were revised from Solomon's VRPTW benchmarks (Solomon (1987)). The set of Solomon's test problems is composed of six different problem types (C1, C2, R1, R2, RC1 and RC2). Each data set contains between eight to twelve 100-customer problems. The categories of the six problem types refer to:

C: with clustered customers whose time windows were generated based on a known solution;

R: with customer locations generated uniformly randomly over a square;

RC: with a combination of randomly placed and clustered customers,

where

Type 1 has narrow time windows and small vehicle capacity, and

Type 2 has large time windows and large vehicle capacity.

By revising from Wang and Chen's [29] FDPPTW test problems, this study generates some FFDPPTW test problems. In each problem, the pickup demands, the service times, the traveling times are revised into triangular fuzzy numbers. Similar to Solomon's VRPTW benchmark problems, the distances are Euclidean distances. Traveling times are fuzzy numbers. Their medians equal to the corresponding distances. Their left spreads and right spreads equal to 0.25 × 'the corresponding distances.'

The primary objective is to minimize the number of vehicles (NV) and the secondary objective is to minimize the total distance (TD). Due to different objective functions used in the literatures, this analysis employs the trade-off parameter α to adjust for different decision criteria, in particular, by setting $\alpha \to 1,$ to reveal the primary concern of minimizing the number of vehicles (NV), than the minimization of the total distance (TD). In our implementation, we set $\alpha = 40/41.$ All experiments were executed on an Intel Core2 Quad 2.4G computer with 1G memory.

5.1. Coevolutionary algorithm

The genetic algorithm (GA) was first proposed by Holland [11]. Due to its global search mechanism, GA has shown its capability to find good solutions for complex mathematical problems, like the VRP and other NP-hard problems, in a reasonable amount of time. The traditional design of a GA faced the dilemma of ‘converging too quickly to non-acceptable local optima’ or ‘converging too slowly and resulting in exhaustive time consumption for deriving an acceptable solution.’

In order to avoid any of the above situations, we use a coevolutionary algorithm (CEA) to solve the problem. The CEA carries out two separate evolutions simultaneously: Population I was employed for the diversification purpose while Population II was employed for the evolutionary intensification. The framework of this algorithm is shown in Figure 2. Once the confidence level Cr^* is chosen, a FFDPPTW can be defuzzified to a FDPPTW by inequalities (6) and (7). Therefore, the coevolutionary algorithm (CEA) is implemented to solve the FFDPPTW in this study due to its capability on solving complex problems.

The heuristic method which generates the initial population is a cheapest insertion method. The cheapest insertion method is developed from the cost saving criterion of Osman [21]. Population I aims to retain the wide searching ability through three operators: Reproduction, Recombination and Selection. Population II aims to reach high quality solutions rapidly and improve them constantly through four operators: Reproduction, Local

Improvement, Crossover, and Selection. For the details of the heuristic method generating the initial population and the genetic operators of the algorithm, please refer to Wang and Chen [29]. By the result of the test runs in Wang and Chen [29], the population sizes of population I and population II are suggested to be 50 and 50. The termination condition is 500 generations without improvement or half an hour.

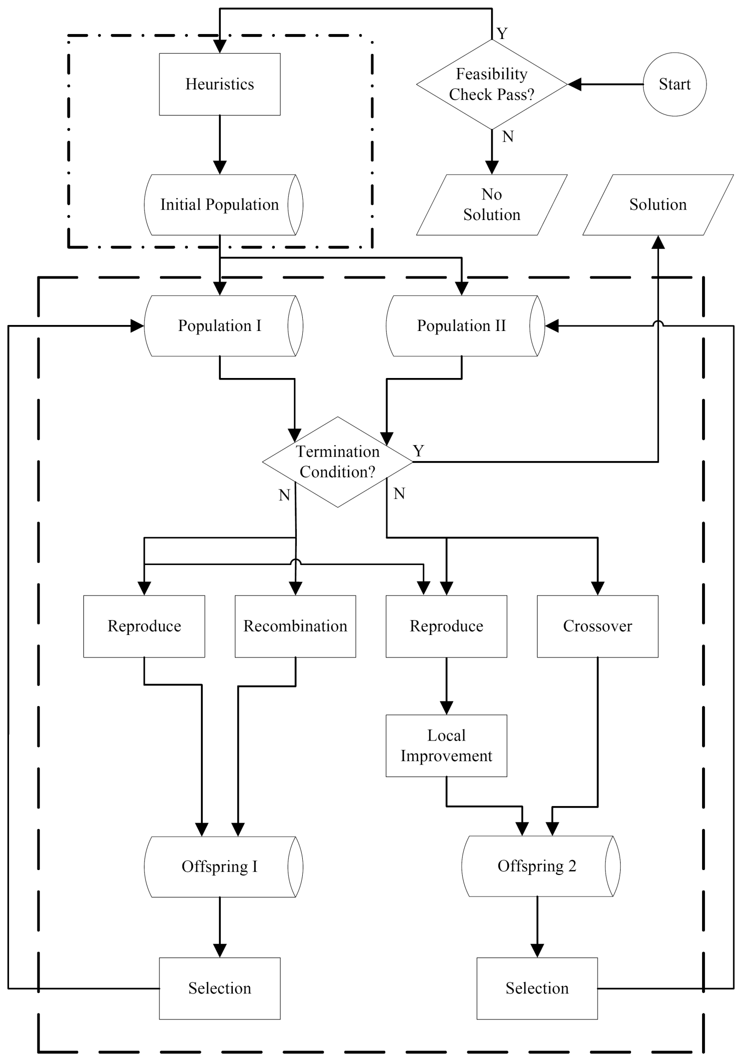

Figure 2. The framework of the coevolutionary algorithm.

5.2. Computational results for the small-scale FFDPPTW

In order to evaluate the accuracy of the CEA, a package of commercial linear programming software, ILOG Cplex, is adopted for comparison. ILOG Cplex can find the optimal solution for the small-scale FFDPPTW. Wang and Chen [29] generated some small-scale problems for the FDPPTW, the deterministic case of the FFDPPTW. There were three 5-customer problems, three 10-customer problems, and three 25-customer problems. In this study, these nine small-scale FDPPTWs are further revised to form nine small-scale FFDPPTWs. They are named as RCff05101, RCff05104, RCff05107, RCff10101, RCff10104, RCff10107, RCff25101, RCff25104, and RCff25107. Three credibility confidence levels (0.5, 0.8 and 1.0) are implemented to get different results for different types of decision makers.

The results of Cplex and the CEA for the small-scale FFDPPTW are listed in Tables 1 and 2. One can see that Cplex is only able to find the optimal solutions of 5-node problems (RCff05101, RCff05104, RCff05107), and 10-node problem (RCff10101) within 1~630 seconds. However, the CEA can get their optimal solutions by only 1~2 second. For the rest of the test problems, Cplex gives the “out of memory” best values for the other two 10-node problems, but it cannot find feasible solutions for all of three 25-node problems. When the number of customer nodes is up to 25, Cplex solver incorrectly shows an error message “presolve determines problem is infeasible or unbounded” due to the truncation errors.

In order to easily compare the results between Cplex and the CEA, the aggregated costs defined as $(2000 \times NV + TD)$ are depicted in Figure 3. For those problems which Cplex cannot solve, the aggregated costs are set as 20,000 like a penalty. One can see that the larger the confidence level is, the larger the aggregated cost is. Furthermore, the CEA is superior to Cplex when the number of customer is larger than 5.

Table 1. The Cplex results for the small-scale FFDPPTW with respect to different credibility levels

	Cr^* = 0.5			Cr^* = 0.8			Cr^* = 1.0		
Problem	NV	TD	Com. Time	NV	TD	Com. Time	NV	TD	Com. Time
RCff05101	3	220.15	2	3	220.15	1	3	220.15	1
RCff05104	2	214.57	630	2	219.88	420	2	223.44	262
RCff05107	2	211.83	96	2	241.92	58	3	242.19	156
RCff10101	3	347.38	2	3	358.19	1	4	371.90	8
RCff10104	*2	*270.32	31072	*3	*363.21	38700	*5	*583.07	38050
RCff10107	*3	*315.50	29812	*4	*386.04	64145	*5	*480.23	58720
RCff25101	#	#	#	#	#	#	#	#	#
RCff25104	#	#	#	#	#	#	#	#	#
RCff25107	#	#	#	#	#	#	#	#	#

*: the "out of memory" values.

#: Cplex cannot solve problems due to truncation errors.

Table 2. The results of the CEA for the small-scale FFDPPTW

	Cr^* = 0.5			Cr^* = 0.8			Cr^* = 1.0		
Problem	NV	TD	Com. Time	NV	TD	Com. Time	NV	TD	Com. Time
RCff05101	3	220.15	1	3	220.15	1	3	220.15	1
RCff05104	2	214.57	1	2	219.88	1	2	223.44	1
RCff05107	2	211.83	1	2	241.92	1	3	242.19	1
RCff10101	3	347.38	1	3	358.19	1	4	371.90	2
RCff10104	2	216.69	1	2	259.44	1	3	281.16	2
RCff10107	3	247.82	1	3	306.40	2	3	306.40	1
RCff25101	5	529.13	6	6	546.77	15	6	551.70	15
RCff25104	4	473.46	9	5	528.74	13	5	532.78	16
RCff25107	5	540.87	7	5	561.81	15	6	568.41	16

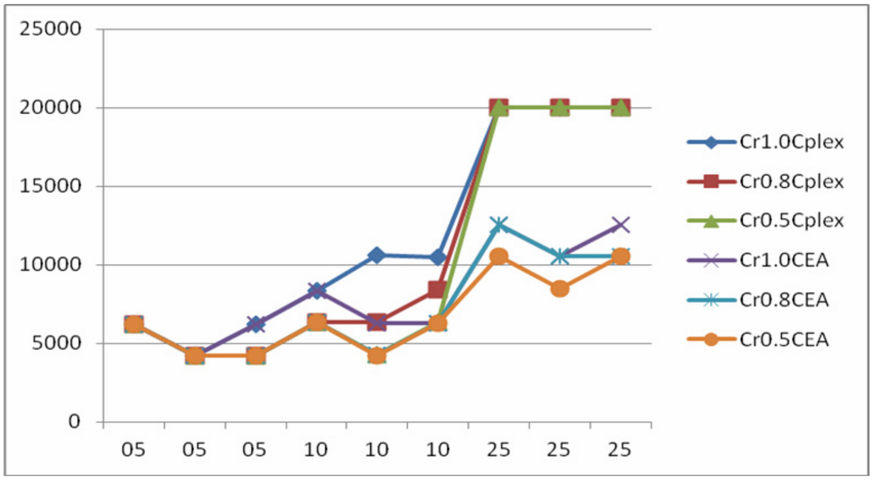

Figure 3. Aggregated cost vs. number of customers.

5.3. Computational results of the large-scale FFDPPTW

Wang and Chen [29] generated fifty-six 100-customer FDPPTW test problems by revising Solomon benchmarks. For evaluating the performance of the CEA for the FFDPPTW, fifty-six 100-customer FFDPPTW test problems are generated by revising those FDPPTWs in this study. In each problem, the pickup demands, the service times, the traveling times are similarly revised into triangular fuzzy numbers. Three credibility confidence levels (0.5, 0.8 and 1.0) are implemented to get different results for different types of decision makers. The CEA results for these 100-node FFDPPTWs are listed in Table 3.

The average computational time is 28.1 minutes. A condensed comparison among different credibility confidence levels is listed in Table 4. The aforementioned observation still holds: the larger is the confidence level, the larger the aggregated cost is. All the generated test problems can be found in the following website. (http://oz.nthu.edu.tw/~d933810/ test.htm).

Table 3. The CEA results for the 100-node FFDPPTW

	$Cr^* = 0.5$		$Cr^* = 0.8$		$Cr^* = 1.0$			$Cr^* = 0.5$		$Cr^* = 0.8$		$Cr^* = 1.0$	
Problem	NV	TD	NV	TD	NV	TD	Problem	NV	TD	NV	TD	NV	TD
R*101	18	1625.57	20	1697.06	20	1744.04	R*201	4	1322.65	4	1371.17	5	1269.46
R*102	15	1452.12	16	1518.2	18	1613.5	R*202	4	1115.85	4	1129.29	4	1200.78
R*103	14	1254	14	1305.81	16	1383.84	R*203	3	1044.86	4	958.41	4	970.02
R*104	10	1083.32	12	1089.64	13	1167.94	R*204	3	763.65	3	778.33	3	857.25
R*105	15	1400.75	16	1458.17	17	1476.54	R*205	3	1138.97	4	1053.13	4	1063.6
R*106	13	1283.74	14	1327.81	15	1358.45	R*206	3	896.66	3	1016.33	4	960.89
R*107	11	1138.15	12	1216.57	13	1261.66	R*207	3	894.82	3	915.88	3	908.09
R*108	10	1021.67	11	1068.67	12	1127.17	R*208	3	738.61	3	734.28	3	758.74
R*109	13	1211.69	13	1288.98	15	1306.59	R*209	3	989.22	4	984.96	4	937.42
R*110	12	1116.11	13	1156.31	14	1238.02	R*210	3	1014.93	4	966.47	4	989.49
R*111	11	1215.21	13	1147.79	13	1221.31	R*211	3	896.66	3	888.56	3	899.99
R*112	11	1039.56	12	1044.02	12	1088.76							
C*101	10	860.11	11	1019.98	12	1135.78	C*201	3	591.56	4	745.14	4	872.22
C*102	10	898.66	11	1027.35	12	1135.46	C*202	3	591.56	4	695.57	4	749.89
C*103	10	850.1	11	1032.1	12	1083	C*203	3	591.17	4	672.64	4	760.9
C*104	10	900.38	11	940.73	12	1053.18	C*204	3	590.6	4	652.66	4	663.69
C*105	10	968.43	11	1026.38	12	1100.86	C*205	3	588.88	4	677.02	4	794.08
C*106	10	862.08	11	1013.6	12	1107.66	C*206	3	588.49	4	680.11	4	768.7
C*107	10	902.68	11	958.86	12	1056.96	C*207	3	588.29	4	677.16	4	701.33
C*108	10	882.17	11	1035.76	12	1010.53	C*208	3	588.32	4	668.4	4	663.99
C*109	10	936.62	11	1001.59	12	1077.9							
RC*101	16	1671.61	18	1768.74	18	1825.74	RC*201	4	1637.64	5	1396.22	5	1547.09
RC*102	14	1507.6	16	1599.96	17	1713.6	RC*202	4	1260.68	4	1205.25	5	1214.19
RC*103	13	1382.81	14	1457.71	14	1492.74	RC*203	4	1019.13	4	1034.63	4	1100.14
RC*104	11	1193.03	13	1332.99	14	1473.83	RC*204	3	862.18	4	808.38	4	833.21
RC*105	15	1535.42	17	1640.37	18	1755.68	RC*205	5	1307.93	5	1285.81	5	1387.02
RC*106	13	1459.05	14	1507.23	15	1585.29	RC*206	4	1131.37	4	1134.1	4	1110.3
RC*107	12	1331.95	14	1390.48	14	1473.55	RC*207	4	1037.31	4	1083.17	4	1085.22
RC*108	11	1220.4	12	1302.44	14	1383.06	RC*208	3	888.17	3	898.96	4	895.3

Table 4. A condensed comparison among different confidence levels for the 100-node FFDPPTW

		C1	C2	R1	R2	RC1	RC2	Cumulative	Comp. Time
$Cr^* = 0.5$	NV	90	24	151	35	101	30	431	99966
	TD	7911.41	4718.87	14495.74	10764.92	11247.80	9264.73	58403.47	
$Cr^* = 0.8$	NV	99	32	166	39	118	33	487	89362
	TD	9056.35	5468.70	15319.03	10796.81	11999.92	8846.52	61487.33	
$Cr^* = 1.0$	NV	108	32	178	41	124	35	518	93834
	TD	9761.33	5974.80	15987.82	10815.73	12703.49	9172.47	64416	

5.4. Validity and managerial insight of FFDPPTW with credibility approach

The proposed model is successfully validated by Cplex. The coevolutionary algorithm (CEA) and Cplex both find the optimal solutions for all the 5-node problems and one of the 10-node problems. When the number of nodes is larger than or equals to 10, Cplex no longer guarantees to find the optimal solution. While Cplex is only able to give the 'out-of-memory' solutions, the CEA finds better solutions in a very short time. While Cplex does not work, the CEA still works well.

In this study, different credibility confidence levels (0.5, 0.8, and 1.0) are implemented to get different results for different types of decision makers. All the results reveal a phenomenon: the larger the confidence level is, the larger the cost is. This phenomenon facilitates the decision support based on the decision maker's preference. If the decision maker is an absolute risk averter, then he/she can set $Cr^* = 1.0$ to get full confidence but also get a plan with the highest cost; on the contrary, if the decision maker is a risk lover, he/she can set $Cr^* = 0.8$ or lower to get a plan with a lower cost but accompanied with a lower confidence.

6. Conclusions

As the reverse logistics and the closed loop supply chain networks have been adopted by enterprises, the delivery and pickup problems with time windows have been drawn much attention and studied extensively recently. Since there are cases that the imprecision/uncertainty concerning pickup demand, traveling time, and service time must be taken into account, a fuzzy flexible delivery and pickup problem with time windows (FFDPPTW) is proposed in this paper. The problem is then formulated into a chance constrained programming (CCP) model based on the fuzzy credibility theory. Different credibility confidence levels can be implemented to get different results for different types of decision makers. One can implement this model by Cplex to get the optimal solution if the scale of the problem is small.

Some test problems are generated by revising the well-known Solomon's benchmarks which are originally used for the vehicle routing problem with time windows. This study then uses a coevolutionary algorithm to get near optimal solutions in an acceptable computational time. The termination conditions are able to prevent exhaustive computations. The comparison between the results of Cplex software and the coevolutionary algorithm shows the coevolutionary algorithm is not only accurate but more efficient. Further comparison between different confidence levels shows that the higher the confidence level is required, the larger the cost is paid. Decision makers can pick out a best suitable plan by their preferences.

In some real-life problems, some customers' time windows can be violated with appropriate penalties. The penalty is usually proportional to the degree of lateness at the customer, as the duration of time in excess of the latest service time prescribed by the customer. How to extend hard time windows to soft ones is a direction of the further study. In some practical applications, the vehicle capacity is small or the planning period is large, performing more than one route per vehicle may be more appropriate for practical implementation. Hence, how to extend one trip to multiple trips is also a direction of the further study.

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