Article

Dynamic Vehicle Routing Problem with Fuzzy Customer Response

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Abstract: This paper proposes a dynamic vehicle routing problem (DVRP) model with fuzzy customer responses and suggests optimal routing strategies. Most DVRP studies have focused on how to create a new route upon the occurrence of dynamic situations such as unexpected demands. However, the customer responses have received little attention. When a pop-up demand is added to one of the planned routes, the service for some optimally planned demands may be delayed. Customers may file complaints or cancel their orders as a result of the delays. As a result, the customer response has a significant impact on current profits as well as future demands. In this research, we consider the customer response in DVRP and address it with a fuzzy number. Changing distances or defining time windows can resolve the problem of customer response. The customer responses are represented by a fuzzy rule. The new routing strategy provides the viability to reduce customer complaints and avoid losing potential customers.

Keywords: dynamic vehicle routing problem; fuzzy number; customer response; fuzzy rules; optimization

1. Introduction

Company profits come mostly from customers. Accordingly, customer responses or relationships with customers are critical issues in operations management. Transportation is on the same line since its main role is to serve customers. This paper deals with customer response issues in transportation, particularly the dynamic vehicle routing problem (DVRP).

Under dynamic environments including demand changes, traffic conditions, and service time changes, the dynamic vehicle routing problem aims to have an optimal routing strategy with minimum costs such as distance, time, and number of vehicles. Although there have been studies about customer service or satisfaction in a lot of fields, the research on the dynamic vehicle routing problem has mainly focused on minimizing transportation costs. This motivation leads us to explore the customer response issue in DVRPs.

This paper considers a capacitated dynamic vehicle routing problem. Once the initial optimal routes, known as optimally planned routes, are found, the optimal routes have to be re-optimized since additional requests, including demand and travel time changes, are added. In the new optimal routes, arrival times for existing customers are changed. Although customers have no time windows, they know the expected time for the service because the transportation service provider may let them know the estimated time to visit in the morning or before the vehicle leaves. Responses to the changes can be different by customers. The responses of customers include understanding, being inconvenienced, complaining, and cancelling. For example, customers may allow the visit to be delayed, request that it not be delayed, or simply cancel the demand. Although the customers understand the delay in service this time, they may change their purchase next time. Thus, that may cause customer churn. These responses may affect the profits of the company or future demand. However, customer responses are subjective and hard to describe...
or predict. Both fuzzy and stochastic programming can be used to deal with the VRP under conditions of uncertainty. Unlike stochastic programming, fuzzy logic does not need to assume the probability distribution, and the fuzzy rule can be nicely applied to any control problem. The stochastic programming needs the number of reliable historic data to fit the probability distribution of uncertain parameters. It also requires a lot of scenarios to represent the uncertainty, which reduces the computational burden for the efficiency of solving the problem ([1]). Thus, this paper uses the fuzzy number to address the customer response to vehicle routing problems. The fuzzy number represents the grade of the customer response. Customer response patterns can be represented by fuzzy rules. Based on the fuzzy customer response, this paper proposes two strategies to reduce the customer complaints. One strategy is to service the most stringent customers earlier than other customers by restricting the distance between the depot and the strict customer so that the vehicle can visit the customer early on the optimal routes. Another strategy is to add time windows constraints for the most demanding customers. The problem is then changed into a vehicle routing problem with time windows for some nodes.

The objective of this paper is to develop a fuzzy customer response in DVRP and propose a solution strategy to reduce customer complaints as the optimal routes are updated dynamically. When one considers the customer response, the transportation can be sustainable since it significantly affects future demand. Thus, customer response is the main source of sustainability of company profits.

The contributions of this paper are as follows: first, this paper considers the customer response to dynamic vehicle routing problems using fuzzy numbers. Service level or customer satisfaction has been studied in the literature. However, most studies have focused on the number of services delivered on time, not customer reactions. On the other hand, this paper addresses the customer responses with fuzzy numbers in dynamic vehicle routing problems. The pattern of the customer responses is then derived by the fuzzy inference rule. Thus, the problem in this paper addresses the vehicle routing problem driven by customer responses. Second, this paper proposes two strategies to reduce customer complaints about changing their service times in dynamic vehicle routing problems. Identifying the strict customers with the fuzzy customer response model, this paper services those customers earlier than other customers or sets up hard time windows for them.

In the following sections, this paper presents the literature about this issue in Section 2. Section 3 describes a mathematical model for dynamic vehicle routing problems with fuzzy numbers for customer responses. Section 4 proposes solutions to keep target customers’ services from being delayed. Patterns of customer responses are presented by fuzzy inference rules in Section 5. Finally, this paper summarizes the paper and discusses future work.

2. Related Works

DVRP has been a challenging issue and studied by many researchers and practitioners in the literature ([2–4]). Like VRP, DVRP studies mainly focused on the routing method from the perspective of the shipper or carrier. However, if the shipper and carrier ignore the customer side, their profits may be significantly decreased in the future. Recently, researchers have started dealing with this issue.

Customer service in the vehicle routing problem has been considered. Psaraftis (1980, [5]) has proposed a dynamic programming model to minimize total degree of dissatisfaction of customers in a dial-a-ride problem under static and dynamic conditions. They assumed that the dissatisfaction was a linear function of the waiting and riding times of each customer. Pavone et al. (2007, [6]) have considered a stochastic and dynamic vehicle routing problem with time windows. In their study, the model has included customer impatience, which is random and minimizes the fraction of service requests missed because of impatience. Demand in their model has a random impatience time. Zhang et al. (2012, [7]) have suggested a multiobjective vehicle routing problem that seeks to optimize both customer satisfaction and travel cost. They solved the problem with a
multiobjective quantum evolutionary algorithm. Customer satisfaction is represented by a fuzzy due time window; a trapezoidal fuzzy number. Ghannadpour et al. (2013, [8]) have explored a vehicle routing problem with fuzzy travel time and fuzzy time windows and represented customer satisfaction as a function of fuzzy time windows. Zhang et al. (2013, [9]) have investigated a stochastic vehicle routing problem with soft time windows. They assumed travel times and service times were uncertain. The trade-off between a carrier’s total cost and customer service has been analyzed. Attila et al. (2014, [10]) have proposed a consistent vehicle routing problem with service consistency constraints and solved the problem with a template-based adaptive large neighborhood search. The model focused on customer satisfaction to increase customer loyalty and obtain a competitive advantage. Sun et al. (2022, [11]) have pointed out time window constraints, including hard time windows, soft time windows, and fuzzy soft time windows, that can enhance on-time deliveries. However, determining the penalty costs is difficult in soft time windows, and the flexibility problem may occur in hard time windows.

Dynamic or stochastic vehicle routing problems also have been studied. Zhang et al. (2023, [12]) have formulated a dynamic vehicle routing problem with stochastic customer requests. They have developed interpretable knapsack-based approximations of the expected reward-to-go to predict the number of requests. Ma et al. (2023, [13]) suggested a dynamic vehicle routing problem with stochastic demand. They have considered real-time stochastic passenger demand and formulated a two stage stochastic programming model. They have used a rolling horizon method to capture the dynamic changes. Zhang and Woensel (2023, [14]) have conducted a comprehensive review of the dynamic vehicle routing problem with stochastic demand for the models and solution approaches.

The problem of demand changing in vehicle routing problems has also been studied. Ismail and Irhamah (2008, [15]) have dealt with the vehicle routing problem with stochastic demand and solved the problem with a genetic algorithm. Real demand is only known when the vehicle arrives at the customer location. Wen et al. (2010, [16]) have studied a dynamic multi-period vehicle routing problem. Their feasible service periods are dynamically revealed over time. In their model, the objective function is to minimize total routing cost, customer waiting time, and balance daily workload over the planning horizon.

Fuzzy logic has been used in the field of VRP. Wang et al. (2002, [17]) solved the Chinese postman problem and introduced the fuzzy time windows. Zheng et al. (2006, [18]) assumed the travel time as a fuzzy variable. Ghannadpour et al. (2013, [8]) used fuzzy travel times in their multiobjective DVRP and considered the customer’s satisfaction level. Kuo et al. (2012, [19]) used fuzzy demand for CVRP. Zhang et al. (2013, [9]) proposed a stochastic programming model for the DVRP that takes into account fuzzy travel time and customer service level. Wang et al. (2022, [20]) have proposed a dynamic electric vehicle routing problem with stochastic availability of charging stations. They have suggested a solution approach based on reuse of knee points using an evolutionary multi objective optimization algorithm. Zhang et al. (2020, [21]) have suggested an electric vehicle routing problem with time windows and fuzzy variables of service time, battery consumption, and travel time. They have adopted an adaptive large neighborhood search (ALNS) algorithm to solve the problem. Sun (2020, [1]) have proposed a vehicle routing problem with uncertainty in a road rail intermodal transportation system and solved the problem with fuzzy set theory and programming. Khaitan et al. (2022, [22]) have proposed a fuzzy vehicle routing problem with a fuzzy variable for travel time. They have considered the drivers’ burnout, stress, and fatigue and suggested a topic model for the problem. Giallanza and Puma (2020, [23]) have proposed a fuzzy vehicle routing problem in a three-echelons supply chain. They have presented the customer demand as a fuzzy variable and solved the problem using a non-dominated sorting genetic algorithm. They also have considered multi-objective functions to minimize total travel costs and CO2 emissions.

The priority of customers has been considered in the vehicle routing problem. Sheu (2007, [24]) has proposed three mechanisms for distributing operations: fuzzy clustering, customer priority, and en route multiobjective delivery. Shetty et al. (2008, [25]) have
investigated an unmanned combat aerial vehicle routing problem. They have assigned weights to targets for priorities and maximized the total weighted amount of service for targets. Ai and Kachitvichyanukul (2009, [26]) have constructed a capacitated vehicle routing problem based on the customer priority and vehicle priority matrices. Smith et al. (2010, [27]) have suggested a dynamic vehicle routing model to minimize the expected delay for demand of a certain class. Using the queuing model, the model has a high coefficient for high priority demand.

The literature listed above shows that dynamic, fuzzy, and customer issues have been of keen interest in recent studies. The vehicle routing problem with uncertainty has been formulated by stochastic vehicle routing or fuzzy vehicle routing models. The solution methods for them have been studied with stochastic programming or fuzzy theory. However, although customer responses, including understanding, complaints, canceling, and so on, can affect the routing of an optimal solution or future demand, which can be an important factor in the vehicle routing problem as well as the profits of the company, there is a lack of documentation for the customer response in DVRP. Thus, this paper can be a trigger to tackle this issue.

3. Fuzzy Customer Response Model

This paper considers a basic vehicle routing problem that has capacity constraints. The basic model of VRP is as follows. Let \( G = (V, A) \) be a complete graph. This paper defines a node set \( V = \{0, 1, 2, \ldots, n + 1\} \) (0: departure of depot, 1 ~ n: nodes of customers, n + 1: destination of depot) and its variant sets are \( N \subset V \) as customer nodes. \( V^+ (i) = \{j \in V \mid (i, j) \in A\} \) as successor nodes of node \( i \), and \( V^- (i) = \{j \in V \mid (j, i) \in A\} \) as predecessor nodes of node \( i \). \( A = \{(i, j) \mid i, j \in V, i \neq j\} \) is an arc set. \( M = \{1, 2, \ldots, m\} \) is a vehicle set. Parameters are as follows. \( d_{i,j} \) is travel cost or distance from node \( i \) to node \( j \). \( d_i \) is demand of customer \( i \), and \( K \) is capacity of each vehicle. The decision variable \( x_{i,j}^m \) is binary variable and is 1 if arc \( (i, j) \in A \) belongs to the optimal routes by vehicle \( m \) and 0 otherwise. The formulation is as follows.

\[
\text{(CVRP)} \quad \text{Min} \quad \sum_{m \in M} \sum_{(i,j) \in A} c_{i,j} x_{i,j}^m \quad (1)
\]

\[
\text{s.t.} \quad \sum_{m \in M} \sum_{j \in V} x_{i,j}^m = 1, \quad \forall i \in N \quad (2)
\]

\[
\sum_{j \in V^+ (i)} x_{0,j}^m = 1, \quad \forall m \in M, \quad (3)
\]

\[
\sum_{j \in V^- (h)} x_{h,j}^m - \sum_{j \in V^+ (h)} x_{h,j}^m = 0, \quad \forall h \in N, \quad \forall m \in M, \quad (4)
\]

\[
\sum_{i \in N} d_i \sum_{j \in V} x_{i,j}^m \leq K_i, \quad \forall m \in M, \quad (5)
\]

\[
x_{i,j}^m \in \{0, 1\}, \quad \forall i, j \in V, \quad m \in M \quad (6)
\]

Objective function (1) is to minimize the total travel cost or distance. (2) ensures that each node is served by exactly one vehicle. (3) enforces that each vehicle leaves the node 0 (depot). (4) denotes that each vehicle leaves the node \( i \) if the vehicle enters the node. (5) ensures that each vehicle returns to the node \( n + 1 \) (depot). (6) is the capacity constraint for each vehicle. (7) is the integer constraint.

In DVRP, additional requests occur after the initial optimal routes (planned routes) are determined. The optimal routes are updated to new optimal routes after including additional requests. Customers respond to the changes in service times. Some customers may be strict about the changes, but others may not. Customer responses are uncertain and subjective. Due to this ambiguity, this paper defines the grade of a customer complaint as a triangular fuzzy number, an LR type, or normal. Depending on the data, fuzzy numbers can be of other types than triangular, but this paper uses the triangular to explain the method for the sake of convenience. Let \( R \) be the grade of customer responses as
where $y$ is the objective function of the vehicle routing problem. However, in that case, finding the customer complaints. The fuzzy variable for the customer complaints can be added to include the new requests and have a slightly different solution from the planned ones. In the same method as the solution in Figure 1.

When one has two new demands, two customer nodes are added to the network, and the planned routes are re-optimized (see Figure 2). The solution in Figure 2 is obtained by the method for the sake of convenience. Let $\pi_i^{l}$ be the fuzzy variable of the grade of customer complaint.

Their fuzzy probabilities are $\pi_i^{l}$, $\pi_i^{m}$, and $\pi_i^{h}$. The membership function of the grade is as follows.

$$
\mu_R(y_i) = \begin{cases} 
\frac{y_i - r_i^l}{r_i^m - r_i^l}, & r_i^l \leq y_i \leq r_i^m \\
1, & y_i = r_i^m \\
\frac{r_i^m - y_i}{r_i^h - r_i^m}, & r_i^m \leq y_i \leq r_i^h \\
0, & \text{Otherwise}
\end{cases}
$$

where $y_i \in R$, $i = 1, \ldots, n$ is the fuzzy variable of the grade of customer complaint.

Let us consider an example of DVRP to see the case of customer responses after re-optimization. This paper considers one of the benchmark datasets of Augerat et al. (1995, [28]) and solves it with the Clark & Wright heuristic method in Figure 1.

![Figure 1](image1.png)  
**Figure 1.** Example of CVRP and its solution.

When one has two new demands, two customer nodes are added to the network, and the planned routes are re-optimized (see Figure 2). The solution in Figure 2 is obtained by the same method as the solution in Figure 1.

![Figure 2](image2.png)  
**Figure 2.** New requests and solutions.

Comparing the new solution in Figure 2 with the solution in Figure 1, two routes include the new requests and have a slightly different solution from the planned ones. In Figure 2, the service for the rest of the customers after the new demands is delayed. In that case, some customers may have complaints for the delays. Thus, the goal is to minimize customer complaints. The fuzzy variable for the customer complaints can be added to the objective function of the vehicle routing problem. However, in that case, finding the optimal solution can be complicated. Thus, we use the fuzzy variable as the state of the
control system and find optimal strategies for each state of the system. This paper proposes two strategies in the following sections.

4. Fuzzy Rules for Customer Responses

This section presents how the customer response is represented by fuzzy logic. Due to the new demand, some customers among the original customers’ network can be delivered later on. The responses of those customers are vague and difficult to measure quantitatively, but they have a significant impact on profits. Thus, one needs to consider the customer’s responses when they have complaints. This problem can be resolved by the fuzzy inference rule ([29]).

The rules of fuzzy logic are defined by the if-then rule. To make the rules, one defines the variables to present the states and controls. Let the variables in the if-statement input variables, and the variables in the then-statement, output variables. In the dynamic vehicle routing problem, one can define these variables as follows.

Input variable \( x \) = customer response

Output variable \( y \) = routing strategy

The terms of \( x \) and \( y \) can be defined as sets of \( A \) and \( B \) as follows.

\[
A = \{ \text{very bad, bad, normal, good, very good} \}
\]

\[
B = \{ \text{earliest, early, as soon as possible, late} \}
\]

Assume the membership functions of the variables are triangular functions. The fuzzy memberships are defined as follows.

Figures 3 and 4 present the membership functions of \( x \) and \( y \). The number of input variable \( x \) represents the degree of patience. If the number is small, the patience is low, so the customer may complain. On the other hand, if the number is large, the customer may understand the delay. The number of the output variable \( y \) represents the response time to the customer. If the number is small, the routing strategy has to be fast. On the other hand, if the number is large, the delay can be adopted.

\[
\mu_{A}(x)
\]

Figure 3. Membership function of \( x \).
Assume that data is given for the customers. One can make the rules based on the data. Then fuzzy rules can be derived.

Figures 5 and 6 show the paired data \( (x, y) \) such as \( (x_1, y_1) \), \( (x_2, y_2) \), and \( (x_3, y_3) \) plotted in their membership functions. With the data, the rules are generated as follows.

Rule 1: If \( x \) is \( x_1 \), then \( y \) is \( y_1 \).
Rule 2: If \( x \) is \( x_2 \), then \( y \) is \( y_2 \).
Rule 3: If \( x \) is \( x_3 \), then \( y \) is \( y_3 \).

For the rules, one calculates the degree of each rule.
Degree of Rule 1 = \(\mu_A(x_1) \times \mu_B(y_1) \times w_1\)
Degree of Rule 2 = \(\mu_A(x_2) \times \mu_B(y_2) \times w_2\)
Degree of Rule 3 = \(\mu_A(x_3) \times \mu_B(y_3) \times w_3\)

Each rule has a weight \(w_i\) that is assigned according to its importance.

Given the rules, one combines the rules to find the pattern of the rules with matrix types as follows.

Figure 7 presents the combinations of the rules driven by the data. If a box has more than two rules, one can pick the rule with the largest degree. Once the boxes are all filled, the pattern or model of the rule is complete.

For the new data or situation, one can forecast the result of the input with defuzzification. Assume that new data is \(x'\). Forecasting the corresponding \(y'\) is calculated as follows:

\[
y' = \frac{\sum_{i=1}^{K} \mu_{R_i}(x') \bar{y}_i}{\sum_{i=1}^{K} \mu_{R_i}(x')} \tag{9}\]

In the above formula, \(\mu_{R_i}(x')\) is the membership degree of \(i\)th rule for \(x'\), \(\bar{y}_i\) is the center value of the consequent fuzzy set, and \(K\) is the number of rules. This provides a guideline for optimal routing for the customer response.

<table>
<thead>
<tr>
<th>(x)</th>
<th>Very good</th>
<th>Good</th>
<th>Normal</th>
<th>Rule 1</th>
<th>Rule 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Earliest</td>
<td>Early</td>
<td>As soon as possible</td>
<td>Late</td>
<td></td>
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</table>

**Figure 7. Combination of the rules.**

5. Solution Methods

In this section, this paper suggests two solution strategies to minimize customer complaints in DVRP. To reduce customer complaints, one should service the strict customers earlier or on time. One strategy is to reduce the distance between the depot and the strict customer to provide service earlier. The reduction of the distance is not changing the physical network, but it is assuming the distance is implicitly near the depot. Assuming that this reduction of the distance is only used for calculations to find the best solution, the vehicle may visit the customer closest to the depot first. Another strategy is to set a strict time window constraint to ensure that the strict customer receives service on time.

5.1. Reduce the Distance from the Depot

The objective function (1) of the vehicle routing problem in this paper is to minimize total distances. Thus, if a node is close to the depot, the node is visited earlier in the optimal routes. Based on this, this paper simply makes strict customers serviced earlier by reducing the distances between the depot and the customers. The amount of distance reduction is dependent on the grade of the customer complaint. In the VRP model, the objective function (1) is modified to change the distance from the depot as follows.

\[
\text{Min} \quad \sum_{m \in M} \sum_{(i,j) \in A} c_{ij} x_{ij}^{m} - \delta \sum_{m \in M} \sum_{(0,j) \in A} \left( y'_c_{0,j} x_{0,j}^{m} \right) \tag{10}\]
In (10), $y'_j = \mu^R_{-1}(y_i)$, $j = 1, \ldots, n$ denotes the calculation of $\alpha$-cut of the fuzzy membership function. $\delta$ is the scale parameter. Without loss of generality, $0 \leq \delta y'_j \leq 1$, $j = 1, \ldots, n$. Thus, based on the grade of complaint, the distance between the depot and the strict customer is reduced from $c_{0,j}$ to $c_{0,j} - \delta y'_j c_{0,j}$. If the value of $\delta y'_j$ is zero, no distance is changed, which denotes that the customer is not strict. As the value of $\delta y'_j$ is close to one, the distance decreases and the customer is visited earlier in the optimal routes. With this strategy, one can service the strict customers earlier than non-strict customers based on the grade of each customer complaint.

5.2. Time Window Constraints

Another strategy to reduce the complaints of customers is to set up time windows constraints for strict customers. Hard time window constraints are used for strict customers. For non-strict customers, no time window constraints are used. One identifies the strict customers which have a high rate of customer complaints based on the expert’s opinion or past history. Time windows constraints are added only for the strict customers as shown in Figure 8.

![Figure 8. Change CVRP to partial VRP-TW.](image)

Figure 8 shows that the strict customers have time window constraints on the right side (CVRP+TW (some nodes)). The hard time windows assure that the strict customers are serviced on time as per the planned schedule since non-strict customers do not have time window constraints.

Let $C_{st} \subset V$ be a set of strict customers. The constraints of time windows are added to (CVRP) problem as follows.

$$t^m_i + s_i + v_{ij} - t'^m_j \leq \left(1 - x^m_{i,j}\right)L, \forall (i,j) \in A, m \in M, i,j \in C_{st} \tag{11}$$

$$a_i + \delta y'_i \leq t'^m_i \leq b_i - \delta y'_i, \forall i \in C_{st}, m \in M. \tag{12}$$

$y'_j = \mu^R_{-1}(a_i)$, $i \in C_{st}$ is the $\alpha$-cut of the fuzzy membership function. Let $[a_i, b_i]$ be time windows for node $i$, $L$ be a large number, $t^m_i$ be arrival time of vehicle $m$ at node $i$ (beginning of service), and $s_i$ be a service time at node $i$. $[a_i, b_i], i \in C_{st}$ is the range of time windows for customers based on the planned routes. $\delta$ is the scale parameter. Without loss of generality, $0 \leq \delta y'_j \leq 1$, $j = 1, \ldots, n$. As $y'_j$ increases, the time, constrains on the windows become tighter. This strategy modifies the basic VRP into a partial VRP-TW to address the customer responses.

Let us consider an example to demonstrate the addition of time windows constraints. This paper considers a benchmark problem: Solomon 25 and C101 (1987 [30]). When this paper removes the time window constraints, the solution is as follows.

Figure 9 shows the solution without time window constraints. Let this solution be the planned optimal routes. After this, one more demand is added as follows. When this paper...
re-optimizes the problem with additional demand, the new optimal solution is in Figure 10. Figure 5 shows the new optimal solution with additional demand. In the new solution, one route has been changed on the right side of Figure 10. Due to this new solution, some customers are served later than planned. Assume that two customers are strict, and this paper adds time window constraints for the two strict customers. The solution to the new problem with two time window constraints is as follows.

Figure 11 presents the solution to the problem with two time window constraints for strict customers. In the new optimal route on the right side of the Figure, two strict customers are visited earlier than other customers. Thus, one can reduce customer complaints by adding time window constraints for strict customers.

Table 1 shows the detailed changes in routes in Figures 9–11. Nodes 1 and 2 were the third and fourth visits in the planned routes, respectively. Due to the additional demand, the optimal route has been changed, and visits to two nodes are delayed. However, after the introduction of time window constraints, nodes 1 and 2 are visited for the first and second time.

![Figure 9. Solution without TW—C101 solomon 25.](image1)

![Figure 10. Solution without TW—C101 solomon, 25 + additional demand.](image2)
This paper proposes a model of dynamic vehicle routing problems with fuzzy customer responses. Due to new requests over the time horizon, the planned routes need to be changed by adding the new demands. New demands cause a delay in service for some customers. Based on the customers’ preferences, some customers have complaints. Those complaints cannot be ignored since they have a significant impact on future profits. This paper addresses this issue in the dynamic vehicle routing problem and describes the customer responses with fuzzy numbers. A fuzzy approach can be used to capture the customer response with vagueness. This paper provides two solutions to reduce customer complaints.

One solution method is to implicitly change the distance between strict customers and the depot, which forces the optimal routes to serve the strict customer earlier. The adjustment parameter can control the impact of customer responses on the routing scheme. The other method is to impose time windows constraints for the strict customers in order for them to be service them within the specified times. The problem has changed from a capacitated vehicle routing problem to a partial vehicle routing problem with time windows. One can solve the partial vehicle routing problem with time windows using the solution method of the VRP-TW. In both approaches, this paper uses a fuzzy number to describe the customer responses. This paper also suggested a fuzzy inference rule to find the pattern of the rules from the data. Defuzzification can then be applied to forecast the result of new input data.

In most studies of the vehicle routing problem, the uncertainty of customer demand has been emphasized. However, the reason for fluctuating demand is the reaction of customers. Thus, this paper has considered the customer responses in the vehicle routing problem and suggested a quantifying approach with fuzzy theory. The proposed approach can be applied to the newly interesting field of vehicle routing studies.

Obtaining real-world scenarios of customer reactions and determining the weights of the customers are limitations of this study which should be tackled in future studies. In the future, one can improve the solution methods. In the current method, this paper changed

<table>
<thead>
<tr>
<th>Table 1. Comparison routes.</th>
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<tbody>
<tr>
<td><strong>Without TW</strong></td>
</tr>
<tr>
<td>Optimal route</td>
</tr>
<tr>
<td>Distance</td>
</tr>
</tbody>
</table>

6. Conclusions

Figure 11. Solution with TW for node 1 and 2—C101 solomon 25 + additional demand.
the distance from the depot for all customers, but one may change only the customers near the new demands. To calculate the service start time after the planned routes, an efficient calculation method must be developed. Developing the solution method for the partial VRP-TW is also a challenging issue.

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