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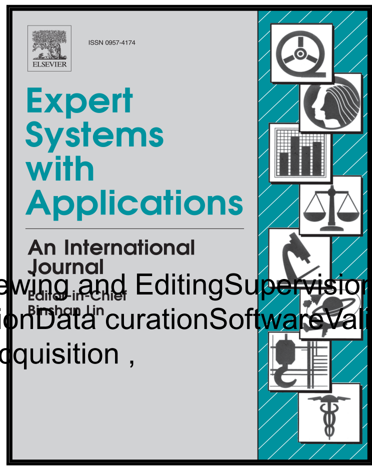


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## Highlights

- Investigated a novel electric VRP considering uncertain environment.
- Proposed a fuzzy optimization model with fuzzy simulation to the presented problem.
- Integrated ALNS algorithm and VND algorithm to solve the presented model.
- Performed experiments to verify the effectiveness of the proposed algorithm.

**Manuscript (Clean Mode)**

# Fuzzy optimization model for electric vehicle routing problem with time windows and recharging stations

Shuai Zhang, Mingzhou Chen, *Wenyu Zhang, Xiaoyu Zhuang

Shuai Zhang
Ph.D., Professor
School of Information, Zhejiang University of Finance and Economics
Hangzhou, China 310018
Email: zhangshuai@zufe.edu.cn

Mingzhou Chen
Postgraduate Student
School of Information, Zhejiang University of Finance and Economics
Hangzhou, China 310018
Email: chenmingzhou@zufe.edu.cn

Wenyu Zhang (*Corresponding author)
Ph.D., Professor
School of Information, Zhejiang University of Finance and Economics
Hangzhou, China 310018
Email: wyzhang@e.ntu.edu.sg

Xiaoyu Zhuang
Undergraduate Student
School of Information, Zhejiang University of Finance and Economics
Hangzhou, China 310018
Email: zhuangxiaoyu@zufe.edu.cn

## Abstract

As fuel prices increase and emission regulations become increasingly strict, electric vehicles have been used in various logistics distribution activities. Most studies have focused on the electric vehicle routing problem under a deterministic environment, neglecting the effects of uncertain factors in practical logistics distribution. Thus, a novel fuzzy electric vehicle routing problem with time windows and recharging stations (FEVRPTW) is investigated in this study, and a fuzzy optimization model is established based on credibility theory for this problem. In the presented model, fuzzy numbers are used to denote the uncertainties of service time, battery energy consumption, and travel time. Moreover, the partial recharge is allowed under the uncertain environment. To solve the model, an adaptive large neighborhood search (ALNS) algorithm enhanced with the fuzzy simulation method is proposed. In the proposed ALNS algorithm, four new removal algorithms are designed and integrated for addressing the FEVRPTW. To further improve the algorithmic performance, the variable neighborhood descent algorithm is embedded into the proposed ALNS algorithm and five local search operators are applied. The experiments were conducted to verify the effectiveness of the proposed ALNS algorithm for solving the presented model.


**Keywords:** Vehicle routing problem; Credibility theory; Electric vehicle; Fuzzy simulation; Adaptive large neighborhood search;

# 1. Introduction

As fuel prices increase and emission regulations become increasingly strict, logistics companies have begun to adopt electric vehicles (EVs) instead of internal combustion engine vehicles. EVs offer several advantages, such as high energy utilization and low maintenance cost, rendering them the popular low-carbon vehicles. La Poste, the French national postal operator, has operated 250 EVs and has signed a contract for the delivery of an additional 10,000 EVs (Kleindorfer et al., 2012). As of 2015, 1.26 billion EVs have been used worldwide, approximately 100 times compared to 2010 (Kim et al., 2018). According to a conservative estimate, plug-in hybrid EVs will achieve 25% market share in 2020 (Hadley and Tsvetkova, 2009). It is foreseeable that EVs will be a major traffic tool in the future. However, the wide adoption of EVs for logistics distribution has not been realized. Over the past few years, many automakers and manufacturers have invested significant amounts of time and capital to develop battery technology for EVs; nevertheless, the results are dissatisfactory. For the majority of EVs, the driving range is within 100–150 miles (Feng and Figliozzi, 2013) and the minimum recharging time is 0.5 hour (Montoya et al., 2017). Under these limitations, companies applying EVs in their daily logistics operations require an efficient fleet management system that can consider the limited driving range and long recharging time.

To respond to this challenge, many researchers have begun to study a new research topic, namely the electric vehicle routing problem (EVRP). EVRP is to find an optimum EVs routing plan to visit a given set of customers. Owing to the limited driving range, an EV routing plan frequently includes planned detours to the recharging stations (Montoya et al., 2017). In previous studies, two important constraints, i.e., vehicle capacity (Lin et al., 2016) and time windows (Schneider et al., 2014) have been elaborated. Meanwhile, researchers have studied various recharging policies such as full recharge (Schneider et al., 2014), partial recharge

(Keskin and Çatay, 2016), and battery swap (Hof et al., 2017). Most previous studies on the EVRP were conducted under a deterministic environment; however, the logistics activity could be affected by many uncertain factors including human behaviors and weather. For example, battery energy consumption will increase in a snow storm because of parasitic losses such as those from air-conditioners, headlights, and heaters (Lave et al., 1995). To address the uncertain parameters, most researchers often use the stochastic optimization method. However, in practical applications, it is difficult to describe these parameters as random variables because of the lack of sufficient historical data to analyze them. Instead, fuzzy variables can be applied to address these uncertain parameters (Liu, 2004).

Fuzzy theory has been widely used in operation research such as the fourth party logistics routing problem (Cui et al., 2013), flexible job shop problem (Gao et al., 2016; Lin et al., 2019), location-routing problem (Zarandi et al., 2011), and vehicle routing problem (VRP) (Ghannadpour et al., 2014; Du et al., 2017). However, it is still a new topic for the EVRP. In this study, a novel fuzzy electric vehicle routing problem with time windows and recharging stations (FEVRPTW) is presented and fuzzy numbers are used to denote the uncertainties of service time, battery energy consumption, and travel time. A fuzzy optimization model is established based on credibility theory (Liu, 2004) for solving the FEVRPTW. The presented model can implement the partial recharge (Keskin and Çatay, 2016) under an uncertain environment. To solve this model, an adaptive large neighborhood search (ALNS) algorithm that integrates several new removal algorithms and existing insertion algorithms is proposed in this study. To estimate the credibility of the obtained solutions, a fuzzy simulation method is employed to enhance the proposed ALNS algorithm. To further improve the algorithmic performance, the proposed ALNS algorithm is combined with the variable neighborhood descent (VND) algorithm and five local search operators. The experimental results indicate that the proposed ALNS algorithm is effective in solving the FEVRPTW.

The remainder of this paper is organized as follows. In Section 2, the relevant work is reviewed. In Section 3, the formulation of the FEVRPTW is provided. In Section 4, the proposed algorithm to solve the FEVRPTW is detailed. In Section 5, the experimental results are provided. Finally, Section 6 summarizes the study.

## 2. Related work

To alleviate the negative effects from conventional vehicles, EVs are highly recommended as the primary carriers in urban logistics. As specific limitations such as long recharging time and limited driving range for EVs exist, researchers have begun to study a special VRP for EVs, namely, the EVRP.

Conrad and Figliozzi (2011) introduced a rechargeable vehicle routing problem (RVRP) with time windows, where vehicles with a limited driving range can be recharged at customer locations during the service process. The RVRP forms the basis of the EVRP in which the customer’s time windows are considered and the recharging time is fixed. To address the RVRP, an iterative route construction and improvement algorithm was employed. Erdoğan and Miller-Hooks (2012) presented the green vehicle routing problem (GVRP), where alternative fuel vehicles exhibit a limited driving range with the limited refueling infrastructures. To address the GVRP, two heuristics, i.e., the modified Clarke and Wright savings heuristic and the density-based clustering algorithm, are proposed. However, the proposed GVRP does not include constraints such as the vehicle capacity and time windows.

Recently, Schneider et al. (2014) introduced an electric vehicle routing problem with time windows and recharging stations (EVRPTW) that was extended from the GVRP (Erdoğan and Miller-Hooks, 2012) by considering electric fleets as transport carrier. The primary goal of the EVRPTW is to minimize the number of employed EVs and total traveling distance. To address the EVRPTW, a hybrid algorithm that integrates the variable neighborhood search (VNS) algorithm and tabu search (TS) algorithm is developed, whose performance is verified using two sets of EVRPTW benchmark problem instances. Desaulniers et al. (2016) introduced four variants of the EVRPTW and presented exact branch-price-and-cut algorithms to address these problems. Hiermann et al. (2016) extended the EVRPTW by considering mix electric fleets where the available EV types differed in their respective transport capacity, battery size, and acquisition cost.

However, the above studies always assumed that the battery state of charge (SoC) would be full after the recharging. In fact, recharging battery to be at any level is more practical. Thus, Keskin and Çatay (2016) formulated the EVRPTW model that supports partial recharge and conducted experiments to verify that the partial recharge could significantly reduce the transportation cost and improve the routing decisions. In addition, most of the existing studies on the EVRP assumed the battery charge level as a linear function of the recharging time, when the function is in fact nonlinear. Therefore, Montoya et al. (2017) extended the traditional EVRP by considering nonlinear charging functions, and proposed a hybrid metaheuristic algorithm combining an iterated local search and a heuristic concentration for solving this problem. Yang and Sun (2015) studied the electric vehicles battery swap stations location and routing problem that replaces recharging stations with battery swap stations, where EVs can replace the existing depleted battery with a fully charged one. Subsequently, Hof et al. (2017) studied the same problem and proposed an effective adaptive VNS algorithm to address it. Schiffer and Walther (2017) investigated a location-routing approach for the routing plan of EVs and siting decision of recharging stations simultaneously, in which three objective functions for different planning perspectives were considered.

As mentioned above, most of the existing studies only assumed that the operation plan was scheduled under a deterministic environment. The study by Schiffer and Walther (2018) is one of the few that addressed the EVRP considering uncertain factors, in which the uncertain customer patterns including the spatial customer distribution, demand, and service time windows are considered. However, the uncertainties of battery energy consumption and travel time were not considered. In our previous work (Zhang et al., 2019a), the authors proposed a stochastic optimization model for determining the minimum cost scheme including the optimal number and location of battery swap stations with an optimal routing plan based on stochastic customer demands and developed a hybrid VNS algorithm to address this model. However, some limitations were revealed. For example, constraints such as time windows were not considered. In addition, the presented model was not applicable to recharging stations, as the recharging time was not considered. Pelletier et al. (2019) also studied the EVRP with consideration of the effect of uncertain factors on energy consumption and proposed a robust optimization model for obtaining a reliable routing plan. An exact method is presented for solving small instances of this problem and a two-phase heuristic method is presented for solving large instances of this problem. However, the proposed model mainly focuses on the application of EVs in city logistics without the consideration of recharging behavior, and is therefore not applicable for EVs in long distance transport.

Although recent studies of EVRP have been conducted on uncertain environment, most of them addressed the uncertain factors by measuring their probability distribution that is difficult to obtain in the real application. For example, the precise service time is hard to assess due to the instability of human behavior. The estimation of probability distributions such as that for energy consumption and travel time are underlain by the sufficient historical data that is hard to collect in most real applications. Thus, the probability-based stochastic optimizations models for EVRP have some limitations for practical applications. To overcome them, the uncertain variables can be assessed by experience and imperfect information. For example, the travel time can be described as “between 15 minutes and 20 minutes” or “approximately 1 hour”. In this situation, the fuzzy variables can be used to deal with uncertain variables with unknown probability distribution by analyzing imperfect information and expert evaluation (Liu, 2004; He and Xu, 2005). The fuzzy optimization method has been used on many studies of VRP (He and Xu, 2005; Zheng and Liu, 2006; Ghannadpour et al., 2014; Du et al., 2017), though it is seldom discussed on solving EVRP.

To build a more realistic EV routing model tackling uncertainty, this study proposes a novel fuzzy optimization model, in which three uncertain parameters including service time, battery energy consumption, and travel time are analyzed. The primary contributions of this study are fourfold. First, the original EVRPTW is extended by considering uncertain factors and a fuzzy optimization model is formulated for the FEVRPTW. Next, an ALNS algorithm enhanced with the fuzzy simulation method is proposed to address the FEVRPTW. Subsequently, the algorithmic performance is improved further by embedding the VND algorithm into the proposed ALNS algorithm and applying five local search operators. Finally, the experiments verify the effectiveness of the proposed ALNS algorithm in solving the FEVRPTW.

## 3. Fuzzy electric vehicle routing problem with time windows and recharging stations

In this section, the formulation of the FEVRPTW is given. The proposed model includes a single depot, a set of customers with known demands, a set of recharging stations, and a homogeneous fleet of EVs with fixed capacity and limited driving range. Because the battery SoC will decrease with the increase in travel distance, the EV may have to visit the recharging stations to recharge its battery before resuming its route. The partial recharge has been proven to be more practical than the full recharge in the real world application owing to a shorter recharging time (Keskin and Çatay, 2016). To address the problem in real case effectively, the proposed model also allows partial recharge. Unlike traditional EVRPs, the presented problem is studied in an uncertain environment. Under this environment, the service time, battery energy consumption, and travel time will not be sufficiently precise. In this study, fuzzy variables are used to address these uncertain parameters and the proposed model for the FEVRPTW is formulated based on the credibility theory (Liu, 2004). The details of this new problem are shown through an illustrative example in the following section.

### 3.1 Illustrative example

Fig. 1 shows an illustrative example that contains a single depot (D), four customers (C1-C4), and a recharging station (R). The EV will depart from the depot, and subsequently serve customers C1 and C2. Before the EV visits customers C3 and C4, it can perform a detour to recharge its battery. If the EV visits customers C3 and C4 after recharging its battery, the credibility that the EV can return to the depot will be high, indicating that it is less likely to experience depleted battery energy. On the contrary, if the EV visits customers C3 and C4 without recharging its battery, the credibility that EV can return to depot will be low, while the total travel distance is short. If the credibility that EV can return to the depot without recharging battery is extremely low, the decision maker will tend to choose a more reliable route to avoid possible failures caused by uncertain factors. However, the reliability of a routing plan in an uncertain environment cannot be well estimated using the existing EV routing model. Thus, the proposed model that can recommend highly reliable routing solutions is significant for a decision maker. In subsection 3.2, the notations and mathematical formulations of the FEVRPTW are introduced.

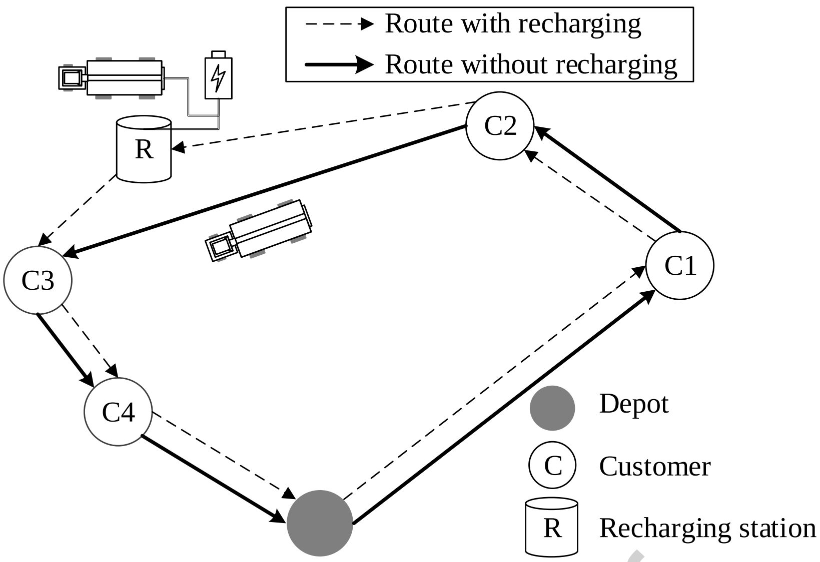


**Fig. 1.** Illustrative example

## 3.2 Mathematical model

### 3.2.1 Notations

In this subsection, the mathematical model for the FEVRPTW is detailed. To clarify the proposed model, the notations used in this model are given as follows.

$D$={0}: Vertex representing the depot.

$A$={1, 2, …, $N$}: Set of vertices representing the customers where $N$ is the number of customers.

$P$: Set of vertices representing the recharging stations.

$P'$={$N$ + 1, $N$ + 2, …, $N$ + $F$}: Inspired from Schneider et al. (2014) for addressing the EVRPTW, a set of dummy vertices are generated to allow for several visits to each recharging station in the set $P$ where $F$ is the number of dummy vertices.

$K$: Number of EVs in use.

$C$: Maximum vehicle capacity of EV.

$W$: Maximum battery capacity of EV.

$d_{ij}$: Distance from vertex $i$ to vertex $j$ ($i, j \in A \cup D \cup P'$).

$t_{ij}$ : Fuzzy travel time from vertex *i* to vertex *j* ($i, j \in A \cup D \cup P'$).

$c_{ij}$ : Fuzzy battery energy consumption from vertex *i* to vertex *j* ($i, j \in A \cup D \cup P'$).

$s_i$ : Fuzzy service time at customer *i* ($\boldsymbol{i} \in \boldsymbol{A}$).

$q_i$ : Demands of vertex *i* ($i \in A \cup D \cup P'$). If $\boldsymbol{i} \notin \boldsymbol{A}$, $q_i = 0$.

[$e_i$ , $l_i$ ]: Time window of customer *i* ($i \in A$).

$\rho$ : Recharging rate.

### 3.2.2 Formulation

In this subsection, Zheng and Liu's (2006) solution representation to the routing plan of internal combustion engine vehicles is extended by including the factors of recharging time and limited driving range that are crucial in the FEVRPTW. A solution is described by three decision variable vectors ***x***, ***y***, and ***z***, where ***x***={$x_1$, $x_2$, ..., $x_m$} are integer decision variables representing *m* vertices with $x_i \in A \cup P'$ and $x_i \neq x_j$ for all $i, j = 1, ..., m, i \neq j$; ***y***={$y_{N+1}$, $y_{N+2}$, ..., $y_{N+F}$}, where each $y_i$ represents the required battery SoC after leaving the recharging station *i* and $0 \le y_i \le W$ ; ***z***={$z_1$, $z_2$, ..., $z_K$} are integer decision variables where $z_0 \equiv 0 \le z_1 \le z_2 \le ... \le z_{K-1} \le m \equiv z_K$. For each EV, if $z_k = z_{k-1}$, the *k*th EV will not be in use; if $z_k > z_{k-1}$, the *k*th EV will be in use. Equation (1) presents the routing plan of the *k*th EV that will depart from depot, visit assigned customers, and then return to depot.

$$0 \to x_{z_{k-1}+1} \to x_{z_{k-1}+2} \to ... \to x_{z_k} \to 0 \tag{1}$$

For example, suppose ***x***={4, 3, 2, 5, 6, 7, 1} and ***z***={3, 7, 7}. Thus, the routing plan of the first EV will be $0 \to 4 \to 3 \to 2 \to 0$, that of the second EV will be $0 \to 5 \to 6 \to 7 \to 1 \to 0$, and the third EV will not be in use.

Unlike traditional studies that consider the battery SoC as a deterministic variable, e.g., the battery SoC is 80%, the proposed FEVRPTW model considers fuzzy battery energy consumption and allows for partial recharge by defining a new SoC function $f_i^k(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z})$ that represents the battery SoC of the *k*th EV arriving at vertex *i*, $i \in A \cup D \cup P'$. If the *k*th EV is in use, its SoC function can be calculated as follows:

$$f^k_{x_{z_{k-1}+1}}(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}) = W - c_{0,x_{z_{k-1}+1}} \tag{2}$$

$$f^k_{x_{z_{k-1}+j}}(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}) = f^k_{x_{z_{k-1}+j-1}}(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}) - c_{x_{z_{k-1}+j-1},x_{z_{k-1}+j}} \quad 2 \le j \le z_k - z_{k-1},\ x_{z_{k-1}+j-1} \in A \tag{3}$$

$$f^k_{x_{z_{k-1}+j}}(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}) = f^k_{x_{z_{k-1}+j-1}}(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}) \vee y_{x_{z_{k-1}+j-1}} - c_{x_{z_{k-1}+j-1},x_{z_{k-1}+j}} \quad 2 \le j \le z_k - z_{k-1},\ x_{z_{k-1}+j-1} \in P' \tag{4}$$

$$f^k_0(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}) = f^k_{x_{z_k}}(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}) - c_{x_{z_k},0} \quad x_{z_k} \in A \tag{5}$$

$$f^k_0(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}) = f^k_{x_{z_k}}(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}) \vee y_{x_{z_k}} - c_{x_{z_k},0} \quad x_{z_k} \in P' \tag{6}$$

where $\vee$ is the maximum operator. Equation (2) presents the battery SoC of an EV when it arrives at a customer or a recharging station from the depot. Equation (3) presents the battery SoC of an EV when it arrives at another customer or a recharging station from a customer. Equation (4) presents the battery SoC of an EV when it arrives at a customer or another recharging station from a recharging station with consideration of the recharging behavior. Equation (5) presents the battery SoC of an EV when it returns to the depot from a customer. Equation (6) presents the battery SoC of an EV when it returns to the depot from a recharging station with consideration of the recharging behavior.

Let $g_i(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z})$ denote the arrival time function of an EV at vertex *i*, $i \in A \cup P'$. In the proposed model, it is assumed that an EV arriving at a customer before the given time window must wait until the time window starts. If an EV arrives at a customer within the given time window, the service will start immediately. If the $k$th EV is in use, its arrival time function can be calculated as follows:

$$g_{x_{z_{k-1}+1}}(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}) = t_{0,x_{z_{k-1}+1}} \tag{7}$$

$$g_{x_{z_{k-1}+j}}(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}) = g_{x_{z_{k-1}+j-1}}(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}) \vee e_{x_{z_{k-1}+j-1}} + s_{x_{z_{k-1}+j-1}} + t_{x_{z_{k-1}+j-1},x_{z_{k-1}+j}} \quad 2 \le j \le z_k - z_{k-1},\ x_{z_{k-1}+j-1} \in A \tag{8}$$

$$g_{x_{z_{k-1}+j}}(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}) = g_{x_{z_{k-1}+j-1}}(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}) + \rho \times (y_{x_{z_{k-1}+j-1}} - f^k_{x_{z_{k-1}+j-1}}(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}) \wedge y_{x_{z_{k-1}+j-1}}) + t_{x_{z_{k-1}+j-1},x_{z_{k-1}+j}} \\ 2 \le j \le z_k - z_{k-1},\ x_{z_{k-1}+j-1} \in P' \tag{9}$$

where $\wedge$ is the minimum operator. Equation (7) presents the arrival time of an EV at a vertex when it departs from the depot. Equation (8) presents the arrival time of an EV at a vertex when it departs from a customer. Equation (9) presents the arrival time of an EV at a vertex when it departs from a recharging station.

Let $h(\boldsymbol{x},\boldsymbol{z})$ denote the total travel distances of the solution that is the sum of travel distances of all EVs, and let $h_k(\boldsymbol{x},\boldsymbol{z})$ denote the travel distance of the $k$th EV. If the $k$th EV is not in use, $h_k(\boldsymbol{x},\boldsymbol{z})$ will be equal to zero. Subsequently, $h(\boldsymbol{x},\boldsymbol{z})$ and $h_k(\boldsymbol{x},\boldsymbol{z})$ can be calculated with the following Equations (10) and (11):

$$h(\boldsymbol{x},\boldsymbol{z}) = \sum_{k=1}^{K} h_k(\boldsymbol{x},\boldsymbol{z}) \tag{10}$$

where

$$h_k(\boldsymbol{x},\boldsymbol{z}) = \begin{cases} d_{0,x_{z_{k-1}+1}} + \sum_{j=z_{k-1}+1}^{z_k-1} d_{x_j x_{j+1}} + d_{x_{z_k},0}, & if\ z_k > z_{k-1} \\ 0, & if\ z_k = z_{k-1} \end{cases} \tag{11}$$

for all $k$=1, 2, …, $K$.

Equation (12) ensures that the total demands of customers in each route will not exceed the capacity of EV. Equation (13) presents the sum of demands of all visited vertexes is equal to the sum of demands of all customers, which ensures that all customers will be visited.

$$\sum_{j=z_{k-1}+1}^{z_k} q_{x_j} \leq C, \quad k = 1,\ 2,\ \ldots, K \tag{12}$$

$$\sum_{i=1}^{m} q_{x_i} = \sum_{i \in A} q_i \tag{13}$$

Considering that the battery energy consumption, travel time, and service time could not be given precisely, fuzzy variables were used to address these uncertain parameters in the current study, and two chance constraints were added to the proposed model. Equation (14) presents one of chance constraints, which ensures that all EVs will not run out of battery SoC during its route with at least the confidence level $\alpha$ $(0 < \alpha \leq 1)$. Equation (15) presents the other chance constraint, which ensures that all EVs will visit customers within their time windows with at least the confidence level $\beta$ $(0 < \beta \leq 1)$. The confidence levels $\alpha$ and $\beta$ are provided by the decision makers.

$$Cr\{f_i^k(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}) > 0, \quad i \in A \cup D \cup P',\ k = 1,\ 2,\ \ldots,\ K\} \geq \alpha \tag{14}$$

$$Cr\{g_i(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}) \in [e_i,\ l_i], \quad i \in A\} \geq \beta \tag{15}$$

In this study, the objective of model is to minimize the total travel distances of all EVs. Thus, according to Equations (1) – (15), the FEVRPTW can be solved using the following mathematical model in Equation (16):

$$\begin{cases} \min \quad h(\boldsymbol{x},\boldsymbol{z}) \\ \text{subject to} \\ x_i \neq x_j, \quad i, j = 1, \ldots, m, \ i \neq j, \\ 0 \leq y_i \leq W, \quad i \in P', \\ 0 \leq z_1 \leq z_2 \leq \ldots \leq z_{K-1} \leq m, \\ Cr\{ f_i^k(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}) > 0, \quad i \in A \cup D \cup P', \ k = 1, \ 2, \ \ldots, \ K\} \geq \alpha, \\ Cr\{ g_i(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}) \in [e_i, \ l_i], \quad i \in A\} \geq \beta, \\ \sum_{j=z_{k-1}+1}^{z_k} q_{x_j} \leq C, \quad k = 1, \ 2, \ \ldots, K, \\ \sum_{i=1}^{m} q_{x_i} = \sum_{i \in A} q_i, \\ x_i, \ z_j \text{ are integers, } i = 1, \ 2, \ \ldots, \ m, \ j = 1, \ 2, \ \ldots, \ m-1. \end{cases} \tag{16}$$

## 4. Proposed method

In this section, the proposed ALNS algorithm for solving the FEVRPTW is detailed. A fuzzy simulation method is employed to enhance the ALNS algorithm. In the proposed ALNS algorithm, four removal algorithms that are special for FEVRPTW are designed and several existing insertion algorithms are integrated. The VND algorithm integrating five local search operators is applied to further improve the quality of the solutions. The primary flow of the proposed ALNS algorithm is shown in Fig. 2. The following subsections describe the detailed process of the proposed ALNS algorithm for solving the FEVRPTW.

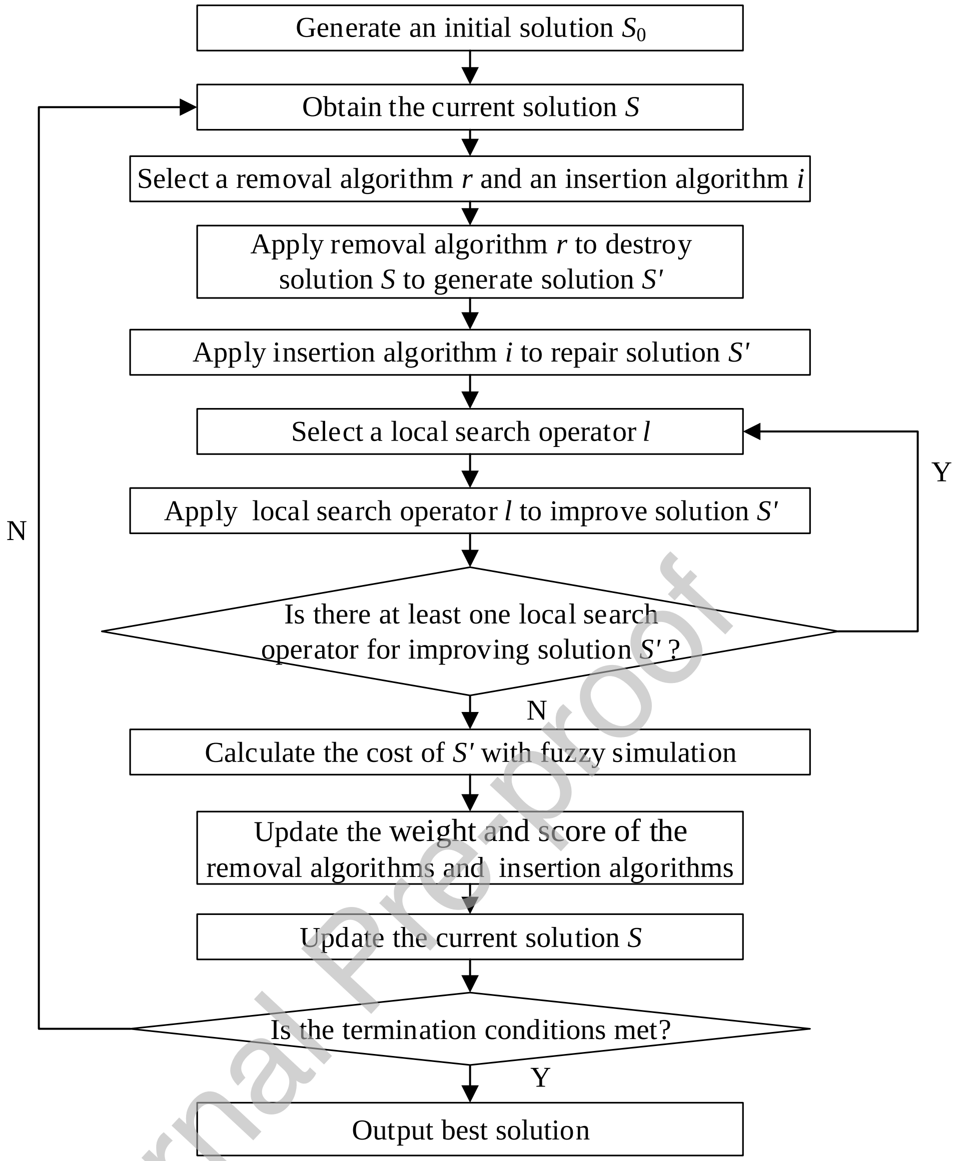


**Fig. 2.** Primary process of proposed ALNS algorithm

## 4.1 Fuzzy simulation

Though the chance constraints with fuzzy variables may be handled by converting the chance constraints to deterministic equivalents, it is only applicable in few special circumstances. Thus, a method of fuzzy simulation (Liu and Iwamura, 1998) has been proposed for estimating the credibility of a solution in chance-constrained programming with fuzzy variables. The numerical experiments have been conducted to verify the effectiveness of fuzzy simulation (Liu and Iwamura, 1998). In this study, the fuzzy simulation (Liu, 2004) is applied to estimate the credibility $F = Cr\{f(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z})(t,c,s) > 0\}$ and $G = Cr\{g(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z})(t,c,s) \in [e,\ l]\}$, where $t = \{t_{ij},\ i, j \in A \bigcup D \bigcup P'\}$, $c = \{c_{ij},\ i, j \in A \bigcup D \bigcup P'\}$, and $s = \{s_k,\ k \in A\}$. Suppose that a solution of the FEVRPTW is ($\boldsymbol{x}$, $\boldsymbol{y}$, $\boldsymbol{z}$). First, several random numbers $t_{ij}^o$, $c_{ij}^o$, and $s_k^o$ are generated from the ε-level sets of fuzzy variables $t_{ij}$, $c_{ij}$, and $s_k$ $(i, j \in A \bigcup D \bigcup P',\ k \in A)$, respectively, where $o$ is the index of the iteration number, and ε is a pre-determined level. In practical, the events with low possibility will not be considered, and thus ε will be set as a sufficiently small number. Let $O$ denote the maximum iteration number. Set $v_o = \min_{i,j \in A \bigcup D \bigcup P'} \{u_{t_{ij}}(t_{ij}^o) \wedge u_{c_{ij}}(c_{ij}^o)\} \wedge \min_{k \in A} u_{s_k}(s_k^o)$, $t^o = \{t_{ij}^o,\ i, j \in A \bigcup D \bigcup P'\}$, $c^o = \{c_{ij}^o,\ i, j \in A \bigcup D \bigcup P'\}$, and $s^o = \{s_k^o,\ k \in A\}$ $(o = 1,\ 2,\ ...,\ O)$, where $\wedge$ is the minimum operator; $u_{t_{ij}}$, $u_{c_{ij}}$, and $u_{s_k}$ are membership functions of $t_{ij}$, $c_{ij}$, and $s_k$, $(i, j \in A \bigcup D \bigcup P',\ k \in A)$, respectively. Thus, the credibility can be calculated with Equations (17) and (18), as shown below:

$$F = \frac{1}{2}\left(\max_{1 \le o \le O}\{v_o \mid f(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z})(t^o, c^o, s^o) > 0\} + \min_{1 \le o \le O}\{1 - v_o \mid f(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z})(t^o, c^o, s^o) \le 0\}\right) \tag{17}$$

$$G = \frac{1}{2}\left(\max_{1 \le o \le O}\{v_o \mid g(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z})(t^o, c^o, s^o) \in [e,\ l]\} + \min_{1 \le o \le O}\{1 - v_o \mid g(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z})(t^o, c^o, s^o) \notin [e,\ l]\}\right) \tag{18}$$

The detailed process of fuzzy simulation is as follows

Step 1: Set $o$ = 1.

Step 2: Generate $t_{ij}^o$, $c_{ij}^o$, and $s_k^o$ from the ε-level sets of fuzzy variables $t_{ij}$, $c_{ij}$, and $s_k$ $(i, j \in A \bigcup D \bigcup P',\ k \in A)$, respectively.

Step 3: Set $v_o = \min_{i,j \in A \bigcup D \bigcup P'} \{u_{t_{ij}}(t_{ij}^o) \wedge u_{c_{ij}}(c_{ij}^o)\} \wedge \min_{k \in A} u_{s_k}(s_k^o)$ $(i, j \in A \bigcup D \bigcup P',\ k \in A)$.

Step 4: If $o$ <= $O$, set $o$ = $o$ + 1 and return to Step 2; Otherwise, go to Step 5.

Step 5: Return $F = Cr\{f(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z})(t,c,s) > 0\}$ and $G = Cr\{g(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z})(t,c,s) \in [e,\ l]\}$ via

Equations (17) and (18).

## 4.2 Adaptive large neighborhood search

The ALNS algorithm proposed by Ropke and Pisinger (2006) is an extension to the large neighborhood search (LNS) algorithm (Shaw, 1998). The ALNS algorithm can improve the current feasible solution using several removal and insertion algorithms. The removal algorithm can destroy the current feasible solution while the insertion algorithm can reconstruct the destroyed solution. At each iteration, either of the removal or insertion algorithm employed for the current solution is selected based on its weight and score that are dynamically and self-adaptively adjusted according to the performance of these algorithms in the previous iterations. The adaptive mechanism is detailed in the reference (Ropke and Pisinger, 2006).

### 4.2.1 Removal algorithms

Four new removal algorithms are designed specifically for addressing the FEVRPTW, including the customer random removal algorithm, station random removal algorithm, customer proximate removal algorithm, and station proximate removal algorithm.

The customer random removal algorithm randomly removes $\psi_1$ percent of customers in the current solution using a uniform distribution, where $\psi_1$ is a fixed number ($0 < \psi_1 < 1$). The station random removal algorithm randomly removes $\psi_2$ percent of the recharging stations in the current solution using a uniform distribution, where $\psi_2$ is a fixed number ($0 < \psi_2 < 1$).

The customer proximate removal algorithm removes the vertices based on a probabilistic mechanism. At each iteration, the customer proximate removal algorithm will randomly select a customer $i$ and subsequently remove other vertices with a certain probability. The removal probability $\eta_{ij}$ of vertex *j* is given by Eq. (19), when customer *i* is selected.

$$\eta_{ij} = \frac{\min_{t \in \Omega} d_{it}}{d_{ij}} \tag{19}$$

where $d_{ij}$ is the distance between the vertices *i* and *j*, and $\Omega$ is the set of all remaining vertices in the current solution. Similarly, the station proximate removal algorithm removes the vertices based on a probabilistic mechanism. At each iteration, the station proximate removal algorithm will randomly select a recharging station *i* and subsequently remove other vertices with a certain probability. The removal probability $\eta_{ij}$ of vertex *j* is obtained by Eq. (19), when recharging station *i* is selected. The aim of the two proximate removal algorithms is to improve the solution by rescheduling several vertices that are relatively close to each other. For example, Fig. 3 shows an illustrative example of the station proximate removal algorithm. The recharging station R is selected and subsequently four customers C3–C6 that are closer to the recharging station R than other customers are more likely to be removed. In addition, two random removal algorithms and the probabilistic mechanism are designed for further enhancing the global search ability by adding some randomness.

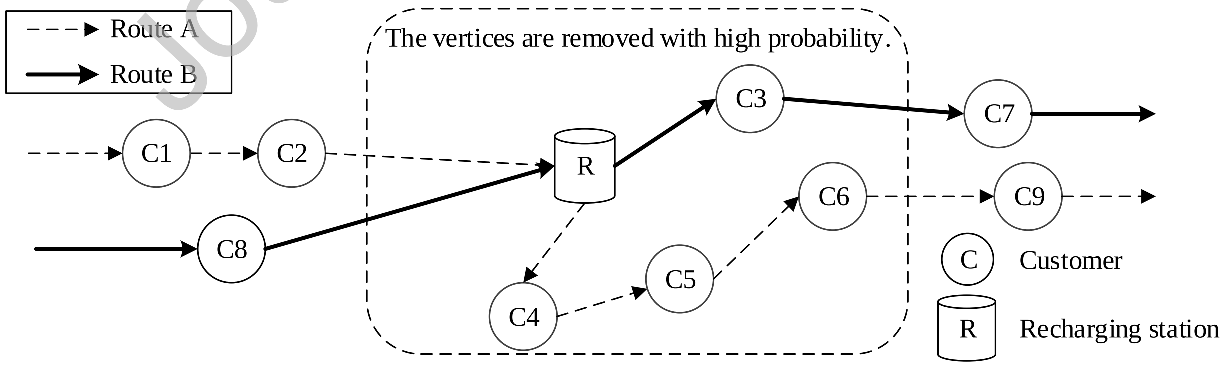


**Fig. 3.** Illustrative example of station proximate removal algorithm

### 4.2.2 Insertion algorithms

The insertion algorithms proposed by Ropke and Pisinger (2006), including the greedy insertion algorithm and regret-*k* insertion algorithm, are applied. The two insertion algorithms have been widely employed to address various VRPs (Ropke and Pisinger, 2006; Li et al., 2016; Avci and Avci, 2019). The insertion algorithm reinserts the removed vertices back into the destroyed solution. The greedy insertion algorithm is a greedy heuristic. The regret-*k* insertion algorithm is similar as the greedy insertion algorithm, except for incorporating several look ahead information. In the proposed ALNS algorithm, the greedy insertion algorithm, regret-2 insertion algorithm, and regret-3 insertion algorithm are applied.

### 4.3 Variable neighborhood descent

In the proposed ALNS algorithm, the VND algorithm is applied to further improve the quality of the solution. The primary idea of the VND is designing multiple local search operators and switching local search operators systematically when the local search operator cannot improve the current solution (Mladenović and Hansen, 1997). In this study, five local search operators are applied, including the insertion operator, inversion operator, exchange operator, recharging station removal operator, and relocation operator.

The insertion operator inserts a vertex of the current solution into another position. The inversion operator inverts a segment of vertices in the current solution. The exchange operator swaps the positions of two vertices in the current solution. The recharging station removal operator removes a recharging station in the current solution. The relocation operator reassigns a vertex to another vehicle in the current solution. Fig. 4 shows several illustrative cases with five local search operators.

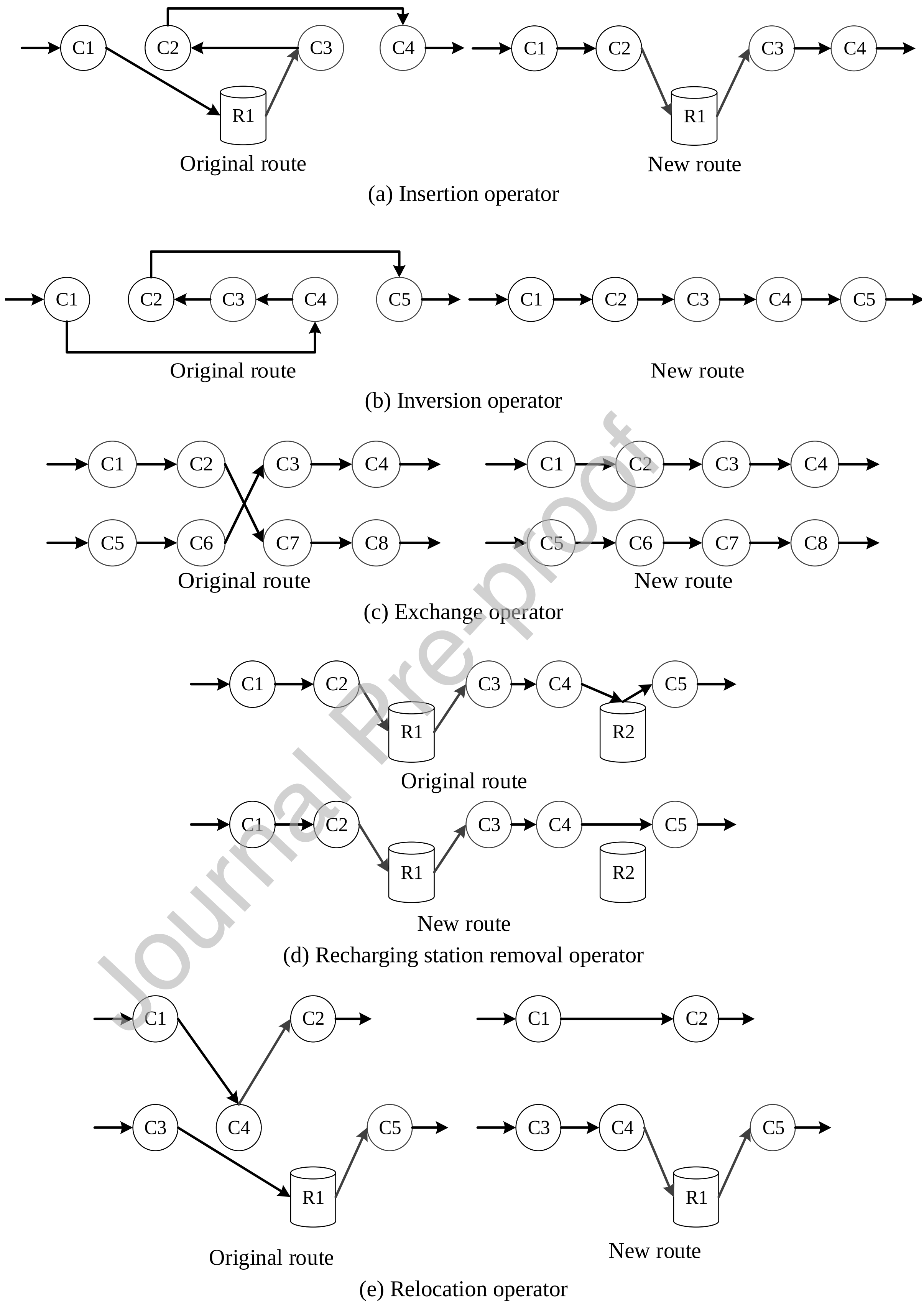


**Fig. 4.** Five local search operators

# 5. Numeric experiments

Numerical experiments were conducted to analyze the proposed model and to evaluate the performance of the proposed ALNS algorithm. To test the proposed ALNS algorithm, it was compared with three other metaheuristic algorithms that are ALNS (Ropke and Pisinger, 2006), LNS (Shaw, 1998), and VNS (Meng et al., 2018). The LNS applies the related removal algorithm (Shaw, 1998) and greedy insertion algorithm. To avoid confusion, in this study, ALNSr represents the ALNS proposed by Ropke and Pisinger (2006). To address the FEVRPTW, the three baseline algorithms are integrated with the fuzzy simulation in this study. All algorithms were implemented in Java and the computational study was conducted on a personal computer with a 3.60-GHz AMD Ryzen 7 3700X CPU having 32 GB of RAM operating Windows 10.

## 5.1 Experimental design

Because most of previous studies focus on the EVRP in deterministic environment, the previous presented benchmark problem instances are not available for this study. Therefore, in this study, several new benchmark problem instances were generated for the FEVRPTW. The numbers of recharging stations are set as 2, 4, 6, and 8 in these instances. The number of customers in these instances varies from 30 to 200. The demand of each customer is set as 5, 10, and 15. The maximum capacity of the EV is set as 100. The locations of the depot, customers, and recharging stations are scattered randomly in a 100 × 100 grid. The maximum distance of the EV with a full charge is set as 150. The recharging rate $\rho$ is set as 2. Triangular fuzzy numbers are used to represent the service time, battery energy consumption, and travel time. The confidence levels $\alpha$ and $\beta$ are set as 0.90 by default.

34 FEVRPTW benchmark problem instances were generated. Each instance is

self-explanatory. For example, the instance R-4-C-30 implies that it involves four recharging stations and 30 customers. These benchmark problem instances are publicly available in the figshare database (https://doi.org/10.6084/m9.figshare.10288326) (Zhang et al., 2019b).

Through trial experiments, the parameters of each algorithm are determined. The parameter settings are shown in Table 1. $\psi_1$ and $\psi_2$ represent the parameters in the customer random removal algorithm and station random removal algorithm respectively to control the number of removed vertices. $\phi_1$, $\phi_2$, $\phi_3$, and $\phi_4$ represent the four Shaw parameters in the Shaw removal algorithm that is applied by the ALNSr algorithm to remove vertices. $\delta$ represents the cooling rate of the simulated annealing that is applied by the proposed ALNS and ALNSr algorithms to determine whether a solution is accepted. $\vartheta$ represents the parameter to control the initial temperature of the simulated annealing. $\gamma_1$ represents the removal determinism factor in the related removal algorithm that is applied by the LNS algorithm to remove vertices. $\gamma_2$ represents the removal determinism factor in the worst removal algorithm that is applied by the ALNSr algorithm to remove vertices. $\gamma_3$ represents the removal determinism factor in the Shaw removal algorithm. $\sigma_1$, $\sigma_2$, and $\sigma_3$ represent the scores of obtaining the best solution, worse solution, and better solution, respectively, in the adaptive weight adjustment mechanism of the proposed ALNS and ALNSr algorithms. $\varsigma$ represents the roulette wheel parameter that is applied by the proposed ALNS and ALNSr algorithms to control the selection of the removal algorithms and insertion algorithms. $\upsilon$ represents the number of segments of the proposed ALNS and ALNSr algorithms. $\kappa$ represents the removal probability of each vertex in the local search of the VNS. The parameter settings of LNS, ALNSr, and VNS are obtained from Shaw (1998), Ropke and Pisinger (2006), and Meng et al. (2018), respectively. The parameter settings of the proposed ALNS can be referred to Ropke and Pisinger (2006). The maximum number of iterations of all algorithms is set as 500, while the maximum number of iterations of fuzzy simulation is set as 3000.

**Table 1** Parameter setting of four algorithms

| Parameter | ALNS | LNS | ALNSr | VNS |
|---|---|---|---|---|
| $\psi_1$ | 0.4 | | | |
| $\psi_2$ | 0.4 | | | |
| $\phi_1$ | | | 9 | |
| $\phi_2$ | | | 3 | |
| $\phi_3$ | | | 2 | |
| $\phi_4$ | | | 5 | |
| $\delta$ | 0.99975 | | 0.99975 | |
| $\vartheta$ | 0.025 | | 0.025 | |
| $\gamma_1$ | | 15 | | |
| $\gamma_2$ | | | 6 | |
| $\gamma_3$ | | | 3 | |
| $\sigma_1$ | 33 | | 33 | |
| $\sigma_2$ | 9 | | 9 | |
| $\sigma_3$ | 13 | | 13 | |
| $\varsigma$ | 0.4 | | 0. 4 | |
| $\upsilon$ | 100 | | 100 | |
| $\kappa$ | | | | 0.1 |

## 5.2 Experimental results

In this subsection, the proposed model for EVRPTW is analyzed first. The experiments are conducted on several existing benchmark problem instances presented by Schneider et al. (2014). Schneider et al. studied the EVRPTW in deterministic environment and solved the proposed model with a hybrid algorithm that is the combination of VNS and TS, namely, VNS/TS. In the current study, four EVRPTW instances are selected, and each instance includes 100 customers and 20 recharging stations. Table 2 lists the parameter settings of the selected instances.

**Table 2** Parameter settings of EVRPTW benchmark problem instances

| Instance | Battery capacity | Vehicle capacity | Recharging rate |
|---|---|---|---|
| c103 | 79.69 | 200.0 | 3.39 |

| | | | |
|---|---|---|---|
| c105 | 79.69 | 200.0 | 3.39 |
| r102 | 62.14 | 200.0 | 0.48 |
| r205 | 198.88 | 1000.0 | 0.15 |

To analyze the proposed model, the selected instances are extended by representing service time, battery energy consumption, and travel time as fuzzy variables. To ensure the fairness of experiment, the partial recharge will not be applied because Schneider et al. (2014) studied the EVRPTW with full recharge. Table 3 lists the comparison results between solving EVRPTW with VNS/TS by Schneider et al. and solving FEVRPTW with the ALNS in this study. Table 3 shows the statistical indexes including objective value, the credibility that each EV will not run out of battery SoC during its route, and the credibility that each customer will be visited within its time window, which are labeled as "Objective", "Cr-A" and "Cr-B" in the columns respectively. It is found that the proposed FEVRPTW model can provide solutions with higher credibility. Although EVRPTW model can provide solutions with higher objective value, its obtained solutions with lower credibility make it less reliable for EV to complete the logistics service according to the routing plan. In solving EVRPTW in the deterministic environment, the low battery SoC of EV is allowed in routing plan for economic benefit, but it increases the risk of experiencing depleted battery energy in the practical application. In fact, a routing plan with lower credibility tends to bring much economic loss, and thus the decision maker tends to select a routing plan with higher credibility. This indicates that the FEVRPTW model has higher practicality than EVRPTW model.

**Table 3** Comparison results of solving EVRPTW and FEVRPTW

| Instance | EVRPTW | | | FEVRPTW | | |
|---|---|---|---|---|---|---|
| | Objective | Cr-A | Cr-B | Objective | Cr-A | Cr-B |
| c103 | 1038.3 | 0.900 | 0.100 | 1174.5 | 0.900 | 0.900 |
| c105 | 1031.8 | 0.100 | 0.900 | 1191.7 | 0.900 | 0.900 |
| r102 | 1614.9 | 0.925 | 0.075 | 1638.5 | 0.925 | 0.925 |
| r205 | 1005.7 | 0.050 | 0.500 | 1105.4 | 0.950 | 0.950 |

To evaluate the performance of the proposed ALNS algorithm, it was compared with three other heuristic algorithms. First, the convergence of the proposed ALNS algorithm was tested and the experiments were conducted on the instance of “R-4-C-40”. Fig. 5 shows the evolutionary trajectories of four algorithms in the best solution. As shown in Fig. 5, the proposed ALNS algorithm can converge within 100 iterations. As the proposed ALNS algorithm has strong local search ability, it can obtain high quality solutions in fewer iterations. The results indicate that the convergence velocity of the proposed ALNS algorithm is faster than that of other baseline algorithms. The comparison result shows that the best solution obtained within 50 iterations by the proposed ALNS algorithm is even better than the best solutions obtained within 500 iterations by the other three baseline algorithms.

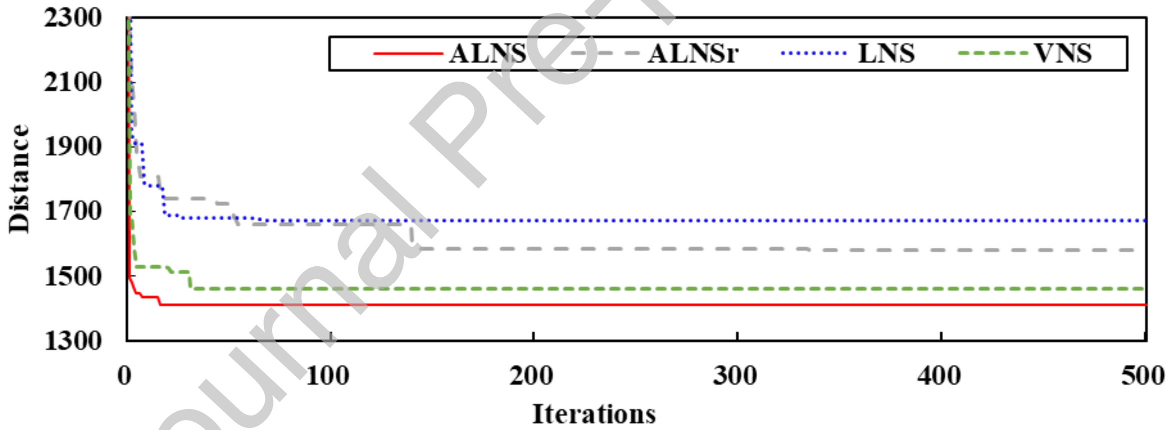


**Fig. 5.** Evolutionary trajectories of the four algorithms

Next, the performance of the proposed ALNS algorithm was tested under different confidence levels and experiments were conducted on the instance of “R-4-C-40”. Figs. 6 and 7 show the performances of the four algorithms with different confidence levels of $\alpha$ and those with different confidence levels of $\beta$, respectively. They reveal that the proposed ALNS algorithm can yield the best solution among all algorithms in most situations. This implies that the proposed ALNS algorithm is robust for solving the FEVRPTW with different confidence levels.

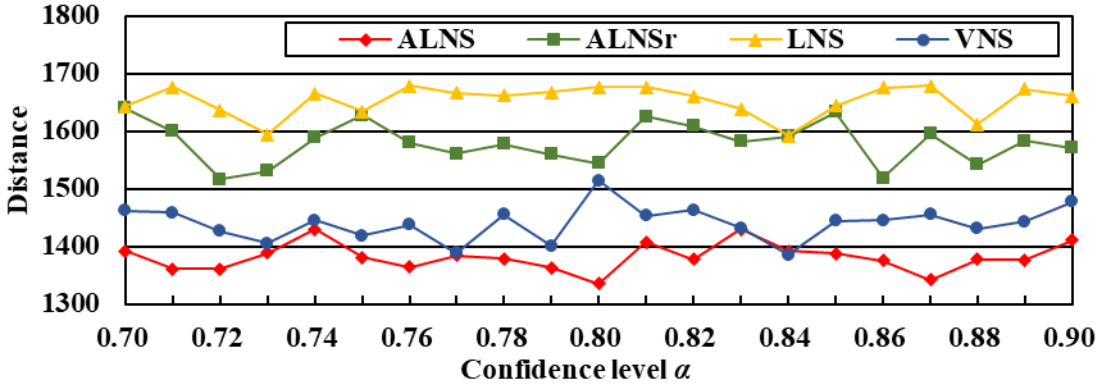


**Fig. 6.** Performances of four algorithms with different confidence levels of $\alpha$

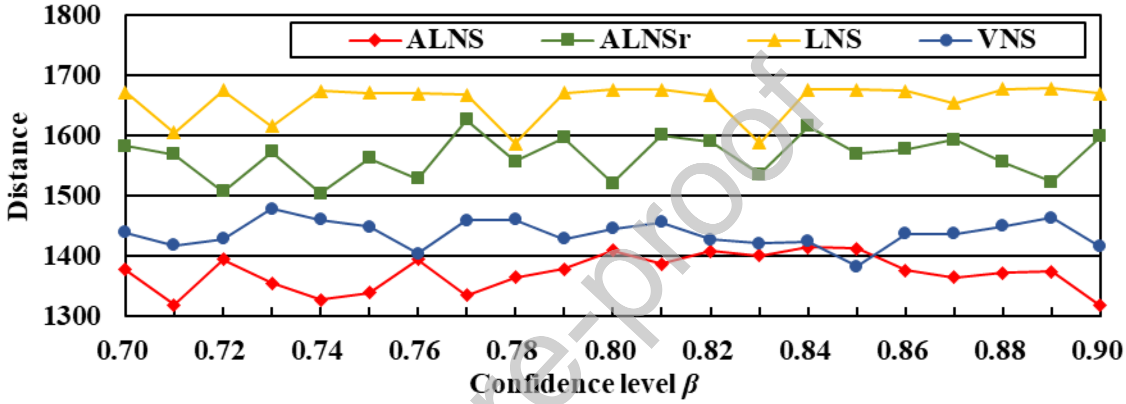


**Fig. 7.** Performances of four algorithms with different confidence levels of $\beta$

Subsequently, the performance of the proposed ALNS algorithm was compared with those of other baseline algorithms in different instances. Table 4 shows the statistical index including the best value, worst value, and average value, which are labeled as "Best", "Worst" and "Mean" in the columns, respectively. Table 5 shows the statistical indexes including the standard deviation and CPU computing time in second, which are labeled as "SD" and "Time" in the columns, respectively. Table 4 shows that the best solution obtained by the proposed ALNS algorithm is not worse than the best solutions obtained by the other baseline algorithms for 32 out of 34 instances. In addition, Table 4 shows that even the worst solution obtained by the proposed ALNS algorithm is still not worse than the best solution obtained by other baseline algorithms for 29 out of 34 instances. This implies that the proposed ALNS algorithm has stronger search ability than the other baseline algorithms to solve the FEVRPTW. Table 5 shows that the standard deviation in the proposed ALNS algorithm is not larger than that of the other baseline algorithms for 14 out of 34 instances, indicating that the performance of the proposed ALNS algorithm for solving the FEVRPTW is stable. Furthermore, the proposed ALNS algorithm consumes more CPU computing time than other baseline algorithms for 24 out of 34 instances, but the computing time is still within the acceptable range. The proposed ALNS algorithm requires considerable time to apply the VND algorithm to obtain a high-quality solution. Meanwhile, with the development of cloud computing technology and computer hardware resources, the computing time will be further reduced in the future.

**Table 4** The best value, worst value, and average value of four algorithms

| Instance | ALNS | | | ALNSr | | | LNS | | | VNS | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Best | Worst | Mean | Best | Worst | Mean | Best | Worst | Mean | Best | Worst | Mean |
| R-2-C-30 | 866.9 | 880.6 | 871.5 | 1001.1 | 1079.8 | 1029.5 | 1043.5 | 1106.2 | 1083.7 | 878.9 | 886.9 | 884.2 |
| R-2-C-40 | 1114.9 | 1138.8 | 1127.5 | 1414.2 | 1449.8 | 1428 | 1426.4 | 1502.5 | 1473.7 | 1176.6 | 1239.5 | 1200.3 |
| R-2-C-50 | 1302.9 | 1331.9 | 1314.3 | 1544.2 | 1592 | 1569.8 | 1566.3 | 1580.5 | 1575.5 | 1334.8 | 1396.9 | 1357.6 |
| R-2-C-60 | 1667.8 | 1671.1 | 1669.7 | 1983.1 | 2043 | 2015.6 | 1830.5 | 1905.8 | 1868.6 | 1784.6 | 1816.2 | 1800.8 |
| R-2-C-70 | 1697.9 | 1737.8 | 1712.8 | 2054.3 | 2130.8 | 2099.9 | 2039.3 | 2067.4 | 2054.2 | 1813.3 | 1875.8 | 1842.2 |
| R-2-C-80 | 1896.1 | 1928.6 | 1913.8 | 2358.7 | 2467.1 | 2413 | 2466.2 | 2549 | 2517.7 | 2083.8 | 2142.5 | 2115.7 |
| R-2-C-90 | 2067.1 | 2101.1 | 2082.6 | 2652.2 | 2764.6 | 2707.7 | 2670 | 2759.5 | 2722.8 | 2281.5 | 2289.8 | 2285.5 |
| R-4-C-30 | 843.5 | 881.3 | 864.1 | 1000 | 1076.1 | 1043.1 | 1074.2 | 1097.2 | 1087.9 | 873.9 | 891.5 | 881.1 |
| R-4-C-40 | 1379.3 | 1410.6 | 1396 | 1534.9 | 1585.4 | 1567.2 | 1657.5 | 1676.1 | 1669.4 | 1422.6 | 1465.8 | 1449.7 |
| R-4-C-50 | 1223.8 | 1230.6 | 1227.2 | 1555.3 | 1615.3 | 1583.6 | 1528.5 | 1536.9 | 1532.8 | 1300.4 | 1355.3 | 1327.9 |
| R-4-C-60 | 1163.9 | 1195.5 | 1180.2 | 1420.9 | 1531.4 | 1484.2 | 1361.9 | 1401.3 | 1386.3 | 1162.8 | 1194.6 | 1178 |
| R-4-C-70 | 1928.9 | 1936.6 | 1933.8 | 2285.9 | 2338.7 | 2310.9 | 2266.2 | 2347.1 | 2305.2 | 2073.8 | 2152 | 2117.1 |
| R-4-C-80 | 1946.2 | 2004.2 | 1972.9 | 2453.1 | 2484 | 2465.9 | 2336.7 | 2412 | 2369.5 | 2173.2 | 2187.4 | 2181.1 |
| R-4-C-90 | 2066.8 | 2128.2 | 2100.6 | 2668.6 | 2716.9 | 2692.9 | 3005.7 | 3188.6 | 3109.8 | 2402.4 | 2456.7 | 2425.6 |
| R-6-C-30 | 782.1 | 798.8 | 788.5 | 980 | 1038 | 1009.1 | 1428 | 1535.4 | 1469.9 | 804.3 | 841.9 | 828.5 |
| R-6-C-40 | 1045.3 | 1057.3 | 1050.2 | 1318.5 | 1412.3 | 1355.3 | 1394.4 | 1400.5 | 1397.2 | 1074.2 | 1139.2 | 1101.7 |
| R-6-C-50 | 1476.6 | 1495.3 | 1485.1 | 1754.9 | 1829.3 | 1784.4 | 2236.1 | 2530.2 | 2417.7 | 1550 | 1563.8 | 1556.9 |
| R-6-C-60 | 1528.9 | 1579.2 | 1556.5 | 1948.7 | 2039.6 | 1996.2 | 2035.9 | 2158.2 | 2080.2 | 1742.7 | 1774.8 | 1754.6 |
| R-6-C-70 | 1583.9 | 1616.1 | 1601.9 | 1974.1 | 2130.9 | 2057.8 | 2174.4 | 2224.5 | 2196.8 | 1739.3 | 1796.4 | 1767.4 |
| R-6-C-80 | 1840.9 | 1915.7 | 1883.5 | 2283 | 2393.8 | 2355 | 2402.6 | 2431.4 | 2418.2 | 1960.9 | 2037.5 | 2008.9 |
| R-6-C-90 | 1281.3 | 1332.9 | 1311.6 | 1723.1 | 1911.7 | 1796.9 | 1629.1 | 1720.2 | 1677.6 | 1269.9 | 1382.6 | 1328.4 |
| R-8-C-30 | 916.3 | 938 | 924.5 | 1105.8 | 1179.4 | 1145.5 | 1328.9 | 1340.1 | 1333.3 | 972 | 989.4 | 983.6 |
| R-8-C-40 | 963.9 | 973 | 969.2 | 1221.3 | 1253.1 | 1235.2 | 1290.3 | 1362.1 | 1326.3 | 1021.5 | 1041.7 | 1032 |
| R-8-C-50 | 1286.1 | 1311.6 | 1296.9 | 1633.8 | 1666.9 | 1646.7 | 1627.2 | 1697.4 | 1672.3 | 1396.3 | 1440.1 | 1419.9 |
| R-8-C-60 | 1407 | 1471.8 | 1446.4 | 1803.8 | 1882.7 | 1836.7 | 2033.2 | 2084.6 | 2060.9 | 1563.1 | 1572.7 | 1568.9 |
| R-8-C-70 | 1748.1 | 1802.4 | 1771 | 2176.2 | 2327.6 | 2242.2 | 2366 | 2414.4 | 2382.7 | 1922.9 | 1955.2 | 1938.4 |
| R-8-C-80 | 2134 | 2175.6 | 2154.7 | 2619.4 | 2676 | 2649 | 2649.9 | 2709.6 | 2687 | 2288.2 | 2425 | 2352.8 |
| R-8-C-90 | 2119.7 | 2154.5 | 2138.7 | 2944.4 | 3030.1 | 2994.9 | 3116.5 | 3186.3 | 3147.9 | 2460.1 | 2532.3 | 2494.2 |
| R-6-C-120 | 1758.9 | 1824 | 1786.3 | 2352.9 | 2577 | 2479.1 | 2089.4 | 2161.4 | 2132.9 | 1799.8 | 1882.9 | 1841.2 |
| R-6-C-160 | 1909.1 | 2008 | 1960.7 | 2614.1 | 2708.1 | 2656.9 | 2440.8 | 2499.6 | 2470.3 | 2038.5 | 2087 | 2066.2 |
| R-6-C-200 | 2870.1 | 2929.9 | 2906.2 | 4285.4 | 4870.7 | 4546.4 | 3680.1 | 3719.1 | 3699.3 | 3170.8 | 3212.6 | 3189.9 |
| R-8-C-120 | 2775.2 | 2862.3 | 2806.5 | 3572.5 | 3622.7 | 3602.1 | 3582.1 | 3640.8 | 3617.3 | 3113.9 | 3220.2 | 3160.5 |
| R-8-C-160 | 1937.7 | 1995 | 1968.2 | 2616.1 | 2670.4 | 2646.7 | 2627.6 | 2655.8 | 2641.3 | 2008.9 | 2013.6 | 2011.8 |
| R-8-C-200 | 2347 | 2412.1 | 2389.5 | 3226.4 | 3298.3 | 3259.3 | 3307.6 | 3364.1 | 3334.4 | 2548.6 | 2657.2 | 2605.9 |

**Table 5** Standard deviation and average operating time of four algorithms

| Instance | ALNS | | ALNSr | | LNS | | VNS | |
|---|---|---|---|---|---|---|---|---|
| | SD | Time (s) | SD | Time (s) | SD | Time (s) | SD | Time (s) |
| R-2-C-30 | 6.5 | 12 | 35.7 | 3 | 28.5 | 4 | 3.8 | 7 |
| R-2-C-40 | 9.8 | 11 | 15.6 | 3 | 33.7 | 5 | 27.9 | 17 |
| R-2-C-50 | 12.6 | 17 | 19.7 | 7 | 6.5 | 12 | 27.9 | 53 |
| R-2-C-60 | 1.4 | 15 | 24.7 | 17 | 30.7 | 17 | 12.9 | 60 |
| R-2-C-70 | 17.8 | 26 | 32.9 | 19 | 11.5 | 25 | 25.7 | 149 |
| R-2-C-80 | 13.4 | 66 | 44.3 | 19 | 36.7 | 32 | 24.2 | 121 |
| R-2-C-90 | 14 | 104 | 45.9 | 28 | 38.3 | 40 | 3.4 | 357 |
| R-4-C-30 | 15.6 | 10 | 31.9 | 11 | 9.9 | 21 | 7.5 | 15 |
| R-4-C-40 | 12.9 | 38 | 22.9 | 4 | 8.4 | 7 | 19.3 | 17 |
| R-4-C-50 | 2.8 | 64 | 24.6 | 24 | 3.4 | 45 | 22.4 | 102 |
| R-4-C-60 | 11.7 | 150 | 41.4 | 7 | 14.8 | 7 | 14.4 | 40 |
| R-4-C-70 | 3.5 | 97 | 21.7 | 50 | 33.1 | 78 | 32.5 | 155 |
| R-4-C-80 | 23.9 | 215 | 13.2 | 57 | 31.5 | 78 | 5.9 | 375 |
| R-4-C-90 | 25.4 | 204 | 19.7 | 61 | 76.8 | 122 | 22.8 | 291 |
| R-6-C-30 | 7.3 | 17 | 23.7 | 23 | 46.9 | 36 | 17.2 | 24 |
| R-6-C-40 | 5.1 | 61 | 40.9 | 36 | 2.5 | 39 | 27.5 | 71 |
| R-6-C-50 | 7.7 | 46 | 32.3 | 49 | 129.6 | 80 | 5.6 | 79 |
| R-6-C-60 | 20.8 | 95 | 37.2 | 67 | 55.3 | 82 | 14.3 | 203 |
| R-6-C-70 | 13.4 | 136 | 64.4 | 76 | 20.8 | 146 | 23.3 | 184 |
| R-6-C-80 | 31.4 | 205 | 51 | 74 | 11.9 | 210 | 34.1 | 406 |
| R-6-C-90 | 20 | 852 | 66.2 | 21 | 29.9 | 25 | 35.9 | 98 |
| R-8-C-30 | 9.6 | 23 | 30.3 | 54 | 4.9 | 53 | 8.2 | 37 |
| R-8-C-40 | 3.9 | 51 | 13.3 | 65 | 29.3 | 103 | 8.3 | 86 |
| R-8-C-50 | 10.8 | 50 | 14.4 | 87 | 31.9 | 138 | 18 | 101 |
| R-8-C-60 | 28.2 | 103 | 33.5 | 111 | 21.2 | 226 | 4.2 | 249 |
| R-8-C-70 | 23 | 107 | 63.3 | 135 | 22.4 | 238 | 13.2 | 315 |
| R-8-C-80 | 17 | 543 | 23.2 | 47 | 26.4 | 103 | 56.1 | 336 |
| R-8-C-90 | 14.4 | 285 | 36.6 | 237 | 28.9 | 516 | 29.6 | 915 |
| R-6-C-120 | 27.6 | 119 | 93.7 | 538 | 31.3 | 537 | 33.9 | 692 |
| R-6-C-160 | 40.5 | 1617 | 38.8 | 839 | 24 | 1054 | 20.4 | 3155 |
| R-6-C-200 | 25.9 | 2256 | 243.1 | 1741 | 15.9 | 2155 | 17.3 | 1764 |
| R-8-C-120 | 39.5 | 886 | 21.5 | 434 | 25.4 | 908 | 44.4 | 2178 |
| R-8-C-160 | 23.5 | 1441 | 22.7 | 1055 | 11.5 | 1258 | 2.1 | 3085 |
| R-8-C-200 | 30.1 | 3864 | 29.7 | 2034 | 23.2 | 3170 | 44.5 | 5585 |

Thus, it is concluded that the proposed ALNS algorithm demonstrates satisfactory performance to address the FEVRPTW in a reasonable computational time.

## 6. Conclusion

A novel EVRP under an uncertain environment was investigated in this study, namely, the FEVRPTW. In this study, a fuzzy optimization model was established for the FEVRPTW based on the credibility theory. In this model, three uncertain parameters including service time, battery energy consumption, and travel time were considered. Under the uncertain environment, the partial recharge was allowed, thus further improving the practicality of the presented model. To address the problem, an ALNS algorithm integrated with several new removal algorithms and existing insertion algorithms was proposed and a fuzzy simulation was designed. To further improve the algorithmic performance, the proposed ALNS algorithm was integrated with the VND algorithm.

To validate the performance of the proposed ALNS algorithm, numerical experiments were conducted, where a new series of benchmark problem instances were generated for the presented problem. In the numerical experiments, three baseline algorithms were implemented for comparison. The numerical experiments indicated that the proposed ALNS algorithm yielded the best solution in most instances. The results indicated that the proposed ALNS algorithm was effective in addressing the FEVRPTW model.

In summary, the current study contributed to the further studies of the EVRP and applications of EVs. However, a few limitations were found in the presented study. First, this model assumed that the recharging function was linear, which is not always realistic and may affect the routing decision. Next, the cases of heterogeneous fleet and varying speed were not considered, although they occurred frequently in many real applications. Subsequently, as in many previous studies on the EVRP, all the recharging stations were always available at any time, unlike in real-world recharging where a queue may be involved. In addition, addressing the very large scale problems needs to apply parallel computing technology, because the computing complexity of proposed model with fuzzy simulation will be several thousand times more than that of previous models without fuzzy simulation when the iteration number of fuzzy simulation is set as several thousand. Thus, as one of future research directions in EVRP, parallel computing technology will be explored to address the very large scale problems.



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## Compliance with ethical standards

**Conflicts of interest:** The authors declare that there is no conflict of interests regarding the publication of this article.

**Ethical standard:** The authors state that this research complies with ethical standards. This research does not involve either human participants or animals.

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# Author Contribution Statement

**Shuai Zhang**: Conceptualization, Methodology, Formal analysis, Writing- Reviewing and Editing, Supervision, Funding acquisition. **Mingzhou Chen**: Methodology, Formal analysis, Writing- Original draft, Validation, Data curation, Software, Validation. **Wenyu Zhang**: Conceptualization, Writing- Reviewing and Editing, Funding acquisition. **Xiaoyu Zhuang**: Data curation, Software.

# CRediT author statement

**Shuai Zhang**: Conceptualization, Methodology, Formal analysis, Writing- Reviewing and Editing, Supervision, Funding acquisition. **Mingzhou Chen**: Methodology, Formal analysis, Writing- Original draft, Validation, Data curation, Software, Validation. **Wenyu Zhang**: Conceptualization, Writing- Reviewing and Editing, Funding acquisition. **Xiaoyu Zhuang**: Data curation, Software.

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**Declaration of interests**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.