The electric vehicle routing problem of a new mobile charging service

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Abstract

A novel mobile charging service that utilizes vehicle-to-vehicle (V2V) charging technology has recently been proposed as a supplement to fixed charging infrastructure (CI), enabling electric vehicles (EVs) to exchange electricity. This study formulates a vehicle routing problem (VRP) of vehicle-to-vehicle (V2V) charging, optimizing the routing of DVs to service RVs while taking into account their willingness to join the V2V charging platform. A mixed integer linear programming (MILP) model is established to optimize the VRP-V2V (i.e., the VRP of V2V charging), which is known to be NP-hard. To solve large-scale instances for real-world applications, we propose an adaptive large neighborhood search (ALNS) algorithm, which, when combined with the structure of the VRP-V2V problem, utilizes four local search procedures to enhance solution quality following destroy and repair operators. Results indicate that the proposed ALNS algorithm outperforms the optimization solver CPLEX in small-scale instances, and can solve large-scale instances that are infeasible using CPLEX solver. In a numerical analysis of Changsha's large-scale network, we demonstrate that the V2V platform can save an average of 33.1% on the charging cost of recharging vehicles, hence raising customer satisfaction with charging services and reducing range anxiety. The platform's profitability is also increased by using V2V charging in areas lacking fixed charging infrastructure.

Keywords: Electric Vehicle; Vehicle-to-Vehicle Charging; Vehicle Routing Problem; ALNS algorithm
1. Introduction

Electric vehicles (EVs) are anticipated to help reduce emissions from the transportation sector, and have enjoyed rapid growth in recent years, accompanying with the massive deployment of fixed charging infrastructure (CI), including charging piles [1, 2], battery swapping stations [3, 4], charging lanes [5, 6]. However, the distribution of EV charging demand and the current design of CI are frequently out of matching [7]. The spatio-temporal heterogeneity of daily charging demand dramatically exacerbates the volatility of urban power system, which leads to a time-sharing electricity price strategy in many countries. In Shanghai, China, the electricity price difference between peak hours and off-peak hours for EVs is as high as 2.12 RMB/kWh [8]. Additionally, the deployment of fixed CI often cannot match with the proliferation of EVs, due to the intrinsic features and limited flexibility of CIs. First of all, fixed CI cannot service EVs running out of electricity, and drivers would incur additional waiting times at charging stations regardless of how the system is constructed [9, 10]. Moreover, it is not cost-effective to deploy dense CI for EV drivers in places with low charging demand due to the high installation and operation cost, and EV drivers would encounter considerable inconvenience when searching for CI. Therefore, focusing solely on the construction of fixed CI may not necessarily and adequately address the charging issues of EVs.

Unlike fixed charging mode, Charging-as-a-service has emerged lately, which can provide recharging for EV drivers through delivery services. Mobile Charging Service (MCS), in which companies can equip the chargers onto a van and then send chargers to serve EVs on demand whenever and wherever possible, is one such application. Nowadays, trials and applications of MCS can be found in China, the US, and Europe [11]. For instance, NIO Power opened its mobile charging service from January 31, 2019 in China [12]. Since all the mobile chargers and vans belong to the companies, MCS is regarded as a business-to-consumer business model. Such a business model with relatively high service price aiming to provide emergency service for EVs running out of electricity, rather than regular service for daily charging demand.

Recently, a novel mobile charging mode, i.e., vehicle-to-vehicle (V2V) charging comes into practice, thanks to the maturity of the compact Bidirectional Charger (BDC). As shown in Figure. 1, two EVs transfer electricity with each other efficiently and safely using BDC, a portable equipment transferring electricity between two EVs. V2V charging, different from the previous business-to-customer MCS, is a customer-to-customer MCS, requiring a platform to match energy providers with energy consumers, comparable to ridesharing firms such as DiDi Chuxing and Uber. It has already been launched by an American company [13], which provides V2V charging service for EVs through a mobile app, with a maximum charging power of 50kW. In China, the new EV brands Huawei AITO M5 and Denza (Mercedes’s joint-product with BYD) is able to provide charging for other EVs [14, 15]. Its BDC unit no longer requires a lot of storage space and is as small as a regular
charger, and the charging power can be up to 60 kW [16]. In this context, EVs are not only capable of serving as means of transportation, but also have the ability to act as mobile energy storage units and serve as distributed energy sources.

For EV owners requesting energy, participating in the V2V charging is clearly motivated by the desire to conveniently meet their energy demand. For EV owners with excess energy and spare time, they can be incentivized to sell their energy to other EVs through V2V if the revenue of discharging is sufficiently high. Under the time-sharing electricity price strategy, energy providers get charged with relatively low price during off-peak hours and provide discharging service in peak hours, which can benefit energy providers and energy consumers, as well as help alleviate energy demand of urban power system. The V2V charging service, if widely and successfully deployed, will undoubtedly alleviate range anxiety of EV drivers and further increase EV market adoption, since every EV equipped with a portable BDC can serve as a mobile charger and charging can occur at any time and place. However, the operation and deployment of the V2V charging are studied to a very limited extent, while current research focuses on the technological feasibility [17] and the matching with urban power system [18].

![Figure 1. Using a mobile app, a Nissan Leaf is transmitting energy to a Tesla Model S [19].](image)

This study examines a V2V charging platform shown in Figure. 2 to provide regular charging service that matches recharging vehicles (RVs) with discharging vehicles (DVIs), as a prospective supplement to the existing charging network. RV owners can request the V2V charging service whenever needed, sending the information of desired charging timeslot and location, as well as power demand, to the V2V platform. The V2V platform then matches RVs with DVs and determines the optimal routing of DVs to serve RVs, receiving service fare from RV owners and paying wage to DV owners. RV owners will choose between the V2V charging service and traditional charging piles, based on the estimated charging costs of both options. Similarly, DV owners will decide to offer the V2V charging service only if they can earn certain revenue from the platform.

To mathematically formulate matching of RVs and DVs, we propose a novel vehicle routing
problem (VRP) of V2V (VRP-V2V) charging, in order to maximize the profit of the V2V platform. Different from traditional VRPs, the choices of RV and DV owners are considered simultaneously. On the demand side, RV owners will choose between charging pile and V2V charging service, where charging pile option has a long charging time but a lower charging price, while the service fare of V2V platform is much higher. On the supply side, DV owners get charged with low electricity price and provide discharging service for RV owners with high wage rate, and they are willing to do so only if the revenue they earn outweighs opportunity cost to provide the service. The V2V platform decides the optimal routing of DVs to serve RVs under time window and energy constraints, to ensure that DVs can offer enough energy to RVs in the prescribed timeslots and locations.

**Figure. 2.** A schematic diagram for the V2V charging platform.

The proposed VRP-V2V model is a mixed integer linear programming (MILP) problem, and therefore it can be solved by exact algorithms or commercial solvers for small-scale networks. To accelerate the computing process for large-scale problems, we develop an Adaptive Large Neighborhood Search (ALNS) algorithm to solve large-scale instances. Specifically, first, we obtain the initial feasible solution through a route construction procedure. Then four individual-based destroy operators and three individual-based repair operators are proposed to find an improved solution. To facilitate the exploration of the solution space and include infeasible solutions, a comprehensive cost function is developed to weigh the violation of RV choice, the remaining power of DVs, and the revenue of DVs. Additionally, after the destroy and repair operators, we use four local search procedures to further improve the quality of the solution, which includes individual-based operations (check all the served and unserved RVs), as well as population-based operation (check all the service routes of DVs).

The remainder of this paper is structured as follows. In Section 2, the relevant literatures are reviewed. The VRP-V2V model is presented as a MILP problem in Section 3. Section 4 develops the ALNS algorithm. Section 5 presents numerical examples to show the effectiveness of ALNS algorithm and conducts sensitivity analysis on important system parameters. Section 6 summarizes the paper and discusses future extension.
2. Literature review

2.1. Mobile Charging Service (MCS)

Recently, mobile charging service (MCS) is beginning to draw attention [20, 21], in which EV companies deploy charging vans to serve EVs with urgent needs. Unlike fixed charging mode, MCS is the equivalent of a movable "charging pile" that acts as a distributed energy source and is used to recharge EVs whenever and wherever possible. Cui et al. [9, 22] considered the mobile charging system and examined a vehicle routing problem with time windows and used CPLEX to solve it. They discovered that increasing the battery capacity or improving the charging rate of the charging facilities can significantly improve the service efficiency of MCS. The study by Tang, He [10] presents an innovative online-to-offline mobile charging system that addresses the integration of both online operation level and strategic planning problems. Specifically, the study proposes a simulation-based optimization framework at the strategic planning level to determine the optimal number of scheduled mobile charging vans and the required battery power for each vehicle. A dynamic VRP model was established for mobile charging vehicle route planning at the level of online operations. In addition, Wang, Lin [20] developed an equilibrium model to explore the competitive relationship between MCS and fixed CI.

The above-mentioned MCS was solely operated by EV companies to provide charging service for their customers, often with high or even unaffordable prices, which therefore is difficult to be widely adopted in regular charging. However, the rise of V2V charging can be a game-changer to transfer previous MCS into peer-to-peer MCS, which can supplement the fixed charging networks and alleviate charging anxiety, especially for the EV owners without home charging. Additionally, the discharging truck belongs to the MCS platform. If it belongs to the private, whether the discharging vehicle is willing to provide discharging service and whether the platform can make profit still needs to be studied.

2.2. Vehicle-to-Vehicle (V2V) charging

The studies of V2V charging mainly focuses on technological feasibility [17, 23, 24] and its impact on urban power system [19, 25, 26]. Ucer, Buckreus [17] designed a compact bidirectional charger (BDC), and demonstrated the transfer of energy between two distinct battery packs of any voltage level. Through simulation, Huang, Chen [27] discovered that the proposed strategy taking into account vehicle-to-vehicle (V2V) charging may lessen the disparity between the peak and valley load of the load curves and ameliorate phase imbalance, and therefore both EV owners and the urban power system benefit financially. At the same time, vehicle-to-vehicle wireless charging is beginning to draw attention [28], which will improve the convenience of V2V charging. The above literature provides theoretical support for V2V energy transfer platform.

Additionally, there are also studies to optimize V2V energy transfer platform at the planning
level. The first theme deals with reducing the cost of recharging vehicles. Based on the predicted price of electricity, it primarily determines the best timetable for EVs to lower their charging costs while still satisfying their charging demand [29, 30]. The second involves effectively and practically pairing EV consumers who need energy with suppliers. Li, Yang [31] proposed a double auction-based energy trading market for EVs to link customers and suppliers with the aim of maximizing the system payoff. Zhang, Cheng [32] studied several strategies to accomplish various goals, such as maximizing social welfare or decreasing the cost, by leveraging a weighted bipartite graph and propose a flexible energy management protocol for cooperative V2V charging. The third theme for the V2V charging focuses on providing solution that guarantee user data and privacy while matching [33, 34].

The existing studies focus on the technological feasibility of V2V charging and matching at the planning level, while the deployment and detailed operation, especially the vehicle routing of V2V charging and willingness of users are left out. As a prospective supplement to the existing charging network, the V2V charging service must be properly designed and operated, in order to attach EV drivers and stimulate the market. Therefore, we model it as a VRP problem, and consider the choice of recharging vehicles between the V2V platform and charging piles, as well as whether discharging vehicles are willing to provide discharge service.

2.3. Solution algorithms of VRP

The Vehicle Routing Problem (VRP) of V2V charging (VRP-V2V) can be viewed as a special VRP that optimizes the combination of collected total profit and total traveling cost [35, 36]. Numerous problems that involve additional features, such as capacity constraints [37, 38], time windows [39, 40], multiple depots [41], and constraints relating to the design of tourist trips [42, 43] can be modeled as VRPs, which have been extensively studied. In many variants, the profit that must be collected at each customer is predetermined and must be collected all at once. In other cases, the collected profit is determined by the amount of time spent on the node [44], the amount of time spent traveling [44, 45], or the location of the visited node along the route [46]. At the same time, in traditional VRPs, there are depots from which all vehicles depart [47-49]. Different with traditional VRPs, the VRP-V2V has the following different features: (i) there is no depot and all DVs are distributed. (ii) There are cost constraints on the demand side to consider the choice of Recharging Vehicles (RVs) between charging piles and the V2V platform. (iii) There are revenue constraints on the supply side to depict whether Discharging Vehicles (DVs) are willing to join the charging platform of V2V.

Besides, all the VRPs can be formulated as MILP problems and solved by two types of solution methods: exact methods and heuristic methods. For small-scale problems, exact methods, such as branch-and-bound algorithms [50, 51], branch-and-cut algorithms [52, 53], and branch-and-price algorithms [54, 55], usually be used to obtain an accurate solution. On the contrary, heuristic methods can provide better solutions for large-scale problems in a reasonable amount of time. Genetic algorithm [56] and artificial bee colony algorithm [57] are population-based heuristic. Individual-
based heuristic includes simulated annealing [58], tabu search algorithm [59, 60], variable neighborhood search algorithm [61, 62], and adaptive large neighborhood search algorithm (ALNS) [63-66]. Individual-based heuristic concentrate more on intensification, whereas population-based heuristic concentrates more on diversification [67].

The iterated local search metaheuristic, ALNS, expands upon the framework of large neighborhood search (LNS) originally proposed by Shaw [68] and Shaw [69]. LNS heuristics can investigate a large number of solutions in a short period of time, but each iteration changes the solution slightly. To address this limitation, Ropke and Pisinger [70] introduced the ALNS heuristic, which explores large moves that reorganize up to 40% of the vertices rather than relying on small moves that only relocate or exchange a few arcs or vertices per iteration. ALNS has been successfully used to resolve diverse VRPs such as time window-constrained electric vehicle VRP [71] and electric vehicle VRP with battery-swapping facilities [72], pollution-routing problem [73], pickup and delivery problems [74], berth and quay crane assignment problem [75], and so on. To speed up the computing process while obtain effective solutions, the ALNS algorithm is employed in this paper to solve the proposed VRP-V2V.

**Research gaps and our contribution:** To the best of our knowledge, our study is the first attempt to tackle the V2V charging problem from the transportation operation perspective and formulate it as a vehicle routing problem with time window and battery capacity constraints, while considering the willingness of recharging/discharging vehicles to participate in the V2V charging platform. Second, we propose an ALNS algorithm to speed up the computing process of the VRP-V2V model for large-scale problems and introduce four local search procedure to improve solution quality. Third, we demonstrate that the introduction of the V2V platform can enhance the overall charging service level, and the V2V platform should initially concentrate on the regions lack of charging infrastructure, to guarantee its profitability.

### 3. Mathematical model

#### 3.1. Model setting

We use a simple network to illustrate the VRP-V2V model, which has two Discharging Vehicles DV-a and DV-b and three Recharging Vehicles RV-1, RV-2, and RV-3, as depicted in Figure. 3. The RV owners RV-i hope to get charged with specific power in a specific timeslot \( [\theta_i^{\text{start}}, \theta_i^{\text{end}}] \). They will send the charging request to the V2V platform including preferred service start time \( \theta_i^{\text{start}} \), preferred service end time \( \theta_i^{\text{end}} \), charging demand and location. Meanwhile, the DV owners also provides the information of location, timeslot, and remaining battery capacity to the platform. The V2V platform matches DVs with RVs, i.e., deploying DVs to serve RVs within specific timeslots, and pays wage to DV owners as well as receives relatively high service fare from RV owners, to maximize the platform's profitability. Both DV and RV owners have the options to participate the V2V platform or not. The DV owners provide the discharging service for the RV owners, on the condition that they
can get profit from discharging service, as detailed by in Subsection 3.3. On the other hand, the RV owners choose the V2V platform if the corresponding cost is less than the overall cost of choosing charging piles, as detailed in Subsection 3.2. For example, RV-3 will choose the nearby charging pile since either DV-a or DV-b cannot fulfill the charging service within the specific timeslot, and it is more cost-effective for RV-3 to head for the nearby-charging pile for recharging. In other word, the V2V platform will not deploy a distant DV to serve RV-3, which is not cost-effective for both the V2V platform and RV owners. Meanwhile, RV-1 and RV-2 will select the charging platform for recharging because the V2V platform can provide better charging services for them.

For instance, if DV-a is deployed to serve RV-1 and RV-2, the service time and remaining power of DV-a between RV-1 and RV-2 are shown in Figure 4. First, DV-a with battery capacity 50 kWh starts from 13:20 and arrives at RV-1 at 13:30. At this time, the remaining power is 49 kWh of DV-a. After 24 minutes, 16 kWh is charged for RV-1, and the remaining power of DV-a is 33 kWh. Then, DV-a leaves RV-1 at 13:54 and arrive at RV-2 at 14:04, with 32 kWh of power remaining. After 30 minutes, 20 kWh is charged for the RV-2, and the remaining power of DV-a is 12 kWh. Final, DV-a leaves RV-2 at 14:34 and returns to start point at 14:44, with remaining power of 11kWh. The energy loss during V2V charging is considered later in the model, which can be incorporated by introducing an exogenous parameter called transaction efficiency [32].

![Figure 3](https://example.com/image3.png)

**Figure 3.** Illustration of the VRP-V2V model in a simple network.

![Figure 4](https://example.com/image4.png)

**Figure 4.** The service route of DV-a.
Table 1. The list of major notations.

<table>
<thead>
<tr>
<th>Abbreviations</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>EV</td>
<td>Electric Vehicle</td>
</tr>
<tr>
<td>DV</td>
<td>Discharging Vehicle</td>
</tr>
<tr>
<td>RV</td>
<td>Recharging Vehicle</td>
</tr>
<tr>
<td>V2V</td>
<td>Vehicle-to-Vehicle</td>
</tr>
<tr>
<td>MCS</td>
<td>Mobile Charging Service</td>
</tr>
<tr>
<td>ALNS</td>
<td>Adaptive Large Neighborhood Search</td>
</tr>
<tr>
<td>VRP-V2V</td>
<td>Vehicle Routing Problem of Vehicle-To-Vehicle (charging)</td>
</tr>
</tbody>
</table>

Sets and indices

- **R**: Set of RVs, \( i, j \in R \)
- **D**: Set of DVs, \( d \in D \)
- **V_d**: Set of RVs and DV \( d \), \( i, j \in V_d \)
- **V**: Set of vehicles, \( i, j \in V \)
- **A_d**: Set of arcs of DV \( d \), \( (i,j) \in A_d \)
- **A**: Set of arcs, \( (i,j) \in A \)
- **(i,j)**: Indices of arcs
- **i, j, d**: Indices of vertices

Parameters

- \( l_{ij} \): Travel distance of DV \( d \) between nodes, \( (i,j) \in A \)
- \( E \): Battery capacity of EVs
- \( y \): EV power consumption per unit mileage of EV
- \( q_i \): Power demand of RV \( i \), \( i \in R \)
- \( \tau \): Vehicle travel speed
- \( p_{low} \): Electricity price during off-peak hours
- \( p_{pile} \): Electricity price of charging piles
- \( p_{V2V} \): Electricity price of the V2V platform
- \( \beta_{RV} \): Value of time for RVs using charging pile service
- \( \beta_{RV2V} \): Value of time for RVs waiting for V2V charging service
- \( \beta_{DV} \): Value of time for DV
- \( w \): Wage rate of the V2V platform paying to DVs
- \( \theta_{i}^{\text{start}} \): The preferred service start time of the RV \( i \), \( i \in R \)
- \( \theta_{i}^{\text{end}} \): The preferred service end time of the RV \( i \), \( i \in R \)
- \( \theta_{d}^{\text{start}} \): Start time of the DV time window, \( d \in D \)
- \( \theta_{d}^{\text{end}} \): End time of the DV time window, \( d \in D \)
- \( g_{pile} \): Charging power of charging piles
- \( g_{V2V} \): Charging power of DVs
- \( \Xi \): Remaining power of DVs at the end of discharging service
- \( T \): Cruising time of RVs to find an available charging pile
- \( \Theta \): Transaction efficiency of V2V charging
- \( M \): Sufficiently large positive constant

Variables

- \( \mu_i \): Remaining power of DV when reaching RV \( i \), \( i \in R \)
- \( \sigma_d \): Remaining power of DV \( d \) arriving at destination node, \( d \in D \)
- \( t_i \): The actual start time of V2V charging service for RV \( i \), \( i \in R \)
Table 1 outlines major notions of the VRP-V2V model for easy comprehension. Since there is no depot in the modeling of the V2V charging, subgraphs are used to represent the routing of DVs, which return to the starting point after completing the discharging service. Let \( R = \{1, \ldots, i, \ldots, j, \ldots, n\} \) represent the set of RV nodes, and \( D = \{1, \ldots, d, \ldots, m\} \) represent the set of DV starting and end node in the V2V platform. For each DV \( d \), we define a subgraph \( G_d = (V_d, A_d), d \in D \), where \( V_d = \{d\} \cup R \) denotes the set of RV nodes and the node of DV \( d \). \( A_d = V_d \times V_d \) denotes the set of arcs for all possible path of DV \( d \). Since the V2V platform optimization involves all DVs, the VRP-V2V is formulated based on a complete directed graph \( G = (V, A) \), where \( V = D \cup R \) and \( A = V \times V \). The decision variables in the VRP-V2V model are defined as follow, which will be discussed later in the supply-side and demand-side constraints, and their relationship is detailed in constraints (11) and (12).

### 3.2. Demand-side constraint of recharging vehicles

RV owners choose between fixed charging infrastructure and the V2V platform, by comparing the time costs and electricity price costs of both options. When choosing charging pile to recharge, vehicle drivers will drive to find an available charging pile. The cost of RV \( i \) with power demand \( q_i \) recharged by charging piles \( C_i^{p\text{ile}} \) is

\[
C_i^{p\text{ile}} = \left(T + \frac{q_i}{g_{\text{pile}}} \right) \beta_{\text{pile}} + P_{\text{pile}} q_i, \quad \forall i \in R
\]

where \( \left(T + \frac{q_i}{g_{\text{pile}}} \right) \beta_{\text{pile}} \) is the time cost of RV \( i \) recharged by charging piles. \( T \) denotes the cruising time to find an available charging pile. \( g_{\text{pile}} \) represents the charging power of the charging pile and \( \beta_{\text{pile}} \) denotes the value of time for charging pile service. \( P_{\text{pile}} \) is the electricity price of charging piles.

Note that charging cost of the charging pile \( C_i^{p\text{ile}} \) is predetermined and known to RV owners, since all the notations in equation (1) are exogenous parameters and unaffected by the vehicle matching and routing of the V2V platform.
When choosing the V2V charging, RV owners can simply submit a request to the platform and wait for the V2V charging service. Thus, the cost of selecting V2V charging $C_{i,v2v}$ includes waiting time cost $(e_i - \theta_i^{\text{start}})\beta_{i,v2v}$ and $P_{v2v}q_i$, as denoted in equation (2). $P_{v2v}$ is electricity price of V2V charging, higher than $P_{\text{pile}}$. It is assumed that RV $i$ has preferred service start time $\theta_i^{\text{start}}$, and the waiting time cost is $(e_i - \theta_i^{\text{start}})\beta_{i,v2v}$, where $e_i$ is the actual end time of V2V charging service for RV $i$. $\beta_{i,v2v}$ is the value of time of RV waiting for the V2V charging service, set to be lower than value of time of RV searching for charging piles $\beta_{i,\text{pile}}$, since RV owners can focus on other activities while waiting.

$$C_{i,v2v} = (e_i - \theta_i^{\text{start}})\beta_{i,v2v} + P_{v2v}q_i, \quad \forall i \in R\#(2)$$

The cost of V2V charging $C_{i,v2v}$ is affected by the matching and routing of the V2V platform, as determined by the actual end time of V2V charging service $e_i$. In fact, $e_i$ is the critical factor in deciding between two charging options. Specifically, each RV owner $i$ has preferred latest service end time $\theta_i^{\text{end}}$ of V2V charging by comparing with charging piles, which can be calculated by equating $C_{i,v2v}$ and $C_{i,\text{pile}}$, as shown in equation (3). In other word, if the actual service end time $e_i$ larger than $\theta_i^{\text{end}}$, RV owner $i$ will not choose V2V charging service, since the charging cost of V2V $C_{i,v2v}$ is greater than that of charging pile $C_{i,\text{pile}}$. If the DV deployed by the V2V platform cannot complete the discharging service before latest service end time $\theta_i^{\text{end}}$, the RV will not be served by the V2V platform, i.e., $\varphi_i$ equals to zero. To sum up, the V2V platform should ensure that each RV $i$ is served within time window $[\theta_i^{\text{start}}, \theta_i^{\text{end}}]$, otherwise it will lose the V2V charging request of RV $i$.

$$(\theta_i^{\text{end}} - \theta_i^{\text{start}})\beta_{i,v2v} + P_{v2v}q_i = \left(T + \frac{q_i}{g_{\text{pile}}}\right)\beta_{i,\text{pile}} + P_{\text{pile}}q_i, \quad \forall i \in R\#(3)$$

Let the actual start of V2V charging service for RV $i$ be $t_i$, we have following constraints to determine the relationship between preferred service time window $[\theta_i^{\text{start}}, \theta_i^{\text{end}}]$ and actual service time window $[t_i, e_i]$ of the V2V charging. Formula (4) shows that the gap between actual service start time $t_i$ and end time $e_i$ equal to the charging time of V2V charging $\frac{q_i}{g_{v2v}}$, where $g_{v2v}$ is charging power of DVs deployed by the V2V platform and $\Theta$ is the transaction efficiency of V2V charging. Constraints (5) and (6) ensure that the actual service time window $[t_i, e_i]$ is within the preferred service time window $[\theta_i^{\text{start}}, \theta_i^{\text{end}}]$ of V2V charging. Constraint (6) means that the charging cost of RVs choosing V2V service is less than that of charging piles, which is equivalent to constraint $C_{i,v2v} \leq C_{i,\text{pile}}$

$$e_i = t_i + \frac{q_i}{\Theta g_{v2v}}, \quad \forall i \in R\#(4)$$

$$\theta_i^{\text{start}} \leq t_i, \quad \forall i \in R\#(5)$$

$$e_i \leq \theta_i^{\text{end}}, \quad \forall i \in R\#(6)$$
3.3. Supply-side constraint discharging vehicles

For DV owners, they are willing to drive to RVs and provide discharging service only if the corresponding benefit outweighs the cost. The cost of DV \( d \) providing V2V charging service \( C_d \) is

\[
C_d = \left( \sum_{i \in R} \frac{q_i}{\Theta g_{2v}} + \frac{L_d}{\tau} \right) \beta_{DV} + \left( \sum_{i \in R} \frac{q_i}{\Theta} + L_d \gamma \right) P_{low}, \quad \forall d \in D \#(7)
\]

where \( \left( \sum_{i \in R} \frac{q_i}{\Theta g_{2v}} + \frac{L_d}{\tau} \right) \beta_{DV} \) is the time cost of DV \( d \) and \( \left( \sum_{i \in R} \frac{q_i}{\Theta} + L_d \gamma \right) \cdot P_{low} \) is the electricity cost. \( L_d \) denotes the total travel distance of DV \( d \) and \( \tau \) denotes the average vehicle speed, so the division is the routing time of DV \( d \). \( \frac{q_i}{\Theta g_{2v}} \) indicates the service time of DV \( d \) for RV \( i \), equal to zero if \( \pi_i^d = 0 \), which means RV \( i \) is not served by DV \( d \). \( \beta_{DV} \) represents the value of time for DVs. Similarly, \( \left( \sum_{i \in R} \frac{q_i}{\Theta} + L_d \gamma \right) \cdot P_{low} \) includes electricity cost of discharging and routing.

\( \sum_{i \in R} \frac{q_i}{\Theta} \) denotes the electricity transferring from DV \( d \) to all RVs. \( \gamma \) represents the power consumption per unit mileage of EV, with unit of kWh/km. \( P_{low} \) is the electricity price during off-peak hours, and it is assumed that DV owners get charged during off-peak hours to save money.

The revenue of DV \( d \) providing discharging service \( \omega_d \) is

\[
\omega_d = \left( \sum_{i \in R} \frac{q_i}{\Theta g_{2v}} + \frac{L_d}{\tau} \right) w, \quad \forall d \in D \#(8)
\]

where \( w \) is the wage rate of DVs paid by the V2V platform. The revenue of DV \( d \) equal to total service time \( \left( \sum_{i \in R} \frac{q_i}{\Theta g_{2v}} + \frac{L_d}{\tau} \right) \) multiplied by wage rate \( w \).

To ensure that the EVs are willing to provide discharging services, the revenue of each deployed DV \( \omega_d \) is greater than the cost of providing the discharging service \( C_d \).

\[
\omega_d - C_d \geq 0, \quad \forall d \in D \#(9)
\]

3.4. Mathematica model of the V2V platform

The V2V platform achieves benefit maximization by matching RVs and DVs while considering the demand and supply sides constraints. The VRP-V2V can be formulated as the following MILP problem:

\[
\text{Max: } \sum_{i \in R} q_i P_{2v} - \left( \sum_{i \in R} \frac{q_i}{\Theta g_{2v}} + \sum_{d \in D} \frac{L_d}{\tau} \right) \#(10)
\]

s.t.
\[
\begin{align*}
\pi_i^d &= \sum_{j \in V_d} x_{ij}^d, \quad \forall d \in D, i \in R \tag{11} \\
\varphi_i &= \sum_{d \in D} \pi_i^d, \quad i \in R \tag{12} \\
l_d &= \sum_{i \in V_d} \sum_{j \in V_d} x_{ij}^d l_{ij}^d, \quad \forall d \in D \tag{13} \\
\sum_{j \in V_d} x_{ij}^d &= \sum_{j \in V_d} x_{ji}^d, \quad \forall d \in D, i \in V_d \tag{14} \\
\sum_{d \in D} \sum_{j \in V_d} x_{ij}^d &= \sum_{d \in D} \sum_{j \in V_d} x_{ji}^d, \quad \forall i \in R \tag{15} \\
\varphi_i^{\text{start}} + \frac{t_{ij}^d}{\tau} - (1 - x_{ij}^d) M &\leq t_j, \quad \forall d \in D, (i, j) \in A_d, i = d \tag{16} \\
t_i + \frac{q_i}{\theta_{g_{v2v}}} + \frac{t_{ij}^d}{\tau} - (1 - x_{ij}^d) M &\leq t_j, \quad \forall d \in D, (i, j) \in A_d, i \neq j \neq d \tag{17} \\
t_i + \frac{q_i}{\theta_{g_{v2v}}} + \frac{t_{ij}^d}{\tau} - (1 - x_{ij}^d) M &\leq \varphi_i^{\text{end}}, \quad \forall d \in D, (i, j) \in A_d, i \neq j \neq d \tag{18} \\
E - l_{ij}^d y + (1 - x_{ij}^d) M &\geq \mu_i, \quad \forall d \in D, (i, j) \in A_d, i \neq j \tag{19} \\
\mu_i - \frac{q_i}{\theta} - l_{ij}^d y + (1 - x_{ij}^d) M &\geq \mu_j, \quad \forall d \in D, (i, j) \in A_d, i \neq j \tag{20} \\
\mu_i - \frac{q_i}{\theta} - l_{ij}^d y + (1 - x_{ij}^d) M &\geq \sigma_d, \quad \forall d \in D, (i, j) \in A_d, j = d \tag{21} \\
q_i &< \mu_i, \quad \forall i \in R \tag{22} \\
\sigma_d &\leq \sigma_i, \quad \forall d \in D \tag{23}
\end{align*}
\]

Objective (10) is to maximize the total profit of the V2V platform that equals the service fares of all served RVs \( \sum_{i \in R} \varphi_i q_i p_{v2v} \) minus the wages paid for DVs \( \left( \sum_{i \in R} \varphi_i \frac{q_i}{\theta_{g_{v2v}}} + \sum_{d \in D} \frac{l_{ij}^d}{\tau} \right) w \), where \( \varphi_i = 1 \) indicates recharging vehicle \( i \) is served by the platform, and equals zero if not. Constraint (11) describes the relationship of the decision variable \( \pi_i^d \) and \( x_{ij}^d \), using the subgraph \( V_d \), i.e., the combination of all RV nodes and the specific DV node \( i \). RV \( i \) is served by DV \( d \) if \( \pi_i^d = \sum_{j \in V_d} x_{ij}^d = 1 \), where \( x_{ij}^d \) indicates whether DV \( d \) travels on arc \( (i, j) \) or not. Constraint (12) defines the relationship of the decision variable \( \varphi_i \) and \( \pi_i^d \). RV \( i \) can only be served by one specific DV \( d \), i.e., \( \varphi_i = \sum_{d \in D} \pi_i^d = 1 \), and it is not served by any DV if \( \varphi_i \) equals zero. Constraint (13) represents the total travel distance of DV \( d \), which includes the travel distance from the starting point to the first RV served by DV \( d \) \( \sum_{j \in V_d} x_{ij}^d l_{ij}^d \), the travel distance from the first RV served by DV \( d \) to the last RV served by DV \( d \) \( \sum_{j \in V_d} x_{ij}^d l_{ij}^d \), and the travel distance from the last RV served by DV \( d \) back to the starting node \( \sum_{j \in V_d} x_{ij}^d l_{ij}^d \). \( l_{ij} \) indicates the travel distance of DV \( d \) for arc \( (i, j) \).

Flow conservation constraints (14) and (15) guarantee that at most one DV can arrive or leave at each node and that the number of DVs arriving and departing is equal.
Constraint (16) is the feasibility constraint of the service start time for DVs. Constraint (17) is the time feasibility constraints for DVs between two RVs, where \( \frac{q_i}{\theta_{g_{2v}}} \) represents the time required of DVs to provide discharging service for RVs with power demand \( q_i \), \( \frac{t_{ij}^d}{\tau} \) represents the time spend of DVs on the arc \((i, j)\), and \( M \) is a very large positive value. If \( x_{ij}^d = 1 \), RV \( j \) is immediately served by the DV \( d \) after serving RV \( i \), and we have \( t_i + \frac{q_i}{\theta_{g_{2v}}} + \frac{t_{ij}^d}{\tau} \leq t_j \); otherwise, as \( M \) is a very large positive value, we always have \( t_i + \frac{q_i}{\theta_{g_{2v}}} + \frac{t_{ij}^d}{\tau} - M \leq t_j \). Constraint (18) refers to the feasibility constraints of DV service end time.

The state of the remaining battery capacity of DVs at the starting nodes, CV nodes and returning to the starting nodes, is captured by constraints (19), (20), and (21). The battery capacity \( E \) serves as a key parameter, with \( \mu_i \) representing the residual power arriving at recharging vehicles (RVs) and \( \sigma_d \) denoting the remaining power of DV \( d \) returning to the starting node. The power consumption of DVs on the arc \((i, j)\) is represented by \( l_{ij}^d Y \). Constraint (22) serves to guarantee that the residual power of DVs never falls below the power demand of RVs, while Constraint (23) ensures that DVs have sufficient residual power to complete the return trip.

4. Solution method

To accelerate the solution of the NP-hard VRP-V2V model, an ALNS framework is proposed. This individual-based heuristic algorithm improves the current solution by a process of destroying and repairing. The methodology consists of a general framework, with specific algorithmic components described in detail below.

4.1. The framework of ALNS algorithm

The structure of the proposed ALNS algorithm is presented in Algorithm 1. The process commences by generating an initial solution, as detailed in Subsection 4.2, and establishing the values of the operator weights and other relevant parameters. The algorithm employs the generalized profit function \( f_{gen}(Sol) \), outlined in Subsection 4.3 is to assess each solution produced. The initial feasible solution is assigned as both the current and best-found solutions in Lines 4 and 5, respectively, prior to the initiation of the iteration. The current solution is destroyed in Line 8 through the implementation of the selected destroy operator, which is outlined in Subsection 4.4. In Line 9, a repair operator, as described in Subsection 4.5, is chosen based on the established weights and applied to the current solution. Subsequently, the local search algorithm, outlined in Algorithm 3, is utilized to further improve the solution quality in Line 10. If the new solution produced is superior to the best-found solution, as determined between Lines 11 to 18, the latter is updated accordingly. To avoid convergence to a local optimum, the solution revision criterion outlined by Haghi et al. (2023) is
implemented. If the new solution is at least $\rho$ times the objective function value of the current solution, it is accepted as the current solution. The operator weights, as outlined in Subsection 4.7, and acceptance parameter are updated at the end of each iteration to enhance the search efficiency. The algorithm terminates when the best-found solution remains unchanged for a predetermined number of iterations or the maximum number of iterations $MaxIter$ is reached, at which point the best-found solution is outputted.

**Algorithm 1:** ALNS general framework

1: **Input:** $MaxIter$, $\zeta_0$, $\eta_0$, $\rho_0$
2: **Initialize:** $\zeta_i \leftarrow \zeta_0$, $\eta_i \leftarrow \eta_0$, $\rho \leftarrow \rho_0$
3: Run Initial Heuristic (Algorithm 2) and obtain a initial solution $Sol^{initial}$ with profit $Pro^{initial}$
4: $Sol^{current} \leftarrow Sol^{initial}$ and $Sol^{best} \leftarrow Sol^{initial}$
5: $Pro^{current} \leftarrow Pro^{initial}$ and $Pro^{best} \leftarrow Pro^{initial}$
6: **for** iteration $= 1$ to $MaxIter$ **do**
7: Randomly select a pair of operators according to their current weights
8: Run selected destroy operator($\zeta$) on $Sol^{current}$ with $Sol^{new}$
9: Run selected repair operator($\eta$) on $Sol^{current}$ with $Sol^{new}$
10: Apply Local Search (Algorithm 3) to possibly improve the solution with $Sol^{new}$ and $Pro^{new}$
11: **if** $Pro^{new} > Pro^{best}$ **then**
12: $Pro^{best} \leftarrow Pro^{new}$
13: $Sol^{best} \leftarrow Sol^{new}$
14: **end if**
15: **if** $Pro^{new} > \rho \times Pro^{current}$ **then**
16: $Pro^{current} \leftarrow Pro^{new}$
17: $Sol^{current} \leftarrow Sol^{new}$
18: **end if**
19: Update the selected weights of destroy operators $\zeta_i$ and repair operators $\eta_i$
20: Update the acceptance parameter $\rho$
21: **Until** stopping criterion
22: Output $Pro^{best}$ and $Sol^{best}$

4.2. The initial solution generation

In order to establish an initial feasible solution, the methodology outlined in Algorithm 2 is employed. The procedure begins by arranging the DVs in a predetermined order and designating the
first DV as the starting point for a new discharging route. Subsequently, an unserved RV that adheres to the defined constraints is inserted into the route, with the objective of maximizing profit as specified in equation (24). This process is repeated until no additional unserved RVs could be accommodated. The next DV is then utilized to initiate a new discharging route and the same procedure was repeated until no unserved RVs remained and all DVs had been evaluated. At this point, the initial feasible solution is obtained.

<table>
<thead>
<tr>
<th>Algorithm 2: Initial feasible solution generation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 : Sort the DVs in turn</td>
</tr>
<tr>
<td>2 : Start a new route with the first DV</td>
</tr>
<tr>
<td>3 : repeat</td>
</tr>
<tr>
<td>4 : Calculate the insertion profits of all unserved RVs to the current route</td>
</tr>
<tr>
<td>5 : if the customer which increases the profit most violates constraints, then</td>
</tr>
<tr>
<td>6 : Start a new route with the next DV</td>
</tr>
<tr>
<td>7 : else</td>
</tr>
<tr>
<td>8 : Select the recharging vehicles which increases the profit most and make the insertion</td>
</tr>
<tr>
<td>9 : end if</td>
</tr>
<tr>
<td>10 : until no RVs can be added and all DVs are checked</td>
</tr>
<tr>
<td>11 : return Initial feasible solution</td>
</tr>
</tbody>
</table>

4.3. The generalized objective function

During the search process for the ALNS algorithm, four primary situations can arise that result in infeasible solutions. Firstly, if the actual time for RVs served through the V2V platform is excessive and the associated charging cost is higher than that incurred at a charging pile, this signifies a violation of constraint (6). Secondly, the time of DVs returning the starting node exceeds the time window limit, which is a violation of constraint (18). Thirdly, if the remaining power of the DV is inadequate to meet the recharging needs of RVs or for the return journey, this implies a violation of constraint (22) or (23). Lastly, if the revenue generated by the DV fails to meet the established requirements, this represents a violation of constraint (9). To balance the generation of infeasible solutions, different penalty coefficients are assigned for the shortage of actual service time for RVs, the insufficient remaining power of DVs, and inadequate revenue of DVs. The evaluation function [21] used in the solution process, denoted as \( f_{gen}(Sol) \), is formulated as follows.

\[
f_{gen}(Sol) = f(Sol) + \alpha P_{rt}(Sol) + \beta P_{dt}(Sol) + \gamma P_{rp}(Sol) + \lambda P_{r}(Sol) \tag{24}
\]

where \( f(Sol) \) denotes the total profit defined in equation (10), \( P_{rt}(Sol) \) represents the actual service
time violation of RVs, \( P_{dv}(Sol) \) represents the service time violation of DVs, \( P_{rp}(Sol) \) represents the remaining power violation of DVs, and \( P_{r}(Sol) \) denotes revenue violation of DVs. \( \alpha, \beta, \gamma, \) and \( \lambda \) are three penalty coefficients respectively related to the four violations.

4.4. Destroy algorithms

In this work, we present four destroy operators that are integrated within the ALNS algorithm. Specifically, three of these operators are designed for the destroy of RVs, and the remaining operator is intended for the destroy of a DV service route. An illustration of the three RVs destroy operators is depicted in Figure. 5, where the removal of RV 2 from Route 1 and RV 4 from Route 2 to the set of unserved RVs is demonstrated. The fourth destroy operator, which involves the removal of routes, is depicted in Figure. 6, where the removal of RVs 4, 5, and 6 from Route 2 to the set of unserved RVs is demonstrated.

**Figure. 5.** The destroy operators of RVs.

**Randomly remove RVs (D1):** Randomly select \( \sigma \% \) of served RVs and remove them from route to the set of unserved RVs.

**Remove RVs with the worst-distance (D2):** We employed the worst-distance removal operator to selectively remove a specified percentage (\( \sigma \% \)) of served RVs, transferring them to the set of unserved RVs. To determine which RVs to remove, the operator calculates the distance \( \Gamma_i \) for each served RV \( i \) in the set \( R_{served} \), using the formula \( \Gamma_i = |l_{mi} + l_{ik}| \), where \( m \) and \( k \) denote the preceding and succeeding RVs, respectively, on the route. The RV with the maximum distance \( \Gamma_i \) is then removed, and the set \( R_{served} \) is updated accordingly. This process is repeated until the desired percentage of \( \sigma \% \) of served RVs have been removed from the set \( R_{served} \).

**Remove RVs with the worst-time (D3):** In this operator, the worst-time removal operator is
employed to transfer a \( \sigma \% \) proportion of the served RVs to the set of unserved RVs. This method takes into account the difference between the actual service time and the preferred service time of the RVs, which is calculated as \( f_i = |t_i - \theta_i^{\text{start}}| \), \( \forall i \in R_{\text{serv}} \). The RV with the greatest difference, \( f_i \), is then selected for removal. The \( R_{\text{serv}} \) set is continually updated after each removal, until the desired \( \sigma \% \) of served RVs have been removed.

Randomly remove DV service routes (D4): Follow Emeç, Çatay [76], randomly select \( \omega \% \) of DV routes and remove the RVs on the route to the set of unserved RVs. In order to mitigate the risk of some RVs being overlooked and not being removed by the destroy operators, a random route removal algorithm has been proposed to systematically explore the solution space. This approach is aimed at improving the effectiveness of the solution by ensuring that all feasible routes are considered during the optimization process.

4.5. Repair algorithms

The proposed ALNS algorithm utilizes three repair operators, which are described below. Figure 7 provides a visual representation of the unserved RVs repair operator. In this illustration, unserved RVs 4, 5, and 6 are respectively reinserted into routes 1, 2, and 3. These repair operators have been adapted from the works of Pisinger and Ropke [77] and Demir, Bektaş [78] and are integrated into the proposed ALNS framework.

Figure 6. The destroy operators of DV service routes.
Figure 7. The repair operators of unserved RVs.

**Insert unserved RVs in random order (R1):** Assign unserved RVs successively to the best possible position, that has the largest profit promotion and is better than current solution, in random order.

**Insert unserved RVs in optimal order (R2):** The greedy insertion operator determines the optimal insertion position for an unserved RV by evaluating the profit of inserting it between all feasible pairs of nodes \( j \) and \( k \). It selects the position with the maximum profit as the optimal insertion point. This process is repeated for all unserved RVs. The unserved RV with the highest insertion profit that improves the current solution is then inserted into its designated position.

**Insert unserved RVs in the order of regret criterion (R3):** The regret insertion operator is similar in nature to the greedy insertion operator. The primary difference between the regret insertion operator and the greedy insertion operator is in their approach for selecting the insertion RV. The regret insertion operator chooses the RV with the maximum difference between the best and second-best profits, resulting in a less myopic strategy than the greedy insertion operator.

### 4.6. Local search procedures

This section describes four local search procedures that are used to improve the quality of the found solution in the ALNS algorithm.

**Algorithm 3:** Local search procedure

1. Let \( Sol^{current} \) be a (feasible or infeasible) solution
2. repeat
3. Obtain \( Sol^{new} \) by changing the service order of RVs (L1); \( Sol^{current} = Sol^{new} \)

4: Obtain $\text{Sol}^{new}$ by swapping the service order of two RVs (L2); $\text{Sol}^{current} = \text{Sol}^{new}$

5: Obtain $\text{Sol}^{new}$ checking all unserved RVs (L3); $\text{Sol}^{current} = \text{Sol}^{new}$

6: Obtain $\text{Sol}^{new}$ checking all DV service routes (L4); $\text{Sol}^{current} = \text{Sol}^{new}$

7: until all vehicles and routes are checked

9: return $\text{Sol}^{new}$

**Change the service order of RVs (L1):** For each current solution, one RV will be relocated to a different position within its current route. If the repositioning results in an increase in platform profit, the RV will be relocated. Figure 8 provides an example of the local search operator. In this scenario, relocating RV 1 to a position behind RV 3 in route 1 and RV 6 before RV 4 in route 2 results in a better solution.

**Figure 8.** Change the service order of one RV (L1).

**Swap the service order of two RVs (L2):** The service order change operator examines all served RVs for each DV. As depicted in Figure 9, if swapping the service order of two RVs results in a larger generalized profit, as defined in equation (24), the service order of these two vehicles will be swapped.
**Check all unserved RVs (L3):** The "position exchange operator" examines all unserved RVs. As depicted in Figure 10, if exchanging the positions of an unserved RV with a served RV in a route results in a larger generalized profit, as defined in equation (24), the positions of these two vehicles will be exchanged.

**Check all DV service routes (L4):** This operation checks all the service routes of DVs. If swapping the service routes of two DVs results in a larger generalized profit, as defined in equation (24), the routes of these two DVs will be swapped. Figure 11 provides an example of this operator, where the route of DV 1 is swapped with the route of DV 2.
4.7. Adaptive searching strategy

The ALNS proposed in this paper are composed of a series of destroy operators and repair operators. Follow Yin, D’Ariano [79], the weights of operators are updated according to the following formulae:

\[
\zeta_i = (1 - \gamma)\zeta_i + \frac{\gamma \pi_i^\xi}{\sum_{i=1}^{N_\zeta} \pi_i^\xi} \quad \text{(#28)}
\]

\[
\eta_i = (1 - \gamma)\eta_i + \frac{\gamma \pi_i^\eta}{\sum_{i=1}^{N_\eta} \pi_i^\eta} \quad \text{(#29)}
\]

where, \( \gamma \in [0,1] \) is a reaction factor that governs how sensitive the weights are to changes in the performance of the operators. \( \pi_i^\xi \) and \( \pi_i^\eta \) represent the score associated with destroy and repair algorithm \( i \), respectively. The following are scores updating rules: if a new best solution is found, weights \( \pi_i^\xi \) and \( \pi_i^\eta \) are increased by \( \omega_1 \); weights \( \pi_i^\xi \) and \( \pi_i^\eta \) are increased by \( \omega_2 \) if the new solution is better than the current solution but worse than the best-found solution; and weights \( \pi_i^\xi \) and \( \pi_i^\eta \) are increased by \( \omega_3 \) if the new solution is not as good as the current solution.

Using a roulette-wheel method, a destroy operator and a repair operator are selected at the beginning of each iteration. The probabilities of selecting a destroy operator are respectively given by

\[
\frac{\zeta_i}{\sum_{i=1}^{N_\zeta} \zeta_i} \quad \text{and} \quad \frac{\eta_i}{\sum_{i=1}^{N_\eta} \eta_i}
\]

where \( \zeta_i \) represents the weight of destroy operator \( i \), \( \eta_i \) represents the weight of repair operator \( i \), \( N_\zeta \) denotes the number of destroy operators, and \( N_\eta \) denotes the number of repair operators.
5. Numerical experiments

In this section, we present a series of numerical experiments to demonstrate the effectiveness of the VRP-V2V model developed in Section 3 and the ALNS algorithm proposed in Section 4. All experiments were conducted on a personal computer equipped with an Intel (R) Core (TM) I7-11700U 3.00 GHz CPU and 16.00 GB of RAM. The commercial optimization solver CPLEX was also utilized to solve the VRP-V2V problem in this study, and was called using YALMIP, a freely available toolbox in MATLAB R2020a.

5.1. Generation of test instances

As there are no benchmark instances for VRP-V2V, 24 small instances are generated based on the well-known VRPTW instances of Solomon [80]. These small instances have 10 or 18 nodes, and each node represents one EV. We divide these EVs into two parts, half of the EVs is DVs, and the other half is the RVs. The instances are classified into three groups based on the locations of EVs: clustered (C), randomly distributed (R), and both clustered and randomly distributed (RC). In these 24 small networks, the distance between nodes is measured using Euclidean distance. Six large instances are generated and named as D-50-50, D-60-40, D-67-33, S-50-50, S-60-40, and S-67-33. The naming format of these instances includes one character and two numbers, where the character captures the distribution of the fixed charging infrastructure (CI). Specifically, "D" in the name represents densely distributed charging piles with a charging time of 20 minutes, while "S" represents sparsely distributed charging piles with a charging time of 40 minutes. The two numbers in the name indicate the number of RVs and DVs, respectively. For example, the name D-60-40 indicates that there are 60 RVs and 40 DVs. The 100 EVs in each of these large instances are located on the real road network in Changsha, China, and the distances between them have been determined using the Dijkstra algorithm (as depicted in Figure. 12).

In accordance with Tang, He [10], a truncated normal distribution with a mean of 14 kWh and a standard deviation of 10 kWh can be used to approximate the charging power demand, which is predominantly concentrated between 0 and 40 kWh. The default values of the parameters used in the numerical examples are listed in Table 2. In order to capture heterogeneous users, the value of time for RVs waiting for charging pile service is randomly generated between 50 RMB/h, 60 RMB/h, 70 RMB/h, 80 RMB/h, 90 RMB/h. The value of time of RV waiting for the V2V charging service, set to be lower than value of time of RV searching for charging piles, since RV owners can focus on other activities while waiting. The value of time of RV waiting for the V2V charging service is randomly generated between 10 RMB/h, 20 RMB/h, 30 RMB/h, 40 RMB/h. Since the value of time for DVs is lower than that of time for CVs, it is willing to give discharge service. Thus, the value of time for DVs is randomly generated between 10 RMB/h, 20 RMB/h, 30 RMB/h, 40 RMB/h, and 50 RMB/h, and the time window duration for DVs is randomly generated between 2 hours, 3 hours, and 4 hours. During off-peak hours, the electricity price $P_{low}$ is 0.5 RMB/kWh, while the price of charging at charging
piles $P_{pile}$ is 1.5 RMB/kWh. The electricity price for the V2V platform $P_{v2v}$ is 3 RMB/kWh and the wage rate $w$ is 30 RMB/h. As established by Cui, Ma [21], the power consumption rate $\gamma$ of EVs during travel is 0.11 kWh/km and the speed $\tau$ of EVs is 1 km/min.

**Table 2.** Parameter definitions and default values.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T^*$</td>
<td>Cruising time of RVs to find an available charging pile</td>
<td>D: 20 min; S: 40 min</td>
</tr>
<tr>
<td>$E$</td>
<td>Battery capacity of EVs</td>
<td>50 kWh</td>
</tr>
<tr>
<td>$q_i$</td>
<td>Power demand of RV, $i \in R$</td>
<td>Normal distribution [10]</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>The power consumption per unit mileage of EV</td>
<td>0.11 kWh/km [21]</td>
</tr>
<tr>
<td>$\tau$</td>
<td>Average travel speed of DVs</td>
<td>1 km/min [21]</td>
</tr>
<tr>
<td>$P_{low}$</td>
<td>Electricity price off-peak hours</td>
<td>0.5 RMB/kWh</td>
</tr>
<tr>
<td>$P_{pile}$</td>
<td>Electricity price of charging piles</td>
<td>1.5 RMB/kWh</td>
</tr>
<tr>
<td>$P_{v2v}^*$</td>
<td>Electricity price of V2V platform</td>
<td>3 RMB/kWh</td>
</tr>
<tr>
<td>$w^*$</td>
<td>Wage rate of DVs</td>
<td>30 RMB/h</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>Remaining power of DVs at the end of discharging service</td>
<td>0 kWh</td>
</tr>
<tr>
<td>$g_{pile}$</td>
<td>Charging power of charging piles</td>
<td>60 kW [81]</td>
</tr>
<tr>
<td>$g_{ev}$</td>
<td>Charging power of V2V</td>
<td>40 kW</td>
</tr>
<tr>
<td>$\Theta^*$</td>
<td>Transaction efficiency of V2V charging</td>
<td>0.9 [32]</td>
</tr>
</tbody>
</table>

*Note that. sensitivity analysis on the parameters indicated by an asterisk (*) will be conducted later.*

**Figure 12.** The locations of EVs in Changsha, China.
5.2. Performance of the ALNS algorithm on small instances

The performance of the proposed ALNS algorithm, as described in Section 4, was first analyzed on the twenty-four newly created small instances. A comparison is made between the (near-)optimal solutions obtained through the use of CPLEX and those generated by the ALNS method. The results, presented in Table 3, highlight the computational complexity of the problem. The columns "T-RV" and "T-DV" denote the total number of served RVs and the total number of used DVs, respectively. The "Profits (RMB)" column represents the profit of the V2V platform, while the "T (s)" column denotes the computation time in seconds. The CPLEX column represents the optimal solution or the best upper bound found by CPLEX within the time limit of 7200 seconds. The ALNS column represents the best feasible solution found in ten runs. ‘Δ_{rv} (%)’ represent the gap between total number of served RVs found by CPLEX and our ALNS, and so are ‘Δ_{dv} (%)’ and ‘Δ_{p} (%)’.

Table 3. The test results of small instances.

<table>
<thead>
<tr>
<th>Instance</th>
<th>CPLEX</th>
<th>ALNS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>T-RV</td>
<td>T-DV</td>
</tr>
<tr>
<td>C101_10</td>
<td>4 3</td>
<td>64.27</td>
</tr>
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<td>89.66</td>
</tr>
<tr>
<td>Average</td>
<td>- -</td>
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</table>

Note. The optimal solution of instances with * in the table is not found within time limit.

The results show that CPLEX found the optimal solution for 22 instances within the time limit, with the exception of instances RC107_18 and RC208_18. From the computing time column of CPLEX, we can see that the computational complexity of this problem increases rapidly with the increase of the network nodes. When the number of vehicle nodes reached 18, the solver could not
complete the calculation in the time limit. The proposed ALNS method, however, efficiently obtains the same optimal solutions in the 22 instances, and finds better solutions when CPLEX fails to solve the optimal solution within the time limit (i.e., RC107_18 and RC208_18). The average run time of ALNS is only 3.6 s, whereas CPLEX spent 1930 s on average. This demonstrates the effectiveness of the ALNS algorithm in solving the VRP-V2V problem proposed in this paper.

5.3. Basic test results of the large instances

The proposed ALNS algorithm incorporates four local search operators aimed at enhancing the solution quality. To examine the impact of these operators, the proposed ALNS algorithm was run with and without these operators, with the maximum number of iterations $\text{MaxIter} = 2000$, for the large instance S-67-33. When the best-found solution remains unchanged for 300 iterations or the maximum number of iterations $\text{MaxIter}$ is reached, the best-found solution will be output. The results, depicted in Figure. 13, demonstrate that the ALNS algorithm converges to a high-quality solution, with or without the local search operators. Furthermore, incorporating the local search operators into the ALNS algorithm enhances its computational efficiency, as evident from the objectives versus iteration number plot in Figure. 13. Additionally, the performance of the proposed VRP-V2V is evaluated using six large instances. The results are illustrated in Figure. 14, which reveal the relationship between the cruising time and the profit of the V2V platform. Instances with greater cruising time, S-50-50, S-60-40, and S-67-33, are observed to generate higher profits compared to instances with less cruising time, D-50-50, D-60-40, and D-67-33. The impact of fixed CI on the operations of the V2V platform is further analyzed in Subsection 5.5.4.
Figure 13. The difference of the proposed ALNS algorithm with or without local search operators.

Figure 14. The results of the six large instances.
5.4. With VS without V2V platform

In order to evaluate the feasibility of the V2V platform scheme, a benchmark is introduced: the charging pile scheme (without V2V platform) which lacks the V2V service. Thereby, an analysis is conducted. In the charging pile scheme, all RVs will choose charging pile to recharge. The total cost of served RVs with V2V platform $TC_{V2V}$ is

$$TC_{V2V} = \sum_{i \in R} q_i \left( t_i^s + q_i / \theta_{V2V} - e_i \right) \beta_{RV}^{V2V}$$ (27)

The total cost of served RVs without V2V platform $TC$ is

$$TC = \sum_{i \in R} q_i \left( t_i + q_i / g_{pile} \right) \beta_{RV}^{pile} + P_{pile} q_i$$ (28)

Based on six large instances, we calculated the total cost of served RVs with $TC_{V2V}$ or without $TC$ V2V platforms shown in equations (27) and (28). The total cost of and the cost saving ratio of RVs are shown in Figure. 15. The cost saving ratio of RVs for instances D-50-50, D-60-40, D-67-33, S-50-50, S-60-40, and S-67-33 are 29.1%, 30.7%, 31.2%, 34.2%, 35.6%, and 37.8%, respectively. By comparing the costs of served RVs with $TC_{V2V}$ or without $TC$ V2V platform, it can be observed that V2V platform can save an average of 33.1% on RV recharging costs. In addition, we can also see from the results that fewer fixed CI, the greater the cost saving ratio of RVs. As seen above, the V2V platform proposed in this paper is attractive to RVs, which can effectively improve recharging service satisfaction and alleviate the range anxiety of RVs.
5.5. Sensitivity analysis

5.5.1. The electricity price of the V2V platform

The impact of electricity prices on the competitiveness of Vehicle-to-Vehicle (V2V) platforms in comparison to traditional fixed charging infrastructure (CI) has been considered. An increase in electricity prices would require V2V platforms to offer improved services such as shorter recharging wait time to attract RVs to the platform. This increase in electricity prices, however, could also make servicing previously unprofitable RVs profitable for the V2V platform. To evaluate the effect of electricity prices on the V2V platform, six different scenarios were analyzed, with electricity prices set at 2 RMB/kWh, 3 RMB/kWh, 4 RMB/kWh, 5 RMB/kWh, 6 RMB/kWh, and 7 RMB/kWh. Figure 16 depicts the results for the six large instances under the preceding six scenarios, with the bar graph displaying the platform profit and total wage of DVs in each instance and the dot plot displaying the average platform profit and total wage of DVs in multiple instances. Figure 17 depicts the number of served RVs and the number of used DVs under different electricity prices.

Figure 16 presents the relationship between electricity price and the financial performance of the platform, including platform income, wage paid to DVs, and platform profit. The results suggest that the profit of the V2V platform does not consistently increase with an increase in electricity price. Instead, a trend of first increase and then decrease is observed. The underlying reasons for this
phenomenon are illustrated in Figure 17, which shows that an increase in electricity price leads to a reduction in the number of RVs that can be served by the platform, as well as a decrease in the number of DVs deployed by the platform. As a result, the profit that the V2V platform can make from the market is not always increasing. Additionally, as demonstrated in Figure 16, instances D-50-50, D-60-40, and D-67-33 exhibit greater sensitivity to changes in electricity price. Notably, when the electricity price is 6 RMB/kWh or 7 RMB/kWh, the profit of the V2V platform becomes zero for these instances, rendering the platform unable to serve any RVs. This highlights that areas with a higher proportion of fixed charging infrastructure (CI) are more sensitive to changes in electricity price. Consequently, to enhance revenue, the platform could consider implementing appropriate spatial differential electricity pricing that takes into account the distribution of fixed CI.

Figure. 16. The total income, wage, and profit of V2V platform under different electricity prices.
Figure 17. The number of served RVs and the number of used DVs under different electricity prices.

Figure 18. The total wage of DVs and V2V platform profit under different wage rates.
5.5.2. The wage rate of DVs

The wage rate of DVs, denoted as $w$, plays a crucial role in the functioning of the V2V platform. To assess the impact of $w$ on the platform, $w$ is set to 20 RMB/h, 30 RMB/h, 40 RMB/h, 50 RMB/h, 60 RMB/h, and 70 RMB/h, respectively. The results are presented in Figure 18 and Figure 19. Figure 18 illustrates the platform profit and total wage of DVs for the six large instances under the different wage rate scenarios, while Figure 19 depicts the number of RVs served and the number of DVs utilized for the six large instances under different wage rate cases.

As depicted in Figure 18, the results demonstrate that both the profit of the V2V platform and the wages of DVs exhibit a trend of first increasing and then decreasing as the wage rate increases. The relationship between wage rate and the platform's ability to deploy DVs is illustrated in Figure 19. Specifically, as the wage rate increases to 20 RMB/h, 30 RMB/h, or 40 RMB/h, the platform can deploy more DVs to serve more RVs, leading to an increase in the platform's profit. However, when the wage growth of DVs exceeds the income growth of the V2V platform, the platform's profit begins to decline gradually (i.e., when the wage rate is 50 RMB/h, 60 RMB/h, or 70 RMB/h). At sufficiently high wage rates, the cost of serving RVs starts to increase, causing a reduction in the number of RVs served by the platform, as well as a decrease in the number of DVs deployed by the platform and the wages of DVs (i.e., when the wage rate is 70 RMB/h). Therefore, it is imperative for the V2V platform to determine an appropriate wage rate that caters to market demand and maximizes its profit.

5.5.3. Transaction efficiency of V2V charging

The subsection investigates the impact of transaction efficiency, a new charging model, on recharging and discharging vehicles as well as the V2V platform. To explore the effects of transaction efficiency, we set it at six different levels, namely 1, 0.95, 0.9, 0.85, 0.8, and 0.75. The results for large
instances under varying transaction efficiencies are presented in Figure 20. As revealed by the figure, the profit of the V2V platform and the wages of DVs decrease gradually with a decline in transaction efficiency. This is because lower transaction efficiency necessitates an increased number of DVs to satisfy the charging demand of RVs, thereby undermining the interests of the V2V platform and DVs. According to [32, 82], the transmission loss is small and the transaction efficiency is as high as 95%. Compared with complete power transmission (i.e., when the transaction efficiency is 1), the conversion loss of 5% has little impact on platform operation.

![Figure 18](https://example.com/figure18.png)

**Figure. 18.** The total wage of DVs and V2V platform profit under different transaction efficiency.

### 5.5.4. Cruising time to find an available charging pile

In Subsection 5.3, our findings indicate that instances with greater cruising time T result in higher profits compared to instances with lower fixed CI. The cruising time, which represents the search for an available charging pile, serves as a proxy for the degree of fixed CI infrastructure development. The bigger the cruising time $T$, the sparse fixed CI have been built. Thus, to investigate the impact of fixed CI on the operations of the V2V platform, three additional instances, designated T-50-50, T-60-40, and T-67-33, were generated. As depicted in **Figure. 12**, each large instance comprises 100 EVs deployed on the real road network in Changsha, China, and the distances between EVs were calculated using the Dijkstra algorithm. The other parameters were set as described in Subsection 5.1. The cruising time $T$ of the instances was set to 10 min, 20 min, 30 min, 40 min, and 50 min, respectively. The total profit of the V2V platform and the number of RVs served by the V2V platform under different cruising times $T$ are illustrated in Figure. 20 and Figure. 21, respectively.
The results show a positive correlation between cruising time $T$ and both the total profit of the V2V platform and the number of RVs served by the platform, as illustrated in Figures 21 and 22. Increasing cruising time $T$ leads to a steady upward trend in both total profit and the number of RVs served by the platform. This suggests that the V2V platform is more profitable in areas with insufficient fixed CI, and that RV owners prefer the V2V platform and more RVs are served by the V2V platform when fixed CI are insufficient. Therefore, prioritizing V2V platform deployment in regions lacking fixed CI can not only improve the platform’s profitability but also supplement fixed CI.
and alleviate range anxiety for electric vehicles in areas with insufficient fixed CI.

6. Conclusion

In this paper, we introduced the V2V charging platform as a novel and flexible solution to the challenges impeding the widespread adoption of EVs, while requiring a small amount of investment in infrastructure and providing additional flexibility. The introduction of the V2V platform provides opportunities for discharging vehicles to generate revenue and enables recharging vehicles to access convenient charging services, reducing the range anxiety associated with EVs. To optimize the scheduling of recharging and discharging activities satisfying the DVs, RVs, and V2V platform, we have formulated the vehicle-to-vehicle charging problem as a mixed-integer linear programming (MILP) problem, which is known to be NP-hard. To address the computational challenge for large-scale problems, we developed an adaptive large neighborhood search algorithm that generates high-quality solutions in a computationally efficient manner, which is critical for practical implementation. Furthermore, to enhance the quality of the solutions obtained by the destroy and repair operators, we have proposed four local search procedures specifically tailored to the VRP-V2V problem structure.

Evaluation results show that the proposed ALNS algorithm outperforms CPLEX in both computational efficiency and solution quality for 24 small-scale instances. Additionally, the performance of the algorithm was evaluated on six large-scale instances on the road network in Changsha, China. Results indicate that the use of local search operators makes the algorithm more computationally efficient. Furthermore, the V2V platform was found to save an average of 33.1% on RV recharging costs, thereby effectively improving recharging service satisfaction and reducing range anxiety. Then, we showed that the electricity price of V2V platform and the wage rate of DVs have significant influences on the performance of the V2V platform. RVs in areas with more fixed charging infrastructure are more price sensitive and thus, the V2V platform should set appropriate electric prices and wage rates based on market conditions and the distribution of fixed charging infrastructure. Finally, comparing the impact of fixed CI on V2V platform operations, we found that priority V2V platform deployment to areas lacking fixed CI can increase the platform’s profitability.

The proposed VRP-V2V can be extended in many directions. How to find appropriate electric price and wage rate in the VRP-V2V is an interesting and important future research direction. Furthermore, based on the parking lot of city shopping centers, we may establish the VRP-V2V model considering EV parking. By renting or outsourcing some parking spaces of city shopping centers to V2V platform [83], RVs and DVs can complete the recharging and discharging activities in a dedicated V2V parking area, and the mall can profit from it by attracting more EV drivers to patronize.

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