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Multi-Parking Lot and Shelter Heterogeneous Vehicle Routing Problem With Split Pickup Under Emergencies

LINA XU¹, ZIYANG WANG², XUDONG CHEN³, AND ZHENGWEI LIN⁴

¹School of Traffic and Transportation, Beijing Jiaotong University, Beijing 100044, China

²Key Laboratory of Transport Industry of Big Data Application Technologies for Comprehensive Transport, Ministry of Transport, Beijing Jiaotong University, Beijing 100044, China

³School of Software Engineering, Beijing Jiaotong University, Beijing 100044, China

⁴Beijing System-Wide Communication Signal Research and Design Institute Company Ltd., Beijing 100044, China

Corresponding authors: Ziyang Wang (wangzy@bjtu.edu.cn) and Xudong Chen (chenxd@bjtu.edu.cn)

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ABSTRACT The vehicle rescue process for individuals in residential areas in disaster scenarios is a typical vehicle routing problem (VRP). However, most studies do not consider the factor of individual mobility. In residential areas, there are two types of individuals: individuals with high mobility and individuals with low mobility, such as the elderly. To improve the evacuation efficiency, besides ordinary vehicles, special vehicles equipped with wheelchairs and volunteers are also in great need. Thus, evacuation vehicles should consist of a heterogeneous fleet. Vehicles depart from parking lots, arrive at residential areas to pick up individuals, and then transport them to shelters. In other words, the origin and destination are different, but they are viewed as the same in classical VRP. Each residential area can be served directly by vehicles departing from parking lots or by vehicles that have already served others, which means demands can be split. All these make the VRP in emergency rescue more complicated than classical VRP. Therefore, we propose an integer liner program model – multi-parking lot and shelter heterogeneous vehicle routing problem with split pickup (MPSHVRPSP) model, which includes matching constraints of individuals and vehicles to satisfy the demands of different types of individuals, and considers the selectivity of parking lots and shelters too. We provide a Tabu Search (TS) algorithm with diversification strategy to solve the model and ensure the high quality of solution. A lot of experiments are carried out on various instances. Our results show that MPSHVRPSP can be applied to efficient evacuation of complicated scenarios that satisfies the demands of all individuals in residential areas. Besides, it is more reasonable compared with classical VRP, and TS can also obtain a satisfactory solution in less time. Furthermore, sensitivity analysis is conducted on factors that may affect the result of objective function.

INDEX TERMS Vehicle routing problem, multi-parking lot and shelter, heterogeneous fleet, split pickup, Tabu Search.

I. INTRODUCTION

In recent years, emergencies have occurred frequently, including natural disasters, such as earthquake, typhoon, debris flow, flood, etc., as well as man-made disasters, such as terrorist attack, chemical leakage, etc. All of these have caused a great threat to individuals' lives. Governments adopt early warning and emergency management mechanisms to minimize the losses. As a significant means to avoid or

reduce the harm of emergencies and avoid secondary injuries, traffic evacuation has become an important part of emergency management [1]–[4]. Considering the low per capita motor vehicle ownership rate, large-capacity vehicles, such as buses, should be used as the main way of traffic evacuation [5], [6]. Furthermore, to improve the evacuation efficiency, wheelchairs and volunteers should be provided for individuals with low mobility, i.e. the elderly and the disabled. Therefore, not only ordinary vehicles but special vehicles equipped with wheelchairs and volunteers must be included to meet the evacuation demands of individuals. However, most literatures

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on vehicle evacuation only consider transportation mode selection, deciding whether to use public transportation or cars [7], [8]. Few consider the factor of individual mobility although it is greatly significant in practice and has an important influence on evacuation effect. Accordingly, it is necessary for us to focus on it.

The vehicle rescue process in disaster scenarios is a typical vehicle routing problem (VRP). This problem studies how to optimize transportation costs from two aspects: rationally organizing vehicles and scientifically planning related routes, and is NP-hard. VRP, first proposed by Dantzig and Ramser in 1959 [9], refers to finding a route set for a fleet of homogeneous vehicles that can meet the demands of all customers and minimize the total route cost with the origin and destination of all vehicles being restricted at the depot. Since then, there have been many researches focusing on the variants of VRP.

(1) Multi-depot vehicle routing problem (MDVRP). In it, vehicles leave from a depot and finally return to it. First proposed by Laporte, Nobert and Arpin [10], this model was defined as an integer linear programming problem with four constraints and was solved with an exact algorithm. Cordeau, Laporte, and Mercier [11] proposed a unified Tabu search procedure to solve the MDVRP and minimized the number of vehicles. Vahed *et al.* [12] applied Modular Heuristic Algorithm to address the MDVRP for determining the optimal vehicle fleet size, and the method could produce better solutions. Sadati *et al.* [13] designed a Variable Tabu Neighborhood Search, obtaining the best-known results and successfully improving the efficiency of solution.

(2) Heterogeneous fleet vehicle routing problem (HFVRP). In it, fleets with different capacities and costs can satisfy customer demands. Choi and Tcha [14] developed a column generation algorithm and found that it was superior to others both in solution quality and in run time. Meliani *et al.* [15] proposed a Tabu Search procedure to HFVRP in urban logistics with minimization of costs. Another study by Li *et al.* [16] presented a novel algorithm, which could obtain satisfactory results of route allocation. Furthermore, compared with a single vehicle type, heterogeneous vehicles help achieve better solutions. Tirkolaee *et al.* [17] formulated a multi-trip location-routing problem for medical waste management. Although the vehicles studied were mixed fleets, the only difference among them is their capacity rather than the types of the goods loaded.

(3) Vehicle routing problem with split delivery (VRPSD). Each customer can be served by more than one vehicle. Thus, in addition to arranging vehicle routes, it is also necessary to determine the quantity of goods delivered to each customer by each vehicle. In fact, both split delivery and split pickup belong to split demand. Thus, we will compare our work with previous studies from the perspective of demand splitting. Dror and Trudeau [18] were the first to introduce the concept of split delivery, which could remarkably save costs in the total distance and the number of vehicles required. Moreno *et al.* [19] provided an extended formulation for VRPSD and presented an algorithm combining column and

cut generation to improve the best known lower bounds for all instances. Xing *et al.* [20] adopted a hybrid discrete differential evolution algorithm for VRPSD to minimize the total path distance in logistics distribution. Ozbaygin *et al.* [21] proposed new exact solution approaches solving the split delivery VRP, which was described by a vehicle-indexed flow formulation. Based on the formulation, they obtained a relaxed model.

There is also substantial amount of work on combination of sub-problems. Since Salhi and Sari [22] proposed the multi-depot heterogeneous fleet vehicle routing problem (MDHFVRP), it has motivated extensive research. Dondo *et al.* [23] formulated a mixed-integer linear programming model to minimize the total route cost. Dondo and Cerdá [24] proposed a three-stage heuristic approach for MDHFVRP. In order to generate a more compact formulation for cluster-based MILP model, they firstly preprocessed the clustered nodes. This kind of problem was also included in the research of Salhi *et al.* [25]. The authors adopted a variable neighborhood search technique, which was proved more competitive than those published in literatures. Nadjafi and Nadjafi [26] used a constructive heuristic method intending to minimize the total vehicle cost.

For multi-depot VRP with split delivery (MDVRPSD), Gulczynski *et al.* [27] proposed an integer programming-based heuristic. The objective of this work is to compare the reduction in driving distance when split deliveries among vehicles are allowed in the same depot and different depots. A heuristic algorithm was investigated by Ray *et al.* [28] for logistics distribution problems. Wang *et al.* [29] evaluated a heuristic to minimize the sum of travel and service times for the longest path.

Belfiore and Yoshizaki [30] considered the heterogeneous fleet VRP with split delivery (HFVRPSD), using heuristics and a scatter search approach. They applied the model to practical problem of Brazil retailing. Shahmiri *et al.* [31] presented a MIP model for HFVRPSD, and an exact hybrid algorithm was used in numerical examples.

Furthermore, there exist many studies that combine the characteristics of emergency rescue to apply VRP to evacuation [32]–[36]. In a disaster scenario, the shelter corresponds to the depot in classical VRP. Vehicles considered in most evacuation studies are homogeneous, i.e. car evacuation, while mass transit evacuation has not received much attention. In heterogeneous VRP, only two modes of buses and private cars are considered, which are different only in capacity [8]. However, in emergency rescue, due to the existence of special groups, special vehicles are also required, and the types of individuals accommodated by vehicles may be incompatible. For example, in the 2008 earthquake in Wenchuan, China, in addition to ordinary vehicles, there were also special vehicles such as medical ambulances to transport special individuals.

Perkins *et al.* [37] addressed the problem of evacuating the crowd by public transportation in toxic gas leakage scenario based on the simulation model. It assumed that buses left from

the depot and each pick-up location needed to be assigned only one bus. The objective is to minimize the total travel time of all buses. However, this model is only suitable for emergency evacuation of smaller scale.

Sayyady and Eksioglu [38] established a mixed integer programming model for dynamic bus evacuation with the objective of minimizing the total evacuation time when there was only one shelter. They allocated buses according to the total number of evacuees at pick-up locations and presented Tabu Search algorithm to solve this problem.

He *et al.* [39] also aimed at minimizing the total evacuation time and proposed a random evacuation route model for public transportation applied in natural disasters. Besides, they developed a hybrid algorithm based on genetic algorithm, artificial neural network algorithm and mountain climbing algorithm. Nevertheless, vehicles departing from the shelter will return to it.

Chan [40] formulated a bus route planning model between pick-up locations and shelters to maximize the number of evacuees within a specified time against evacuation problems in early warning events. Buses needed to shuttle evacuees multiple times.

Shen *et al.* [41] generated evacuation routes in advance in the planning stage for large-scale bioterrorism attack, allowing split delivery. Wang *et al.* [42] established a multi-objective nonlinear integer model, which was optimized by SDVRP for vehicle route selection in post-earthquake rescue operations.

It can be seen that many researches on VRP during evacuation process focus on classical VRP or one of its variants, while few consider multi-depot, heterogeneous fleet, and split delivery simultaneously. In disaster scenarios, transportation service process of vehicle evacuation is more complicated and the solution is more time-consuming, which brings great challenges to classical VRP. Thus, it is necessary to find suitable methods for tackling the practical problems faced by the government when evacuating individuals with different mobilities in residential areas during emergencies.

Firstly, the age of the individuals in each residential area covers a wide range, and individuals can be classified into two types: individuals with low mobility and individuals with high mobility. For individuals with low mobility, wheelchairs and volunteers are needed, which will generate additional costs. Therefore, we divide vehicles into three types according to different service objects. The first type are conventional vehicles, which only transport individuals with high mobility, such as adults, teenagers, etc. The second are vehicles that only transport individuals with low mobility. The third can transport both kinds of individuals above at the same time.

Secondly, each residential area may be served by multiple types of vehicles, and each vehicle may serve multiple residential areas. Since the number of individuals in most residential areas is greater than the capacity of a single vehicle and the loads of the first and second types of vehicles are incompatible, each residential area needs multiple vehicles. These vehicles include not only those that depart from the

parking lot and will directly serve this residential area, but also those that have already served other residential areas and will continue to serve it. In other words, the demand can be split. Moreover, it is difficult to determine the distribution proportion of various types of vehicles, the order of service, and the distribution of vehicle load in residential areas. All these decisions need to be made by the new vehicle routing model.

Then, we need multiple parking lots to provide service. Because emergencies always bring tremendous damage to residents in a large area, it is obviously unrealistic and inefficient to rely on vehicles in a parking lot for rescue and evacuation. Besides, there should exist more than one shelter. Vehicles pick up individuals in each residential area and take them to shelters. However, residential areas are not usually clustered together, but relatively scattered. Multiple shelters can meet the demands of several residential areas simultaneously and more reasonably.

In conclusion, for a set of known residential areas during the rescue process, reasonable planning of vehicle routes can not only save costs, but also improve evacuation efficiency and reduce casualties. These are all important issues that the government is concerned about. Therefore, based on the above characteristics, we propose a multi-parking lot and shelter heterogeneous vehicle routing problem with split pickup (MPSHVRPSP) model.

Figure 1 illustrates a simple example of one MPSHVRPSP instance. It involves two parking lots (P1 and P2), five residential areas (R1-R5) and two shelters (S1 and S2). All vehicles depart from parking lots and arrive at shelters eventually. During this period, vehicles go to residential areas to pick up persons. In order to complete the evacuation reasonably and efficiently, each residential area may be served not only by vehicles departing from the parking lot and aiming directly at it, but also by vehicles that have served other residential areas, such as R2 and R3. Moreover, there may be more than one type of vehicles visiting a residential area.

There are three differences between the variants of VRP and MPSHVRPSP.

(i) In VRPSD, all demands of each customer can be satisfied with one type of vehicles, while in MPSHVRPSP, there are two types of individuals and the number of individuals with high mobility far exceeds that with low mobility. The number of individuals with high mobility in most residential areas is much more than the capacity of the third type of vehicles. Therefore, if we use this type of vehicles to evacuate all individuals, when all individuals with high mobility are evacuated, total capacities of vehicles to accommodate individuals with low mobility will be much larger than the number of these individuals. This will cause a massive waste of wheelchair and volunteer resources and generate a lot of unnecessary costs. In other words, the load factors of vehicles are reduced, and evacuation cost is greatly increased. For the second and third types of vehicles, although they can transport individuals with low mobility, their capacity to accommodate them is different, while the cost is proportional

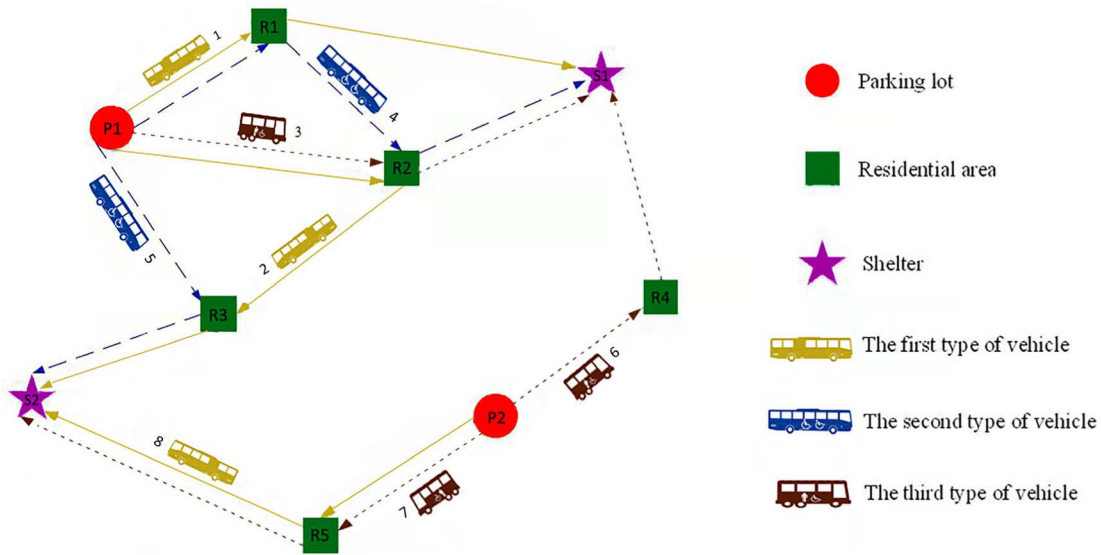


FIGURE 1. An illustrate example of MPSHVRPSP.

to the maximum capacity of vehicle for holding individuals with low mobility. Besides, the number of individuals with low mobility varies in different residential areas. Therefore, in MPSHVRPSP, it is necessary to use three types of vehicles instead of one to meet all demands of residential areas.

(ii) In VRPSD, demands of customers can be split arbitrarily, but only integer splits can be performed in MPSHVRPSP, which is consistent with the actual evacuation operation.

(iii) In HFVRP, vehicles differ only in capacity and cost, while in MPSHVRPSP, the types of individuals accommodated in the vehicle are also different.

One of the main contributions of this paper is considering the factor of individual mobility in residential areas during evacuation. In other words, the age of the individuals in residential areas covers a wide range, hence their mobility is not completely the same, which can be classified into high mobility and low mobility. Special vehicles equipped with wheelchairs and volunteers are required for evacuation of individuals with low mobility. On the other hand, to solve the practical problems in evacuation process, an integer linear programming (ILP) model is established that simultaneously considers four situations: multi-parking lot, multi-shelter, heterogeneous fleet and split demand. Among a heterogeneous fleet, not only the capacities are different, but the types of individuals that some vehicles can accommodate are incompatible. The established model includes matching constraints of individuals and vehicles to satisfy demands of different types of individuals, and considers the selectivity of parking lots and shelters. To obtain high-quality solutions, we propose a Tabu Search algorithm with diversification strategy. Finally, all instances are solved to validate the reasonability and advantages of MPSHVRPSP and verify the effectiveness of the proposed algorithm. Moreover, we conduct the sensitivity analysis.

The paper is organized as follows. Section II defines the MPSHVRPSP and formulates an integer linear program model for it. A Tabu Search algorithm is proposed in Section III. Section IV presents numerical instances and the results obtained. Moreover, the corresponding analysis is carried out. Finally, conclusion and future directions are depicted in Section V.

II. PROBLEM DESCRIPTION AND MATHEMATICAL MODEL

A. PROBLEM DESCRIPTION

In emergencies, in order to shorten rescue time, maximize resources usage and save cost, it is particularly important to optimize route of vehicles during an evacuation. Due to the limited public resources of one country, if the cost of emergency rescue is too high, it will cause a heavy burden to the country's finance, which is detrimental to the long-term development of economy. Therefore, the government needs to make scientific and overall arrangements for the emergency rescue process, which will ensure the safety of people's lives and the success of the rescue, and will reduce the waste of public resources in the rescue process at the same time. In this paper, some characteristics are defined based on rescue scenarios, which makes assumptions of MPSHVRPSP reasonable.

The characteristics of MPSHVRPSP are as follows.

(i) On the evacuation network, there exist several parking lots and the number of vehicles in each parking lot is fixed. In order to facilitate unified dispatch and command, parking lots are specified as the initial locations of evacuation vehicles.

(ii) All the three types of vehicles in all parking lots can be dispatched once.

TABLE 1. Parameters.

Indices and set	
i, j, m, n	Index of a parking lot or a residential area or a shelter
V	Node set, $V = V^p \cup V^r \cup V^s$
V^p	Parking lot set
V^r	Residential area set
V^s	Shelter set
k	Index of a vehicle
K_1	The first type of vehicle set
K_2	The second type of vehicle set
K_3	The third type of vehicle set
Parameters	
c^t	Transportation cost per unit distance for vehicles
c^w	Cost of per wheelchair
c^v	Cost of per volunteer
d_{ij}	Distance of nodes i and j ($i, j \in V$), supposing $d_{ij} = d_{ji}$
L^p	The maximum capacity of the first type of vehicles
L^w	The maximum capacity of the second type of vehicles
L^p	The maximum capacity of holding individuals with high mobility of the third type of vehicles
$L^{w'}$	The maximum capacity of holding individuals with low mobility of the third type of vehicles
h_j	Total number of individuals at residential area j ($j \in V^c$)
h'_j	The number of individuals with low mobility at residential area j ($j \in V^c$)

(iii) In order to improve evacuation efficiency, it is assumed that each individual with low mobility needs to be served by a wheelchair and a volunteer, which are provided in the second and third types of vehicles, as mentioned in the Introduction.

(iv) The wheelchair is large and occupies more space than one individual does. For each type of vehicles, it must hold no more individuals than its maximum capacity.

(v) In emergency rescue, it is expected that various resources can be utilized to the maximum extent and waste can be reduced. Therefore, after vehicles serve one residential area, they can also serve other residential areas.

(vi) Vehicles departing from the parking lot will eventually arrive at the shelter. There are also multiple shelters, and capacity limitation of the shelter is not considered.

The objective of MPSHVRPSP is to minimize the total cost, including the transportation cost of three types of vehicles and the cost of employing wheelchairs and volunteers.

B. MATHEMATICAL MODEL

In this section, a mathematical model for MPSHVRPSP is developed.

1) PARAMETERS AND DECISION VARIABLES

The parameters are defined in Table 1.

The decision variables are the following:

x_{ijk} : Equals 1 if the first type of vehicle k ($k \in K_1$), which only transports individuals with high mobility, moves from node i to adjacent node j ($i, j \in V, i \neq j$), and 0 otherwise.

y_{ijk} : Equals 1 if the second type of vehicle k ($k \in K_2$), which only transports individuals with low mobility, moves from node i to adjacent node j ($i, j \in V, i \neq j$), and 0 otherwise.

z_{ijk} : Equals 1 if the third type of vehicle k ($k \in K_3$), which can transport the above two kinds of individuals at the same time, moves from node i to adjacent node j ($i, j \in V, i \neq j$), and 0 otherwise.

SCH_{jmk} : The surplus capacity of the first type of vehicle k ($k \in K_1$) to continue to serve residential area m ($m \in V^c, m \neq j$) after serving residential area j ($j \in V^c$).

SCl_{jmk} : The surplus capacity of the second type of vehicle k ($k \in K_2$) to continue to serve residential area m ($m \in V^c, m \neq j$) after serving residential area j ($j \in V^c$).

$SCBH_{jmk}$: The surplus capacity of the third type of vehicle k ($k \in K_3$) to continue to serve individuals with high mobility at residential area m ($m \in V^c, m \neq j$) after serving residential area j ($j \in V^c$).

$SCBL_{jmk}$: The surplus capacity of the third type of vehicle k ($k \in K_3$) to continue to serve individuals with low mobility at residential area m ($m \in V^c, m \neq j$) after serving residential area j ($j \in V^c$).

2) THE OBJECTIVE FUNCTION

The formulation is given by Equation (1).

$$\begin{aligned} \min \sum_{i \in V} \sum_{j \in V} \sum_{k \in K_1} c^t d_{ij} x_{ijk} &+ \sum_{i \in V} \sum_{j \in V} \sum_{k \in K_2} c^t d_{ij} y_{ijk} \\ &+ \sum_{i \in V} \sum_{j \in V} \sum_{k \in K_3} c^t d_{ij} z_{ijk} \\ &+ \sum_{i \in V^p} \sum_{j \in V^r} \sum_{k \in K_2} (c^w + c^p) L^w y_{ijk} \\ &+ \sum_{i \in V^p} \sum_{j \in V^r} \sum_{k \in K_3} (c^w + c^p) L^{w'} z_{ijk} \end{aligned} \quad (1)$$

The objective is to minimize the total cost. As shown above, function (1) includes five parts. The first three parts denote the transportation cost of the three types of vehicles. For the second and third types of vehicles, when determining the used type, additional costs generated are also determined, and they are independent of the vehicles' actual capacity. Therefore, we call this additional cost "fixed cost". The fourth and fifth parts denote the fixed cost using the second and third types of vehicles respectively.

3) CONSTRAINTS ON DEMANDS OF EACH RESIDENTIAL AREA AND VEHICLE CAPACITY

$$\begin{aligned} \sum_{i \in V^p} \sum_{k \in K_1} L^p x_{ijk} &+ \sum_{i \in V^p} \sum_{k \in K_3} L^p z_{ijk} + \sum_{m \in V^r, m \neq j} \sum_{k \in K_1} SCH_{mjk} \\ &+ \sum_{m \in V^r, m \neq j} \sum_{k \in K_3} SCBH_{mjk} \\ &- \sum_{n \in V^r, n \neq j} \sum_{k \in K_1} SCH_{jnk} \\ &- \sum_{n \in V^r, n \neq j} \sum_{k \in K_3} SCBL_{jnk} \geq h_j - h'_j, \quad \forall j \in V^r \end{aligned} \quad (2)$$

$$\begin{aligned} & \sum_{i \in V^p} \sum_{k \in K_2} L^W y_{ijk} + \sum_{i \in V^p} \sum_{k \in K_3} L^{W'} z_{ijk} + \sum_{m \in V^r, m \neq j} \sum_{k \in K_2} SCL_{mjk} \\ & + \sum_{m \in V^r, m \neq j} \sum_{k \in K_3} SCBL_{mjk} \\ & - \sum_{n \in V^r, n \neq j} \sum_{k \in K_2} SCL_{jnk} \\ & - \sum_{n \in V^r, n \neq j} \sum_{k \in K_3} SCBL_{jnk} \geq h'_j, \quad \forall j \in V^r \end{aligned} \quad (3)$$

$$SCH_{jmk} \leq L^P x_{jmk}, \quad \forall j \in V^r, m \in V^r, m \neq j, k \in K_1 \quad (4)$$

$$SCL_{jmk} \leq L^W y_{jmk}, \quad \forall j \in V^r, m \in V^r, m \neq j, k \in K_2 \quad (5)$$

$$SCBH_{jmk} \leq L^P z_{jmk}, \quad \forall j \in V^r, m \in V^r, m \neq j, k \in K_3 \quad (6)$$

$$SCBL_{jmk} \leq L^{W'} z_{jmk}, \quad \forall j \in V^r, m \in V^r, m \neq j, k \in K_3 \quad (7)$$

Constraints (2) and (3) indicate that the total capacity of all vehicles arriving at each residential area cannot be less than the total number of individuals in this area. It is thus guaranteed that all individuals at each residential area can be evacuated. Constraints (4) - (7) ensure all vehicles capacity feasibility. After serving residential area j , the surplus capacity of each vehicle to continue to serve residential area m does not exceed its maximum capacity.

4) CONSTRAINTS ON VEHICLE-VISITING NODES

$$\sum_{i \in V^p \cup V^r} x_{ijk} = \sum_{m \in V^r \cup V^s} x_{jmk}, \quad \forall j \in V^r, k \in K_1 \quad (8)$$

$$\sum_{i \in V^p \cup V^r} y_{ijk} = \sum_{m \in V^r \cup V^s} y_{jmk}, \quad \forall j \in V^r, k \in K_2 \quad (9)$$

$$\sum_{i \in V^p \cup V^r} z_{ijk} = \sum_{m \in V^r \cup V^s} z_{jmk}, \quad \forall j \in V^r, k \in K_3 \quad (10)$$

$$\sum_{j \in V^r} \sum_{m \in V^r, m \neq j} x_{jmk} \leq 1, \quad \forall k \in K_1 \quad (11)$$

$$\sum_{j \in V^r} \sum_{m \in V^r, m \neq j} y_{jmk} \leq 1, \quad \forall k \in K_2 \quad (12)$$

$$\sum_{j \in V^r} \sum_{m \in V^r, m \neq j} z_{jmk} \leq 1, \quad \forall k \in K_3 \quad (13)$$

Constraints (8) - (10) ensure the equal numbers of the incoming and outgoing vehicles at each residential area. After arriving at a residential area to pick up individuals, vehicles cannot stop there but must continue to set out and complete the evacuation. Constraints (11) - (13) indicate that one vehicle can be allowed to serve two residential areas at most. In emergency rescue, drivers must always drive carefully to ensure the safety of individuals, that is, they are in a state of high physical and mental tension. After serving a certain number of residential areas, the executive ability of drivers begins to decline due to instinctive anxiety, fear and physical and mental exhaustion. Even traffic accidents such as rear-end collisions may occur because of improper driving. This not only makes drivers fail to complete rescue tasks safely and timely, but may also causes secondary injuries to individuals. On the other hand, for some special vehicles, such as medical

ambulances, the number of residential areas they serve is also limited owing to requirements such as regular disinfection. Accordingly, each vehicle is allowed to visit two residential areas at most.

5) CONSTRAINTS ON ROUTE INTEGRITY

$$\sum_{i \in V^p} \sum_{j \in V^r} x_{ijk} = \sum_{j \in V^r} \sum_{m \in V^s} x_{jmk}, \quad \forall k \in K_1 \quad (14)$$

$$\sum_{i \in V^p} \sum_{j \in V^r} y_{ijk} = \sum_{j \in V^r} \sum_{m \in V^s} y_{jmk}, \quad \forall k \in K_2 \quad (15)$$

$$\sum_{i \in V^p} \sum_{j \in V^r} z_{ijk} = \sum_{j \in V^r} \sum_{m \in V^s} z_{jmk}, \quad \forall k \in K_3 \quad (16)$$

$$\sum_{i \in V^p} \sum_{j \in V^r} x_{ijk} \leq 1, \quad \forall k \in K_1 \quad (17)$$

$$\sum_{i \in V^p} \sum_{j \in V^r} y_{ijk} \leq 1, \quad \forall k \in K_2 \quad (18)$$

$$\sum_{i \in V^p} \sum_{j \in V^r} z_{ijk} \leq 1, \quad \forall k \in K_3 \quad (19)$$

Constraints (14) - (16) confirm that vehicles leaving parking lot must arrive at shelter, which ensures the safety of all individuals. Constraints (17) - (19) indicate that each vehicle leaves parking lot at most once. In disaster scenarios, all individuals hope to be rescued as soon as possible. Therefore, none of the vehicles should be reused, which keeps individuals in residential areas from waiting.

6) MODEL COMPLEXITY

a: VARIABLES

In our proposed model, the numbers of variables x_{ijk} , y_{ijk} , z_{ijk} are $i^*j^*k_1$, $i^*j^*k_2$, and $i^*j^*k_3$ respectively. The numbers of variables SCH_{jmk} , SCL_{jmk} , $SCBH_{jmk}$, $SCBL_{jmk}$ are $j^*m^*k_1$, $j^*m^*k_2$, $j^*m^*k_3$, and $j^*m^*k_3$ respectively. Thus, the total number of variables is $i^*j^*k_1 + i^*j^*k_2 + i^*j^*k_3 + j^*m^*k_1 + j^*m^*k_2 + 2j^*m^*k_3 = i^*j^*(k_1 + k_2 + k_3) + j^*m^*(k_1 + k_2 + 2k_3)$.

b: CONSTRAINTS

In the proposed model, the numbers of constraints (2) and (3) are all j' . The numbers of constraints (4) - (7) are $j^*(m-1)^*k_1$, $j^*(m-1)^*k_2$, $j^*(m-1)^*k_3$, and $j^*(m-1)^*k_3$ respectively. The numbers of constraints (8) - (10) are j^*k_1 , j^*k_2 , and j^*k_3 respectively. The numbers of constraints (11) - (13) are k_1 , k_2 , and k_3 respectively. The numbers of constraints (14) - (16) are k_1 , k_2 , and k_3 respectively. The numbers of constraints (17) - (19) are also k_1 , k_2 , and k_3 respectively. Thus, the total number of constraints is $j' * (m - 1) * (k_1 + k_2 + 2k_3) + j' * (k_1 + k_2 + k_3) + 3(k_1 + k_2 + k_3) = j' * (m - 1) * (k_1 + k_2 + 2k_3) + (j' + 3) * (k_1 + k_2 + k_3)$.

MPSHVRPSP is an integer programming model from the model construction perspective, because all decision variables are of integer types. It simultaneously considers multiple parking lots and shelters as well as heterogeneous fleet and split demand. Besides, the origin and destination of

evacuation vehicles are different. Obviously, compared with classical VRP, the modeling of MPSHVRPSP is more difficult. Therefore, as classical VRP is known as NP-hard, MPSHVRPSP can also be referred to as NP-hard. And we propose a heuristic procedure - TS algorithm to solve it. For small-size instances, CPLEX 12.6 and TS are used to solve the problem, because CPLEX 12.6 can obtain exact solutions, both proving the validity of the model and verifying the effectiveness of the algorithm. For large-size instances, CPLEX 12.6 is rarely used to get exact solutions in practical applications, whereas heuristic algorithm can obtain satisfactory solutions in a shorter time. Therefore, we use TS to obtain solutions for large-size instances.

III. TABU SEARCH ALGORITHM

In order to solve the mathematical model, we employ a meta-heuristic procedure-Tabu Search (TS) algorithm. This method shows superiority in solving large-size and complex problems, obtains high quality solutions, and is widely used in practice [43], [44].

A. INITIAL SOLUTION

The initial solution is generated randomly and we prefer to give TS more opportunities to further improve the quality of the solution. In the traditional neighborhood movement, there is a basic assumption that the moving objects are customers, while the operator object of MPSHVRPSP is jointly determined by vehicles and customers (i.e. residential areas). This is because there are multiple parking lots and various vehicle types. Which type of vehicles is used? From which parking lot they depart? Which residential area is served? These are important issues we focus on in model solving, and they have a great impact on the results of objective function. Thus, it cannot reflect the characteristics of MPSHVRPSP to simply use customers as the operator object without considering vehicles. Considering the above situation, we propose a method to generate the initial solution.

Firstly, priority encoding and decoding are carried out for residential areas and vehicles in all parking lots.

1) INDIVIDUAL INITIALIZATION AND ENCODING

Individual dimension is calculated by:

$$Dim = 2 \times num_N \times \sum_P \sum_C num_V_{PC}$$

Here, num_N denotes the number of residential areas, P is the set of parking lots, C is the set of vehicle types, and num_V_{PC} denotes the number of C -type vehicles in parking lot P . The first $num_N \times \sum_P \sum_C num_V_{PC}$ items are residential area selection variables, adopting priority encoding. The upper limit of the individual value is 1 and the lower limit is 0. We define priority as the distance between the node where the vehicle is located and the residential area it serves multiplied by the individual value. The smaller the priority is, the more likely a vehicle is to choose to serve the

residential area. The last $num_N \times \sum_P \sum_C num_V_{PC}$ items are decision variables of vehicle surplus capacity, which indicate the ability of different vehicles to continue to serve other residential areas after serving one. The upper limit is the vehicle's maximum capacity and the lower limit is 0.

Furthermore, a random matrix with a size of $num_P * Dim$ is generated, where each row represents an individual and each column represents a dimension of the individual.

2) DECODING

First, we should judge whether each residential area and vehicle satisfy relevant constraints. If not, the distance is set to infinity, and the corresponding priority becomes infinity, which indicates that it cannot be selected. If all relevant constraints are satisfied, the priority is the distance between the nodes where the vehicle is located and the residential area multiplied by the individual value. If there are multiple residential areas that satisfy the conditions of vehicle service, the one that corresponds to the minimum priority value is selected as the object of the vehicle service. This is described in Algorithm 1.

Then, all vehicles select shelters based on the shortest distance. Finally, one initial solution is formed.

Algorithm 1

Decoding:

```

while (Demand not met):
  For ( all Vehicle):
    if (satisfy relevant constraints)
      P=D*X; % Calculate priority. P: Priority; D: Distance;
      X: Individual value
      Node=Choose min(P);
    end
  end
end
end

```

B. NEIGHBORHOOD STRUCTURE

Tabu Search is based on the current solution and generates a new one through neighborhood movement. There exist three types of neighborhood structures in our implementation: Swap, Rearrangement and Shift, which are randomly selected with a certain probability.

1) SWAP

Randomly select two elements a and b in a solution and swap them to form a new one, as illustrated in Figure 2.

2) REARRANGEMENT

In a solution, randomly select N ($2 \leq N \leq$ code length) elements. Rearrange them and produce a new solution, which is indicated by Figure 3.

3) SHIFT

Generate a 0-1 random number matrix of the same size as solution 1. Meanwhile, randomly select another solution 2

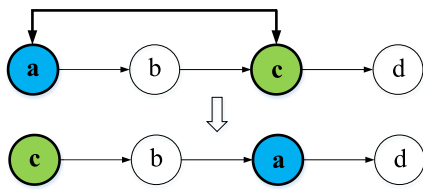


FIGURE 2. Swap.

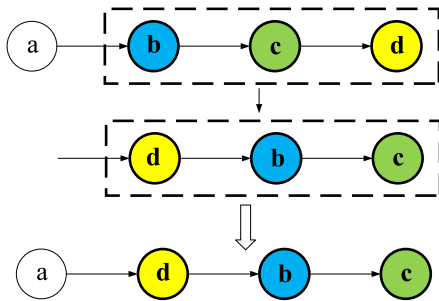


FIGURE 3. Rearrangement.

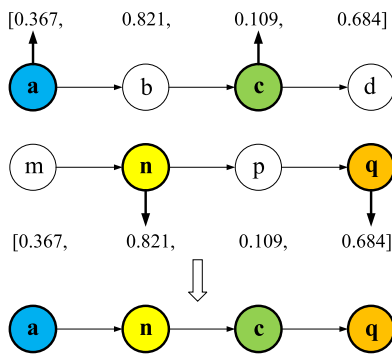


FIGURE 4. Shift.

with the same size. We make solution 1 as a substitute for elements less than or equal to 0.5 in this matrix, and solution 2 as a substitute for elements greater than 0.5, as shown in Figure 4.

C. TABU LIST

As the most commonly used short-term table, tabu list records the local optimal solution that has been searched with a fixed tabu tenure θ to prevent the search from looping, thus achieving global optimization. That is, in the current iteration (iter), if one solution is set to a tabu state, then until iteration $iter + \theta$ this state can be invalidated.

D. ASPIRATION CRITERION

Aspiration criterion is a moderate relaxation for tabu list. Since tabu status is extremely strict and blocks good moves, no better solutions can be found. Thus, when a tabu move obtains a better solution than the known optimal solution, the algorithm should accept this move without the restriction of tabu list.

E. DIVERSIFICATION STRATEGY

Diversification strategy broadens the search area and covers the whole solution space more widely. When multiple iterations are carried out and the known optimal solution remains unchanged, which is called search stagnation, we implement diversification search. It can be seen from MPSHVRPSP model that the total cost is closely related to distances traveled by vehicles. When the total traveling distance of vehicles is the shortest, the total cost is also the minimum. However, in the process of initial solution generation and neighborhood movement, it is impossible to minimize the total traveling distance of vehicles. This is because it includes three parts, the first part is the distance from parking lots to residential areas, the second part is the distance between residential areas, and the third part is the distance from residential areas to shelters. At present, we can only determine that vehicles go to the nearest shelter after serving residential areas, that is, the third part of the total traveling distance is minimized. The minimization of first and second parts cannot be guaranteed. Thus, the goal of diversification strategy is to minimize the total traveling distance of vehicles. After several iterations, most of solutions are replaced and the original objective is resumed until stagnation occurs again.

F. STOPPING CRITERION

After the specified maximum number of iterations, the search is terminated, and the solution obtained is the best.

IV. COMPUTATIONAL EXPERIMENTS

In this section, test instances for computational research are introduced firstly. Next, we validate the developed model and verify the effectiveness and applicability of TS. Then, MPSHVRPSP and variants of VRP are compared to prove the rationality and superiority of the developed model. We also examine the influence of diversification strategy on solution quality. Finally, sensitivity analysis is conducted on factors that may affect the total cost. For small-size instances, we use CPLEX 12.6 to solve the mathematical model. All experiments are performed on a Windows 10 computer configured with an Inter(R) Core(TM) i7-8550U CPU1.99Ghz and16.0GB RAM. TS algorithm is coded in MATLAB R2021a.

A. TEST INSTANCES

Since there are no instances directly applicable to the MPSHVRPSP, we select some test instances from the standard Cordeau p01 (<https://neo.lcc.uma.es/vrp/vrp-instances/>) and convert them to fit complex scenarios. Cordeau p01 instance has four depots, and the maximum load of a vehicle is 80. Each customer has a demand. In order to accommodate instances to MPSHVRPSP, we assume that depots and customers correspond to parking lots and residential areas respectively. The number of individuals with low mobility in each residential area equals the demand of each customer, which accounts for one-tenth of the total individuals.

TABLE 2. Four locations for shelters.

shelter	X coordinate	Y coordinate
1	10	30
2	40	50
3	60	60
4	70	40

TABLE 3. Value of model parameters.

Parameter	Value (unit)	Parameter	Value (unit)
c^f	0.82 (Chinese Yuan per km)	L^w	20 (person)
c^w	10 (Chinese Yuan)	$L^{p'}$	40 (person)
c^p	15 (Chinese Yuan)	$L^{w'}$	10 (person)
L^p	80 (person)		

Moreover, we randomly generate four locations for shelters, as presented in Table 2.

Each instance is denoted by d-c-s, where d, c and s indicate the number of parking lots, residential areas and shelters, respectively. For small-size instances, $d = s = 2, 3$, or 4 , and $c = 6, 7, \dots, 10, 15, 20$. For large-size instances, $d = s = 2, 3$, or 4 , and $c = 21, 22, \dots, 25$. Thus, we perform experiments with a total of 21 small-size instances and 15 large-size instances. Parameters involved in MPSHVRPSP formulation are listed in Table 3. Among them, the value of parameter c^f is set to 0.82 (Chinese Yuan per km) because fuel consumption of vehicles is about 0.15 liter/km and oil cost is about \$0.83 per liter [45]. The exchange rate between the dollar and the RMB is approximately 6.58.

Furthermore, we assume that each wheelchair occupies the space of three individuals. If the maximum capacity of the first type of vehicle is y , the maximum capacity of the second type of vehicle is x , the maximum capacity of the third type of vehicle to accommodate individuals with low mobility is m , and the maximum capacity to accommodate individuals with high mobility is n , then $4x = y$, $4m + n = y$. The first type of vehicles can accommodate 80 individuals, we thus work out that the second type of vehicles has a maximum capacity of 20. For the third type of vehicle, we suppose that the maximum capacity for individuals with high mobility is half of the maximum capacity of the first type of vehicle, i.e. 40. Then, the maximum capacity for individuals with low mobility is 10.

For simplicity, it is assumed that parking lots are homogeneous, which means that they accommodate the same number of vehicles. The number of each type of vehicle in each parking lot is also the same. For each instance, the number of vehicles is only determined by the number of individuals in residential areas. It is assumed that vehicles in a single parking lot are sufficient to satisfy all the needs of a residential area. If the number of each type of vehicles in each parking lot is a , then the capacity of vehicles that can accommodate individuals with low mobility is $30a$, and that can accommodate

TABLE 4. Value of a.

c	6	7	8	9	10	15	20	21	22	23	24	25
a	8	9	11	12	12	20	27	28	28	29	30	32

individuals with high mobility is $120a$. If the number of individuals with low mobility in all residential areas is b , then the number of individuals with high mobility is $9b$. In this case, the number of vehicles in each parking lot must satisfy the following conditions: $120a \geq 9b$, $30a \geq b$. Therefore, as long as individuals with high mobility in residential areas are evacuated, all the individuals in residential areas can be guaranteed to be evacuated. To sum up, for instances with different residential areas, the number of each type of vehicles in each parking lot is shown in Table 4. The total number of each type of vehicles is the number of parking lots multiplied by the number of each type of vehicles in each parking lot, i.e. $K_1 = K_2 = K_3 = d \cdot a$.

B. PARAMETER TUNING

In the TS algorithm, there are six main parameters: δ , number of candidate solutions; θ , tabu tenure; λ , number of consecutive iterations without improvement to implement diversification search; p , selection probability of three neighborhood structures; ω , number of iterations in diversification search; and T_{max} , the maximum number of iterations.

Parameters in heuristic algorithm directly affect the performance of the algorithm. Therefore, finding the proper parameter value is critical. We set the values of five parameters equal to a function of V^r [44], [46].

$$\begin{aligned} \delta &= 3V^r/2, 2V^r, 5V^r/2, 3V^r \\ \theta &= V^r/3, V^r/2, V^r, 3V^r/2 \\ \lambda &= V^r, 2V^r, 5V^r/2 \\ \omega &= V^r/5, V^r/3, V^r/2, V^r \\ T_{max} &= 15V^r, 20V^r, 25V^r \end{aligned}$$

Since the three types of neighborhood structure are randomly selected, for fairness, we stipulate that they are all selected with a probability of $1/3$, i.e. $p = 1/3$.

Accordingly, there are a total of $4 \times 4 \times 3 \times 4 \times 3 \times 1 = 576$ parameter combinations. We select 4 out of 21 small-size instances: 3-6-3, 3-10-3, 3-15-3, and 3-20-3. Each instance is run 10 times with each parameter combination, and the gaps between them and the exact solution are compared. Then, the average value of ten gaps is found. We find that the average gap value is the smallest when the parameter values are as follows: $\delta = 3V^r$, $\theta = V^r$, $\lambda = V^r$, $\omega = V^r/2$, $T_{max} = 15V^r$.

Table 5 reports how the objective value of the proposed model evolves when one parameter changes and other parameters are fixed at their optimal value. Thus, we have $4 + 4 + 3 + 4 + 3 = 18$ parameter combinations in total. For

TABLE 5. Parameter tuning.

Parameter					
δ	$3V^r/2$	$2V^r$	$5V^r/2$	$3V^r$	
	0.1610	0.1427	0.2051	0.1360	
θ	$V^r/3$	$V^r/2$	V^r	$3V^r/2$	
	0.1652	0.1327	0.1311	0.1369	
λ	V^r	$2V^r$	$5V^r/2$		
	0.1196	0.2125	0.1353		
ω	$V^r/5$	$V^r/3$	$V^r/2$	V^r	
	0.1493	0.1136	0.1125	0.1943	
T_{max}	$15V^r$	$20V^r$	$25V^r$		
	0.1233	0.1995	0.1443		

each parameter combination, we run each instance 10 times to find the average gap between it and the exact solution. Then, the average gap of the four instances is calculated. Each entry corresponds to the average percentage gap of four instances. The selected parameter values are shown in bold, and their corresponding average gaps are also the smallest.

C. VALIDITY TEST OF MODEL AND TS

CPLEX 12.6 runs with the default system configuration to solve small-size instances until it finds the exact solution or automatically stops due to predetermined solution time or insufficient computer memory. The results of small-size instances are presented in Table 6. Column ‘‘Instance’’ provides the instance name. Column ‘‘Cost0’’ shows the exact solution of the objective value. Columns ‘‘k1’’, ‘‘k2’’ and ‘‘k3’’ show the number of the first, second and third types of vehicles in use respectively. Column ‘‘Cpu0 (s)’’ shows the computation time in seconds. Column ‘‘Gap0 (%)’’ reports the upper and lower bounds percentage deviation of results output by CPLEX 12.6, as defined by $Gap0 = (\text{upper bound} - \text{lower bound})/\text{upper bound} \times 100\%$.

Table 7 reports the results of TS algorithm. Similar to Table 6, columns ‘‘Instance’’, ‘‘k1’’, ‘‘k2’’ and ‘‘k3’’ provide the instance name, the number of three types of vehicles in use, respectively. Columns ‘‘Cost1’’ and ‘‘Cpu1 (s)’’ indicate TS results and computation time. Column ‘‘Gap1 (%)’’ indicates the gap in percentage between the exact solution solved by CPLEX 12.6 and the objective value obtained by TS, that is $Gap1 = (\text{Cost1} - \text{Cost0})/\text{Cost0} \times 100\%$.

The exact solutions of small-size instances reveal that mathematical model performs well. Of the 21 instances, the solving time of 14 instances reaches the full four-hour limit, indicating that CPLEX 12.6 does not apply to large-size instances. Although for these 14 instances, feasible solution can be obtained by CPLEX 12.6, where Gap0 is between 0.09% and 4.83%, the solving time is too long.

Table 7 shows that TS is effective in solving MPSHVRPSP. Compared with the exact method by CPLEX 12.6, TS can output the satisfactory solution in less time for all instances. From the objective value perspective, TS solution is very

TABLE 6. Exact results for small-size instances.

Instance/ d-c-s	CPLEX					
	Cost0	k1	k2	k3	Cpu0 (s)	Gap0 (%)
2-6-2	2974.76	9	2	6	1379.83	0.02
2-7-2	3623.24	10	2	8	6128.39	0.01
2-8-2	4232.69	11	2	10	363.66	0.03
2-9-2	4815.63	13	3	10	14400	0.25
2-10-2	4869.01	11	1	14	14400	2.02
2-15-2	7771.49	22	5	16	14400	1.35
2-20-2	10736.60	31	8	20	14400	2.41
3-6-3	2929.63	10	3	4	3058.09	0.03
3-7-3	3578.11	9	1	10	14400	1.75
3-8-3	4187.56	12	3	8	357.67	0.03
3-9-3	4732.65	12	2	12	14400	0.09
3-10-3	4772.84	12	2	12	14400	2.28
3-15-3	7683.82	21	4	18	14400	1.23
3-20-3	10527.90	24	1	34	14400	2.14
4-6-4	2867.41	9	2	6	1907.09	0.03
4-7-4	3515.89	9	1	10	14400	1.53
4-8-4	4125.34	11	2	10	462.45	0.03
4-9-4	4668.01	12	2	12	14400	4.83
4-10-4	4702.53	12	2	12	14400	2.35
4-15-4	7614.55	20	3	20	14400	1.17
4-20-4	10382.36	31	9	18	14400	2.16

TABLE 7. TS results for small-size instances.

Instance/ d-c-s	TS					
	Cost1	k1	k2	k3	Cpu1 (s)	Gap1 (%)
2-6-2	2992.14	7	0	10	105.56	0.58
2-7-2	3676.69	9	1	10	254.03	1.48
2-8-2	4326.39	9	0	14	302.31	2.21
2-9-2	4912.13	11	0	16	600.54	2.00
2-10-2	4990.48	11	0	16	933.68	2.49
2-15-2	8022.60	19	0	26	2231.97	3.23
2-20-2	11052.71	26	0	36	3865.44	2.94
3-6-3	2946.92	7	0	10	86.71	0.59
3-7-3	3624.52	8	0	12	150.02	1.30
3-8-3	4290.91	11	1	12	246.86	2.47
3-9-3	4816.34	11	0	16	658.71	1.77
3-10-3	4883.69	10	0	16	381.36	2.32
3-15-3	7951.98	20	1	24	2019.51	3.49
3-20-3	10778.13	27	1	34	4019.81	2.38
4-6-4	2925.94	7	0	10	82.11	2.04
4-7-4	3587.79	9	1	10	129.11	2.05
4-8-4	4235.79	10	0	14	320.25	2.68
4-9-4	4751.67	11	0	16	455.92	1.79
4-10-4	4826.23	11	0	16	462.50	2.63
4-15-4	7868.32	20	1	24	2456.95	3.33
4-20-4	10716.72	26	0	36	4123.48	3.22

close to the solution found by CPLEX 12.6. The minimum Gap1 is 0.58% and the maximum is 3.49%.

Table 8 provides the results of the load factors of heterogeneous vehicles. The columns ‘‘u1 (%)’’, ‘‘u2 (%)’’, ‘‘u3 (%)’’ and ‘‘u4 (%)’’ report load factors of vehicles capable of transporting individuals with high mobility (‘‘u1 (%)’’) and individuals with low mobility (‘‘u2 (%)’’) under exact solutions; and load factors of vehicles used to transport individuals with high mobility (‘‘u3 (%)’’) and individuals with low mobility (‘‘u4 (%)’’) under algorithm solutions, respectively. They are calculated by the equation below:

$$u(\%) = \frac{\text{Demand}}{\text{The load factor}} \times 100\% \tag{20}$$

TABLE 8. Load factors of vehicles for small-size instances.

Instance/ d-c-s	CPLEX		TS	
	u1 (%)	u2 (%)	u3 (%)	u4 (%)
2-6-2	91.88	98.00	91.88	98.00
2-7-2	94.02	97.50	94.02	97.50
2-8-2	98.44	100.00	98.44	100.00
2-9-2	94.38	94.38	89.41	94.38
2-10-2	97.50	97.50	92.37	97.50
2-15-2	96.75	99.23	90.70	99.23
2-20-2	97.13	98.33	90.51	98.33
3-6-3	91.88	98.00	91.88	98.00
3-7-3	94.02	97.50	94.02	97.50
3-8-3	98.44	100.00	92.65	100.00
3-9-3	94.38	94.38	89.41	94.38
3-10-3	97.50	97.50	97.50	97.50
3-15-3	96.75	99.23	90.70	99.23
3-20-3	97.13	98.33	90.51	98.33
4-6-4	91.88	98.00	91.88	98.00
4-7-4	94.02	97.50	94.02	97.50
4-8-4	98.44	100.00	92.65	100.00
4-9-4	94.38	94.38	89.41	94.38
4-10-4	97.50	97.50	92.37	97.50
4-15-4	96.75	99.23	90.70	99.23
4-20-4	99.56	98.33	90.51	98.33

We observe that load factors of vehicles used to transport individuals with low mobility are identical through the two methods, i.e., $u2(\%) = u4(\%)$. Moreover, all of them are high, and some even reach 100%. For vehicles used to transport individuals with high mobility, the lowest and highest load factors obtained by CPLEX 12.6 are 91.88% and 99.56% and by TS are 89.41% and 98.44%. Obviously, for different demands, vehicles are fully utilized, and almost no resources are wasted, which is rather important and instructive in reality.

D. PERFORMANCE ON THE MP SHVRPSP

To better judge advantages of the model developed in this paper, we compare the exact results obtained by it and various variants of classical VRP, as displayed in Tables 9-11. HVRP represents heterogeneous vehicle routing problem; HVRPSP represents heterogeneous VRP with split pickup; MP SHVRP represents multi-parking lot and shelter heterogeneous VRP. Column “Gap (%)” shows the percentage deviation between upper and lower bounds of results. Columns “Cost (%)” and “Distance (%)” show gaps between the current model and MP SHVRPSP (Instance 2-x-2) in total cost and traveling distance, as defined by

$$\text{Cost}(\%) = (\text{Cost} - \text{Cost}_0) / \text{Cost} \times 100\% \quad (21)$$

$$\text{Distance}(\%) = (\text{Dis} - \text{Dis}_0) / \text{Dis} \times 100\% \quad (22)$$

It's found that for VRP during evacuation process, if only considering the characteristic of heterogeneous fleet, the computation time of each instance is quite short, no more than 1s. However, both the total cost and traveling distance are

much higher than those of the model we proposed. As listed in Table 9, for HVRP, Cost (%) is between 24.47% and 29.84%, and Distance (%) is between 51.94% and 55.21%. If considering characteristics of heterogeneous fleet and split demand, the computation time of each instance is not reduced compared with our proposed model, while the gaps, both of the total cost and of vehicle traveling distance, are narrowing. As listed in Table 10, for HVRPSP, Cost (%) and Distance (%) are 13.16%-14.16% and 45.92%-50.84%, respectively. If multi-parking lot, multi-shelter and heterogeneous fleet are taken into account, both the gaps of the total cost and of vehicle traveling distance decrease, and the latter decreases by a larger margin. As listed in Table 11, for MP SHVRP, Cost (%) is between 13.02% and 19.16%, and Distance (%) is between 3.57% and 15.03%.

From the above results, it can be seen that the number of parking lots and shelters and whether the demand can be split will affect the total cost and traveling distance. The reason is mainly in two aspects.

On the one hand, the initial locations and destinations of evacuation vehicles serving each residential area are always selected from the existing sets of parking lots and shelters. When the range of available sets becomes larger on the original basis, vehicles have more options, and they are more possible to make a better choice. Concerning Table 4 again, we can also see that with the same number of residential areas, as parking lots and shelters increase, the total transportation cost decreases. For example, when the number of residential areas is 6, and the number of parking lots and shelters changes from 2 to 4, the total cost is 2974.76, 2929.63, and 2867.41 in turn. Figure 5 illustrates three examples, in which the number of parking lots and shelters is different, but the number of residential areas is the same. Residential areas, parking lots and shelters are numbered 1-6, 7-10, and 11-14 respectively. Contents in dashed boxes indicate the distance between two nodes. In Figures 5(a), 5(b), and 5(c), the distance between residential area 2 and the parking lot serving it is 21.02, 19.03, and 11.05 respectively, while the distance between residential area 2 and the shelter serving it is the same. The distance between residential area 3 and the parking lot serving it is 32.56, 32.56, and 16.12, respectively, and the distance between residential area 3 and the shelter serving it is 18.44, 8.94, and 8.94, respectively. Obviously, as the number of parking lots and shelters increases, the distance traveled by vehicles serving certain residential areas becomes shorter. Transportation cost, one part of the total cost, is positively correlated with the distance, so the total cost decreases. Currently, most classical VRP and its different variants have only one depot where vehicles will eventually return without any options. From results of the established model, within a certain area, selecting multiple parking lots and shelters simultaneously has greater advantages, especially in emergencies where rescue can be completed with higher efficiency.

On the other hand, when the demand cannot be split, each residential area can only be served directly by vehicles departing from the parking lot, which increases the total number

TABLE 9. Comparison between results from MPSHVRPSP and HVRP.

Instance/ d-c-s	HVRP							
	Cost	k1	k2	k3	Cpu (s)	Gap (%)	Cost (%)	Distance (%)
1-6-1	4044.85	10	3	6	0.05	0.00	26.46	54.56
1-7-1	4796.88	9	0	14	0.14	0.00	24.47	51.94
1-8-1	5881.82	17	6	5	0.17	0.00	28.04	55.10
1-9-1	6570.37	17	5	9	0.25	0.00	26.71	55.19
1-10-1	6940.08	16	3	14	0.30	0.00	29.84	55.21

TABLE 10. Comparison between results from MPSHVRPSP and HVRPSP.

Instance/ d-c-s	HVRPSP							
	Cost	k1	k2	k3	Cpu (s)	Gap (%)	Cost (%)	Distance (%)
1-6-1	3465.65	8	1	8	5028.73	0.04	14.16	50.84
1-7-1	4173.20	10	2	8	8516.38	0.08	13.18	46.88
1-8-1	4909.41	12	3	8	10565.22	0.12	13.78	48.01
1-9-1	5547.14	12	3	10	14400	0.36	13.19	47.28
1-10-1	5606.90	13	3	10	14400	2.12	13.16	45.92

TABLE 11. Comparison between results from MPSHVRPSP and MPSHVRP.

Instance/ d-c-s	MPSHVRP							
	Cost	k1	k2	k3	Cpu (s)	Gap (%)	Cost (%)	Distance (%)
2-6-2	3492.33	8	1	10	0.08	0.00	14.82	3.57
2-7-2	4165.64	9	0	14	0.23	0.00	13.02	6.37
2-8-2	5067.44	11	0	17	0.20	0.00	16.47	10.37
2-9-2	5675.42	14	2	15	0.41	0.00	15.15	11.86
2-10-2	6022.73	17	4	12	0.23	0.00	19.16	15.03

of vehicles required. Therefore, the total cost and traveling distance will increase. This is illustrated in a small example of Figure 6. In the evacuation network, there are two residential areas, one depot and one shelter. The number of individuals with high mobility and individuals with low mobility, as shown in parentheses, are separated by a comma. The figure beside each edge represents the corresponding traveling distance (transportation cost), and the distance (transportation cost) matrix satisfies the triangle inequality. Vehicles are classified into three types. The first type k1 only transports individuals with high mobility and the maximum capacity is 10. The second type k2 only transports individuals with low mobility, with a maximum capacity of 5 and a fixed cost of 5. The third type k3 can transport both individuals with high mobility and individuals with low mobility, and the corresponding maximum capacity is 6 and 2 respectively, with a fixed cost of 2.

If the demand cannot be split, the optimal solution is that one vehicle of k3 and two vehicles of k1 serve residential area 1; two vehicles of k1 and two vehicles of k3 serve residential area 2. The total cost (vehicle traveling distance) is 57, and the total number of vehicles used is 7. The paths are shown in Figure 7. If the demand can be split, the optimal solution is that one vehicle of k2 and two vehicles of k1 serve residential area 1; three vehicles of k1 and one

vehicle of k2 that has already served residential area 1 serve residential area 2. The total cost (vehicle traveling distance) is 51, and the total number of vehicles used is 6. The paths are shown in Figure 8. Obviously, when the demand can be split, vehicles are used more rationally. Thus, the total cost and vehicle traveling distance are reduced accordingly. In conclude, MPSHVRPSP is more reasonable for both the total cost and route planning.

Table 12 shows the empty-loading ratios of vehicles output by several models, which are calculated as

$$Ept(\%) = 100 - u(\%) \tag{23}$$

The columns “Ept1 (%)” and “Ept2 (%)” respectively report the empty-loading rates of vehicles capable of transporting individuals with high mobility and individuals with low mobility. We observe that empty-loading ratio is mainly related to whether the demand can be split, rather than the number of parking lots and shelters. Furthermore, when the demand cannot be split, it will greatly increase empty-loading ratio. This is because each vehicle can only serve one residential area at this situation, thus the total number of vehicles required to complete evacuation increases, and the total capacity of vehicles transporting individuals of each type of mobility increases. However, the demand of residential areas is determined. Thus, load factors of

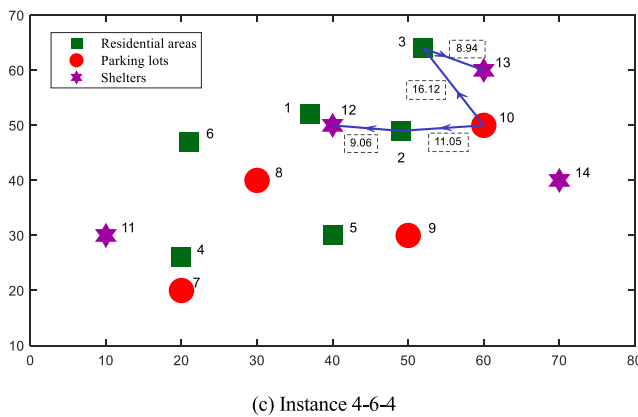
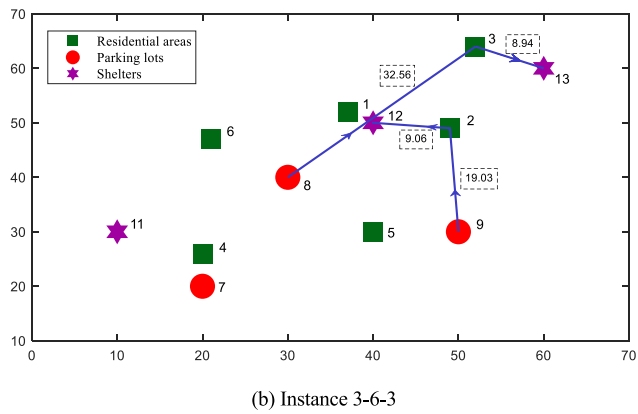
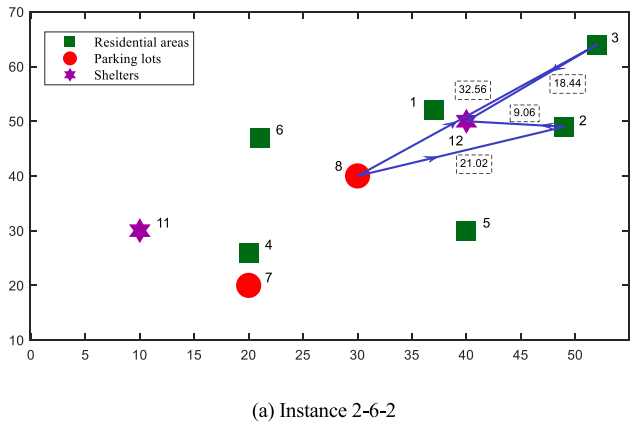


FIGURE 5. Three examples where the number of parking lots and shelters is different, and the number of residential areas is the same.

vehicles will decrease and empty-loading ratios of vehicles increase, resulting in a large waste of vehicle capacity. These imply that MPSHVRPSP possesses strong applicability. Therefore, in disaster scenarios, it is necessary for relevant departments to take joint action and mobilize the surrounding resources as much as possible, such as adequate parking lots, vehicles and shelters. At the same time, management must reasonably plan vehicle evacuation routes to ensure the reasonable and efficient implementation of rescue.

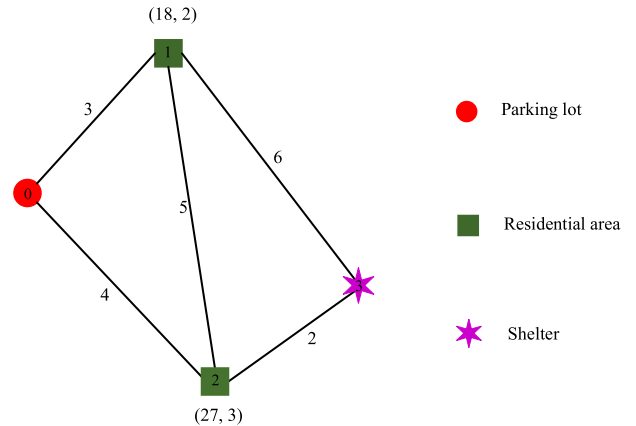


FIGURE 6. Residential area demand and the corresponding traveling distance (transportation cost) for a small example.

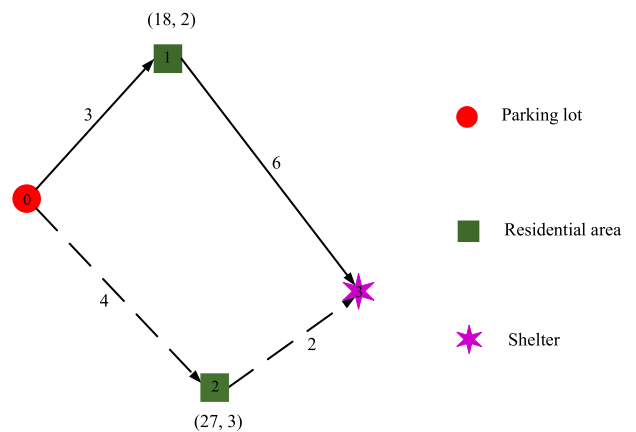


FIGURE 7. The optimal solution when the demand cannot be split.

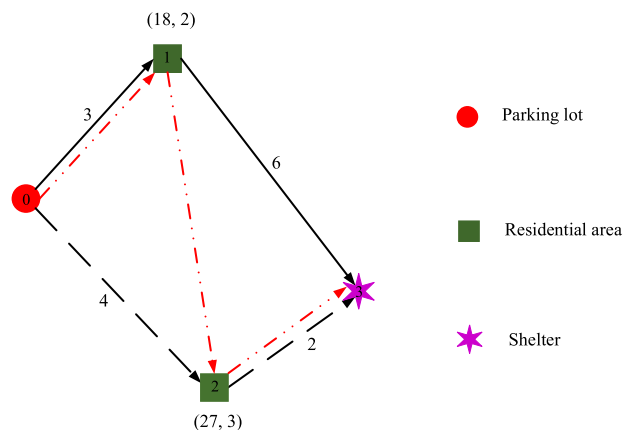


FIGURE 8. The optimal solution when the demand can be split.

E. APPLICATION OF TS IN LARGE-SIZE INSTANCES

We perform 10 runs for each large-size instance and observe that TS has good performance in solution quality and speed. In 10 runs, the best, worst and average results of the objective function obtained by TS are illustrated in Figure 9(a). Figure 9(b) shows the Gap2 and Gap3 between the best value,

TABLE 12. The empty-loading ratios of vehicles for various models.

Instance/ d-c-s	MPSHVRPSP		HVRP		HVRPSP		MPSHVRP	
	Ept1 (%)	Ept2 (%)	Ept1 (%)	Ept2 (%)	Ept1 (%)	Ept2 (%)	Ept1 (%)	Ept2 (%)
2-6-2	8.12	2.00	15.19	18.33	8.12	2.00	15.19	18.33
2-7-2	5.98	2.50	17.73	16.43	5.98	2.50	17.73	16.43
2-8-2	1.56	0.00	19.23	17.65	1.56	0.00	19.23	17.65
2-9-2	5.62	5.62	20.99	20.53	0.07	5.62	20.99	20.53
2-10-2	2.50	2.50	23.70	22.00	2.50	2.50	23.70	22.00

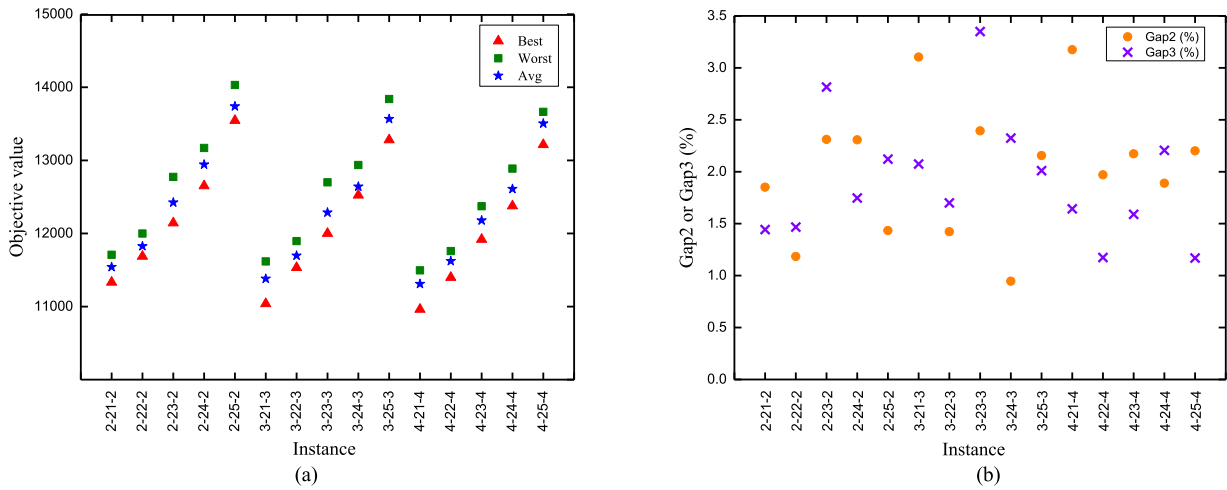


FIGURE 9. The best, worst and average value of the objective function obtained by TS in 10 runs.

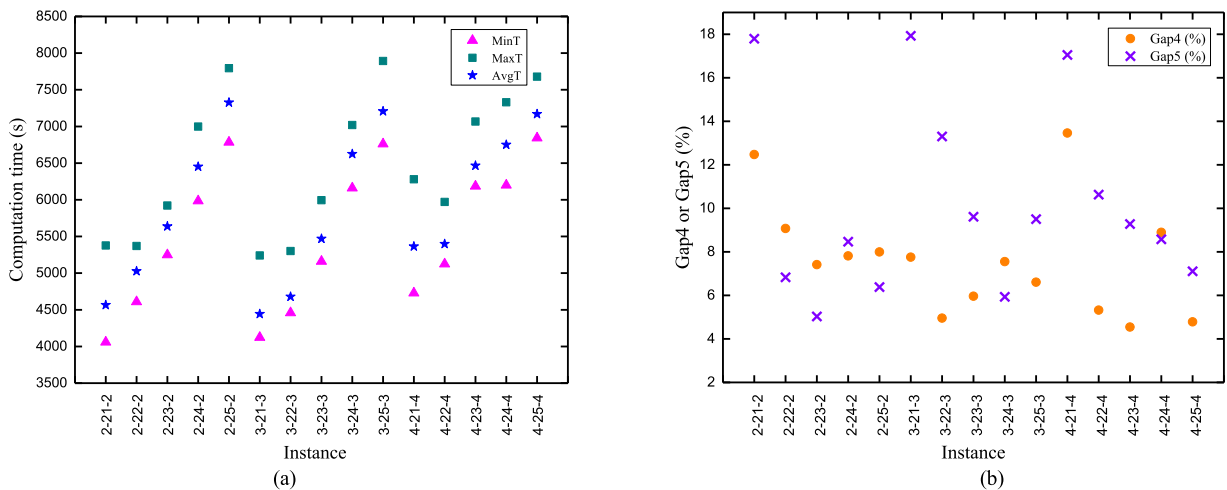


FIGURE 10. The longest, shortest, and average running times of TS in 10 runs.

the worst value and the average value, which are described as $(Avg-Best)/Best \times 100\%$ and $(Worst-Avg)/Avg \times 100\%$, respectively. Gap2 ranges from 0.95% to 3.17%, with an average of 2.03%. Gap3 ranges from 1.17% to 3.35%, with an average of 1.92%.

The longest, shortest, and average running time of TS in 10 runs is given in Figure 10(a). Figure 10(b) shows the Gap4 and Gap5 between the longest, shortest, and average running time, which are described as $(AvgT-MinT)/MinT \times 100\%$

and $(MaxT-AvgT)/AvgT \times 100\%$, respectively. Gap4 ranges from 4.54% to 13.46%, with an average of 7.29%. Gap5 ranges from 5.03% to 17.92%, with an average of 9.69%. These demonstrate that the TS is reliable and ensure the robustness of algorithm at the same time.

The best result of the objective function and load factors of vehicles in 10 runs are reported in Table 13. Column “Gap6 (%)” indicates the percentage gap between the initial solution and the best solution, i.e. Cost2, and

TABLE 13. TS results and the load factors of vehicles for large-size instances.

Instance/ d-c-s	The solution initial	Cost2	k1	k2	k3	Cpu2 (s)	Gap6 (%)	u5 (%)	u6 (%)
2-21-2	17513.32	11332.12	26	0	37	4263.49	35.29	91.52	97.84
2-22-2	16649.77	11687.74	29	1	36	4608.61	29.80	88.56	97.37
2-23-2	18516.09	12143.41	29	0	39	5576.25	34.42	89.54	98.97
2-24-2	19261.16	12652.15	31	2	37	6806.67	34.31	90.00	96.59
2-25-2	20446.32	13545.84	31	1	42	7160.43	33.75	91.73	96.36
3-21-3	16772.02	11038.54	27	1	35	4360.35	34.20	91.52	97.84
3-22-3	17932.81	11532.44	26	0	38	4536.79	35.69	92.50	97.37
3-23-3	18013.04	12000.02	28	1	38	5843.48	33.38	92.39	96.50
3-24-3	18631.79	12471.50	32	2	37	5959.19	33.06	88.22	96.59
3-25-3	20431.77	13280.35	31	1	42	7215.65	35.00	91.73	96.36
4-21-4	16596.57	10961.61	25	0	37	4881.73	33.95	93.62	97.84
4-22-4	17930.83	11397.90	28	1	36	5970.84	36.43	90.49	97.37
4-23-4	19036.12	11919.47	30	2	36	6283.24	37.39	90.47	96.50
4-24-4	18747.00	12376.05	30	2	37	6561.43	33.98	91.86	96.59
4-25-4	21057.37	13214.15	32	2	40	7031.99	37.25	91.73	96.36

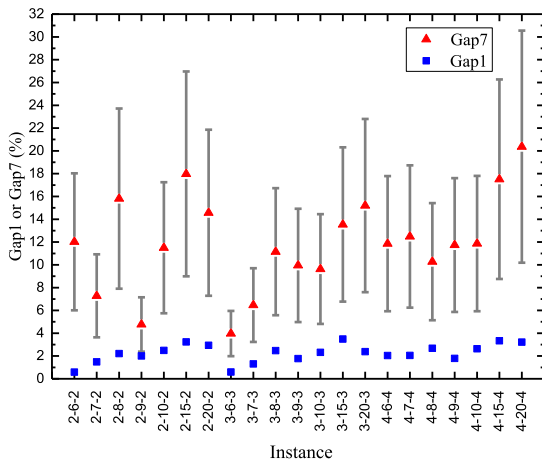
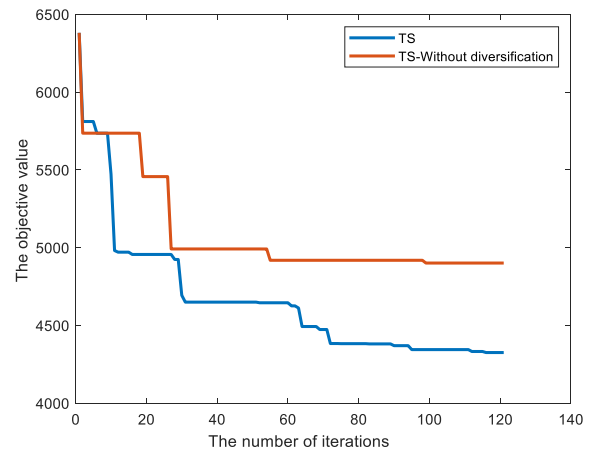


FIGURE 11. The gap between the TS algorithm and CPLEX 12.6.

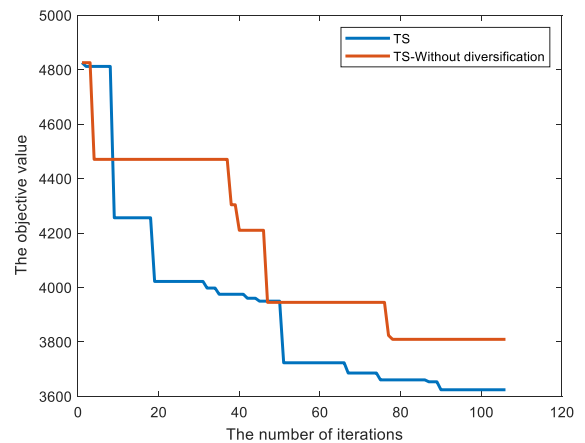
Gap6 (%) = (The initial solution – Cost2)/The initial solution × 100%. Columns “Cpu2 (s)”, “u5 (%)” and “u6 (%)” present the computation time, and the load factors of vehicles transporting individuals with high mobility and individuals with low mobility, respectively. We find that the proposed TS can solve large-size instances relatively quickly. Moreover, the minimum value of Gap6 is 29.80%, and the maximum is 37.39%, indicating that the TS is important and necessary. Of 15 large-size instances, the load factors of vehicles used to transport individuals with high mobility vary between 88.22% and 93.62%, and the load factors of vehicles used to transport individuals with low mobility vary between 96.36% and 98.97%. Although the scale of instances increases, the solution quality almost remains unaffected.

F. THE INFLUENCE OF DIVERSIFICATION STRATEGY ON RESULTS

Here, we investigate the impact of diversification strategy on results. TS-Without diversification results of small-size



(a) Instance 2-8-2



(b) Instance 3-7-3

FIGURE 12. Evolution of objective value.

instances are given in Table 14. Column “Gap7 (%)” provides the percentage deviation of column “Cost3” from those

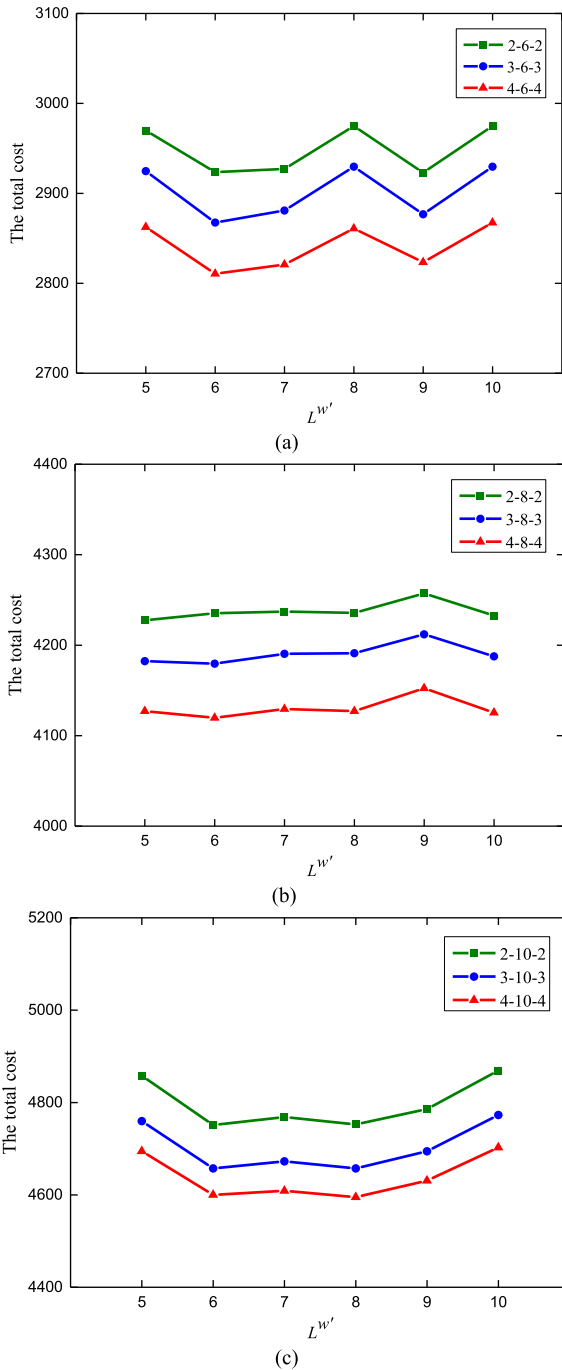


FIGURE 13. Illustration of the total cost for different $L^{w'}$.

of the optimal solutions, i.e. column “Cost0” in Table 4. Although all Cpu time required to solve small-size instances by TS-Without diversification is less than that of CPLEX 12.6, Gap7 (%) is larger than Gap1 (%). That is to say, diversification strategy improves the solution quality, greatly reducing the gap between the algorithm solution and the exact solution by more than half, as Figure 11 presents (the error bar is 50% of Gap7).

Figure 12 depicts the evolution of objective value on instances 2-8-2 and 3-7-3 when the proposed algorithm, i.e.

TABLE 14. TS-Without diversification results for small-size instances.

Instance/ d-c-s	TS-Without diversification					
	Cost3	k1	k2	k3	Cpu3 (s)	Gap7 (%)
2-6-2	3332.33	7	1	9	27.49	12.02
2-7-2	3887.13	11	0	12	57.80	7.28
2-8-2	4901.77	12	1	14	69.30	15.81
2-9-2	5045.40	13	0	16	117.07	4.77
2-10-2	5428.75	13	0	17	175.62	11.50
2-15-2	9168.76	21	2	26	316.41	17.98
2-20-2	12301.00	27	1	38	482.35	14.57
3-6-3	3046.06	8	0	10	20.73	3.97
3-7-3	3809.76	11	1	10	33.60	6.47
3-8-3	4654.63	12	2	11	54.18	11.15
3-9-3	5203.31	12	0	17	120.13	9.95
3-10-3	5232.63	11	0	17	68.34	9.63
3-15-3	8724.31	23	0	28	381.31	13.54
3-20-3	12128.34	27	3	34	451.86	15.20
4-6-4	3207.62	8	1	9	22.63	11.86
4-7-4	3955.08	9	1	11	29.76	12.49
4-8-4	4549.43	11	0	15	70.24	10.28
4-9-4	5216.16	13	1	15	86.72	11.74
4-10-4	5260.71	14	0	17	100.17	11.87
4-15-4	8948.06	21	1	27	413.22	17.51
4-20-4	12497.46	30	2	38	701.90	20.37

TS and TS-Without diversification are used, respectively. It can be seen that no matter how much diversification helps to improve the solution quality, it does not increase the solution’s decline speed at the initial stage of iteration. However, as the number of iterations increases, the descent rate and range of the solution obtained by TS is obviously higher than those of the solution obtained by TS-Without diversification. At the end of iteration, while approaching the algorithm termination condition, diversification has little effect on solution updating.

G. SENSITIVITY ANALYSIS

In emergency rescue, the maximum capacity of the third type of vehicles to accommodate individuals with different mobility may vary according to the number of individuals in each residential area, and this may lead to different total cost. If the capacity of the third type of vehicle is considered as a decision variable, not only the model will become harder to establish, the solution time will also increase greatly. In this experiment, we conduct sensitivity analysis by changing the number of low-mobility individuals that the third type of vehicles accommodates. Set $L^{w'}$ parameter to 5, 6, 7, 8, 9, and the corresponding L^p are 60, 56, 52, 48, and 44.

Figure 13 illustrates total cost of nine small-size instances when the parameter $L^{w'}$ is 5-10. It shows that although the total cost fluctuates with the change of $L^{w'}$, the fluctuation range is relatively gentle. Besides, if the number of residential areas is the same, regardless of the value of $L^{w'}$, the total cost decreases with the increase of parking lots and shelters. There is a percentage deviation between the corresponding

TABLE 15. Cost comparison with different values of $L^{W'}$.

$L^{W'}$	Gap8 (%)								
	2-6-2	3-6-3	4-6-4	2-8-2	3-8-3	4-8-4	2-10-2	3-10-3	4-10-4
5	-0.17	-0.17	-0.17	-0.12	-0.13	0.04	-0.22	-0.27	-0.17
6	-1.72	-2.12	-1.98	-0.19	-0.19	-0.14	-2.42	-2.42	-2.18
7	-1.60	-1.66	-1.63	0.11	0.07	0.10	-2.07	-2.10	-1.99
8	0.00	0.00	-0.23	0.07	0.08	0.04	-2.39	-2.42	-2.29
9	-1.74	-1.81	-1.54	0.58	0.58	0.65	-1.71	-1.65	-1.53

total cost when the value of $L^{W'}$ varies between 5 and 9 and the total cost when the value of $L^{W'}$ is 10, which is reported in Table 15. We can observe that Gap8 (%) is very small, between -2.42% and 0.65% . In other words, the value of $L^{W'}$ has little effect on the result of objective function. In summary, the objective function is not sensitive to the maximum capacity of the third type of vehicles. Therefore, it can be used as a parameter of the proposed model to set its value. This not only simplifies the model, but also shortens the solution time.

When a disaster occurs, management and decision-makers can directly determine the ratio of capacity allocation of vehicles that can simultaneously transport both types of individuals based on experience, thus shortening rescue preparation time.

V. CONCLUSION

Considering some important practical characteristics of vehicle routing problem in emergency rescue, we develop the MPSHVRPSP model to solve the challenges it brings compared with the classical VRP. There are two types of individuals in residential areas, namely, individuals with low mobility and individuals with high mobility. Evacuation vehicles are divided into three types according to different service objects. In the event of a disaster, heterogeneous fleet departs from parking lots, arrives at residential areas to pick up individuals, and then transports them to shelters. Besides, individuals' demands can be split.

In this work, we formulate an integer liner program model and propose a meta-heuristic algorithm for MPSHVRPSP called TS. Based on the computational experiments, the validity and effectiveness of the model and algorithm are verified, and the proposed algorithm can achieve a satisfactory solution in less time. In order to prove the reasonability and superiority of MPSHVRPSP, we compare it with various variants of the VRP. Then, we employ TS-Without diversification to solve small-size instances and the results show that diversification strategy can improve the solution quality. In the sensitivity analysis, it is found that the objective function is not sensitive to the maximum capacity of the third type of vehicle. Therefore, it can be used as a parameter of the proposed model to set its value. This not only simplifies the model, but also shortens the solution time.

In future studies, other heuristic and meta-heuristic algorithms are expected, which may improve the solution quality

and efficiency. In addition, taking the factor of time window into account also makes the problem more extensive.

REFERENCES

- [1] M. Pidd, F. N. de Silva, and R. W. Eglese, "A simulation model for emergency evacuation," *Eur. J. Oper. Res.*, vol. 90, no. 3, pp. 413–419, May 1996.
- [2] H. Dong, M. Zhou, Q. Wang, X. Yang, and F.-Y. Wang, "State-of-the-art pedestrian and evacuation dynamics," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 5, pp. 1849–1866, May 2020.
- [3] M. Zhou, H. Dong, P. A. Ioannou, Y. Zhao, and F.-Y. Wang, "Guided crowd evacuation: Approaches and challenges," *IEEE/CAA J. Automatica Sinica*, vol. 6, no. 5, pp. 1081–1094, Sep. 2019.
- [4] Q. Li, S. Zhong, Z. Fang, L. Liu, W. Tu, and B. Chen, "Optimizing mixed pedestrian-vehicle evacuation via adaptive network reconfiguration," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 3, pp. 1023–1033, Mar. 2020.
- [5] E. Urbina and B. Wolshon, "National review of hurricane evacuation plans and policies: A comparison and contrast of state practices," *Transp. Res. A, Policy Pract.*, vol. 37, no. 3, pp. 257–275, Mar. 2003.
- [6] N. Dash and H. Gladwin, "Evacuation decision making and behavioral responses: Individual and household," *Natural Hazards Rev.*, vol. 8, no. 3, pp. 69–77, Aug. 2007.
- [7] R. Swamy, J. E. Kang, R. Batta, and Y. Chung, "Hurricane evacuation planning using public transportation," *Socio-Economic Planning Sci.*, vol. 59, pp. 43–55, Sep. 2017.
- [8] M. Zeng, M. Wang, Y. Chen, and Z. Yang, "Dynamic evacuation optimization model based on liect-eliminating cell transmission and split delivery vehicle routing," *Saf. Sci.*, vol. 137, p. 105266, May 2021.
- [9] G. B. Dantzig and J. H. Ramser, "The truck dispatching problem," *Manage. Sci.*, vol. 6, no. 1, pp. 80–91, Oct. 1959.
- [10] G. Laporte, Y. Nobert, and D. Arpin, "Optimal solutions to capacitated multidepot vehicle routing problems," *Congressus Numeratum*, vol. 44, pp. 283–292, Dec. 1984.
- [11] J.-F. Cordeau, G. Laporte, and A. Mercier, "A unified Tabu search heuristic for vehicle routing problems with time windows," *J. Oper. Res. Soc.*, vol. 52, no. 8, pp. 928–936, Aug. 2001.
- [12] A. Rahimi-Vahed, T. G. Crainic, M. Gendreau, and W. Rei, "Fleet-sizing for multi-depot and periodic vehicle routing problems using a modular heuristic algorithm," *Comput. Oper. Res.*, vol. 53, pp. 9–23, Jan. 2015.
- [13] M. E. H. Sadati, B. Çatay, and D. Aksent, "An efficient variable neighborhood search with Tabu shaking for a class of multi-depot vehicle routing problems," *Comput. Oper. Res.*, vol. 133, pp. 1–22, Sep. 2021.
- [14] E. Choi and D.-W. Tcha, "A column generation approach to the heterogeneous fleet vehicle routing problem," *Comput. Oper. Res.*, vol. 34, no. 7, pp. 2080–2095, Jul. 2007.
- [15] Y. Meliani, Y. Hani, S. L. Elhaq, and A. E. Mhamedi, "A developed Tabu search algorithm for heterogeneous fleet vehicle routing problem," *IFAC-PapersOnLine*, vol. 52, no. 13, pp. 1051–1056, 2019.
- [16] P. Li, C. Zhi, and W. Li, "An algorithm to solve heterogeneous vehicle routing problem with second trip," *IEEE Access*, vol. 9, pp. 12241–12255, 2021.
- [17] E. B. Tirkolaee, P. Abbasian, and G. Weber, "Sustainable fuzzy multi-trip location-routing problem for medical waste management during the COVID-19 outbreak," *Sci. The Total Environ.*, vol. 156, pp. 1–13, Mar. 2021.
- [18] M. Dror and P. Trudeau, "Savings by split delivery routing," *Transp. Sci.*, vol. 23, no. 2, pp. 141–145, May 1989.

- [19] L. Moreno, M. P. de Aragão, and E. Uchoa, "Improved lower bounds for the split delivery vehicle routing problem," *Operations Res. Lett.*, vol. 38, no. 4, pp. 302–306, Jul. 2010.
- [20] L.-N. Xing, Y. Liu, H. Li, C.-C. Wu, W.-C. Lin, and W. Song, "A hybrid discrete differential evolution algorithm to solve the split delivery vehicle routing problem," *IEEE Access*, vol. 8, pp. 207962–207972, 2020.
- [21] G. Ozbaygin, O. Karasan, and H. Yaman, "New exact solution approaches for the split delivery vehicle routing problem," *EURO J. Comput. Optim.*, vol. 6, no. 1, pp. 85–115, Mar. 2018.
- [22] S. Salhi and M. Sari, "A multi-level composite heuristic for the multi-depot vehicle fleet mix problem," *Eur. J. Oper. Res.*, vol. 103, no. 1, pp. 95–112, Nov. 1997.
- [23] R. Dondo, C. A. Mendez, and J. Cerdá, "An optimal approach to the multiple-depot heterogeneous vehicle routing problem with time window and capacity constraints," *Latin Amer. Appl. Res.*, vol. 33, no. 2, pp. 129–134, Apr. 2003.
- [24] R. Dondo and J. Cerdá, "A cluster-based optimization approach for the multi-depot heterogeneous fleet vehicle routing problem with time windows," *Eur. J. Oper. Res.*, vol. 176, no. 3, pp. 1478–1507, Feb. 2007.
- [25] S. Salhi, A. Imran, and N. A. Wassan, "The multi-depot vehicle routing problem with heterogeneous vehicle fleet: Formulation and a variable neighborhood search implementation," *Comput. Oper. Res.*, vol. 52, pp. 315–325, Dec. 2014.
- [26] B. Afshar-Nadjafi and A. Afshar-Nadjafi, "A constructive heuristic for time-dependent multi-depot vehicle routing problem with time-windows and heterogeneous fleet," *J. King Saud Univ. Eng. Sci.*, vol. 29, no. 1, pp. 29–34, Jan. 2017.
- [27] D. Gulczynski, B. Golden, and E. Wasil, "The multi-depot split delivery vehicle routing problem: An integer programming-based heuristic, new test problems, and computational results," *Comput. Ind. Eng.*, vol. 61, no. 3, pp. 794–804, Oct. 2011.
- [28] S. Ray, A. Soeanu, J. Berger, and M. Debbabi, "The multi-depot split-delivery vehicle routing problem: Model and solution algorithm," *Knowl.-Based Syst.*, vol. 71, pp. 238–265, Nov. 2014.
- [29] X. Wang, B. Golden, E. Wasil, and R. Zhang, "The min–max split delivery multi-depot vehicle routing problem with minimum service time requirement," *Comput. Oper. Res.*, vol. 71, pp. 110–126, Jul. 2016.
- [30] P. Belfiore and H. T. Y. Yoshizaki, "Scatter search for a real-life heterogeneous fleet vehicle routing problem with time Windows and split deliveries in Brazil," *Eur. J. Oper. Res.*, vol. 199, no. 3, pp. 750–758, Dec. 2009.
- [31] R. S. Shahmiri, S. Asian, R. T. Moghaddam, S. M. Mousavi, and M. Rajabzadeh, "A routing and scheduling problem for cross-docking networks with perishable products, heterogeneous vehicles and split delivery," *Comput. Ind. Eng.*, vol. 157, pp. 1–21, Jul. 2021.
- [32] C.-C. Chen and C.-S. Chou, "Modeling and performance assessment of a transit-based evacuation plan within a contraflow simulation environment," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2091, no. 1, pp. 40–50, Jan. 2009.
- [33] L. Margulis, P. Charosky, J. Fernandez, and M. A. Centeno, "Hurricane evacuation decision-support model for bus dispatch," in *Proc. 4th LACCEI Int. Latin Amer. Caribbean Conf. Eng. Technol.*, Mayaguez, Puerto Rico, Jun. 2006, p. 201.
- [34] C. Mastrogiannidou, M. Boile, M. Golias, S. Theofanis, and A. Ziliaskopoulos, "Using transit to evacuate facilities in urban areas: A micro-simulation based integrated tool," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 3439, pp. 1–15, Jan. 2009.
- [35] H. Abdelgawad and B. Abdulhai, "Large-scale evacuation using subway and bus transit: Approach and application in city of Toronto," *J. Transp. Eng.*, vol. 138, no. 10, pp. 1215–1232, Oct. 2012.
- [36] E. B. Tirkolaee, I. Mahdavi, M. M. S. Esfahani, and G.-W. Weber, "A robust green location-allocation-inventory problem to design an urban waste management system under uncertainty," *Waste Manage.*, vol. 102, pp. 340–350, Feb. 2020.
- [37] J. A. Perkins, I. K. Dabipi, and L. D. Han, "Modeling transit issues unique to hurricane evacuations: North Carolina's small urban and rural areas," North Carolina Agricult. Tech. State Univ. Transp. Inst., Greensboro, NC, USA, Tech. Rep. DTRS98-G-0033, Dec. 2001.
- [38] F. Sayyady and S. D. Eksioğlu, "Optimizing the use of public transit system during no-notice evacuation of urban areas," *Comput. Ind. Eng.*, vol. 59, no. 4, pp. 488–495, Nov. 2010.
- [39] S. He, L. Zhang, R. Song, Y. Wen, and D. Wu, "Optimal transit routing problem for emergency evacuations," in *Proc. Transp. Res. Board 88th Annu. Meeting*, Washington, DC, USA, Jan. 2009, p. 13.
- [40] C. P. Chan, "Large scale evacuation of carless people during short- and long-notice emergency," Ph.D. dissertation, Comput. Sci. Dept., Univ. Arizona, AZ, USA, 2010.
- [41] Z. Shen, M. M. Dessouky, and F. Ordóñez, "A two-stage vehicle routing model for large-scale bioterrorism emergencies," *Networks*, vol. 54, no. 4, pp. 255–269, Dec. 2009.
- [42] H. Wang, L. Du, and S. Ma, "Multi-objective open location-routing model with split delivery for optimized relief distribution in post-earthquake," *Transp. Res. E*, vol. 69, no. 3, pp. 160–179, Sep. 2014.
- [43] G. Laporte, S. Ropke, and T. Vidal, "Chapter 4: Heuristics for the vehicle routing problem," in *Vehicle Routing: Problems, Methods, and Applications*, 2nd ed. Philadelphia, PA, USA, 2014, pp. 87–116. [Online]. Available: <http://www.siam.org/journals/ojsa.php>
- [44] M. Gmira, M. Gendreau, A. Lodi, and J.-Y. Potvin, "Tabu search for the time-dependent vehicle routing problem with time Windows on a road network," *Eur. J. Oper. Res.*, vol. 288, no. 1, pp. 129–140, Jan. 2021.
- [45] (2021). *Global Petrol Prices*. Accessed: Jul. 12, 2021. [Online]. Available: https://www.globalpetrolprices.com/gasoline_prices/
- [46] J. Brandão, "A deterministic Tabu search algorithm for the fleet size and mix vehicle routing problem," *Eur. J. Oper. Res.*, vol. 195, no. 3, pp. 716–728, Jun. 2009.



LINA XU was born in 1991. She is currently pursuing the Ph.D. degree with Beijing Jiaotong University, China. Her research interest includes pedestrian and vehicle evacuation during emergencies.



ZIYANG WANG was born in 1978. He received the Ph.D. degree from the University of Science and Technology of China, in 2007. He is currently a Professor with Beijing Jiaotong University, China. His current research interest includes transportation information engineering and safety.



JUDONG CHEN was born in 1968. He received the M.S. degree from Beijing Jiaotong University, China, in 1996. He is currently a Senior Engineer with Beijing Jiaotong University. His current research interest includes intelligent transportation systems.



ZHENGWEI LIN was born in 1996. He received the M.S. degree from Beijing Jiaotong University, China, in 2021. He is currently working at Beijing System-Wide Communication Signal Research and Design Institute Company Ltd. His research interest includes research on the scheme of railway intelligent operation and maintenance platform.