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Ridesharing in urban areas: multi-objective optimisation approach for ride-matching and routeing with commuters' dynamic mode choice

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ABSTRACT

The daily home-office commute of millions of people in crowded cities strains air quality and increases travel time, which motivates the generation of ridesharing. Ridesharing offers many benefits, such as reducing travel costs, congestion, and pollution. Commuter ridesharing is an important theme of urban transportation. This paper studies a ridesharing problem aiming at enlarging the ridesharing market at a limited cost, which enlighten the decision-making problem in city logistics. We establish a novel multi-objective optimisation model based on cumulative prospect theory (CPT) to address the preferred travel mode of commuters. The commuters' perceived value influences their choice of travel mode. Meanwhile, the perceived value changes with the commuters' experience of travel mode choice. We give the NP-hardness proof of the ridesharing scheduling problem and develop a heuristic algorithm to solve it in a small-scale scenario. For large-scale problems, a hybrid VNS-NSGAII algorithm combining variable neighbourhood search (VNS) with NSGAII (Non-dominated Sorting Genetic Algorithm II) is proposed to generate an approximate optimal Pareto front. A series of computational experiments are conducted to demonstrate the effectiveness and efficiency of the proposed algorithm based on the actual traffic data in Beijing, China.

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Ridesharing; multi-objective optimisation; cumulative prospect theory; heuristic algorithm; VNS-NSGAII; city logistics

1. Introduction

The development of the urban economy and the growth of population have resulted in severe traffic congestion in many cities. The permanent population of Beijing increased from 15.4 million in 2005 to 21.5 million in 2018, and approximately 86.5% was in urban areas (https://www.stats.gov.cn/). Large population results in heavy economic losses due to the increase in travel time and energy consumption. Long and Thill survey people's home and office location distribution in Beijing, China (2015). In their survey, office locations in Beijing are concentrated in several hotspots, whereas residential areas are relatively scattered throughout the city. Daily commuting by residents has put much pressure on the transportation network (Feng, Saito, and Liu 2016; Cisneros-Saldana, Hosseinian, and Butenko 2018; Glover et al. 2018). At the same time, commuting is one of the significant branches of urban transportation activities.

Ridesharing can provide more flexible service and induce lower costs for commuters compared to other modes of transportation. Bus services typically carry multiple passengers and can help to reduce total vehicle operation mileage and alleviate traffic pressure. However, one drawback of transit services is that they operate on fixed routes and schedules, which limits their coverage area of the urban network. Taxis provide door-to-door transportation service, but at a high cost that not every commuter can afford. Ridesharing refers to the behaviour in which passengers negotiate to jointly ride the same car, so as to improve transportation efficiency, reduce fuel consumption and carbon emission (Dimitrakopoulos, Demestichas, and Koutra 2012; Lin et al. 2012). In addition, this mode has better flexibility than public transportation. Ridesharing platforms, such as Uber, Lyft, Didi, and Ctrip, are widely used in commuting by matching drivers and riders in real-time and coordinating drivers who offer rides to travellers with

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similar itineraries (Tan, Carrillo, and Cheng 2016; Tan et al. 2017).

Since city transportation is a complex problem concerning managerial, social and engineering aspects, it is crucial to carefully consider the requirements and interests of different stakeholders involved. For this purpose, the decision behaviours and revenues of suppliers, retailers, consumers and administrators should be comprehensively investigated in providing efficient directions (Dolati Neghabadi, Samuel, and Espinouse 2019; Jamshidi et al. 2019). The commuters' willingness of choosing their travel mode is important to city traffic optimisation. In Beijing, due to changes in urban planning, such as the establishment of a large airport, the collective relocation of households has made commuting difficulties for residents. The dial-a-ride problem (DARP) provides shared trips between any origin and destination in response to reserve requests of passengers within a specific area (Masson, Lehuédé, and Péton 2014). As such, it is flexible and efficient to solve the reservation travel problem, however, the demand of perceived value should be satisfied to improve the ridesharing willingness.

Ridesharing can reduce the cost of commuting, but it comes with time-related risks. Meanwhile, if the commuters' impression of dissatisfied with this travel mode exceeds their expectations, they will change their choices. Figure 1 presents the travel itineraries of commuters 1, 2, 3, and 4, who have nearby trip origins, destinations, and departure time, and they can be grouped into the same ride. Solution 1 describes that a single car provides service for commuters 1, 2, 3, and 4. However, the commuters have low perceived value due to excessively extra travel time, which will change the ridesharing decisions of commuters in their subsequent trips. Therefore, we suggest solution 2 in which commuters 1 and 2 are grouped into the same ride, and commuters 3 and 4 are grouped into another ride. This solution can reduce commuters' extra travel time, thus improving the commuters' perceived value for ridesharing. As such, drivers need to make a trade-off between ridesharing time of commuters and the costs of the vehicle. The same is true for passengers 5, 6, 7, and 8. In Figure 1, the vehicles' cost in solution 2 is higher than that in solution 1. It is essential to balance the vehicle costs and commuters' utility in ridesharing platforms.

This study aims to examine the decision-making behaviour of the home-to-work commuters to address the ridesharing problem. Unlike the previous ridesharing studies, our first objective is to maximise the number of commuters that willing to choose ridesharing, according to the decision-making behaviour of commuters in ridesharing system. Meanwhile, another objective that minimises the total cost of the vehicles is also considered. The decision variables are routes and schedules of the vehicles (including commuter-driver assignment) in the presence of conflicting objectives. This study can enlighten the decision-making problem in city logistics.

The main contributions of this work can be summarised as follows:

(a) Considering the perceived value of commuters, we establish a bi-objective ridesharing model, in which the decision-making behaviour of ridesharing

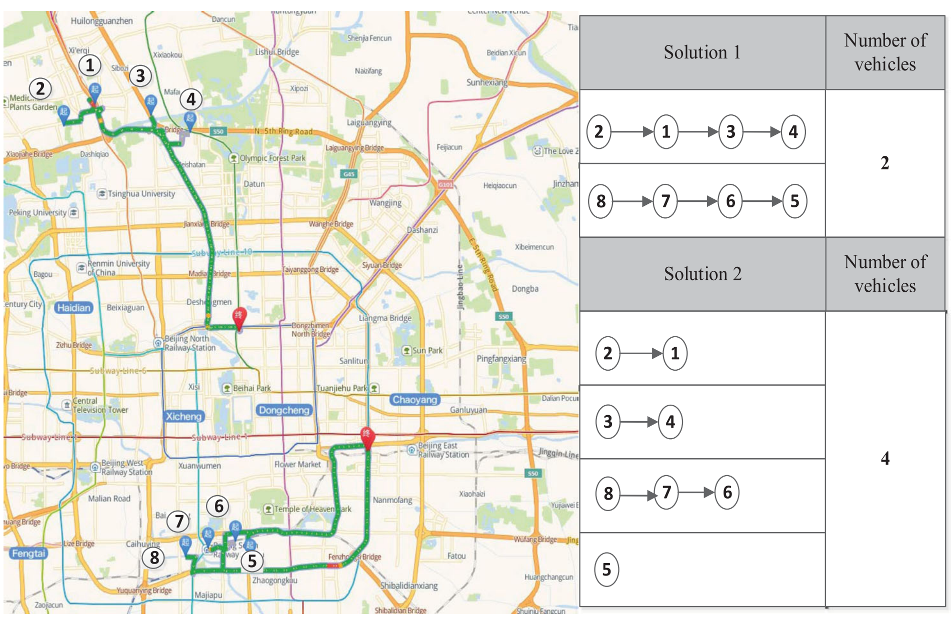

Figure 1. Illustration of the commuters' ridesharing.

commuters is simulated based on cumulative prospect theory (CPT).

(b) We analyse a method of fast non-dominated solution (FNDS). Based on structural properties, a heuristic algorithm is developed to solve small-scale problems.

(c) An effective hybrid VNS–NSGAII algorithm which combines Variable Neighbourhood Search (VNS) and Non-dominated Sorting Genetic Algorithm II (NSGAII) is proposed to solve large-scale problems. A series of computational experiments are conducted to validate the effectiveness and efficiency of the proposed algorithm.

The remainder of the paper is organised as follows. Related studies are reviewed in Section 2. The ridesharing optimisation model considering the decision-making behaviour of commuters is described in Section 3. In Section 4, the solution algorithm is presented. An experimental case is simulated and analysed in Section 5. The conclusions of this study are discussed in Section 6.

2. Literature review

In recent years, ridesharing has received growing interest from both academia and business. A comprehensive review of the conditions for a successful ridesharing system can be found in Agatz et al. (2011, 2012). Furuhata et al. (2013) provided an extensive overview of the literature by presenting the state of the art of existing ridesharing systems and discussing the critical challenges in the widespread use of ridesharing.

The extant literature on ridesharing mainly focused on the optimisation methods of vehicle routes and the improvment of ridesharing matching rate. For example, Manzini and Pareschi (2012) designed an auxiliary decision support system for ridesharing and matching. Jiau, Huang, and Lin (2013) applied a genetic algorithm to address the problems in ridesharing path matching. As a special application of ridesharing, DARP was first proposed by Baldacci, Maniezzo, and Mingozzi (2004). They established a model and developed exact algorithms to solve certain complexities of real-world problems. The DARP is also similar to the well-known pick-up and delivery problems with time windows (PDPTW). A branch-and-cut algorithm was developed by Lu and Dessouky (2004) to optimally solve the integer-programming formulation of the PDPTW. Le-Anh, De Koster, and Yu (2010) introduced three basic scheduling approaches (insertion, combination, and column generation) for the resolution of the PDPTW in Vehicle-Based Internal Transport (VBIT) Systems. In a recent study, Harbaoui Dridi et al. (2019) investigated a problem considering multiple vehicles, multiple depots, pickup, and delivery with time windows (m-MDPDPTW), and developed an algorithm based on the particle swarm optimisation (PSO) algorithm to solve it.

The objective of optimisation problems in city logistics research is the focus of logistics research. Considering the characteristics of stakeholders in logistics, we classify the following stakeholders: suppliers, retailers, consumers and administrators. The overview of key relevant papers delineating the main features of the model, components of objective function and the solution methods used are compared in Table A1 of Appendix. Specifically, some researches have addressed the retailers and administrators considering transportation costs and greenhouse gas emissions. Other studies have considered both suppliers and retailers to minimise transportation costs and satisfy passenger time window requirements. Moreover, several studies have explored the consumer service processes. For instance, Pureza, Morabito, and Reimann (2012) investigated the arrangement of servicemen to improve customers' service times, but they did not concern the multi-period dynamic willingness of consumer service acceptance.

Prospect Theory (PT) and CPT are widely used in transportation studies, especially in the route choice model. It is a model of bounded rational human decision making. However, the application of the CPT for mode choice model is still rare. Zhao and Yang (2013) argued that the mode choice model based on CPT could be successfully developed to explain a traveller's mode choice behaviour. Zhang and He (2014) proposed the choice of travel mode based on PT and found that the expected reference point influences the choice of travel mode greatly.

A flexible ridesharing system can obtain an effective solution for routeing and ride-matching within a reasonable time. For the multi-objective ridesharing problem, many studies have proposed effective solving methods. The generalised label-correcting (GLC) algorithm is a deterministic algorithm to search the Pareto-optimal set of route plans, but its exponential worst-case complexity is of concern (Skriver and Andersen 2000). Kar et al. (2018) and Majumder et al. (2019) proposed and solved the uncertain multi-objective solid transportation problem. NSGAII has been widely used to solve the multi-objective problems (Deb et al. 2000; Kannan et al. 2009). Majumder, Kar, and Pal (2019) applied NSGAII and multi-objective cross-generational elitist selection, heterogeneous recombination, and cataclysmic mutation (MOCHC) algorithms to address the uncertain multi-objective Chinese postman problem. However, it performs poorly in terms of convergence speed and accuracy when the solution space is large

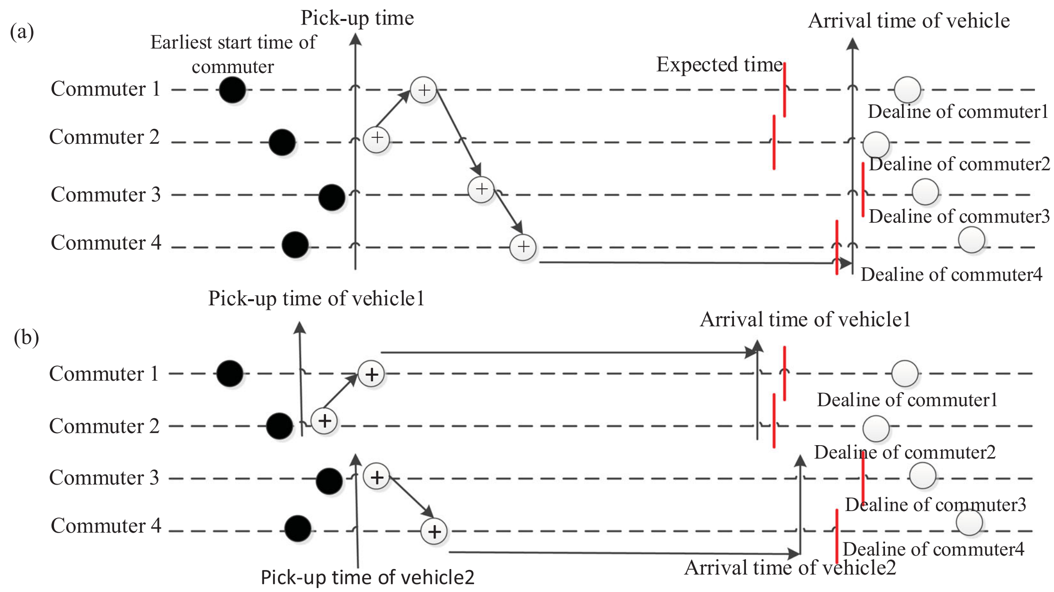

Figure 2. Operation of ridesharing service.

(Abedi et al. 2015; Majumder, Kar, and Pal 2019). In this study, we propose a heuristic algorithm based on the method of FNDS-G_{ps} to solve the small-scale problems. Since that the complexity of the heuristic algorithm will increase exponentially as the scale expands, we design a hybrid algorithom combining NSGAII and VNS to solve the proposed bi-objective optimisation problem.

3. Problem statement and the model

In this section, we introduce the ridesharing problem with the commuter decision-making behaviour consideration. We first give a brief description of the studied problem. Subsequently, a bi-objective model for ridesharing vehicle scheduling is proposed. Finally, we simulate commuters' decision-making behaviour in this model.

3.1. Problem statement

In this subsection, a variant of the PDPTW is used to model the ridesharing problem. A ridesharing demand can be regarded as a couple of pick-up and delivery locations. Drivers select the riders at different pick-up locations, but with the same drop-off locations. Regarding the time-constrained feature of both riders and drivers, we define a hard time window for each ridesharing. That is, a rider must be delivered to the destination before his latest arrival time. Specifically, a vehicle is allowed to arrive at a pick-up location after the riders' earliest start time window, and the riders wait until the vehicles' arrival. The service time at each location is set as zero. Each commuter has the same daily schedule as the time window. Figure 2 demonstrates the operation of the ridesharing service. The system satisfies commuters' requests with arrival deadlines and destinations. When passengers choose the service, they have an expected travel time. Figure 2(a) illustrates the schedule of the vehicle services for four commuters. The arrival time of the vehicle is later than the expected time of commuters 1, 2, and 4. Figure 2(b) shows the schedule of two vehicle services for four commuters. The arrival time of the vehicles is earlier than the expected time of commuters 1, 2, 3, and 4.

In our study problem, the decision on ride matching and vehicle routeing needs to be made to realise the two main objectives, which are as follows:

(i) Increasing the number of commuters who choose ridesharing;
(ii) Reducing the costs of ridesharing services.

3.2. Model structure

In this subsection, a mixed integer linear program (MILP) model is proposed for the vehicle scheduling problem based on the simulation of commuters' behaviour rule. Notations of the model are shown in Table 1.

The optimisation problem is formulated as follows.

$$F1: \max \sum_{i=1}^{N} X_i \tag{1}$$

$$F2: \min \sum_{j=1}^{m} \sum_{l=1}^{L} \mathrm{Cost}_{jl} = \sum_{j=1}^{m} \left(\sum_{l=1}^{L} D_{lj}^{or} \cdot f + \sum_{l=1}^{L} B_{lj} \right) \tag{2}$$

Table 1. Notations of the model for vehicle routeing optimisation.

Notations	Definitions
i	Index of commuter
N	The number of commuters
j	Index of day
m	The length of people's memory time of travel perception
L	The number of vehicles
l	Index of vehicle
X_i	0–1 decision variable, equals to 1 if commuter i decides to take ridesharing, 0 otherwise
$Cost_{lj}$	Cost of vehicle l on day j
or	A pair of origin and destination
D_{lij}^{or}	The distance of commuter i in the vehicle l on day j
f	Fuel cost per kilometre
B_{lj}	Fixed cost of the vehicle l on day j
x_{ijl}	0–1 decision variable, equals to 1 if commuter i selects ridesharing on day j, and vehicle l services commuter i, 0 otherwise
LT_{ij}	The latest arrival time requested by commuter i on day j
ET_{ij}	The earliest start time requested by commuter i on day j
t_{ij}	Time of commuter i from origin to destination on day j
tw_{ij}	The start service time of the commuter i on day j
CV_{lj}	The average speed of vehicle l on day j
MQ	The capacity of the vehicle

$$\text{s.t} \sum_{l=1}^{L} x_{ijl} = 1 \quad i = 1, \ldots, N \quad j = 1, \ldots, m \tag{3}$$

$$\sum_{i=1}^{N} x_{ijl} \leq MQ \quad l = 1, \ldots, L \quad j = 1, \ldots, m \tag{4}$$

$$tw_{ij} \geq ET_{ij} \quad i = 1, \ldots, N \quad j = 1, \ldots, m \tag{5}$$

$$tw_{ij} + t_{ij} \leq LT_{ij} \quad i = 1, \ldots, N \quad j = 1, \ldots, m \tag{6}$$

$$t_{ij} = D_{lij}^{or}/CV_{lj} \quad i = 1, \ldots, N \quad j = 1, \ldots, m \quad l = 1, \ldots, L \tag{7}$$

Equations (3)–(7) express the constraints of the model. Specifically, Equation (3) indicates that the commuters can only be served once a day. Equation (4) indicates that the number of commuters in a vehicle cannot exceed the capacity of the vehicle. Equations (5) and (6) describe the time-constrained feature of riders and drivers. Equation (7) reflects the relationship between the commuter's travel time, distance, and speed.

3.3. *Simulation of commuters' behaviour*

The decision of commuters' ridesharing is affected by many factors, among which travel time and cost are two critical indicators of commuters' perceived utility. A scheduling scheme for ridesharing will generate commuters' perceived time and price. Figure 3 illustrates the relationship between ridesharing scheme and commuter decision behaviour. A period of ridesharing experiences forms the perceived value of commuters in this travel mode. The perceived value is the basis for the commuters' decision-making.

The simulation system is on the basis of CPT, which models the commuters' choice of ridesharing. In order to reflect the impact of time and commuting costs on commuters' perceived utility, this study analyses the prospect value by separately using time and commuting costs as two factors under different conditions. Commuters can choose between two travel modes, namely, ridesharing or ride alone in a vehicle. Travel mode is defined as $s = (1, 2)$. We calculate the prospect value under different modes as follows.

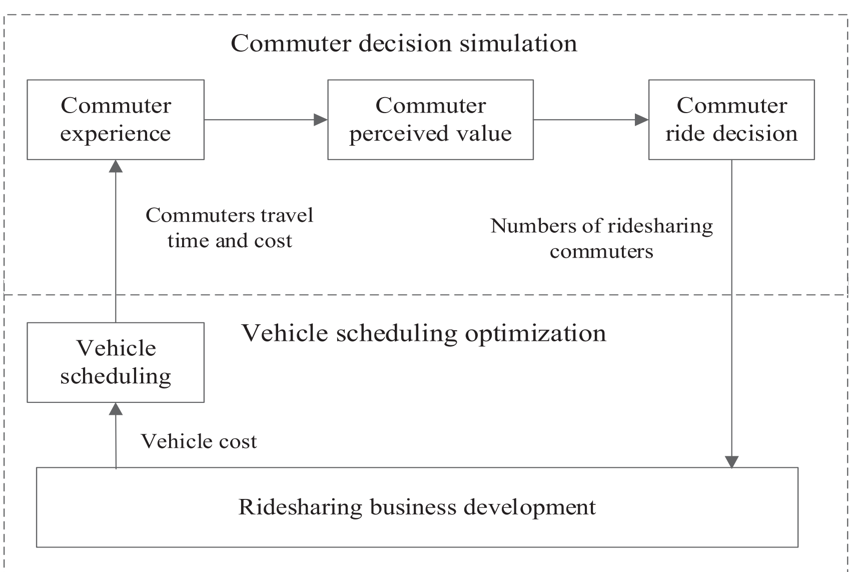

Figure 3. Relationship of ridesharing scheme and commuter decision behaviour.

3.3.1. Prospect value of travel time

Equation (8) depicts the value function of travel time according to that of CPT (Tversky and Kahneman 1992).

$$v(t_i^s) = \begin{cases} (bt_i^s - t_i^s)^{\alpha}, t_i^s < bt_i^s \\ -\lambda(t_i^s - bt_i^{sk})^{\beta}, t_i^s \geq bt_i^s \end{cases} \quad (8)$$

In Equation (8), t_i^s denotes the travel time of commuter i in travel mode s; bt_i^s denotes the reference point of the travel time in travel mode s; parameters $\alpha, \beta (0 < \alpha \leq 1, 0 < \beta \leq 1)$measure the sensitivity degree of diminishing the value function; λ is the coefficient of loss aversion, which indicates that individuals are more sensitive to losses than gains. The value function curve exhibits an S-shape with convex and concave functions in the gain and loss parts, respectively.

Eq (9) presents the reference point value of the travel time. The value of the reference point is related to the passenger's reserved time, which is the difference between the length of the time window and the shortest travel time.

$$bt_i^s = D_i^{or}/CV_l \cdot \left(1 + \frac{LT_i - ET_i - D_i^{or}/CV_l}{LT_i - ET_i}\right) \quad (9)$$

Equations (10) and (11) present the weight functions of travel time according to the CPT (Tversky and Kahneman 1992):

$$w^+(tp_i^s) = \frac{(tp_i^s)^{\gamma}}{|(tp_i^s)^{\gamma} + (1 - tp_i^s)^{\gamma}|^{1/\gamma}} \quad (10)$$

$$w^-(tp_i^s) = \frac{(tp_i^s)^{\delta}}{|(tp_i^s)^{\delta} + (1 - tp_i^s)^{\delta}|^{1/\delta}} \quad (11)$$

where $tp_i^s$is the probability of travel time t_i^s in travel mode s, and parameters γ, δ determine the curvature of the weight function. Probability weights function is present as an inverted S-type, which reflects the characteristics of overestimating small probability events and underestimating medium and large probability events.

Commuters' perceived travel time may differ from real travel time. Travellers' perceptions of travel time are constantly updated with the increase of travel experiences. Polak (1998) proposed a traveller learning model that calculates perceived travel time based on historical travel time in the traveller's memory. We formulate the perceived travel time into the learning model as shown in Equations (12) and (13).

$$t_i^{s'} = \sum_{r=1}^{m} tp_{ir}^s t_{i(j-r)}^s \, i = 1, \ldots N, \quad j = 1, \ldots, m \quad (12)$$

$$tp_{ir}^s = \frac{(m - r + 1)}{\sum_{r=1}^{m} r} i = 1, \ldots, N \quad r = 1, \ldots, m \quad (13)$$

where $t_i^{s'}$ is the perceived travel time of commuter i on day $m+1$, and tp_{ir}^s is the weight of historical travel time from days 1 to m. The parameter m is the length of commuter's memory time. At the same time, tp_{ir}^s is also the probability value of the commuter's travel time $t_{i(j-r)}^s$. When travel time changes with the route and schedule, the commuter will update the travel experience and form a new cognition for travel time.

We combine the travel time $(t_{i(j-r)}^s, tp_{ir}^s)$ in the commuters memory of day m to form a possible set of driving time (t_{iz}^s, tp_{iz}^s), in which $-a \leq z \leq b$. The time t_{iz}^s is sorted in an incremental manner and is divided into three sets according to the value function: positive, negative, and neutral results. Then, the decision weights of travel time $t\pi_z^+$ and $t\pi_z^-$ are shown in Equations (14) and (15):

$$t\pi_z^+ = w^+(tp_{iz}^s + \cdots + tp_{ib}^s) - w^+(tp_{i(z+1)}^s + \cdots + tp_{ib}^s) 0 \leq z \leq b \quad (14)$$

$$t\pi_z^- = w^-(tp_{i(-a)}^s + \cdots + tp_{iz}^s) - w^-(tp_{i(-a)}^s + \cdots + tp_{i(z-1)}^s) - a \leq z \leq 0 \quad (15)$$

Equation (16) displays the cumulative prospect value of travel time according to that of CPT.

$$V(t_i^{s'}) = \sum_{z=1}^{p} t\pi_z^+ v(t_{iz}^{s\,\prime}) + \sum_{z=-q}^{0} t\pi_z^- v(t_{iz}^{s\,\prime}) \quad (16)$$

3.3.2. Prospect value of commuting cost

Commuting cost is an essential indicator of ridesharing decision-making. This study uses the following charging method in Equation (17).

$$c_{ij} = D_{lij}^{or}/Q_{lj} \cdot fp \, i = 1, \ldots, N \, j = 1, \ldots, m \quad l = 1, \ldots, L \quad (17)$$

where D_{lij}^{or} is the distance from the origin to destination by commuter i in the vehicle l on day j, Q_{lj} is the number of commuters in the vehicle l on day j; fp denotes the cost ratio of commuters, $fp \epsilon [0, 1]$. The ridesharing commuters' payment is related to the number of commuters in one vehicle, and it decreases with the number of commuters.

Equation (18) shows the value function of commuting cost according to the CPT value function:

$$v(c_i^s) = \begin{cases} (bc_i^s - c_i^s)^{\alpha}, c_i^s < bc_i^s \\ -\lambda(c_i^s - bc_i^{sk})^{\beta}, c_i^s \geq bc_i^s \end{cases} \quad (18)$$

where c_i^s refers to the travel cost of commuter i in travel mode s; bc_i^s pertains to the reference point of commuting cost in travel mode s. The value of reference point is the cost of ride alone in a vehicle. $bc_i^s = D_i^{or} \cdot fp$.

Equations (19) and (20) present the weight function of commuting cost according to the CPT (Tversky and Kahneman 1992):

$$w^{+}(cp_i^s) = \frac{(cp_i^s)^{\gamma}}{|(cp_i^s)^{\gamma} + (1 - cp_i^s)^{\gamma}|^{1/\gamma}} \tag{19}$$

$$w^{-}(cp_i^s) = \frac{(cp_i^s)^{\delta}}{|(cp_i^s)^{\delta} + (1 - cp_i^s)^{\delta}|^{1/\delta}} \tag{20}$$

where cp_i^s is the probability of the commuting cost c_i^s in travel mode s.

Commuters' perceived travel cost may differ from actual travel cost. That is, travellers' perception of travel cost is constantly updated with their travel experience. We formulate the perceived travel cost in the learning model, as shown in Equation (21).

$$c_i' = \sum_{r=1}^{m} cp_{ir}^s c_{i(j-r)}^s \quad i = 1, \ldots, N \quad j = 1, \ldots, m \tag{21}$$

where c_i' is the perceived travel cost of commuter i on day $m+1$, and cp_{ir}^s is the weight of historical travel cost in the commuter's memory time. At the same time, cp_{ir}^s is also the probability value of the commuter's travel cost $c_{i(j-r)}^s$.

We combine the travel cost $(c_{i(j-r)}^s, cp_{ir}^s)$ in the commuters memory of day m to form a possible set of travel cost (c_{iz}^s, cp_{iz}^s), where $-a \le z \le b$. The travel cost c_{iz}^s is sorted in an incremental manner and divided into three sets according to the value function: positive, negative, and neutral results. Then the decision weights of commuting cost $c\pi_z^+$ and $c\pi_z^-$ are shown in Equations (22) and (23).

$$\begin{aligned} c\pi_z^+ &= w^{+}(cp_{iz}^s + \ldots + cp_{ib}^s) - w^{+}(cp_{i(z+1)}^s + \ldots \\ &\quad + cp_{ib}^s) 0 \le z \le b \end{aligned} \tag{22}$$

$$\begin{aligned} c\pi_z^- &= w^{-}(cp_{i(-a)}^s + \ldots + cp_{iz}^s) - w^{-}(cp_{i(-a)}^s + \ldots \\ &\quad + cp_{i(z-1)}^s) - a \le z \le 0 \end{aligned} \tag{23}$$

Equation (24) illustrates the cumulative prospect value of commuting cost according to the aforementioned description:

$$V(c_i^{s\prime}) = \sum_{z=1}^{p} c\pi_z^+ v(c_{iz}^{s}{}') + \sum_{z=-q}^{0} c\pi_z^- v(c_{iz}^{s}{}') \tag{24}$$

3.3.3. Comprehensive prospect value

Equation (25) illustrates the comprehensive prospect value of each travel mode by integrating time and cost indicators:

$$V_i^s = tw_i^s V'(t_i^{s\prime}) + cw_i^s V'(c_i^{s\prime}) \tag{25}$$

where $V'(t_i^{s\prime})$ and $V'(c_i^{s\prime})$ are the standardised prospect value of time and commuting cost, respectively, as shown in Equation (26):

$$\begin{aligned} V'(t_i^{s\prime}) &= \frac{V(t_i^{s\prime})}{|V(t_i')|_{\max}} V'(c_i^{s\prime}) = \frac{V(c_i^{s\prime})}{|V(c_i')|_{\max}} - 1 \\ &\le V'(t_i^{s\prime}) \le 1 - 1 \le V'(c_i^{s\prime}) \le 1 \end{aligned} \tag{26}$$

where tw_i^s and cw_i^s are the weights of time and commuter cost, respectively. Considering the differences between commuters, customers have varied weights of diverse indexes. This study determines the index weights via a quantitative method based on reference points, as shown in Equation (27) (Zhang et al. 2016).

$$tw_i^s : cw_i^s = \frac{|t_i^{s\prime}|_{min}}{bt_i^{sk}} : \frac{|c_i^{s\prime}|_{min}}{bc_i^{sk}} \tag{27}$$

Comprehensive prospect value increases with the perceived value of commuters, who choose the travel mode with the highest prospect value. In other words, the decision of the commuter to opt ridesharing is determined by the relative prospect value, as is expressed in Equation (28).

$$V_i = V_i^1 - V_i^2 \tag{28}$$

Equation (29) describes the decision of commuters to take a ride as follows:

$$X_i = \begin{cases} 1, & V_i > 0 \\ 0, & \text{otherwise} \end{cases} \tag{29}$$

4. Solution algorithm

The studied ridesharing problem is a complex bi-objective problem which considers the scheduling of vehicles for m days. Hence, the searching space of the solution is large since the problem is quickly intractable. In order to obtain a good Pareto-optimal solution set, we consider the small-scale and large-scale instances of the problem, respectively. In this section, we design two novel algorithms to get better solutions for large-scale and small-scale problems. First, we give some related definitions for a heuristic algorithm FNDS-G$_{ps}$ in Section 4.1. Then, a heuristic algorithm FNDS-G$_{ps}$ is developed to solve small-scale problems in Section 4.2. Finally, a hybrid VNS–NSGAII algorithm is proposed to solve large-scale problems in Section 4.3.

4.1. Related definition

Commuter grouping is the key to the ridesharing problem. We solve the combinatorial optimisation problem by converting it into graph $G_{comb}(V, E)$, as shown in Figure 4. In contrast to group rides, nodes $v \in V$ in G_{comb} not

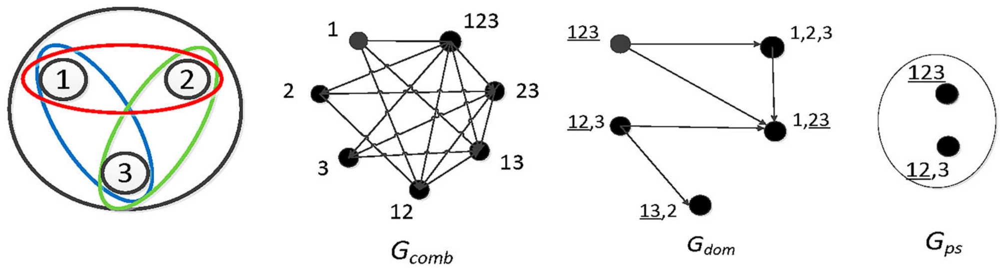

Figure 4. Example of construction of G_{ps} for a case of three commuters.

only pertain to single commuter, but also all stable group rides. Each edge between nodes indicates that there is at least one same element. We define the oriented graph $G_{dom}(V, E)$ and the nodes $v \in V$ in G_{dom} to illustrate the combinations of commuters. Edges between nodes indicate the dominating relationships between the two combinations. G_{ps}, the nodes $v \in V$ in G_{ps} is the combination of commuters in the Pareto optimal solution. The following preprocessing steps are undertaken during the solution process:

(1) Construct a graph $G_{comb}(V, E)$.
(2) Construct an oriented dominate graph $G_{dom}(V, E)$.
(3) Find the Pareto optimal solution set in graph G_{ps}.

The set of the Pareto optimal solution is obtained by a non-dominated sorting of a feasible solution, which typically uses a pairwise comparision method. The time complexity is $O(n^2)$.

Proposition 4.1: *The time complexity of G_{ps} construction is $O(4^n)$.*

Proof: For n commuters, the time complexity of enumerating all stable group rides is $O(2^n)$. The time complexity of dominate relationship is$O(k^2)$, and the time complexity of G_{ps} construction is $O(4^n)$. ■

4.2. Heuristic algorithm

A FNDS-G_{ps} algorithm is developed to reduce computational complexity.

Theorem 4.1: *Dominance relationship is transitive for any $s_1, s_2, s_3 \in S$. If $s_1 s_2$, $s_2 s_3$, then $s_1 s_3$* (Deb 2000).

Lemma 4.1: *If a feasible solution is dominated by any other solution, then the feasible solution is not in the non-dominance solution set. The set $\{s_1, s_2, \ldots, s_p\}$ is the non-dominate set. If s_i is a feasible solution, $\forall s_j s_i$, then $\nexists\, s_i \in \{s_1, s_2, \ldots, s_p\}$.*

Proof: If $\forall s_j s_i$, $\exists s_i \in \{s_1, s_2, \ldots, s_p\}$, then the set $\{s_1, s_2, \ldots, s_p\}$ is not the non-dominate set, which contradicts the given conditions. ■

Theorem 4.2: *Let X and Y be finite graphs, then X is a subgraph of Y if and only if graphs $G_0, \ldots, G_n$ exist. Thus, $G_0 = y$, $G_n = x$, and each G_{i+1} is obtained by deleting one edge from G_i* (Diestel 2000).

A method that can reduce the number of comparisons of the solution is used for the Pareto non-dominated solution set. The solution can be directly removed if it is dominated by another solution (i.e. comparative solution) to avoid repeatedly comparing the dominating solution with other solutions according to Lemma 4.1. According to Theorem 4.1, when the current non-dominated solution appears, which dominates the comparative solution, the dominate solutions of the comparative solution should be removed because they should be dominated by the current non-dominated solution. If the current non-dominated solution is used to replace the comparative solution, then the speed of removing the dominating solution is accelerated, and the frequency of comparison is reduced. From the above properties, the construction method of the fast non-dominated solution (FNDS) set is as Table 2.

Table 2. The pseudocode of construction FNDS-G_{ps}

Algorithm 1. FNDS-G_{ps}
Input: GRG $G_{comb}(V, E)$
Construct empty graph G_n, G_m
For $i \in N$ do
Enumerate all stable group rides K^i of G_{comb};
End
For $k \in K^i$ do
If $\forall k_i k_j$
$G_n = G_n + k_i$
Else If $\forall k_j k_i$
$G_m = G_m + k_i$
For $k_r \in K^i$ do
If $\forall k_r k_i$ Then $G_m = G_m + k_r$
End
End
$G_{comb} = G_{comb} - G_m$
End
$G_{ps} = G_{comb}$

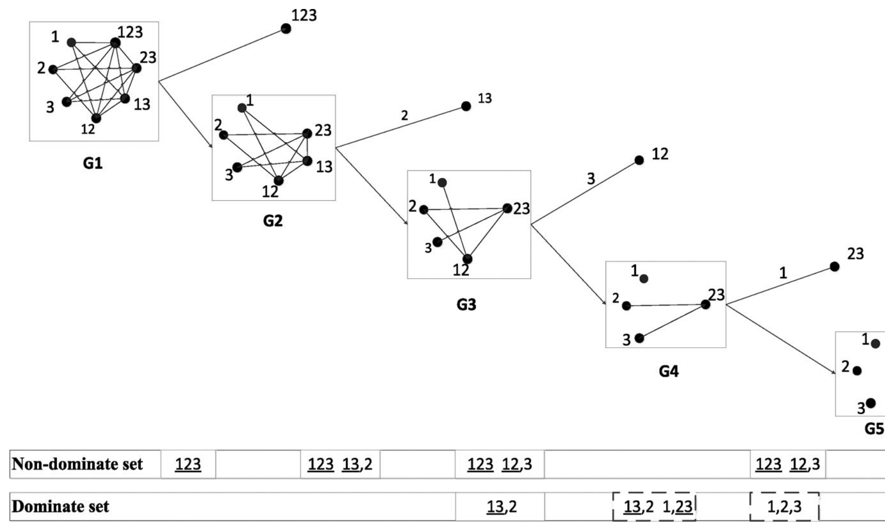

Figure 5. FNDS-G_{ps} for the case of 3 commuters.

The time complexity of the fast non-dominated set of G_{ps} is discussed as follows:

(1) Worst-case time complexity
Assume that all feasible solutions are non-dominated solutions, then we have the largest number of pairs of comparisons. The time complexity of dominate set is $O(k^2)$.

(2) Average time complexity
Suppose that half of the feasible solutions are non-dominated solutions, the time complexity of dominate set is $O(k^2/4)$.

(3) Best-case time complexity
When the non-dominated solution is 1, a unique non-dominated solution can be obtained by performing a dominant relationship comparison, and the time complexity is $O(k)$.

For the case of three commuters, the fast construction method of the Pareto non-dominated solution is illustrated as Figure 5, and the steps of FNDS-G_{ps} is as Table 3.

In the small-scale problem, we denote G as the r-partite graph. For the graph G, we divide the nodes V into r classes according to their dispersion. Then, we obtain the Pareto optimal solution set G_{ps} in each part.

Table 3. Steps of FNDS-G_{ps} for the case of 3 commuters.

FNDS-G_{ps} for the example of 3 commuters	
Step 1:	Identify connected components, which give all components set V.
Step 2:	The highest degree node in G_1 is the node$(1,2,3)$, and the degree is 5. Calculate the weights of the combination of this point and other unconnected points. The solution s_i is the node $(\underline{123})$. Put the solution s_i in the non-dominate solution set V_n. $V_n = V_n + s_i, G_2 = G_1 - s_i$.
Step 3:	The highest degree nodes in G_2 are nodes $(1,3)$, $(2,3)$, and $(1,2)$. Their degree is 4. Select node $(1,3)$ and calculate the weights of the combination of this point and other unconnected points. The solution s_j is $(\underline{13},2)$. If $s_j s_i, s_i \in V_n$, put the s_j instead s_i in the set V_n. Let the dominate solution set $V_m = V_m + s_i$. If $s_i s_j, s_i \in V_n$, Let the solution set $V_m = V_m + s_j$. If s_i and s_j have no dominate relationship. Let $V_n = V_n + s_j$.
Step 4:	Find the dominate solution set of $s_j, s_j \in V_m$. The other nodes in G_3 are node $(1,2)$, $(2,3)$, and $1,2,3$. As they are identical, calculate the weights of the combination of this point and other unconnected points. The solution $s_k, k = 1,2,3$ are $(\underline{12},3)$, $(\underline{23},1)$. $(1,2,3)$ If $\forall s_j s_k$, let the solution set $V_m = V_m + s_k . V = V - V_m$. $G_1 = G_1 - V_m, V_m = \emptyset$. Go to the step 2.
Step 5:	If all branches have not dominated solution, return the non-dominate set V_n.

Proposition 4.2: *The combination of the optimal solutions in each subgraph should contain the optimal solution of the r-partite graph G_{ps}.*

Proof: Counter-evidence. The non-dominate solution set of subgraph G_1 is M_1, the solutions $a, b \in M_1$. M_2 is the non-dominate solution set of subgraph G_2. $c, d \in M_2$. We have $f_1(a) > f_1(b)$, $f_2(a) < f_2(b)$, $f_1(c) > f_1(d)$,$f_2(c) < f_2(d)$. $f_1(a+c) = f_1(a) + f_1(c)$, $f_1(b+d) = f_1(b) + f_1(d)$. If $m + c$ is the non-dominate solution of the G. $m \in G_1$,$\neg\exists m \in M_1$, $f_1(m+c) = f_1(m) + f_1(c)$,$f_2(m+c) = f_2(m) + f_2(c)$. Since $a + c$ and $b + c$ are the non-dominate solutions of the G. If $f_1(m+c) > f_1(a+c)$, then $f_2(m+c) < f_2(a+c)$, m and a have no dominated relationship. If $f_1(m+c) > f_1(b+c)$, then $f_2(m+c) < f_2(b+c)$, m and b have no dominated relationship. Therefore $m \in M_1$, which contradicts with known conditions. ■

Proposition 4.3: *The problem of finding the Pareto optimal solution in the r-partite graph is NP-hard.*

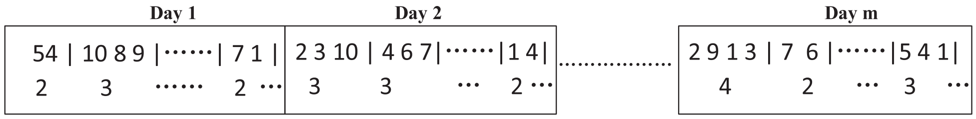

Figure 6. The chromosome coding of the algorithm.

Proof: We establish an r-partite graph G_{ps}. It is well accepted that r-dimensional matching problem is NP-complete when $r \geq 3$. Our problem is an r-dimensional matching problem. Given a collection $S \in S_1 \times S_2 \times \ldots \times S_r$ of r-tuples, where $\{S_1 \times S_2 \times \ldots \times S_r\}$ consists of all optimal solution set. Each part S_i has found a dominate subset $S_i{}'$. The decision problem is: find a subset $\nexists S' \in S$, where S is the non-dominated optimal solution set. The problem takes $O(|S|)$ time, which is polynomial. This suggests that our problem is NP-hard and completes the proof. ■

Since the problem is NP-hard, the heuristic algorithm FNDS-$\mathrm{G_{ps}}$ could generate approximate solutions. However, it is still exponential in complexity but with a small growth factor. The FNDS-$\mathrm{G_{ps}}$ algorithm may work efficiently for small-scale instances. Nevertheless, it will fail with the growing size. In Section 4.2, we present a FNDS-$\mathrm{G_{ps}}$ algorithm for optimally solving small-scale instances. We develop a hybrid VNS-NSGAII algorithm, aiming at reaching the best compromise between solution quality and computational efficiency for large-scale instances.

4.3. Hybrid VNS-NSGAII

According to Deb et al. (2000), NSGAII algorithm performs well compared with other MOEA algorithms. Kannan et al. (2009) reported evidence that NSGAII algorithm can successfully maintain a better spread solution and convergence. However, In the case of large solution space, NSGAII algorithm still has the disadvantage of being easily trapped in local optimum and poor stability. In this study, we use a hybrid VNS-NSGAII algorithm to solve it. The key procedures are given as follows:

4.3.1. Proposed heuristic

Proposition 4.3 shows that the ridesharing optimisation problem can be solved by the FNDS-$\mathrm{G_{ps}}$ algorithm for small-scale instances. To efficiently solve large-scale problems, we divide this problem into the following stages. First, all commuters for r-parts are divided according to their dispersion. Then, the Pareto optimal solution set for each part is generated. Finally, the global optimal solution set is obtained.

Table 4. The pseudocode of calculate the fitness.

Pseudocode of calculate the fitness
For the commuter demand $C = \{X_{ij}\}$, processing set $Pop_p^a = Pop_p^a \cap C$; Choose ridesharing commuters each day.
For $j = 1$ to M do
Classify commuter set N according to Pop_p^b based on the FNDS-$\mathrm{G_{ps}}$algorithm, obtain set N_L,$N_L = \{n_1, \cdots, n_l, \cdots, n_L\}$, where n_l is the commuters' set of vehicle l. $n_l = \{x_{l1}, \cdots, x_{li}, \cdots, x_{lq}\}$, where x_{li} indicates commuter x in the vehicle l of order i.
For $l = 1$ to L do
Adjust the order of commuter x_{li} in n_l according to the order of commuter in Pop_0^a
Calculate the cost of each vehicle $cost_l$
Calculate time $t_{ij}$of commuter x_i in set n_l.
Calculate cost p_{il} of each commuter x_i in set n_l.
$Cost = Cost + cost_l$
End
End
$C' = 1 - C$
For $i = 1$ to N do
Calculate the prospect value of each commuter x_i for ridesharing $V^C(x_i)$.
Calculate the prospect value of each commuter x_i for not ridesharing $V^{C'}(x_i)$.
Calculate the prospect of each commuter x_i would choice ridesharing for travel$V(x_i) = V^C(x_i) - V^{C'}(x_i)$.
End

4.3.2. Chromosome representation

Chromosome design is an essential part of the algorithm. In this study, the ridesharing scheme consists of the order of commuters in ridesharing and the number of commuters per vehicle. We construct a two-dimensional chromosome coding form, as shown in Figure 6. We optimise the ridesharing chromosome within memory time m. Chromosome coding consists of m parts, where each part represents a scheme used in one day.

Based on the coding design, the pseudocode of calculate the fitness is shown in Table 4.

4.3.3. Crossover and mutation

Crossover and mutation are based on the initial solution to get a better solution set. According to the characteristics of the operator, this study designs the real matrix coding to cross and mutate the operators.

The chromosome is transformed into a matrix by day, and the matrix of the crossover operation is selected. Matrix A_{ij} indicates the service order of commuter i on day j. The positions of the matrixes are exchanged from two parents' chromosomes. Conflict detection is then performed, and the order is

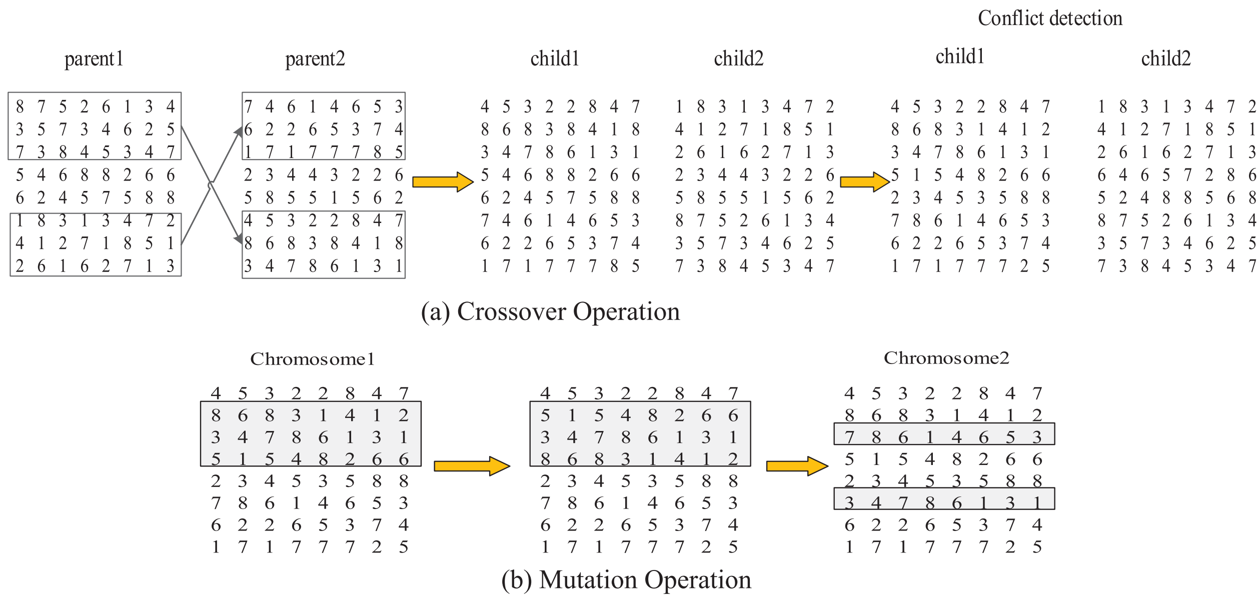

Figure 7. Crossover operation and mutation operation.

adjusted to render a feasible solution. Two child chromosomes are thus obtained. Figure 7(a) depicts the operation.

Select the matrix of the mutation operation, which adopts the method of reverse sequence mutation and exchange mutation. Figure 7(b) illustrates the specific operation.

4.3.4. The framework of the VNS-NSGAII algorithm

VNS was first proposed by Mladenović and Hansen (1997). VNS has been long recorded to perform good results obtained with hybrid methods. For instance, Jarboui, Eddaly, and Siarry (2011) developed a hybrid GA and VNS to solve no-wait flowshop scheduling problems. Liu et al. (2018) proposed a hybrid VNS and harmony search (HS) algorithm to solve the supply chain scheduling problem. In order to improve the algorithm efficiency, a VNS algorithm is applied in each solution for a specific number of iterations (Yang et al. 2018). In this manner, the method can explore neighbourhood structures by the VNS operator, and exploit the population with NSGAII. The detail of VNS-based local search operation is described in Table 5.

Table 5. Steps of VNS-based local search operation.

VNS-based local search operation	
Step 1:	Define neighbourhood structures $U_e(e = 1, \dots, e_{max})$.
Step 2:	Obtain offspring S, which is produced by NSGAII.
Step 3:	Execute sth Local Search for each individual $s \in S$ to obtain a solution s'.
Step 4:	If the solution s' is better than s, then set $s = s'$, $e = 1$ and go to step3. Otherwise, set $e = e + 1$, go to step 5.
Step 5:	If $e \le e_{max}$, then go to step 3, stop the iteration.

In our experiment, 2-opt, 3-opt are selected to define neighbourhood structure U_e for VNS-based local search operation. The main framework of the proposed algorithm is described in Figure 8.

5. Numerical experiments

5.1. Data

We used actual datasets of commuters that travel in Beijing to comprehensively understand the performance of our algorithms and the benefits of ridesharing. The data, collected from Beijing taxi in 2012, contains information related to time and location of trip origin and destination, trip cost, and trip length (https://research.microsoft.com/en-us/projects/urbancomputing/). All data were preprocessed. After cleaning, data were reformatted for experiment inputs.

5.2. Parameters setting

For the experiment, we created different size scenarios to investigate the solution quality and computational efficiency of the algorithms. The number of commuters is set as $N = 20, 25, 30, 35, 40, 45, 50, 80, 100, 150$. The memory length of commuter's travel perception is set as $m = 7$. The fuel cost per kilometre of vehicle is set as $f = 1.4$. The fixed cost of the vehicle l is set as $B_l = 30$. The average speed of vehicle l is set as $CV_l = 60$. The capacity of the vehicle is set as $MQ = 4$. The passenger cost per kilometre is set as $fp = 3$. The parameters values of the cumulative prospect model are set as $\alpha = 0.68$, $\beta = 0.72$, $\lambda = 1.94$, $\gamma = 0.82$, and $\delta = 0.78$, which are the value

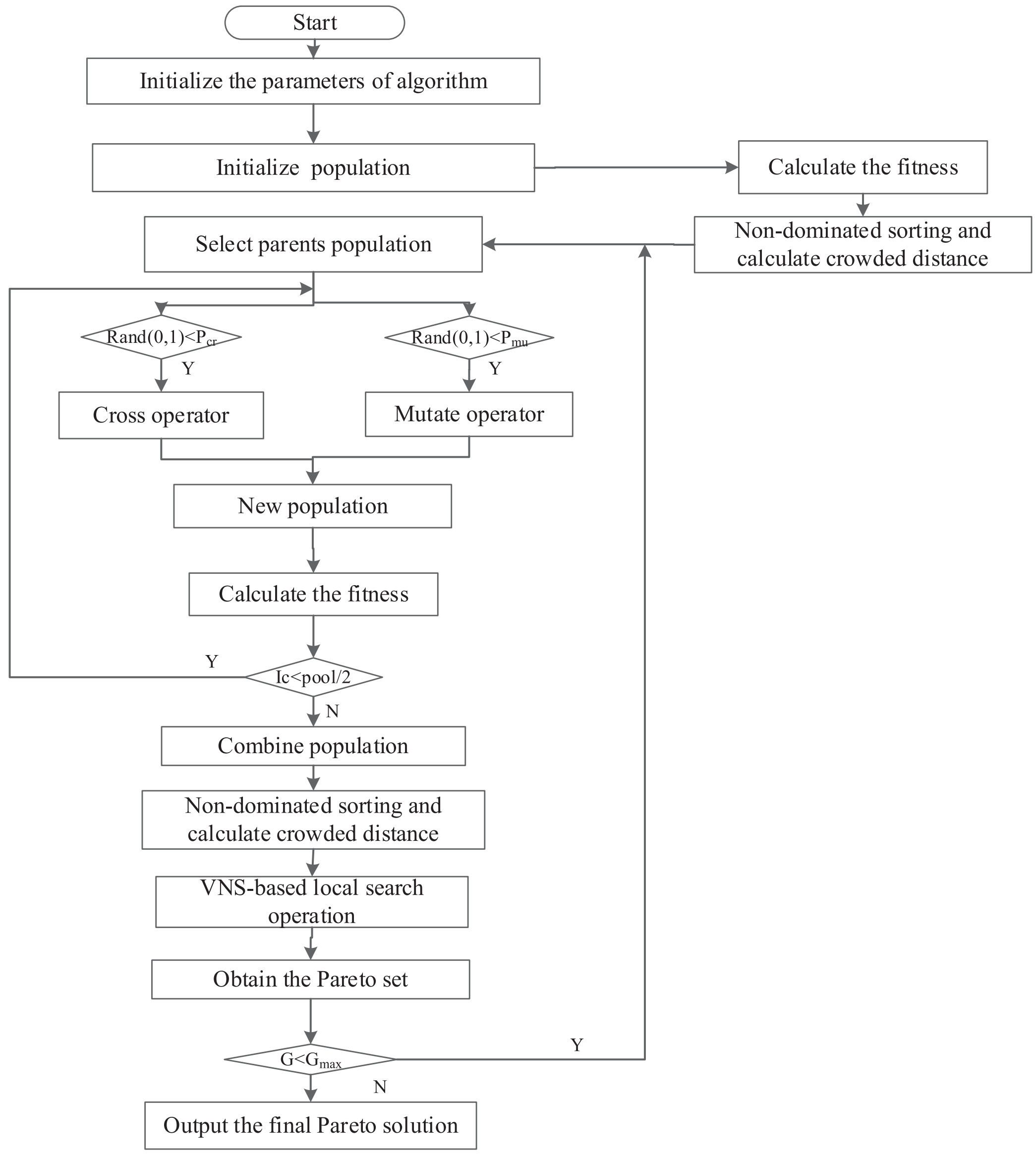

Figure 8. Flowchart of the solution algorithm.

estimated by Zhao and Yang (2013) for travellers mode choice in travel.

5.3. Computational results

In this section, we conduct computational experiments to evaluate the performance of our proposed FNDS-G_{ps} algorithm and VNS-NSGAII algorithm, with four classic algorithms, that is, NSGAII algorithm (Deb et al. 2002), MOCELL algorithm (Nebro et al. 2009), SPEA2 algorithm (Zitzler, Laumanns, and Thiele 2001), and MOPSO algorithm (Coello and Lechuga 2002). Actually, NSGAII, MOCELL, SPEA2, and MOPSO algorithms have already been applied in many other complexity multi-objective problems with excellent performance (Kar et al. 2019; Majumder et al. 2019). Therefore, they are often regarded as very representative methods and we use them in the comparison experiments.

Four different performance metrics: (1) hypervolume (HV), (2) generational distance (GD), (3) inverted generational distance (IGD) and (4) spread (S) (Kar et al. 2019; Majumder et al. 2019) are used to compare different algorithms. For a better solution, the HV metric value is higher and the other metric values are smaller. Among these performance metrics, HV and IGD ensure both convergence and diversity of the nondominated solutions generated by an algorithm, S assures the diversity of the nondominated solutions, while GD promises the convergence of an algorithm. For each instance, all algorithms have been run 30 times. The mean and standard deviation

Table 6. Comparison of the algorithms' performances for small-scale instances.

		FNDS-G_{ps}		VNS-NSGAII		NSGAII		SPEA2		MOPSO		MOCELL	
Metric Value	*N*	Mean	sd	mean	Sd	mean	Sd	mean	sd	mean	sd	Mean	sd
HV	20	8.58E+03	2.9E+02	5.20E+03	4.4E+02	2.41E+03	6.8E+02	8.33E+03	5.0E+02	3.19E+03	6.2E+02	1.14E+03	4.7E+02
	25	9.05E+03	5.1E+02	8.26E+03	5.3E+02	2.86E+03	6.3E+02	4.99E+03	7.7E+02	6.43E+03	7.9E+02	1.17E+03	8.3E+02
	30	1.13E+04	4.3E+02	9.27E+03	5.5E+02	3.48E+03	8.8E+02	2.80E+03	5.6E+02	1.11E+03	6.4E+02	2.32E+03	6.8E+02
	35	1.43E+04	5.7E+02	1.28E+04	8.3E+02	3.68E+03	5.9E+02	1.18E+04	6.2E+02	5.40E+03	7.3E+02	2.99E+03	7.6E+02
	40	1.57E+04	3.8E+02	1.48E+04	4.2E+02	4.09E+03	5.5E+02	5.91E+03	5.1E+02	1.07E+03	4.6E+02	1.51E+03	4.2E+02
	45	2.03E+04	5.5E+02	2.26E+04	5.2E+02	8.40E+03	6.3E+02	4.17E+03	5.8E+02	4.66E+03	7.1E+02	2.35E+03	6.5E+02
GD	20	1.68E−01	3.6E−02	1.53E−01	2.0E−02	2.58E−01	4.8E−02	8.77E−01	7.4E−02	2.27E−01	5.5E−02	5.34E−01	6.2E−02
	25	1.25E−01	3.8E−02	5.36E−01	4.6E−02	2.37E−01	4.6E−02	6.13E−01	5.7E−02	3.34E−01	5.1E−02	1.40E−01	4.4E−02
	30	8.88E−02	3.2E−02	2.00E−01	2.3E−02	4.07E−01	6.5E−02	3.92E−01	6.3E−02	7.53E−02	2.4E−02	1.74E−01	7.1E−02
	35	2.30E−01	6.5E−02	9.81E−02	3.0E−02	4.72E−01	6.2E−02	5.18E−01	3.8E−02	1.87E−01	6.5E−02	1.62E−01	4.6E−02
	40	9.55E−02	4.5E−02	4.59E−01	7.2E−02	1.55E−01	5.5E−02	3.42E−01	4.9E−02	9.92E−02	5.1E−02	2.62E−01	8.2E−02
	45	4.34E−01	7.5E−02	1.16E−01	4.9E−02	8.82E−02	3.6E−02	1.75E−01	5.0E−02	3.78E−01	6.3E−02	1.27E−01	5.2E−02
IGD	20	6.92E−01	2.6E−02	7.07E−01	3.8E−02	7.92E−01	7.2E−02	2.23E+00	8.8E−02	9.19E−01	7.7E−02	1.13E+00	9.2E−02
	25	5.87E−01	4.1E−02	6.33E−01	4.9E−02	7.63E−01	5.8E−02	1.23E+00	7.5E−02	8.22E−01	6.2E−02	1.08E+00	8.9E−02
	30	1.45E−01	2.4E−02	1.05E+00	9.2E−02	8.22E−01	4.7E−02	3.23E−01	3.5E−02	8.05E−01	5.3E−02	7.83E−01	4.4E−02
	35	7.78E−01	5.7E−02	6.43E−01	4.1E−02	8.49E−01	7.7E−02	8.83E−01	6.2E−02	9.46E−01	4.3E−02	8.59E−01	5.9E−02
	40	3.28E−01	3.8E−02	4.38E−01	5.3E−02	5.12E−01	5.0E−02	9.66E−01	6.5E−02	1.17E+00	7.9E−02	1.12E+00	8.6E−02
	45	5.57E−01	5.0E−02	5.22E−01	4.5E−02	9.32E−01	5.8E−02	6.74E−01	4.7E−02	7.97E−01	5.4E−02	9.53E−01	5.4E−02
S	20	1.75E−01	4.6E−02	3.53E−01	6.1E−02	1.68E−01	4.4E−02	3.90E−01	6.6E−02	2.26E−01	5.0E−02	1.64E−01	3.2E−02
	25	1.40E−01	3.5E−02	3.06E−01	7.2E−02	2.12E−01	3.8E−02	2.48E−01	3.5E−02	2.71E−01	6.9E−02	1.22E−01	2.8E−02
	30	8.54E−02	1.8E−02	8.89E−02	6.8E−02	2.86E−01	6.9E−02	1.77E−01	5.5E−02	1.64E−01	4.4E−02	1.55E−01	5.6E−02
	35	2.95E−01	4.3E−02	1.43E−01	3.7E−02	1.35E−01	2.1E−02	2.87E−01	2.8E−02	2.05E−01	3.2E−02	1.45E−01	4.8E−02
	40	1.14E−01	3.8E−02	3.21E−01	5.3E−02	1.28E−01	4.3E−02	2.41E−01	4.4E−02	1.08E−01	3.3E−02	1.77E−01	6.7E−02
	45	1.46E−01	4.8E−02	2.28E−01	6.3E−02	2.40E−01	5.0E−02	1.26E−01	6.6E−02	1.18E−01	4.5E−02	1.15E−01	4.8E−02

Notes: The elements in the grey colour are the best metric values.

Table 7. Comparison of the algorithms' performances for large-scale instances.

		VNS-NSGAII		NSGAII		SPEA2		MOPSO		MOCELL	
Metric value	*N*	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
HV	50	1.25E+04	2.3E+02	5.04E+03	3.3E+02	1.20E+04	5.4E+02	9.85E+03	3.8E+02	4.33E+03	3.5E+02
	80	1.85E+04	3.1E+02	6.19E+03	3.8E+02	6.47E+03	3.5E+02	5.47E+03	3.3E+02	9.08E+03	4.3E+02
	100	1.73E+04	3.5E+02	7.87E+03	4.2E+02	5.32E+03	2.8E+02	1.50E+04	5.1E+02	6.49E+03	3.7E+02
	150	4.94E+04	4.3E+02	2.98E+04	5.3E+02	3.37E+04	5.7E+02	2.65E+04	5.7E+02	1.80E+04	5.2E+02
GD	50	1.55E−01	4.6E−02	1.77E−01	7.5E−02	2.47E−01	6.3E−02	2.64E−01	5.5E−02	7.67E−02	5.3E−02
	80	1.40E−02	6.5E−02	9.50E−02	8.8E−02	2.59E−01	7.9E−02	7.79E−02	7.5E−02	8.25E−02	7.2E−02
	100	7.95E−02	6.5E−02	9.47E−02	6.8E−02	1.69E−01	8.3E−02	1.61E−01	7.2E−02	1.04E−01	7.5E−02
	150	1.68E−01	5.1E−02	2.09E−01	5.3E−02	1.78E−01	6.2E−02	1.80E−01	4.9E−02	1.08E−01	4.5E−02
IGD	50	5.53E−01	3.5E−02	6.76E−01	5.1E−02	8.83E−01	6.3E−02	7.65E−01	6.2E−02	5.83E−01	3.5E−02
	80	1.85E−01	3.7E−02	2.49E−01	4.5E−02	5.34E−01	5.2E−02	2.66E−01	4.8E−02	2.14E−01	5.5E−02
	100	2.18E−01	2.8E−02	1.97E−01	2.6E−02	4.15E−01	3.7E−02	4.93E−01	3.1E−02	3.00E−01	4.3E−02
	150	2.86E−01	4.1E−02	4.84E−01	7.7E−02	4.54E−01	4.8E−02	3.63E−01	5.2E−02	2.79E−01	6.3E−02
S	50	1.26E−01	5.4E−02	1.77E−01	3.6E−02	1.66E−01	3.9E−02	1.99E−01	4.5E−02	1.05E−01	6.9E−02
	80	7.31E−02	2.2E−02	8.88E−02	3.5E−02	1.95E−01	4.1E−02	7.87E−02	5.5E−02	8.39E−02	2.9E−02
	100	7.75E−02	6.7E−02	1.31E−01	5.3E−02	1.04E−01	9.1E−02	7.24E−02	3.3E−02	8.52E−02	4.1E−02
	150	1.26E−01	3.6E−02	1.27E−01	5.8E−02	9.80E−02	3.3E−02	1.36E−01	4.7E−02	7.70E−02	8.8E−02

Notes: The elements in the grey colour are the best metric values.

(sd) are used to measure the performance of each metric. It should be mentioned that encoding and decoding processes are the same for each selected algorithm, that is, identical coding space is searched by the algorithms themselves.

We compare the solutions of small-scale and large-scale problems, respectively. For the small-scale instances with 20–45 commuters, the metric values are given in Table 6, generated by the FNDS-G_{ps}, VNS-NSGAII, NSGAII, MOCELL, SPEA2, and MOPSO algorithms. In order to increase the readability in the tables, the best metric values have been shown in grey colour. In Table 6, it is clear that the FNDS-G_{ps} algorithm is the most competitive algorithm for the HV and IGD metrics, as it has the best value in 9 instances. The VNS-NSGAII algorithm is the second-most competitive algorithm for the HV and IGD metrics, as it has the best value in 3 instances. FNDS-G_{ps} and VNS-NSGAII algorithms have similar performance for GD metric with the best value in 2 instances. Other algorithms have displayed a much worse performance than FNDS-G_{ps} and VNS-NSGAII algorithms using the GD metric. However, the MOCELL algorithm is the most competitive algorithm for the S metric, as it has the best value in 3 instances.

For the large-scale instances with 50–150 commuters, the metric values are given in Table 7, generated by the

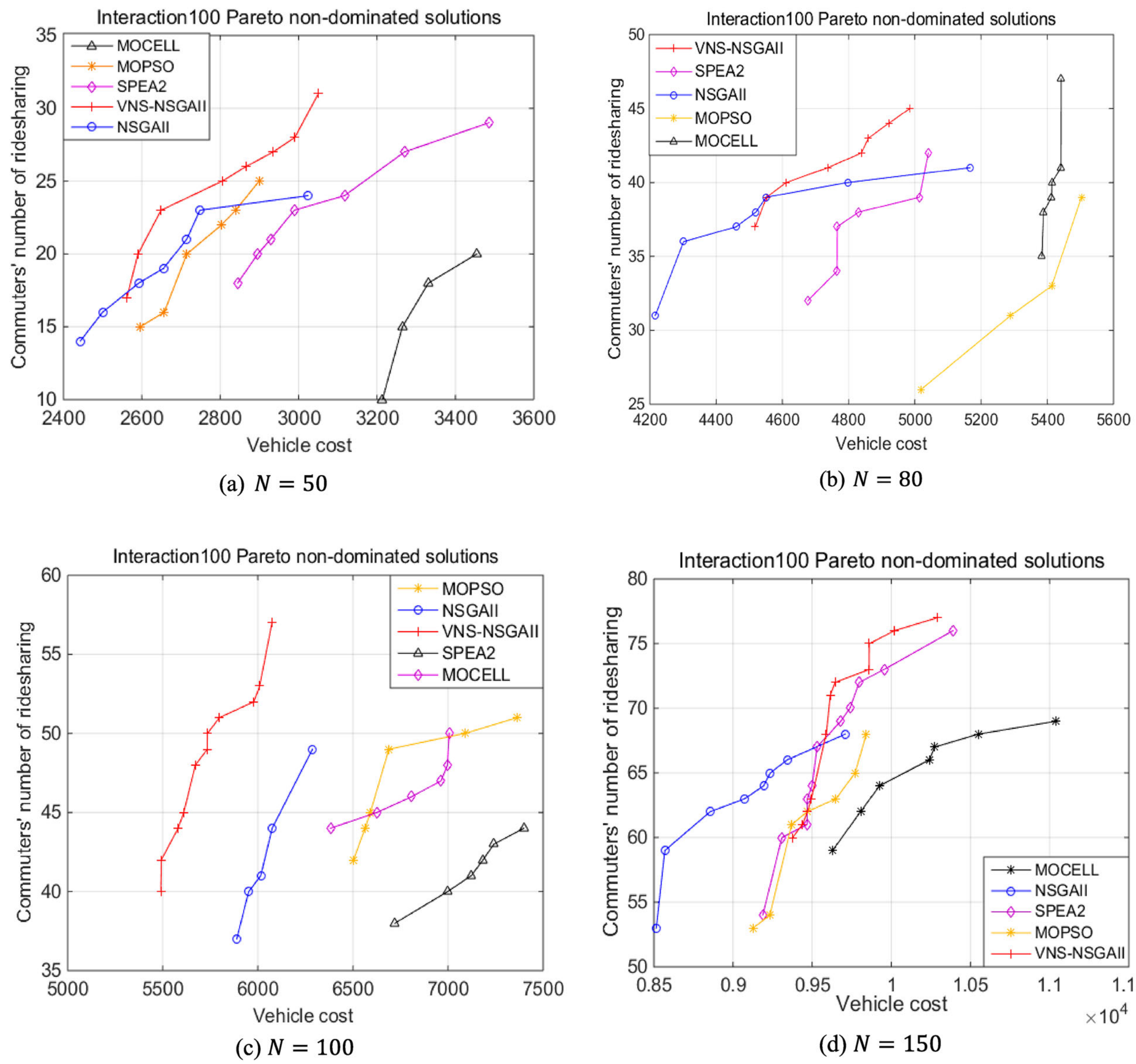

Figure 9. The Pareto fronts derived from five algorithms.

VNS-NSGAII, NSGAII, MOCELL, SPEA2, and MOPSO algorithms. It is clear that the VNS-NSGAII algorithm is the most competitive algorithm for the HV, GD, and IGD metrics, as it has the best value in 9 instances. For S metric, it can be seen that VNS-NSGAII, NSGAII, SPEA2, and MOPSO algorithms have the similar performance with the best value in 1 instance.

To analyse the performance of different algorithms in different instances, we observe that for small-scale instances, out of four performance metrices, the performance of the FNDS-G_{ps} algorithm is the best for this problem. For large-scale instances, it can be found that VNS-NSGAII performs much better than other four algorithms in most instances. Besides, the VNS-NSGAII algorithm performs the best in small-scale instances except for FNDS-G_{ps} algorithm.

We compared the Pareto front results of different algorithms for large-scale instances, which are displayed in Figure 9. The subpanels in Figure 9(a) report the solutions of the model when $N = 50$. It shows that the solutions' quality using VNS-NSGAII is better than those of other algorithms. Figure 9(b) reports the solutions of the model when $N = 80$. The solutions of VNS-NSGAII and NSGAII perform better than others. The solutions of NSGAII are better than those of the VNS-NSGAII when the cost is low. However, the solutions of the VNS-NSGAII are better than those of NSGAII when the cost is high. Figure 9(c) reports the solutions of model for $N = 100$. Hence, it is clear that the solutions of VNS-NSGAII are better than those of other algorithms. Figure 9(d) reports the solutions of model for $N = 150$. The solutions of VNS-NSGAII and NSGAII perform better than those

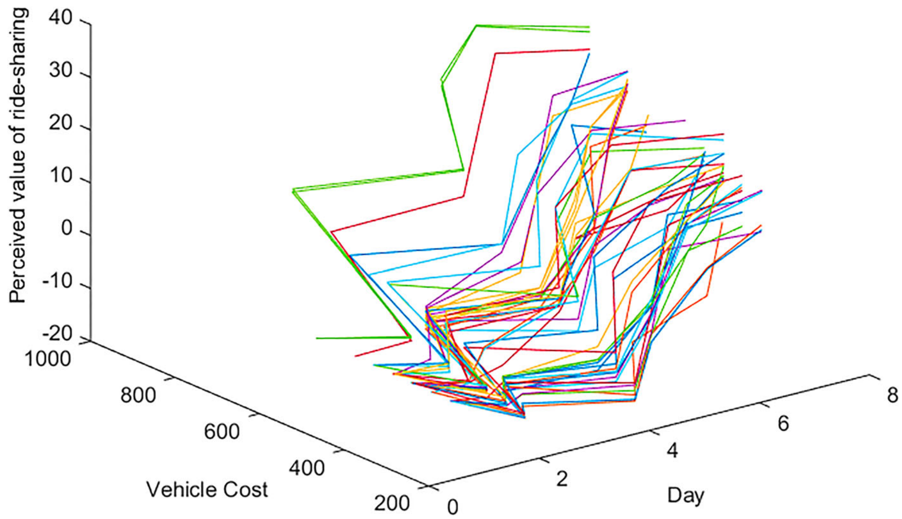

Figure 10. Perceived value change of a group of Pareto solutions in people's memory time.

of other algorithms. Moreover, for VNS-NSGAII, a small increase in vehicles' cost will lead to a significant increase in the number of commuter.

Next, we study the impact of optimisation on commuter decision-making. Commuter's decision on the travel mode is analysed based on the evaluation of their perceived value. According to the CPT, the perceived value is relative to the psychological expectation and gradually changes within a certain period of time. Figure 10 shows a Pareto solution set with parameters $N = 40, m = 7$. It can be seen that the perceived value of ridesharing commuters increases with the number of days. At the same time, as the number of vehicles increases, the perceived value of commuters will gradually increase.

6. Conclusion

This paper studies the optimisation problem of the bounded rational commuters' travel decision-making. A ridesharing multi-objective optimisation model is established. The method can enhance the loyalty of customers and is conducive to the long-term development of the industry. The model also has some enlightenment to the management of city logistics industry. The model simulates the ridesharing commuter's decision-making behaviour base on CPT. A heuristic algorithm FNDS-G_{ps} is developed for the optimisation problem in small-scale scenarios. Besides, a hybrid VNS-NSGAII algorithm is designed to solve the optimisation problem in large-scale scenarios. Extensive experiments were performed to test the performance of the proposed algorithm based the actual data. Results show that the FNDS-G_{ps} algorithm is effective for small-scale scenarios. Hybrid VNS-NSGAII is better than the NSGAII, SPEA2, MOPSO, and MOCELL algorithms with respect to the quality of solutions for large-scale scenarios. Moreover, we analyse the impact of ride-matching and routeing on the ridesharing decision, which has an essential contribution to the real-world applicability of ridesharing. In real life, our study on ridesharing provides a new perspective for city logistics.

Future research may include the following directions. First, the model can be modified such that it can reflect the heterogeneity of commuters, since people's attitudes toward time and costs risk are different. These aspects will significantly improve the commuters' perceived value. Second, real-time car appointment is a new trend in the mobile internet era, which should be deeply considered. Third, the driver's enthusiasm and incentives, which is especially crucial for the business development of the ridesharing industry, must be considered as well.

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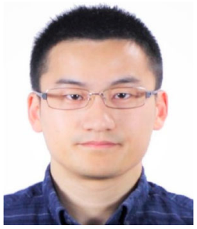

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References

Abedi, M., H. Seidgar, H. Fazlollahtabar, and R. Bijani. 2015. "Bi-Objective Optimisation for Scheduling the Identical Parallel Batch-Processing Machines with Arbitrary Job Sizes, Unequal Job Release Times and Capacity Limits." *International Journal of Production Research* 53 (6): 1680–1711. doi:10.1080/00207543.2014.952795.

Agatz, N., A. L. Erera, M. W. Savelsbergh, and X. Wang. 2011. "Dynamic Ride-Sharing: A Simulation Study in Metro Atlanta." *Procedia - Social and Behavioral Sciences* 17: 532–550. doi:10.1016/j.sbspro.2011.04.530.

Agatz, N., A. Erera, M. Savelsbergh, and X. Wang. 2012. "Optimization for Dynamic Ride-Sharing: A Review." *European Journal of Operational Research* 223 (2): 295–303. doi:10.1016/j.ejor.2012.05.028.

Baldacci, R., V. Maniezzo, and A. Mingozzi. 2004. "An Exact Method for the Car Pooling Problem Based on Lagrangean Column Generation." *Operations Research* 52 (3): 422–439. doi:10.1287/opre.1030.0106.

Ben Mohamed, I., W. Klibi, O. Labarthe, J. C. Deschamps, and M. Z. Babai. 2017. "Modelling and Solution Approaches for the Interconnected City Logistics." *International Journal of Production Research* 55 (9): 2664–2684. doi:10.1080/00207543.2016.1267412.

Cisneros-Saldana, J. I., Hosseinian, S., and Butenko, S. 2018. "Network-Based Optimization Techniques for Wind Farm Location Decisions." *Frontiers of Engineering Management* 5 (4): 533–540. doi:10.15302/J-FEM-2018025.

Coello, C. C., and M. S. Lechuga. 2002. "MOPSO: A Proposal for Multiple Objective Particle Swarm Optimization." Proceedings of the 2002 Congress on Evolutionary Computation, CEC'02 (Cat. No. 02TH8600), Vol. 2, pp. 1051-1056.

Crainic, T. G., P. K. Nguyen, and M. Toulouse. 2016. "Synchronized Multi-Trip Multi-Traffic Pickup & Delivery in City Logistics." *Transportation Research Procedia* 12: 26–39. doi:10.1016/j.trpro.2016.02.023.

Deb, Kalyanmoy. 2000. "Multi-Objective Evolutionary Optimization: Past, Present, and Future." In *Evolutionary Design and Manufacture*, 225–236. London: Springer. doi:10.1007/978-1-4471-0519-0_18.

Deb, K., A. Pratap, S. Agarwal, and T. Meyarivan. 2002. "A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II." *IEEE Transactions on Evolutionary Computation* 6 (2): 182–197. doi:10.1109/4235.996017.

Deb, K., Agrawal. S, Pratap. A, and Meyarivan. T. 2000. "A Fast Elitist non-Dominated Sorting Genetic Algorithm for Multi-Objective Optimization: NSGA-II." In *International Conference on Parallel Problem Solving from Nature*, 849–858. Berlin, Heidelberg: Springer. doi:10.1007/3-540-45356-3_83.

Diestel, Reinhard . 2000. *Graph Theory*. Vol. 173 (502), 67–128. Berlin: Springer. doi: 10.2307/3620535.

Dimitrakopoulos, G., P. Demestichas, and V. Koutra. 2012. "Intelligent Management Functionality for Improving Transportation Efficiency by Means of the Car Pooling Concept." *IEEE Transactions on Intelligent Transportation Systems* 13 (2): 424–436. doi:10.1109/TITS.2011.2169669.

Dolati Neghabadi, P., K. E. Samuel, and M.-L. Espinouse. 2019. "Systematic Literature Review on City Logistics: Overview, Classification and Analysis." *International Journal of Production Research* 57 (3): 865–887. doi:10.1080/00207543.2018.1489153.

Euchi, J., and R. Mraihi. 2012. "The Urban Bus Routing Problem in the Tunisian Case by the Hybrid Artificial Ant Colony Algorithm." *Swarm and Evolutionary Computation* 2: 15–24. doi:10.1016/j.swevo.2011.10.002.

Feng, X., M. Saito, and Y. Liu. 2016. "Improve Urban Passenger Transport Management by Rationally Forecasting Traffic Congestion Probability." *International Journal of Production Research* 54 (12): 3465–3474. doi:10.1080/00207543.2015.1062570.

Furuhata, M., M. Dessouky, F. Ordóñez, M. E. Brunet, X. Wang, and S. Koenig. 2013. "Ridesharing: The State-of-the-Art and Future Directions." *Transportation Research Part B: Methodological* 57: 28–46. doi:10.1016/j.trb.2013.08.012.

Gianessi, P., L. Alfandari, L. Létocart, and R. Wolfler Calvo. 2016. "The Multicommodity-Ring Location Routing Problem." *Transportation Science* 50 (2): 541–558. doi:10.1287/trsc.2015.0600.

Glover, F., S. Hanafi, O. Guemri, and I. Crevits. 2018. "A Simple Multi-Wave Algorithm for the Uncapacitated Facility Location Problem." *Frontiers of Engineering Management* 5 (4): 451–465. doi:10.15302/J-FEM-2018038.

Harbaoui Dridi, I., E. Ben Alaïa, P. Borne, and H. Bouchriha. 2019. "Optimisation of the Multi-Depots Pick-Up and Delivery Problems with Time Windows and Multi-Vehicles Using PSO Algorithm." *International Journal of Production Research* (8): 1–14.

Huang, Y., C. Shi, L. Zhao, and T. Van Woensel. 2012. "A Study on Carbon Reduction in the Vehicle Routing Problem with Simultaneous Pickups and Deliveries." Proceedings of 2012 IEEE International Conference on service Operations and logistics, and Informatics pp 302-307.

Jamshidi, A., F. Jamshidi, D. Ait-Kadi, and A. Ramudhin. 2019. "A Review of Priority Criteria and Decision-Making Methods Applied in Selection of Sustainable City Logistics Initiatives and Collaboration Partners." *International Journal of Production Research* 57: 5175–5193. doi:10.1080/00207543.2018.1540892.

Jarboui, B., M. Eddaly, and P. Siarry. 2011. "A Hybrid Genetic Algorithm for Solving No-Wait Flowshop Scheduling Problems." *The International Journal of Advanced Manufacturing Technology* 54 (9): 1129–1143. doi:10.1007/s00170-010-3009-4.

Jiau, M. K., S. C. Huang, and C. H. Lin. 2013. "Optimizing the Carpool Service Problem with Genetic Algorithm in Service-Based Computing." 2013 IEEE International Conference on services Computing IEEE. pp: 478-485.

Kannan, S., S. Baskar, J. D. McCalley, and P. Murugan. 2009. "Application of NSGA-II Algorithm to Generation Expansion Planning." *IEEE Transactions on Power Systems* 24 (1): 454–461. doi:10.1109/TPWRS.2008.2004737.

Kar, M. B., S. Kar, S. Guo, X. Li, and S. Majumder. 2019. "A New Bi-Objective Fuzzy Portfolio Selection Model and Its Solution Through Evolutionary Algorithms." *Soft Computing* 23 (12): 4367–4381. doi:10.1007/s00500-018-3094-0.

Kar, M. B., P. Kundu, S. Kar, and T. Pal. 2018. "A Multi-Objective Multi-Item Solid Transportation Problem with Vehicle Cost, Volume and Weight Capacity Under Fuzzy Environment." *Journal of Intelligent & Fuzzy Systems* 35 (2): 1991–1999. doi:10.3233/JIFS-171717.

Le-Anh, T., R. B. M. De Koster, and Y. Yu. 2010. "Performance Evaluation of Dynamic Scheduling Approaches in Vehicle-Based Internal Transport Systems." *International Journal of Production Research* 48 (24): 7219–7242. doi:10.1080/00207540903443279.

Lin, C. K. Y. 2011. "A Vehicle Routing Problem with Pickup and Delivery Time Windows, and Coordination of Transportable Resources." *Computers & Operations Research* 38 (11): 1596–1609. doi:10.1016/j.cor.2011.01.021.

Lin, Y., W. Li, F. Qiu, and H. Xu. 2012. "Research on Optimization of Vehicle Routing Problem for Ride-Sharing Taxi." *Procedia - Social and Behavioral Sciences* 43: 494–502. doi:10.1016/j.sbspro.2012.04.122.

Liu, X., S. Lu, J. Pei, and P. M. Pardalos. 2018. "A Hybrid VNS-HS Algorithm for a Supply Chain Scheduling Problem with Deteriorating Jobs." *International Journal of Production Research* 56 (17): 5758–5775. doi:10.1080/00207543.2017.1418986.

Long, Y., and J. C. Thill. 2015. "Combining Smart Card Data and Household Travel Survey to Analyze Jobs–Housing Relationships in Beijing." *Computers, Environment and Urban Systems* 53: 19–35. doi:10.1016/j.compenvurbsys.2015.02.005.

Lu, Q., and M. Dessouky. 2004. "An Exact Algorithm for the Multiple Vehicle Pickup and Delivery Problem." *Transportation Science* 38 (4): 503–514. doi:10.1287/trsc.1030.0040.

Majumder, S., M. B. Kar, S. Kar, and T. Pal. 2019. "Uncertain Programming Models for Multi-Objective Shortest Path Problem with Uncertain Parameters." *Soft Computing* (1): 1–22.

Majumder, S., S. Kar, and T. Pal. 2019. "Uncertain Multi-Objective Chinese Postman Problem." *Soft Computing* 23 (22): 11557–11572. doi:10.1007/s00500-018-03697-3.

Majumder, S., P. Kundu, S. Kar, and T. Pal. 2019. "Uncertain Multi-Objective Multi-Item Fixed Charge Solid Transportation Problem with Budget Constraint." *Soft Computing* 23 (10): 3279–3301. doi:10.1007/s00500-017-2987-7.

Manzini, R., and A. Pareschi. 2012. "A Decision-Support System for the Car Pooling Problem." *Journal of Transportation Technologies* 2 (2): 85–101. doi:10.4236/jtts.2012.22011.

Masson, R., F. Lehuédé, and O. Péton. 2014. "The Dial-a-Ride Problem with Transfers." *Computers & Operations Research* 41: 12–23. doi:10.1016/j.cor.2013.07.020.

Mladenović, N., and P. Hansen. 1997. "Variable Neighborhood Search." *Computers & Operations Research* 24 (11): 1097–1100. doi:10.1016/S0305-0548(97)00031-2.

Muelas, S., A. LaTorre, and J.-M. Peña. 2013. "A Variable Neighborhood Search Algorithm for the Optimization of a Dial-a-Ride Problem in a Large City." *Expert Systems with Applications* 40 (14): 5516–5531. doi:10.1016/j.eswa.2013.04.015.

Nebro, A. J., J. J. Durillo, F. Luna, B. Dorronsoro, and E. Alba. 2009. "MOCell: A Cellular Genetic Algorithm for Multiobjective Optimization." *International Journal of Intelligent Systems* 24 (7): 726–746. doi:10.1002/int.20358.

Polak J, W. 1998. "The Influence of Alternative Traveller Learning Mechanisms on the Dynamics of Transport Systems." *Transportation Planning Methods* 1: 83–95.

Pureza, V., R. Morabito, and M. Reimann. 2012. "Vehicle Routing with Multiple Deliverymen: Modeling and Heuristic Approaches for the VRPTW." *European Journal of Operational Research* 218 (3): 636–647. doi:10.1016/j.ejor.2011.12.005.

Skriver, A. J., and K. A. Andersen. 2000. "A Label Correcting Approach for Solving Bicriterion Shortest-Path Problems." *Computers & Operations Research* 27 (6): 507–524. doi:10.1016/S0305-0548(99)00037-4.

Tan, Y., J. E. Carrillo, and H. K. Cheng. 2016. "The Agency Model for Digital Goods." *Decision Sciences* 47 (4): 628–660. doi:10.1111/deci.12173.

Tan, Y. R., A. A. Paul, Q. Deng, and L. Wei. 2017. "Mitigating Inventory Overstocking: Optimal Order-Up-to Level to Achieve a Target Fill Rate Over a Finite Horizon." *Production and Operations Management* 26 (11): 1971–1988. doi:10.1111/poms.12750.

Tversky, A., and D. Kahneman. 1992. "Advances in Prospect Theory: Cumulative Representation of Uncertainty." *Journal of Risk and Uncertainty* 5 (4): 297–323. doi:10.1007/BF00122574.

Yang, S., J. Wang, L. Shi, Y. Tan, and F. Qiao. 2018. "Engineering Management for High-End Equipment Intelligent Manufacturing." *Frontiers of Engineering Management* 5 (4): 420–450. doi:10.15302/J-FEM-2018050.

Zhang, W., and R. He. 2014. "Residents Travel Mode Choice Based on Prospect Theory." *Journal of Computer Applications* 34 (3): 749–753.

Zhang, W., R. He, Q. Xiao, and C. Ma. 2016. "Research on Strategy Control of Taxi Carpooling Detour Route Under Uncertain Environment." *Discrete Dynamics in Nature and Society* (2016): 1–11.

Zhao, Q., W. Wang, and R. De Souza. 2017. "A Heterogeneous Fleet Two-Echelon Capacitated Location-Routing Model for Joint Delivery Arising in City Logistics." *International Journal of Production Research* (2017): 1–19.

Zhao, L. Y., and C. Yang. 2013. "Mode Choice with Cumulative Prospect Theory Under Uncertainty." The 10th International Conference of Eastern Asia Society for transportation studies, EASTS_ISC-D-13-00265.

Zitzler, E., M. Laumanns, and L. Thiele. 2001. "SPEA2: Improving the Strength Pareto Evolutionary Algorithm." TIK-report, 103.

Appendix

Table A1. Comparative study of relevant literature with present work.

Study	Model features: Multi-period	Model features: Multi-level	Model features: Modelling	Objective functions: Suppliers — Maximise the level of service	Objective functions: Retailers — Minimise cost of transportation	Objective functions: Consumers — Maximise the consumers' willingness	Objective functions: Administrators — Minimise the greenhouse gas emissions	Solution
Euchi and Mraihi (2012)	×	×	MIP	√	√	×	√	Ant colony optimisation
Pureza, Morabito, and Reimann (2012)	×	×	MIP	√	√	√	×	Heuristic
Lin (2011)	×	×	MIP	√	√	×	×	Heuristic
Muelas, LaTorre, and Peña (2013)	×	×	MIP	×	√	×	×	VNS
Huang et al. (2012)	×	×	MILP	×	√	×	√	Epsilon constraint
Gianessi et al. (2016)	×	√	MIP	×	√	×	×	Matheuristic
Crainic, Nguyen, and Toulouse (2016)	×	√	MIP	√	√	×	×	Tabu search
Ben Mohamed et al. (2017)	√	√	MIP	√	√	×	×	Heuristic
Zhao, Wang, and De Souza (2017)	×	√	MIP	√	√	×	√	Heuristic
Our study	√	×	MIP	√	√	√	×	Heuristic andVNS-NSGAII

Modelling: MIP = Mixed integer programming; MILP = Mixed integer linear programming.