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Demand control model with combinatorial incentives and surcharges for one-way carsharing operation

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ABSTRACT

One-way carsharing is an alternative shared-use transportation mode that provides flexible travel accommodations for urban mobility. However, vehicle distributions can be mismatched with demand distributions because users are not required to return to their departure locations. Conventional operator-based vehicle relocation is limited by labor resources, but user-based and demand-controlled approaches can open new avenues for mitigating vehicle imbalance. This paper proposes a method for controlling demand patterns by applying measures of combinatorial monetary incentives and surcharges. A two-level nested logit model is adopted to analyze user decisions regarding the travel process in response to differentiated pricing combinations. A user choice model is aggregated and loaded into a time-space network that reveals the dynamics of the carsharing system. An optimization framework is proposed to determine the incentives and surcharges at different stations and times of day. This paper presents an algorithm for solving the proposed optimization model, as well as an example of parameter calibration and the solving process. Case analysis suggests that the proposed method can increase revenues by 22.5% compared to a scenario without demand control and vehicle relocation policies. Comparisons suggest that the proposed demand-based control policy can achieve higher revenues than operator-based relocation, whereas operator-based relocation could satisfy greater demand.

1. Introduction

Rapid modern urbanization has generated growing transportation demand and challenges for future urban transportation and humanized mobility. Carsharing has been considered as an alternative shared-use urban transportation mode since the introduction of mobile internet and the shared economy has accelerated the emergence of a new market for urban mobility (Shaheen et al., 2015a). Carsharing is promising for mitigating transportation problems by providing better mobility, increasing vehicle usage, saving expenses relating to car ownership, reducing energy consumption, and economizing parking spaces (Barth and Shaheen, 2002).

There are various carsharing service models, including one-way and round-trip models. A one-way model allows users to pick up vehicles from one station and drop them off at a different station, providing more convenient travel experiences for users (Jorge et al.,

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Table 1
Literature on user-based relocation for one-way carsharing.

Studies	Policies	Methodology
Barth et al. (2004)	Trip merging and splitting	Logics and simulation
Di Febbraro et al. (2012)	Destination change	Discrete event system and optimization on rolling horizon
Waserhole and Jost (2014)	Price leverage	Queuing system and convex integer programming solved by greedy algorithm
Herrmann et al. (2014)	Multiple	Survey and discrete event simulation
Jorge et al. (2015b)	Price leverage	Mixed integer non-linear programming
Wagner et al. (2015)	Destination change	Logic, system design, and simulation
Angelopoulos et al. (2016)	Suggesting trips for users	Graph and simulation
Di Febbraro et al. (2018)	Incentive for destination suggestion	Two-stage optimization
Huang et al. (2018)	Overall price	Mixed integer non-linear programming
Clemente et al. (2018)	Economic incentives	Discrete event system and closed-loop control strategy
Lippoldt et al. (2018)	Bonus minute incentive	Two-stage logic
Wang et al. (2019a)	Incentive	Field test and practice approach

2015a; Shaheen et al., 2015b). However, vehicles floating through networks can lead to imbalances between fleet allocation and demand. A lack of available vehicles in high-demand areas negatively impacts user experiences and decreases customer satisfaction. Additionally, idle vehicles in the low-demand areas lose the opportunity to make profits for the service provider, which can lead to a negative feedback loop.

The fleet balancing problem can be considered during the planning stage. For example, Correia and Antunes (2012) proposed a depot location method and Huang et al. (2018) designed a network planning method considering the relocation problem. In the operation stage, approaches for coping with imbalance problems fall into two main categories: 1) operator-based vehicle relocation and 2) user-based vehicle relocation. Operator-based vehicle relocation approaches change the vehicle distribution on the supply side, whereas user-based approaches influence user behaviors on the demand side (Cepolina and Farina, 2012).

The operator-based vehicle relocation problem has been studied for more than a decade. Some representative studies can be categorized as follows. When demand is known, deterministic mathematical programming methods such as mixed-integer linear programming have been successfully applied to solve the relocation problem (Alfian et al., 2014; Boyacı et al., 2015; Nourinejad and Roorda, 2014). For unknown demand, various approaches have been proposed, including inventory control methods based on threshold triggering (Kek et al., 2009), mathematical programming with predictive demand (Bruglieri et al., 2014), and stochastic programming (Fan et al., 2008). However, it has been shown that the number of relocation workers limits relocation capabilities (Kim et al., 2014), which could be a bottleneck for carsharing network expansion. Another side-effect is the relocation and scheduling of workers because their positions will also become imbalanced, which makes operator-based vehicle relocation even more complicated (Bruglieri et al., 2018).

To overcome the limitations of operator-based vehicle relocation, some researchers have considered new approaches from the perspective of demand. Some studies refer to this type of problem as user-based relocation, as opposed to operator-based relocation. Barth et al. (2004) originally proposed the concept of user-based relocation, which attempts to motivate users to merge trips or split trips. Representative studies on user-based relocation and demand control approaches are summarized in Table 1.

Incentives are effective tools for motivating users and controlling demand in a system. Herrmann et al. (2014) conducted a survey of user intentions to accept incentives and summarized four major policies: 1) destination changes, 2) origin location changes, 3) both origin and destination changes, and 4) pooling. Angelopoulos et al. (2016) proposed a trip suggestion policy that suggests not only destinations, but also departure locations. Di Febbraro et al. (2012), Di Febbraro et al. (2018), and Wagner et al. (2015) proposed methods based on incentive policies to motivate users to change their destinations, which will increase operator profits. Incentive-based approaches have also been studied from a practical perspective (Clemente et al., 2018; Lippoldt et al., 2018). We conducted an experimental study combining field operations for a one-way station-based electric vehicle sharing enterprise in Shanghai and discovered that incentives are practical and applicable for changing demand patterns (Wang et al., 2019a).

In addition to incentives, surcharges are also useful tools for reducing demand by charging extra fees. Incentives and surcharges can be used for variable pricing schemes. One important task is to reveal the relationship between price and demand. Jorge et al. (2015b) applied a pricing model for each origin–destination (O-D) pair based on a linear elastic demand assumption with a unified elasticity factor E. However, linear elasticity may not fit user choice behaviors accurately because demand would asymptotically approach a maximum value, regardless of how much an operator subsidizes users with incentives, and change relationships are not linear. Waserhole and Jost (2014) proposed a continuous elastic demand curve (presented as an S-shaped curve) that is more appropriate for depicting the price-demand relationship for each O-D pair. However, it is almost impossible to calibrate all curves for every O-D pair individually using limited samples. Jorge et al. (2015b) assumed a homogenous elastic coefficient E for every O-D pair, but this is a strict assumption that ignores the possible variation of different O-D pairs with different demand intensities. Waserhole and Jost (2014) did not discuss the variability of price-demand curves for each O-D pair either. Another important problem is that O–D matrices are typically sparse. There can be zero demand between some O-D pairs, which represents the background demand. The quantity of demand influenced by price cannot be calculated using a linear elastic function if the background demand is zero. Additionally, the S-curve is difficult to calibrate and it is difficult to determine if the background demand is zero.

One feasible method for avoiding the sparse O-D matrix problem is to introduce a disaggregated model. User behavior properties can be used to bridge the gap between price factors and demand patterns. Previous studies have considered user choice mechanisms using logit models (Efthymiou and Antoniou, 2016; Zoepf and Keith, 2016). Discrete choice models and agent-based simulations (Horni et al., 2016; Mallig et al., 2013) have also been introduced to study the cost-benefit tradeoff of one-way carsharing with relocation strategies (Wang et al., 2018). A discrete choice model can typically be calibrated using stated preference (SP) survey techniques (Remane et al., 2016). Huang et al. (2018) used a binary logit (BL) model to account for travel mode splitting between carsharing and private cars based on the influence of overall price. However, their model does not consider the price as a variable over different O-D pairs, so pricing cannot influence the spatial distribution of demand to match the vehicle distribution accurately. One potential method for resolving this issue is to let the price be variable over different O-D pairs, but this makes the nonlinear programming problem more complex.

We also discovered another problem with variable pricing schemes. Existing studies assume that the demand patterns across different O-D pairs are independent and ignore the correlations among O-D pairs. A user may be forced to travel to a nearby origin station if the price of their originally intended departure station increases. A user can also be attracted to a nearby station if the price is cheaper. The pricing behavior at a station will influence demand not only at that station, but also at nearby stations. This phenomenon implies that demand at nearby stations is correlated. However, the O-D pair pricing mechanisms proposed by Jorge et al. (2015b), Waserhole and Jost (2014) and Huang et al. (2018) assume that demand at stations is independent and that the demand for an O-D pair is binary, which ignores the fact that some demand may shift to (or shift from) nearby O-D pairs, rather than simply disappearing (or emerging). In our model, in addition to a user's O-D pair, we introduce departure and arrival stations, resulting in a path of origin-departure station-arrival station-destination. Users can choose from different paths and the proposed model can reflect the demand shifts among departure and arrival stations. User choice chains can be modeled by generalized nested logit (GNL) models (Wen and Koppelman, 2001). According to the specific characteristics of carsharing, this study adopted a two-level nested GNL model that captures both the elastic and shifting properties of demand.

However, adopting a logit model significantly increases the complexity of the proposed model compared to simple networks. This problem cannot be simplified as a strict optimization problem, such as mixed-integer linear programming, because the characteristics of user behaviors over networks will be lost. A simpler example of optimization using a logit model is the assortment optimization problem (Jiang et al., 2017). Jiang et al. (2017) found that the objective of revenue is not quasi-concave for price variables and indicated that logit optimization is NP-complete. Our problem is much more complex than modeling over networks. Additionally, the uniqueness of a solution cannot be guaranteed based on the characteristics of non-convexity and NP-completeness. One feasible solution is to transform the proposed complex model into a more practical model based on the specific characteristics of operators and to employ a heuristic algorithm for deriving a solution. Traditional simulated annealing is feasible for complex problems and is capable of jumping out of local optima.

In this study, we attempted to establish a demand control model for carsharing system operation. Monetary measures can be adopted to adjust demand patterns to match the supply of vehicles. Both incentives (providing rewards to attract users) and surcharges (setting extra fees to reduce demand) are introduced as economic tools for controlling demand patterns.

The main contributions of this paper can be summarized as follows.

- We adopted a two-level nested logit (NL) model to capture user choice probabilities under the influence of the incentives, surcharges, and price variations, which can not only reflect overall demand characteristics, but also demand distribution patterns over a network.
- The proposed model can fix the inappropriate fitting of linear elastic price demand, address the sparse O-D matrix problem, and capture the demand interactions among nearby O-D pairs.
- We adopted a time-space network for user choice probability aggregation and modeling system dynamics.
- We also present an algorithm based on practical conditions to determine the optimal combination of incentives and surcharges dynamically by maximizing the revenue of the system.
- We propose a method for incorporating a logit model into the target problem based on an optimization model for the demand control problem in a carsharing system.

The remainder of this paper is organized as follows: Section 2 presents the proposed model for capturing the user trip and path choice behaviors, time–space networks, and an optimization framework for determining incentives and surcharges. Section 3 presents a solution algorithm for the proposed optimization model. Section 4 presents a case study on user choice model calibration and the optimization process. Finally, Section 5 concludes this paper.

2. Methods

2.1. Problem setting and assumptions

The problem considered in this paper is how to design a scheme for incentive and surcharge combinations for carsharing networks to control the distribution of demand to maximize the value of a system in operation. Incentives and the surcharges can change user choices regarding pick-up stations and drop-off stations, which will influence the demand volume and distribution at each station in a system and affect profits. Differentiated pricing policies among stations and O-D pairs are considered in this study instead of attempting to optimize a comprehensive pricing strategy. Operator-based vehicle relocation will not be discussed in this paper.

In this study, we developed three basic policies: a 1) pick-up policy, 2) drop-off policy, and 3) O-D policy. The pick-up policy (denoted as p_{Di}^{t}) is that users who pick up vehicles from a station under this policy will receive additional rewards (incentives) or will be charged additional fees (surcharges). The drop-off policy (denoted as p_{Rj}^{t}) is that users will receive extra rewards or incur additional charges when dropping vehicles off at stations. The O-D policy (denoted as p_{ij}^{t}) is valid for a specific O-D pair, meaning users will be rewarded or charged if they travel through an O-D pair under this policy. All three policies have two sides, where a negative value indicates that a policy uses incentives and a positive value indicates that a policy uses surcharges.

The methodology for this study combines two major types of models: the logit-based user choice model and time–space network model. The user choice model establishes a relationship between pricing policies and demand patterns, and the time–space network loads the demand model into a network to capture the volume patterns of the system.

The basic assumptions adopted in this study are defined are as follows.

- User travel requests are known in advance or can be accurately predicted. Specifically, users provide their origin location, the destination location, and departure time to the system to book a trip at least one hour before departure or user-level travel requests can be predicted.
- Vehicles in the carsharing system are regular internal combustion automobiles, meaning they can be instantly refueled and immediately accessed by the next set of users. Therefore, refueling times and driving range limitations can be ignored. Additionally, the maintenance of vehicles is not considered.
- Incentives and surcharge policies at specific stations and time periods are available to all users and users can fully understand the impact of the policies and make their choices based on rational judgments.
- Incentives and surcharge policies are only valid during the time period t for a user when that user picks up a vehicle at station i with a nonzero policy p_{Di}^{t}, travels through a path from i to j with a nonzero policy p_{Di}^{t}, or drops a vehicle off at station j with a nonzero policy p_{ij}^{t}.

2.2. Notations

The notations that appear in this paper are defined below.

(1) Sets:

$S:\{s\}$	Set of all stations
$N:\{n\}$	Set of all users
$T:\{t\}$	Set of all time instances (the time horizon is discretized into time instances and the elements of this set are ordered)
$I_n \subset S$	Sets of departure stations for user n, $\forall n \in N$
$J_n \subset S$	Sets of arrival stations for user n, $\forall n \in N$

(2) Parameters:

1) Parameters for the optimization model:

l	Length of time between $t-1$ and t, minutes
p	Hourly rental price that does not contain incentives and surcharges for calculating basic expenses for users, ¥ per hour
d_{Dni}	Walking duration of user n from the origin to the departure station i, minutes, $\forall n \in N, \forall i \in S$
d_{Rnj}	Walking duration of user n from the arrival station j to the destination, minutes, $\forall n \in N, \forall i \in S$
t_{ij}	Driving time from station i to station j, minutes, $\forall i \in S, \forall j \in S$
x_s^0	Initial number of vehicles at station i,$\forall s \in S$
C_s	Number of parking spaces at station i, $\forall s \in S$

2) Parameters for profiling users:

XI_g	0–1 variables to group users according to monthly income, where g denotes the income groups (denoted by the set $G_I:\{XI_g\}$) (e.g., group user monthly income as ¥0~¥5000, ¥5001~¥10000, ¥10001~¥15000, and >¥15000 by XI_1, XI_2, XI_3, and XI_4, respectively) $\forall n \in N$ given XI_{gn} (e.g., if the income of user n falls into ¥10001~¥15000, then $XI_{1n}=0$, $XI_{2n}=0$, $XI_{3n}=1$, and $XI_{4n}=0$)
XG_g	0–1 variables to denote the genders of users; let XG_1 and XG_2 denote male and female, respectively, where g denotes the groups (denoted by the set $G_G:\{XG_g\}$) and for $\forall n \in N$ we have XG_{gn}; if user n is male, let $XG_{1n}=1$; if user n is female, let $XG_{2n}=0$
XA_g	0–1 variables to group users by age, where g denotes the groups (denoted by the set $G_A:\{XA_g\}$) (e.g., group users as <21, $21\sim30$, $31\sim40$, $41\sim50$, and >50 by XA_1, XA_2, XA_3, XA_4, and XA_5, respectively) $\forall n \in N$ given XA_{gn}; a user n should fall into one group
XF_g	0–1 variables to denote the activeness (usage frequency) of a user, where g denotes the groups (denoted by the set $G_F:\{XF_g\}$) (e.g., group users as “less than once a week,” “$2\sim3$ times a week,” and “more than once a day,” by XF_1, XF_2, and XF_3, respectively) $\forall n \in N$ given XF_{gn}; user n should fall into one group
XB	0–1 variables to denote whether a user is a bikesharing user; if user n is a bikesharing user, they are assigned a value of one; otherwise, they are assigned a value of zero

(3) Variables:

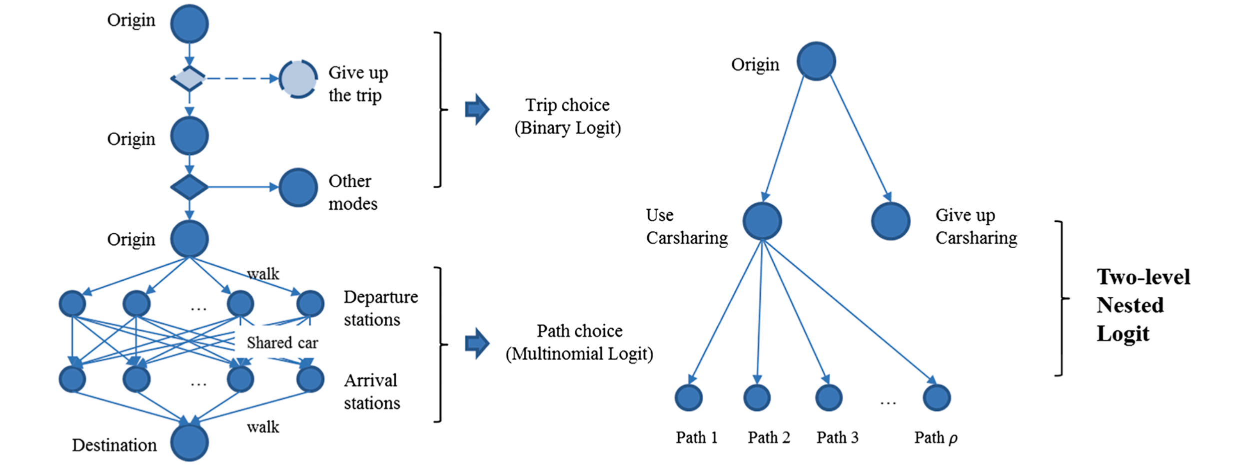


Fig. 1. User decision process during a trip.

1) Decision and auxiliary variables:

p^t_{Di}	The pick-up incentive and surcharge policy at station i at time t, ¥, $\forall i \in S,\ \forall t \in T$; $p^t_{Di} < 0$ represents incentives, $p^t_{Di} > 0$ represents surcharges, and $p^t_{Di} = 0$ represents no policy
p^t_{Rj}	The drop-off incentive and surcharge policy at station j at time t, ¥, $\forall j \in S, \forall \in T$; $p^t_{Ri} < 0$ represents incentives, $p^t_{Ri} > 0$ represents surcharges, and $p^t_{Ri} = 0$ represents no policy
p^t_{ij}	The O-D incentive and surcharge policy for vehicles picked up from station i at time t and dropped off at station j at any time, ¥, $\forall i \in S, \forall j \in S, \forall t \in T$; $p^t_{ij} < 0$ represents incentives, $p^t_{ij} > 0$ represents surcharges, and $p^t_{ij} = 0$ represents no policy
k^t_i	Ratio of satisfied demands at station i based on the limitation of available vehicles

2) Dependent variables:

$\mathscr{P}^t_{nij}$	The probability that user n chooses to start at station i and drop off at station $j, \forall n \in N, \forall t \in T, \forall i \in I_n, \forall j \in J_n$
$P^{t^0 t^1}_{nij}$	The probability that user n chooses to pick up from station i at time t^0 and drop off at station j at time t^1, $\forall n \in N$, $\forall i \in S$, $\forall j \in S$, $\forall t^0 \in T, \forall t^1 \in T$
$q^{t^0 t^1}_{ij}$	Number of requests from station i at time t^0 to station j at time $t^1, \forall i \in S$, $\forall j \in S$, $\forall t^0 \in T, \forall t^1 \in T$
D^t_i	Demand of station i at time t, $\forall i \in S, \forall t \in T$
$\widehat{D}^t_i$	Satisfied demand of station i at time t, $\forall i \in S, \forall t \in T$
R^t_j	Number of returned vehicles at station j at time t, $\forall i \in S, \forall t \in T$
x^t_s	Number of vehicles at station i at time t, $\forall i \in S, \forall t \in T$

2.3. User choice model

Factors such as incentives and surcharges can influence user choices during trips. A user must make decisions at different stages during a trip. The decision process can be generalized as shown in Fig. 1. In the first stage, the user has the option to start a trip or stay home (in other words, to give up the trip). Then, there are transportation modes to be selected, including carsharing, if the user chooses to start a trip. After choosing the carsharing mode, the user selects a departure station to pick up a car and an arrival station to drop it off. The possible departure stations should be near the origin position of the user and the arrival stations should be near the destination position.

Incentives and surcharges differentiated over networks can affect not only user intentions regarding carsharing trips, but also the exact departure and arrival stations that users will choose. Existing studies have adopted discrete choice models to reveal mode choice mechanisms. For example, Huang et al. (2018) adopted a BL model to reflect user choices between carsharing and private cars. Catalano et al. (2008) adopted a multinomial logit (MNL) model that represents the competition between carsharing, private cars, carpooling, and public transit. These models successfully revealed macroscopic mode splitting. However, they are not adequate for explaining the routing of users or demand patterns distributed over networks. Di Febbraro et al. (2012) developed a BL model for users to choose to accept changing destinations if incentives are offered at some alternative destinations. This model captures drop-off demand, but loses expansibility for pick-up demands influenced by incentives or even surcharges. It also ignores that incentives may increase the attractiveness of carsharing and change total demand as well. Therefore, a general user choice model should be derived to cover the full process of user decision making to reflect overall demand and demand distributions. The GNL model (Wen and Koppelman, 2001) has attractive properties for hierarchical decision processes.

However, the user choice model should not be overly complicated so that it can be aggregated into a network model and included in

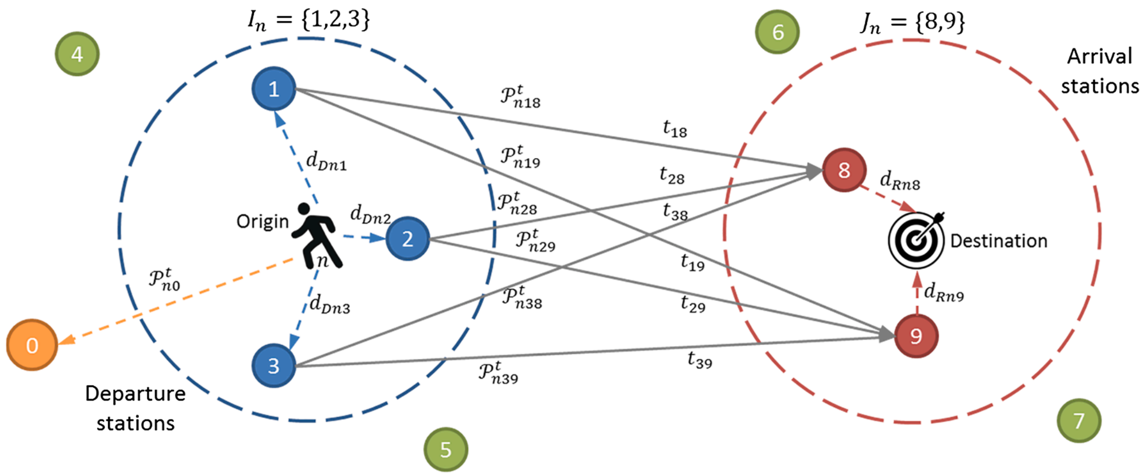


Fig. 2. An example of a user's choices.

optimization problems. As shown in Fig. 1, the trip intention stage merges with the mode choice stage in a single trip choice stage, which is simplified into a BL model to reflect whether a user chooses a carsharing mode without considering whether the user chooses another mode or gives up on a trip. For the departure and arrival choice stages, a pair of departure and arrival stations dictates a path, meaning departure and arrival station choices can be merged into one path choice model and implemented as an MNL model. This model is a two-level NL model that is a specific instance of GNL.

The trip choice model and path choice model are linked together and formulated as a two-level NL model, which is suitable for solving hierarchical multi-stage decision problems (Kockelman and Lemp, 2011; Koppelman and Wen, 1998; Wen and Koppelman, 2001). The incentives and surcharges affecting path choices are also fed back to the trip choice level. It should be noted that varying user socio-economic properties result in different choice probabilities for different users. Therefore, we consider user profiling information such monthly income, gender, age, carsharing usage frequency, and whether the user participates in bikesharing as variables in our model.

We assume that user profiles will influence both the trip choice level and path choice level. The corresponding utility functions are defined as follows.

1) Utility on the trip choice level:

$$V_1 = \theta_0 + \theta_1 p + U_1 \tag{1}$$

$$U_1 = \sum_{g\in G_I}\theta_{Ig}XI_g + \sum_{g\in G_G}\theta_{Gg}XG_g + \sum_{g\in A_G}\theta_{Ag}XA_g + \sum_{g\in A_G}\theta_{Fg}XF_g + \theta_B XB \tag{2}$$

2) Utility on the path choice level:

$$V_n^t(ij|1) = \varphi_0 + \varphi_1 p^t_{Di} + \varphi_2 p^t_{Rj} + \varphi_3 p^t_{ij} + \varphi_4 d_{Dni} + \varphi_5 d_{Rnj} + \varphi_6 t_{ij} + U_2, \forall t\in T, \forall i \in I_n, \forall j\in J_n, \forall n \in N \tag{3}$$

$$U_2 = \sum_{g\in G_I}\varphi_{Ig}XI_g + \sum_{g\in G_G}\varphi_{Gg}XG_g + \sum_{g\in A_G}\varphi_{Ag}XA_g + \sum_{g\in A_G}\varphi_{Fg}XF_g + \varphi_B XB \tag{4}$$

$$\Gamma^t_{1n} = \frac{1}{\mu_1}\ln \sum_{i\in I_n, j\in J_n} \exp\left(V_n^t(ij|1)\right), \forall t\in T, \forall n\in N \tag{5}$$

where V_1 denotes the utility of choosing carsharing at the trip choice level and U_1 denotes the utility of user profiling that influences the trip choice level. $V_n^t(ij|1)$ denotes user$n$'s utility for choosing a path from departure station i to arrival station j at time instance t at the path choice level. U_2 denotes the utility of user profiling that influences the path choice level. Γ^t_{1n} denotes the inclusive value (logsum of utility at the path choice level) of user$n$ at t that is fed back to the trip choice level. The inclusive value contains the utility from the lower level that can be reflected in the upper level. Additional explanation of the logsum can be found in previous papers (Kockelman and Lemp, 2011; Koppelman and Wen, 1998; Wen and Koppelman, 2001). p is the basic general price that users should pay (charging by the hour, ¥ per hour). ,p^t_{Di}, p^t_{Rj}, and p^t_{ij} denote the pick-up incentive or surcharge policy at station i, drop-off policy at station j, and O-D policy from i to j at time instance t, respectively, which are negative if incentives apply and positive if surcharges apply. d_{Dni} and d_{Rnj} are the walking times for user n from the origin to the departure station i and from the arrival station j to the destination, respectively. t_{ij} is the driving duration from station i to station j. Notations containing θ, φ, and μ are the parameters that must be calibrated, where θ denotes parameters on the trip choice level, φ denotes parameters on the path choice level, and μ denotes scalar factors interacting between the two levels.

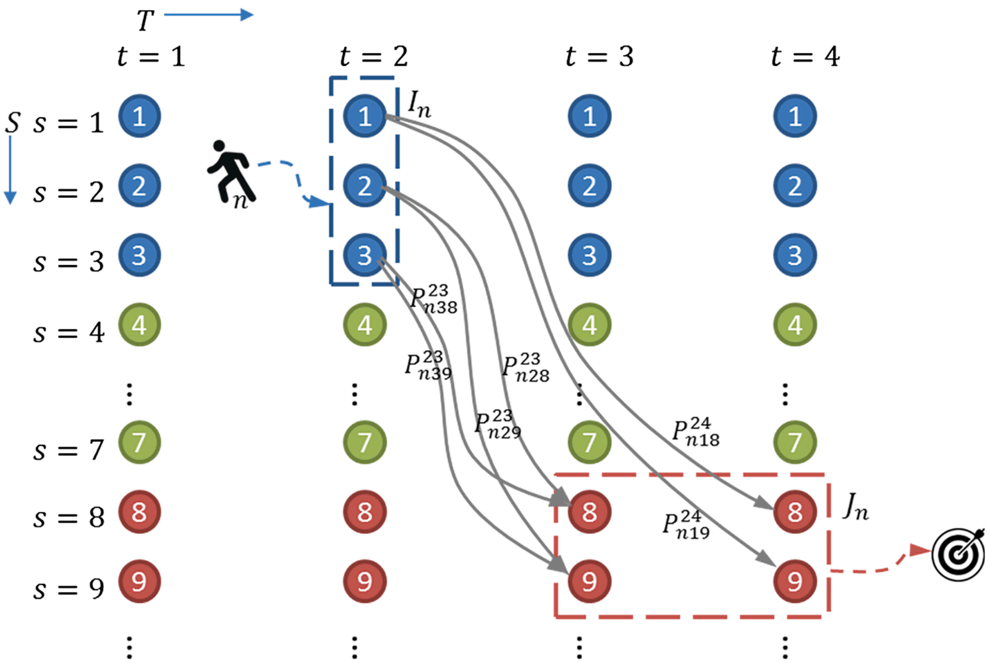


Fig. 3. User choices loaded onto a time–space network.

Additionally, I_n consists of stations near the origin position of the user and J_n consists of stations near the destination. $I_n \subseteq S$ and $J_n \subseteq S$. Let d_ε be the maximum acceptable walking duration. Then, we have

$$I_n = \{i | i \in S \wedge d_{Dni} \leq d_\varepsilon\}, \forall n \in N \tag{6}$$

$$J_n = \{j | j \in S \wedge d_{Rnj} \leq d_\varepsilon\}, \forall n \in N \tag{7}$$

Therefore, the probability $\mathscr{P}^t_{nij}$ that a user $n \in N$ who picks up a vehicle from station i drops it off at station j and the probability $\mathscr{P}^t_{n0}$ that the user does not use carsharing at time instance t should be calculated as

$$\mathscr{P}^t_{nij} = \frac{\exp(\mu_1 V^t_n(ij|1))}{\sum_{i \in I_n, j \in J_n} \exp(\mu_1 V^t_n(ij|1))} \bullet \frac{\exp(\mu_2(V_1 + \Gamma^t_{1n}))}{1 + \exp(\mu_2(V_1 + \Gamma^t_{1n}))}, \text{and } \forall t \in T, \forall i \in I_n, \forall j \in J_n, \forall n \in N \tag{8}$$

$$\mathscr{P}^t_{n0} = \frac{1}{1 + \exp(\mu_2(V_1 + \Gamma^t_{1n}))}, \forall t \in T, \forall n \in N, \quad \text{respectively.} \tag{9}$$

An example of a user n's choices is illustrated in Fig. 2. Stations 1, 2, and 3 comprise I_n and stations 8 and 9 comprise J_n. Stations 4, 5, 6, and 7 are outside the walking range. Node 0 is a dummy node that represents the chance that the user will not use carsharing. Each pair of i and j indicates a path with a chosen probability $\mathscr{P}^t_{nij}$, which is computable based on d_{Dni}, d_{Rnj}, and t_{ij}.

2.4. Time-space network

The time–space network captures carsharing system dynamics on both the spatial and temporal horizons. Fan et al. (2008) initially described a carsharing system based on a station network with a time horizon extension and established demand flow transitions between adjacent time periods $t-1$ and t. (Kek et al., 2009) introduced a time–space network with arcs across both the space and time dimensions. Subsequent studies on carsharing networks with dynamics on time horizons have essentially considered systems on time–space networks, but with disparate perspectives and notations (Boyacı et al., 2017; Jorge et al., 2014; Jorge et al., 2015b). The length of each time period is typically set to 15 min in such studies to provide adequate precision. For consistency, we also set the time period length l to 15 min.

The basic structure of the time–space network for a carsharing system is defined as $X\{(i,j)\} = S \times T$. As shown in Fig. 3, the columns represent all stations in the same time instance and the rows represent one station in all time instances.

Suppose that a user n departs from i at time instance t^0_{nij} and should arrive at j at t^1_{nij}, where $t^1_{nij} = t^0_{nij} + \lceil t_{ij}/l \rceil, \forall i \in I_n, \forall j \in J_n$, and $\forall n \in N$. Here, the arrival time can vary. The probabilities on arcs should cross the time horizon and should be sparse over the dimensions of $n \in N$, $i \in S$, $j \in S$, and $t \in T$. To limit the number of choice branches in the path choice level model and project the choice probabilities onto the time–space horizon, we transform the choice probabilities as

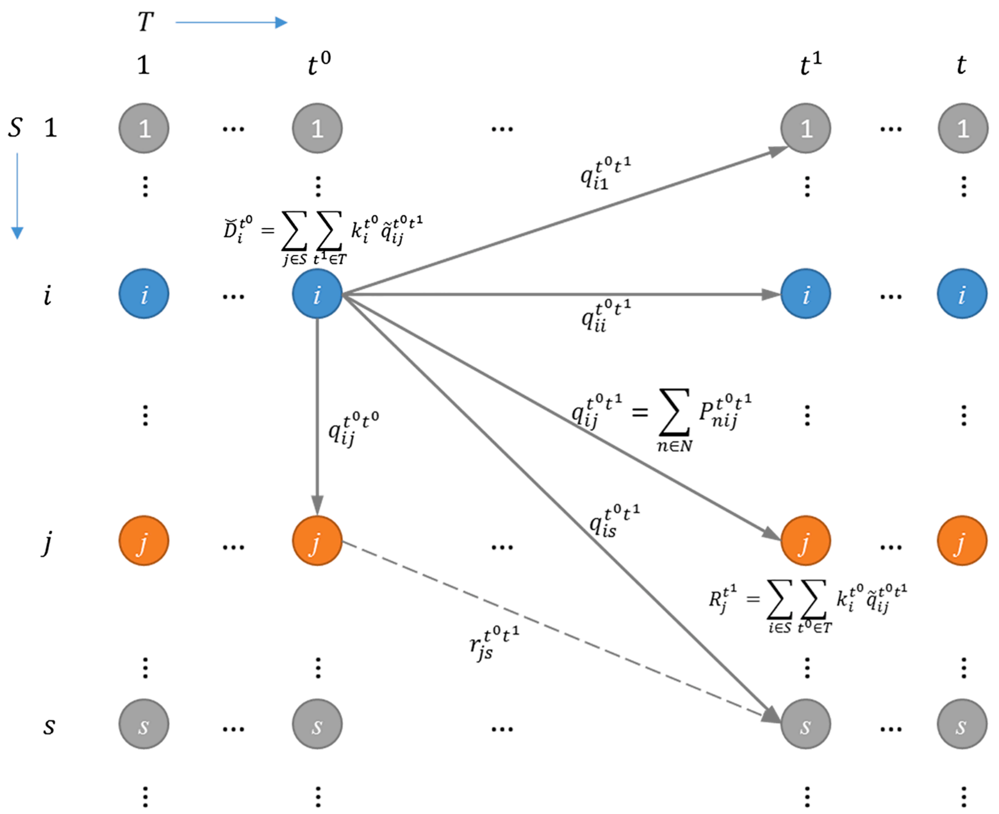


Fig. 4. Time-space network variables.

$$P_{nij}^{t^0t^1} = \begin{cases} \mathscr{P}_{nij}^{t^0}, & i \in I_n \wedge j \in J_n \wedge t^0 = t_{nij}^0 \wedge t^1 = t_{nij}^1 \\ 0, & i \notin I_n \vee j \notin J_n \vee t^0 \neq t_{nij}^0 \vee t^1 \neq t_{nij}^1 \end{cases}$$

$$\forall n \in N, \forall i \in S, \forall j \in S, \forall t^0 \in T, \forall t^1 \in T \quad (10)$$

which represents the probability that user n departs from station i at time instance t^0 and arrives at station j at instance t^1. Fig. 3 presents an example of a user n whose choices are loaded onto a network. Only a subset of the nodes and arcs in the network are necessary for this user's choices.

Generally, a time–space network for carsharing can be summarized as shown in Fig. 4. The following formulae are defined for such a network:

$$q_{ij}^{t^0t^1} = \sum_{n\in N} P_{nij}^{t^0t^1}, \forall i \in S, \forall j \in S, \forall t^0 \in T, \forall t^1 \in T, \quad (11)$$

$$\widehat{D}_i^{t^0} = k_i^{t^0} \sum_{j\in S}\sum_{t_1 \geq t_0} q_{ij}^{t^0t^1}, \forall i \in S, \forall t^0 \in T \quad (12)$$

$$R_j^{t^1} = \sum_{i\in S}\sum_{t_0 < t_1} k_i^{t^0} q_{ij}^{t^0t^1}, \forall j \in S, \forall t^1 \in T, \quad (13)$$

$$x_s^t = x_s^{t-1} + R_s^t - \widehat{D}_s^t, \forall s \in S, \forall t \in T \quad (14)$$

$$x_s^t \leq C_s, \forall s \in S, \forall t \in T. \quad (15)$$

Eq. (11) aggregates user choice probabilities into demand from i to j and from t^0 to t^1. However, not all demand can be satisfied based on the limitation of vehicle supplies. Eq. (12) introduces a ratio $k_i^{t^0}$ to represent the proportion of satisfied demand. A method for determining the ratio of demand that can be satisfied by available vehicles is discussed in Section 3.2.2. The number of returned vehicles at j and t^1 is the aggregation of all satisfied demand from all stations and all departure times, as shown in Eq. (13). Eq. (14) represents a conservation in which the number of vehicles at a station s at the end of time instance t is equal the number of vehicles at the end of the previous time instance plus the number of dropped-off vehicles minus the satisfied demand during time instance t.

It should be noted that the users and demand loaded onto the network are depicted in a probabilistic manner, rather than using deterministic integers. Demand can emerge on multiple locations or paths according to these probabilities. Therefore, demand is represented in a decimal format in the time–space network. The aggregation of user choice probabilities can be regarded as the expectation of demand across different O-D pairs according to the law of large numbers. Consequently, the vehicles that satisfy demand are also described in decimal format based on aggregated probabilities or expectations.

Additionally, this time–space network model can also be extended to operator-based vehicle relocation by adding virtual demand links. A virtual link is denoted as $r_{js}^{t^0t^1}$ and represented as a dashed line in Fig. 4, which indicates the number of relocated vehicles from station j to station s. In this study, we focus on the demand control problem and do not consider this variable, but it is a worthwhile topic for future study.

2.5. Optimization

Based on the user choice model loaded onto the time-space network, the optimization framework for designing incentive and surcharge combinatorial schemes can be summarized as follows:

P1:

$$\max_{\substack{p_{Di}^{t^0}, p_{Rj}^{t^0}, p_{ij}^{t^0}, \\ \forall i \in S, \forall j \in S, \forall t^0 \in T}} \quad F = F_1 + F_2, \tag{16}$$

$$F_1 = \sum_{i \in S}\sum_{j \in S}\sum_{t^0 \in T}\sum_{t^1 \in T} k_i^{t^0} q_{ij}^{t^0t^1} t_{ij} p/60, \tag{17}$$

$$F_2 = \sum_{i \in S}\sum_{j \in S}\sum_{t^0 \in T}\sum_{t^1 \in T} k_i^{t^0} q_{ij}^{t^0t^1} \left(p_{Di}^{t^0} + p_{Rj}^{t^0} + p_{ij}^{t^0}\right), \tag{18}$$

subject to

$$V_n^t(ij|1) = \varphi_0 + \varphi_1 p_{Di}^t + \varphi_2 p_{Rj}^t + \varphi_3 p_{ij}^t + \varphi_4 d_{Dni} + \varphi_5 d_{Rnj} + \varphi_6 t_{ij},$$

$$\forall t \in T, \forall i \in I_n, \forall j \in J_n, \forall n \in N, \tag{19}$$

$$\Gamma_{1n}^t = \frac{1}{\mu_1} \ln \sum_{i \in I_n, j \in J_n} \exp\left(V_n^t(ij|1)\right), \forall t \in T, \forall n \in N, \tag{20}$$

$$I_n = \{i | i \in S \wedge d_{Dni} \le d_\varepsilon\}, \forall n \in N, \tag{21}$$

$$J_n = \{j | j \in S \wedge d_{Rnj} \le d_\varepsilon\}, \forall n \in N, \tag{22}$$

$$\mathscr{P}_{nij}^t = \frac{\exp\left(\mu_1 V_n^t(ij|1)\right)}{\sum_{i \in I_n, j \in J_n} \exp\left(\mu_1 V_n^t(ij|1)\right)} \cdot \frac{\exp\left(\mu_2\left(V_1 + \Gamma_{1n}^t\right)\right)}{1 + \exp\left(\mu_2\left(V_1 + \Gamma_{1n}^t\right)\right)},$$

$$\forall t \in T, \forall i \in I_n, \forall j \in J_n, \forall n \in N, \tag{23}$$

$$P_{nij}^{t^0t^1} = \begin{cases} \mathscr{P}_{nij}^{t^0}, & i \in I_n \wedge j \in J_n \wedge t^0 = t_{nij}^0 \wedge t^1 = t_{nij}^1 \\ 0, & i \notin I_n \vee j \notin J_n \vee t^0 \ne t_{nij}^0 \vee t^1 \ne t_{nij}^1 \end{cases},$$

$$\forall n \in N, \forall i \in S, \forall j \in S, \forall t^0 \in T, \forall t^1 \in T \tag{24}$$

$$t_{nij}^1 = t_{nij}^0 + \lceil t_{ij}/l \rceil, \forall i \in I_n, \forall j \in J_n, \forall n \in N, \tag{25}$$

$$q_{ij}^{t^0t^1} = \sum_{n \in N} P_{nij}^{t^0t^1}, \forall i \in S, \forall j \in S, \forall t^0 \in T, \forall t^1 \in T, \tag{26}$$

$$\widehat{D}_i^{t^0} = k_i^{t^0} \sum_{j \in S}\sum_{t_1 \ge t_0} q_{ij}^{t^0t^1}, \forall i \in S, \forall t^0 \in T \tag{27}$$

$$R_j^{t^1} = \sum_{i \in S}\sum_{t_0 < t_1} k_i^{t^0} q_{ij}^{t^0t^1}, \forall j \in S, \forall t^1 \in T, \tag{28}$$

$$x_s^t = x_s^{t-1} + R_s^t - \widehat{D}_s^t, \forall s \in S, \forall t \in T \tag{29}$$

$$0 \le x_s^t \le C_s, \forall s \in S, \forall t \in T, \tag{30}$$

where the goal is to derive the combination of $p_{Di}^{t^0}$, $p_{Rj}^{t^0}$, and $p_{ij}^{t^0}$ that generates the maximum revenue. The objective function in Eq. (16) consists of two parts: F_1 is the common revenue calculated using the basic price, which is the sum of satisfied demand charging by time of use, and F_2 is the additional revenue generated by losing incentives or gaining surcharges.

The constraints in Eqs. (19)–(25) capture the user choice probabilities. The constraints in Eqs. (26)–(30) represent the demand pattern and system dynamics in the time-space network.

This model is extensible for carsharing network analysis because the incentive and surcharge policy is not limited to pick-up, drop-off, and O-D policies. Other innovative incentive and pricing strategies can also be included in this model. However, the model faces two problems. One is that the two-level NL model introduces complex nonlinear properties through two-level interactions. The other is that time-space network dynamics increase the dimensionality and complexity of sets and variables. Overall, this model can be regarded as a complex nonlinear programming problem. To solve this problem efficiently, some conditions based on practical operations are adopted in the specific solution algorithm discussed in the following section.

3. Calibration and solution algorithms

3.1. Calibration of the two-level NL model

The proposed logit model can be calibrated using SP survey data. Given a set $N^{'}$ that includes all respondents with known personal socioeconomic profiles, we let $\delta_1(ij)_n = 0, 1, \forall n \in N'$ denote the choices of user n on path i-j, $\forall i \in I_n, \forall j \in J_n$, $\delta_{0n} = 0, 1$, and $\forall n \in N'$ denote the choice of user n regarding the use of carsharing. Let $\delta_1(ij)_n = 1$ if n chooses the path from i to j; $= 0$ if n does not choose the path from i to j. Let $\delta_{0n} = 0$ if n uses carsharing and let $\delta_{0n} = 1$ if n it does not travel via carsharing. An example SP survey for calibrating the logit model can be found in Section 4.1. $\delta_1(ij)_n$ and δ_{0n} should satisfy the following condition:

$$\sum_{i \in I_n} \sum_{j \in J_n} \delta_1(ij)_n + \delta_{0n} = 1, \forall n \in N^{'}. \tag{31}$$

The calibration of the parameters θ, φ, and μ can be performed using a statistical software package such as nlogit in the R language. Here, we adopted a stepwise parameter estimation approach based on a maximum likelihood estimator (Amemiya, 1978) (detailed in Appendix C), which has been proven to be a consistent and asymptotically low-efficiency estimator. However, this problem can also be easily solved using other commercial software such as SPSS.

3.2. Solution approach to the optimization model

To solve the optimization model for carsharing operation implementation, this section proposes some approximate transformation methods for conditions based on real operational properties.

3.2.1. Dynamically solving processes

The optimization model **P1** provides an overall optimization scope for the entire network, including the time and space dimensions. The scale of a two-dimensional network makes this problem very complex and leads to higher computational costs. One factor is that the dimension of time takes on the complexity of the solution space. Therefore, reducing the number of time instances in T would reduce the calculation time. Dividing T into discrete periods and dynamically solving the model in period-by-period fashion would relieve the complexity introduced by the time dimension. Another advantage of solving periodically is that some variables are observable and can be directly read from the operation data system instead of being calculated using formulae, which reduces calculation costs and introduces reliable data that can replace estimated variables. Additionally, from the perspective of real-world operations, operators may prefer dynamically releasing and adjusting incentive and surcharge policies periodically, rather than calculating a full-day plan at once.

First, we divide T into U periods. Specifically, we let the subset $T_u \subseteq T$, where $u = 1, \cdots, U$ and $T_{u_1} \cap T_{u_2} = \varnothing, \forall u_1, u_2 = 1, \cdots, U$ and $u_1 \ne u_2$. For example, we can divide a day into 24 h as $T_1, T_2, \cdots, T_{24}$, where every four time instances ts (if the length of a time instance is 15 min) belong to a time period. Therefore, the problem can be solved within a smaller time dimension. Operators can also divide a day into peak hours and non-peak hours according to real operation requirements.

We localize the time–space network model **P1** to the time period T_u, $\forall T_u \subseteq T$ as follows:

P2:

$$\max_{\substack{p_{Di}^t, p_{Rj}^t, p_{ij}^t, \\ \forall t \in T_u, i \in S, j \in S}} F^{T_u} = \sum_{i \in S} \sum_{j \in S} \sum_{t \in T} \sum_{t^1 \in T} k_i^t q_{ij}^{tt^1} t_{ij} p/60 + \sum_{i \in S} \sum_{j \in S} \sum_{t \in T} \sum_{t^1 \in T} k_i^t q_{ij}^{tt^1} \left(p_{Di}^t + p_{Rj}^t + p_{ij}^t\right), \forall T_u \subseteq T \tag{32}$$

Solving the problem for T_u is much faster than solving for T. Note that Eq. (19) to Eq. (25) are used for a complete user set, but users with reservation requests also vary over time and can be divided into subsets $N_{T_u}, \forall T_u \subseteq T$. The equations hold for $\forall n \in N_{T_u}$ when considering one time period T_u. In practice, the variables x_s^t (number of vehicles at station s) and R_s^t (number of vehicles returning to station s) can be captured directly from real-time operation monitoring systems at the first time instance in the time period T_u. These values can replace the derived variables in Eqs. (28) and (29).

3.2.2. Calculation of satisfied demand

The variable k_s^t is calculable using a logic-based approach. To calculate k_s^t, we propose the following equations for $\forall s \in S, \forall t \in T$:

$$x^{E^t}_s = x_s^{t-1} + R_s^t - D_s^t, \tag{33}$$

$$D^{-t}_s = \max\left(0, -x^{E^t}_s\right), \tag{34}$$

$$\widehat{D}_S^t = D_s^t - D^{-t}_s = D_s^t - \max\left(0, -x^{E^t}_s\right) \tag{35}$$

$$k_s^t = \frac{\widehat{D}_S^t}{D_s^t} = 1 - \max\left(0, -x^{E^t}_s\right) \Big/ D_s^t \tag{36}$$

where $x^{E^t}_s$ is the expected number of vehicles at station s at the end of t. The unsatisfied demand is D^{-t}_s if the number of vehicles is not sufficient. Therefore, the satisfied demand should be $\widehat{D}_S^t$ and the satisfied demand ratio is denoted as k_s^t.

3.2.3. Setting incentives and surcharges as integers

Intuitively, incentives and surcharges are offered to users as currency and are not continuous variables. For convenience, a real operation may choose integer values (e.g., ¥1, ¥5, or ¥10). Although the optimal values may be close to integer values, a simple nearest-integer solution may not be suitable.

To search for a solution in a finite region we use the following steps:

1) Define the basic pricing steps p_{Di}, p_{Rj}, and, p_{ij}, and scale factors λ_{Di}^t, λ_{Rj}^t, and, λ_{ij}^t, where the scale factors should be integers. Therefore, the scale factors will be decision variables. In this study, we set $p_{Di} = p_{Rj} = p_{ij} =$ ¥1.

2) Define a bound for the maximum acceptable incentives or surcharges for an operation. In this study. we set $\lambda_{Di}^t, \lambda_{Rj}^t, \lambda_{ij}^t \in [-50, 50]$.

3.2.4. Triggering by thresholds

The network scale for carsharing is huge and complex. If the numbers of vehicles at stations are balanced, then stations do not require incentive and surcharge policies. Additionally, in real operations, users must receive stable incentive offers and surcharge information, rather than receiving unstable and changeable information. Therefore, there should be a mechanism for filtering suitable stations for deploying incentives and surcharges at specific times. Our previous study (Ma et al., 2018) introduced a triggering mechanism and proposed a method for determining triggering thresholds. In this study, we directly used triggering thresholds to filter imbalanced stations. Triggering is applied using the following equation for $\forall s \in S, \forall t \in T$:

$$x^{E0^t}_s = x_s^{t-1} + R_s^t - D^{0^t}_s, \tag{37}$$

where $x^{E0^t}_s$ is the expected number of vehicles of station s at the end of t if no incentives or surcharges apply and $D^{0^t}_s$ can be calculated using Eqs. (19)–(27) if $p_{Di}^t = p_{Rj}^t = p_{ij}^t = 0$. We set the indicators $\lambda^{u^t}_s$ and $\lambda^{l^t}_s$ as follows:

$$\lambda^{u^t}_s = \begin{cases} 1, x^{E0^t}_s - S_{upper,s} \geq 0 \\ 0, x^{E0^t}_s - S_{upper,s} < 0 \end{cases}, \forall s \in S, \forall t \in T, \tag{38}$$

$$\lambda^{l^t}_s = \begin{cases} 1, S_{lower,s} - x^{E0^t}_s \geq 0 \\ 0, S_{lower,s} - x^{E0^t}_s < 0 \end{cases}, \forall s \in S, \forall t \in T. \tag{39}$$

If the indicators are both zero, then the expected number of vehicles should be within a reasonable range, meaning it is unnecessary for stations to apply incentives and surcharges. Therefore, the values of the policy variables should be

$$p_{Ds}^t = \left(\lambda^{u^t}_s + \lambda^{l^t}_s - \lambda^{u^t}_s \lambda^{l^t}_s\right) p_{Ds}^t, \forall s \in S, \forall t \in T\text{m} \tag{40}$$

$$p_{Rs}^t = \left(\lambda^{u^t}_s + \lambda^{l^t}_s - \lambda^{u^t}_s \lambda^{l^t}_s\right) p_{Rs}^t, \forall s \in S, \forall t \in T, \tag{41}$$

$$p_{ij}^t = \left(\lambda^{u^t}_i \lambda^{l^t}_j + \lambda^{l^t}_i \lambda^{u^t}_j\right) p_{ij}^t, \forall i \in S, \forall j \in S, \forall t \in T. \tag{42}$$

Table 2
Data collected from one example respondent.

User ID	13				
Monthly income	0~¥5000 $XI_1 = 0$	¥5001~¥10000 $XI_2 = 0$	¥10001~¥15000 $XI_3 = 1$		>¥15000 $XI_4 = 0$
Gender	Male $XG_1 = 1$		Female $XG_2 = 0$		
Age	< 21 $XA_1 = 0$	21 ~ 30 $XA_1 = 1$	31 ~ 40 $XA_1 = 0$	41 ~ 50 $XA_1 = 0$	>50 $XA_1 = 0$
EVCARD usage frequency	less than once a week $XF_1 = 1$	2 ~ 3 times a week $XF_1 = 1$	more than once a day $XF_1 = 1$		
Is Bikesharing user	Yes,$XB = 1$				
Scenarios	1: 3 departure stations and 3 arrival stations (Instance in Table 3) 2: 2 departure stations and 2 arrival stations 3: 2 departure stations and 4 arrival stations 4: 3 departure stations and 2 arrival stations 5: 4 departure stations and 3 arrival stations				

To determine the proper search direction, we consider the following factors. If the expected number of vehicles at station s exceeds the upper threshold, then incentives are required to increase pick-up demand (negative p^t_{Ds}) and surcharges are required to reduce drop-off demand (positive p^t_{Rs}). If the expected number of vehicles is below the lower threshold, then surcharges are required to reduce pick-up demand (positive p^t_{Ds}) and incentives are required to attract drop-off demand (negative p^t_{Rs}). This logic can be implemented as

$$p^t_{Ds} = \left(\lambda^{l^t}_{s} - \lambda^{u^t}_{s}\right)\lambda^t_{Ds}p_{Ds}, \forall s \in S, \forall t \in T, \tag{43}$$

$$p^t_{Rs} = \left(\lambda^{u^t}_{s} - \lambda^{l^t}_{s}\right)\lambda^t_{Rs}p_{Rs}, \forall s \in S, \forall t \in T. \tag{44}$$

For p^t_{ij}, the logic is defined as follows. If the expected number of vehicles at station i exceeds the upper threshold and the expected number of vehicles at station j is below the lower threshold, then incentives on i-j (negative p^t_{ij}) should be offered. If the expected number of vehicles at station i is below the lower threshold and the expected number of vehicles at station j exceeds the upper threshold, then surcharges on i-j (positive p^t_{ij}) should be applied. Otherwise, the O-D policy is not appropriate for application. This logic can be implemented as

$$p^t_{ij} = \left(\lambda^{u^t}_{i}\lambda^{l^t}_{j} - \lambda^{l^t}_{i}\lambda^{u^t}_{j}\right)\lambda^t_{ij}p_{ij}, \forall i \in S, \forall j \in S, \forall t \in T. \tag{45}$$

3.2.5. Solution algorithm

Based on the transformations described above, the solution algorithm is derived from a simulated annealing method as follows. At $t = 0$, we obtain the initial number of vehicles $x^0_s, \forall s \in S$ and separate the model $\forall T_u \subseteq T$ into sub-models as follows:

P3:

$$\min F^{T_u}\left(\lambda^t_{Di}, \lambda^t_{Rj}, \lambda^t_{ij}\right) = -(F_1 + F_2) = -\sum_{i\in S}\sum_{j\in S}\sum_{t\in T}\sum_{t^1\in T}k^t_i q^{tt^1}_{ij} t_{ij} p/60 - \sum_{i\in S}\sum_{j\in S}\sum_{t\in T}\sum_{t^1\in T}k^t_i q^{tt^1}_{ij}\left(\lambda^t_{Di}p_{Di} + \lambda^t_{Rj}p_{Ri} + \lambda^t_{ij}p_{ij}\right) \tag{46}$$

Pseudo-code is provided in Algorithm 1. The solution procedure is described below.

Step 1: Set the basic configuration parameters, where $\tau_{\max}$ is the initial temperature for simulated annealing, $\tau_{\min}$ is the final temperature, c is the cooling rate, and K is the maximum number of iterations.

Step 2: Set the initial conditions, including λ^{t0}_{Ds}, λ^{t0}_{Rs}, $\forall s \in S$, λ^{t0}_{ij}, $\forall i \in S$, and $\forall j \in S$. Set the initial p^{t*}_{Ds}, p^{t*}_{Rs}, and p^{t*}_{ij}, and then calculate $F^{T_u 0}$.

Step 3: Calculate $x^{E0^t}_s$ fromx^{t-1}_s and determine $\lambda^{u^t}_s$ and $\lambda^{l^t}_s$. Note that x^{t-1}_s can input the observed number of vehicles at the end of time instance $t-1$ in a real operation.

Step 4: Based on the previously generated solution, generate a new random solution for λ^{tk}_{Ds}, λ^{tk}_{Rs}, and λ^{tk}_{ij}, and then calculate the objective $F^{T_u k}$.

Step 5: Judge whether the new objective $F^{T_u k}$ is lower than the current best solution. If it is, then set the new solution as the best solution. Otherwise, accept the new solution according to the acceptance probability, which decreases with τ.

Step 6: If the number of iterations is less than K, then return to Step 4. Otherwise, continue to the next step.

Step 7: If the temperature is above $\tau_{\min}$, then return to Step 2. Otherwise, end the algorithm and export the current best solution and $F^{T_u *}$ as the best solution that has ever been found.

Algorithm 1..

$\tau := \tau_{\max}$
While $\tau > \tau_{\min}$
  $k := 0$
  $\lambda_{Ds}^{tk} := 0, \lambda_{Rs}^{tk} := 0, p_{Ds}^{t*} := 0, p_{Rs}^{t*} := 0, \forall s \in S$
  $\lambda_{ij}^{tk} := 0, p_{ij}^{t*} := 0, \forall i \in S, \forall j \in S$
  $F^{T_u k} := F^{T_u}\left(\lambda_{Di}^{tk}, \lambda_{Rj}^{tk}, \lambda_{ij}^{tk}\right), F^{T_u *} := F^{T_u k}$
  $\lambda^{ut}_{s} := 1, \mathbf{if} x^{E0t}_{s} - S_{upper,s} \geq 0, \mathbf{else} 0, \forall s \in S$
  $\lambda^{lt}_{s} := 0, \mathbf{if} S_{lower,s} - x^{E0t}_{s} \geq 0 \geq 0, \mathbf{else} 0, \forall s \in S$
  $k := 1$
  Whilek $\leq K$
    $p_{Ds}^{tk} := p_{Ds}^{t(k-1)} - \lambda^{ut}_{s}\lambda_{Ds}^{tk} p_{Ds} \cdot rand \cdot \gamma + \lambda^{lt}_{s}\lambda_{Ds}^{tk} p_{Ds} \cdot rand \cdot \gamma, \forall s \in S$
    $p_{Rs}^{tk} := p_{Rs}^{t(k-1)} - \lambda^{lt}_{s}\lambda_{Rs}^{tk} p_{Rs} \cdot rand \cdot \gamma + \lambda^{ut}_{s}\lambda_{Rs}^{tk} p_{Rs} \cdot rand \cdot \gamma, \forall s \in S$
    $p_{ij}^{tk} := p_{ij}^{t(k-1)} - \lambda^{ut}_{i}\lambda^{lt}_{j}\lambda_{ij}^{tk} p_{ij} \cdot rand \cdot \gamma + \lambda^{lt}_{i}\lambda^{ut}_{j}\lambda_{ij}^{tk} p_{ij} \cdot rand \cdot \gamma, \forall i \in S, \forall j \in S$
    $F^{T_u k} := F^{T_u}\left(\lambda_{Di}^{tk}, \lambda_{Rj}^{tk}, \lambda_{ij}^{tk}\right)$
    If $F^{T_u k} < F^{T_u *}$
    $F^{T_u *} := F^{T_u k}, p_{Ds}^{t*} := p_{Ds}^{tk}, p_{Rs}^{t*} := p_{Rs}^{tk}, p_{ij}^{t*} := p_{ij}^{tk}$
    Else if $exp\left(-\left(F^{T_u k} - F^{T_u *}\right)/\tau\right) > (\mathrm{rand} + 1)/2$
    $F^{T_u *} := F^{T_u k}, p_{Ds}^{t*} := p_{Ds}^{tk}, p_{Rs}^{t*} := p_{Rs}^{tk}, p_{ij}^{t*} := p_{ij}^{tk}$
    $k := k + 1$
  End
  $\tau := \tau \cdot c$
End

Note:
a. in this paper, set $K = 100$ iterations, $\tau_{\min} = 80$, $\tau_{max} = 90$, and $c = 0.99$;
b. *rand* is the function to randomly generate 0 and 1 at 50% probability;
c. γ denotes the randomness scale that decides the unit length of change to the previous decision variables.

4. Case study

4.1. Parameter calibration for the user choice model

4.1.1. Data and input descriptions

To calibrate the two-level NL model, we conducted an SP survey of registered users of EVCARD (an electric car sharing system

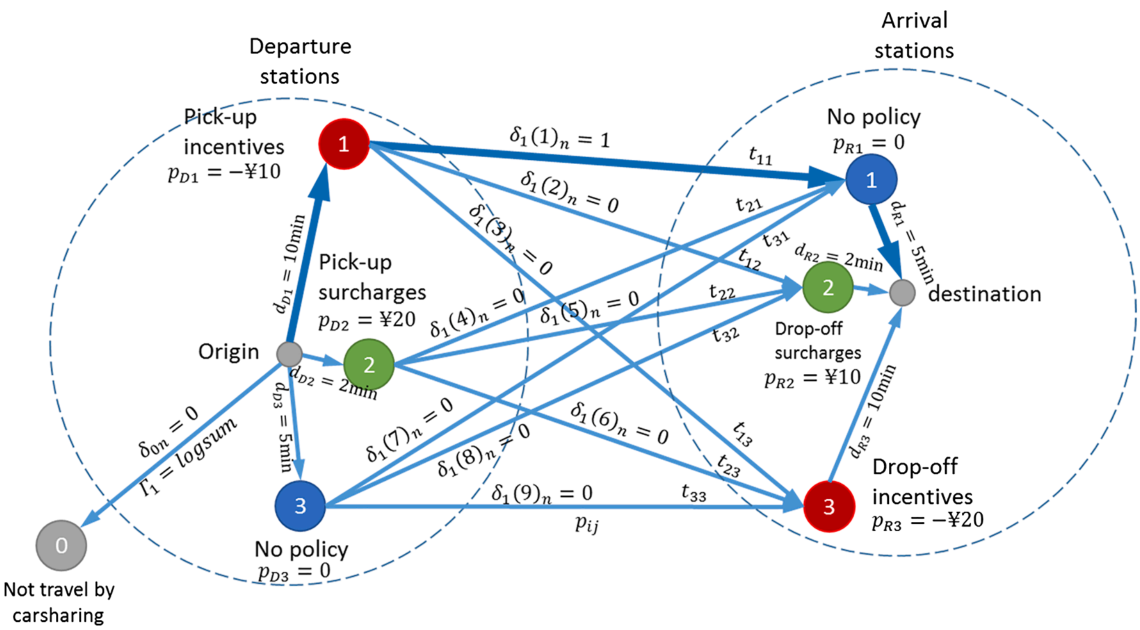


Fig. 5. An example scenario for one respondent.

Table 3
Detailed data for one example scenario for one respondent.

No.	Subscript			Respondent answer		Path choice variables						Trip choice variables	
	ij	i	j	$\delta_1(ij)_n$	δ_{0n}	p_{Di}	p_{Rj}	p_{ij}	d_{Di}	d_{Rj}	t_{ij}	p	Γ_1
1	1	1	1	1		−10	0	–	10	5	30		
2	2	1	2	0		−10	10	–	10	2	30		
3	3	1	3	0		−10	−20	–	10	10	38		
4	4	2	1	0		20	0	–	2	5	32		
5	5	2	2	0		20	10	–	2	2	26		
6	6	2	3	0		20	−20	–	2	10	30		
7	7	3	1	0		0	0	–	5	5	38		
8	8	3	2	0		0	10	–	5	2	34		
9	9	3	3	0		0	−20	–	5	10	30		
10	–	–	–		0							30	-.767[a]

Note: We adopt a stepwise estimator to calibrate parameters (i.e., the path choice level is calibrated first, followed by the trip choice level). Therefore, Γ_1 can be calculated once the path-level parameters are calibrated.

Table 4
Parameter estimation for the path choice level.

Variables	Parameters	Estimation	S. E.	Wals	df	Sig.	Exp (B)
Constant	$\mu_1\varphi_0$	1.871	0.970	3.721	1	0.054	6.495
p_{Di}	$\mu_1\varphi_1$	−0.043	0.008	29.295	1	0.000	0.958
p_{Rj}	$\mu_1\varphi_2$	−0.037	0.010	13.469	1	0.000	0.964
p_{ij}	$\mu_1\varphi_3$	−0.032	0.010	9.923	1	0.002	0.969
d_{Di}	$\mu_1\varphi_4$	−0.109	0.041	7.068	1	0.008	0.897
d_{Rj}	$\mu_1\varphi_5$	−0.132	0.041	10.365	1	0.001	0.876
t_{ij}	$\mu_1\varphi_6$	−0.107	0.032	11.181	1	0.001	0.899
XI_1	$\mu_1\varphi_{I1}$	−0.053	0.031	2.970	1	0.085	0.948
XI_2	$\mu_1\varphi_{I2}$	−0.067	0.019	12.435	1	0.000	0.935
XI_3	$\mu_1\varphi_{I3}$	0.011	0.028	0.154	1	0.694	1.011
XI_4	$\mu_1\varphi_{I4}$	0.023	0.031	0.550	1	0.458	1.023
XG_1	$\mu_1\varphi_{G1}$	−0.051	0.009	32.543	1	0.000	0.950
XG_2	$\mu_1\varphi_{G2}$	−0.054	0.022	6.084	1	0.014	0.947
XA_1	$\mu_1\varphi_{A1}$	−0.065	0.009	52.160	1	0.000	0.937
XA_2	$\mu_1\varphi_{A2}$	−0.034	0.009	14.272	1	0.000	0.967
XA_3	$\mu_1\varphi_{A3}$	−0.040	0.011	13.223	1	0.000	0.961
XA_4	$\mu_1\varphi_{A4}$	−0.013	0.044	0.087	1	0.768	0.987
XA_5	$\mu_1\varphi_{A5}$	−0.060	0.090	0.444	1	0.505	0.942
XF_1	$\mu_1\varphi_{F1}$	−0.038	0.032	1.378	1	0.240	0.963
XF_2	$\mu_1\varphi_{F2}$	−0.048	0.010	23.264	1	0.000	0.953
XF_3	$\mu_1\varphi_{F3}$	−0.045	0.010	20.037	1	0.000	0.956
XB	$\mu_1\varphi_B$	−0.143	0.025	32.718	1	0.000	0.867

operating in Shanghai, China) during March of 2020. An SP survey is a typical method for calibrating user choice models if real actions have not yet been implemented (Remane et al., 2016). In our study, respondents were required to submit their personal information, including monthly income, gender, age, EVCARD usage frequency, and whether or not they are bikesharing users. They were also required to provide answers for five scenarios. One scenario contained several paths that the user might choose. One path had randomly (following a uniform distribution) generated incentives and surcharges that could influence the user's choice. A user could only choose one path in each scenario or choose not to travel via carsharing. A total of 96 respondents were randomly selected from the user database and surveyed through offline interviews. They participated in the survey and returned 404 valid scenarios with 4,233 valid choice samples, including path selection and whether or not to travel via carsharing.

An example response is presented in Table 2. An example of one scenario for this user with nine paths is presented in Fig. 5. Details regarding this scenario are provided in Table 3. For each path, the respondent would receive descriptions of incentives and surcharges at pick-up stations and drop-off stations, as well as information regarding walking and driving durations.

4.1.2. Calibration results

Calibration was conducted using the IBM SPSS software with the two-step estimation approach. The calibration results for the path choice level and trip choice level are presented in Table 4 and Table 5 respectively. The significance levels of the parameters are also shown in these tables. These values indicate which of the calibrated parameters are significant for explaining the model. In the

Table 5
Parameter estimation for the trip choice level.

Variables	Parameters	Estimation	S. E.	Wals	df	Sig.	Exp (B)
Constant	$\mu_2\theta_0$	−5.110	1.900	7.233	1	0.007	0.006
p	$\mu_2\theta_1$	0.189	0.051	13.734	1	0.000	1.208
XI_1	$\mu_2\theta_{I1}$	−0.715	0.120	35.457	1	0.000	0.489
XI_2	$\mu_2\theta_{I2}$	−0.475	0.140	11.502	1	0.001	0.622
XI_3	$\mu_2\theta_{I3}$	−0.211	0.099	4.542	1	0.033	0.810
XI_4	$\mu_2\theta_{I4}$	0.082	0.157	0.273	1	0.601	1.085
XG_1	$\mu_2\theta_{G1}$	−0.504	0.233	4.683	1	0.030	0.604
XG_2	$\mu_2\theta_{G2}$	−0.560	0.163	11.792	1	0.001	0.571
XA_1	$\mu_2\theta_{A1}$	−0.357	0.209	2.918	1	0.088	0.700
XA_2	$\mu_2\theta_{A2}$	−0.435	0.168	6.707	1	0.010	0.647
XA_3	$\mu_2\theta_{A3}$	−0.537	0.075	51.359	1	0.000	0.584
XA_4	$\mu_2\theta_{A4}$	−0.199	0.122	2.661	1	0.103	0.820
XA_5	$\mu_2\theta_{A5}$	−0.020	0.071	0.079	1	0.778	0.980
XF_1	$\mu_2\theta_{F1}$	−0.533	0.173	9.499	1	0.002	0.587
XF_2	$\mu_2\theta_{F2}$	−0.427	0.165	6.709	1	0.010	0.652
XF_3	$\mu_2\theta_{F3}$	−0.531	0.143	13.792	1	0.000	0.588
XB	$\mu_2\theta_B$	−1.477	0.653	5.116	1	0.024	0.228

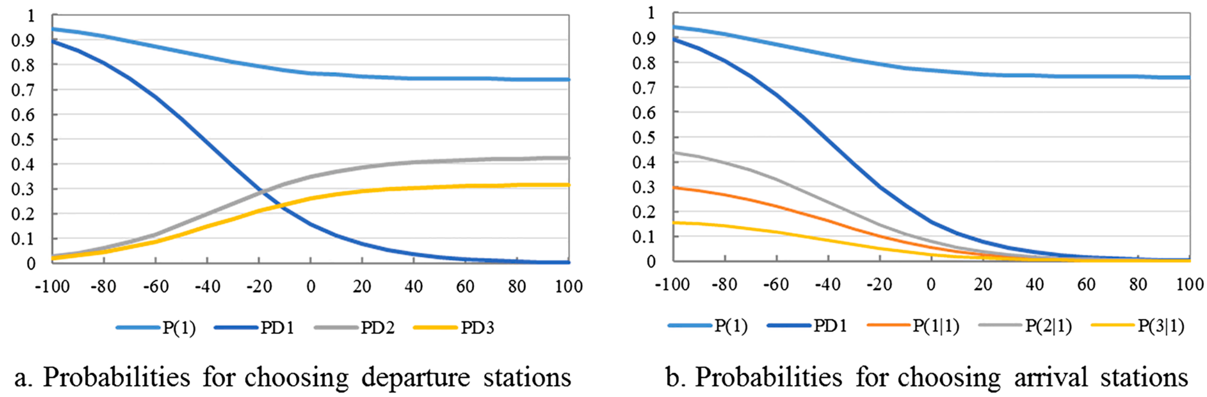


Fig. 6. User choice probability changes for different incentives and surcharges at station 1.

following section, these estimated parameters are applied as known parameters for the optimization model.

4.1.3. User behavior analysis

(1) *User profile influence*

Tables 4 and 5 present the estimated parameters for the path choice level and trip choice level, respectively. For the path choice level, the variables XI_3 and XI_4, which represent monthly incomes over ¥10000, are not significant, indicating that users with high incomes are not sensitive to incentives and surcharges. XI_1 is less significant than XI_2 and the absolute value of the parameter XI_2 is greater than that of XI_1, indicating that users whose incomes are in the range of ¥5001–¥10000 are the most sensitive incentive and surcharge policies. However, the parameter XI_1 in the trip choice level is the most significant and the absolute value of the parameter XI_1 is the greatest among the four variables, indicating that users whose incomes are below ¥5000 are more sensitive to prices for making trip choices. The results also suggest that males influenced more heavily by incentives and surcharges, while females are more influenced by trip choice. For age groups, significant values indicate that people below 40 y old are likely to be influenced by incentives and surcharges. Users younger than 21 y are more sensitive when choosing different departure and arrival stations. Users older than 40 y are not significantly influenced. The frequency of using the proposed carsharing system also influences results, where people who travel using the system more frequently are more sensitive to pricing policies. Additionally, XB contributes significantly, which implies that people who are also bikesharing users are more sensitive to incentives and surcharges.

(2) Discussion of variables related to incentives and surcharges

The results discussed above verify that the parameters of incentives and surcharges are significant. By applying calibrated parameters to the NL model, a user choice probability change figure can be drawn. Considering the scenario with three departure and three arrival stations as an example, we changed the pick-up price p_{D1} at station 1. The resulting changes in user choice probabilities regarding departures from stations 1, 2, and 3 are plotted plotted in Fig. 6a, which indicates that when increasing surcharges at station

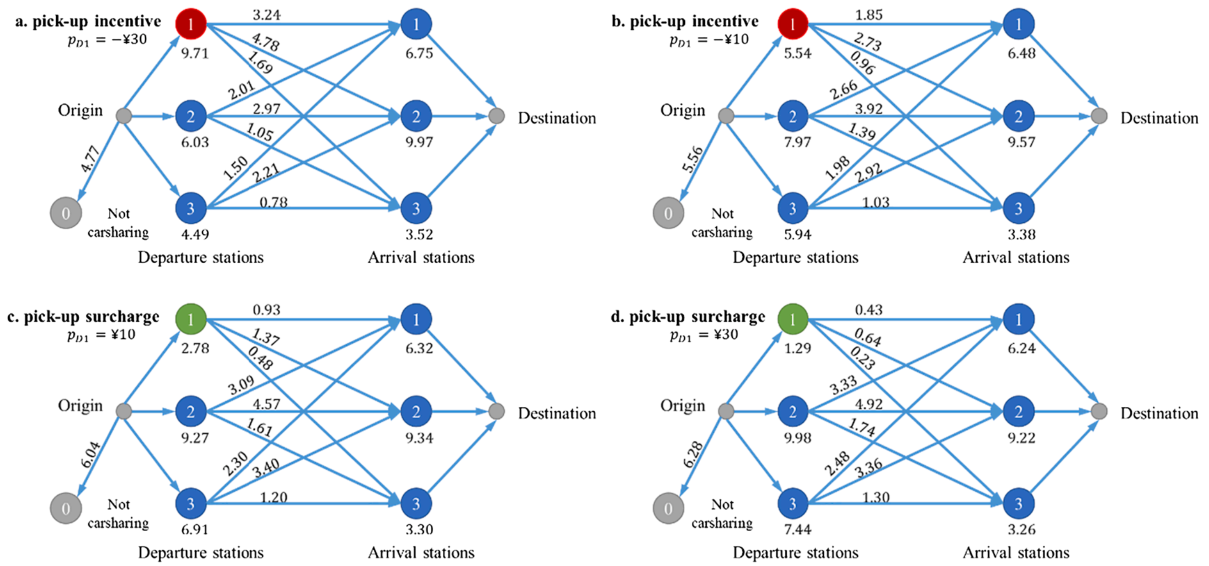


Fig. 7. User choice aggregation for observing demand patterns.

Table 6
Data summary.

Data	Description
Stations	$S = \{1, \cdots, 56\}$, there are 56 stations involved in the network.
Period dividing	$T = \{T_1, \cdots, T_{24}\}$, a day is divided into 24 h.
Time splitting	$T_1 = \{1,2,3,4\}$, $T_2 = \{5,6,7,8\}$, …, $T_{24} = \{93,94,95,96\}$, where each time period is divided into four instances of 15 min.
User set	Involving all the users who provided requests on Dec. 29, 2017 collected by the user log data and their profiles are randomly generated according to SP profiles.
Initial vehicles	Adopting the number of vehicles in each hour on Dec. 29, 2017.
Acceptable walking duration	Adopting the maximum acceptable walking duration of EVCARD which is 27.8 min. Therefore, the nearby departure stations I_n and arrival stations J_n for user n can be confined.
Basic price	Set as known parameter; $p = ¥36$ per hour.
Driving timet_{ij}	Fetched by BaiduMap API which returns driving directions and driving duration between two locations on a map, where the driving time involves the impact of real-time traffic congestion.
Walking duration	Fetched by BaiduMap API which returns walking duration between two locations on a map.
Triggering threshold	Using the same stations and thresholds as the previous study (Ma et al., 2018)

1, users are more likely to depart from stations 2 and 3, and the overall probability of choosing carsharing for a trip also decreases. When changing toward more incentives, users are more likely to choose station 1 compared to other stations. Fig. 6b presents the probabilities of choosing different drop-off stations. The differences can be attributed to the parameters of walking distance and travel time. This pattern captures both the path choice behavior and carsharing mode adoption probability, which are influenced by local pricing changes.

For multiple users traveling between a pair of departure and arrival stations, the calibrated choice probabilities can be aggregated (Fig. 7). User paths are distributed over the network, where incentives and surcharges influence the demand-flow distribution. For example, Fig. 7 presents different pick-up incentives and surcharges for departure station 1 and the results of aggregating each user's choice probabilities into a volume at each station and path. When incentives are provided, users are attracted to station 1. If surcharges are applied, users tend to prefer stations 2 and 3, and some decide not to use carsharing. This phenomenon closely matches real demand pattern features and resolves the assumption that price-demand curves only change independently at isolated stations. The probability aggregations represent expectations of demand, which are decimal values. In the real world, demand should be discrete and distributed according to the probabilities.

4.2. Solving the optimization model

4.2.1. Data description

The data and parameters for used the optimization model are summarized in Table 6. The data are operating data and user log data from the EVCARD carsharing system. For consistency, we adopted the same 56 stations as our previous study on triggering thresholds (Ma et al., 2018). For detailed information regarding the stations and demand, please refer to Appendix A, which provides an online

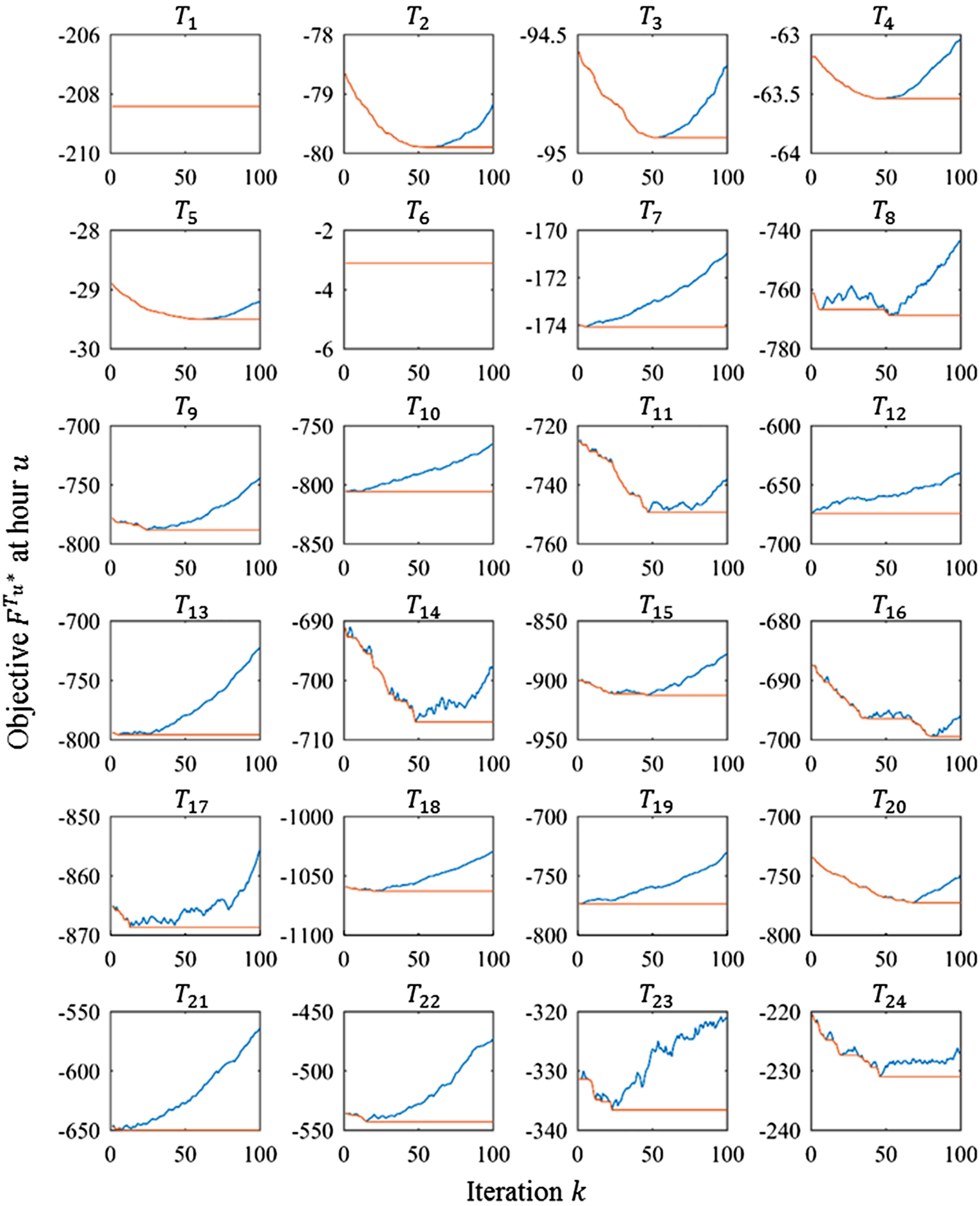


Fig. 8. Searching process with iterations at each time instance.

repository storing the O-D-level and user-log-level data. User-log data tracks finger clicks on a smartphone reservation app, which can be adopted to estimate the true demand that may not be satisfied (Wang et al., 2020). There are 1750 trip requests in the user dataset according to our previously proposed method (Wang et al., 2020). Some of these requests were satisfied, while others were not. User profiles are not collected in the system and can be randomly generated according to the user profiles in the SP survey (depicted in Appendix B).

The time instances are divided by hour because pricing policies are assumed to be stable for at least one hour so that users can acquire and react to the policies. Therefore, one hour is adopted as the length of a time period. Each time period is divided into four instances of 15 min. The rental time used for calculating revenue is exact rental time, rather than a summation of time slices (see Eqs. (14) and (40), as well as parameter t_{ij}), which ensures that the objective measure is accurate.

4.2.2. *Solving process*

(1) Solving process for a full-day scenario

Here, we present the solving process for a full day T. The day is divided into 24 h ($T = \{T_1, \cdots, T_{24}\}$) and 96 time instances with

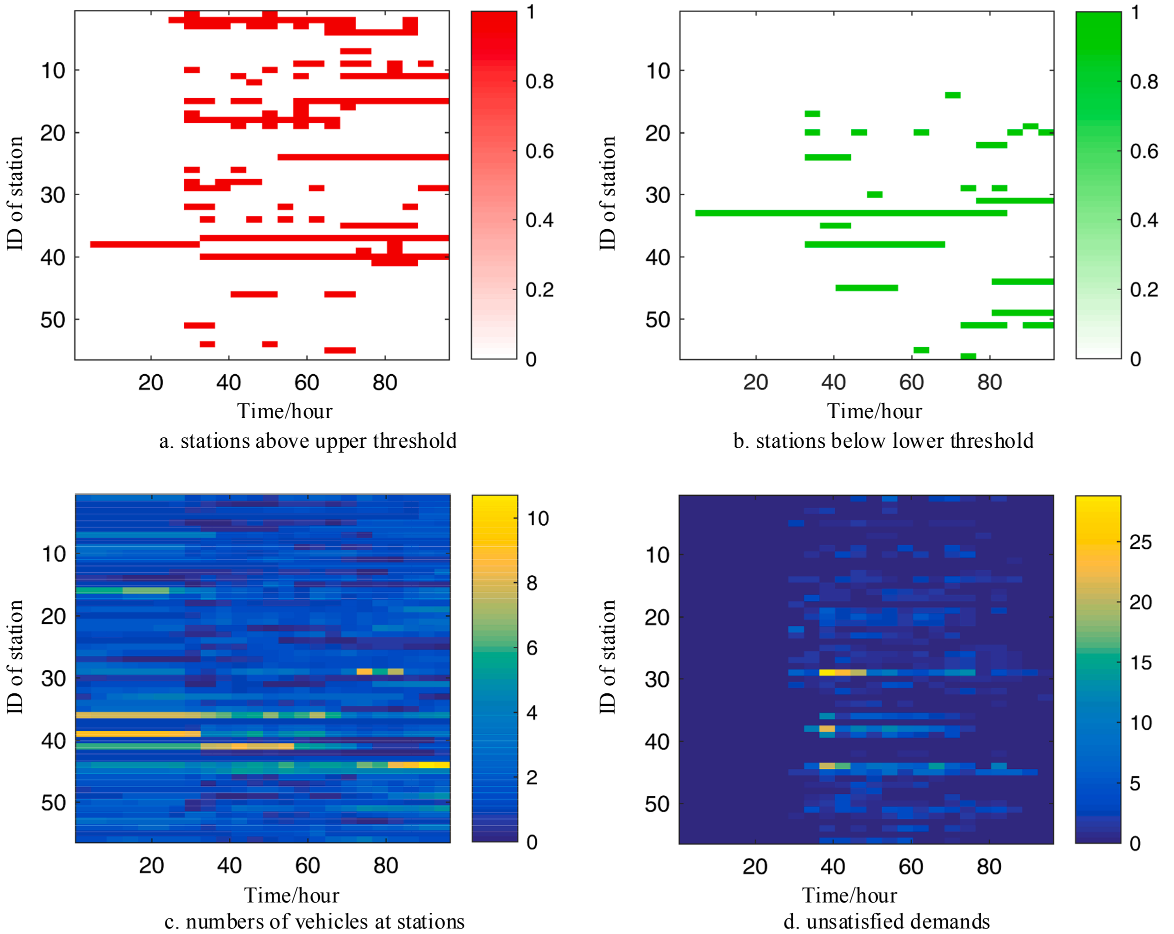


Fig. 9. Status indices of stations and unsatisfied demand over 24 h.

lengths of 15 min. The operation monitoring and log system deliver real-time vehicle counts at stations to our model at the beginning of each hour. In this study, we predefined the hourly data as real-time data for calculation. The solving process starts at time instance $t = 1$ and the algorithm executes four times each hour. $\forall T_u \subseteq T$ and the minimum of $F^{T_u}\left(\lambda^t_{Di}, \lambda^t_{Rj}, \lambda^t_{ij}\right)$ were approximated using the solution algorithm. The process for each time instance and iteration is presented in Fig. 8. Each subgraph displays the searching process for the time period T_u, which contains four time instances, where the horizontal axis represents the number of iterations and the vertical axis represents the value of F^{T_u}. The blue lines represent the objective F^{T_u} values of newly generated solutions and the orange lines represent the current best F^{T_u*} values of the current best solution. In this scenario, the total calculation time is 654.1 s for all 96 time instances over 24 h for the 56 target stations. The proposed solutions requires an average of 27.2 s for hourly computations.

For all of the time instances, there are no new solutions generated (no blue lines) at T_1 or T_6, indicating that during these two time periods, the numbers of vehicles at each station remained within reasonable ranges and no control policies were triggered. For T_7, T_{13}, and T_{19}, although new solutions are generated, $F^{T_u k}$ increases with the number of iterations, indicating that the incentive and surcharge policies applied during these time instances lead to a loss of revenue. These results suggest that incentives and surcharges may not always benefit operators.

During other time instances, better solutions can be found. The total revenue for the 56 stations over 24 h is ¥16,053, whereas the total revenues would only be ¥13,109 if no incentives or surcharges were applied, demonstrating that incentives and surcharges were able to increase revenue by 22.5% in this case.

(2) Performance evaluation

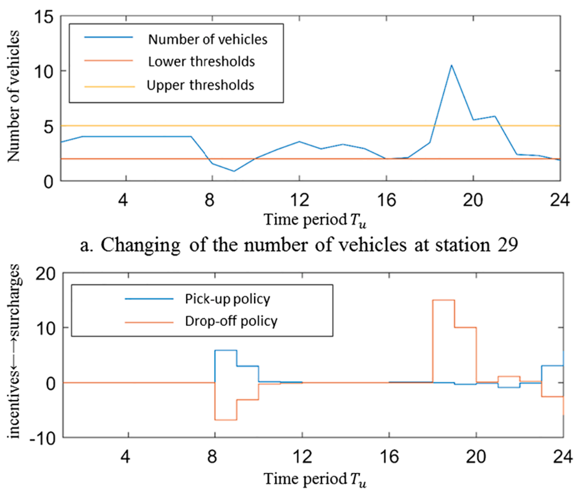
To evaluate the proposed process further, we analyzed the status of the stations by determining whether the numbers of vehicles at each station exceeded the upper threshold or were below the lower threshold. The ratios of unsatisfied demand and numbers of vehicles at stations were also analyzed for each station and each hour in a day. Fig. 9a presents the stations whose numbers of waiting vehicles exceeded the upper threshold during the 24 h period. Fig. 9b presents the stations whose numbers of vehicles were below the lower threshold. These plots suggest that out-of-balance scenarios still exist after deploying a control policy using incentives and surcharges. Fig. 9c presents the expected numbers of vehicles stopping at stations during different hours after applying incentives and surcharges. At the beginning of the day, vehicles are concentrated at certain stations. Throughout the day, vehicles are redistributed in the network with a relatively balanced pattern. Fig. 9d presents the amount of unsatisfied demand at each station throughout a day. One can see that some of the stations are out of supply cannot satisfy demand in certain periods. This scenario may suggest that the situation was beyond the capabilities of the demand control method, meaning demand control at an unsatisfied station could not reduce the background demand, even under the maximum surcharge, and was unable to attract more drop-off vehicles from nearby stations. This situation indicates the boundaries of the demand control approach.

(3) Algorithm analysis

The algorithm for solving each time instance introduces randomness and is sensitive to the parameter of the randomness scale (refer to note c in the algorithm). To test the stability of the proposed algorithm and examine whether it can produce feasible solutions for operation support, we tested the algorithm on scenarios with randomness scales of $\gamma = 1, 2, 5$, and 10. Because there are many variables and stations that complicate the presentation of these scenarios, we selected four representative stations, namely 36, 34, 29, and 44, which are the same as those considered in our previous paper (Ma et al., 2018). p^t_{Di} and p^t_{Ri} are presented for $i = 36, 34, 29$, and 44. Specifically, the time period at $t = 8{:}00$ was selected as the target case instead of a full day because the observed demand pattern is typical. We executed the proposed algorithm 50 times for each γ and calculated the mean values and variances of the final approximated solutions of p^t_{Di} and p^t_{Ri} (denoted as *), as well as the objective F^t, where $\text{mean}(.)$ and $\delta^2(.)$ denote the mean value and variance, respectively (see Table 7).

Table 7
Sensitivity to the parameter of the randomness scale.

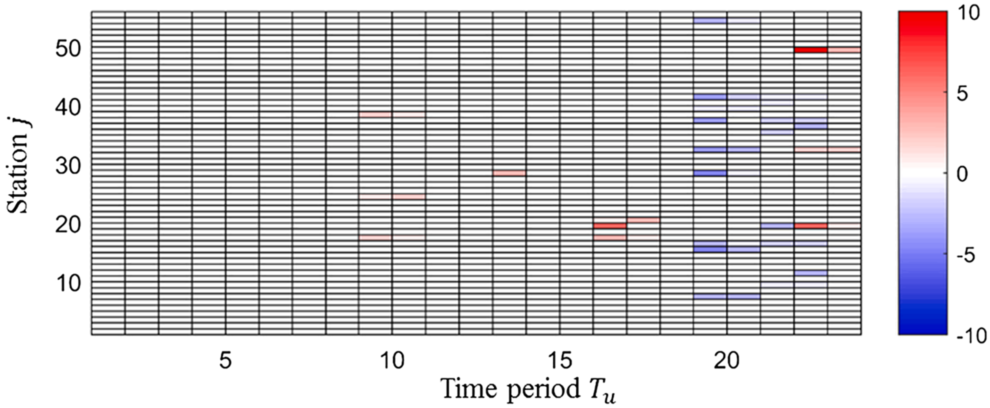
i	randomness scale	$\text{mean}(p^{t*}_{Di})$	$\delta^2(p^{t*}_{Di})$	$\text{mean}(p^{t*}_{Ri})$	$\delta^2(p^{t*}_{Ri})$	$\text{mean}(F^{t*})$	$\delta^2(F^{t*})$
36	1	4.53	0.83	−4.58	0.95	−947.02	90.93
	2	5.03	1.20	−4.68	0.88	−967.05	86.65
	5	8.34	3.18	−4.57	4.23	−976.06	96.10
	10	10.81	11.80	−4.46	13.11	−954.11	111.57
34	1	−5.89	1.27	5.85	0.40	−947.02	90.93
	2	−4.49	1.81	6.88	1.37	−967.05	86.65
	5	−3.08	4.16	8.18	6.86	−976.06	96.10
	10	−2.12	9.80	12.30	10.43	−954.11	111.57
29	1	4.70	0.94	−4.56	0.81	−947.02	90.93
	2	4.57	1.24	−4.81	2.34	−967.05	86.65
	5	4.70	6.41	−4.96	6.88	−976.06	96.10
	10	5.33	17.96	−5.12	9.80	−954.11	111.57
44	1	4.62	0.85	−4.56	0.16	−947.02	90.93
	2	5.31	1.17	−3.66	1.03	−967.05	86.65
	5	8.17	4.25	−3.14	3.48	−976.06	96.10
	10	10.59	9.23	−2.07	7.16	−954.11	111.57



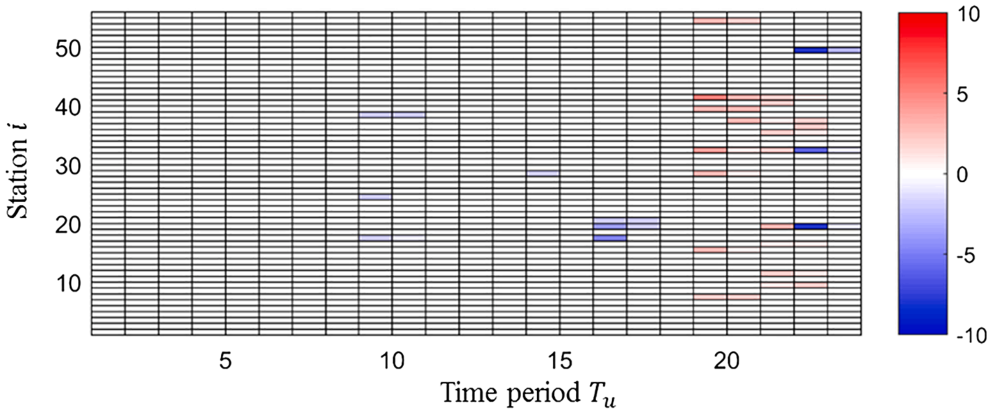
a. Changing of the number of vehicles at station 29

b. Solutions of pick-up policy and drop-off policy

Fig. 10. Pick-up and drop-off policies of station 29.



a. O-D policies from station 29 to station j



b. O-D policies from station i to station 29

Fig. 11. O-D policies of station 29.

For a small randomness scale ($\gamma = 1$), the variances of the decision variables are relatively small and indicate that the proposed algorithm produces relatively stable outputs. The variances become larger with the randomness scale, indicating that the algorithm has a wide range for generating random seeds and is able to search for more combinations of pricing policies. However, the proposed algorithm can output different results in each run, meaning it is unstable if the randomness scale is large ($\gamma = 10$). These results also suggest that there will be very different solutions, but similar objective values can be achieved. This implies the non-uniqueness of solutions when feasible solutions are variable.

4.3. Result presentation for stations

For each station s, the pick-up incentive and surcharge policies p_{Ds}^t, drop-off incentive and surcharges policies p_{Rs}^t, and O-D incentive and surcharges policies p_{ij}^t can be outputted by the proposed model. For example, Fig. 10 presents the outputs of the pick-up and drop-off policies at station 29. Fig. 10a plots the changes in the number of vehicles with the upper and lower thresholds for triggering policies and Fig. 10b presents the solutions for the pick-up policies (p_{D29}^t) and drop-off policies (p_{R29}^t) from T_1 to T_{24}.

The changes in the number of vehicles suggest that the number falls below the lower threshold during T_8 and T_9, so drop-off incentives are applied to attract vehicles and pick-up surcharges are applied to reduce demand. During T_{19} and T_{21}, the number of vehicles climbs above the upper threshold, so pick-up incentives are adopted to attract users and drop-off surcharges are adopted to reduce the number of vehicles coming in.

The proposed model also exports incentive and surcharge policies for a specific O-D pair (p_{ij}^t). Consider station 29 as an example. The O-D policies of station 29 are presented in Fig. 11, where the horizontal axis represents the time periods from 1 to 24 and the vertical axis represents stations. Fig. 11a presents the O-D policies between station 29 and any station j (p_{29j}^t), and Fig. 11b presents the

Table 8
Comparisons among different combinations of policies.

Combination	Description	Revenues	Served demand
pick-up, drop-off, and O-D	Set $p^t_{Di}, p^t_{Rj}, p^t_{ij}$ as decision variables.	¥16,053	1046
pick-up, drop-off	Set p^t_{Di}, p^t_{Rj} as decision variables, and let $p^t_{ij} = 0, \forall t \in T, \forall i \in S, \forall j \in S$	¥15,411	1044
O-D	Set p^t_{ij} as decision variables, and let $p^t_{Di} = p^t_{Rj} = 0, \forall t \in T, \forall i \in S, \forall j \in S$	¥14,443	1073
No incentives and surcharges	Let all the policies be 0, $p^t_{Di} = p^t_{Rj} = p^t_{ij} = 0, \forall t \in T, \forall i \in S, \forall j \in S$	¥13,109	1072
Operator-based vehicle relocation	A threshold-based vehicle relocation method (Wang et al., 2019a,b)	¥14,278	1112

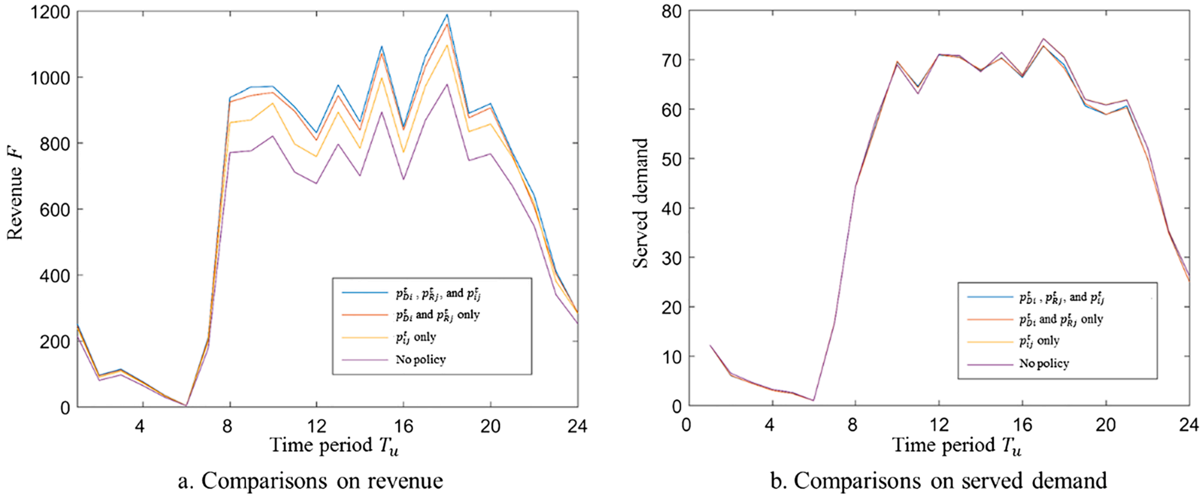


Fig. 12. Revenues and satisfied demand under different combinations of policies.

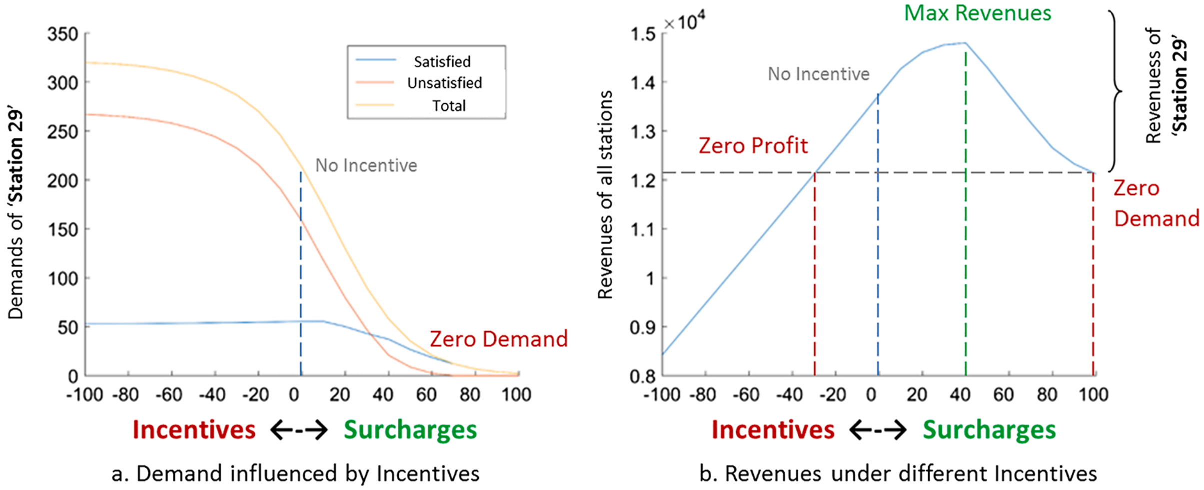


Fig. 13. Mechanisms of pricing, demand patterns, and revenue at station 29.

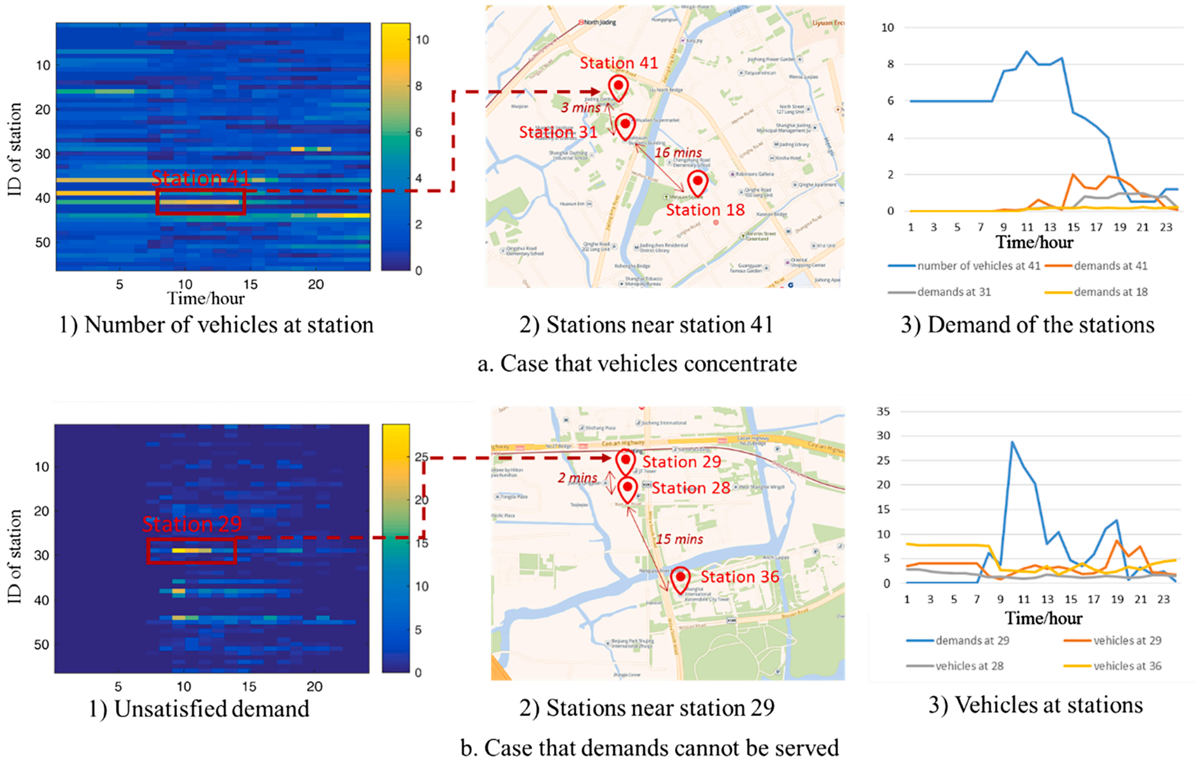


Fig. 14. Scenarios in which incentives and surcharges may lose efficacy.

O-D policies between any station i and station 29 (p^t_{i29}). The blue cells in the figure represent incentives and the red cells represent surcharges.

The results suggest that the O-D policies are mainly incentives for attracting demand to drive vehicles to other stations when the number of vehicles exceeds the upper threshold during T_{19} and T_{20} (represented by blue cells in Fig. 11a). The O-D policies are mainly surcharges at some other stations to avoid vehicles being driven from those stations to station 29 (represented by red cells in Fig. 11b).

4.4. Comparison of different combinations of policies

The pick-up, drop-off, and O-D incentive and surcharge policies ($p^t_{Di}, p^t_{Rj}, p^t_{ij}$) are controllable policies in the proposed model. To analyze the effectiveness of these three policies, we conducted comparisons among different combinations of policies. The combinations are listed in Table 8.

For different time instances, the revenue and satisfied demand are plotted in Fig. 12. A combination of pick-up, drop-off, and O-D policies yields the highest revenue. In other words, station policies or O-D policies alone cannot achieve the highest level of revenue. The pick-up and drop-off combination yields higher revenue than O-D policies alone. However, O-D policies alone satisfy more demands, whereas the pick-up and drop-off policies satisfy less demand when they reached high revenue. This can be attributed to possible surcharges that bring higher revenue, but discourage users.

To compare the demand control approach to the operator-based vehicle relocation method, we added the revenue and satisfied demand for a threshold-based relocation method to Table 8 This method was established by (Wang et al., 2019b) under the same 56 station scenario with the same input data. The revenue of the operator-based method is the total income minus the relocation labor cost. The results suggest that operator-based relocation can serve more users than any combination of demand control policies or the no-relocation condition. The operator-based relocation method generates more revenue than the no-relocation condition and OD demand control policy alone, but does not exceed the revenue generated by the pick-up and drop-off demand control policy.

4.5. Discussion

4.5.1. Value of the incentive and surcharge approach

The comparisons above implied that the incentive and surcharge approach can collect more revenue than the operator-based vehicle relocation approach, but cannot satisfy more users. This is because operator-based relocation forces workers to move vehicles to satisfy more trip requests. This newly served demand is able to create revenue that exceeds the cost of labor. However, the demand control policy collects more revenue from demand concentration stations, resulting in higher total revenue while pushing some users to quit using carsharing.

These findings are evident at representative stations such as station 29. Fig. 13 presents the mechanism of the price-demand relationship. By changing the incentives and surcharges for pick-up demand at station 29, one can observe the influence of pricing on demand at this station, as well as the total revenue. Increasing surcharges loses some demand, but yields more revenue. Increasing incentives attracts more users, but demand may not be satisfied based on the limitation of the vehicle supply, which results in a loss of revenue.

If one raised the surcharge to ¥100, no demand would remain at this station, meaning it would generate no revenue. One can see that profit trends toward zero when offering incentives above approximately ¥30 because the cost of incentives cancels out the revenue collected from the corresponding satisfied demands. Hence, the optimal strategy for collecting more revenue is to set surcharge value to ¥40. The corresponding satisfied demand is lower than that when applying no incentives or surcharges at this station.

Another factor influencing these results is that station 29 is an oversaturated station whose demand exceeds the available vehicle supply. The proposed system cannot satisfy more demand if it offers incentives, but it can gain more revenue if surcharges are applied. We analyzed all 56 stations and discovered that 40 stations are oversaturated stations with surcharges, while the remaining 16 stations have incentive policies. Stations with incentives are able to gain revenue by satisfying more demand, but the total satisfied demand decreases.

4.5.2. Capabilities of the incentives and surcharges approach

The results in Fig. 9 regarding the numbers of vehicles at stations and unserved demand demonstrate that vehicles tend to concentrate at some stations and demand is rarely satisfied at some stations, even if incentives and surcharges are applied. This phenomenon implies that the incentives and surcharges approach loses efficacy under some extreme circumstances.

We identify two interesting scenarios in Fig. 14. One is a station overflow condition (Fig. 14a), where many vehicles arrive at station 41 at 8:00 AM and are not utilized until 3:00 PM. Investigation of the nearby stations 31 and 18 suggests that no potential demand could be motivated by incentives. Even if drop-off surcharges are applied at station 41, the number of drop-off vehicles continues to increase. The other scenario is the unsatisfied demand at station 29, where reserved vehicles are instantly occupied to serve the morning peak demand. The nearby stations 28 and 36 are also out of vehicle supply, meaning no more emerging demand can be satisfied.

These two scenarios suggest that the demand control policy has limitations based on background demand patterns that could be influenced by pricing policies. They also suggest that the incentives and surcharges approach is limited to acceptable walking distances. Introducing bikesharing cooperation with carsharing may help extend the range of possible stations.

Additionally, operator-based relocation is still necessary to mobilize the vehicle fleet and increase capacity, which forces workers to move vacant vehicles from overflowing stations. Additional demand cannot be satisfied based on the limitations of vehicle availability and system capacity. These results also suggest that combining operator-based and user-based relocation is desirable for achieving better efficiency based on their different advantages.

4.5.3. Limitations and potential improvements

Accuracy by involving probability. In this study, the price-demand model was based on the discrete choice model, which is a probabilistic model. The demand loaded onto the time–space network was represented by indeterminate values, rather than deterministic integers. This resulted in a phenomenon in which one user could appear on multiple positions or paths according to probability values. Correspondingly, the utilization of vehicles would also be fractional. Although including probabilities can be helpful for finding idealistic solutions for incentives and surcharges, realistic cases may not always correspond to the optimal solutions. This feature reduces the accuracy of the proposed method when processing specific deterministic operation scenarios. A possible improvement is to involve a simulation method that can capture deterministic user choice results and system dynamics.

Diversity of user profiles. Users are assumed to be homogeneous in a uniform discrete choice model. This may ignore the diversity of different reactions from users with different characteristics. Although a probabilistic approach can explain some randomness and possible variations in the proposed model, the varying sensitivity of users is a potential topic for future study. Fig. 6 reveals the sensitivity characteristics of homogeneous users, but it is more realistic for different users to have different attitudes toward pricing offers. To consider the varied properties of users, we adopted profiling variables in our logit models. The user clustering approach is also a potential method for considering the variability of users by grouping similar users. To customize various schemes of surcharges and rewards for different user groups, we can let the decision variables be different for each group of users, which can improve the diversity of the proposed method for differentiated users.

Weakness of the solution algorithm. The target problem is very complex. The complexity of the proposed model stems from two main aspects: (1) the strong nonlinear properties of the logit model and (2) a network model with a massive number of nodes and huge solution space. This study used a model that mimics the features of the natural problem because nonlinear properties are difficult to represent using known convex or linear models without losing properties. A meta-heuristic solution algorithm was proposed to provide feasible solutions for implementation, but a traditional heuristic method could export feasible solutions approximating the optimal solution. We suggest that the nonlinearity of this problem is worthy of further study for guaranteeing optimality, which would improve the performance of the solution algorithm.

5. Conclusions

This paper proposed a method to determine incentive and surcharge combinations dynamically to control demand patterns in one-way carsharing systems to mitigate the demand and supply imbalance problem and increase profits.

In this study, a two-level NL model was adopted to capture user choice behavior mechanisms and reveal user reactions to various combinations of incentives and surcharges. User reaction mechanisms are reflected in the probabilities of each choice branch for departure stations, arrival stations, and whether to travel via carsharing. The proposed model provides a deeper understanding of the disaggregated characteristics of users, which can describe user behaviors more accurately than the traditional price leverage function and can overcome the weakness of the linear elasticity model in terms of both the fitness of change curves and difficulties arising from sparse O-D matrices.

This paper also presented a time–space network structure and equations for aggregating user choice probabilities into the demand dynamics of the network. The proposed optimization model operates based on the time–space network with the user choice model loaded onto it. To maximize the total revenue of the system, the model can determine the proper combination of pick-up, drop-off, and O-D policies, and the amounts of incentives and surcharges for specific stations and O-D pairs. To solve the optimization model, we investigated some conditions of real operations and presented an approximate algorithm to search for optimal solutions.

Analysis results for an example study demonstrated that based on an approximate optimization solution for a combination of incentives and surcharges policies, the proposed system can improve revenue by 22.5%. The solving process of the proposed model also revealed that implementing policies is not necessary for all time periods and that incentives and surcharges may not yield greater profits under some circumstances. This result also implies that improper settings for incentives and surcharges can also lose profits. A comparative study demonstrated that all of the combinational policies for pick-up, drop-off, and O-D pairs can achieve better revenue than using only a portion of these policies.

However, some insufficiency still exists in this study. First, the two-level NL model loaded onto a time–space network is a complex and difficult problem to solve, meaning it requires additional theoretical study. Driving range and refueling properties were not considered in this study, so the proposed model should be further supplemented under certain conditions and constraints for considering electric vehicles. The results of pricing policies computed by the proposed method have not yet been tested in real operations. It should be possible to test the performance of these policies in the field in future studies. This paper focused on pick-up, drop-off, and O-D policies, but it should be noted that the proposed model is extensible for additional studies on carsharing user behaviors and system dynamics. The trip splitting and merging policy, overall pricing determination, and even operator-based relocation can also be integrated into the framework proposed in this paper, which could reveal more efficient operating measures in future studies.

CRediT authorship contribution statement

Lei Wang: Software, Investigation, Formal analysis, Writing - original draft. **Wanjing Ma:** Conceptualization, Methodology, Validation, Supervision. **Meng Wang:** Methodology, Validation. **Xiaobo Qu:** Methodology, Writing - review & editing.

Declaration of Competing Interest

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

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Appendix A. Data repository

This appendix provides detailed information about the 56 stations in the example, including the locations, triggering thresholds, and hourly demands of the stations during a day. Fig. 15 shows the position of the 56 stations. Detailed information station information and hourly aggregated demands of each stations which were collected from the EVCARD operation system during April 2015. The hourly demands could be generated from the origin–destination (O-D) data, which is the input of our model. Note that the O-Ds for all time intervals could not be presented here due to the page limitation, but the readers can access data with detailed station and O-D information at the following online repository: https://github.com/wangleicuail/EVsharingBasicData

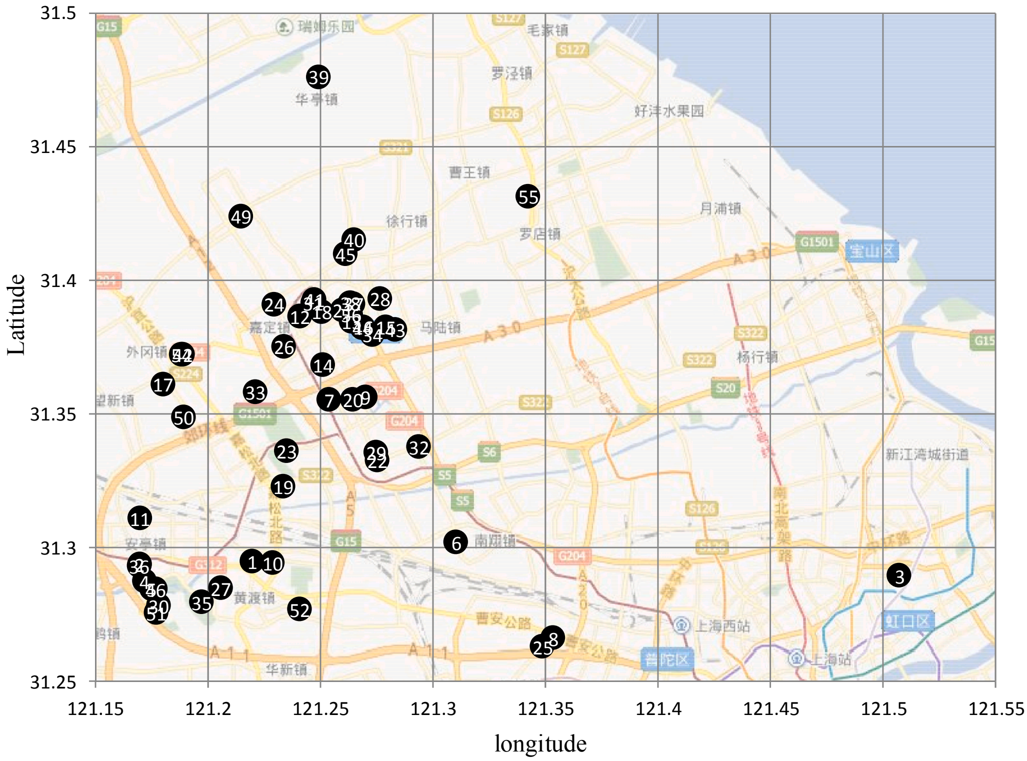

Fig. 15. IDs and locations of the stations of the example.

Appendix B. Demand generation

Considering the system transaction/trip data only contains the served demands, the unserved and background demands are unknown. Our previous study (Wang et al., 2020) adopted the user application log data to derive the background demands through app-user interaction data, which means that served and unserved demands can both be generated.

By this method, we generated 1750 trip requests, which contains user ID, origin, destination, reservation time and departure time. However, User profiles were not collected in the system but can be randomly generated according to the user profiles in the SP survey. Information is summarized in the graph below.

For each trip in the 1750 trips we randomly generate user profile. Supposing user properties follow the experienced distribution in Fig. 16, for one user generate five random number in (0, 1] following uniform distribution. If the random number falls into the cumulative frequency of one group, then give the property of the group to the user. Hence the profile of the 1750 users can be generated.

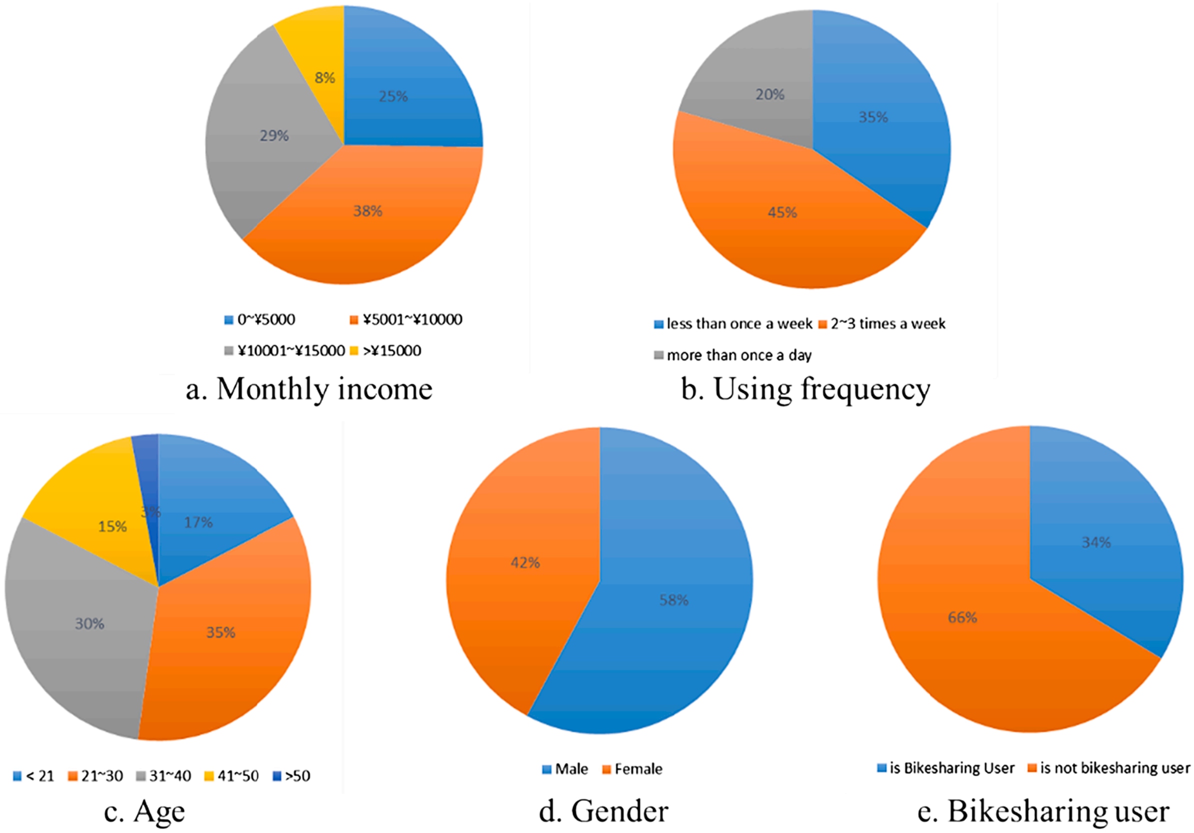

Fig. 16. Profiles of users in the SP survey.

Appendix C. Calibration of the two-level choice model

Construct the likelihood function as:

$$L\left(\delta_1(ij)_n, \delta_{0n}; \boldsymbol{\theta}, \boldsymbol{\varphi}, \boldsymbol{\mu}\right) = \prod_{n\in N'}\prod_{i\in I_n}\prod_{j\in J_n}\left(\mathscr{P}_{nij}^{t\ \delta_1(ij)_n} \cdot \mathscr{P}_{n0}^{t\ \delta_{0n}}\right) \tag{47}$$

where $\boldsymbol{\theta} = \{\theta_i | i = 1, 2\}$, $\boldsymbol{\varphi} = \{\varphi_i | i = 1, \cdots, 6\}$, and $\boldsymbol{\mu} = \{\mu_i | i = 1, 2\}$. The log likelihood function should be as follows.

$$L = \ln L\left(\delta_1(ij)_n, \delta_{0n}; \boldsymbol{\theta}, \boldsymbol{\varphi}, \boldsymbol{\mu}\right) = \sum_{n\in N'}\sum_{i\in I_n}\sum_{j\in J_n}\left(\delta_1(ij)_n \ln\mathscr{P}_{nij}^t + \delta_{0n}\ln\mathscr{P}_{n0}^t\right) \tag{48}$$

The estimation of the parameters $\boldsymbol{\theta}, \boldsymbol{\varphi}, \boldsymbol{\mu}$ is to solve the problem

$$\max_{\boldsymbol{\theta},\boldsymbol{\varphi},\boldsymbol{\mu}} L = \ln L\left(\delta_1(ij)_n, \delta_{0n}; \boldsymbol{\theta}, \boldsymbol{\varphi}, \boldsymbol{\mu}\right) \tag{49}$$

The log likelihood function does not guarantee convexity due to the interrelationship of $\mathscr{P}_{nij}^t$ and $\mathscr{P}_{n0}^t$ through Γ_{1n}^t, and makes it difficult to find optimal $\boldsymbol{\theta}, \boldsymbol{\varphi}, \boldsymbol{\mu}$.

Note the following relation:

$$\mathscr{P}_{nij}^t = \mathscr{P}_n^t(ij|1) \cdot \mathscr{P}_{n1}^t \tag{50}$$

$$\mathscr{P}_{n1}^t = 1 - \mathscr{P}_{n0}^t \tag{51}$$

Then

$$L = \sum_{n\in N'}\sum_{i\in I_n}\sum_{j\in J_n}\delta_1(ij)_n \ln\mathscr{P}_n^t(ij|1) + \sum_{n\in N'}\sum_{i\in I_n}\sum_{j\in J_n}\delta_1(ij)_n \ln\mathscr{P}_{n1}^t + \sum_{n\in N'}\sum_{i\in I_n}\sum_{j\in J_n}\delta_{0n}\ln\mathscr{P}_{n0}^t \tag{52}$$

Split the function as:

$$L = L_1 + L_2 + L_3$$

$$L_1 = \sum_{n \in N'} \sum_{i \in I_n} \sum_{j \in J_n} \delta_1(ij)_n \ln \mathscr{P}^t_n(ij|1) \tag{53}$$

$$L_2 = \sum_{n \in N'} \sum_{i \in I_n} \sum_{j \in J_n} \delta_1(ij)_n \ln \mathscr{P}^t_{n1} = \sum_{n \in N'} (1 - \delta_{0n}) \ln\left(1 - \mathscr{P}^t_{n0}\right) \tag{54}$$

$$L_3 = \sum_{n \in N'} \delta_{0n} \ln \mathscr{P}^t_{n0} \tag{55}$$

It has been proved that to estimate parameters stepwise is consistent but asymptotically less efficient than the overall maximum likelihood estimator (Amemiya, 1978) and its computation is considerably simpler. The two-step estimation could be:

Step 1,

$$\max_{\boldsymbol{\theta}} L_1 = \sum_{n \in N'} \sum_{i \in I_n} \sum_{j \in J_n} \delta_1(ij)_n \ln \mathscr{P}^t_n(ij|1) \tag{56}$$

Step 2,

$$\max_{\boldsymbol{\varphi},\boldsymbol{\mu}} L_2(\delta_{0n}, \boldsymbol{\theta}^*; \boldsymbol{\varphi}, \boldsymbol{\mu}) + L_3(\delta_{0n}, \boldsymbol{\theta}^*; \boldsymbol{\varphi}, \boldsymbol{\mu}) = \sum_{n \in N'} (1 - \delta_{0n}) \ln\left(1 - \mathscr{P}^t_{n0}\right) + \sum_{n \in N'} \delta_{0n} \ln \mathscr{P}^t_{n0} \tag{57}$$

Note that $\boldsymbol{\theta}$ are independent from $L_2 + L_3$ which is reasonable to be calibrated in Step 1. With estimated $\boldsymbol{\theta}^*$ in Step 2 the parameters $\boldsymbol{\varphi}$ and $\boldsymbol{\mu}$ can be calibrated subsequently. Since the two steps can be regarded as isolated logit models, modern statistics software is feasible for logit model calibration.

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