Dynamic Trip Pricing Considering Car Rebalances for Station-based Carsharing Services

Ruiyou Zhang, Haiyu Kan

College of Information Science and Engineering, Northeastern University, Shenyang 110819, China
E-mail: zhangruiyou@ise.neu.edu.cn

Abstract: This study proposes a dynamic trip pricing (DTP) problem considering the distribution imbalances of cars in one-way station-based carsharing systems. In the DTP problem, the trip prices are functions of the balancing degrees of both origin and destination stations. The DTP problem aims to maximize the expected profit of the carsharing system in a given planning horizon. A non-linear programming model is built for the DTP problem and solved by a particle swarm optimization algorithm. The proposed methods are validated and evaluated based on a larger number of randomly generated instances. The results indicate that the DTP scheme results in profit increment and car distribution improvement, which helps enhance user satisfactions. The sensitivity analysis shows that the scheme is also helpful when the user price elasticities are varied. Furthermore, the DTP scheme is applicable to different types of price-demand relationship.

Key words: One-way station-based carsharing; Car distribution imbalances; Dynamic trip pricing; Non-linear programming model

1 INTRODUCTION

Carsharing systems have diffused increasingly around the world in recent two decades. The wide adoption of carsharing systems generates enormous economic and environmental benefits [1, 2]. Car distribution imbalances is a universal operational difficulty faced by service operators. Measures to eliminate or alleviate imbalances of car distribution could be classified into three strategies: operator-based relocation, user-based relocation and relocation-oriented pricing.

Operator-based relocation means service operators employ staff to rebalance cars from stations with surplus cars to car-deficit stations. Article [3] developed a chance constraint model to determine the numbers of periodic relocated cars. In their problem, phantom cars and parking space were introduced with large penalty costs. Article [4] proposed a multi-objective programming model for an electric carsharing network planning problem. Article [5] and article [6] focused on the feasibilities of the staff routes, making their problems similar to paired truckload pickup and delivery problems.

User-based relocation means service operators make use of user flexibilities to slightly adjust users' itinerary attributes. As the staff relocation activity leads to additional operational costs, user-based relocation has received increasing attention. Article [7] proposed a "second and third nearest stations to desired stations" strategy and evaluated its efficiency based on an integer programming model. For a carsharing system that adopted slightly adjusting some users' pick-up stations and employing staff to perform relocation activities, article [8] developed a time-rolling formulation to save operational costs and maximize users' utilities. Article [9] measured the benefit of demand space-time flexibilities for two-way carsharing systems.

Relocation-oriented pricing means service operators adjust demand patterns by changing service prices to achieve more desired relationships between car supply and demand at each station (zone). Compared to the above two strategies, this strategy receives less attention. Article [10] built a mix integer programming model to optimize trip prices. Article [11] made the first attempt to jointly determine trip prices, car fleet and car relocation activities along with staff assignment. Article [12] extended the study of [10] and proposed a model with two Price Adjustment Level decision variables for an electric carsharing system, where the trip times were also adjusted by prices for the saving of electricity costs.

We focus on the relocation-oriented pricing for one-way, station-based carsharing systems. The carsharing systems in the city of Beijing inspired our research. These systems suffer regular car distribution imbalances during peak hours. However, operator-based and user-based relocation are not mature or not even be applied because of expensive employment costs or shortage of reasonable incentive mechanisms. We try to address the imbalances by obtaining more desired relationships between car availability and demand at each station with the help of a dynamic trip pricing (DTP) scheme.

The most similar articles focusing on DTP scheme in carsharing services came from [10] and [11], both of which made integrated optimizations by determining system configurations and trip prices in a MIP model from a systemic perspective. Although system configurations and trip prices affect mutually, it is not easy to alter system configurations with varied demand frequently in practice, especially when carsharing system networks have been built.

This work is partially supported by the National Natural Science Foundation of China (Nos. 71971050, 71831006, and 71471034), Specific Support for Developments of Teachers by Northeastern University, and National Key R&D Program of China (2019YFB1705002).

The carsharing system applies the "first come first served" service principle. As far as we concerned, no literature reported has studied a DTP scheme with this service principle in the operational perspective, where the system configuration is fixed. The unique feature of fixed system configurations with an inexecutable trip selection strategy makes this study disparate from the previously published ones. Under this problem setting, how to formulate car allocations when the number of cars cannot meet all the potential demand is complicated and at the same time not being addressed. To solve this issue, we introduce binary values to judge whether the number of cars available at each station in each time period can satisfy all the potential demand.

The remainder of this paper is structured as follows. The next section gives the problem description of the DTP problem, followed by the mathematical formulation and solution method in Section 3. The proposed methods are validated and evaluated in Section 4. This paper ends with conclusions in Section 5.

2 DYNAMIC TRIP PRICING PROBLEM

2.1 Problem description

A carsharing network owns determined numbers of predetermined stations and homogeneous shared cars. The set of stations is denoted as I. The stations are located in different functional districts such as residential areas and commercial areas. The shared cars are scattered among the stations at the beginning of each planning horizon.

The system applies the "first come first served" principle, which means the system does not deny any rental requests unless the user abandons the system due to the unavailability of cars. In other words, a car that is not used could be reserved by any registered members and the system would not select user demand to satisfy for the purpose of profit maximization.

Potential users can be classified into commuters and leisure travelers based on their sensitivities to trip price variations and demand characteristics [13]. Commuters are relatively insensitive to price variations and have larger demand during peak hours. Leisure travelers are more likely to switch to alternative transportation modes when car rental prices increase and require cars steadily throughout the planning horizon.

During morning peak hours, commuters make larger car requests from where they live to their workplaces. During evening peak hours, the pouring direction is opposite. Because of the asymmetric demand fluctuation, regular car imbalances occur during peak hours. According to the degrees of car adequacy or inadequacy of these stations, 5 status levels: seriously inadequate (I), slightly inadequate (II), balanced (III), slightly adequate (IV) and seriously adequate (V) exist.

To solve the car imbalances problem, a DTP scheme is proposed under the assumption of elastic demand. Nine trip prices are set during peak hours, which are related to both pick-up and drop-off stations. Trips with similar effects on car balances are charged the same price for per-time-unit usage. For example (see Figure 1), the trips whose origin-destination station status levels fall into I and II, respectively, and the trips with origin-destination station status levels belonging to II and III, respectively, could produce similar effects on car balanced distribution because the status level of the origin stations is one less than that of the destination stations. Based on the similar effect principle, the trip classification during peak hours is shown in Table 1. Each value in Table 1 is the price type of the corresponding trips. Besides, the trips starting off-peak hours are charged the current price.

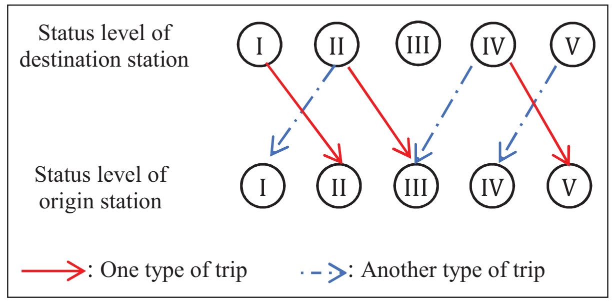

Figure 1 Example of similar trips

Table 1 Trip classification during peak hours

Status of origin station \ Status of destination station	I	II	III	IV	V
I	5	4	3	2	1
II	6	5	4	3	2
III	7	6	5	4	3
IV	8	7	6	5	4
V	9	8	7	6	5

The goal is to determine the trip prices of the nine trip categories to maximize the expected profit of the system for a given planning horizon (one day). The planning horizon is discretized into multiple time periods, say $T = \{1,2,\cdots t,\cdots t_{max}\}$. Considering the time continuity, the starting time point of time period $t+1$ overlaps the ending time point of time period t.

2.2 Assumptions

- Potential commuter and leisure traveler car demand for each O-D station pair in each time period at the current trip price can be acquired based on historical data [13, 14].
- Car Demand varies with trip prices. We separately referred to the linear and nonlinear relationships of trip price and car demand proposed by [10] and [11]. The model is built under the linear relationship. The results under the nonlinear relationship are also presented in Section 4.4.
- In the model of linear relationship, it is assumed that for each category of user, price elasticity is the same in the price variation interval. Although, this may be less realistic for large price variations, a changed price beyond a realistic interval is not expected in the DTP scheme [10].
- The demand losses at each station in each time period

will immediately disappear and will not rolled over to the future periods [11].

- The maintenance activities of the cars, such as cleaning and refueling are not considered during the operation time.

2.3 Parameters

α: car fuel consumption cost per temporal unit
p_0: current trip price per temporal unit
E^m: commuter and leisure traveler price elasticity of demand when $m = 1$ and $m = 2$, respectively
D_{ij}^{tm}: commuter and leisure traveler demand from station i to j at the beginning of time period t when $m = 1$ and $m = 2$, respectively, $\forall t \in T, \forall i \in I, \forall j \in I$
n_i^1: number of cars available at station i at the beginning of the operation, $\forall i \in I$
Δ: temporal duration of a time period
δ_{ij}: traveling time from station i to j, $\forall i \in I, \forall j \in I$
p_l: minimal trip price per temporal unit
p_u: maximal trip price per temporal unit
M: sufficiently big constant

3 MATHEMATICAL FORMULATION AND SOLUTION METHOD

3.1 Variables

p_k: carsharing price per temporal unit of the kth trip, $k \in \{1,2,\cdots,8,9\}$
p_{ij}^t: carsharing price per temporal unit for the trips from station i to j starting in time period t, $\forall t \in T, \forall i \in I, \forall j \in I$
d_{ij}^t: car demand traveling from station i to j starting in time period t, $\forall t \in T, \forall i \in I, \forall j \in I$
s_{ij}^t: car supply traveling from station i to j starting in time period t, $\forall t \in T, \forall i \in I, \forall j \in I$
n_i^t: number of cars available at station i at the beginning of time period t, $\forall t \in T, \forall i \in I$
x_i^t: if the number of cars available at station i at the beginning of time period t is no smaller than the number of cars requested, $x_i^t = 1$. Otherwise, $x_i^t = 0$, $\forall t \in T, \forall i \in I$

3.2 Mathematical formulation

$$\max \sum_{t \in T} \sum_{i \in I} \sum_{j \in I} (p_{ij}^t - \alpha) s_{ij}^t \, \delta_{ij} \tag{1}$$

$$d_{ij}^t = \sum_{m=1}^{2} \max\left\{0, 1 + \frac{E^m \left(p_{ij}^t - p_0\right)}{p_0}\right\} D_{ij}^{tm} \qquad \forall t \in T, \forall i \in I, \forall j \in I \tag{2}$$

$$-x_i^t M + n_i^t \leq \sum_{j \in I} d_{ij}^t \leq (1 - x_i^t) M + n_i^t \qquad \forall t \in T, \forall i \in I \tag{3}$$

$$\frac{d_{ij}^t}{\sum_{j \in I} d_{ij}^t} n_i^t - x_i^t M \leq s_{ij}^t \leq \frac{d_{ij}^t}{\sum_{j \in I} d_{ij}^t} n_i^t + x_i^t M \qquad \forall t \in T, \forall i \in I \tag{4}$$

$$d_{ij}^t - (1 - x_i^t) M \leq s_{ij}^t \leq d_{ij}^t + (1 - x_i^t) M \qquad \forall t \in T, \forall i \in I \tag{5}$$

$$n_i^t = n_i^{t-1} - \sum_{j \in I} s_{ij}^{t-1} + \sum_{\tau=1}^{t-1} \sum_{j \in I: t-1 < \delta_{ij}/\Delta + \tau \leq t} s_{ji}^{\tau} \qquad \forall t \in T \backslash \{1\}, \forall i \in I \tag{6}$$

$$x_i^t \in \{0,1\}, \forall t \in T, \forall i \in I \tag{7}$$

$$s_{ij}^t \geq 0, \forall t \in T, \forall i \in I, \forall j \in I \tag{8}$$

$$p_l \leq p_{ij}^t \leq p_u, \forall t \in T, \forall i \in I, \forall j \in I \tag{9}$$

Objective Function (1) is to maximize the expected profit from rental in the planning horizon under the DTP scheme. Please note that the amortization cost of car depreciation is also a part of the operational expense. As the number of cars is determined, the determinate-const term is excluded from the Objective Function (1).

Constraints (2), which are derived under the assumption of linear price-demand relationship, compute the total car demand of two categories of users for each O-D pair station at each time period.

Constraints (3) judge the values of the binary variable x_i^t for all the combinations of $t \in T$ and $i \in I$. When the number of cars available at station i at the beginning of time period t is no smaller than the number of cars requested, i.e., $n_i^t \geq \sum_{j \in I} d_{ij}^t$, x_i^t is equal to 1. At this time, the right part of the constraint takes effects with the left part being relaxed. Similarly, when the opposite situation is true ($n_i^t < \sum_{j \in I} d_{ij}^t$), x_i^t is equal to 0. Then the left part of the constraint takes effects and the right part is relaxed.

Constraints (4) and (5) jointly determine car allocations. When $x_i^t = 1$, Constraints (5) take effects, then the supply of cars to each station equals the corresponding demand ($s_{ij}^t = d_{ij}^t$). When Constraints (4) take effects ($x_i^t = 0$), cars towards each station are proportionally distributed ($\frac{d_{ij}^t}{\sum_{j \in I} d_{ij}^t} n_i^t$), in accordance with to the number of cars available and car requests to each station.

Constraints (6) ensure the conservations of car flow, updating the number of cars available at each station during the planning horizon except in Time period 1. Constraints (6) indicate that the number of cars available at a certain station at the beginning of time period t ($t > 1$) is dependent on that of in time period $t - 1$ and the numbers of renting and returning cars in $t - 1$. Expressions (7)-(9) set the ranges of the decision variables.

3.3 Particle swarm optimization

The multiplied and divided operators on the decision variables of car supply and trip prices in Objective Function (1) and Constraints (4) leave the model non-linear and non-concave and cannot be linearized, the natures of which make it unsolvable by commercial solvers. We used a particle swarm optimization (PSO) algorithm to get solutions based on the feature that the PSO performs well in continuous optimization problems.

The solutions are coded in real number with each trip price in the range of $[p_l, p_u]$. When the current price vector, the current price adjustment vector and the best price vector of the i th particle are $\boldsymbol{p}_i = (p_{i1}, p_{i2}, \cdots, p_{i8}, p_{i9},)$, $\boldsymbol{v}_i = (v_{i1}, v_{i2}, \cdots, v_{i8}, v_{i9})$, and $\boldsymbol{x}_i = (x_{i1}, x_{i2}, \cdots, x_{i8}, x_{i9})$, respectively and the best price vector for all the particles is $\boldsymbol{p}_g = (p_{g1}, p_{g2}, \cdots p_{g8}, p_{g9})$, the adjustment of the kth trip price for the ith particle can be expressed using the following two equations [15]:

$$v_{ik} = \omega \times v_{ik} + c_1 \times \mathbf{rand}(\,) \times (x_{ik} - p_{ik}) + c_2 \times \mathbf{rand}(\,) \times (p_{gk} - p_{ik})$$

$$p_{ik} = p_{ik} + v_{ik}$$

Where $\mathbf{rand}(\,)$ generates a random number in [0,1], ω is inertia, c_1 cognition acceleration coefficient, and c_2 is social acceleration coefficient.

In our solution method, time-varying inertia weight and acceleration coefficients were applied [15].

$$\omega = (\omega_1 - \omega_2) \times \frac{(n_{ITER} - iter)}{n_{ITER}} + \omega_2$$

$$c_1 = (c_{1f} - c_{1i}) \times \frac{(n_{ITER} - iter)}{n_{ITER}} + c_{1f}$$

$$c_2 = (c_{2f} - c_{2i}) \times \frac{(n_{ITER} - iter)}{n_{ITER}} + c_{2f}$$

where ω_1 and ω_2 are the initial and final values of the inertia weight, respectively, $iter$ is the current iteration number; c_{1i} and c_{1f} are the initial and final value of the cognition acceleration coefficient, respectively; c_{2i} and c_{2f} are the initial and finial value of the social acceleration coefficient, respectively.

4 VALIDATION AND EVALUATION

4.1 Setting of experiments and instances

The experiments were carried out based on randomly generated instances. All the instances were executed on a personal computer equipped with Intel (R) Core (TM) i5-7300HQ CPU @2.50GHz and @2.50GHz and 15.7GB of RAM. The solution method was programmed in Visual Studio C++. The initial values and final values of the inertia weight and acceleration coefficients are set by recommendations [15]. The number of particles and iterations are 30 and 80, respectively, which were shown to be enough to obtain better objective values and make the algorithm converge in the exploratory experiments. For each instance, the solution method was independently implemented five times. The variance of the objective values from five runs does not exceed 1 and the computation time for each run is around 40s.

The service area is assumed to be a 40-kilometer-length and 25-kilometer-width rectangle. The planning horizon is from 6:00 am to 10:00 pm with 30 minutes a period. The morning and evening peak hours range from 6:00 am to 9:00 am and from 5:00 pm to 8:00 pm. 60 stations are randomly scattered in the service areas. Stations with the abscissa in the ranges of [0, 4) km and [36, 40] km belong to morning I stations; stations with the abscissa in the ranges of [4, 8) km and [32, 36) are morning (II) stations; stations with the abscissa in the ranges of [8, 12) km and [28, 32) fall into morning (III) stations, stations with the abscissa in the ranges of [12, 16) km and [24, 28) morning (IV) stations and the other stations are morning (V) stations.

The car adequacy or inadequacy condition is opposite during evening peak hours for each station. The station-type division is based on the fact that many users commute to the city center in the morning and drive back to the outer districts in the afternoon. The number of cars is set to 1980 and the cars are distributed across the stations evenly at the beginning of the planning horizon. We assumed the traveling times do not change along the planning horizon and that all one-way users travel directly to their destination stations [10,11]. All the two-way trips are assumed to be 1 hour. The speed of traveling is 15km/h.

D_{ij}^{t1} is assumed a random real number in the interval $[L_{ij}, U_{ij}]$ at p_0, which is characterized by the origin-destination stations and the starting times [11]. The intervals of $[L_{ij}, U_{ij}]$ for different O-D station pairs during peak hours are presented in Table 2. $[L_{ij}, U_{ij}]$ is set to $[0.0, 0.2]$ during off-peak hours for all O-D station pairs. Commuter demand for two-way trips and more than 1.5 hours' duration trips are set as 0 to filter trips with rare probability. The leisure traveler demand is assumed to be a uniformly random real number in the interval $[0.0, 0.3]$ at p_0 for all O-D station pairs at any time period.

The cost related coefficients are set based on an investigation activity in 2018. The values are: α =0.5Yuan/min, p_0 =0.7 Yuan /min, p_l =0.5 Yuan /min, p_u =1.4 Yuan/min (when all the potential demand being 0). The values of E^1 and E^2 in the base scenarios are -1.3 and -1.8, respectively, which are close to the price elasticities used by [10].

Table 2 Intervals of $[L_{ij}, U_{ij}]$ for commuters during peak hours

State of origin station \ State of destination station	I	II	III	IV	V
I	$[0.0, 0.2]$	$[0.3, 0.5]$	$[0.5, 0.7]$	$[0.7, 0.9]$	$[0.9, 1.1]$
II	$[0.0, 0.2]$	$[0.0, 0.2]$	$[0.3, 0.5]$	$[0.5, 0.7]$	$[0.7, 0.9]$
III	$[0.0, 0.2]$	$[0.0, 0.2]$	$[0.0, 0.2]$	$[0.3, 0.5]$	$[0.5, 0.7]$
IV	$[0.0, 0.2]$	$[0.0, 0.2]$	$[0.0, 0.2]$	$[0.0, 0.2]$	$[0.3, 0.5]$
V	$[0.0, 0.2]$	$[0.0, 0.2]$	$[0.0, 0.2]$	$[0.0, 0.2]$	$[0.0, 0.2]$

4.2 Analysis on the DTP scheme

When car distribution imbalances occur, higher resource usage rates and system returns cannot be guaranteed; users' demand cannot be well satisfied as well, resulting in lower user satisfaction. As a result, besides daily profit, car usage ratio (CUR) and two service-oriented indicators: the number of served users (SU) and demand acceptance ratio (DAR), are measured.

Five instances (I1-I5) were generated. The results under the fixed trip pricing (FTP) scheme and the DTP scheme are shown in Table 3. As is shown in Table 3, averagely, 30.45% profit and 0.92% CUR increments are achieved by the DTP scheme. More ideal demand patterns and the consequent car supply contribute to the increased CUR, which can be concluded from the optimized trip prices. Take the solutions of I1 and I2 for demonstration. The trip prices per time unit usage are

$$(1.064_1, 1.052_2, 0.983_3, 0.914_4, 0.843_5, 0.806_6, 0.763_7, 0.719_8，0.709_9)$$

and

$$(1.071_1, 1.059_2, 0.997_3, 0.913_4, 0.840_5, 0.806_6, 0.759_7, 0.723_8, 0.725_9)$$

respectively. Differentiated trip prices are obtained in the DTP scheme. As expected, trips from car inadequate stations to car adequate stations are charged much higher and trips with the opposite direction are charged relatively less under the DTP scheme. The increased profit is due to higher trip prices and more served users.

Table 3 Comparison results under the FTP scheme and DTP scheme

Instance	FTP scheme				DTP scheme				Improvements			
	Profit (Yuan)	CUR (%)	SU (no.)	DAR (%)	Profit (Yuan)	CUR (%)	SU (no.)	DAR (%)	Profit (%)	CUR (%)	SU (%)	DAR (%)
I1	306156	80.53	22963.5	68.38	401086	82.07	23494.9	88.84	31.00	1.90	2.31	29.92
I2	308606	81.18	22492.5	68.00	405852	82.79	22983.3	88.13	31.51	1.98	2.18	29.60
I3	310154	81.59	23198.5	67.92	402319	81.75	23307.1	87.46	29.72	0.20	0.47	28.76
I4	306184	80.54	24452.0	69.52	395102	80.40	24489.4	89.59	29.04	-0.17	0.15	28.87
I5	305229	80.29	24013.1	68.00	399805	80.83	24222.8	88.77	30.98	0.68	0.87	30.59
Average									30.45	0.92	1.20	29.55

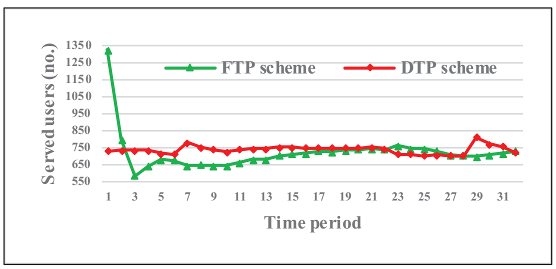

Figure 2 Numbers of served users of I1

In the aspect of service-oriented performances, averagely, the SU arises 1.20% and the ADAR increases 29.55%. To further illustrate the superiority of the DTP scheme on improving service level, the numbers of served users in each period of I1 are presented in Figure 2. As shown in Figure 2, the number of served users remains steady throughout the planning horizon in the DTP scheme. The DTP scheme can serve more users than the FTP scheme in most of the time periods, which can be seen from Table 3. Please note that the FTP scheme makes more users served in Time Periods 1 and 23 that are the beginnings of the morning and evening peak hours, respectively. The reason could be that the expected historical car demand aggravating car imbalances in the two periods is slightly underestimated.

4.3 The effects of price elasticities of demand

Two instances (I2 and I3) are selected for sensitivity analysis of the price elasticities E^1 and E^2 (see Table 4 and Table 5). Table 4 and Table 5 show that with the increment of the demand elasticities, the profit decreases, CUR and SU slightly increase and DAR has no obvious changes. The results demonstrate the dependence of carsharing systems profitability on the demand elasticities and that the significance to incorporate demand elasticities into the decision-making processes of carsharing operators. The opposite varied directions of the profit and the CUR indicate that more symmetrical demand can be reached with increased price sensitivities, whereas the added revenue from trips alleviating car imbalances cannot compensate the minus revenue from trips aggravating car imbalances.

Table 4 Improvements under different price elasticities for I2

Improvements / Price elasticities	Profit (%)	CUR (%)	SU (%)	DAR (%)
$E^1 = -1.1,\ E^2 = -1.6$	35.83	1.36	1.66	29.61
$E^1 = -1.2,\ E^2 = -1.7$	33.51	1.72	1.96	29.57
$E^1 = -1.3,\ E^2 = -1.8$	31.51	1.98	2.18	29.60
$E^1 = -1.4,\ E^2 = -1.9$	29.76	2.16	2.32	29.59
$E^1 = -1.5,\ E^2 = -2.0$	28.22	2.34	2.48	29.61

Table 5 Improvements under different price elasticities for I3

Improvements / Price elasticities	Profit (%)	CUR (%)	SU (%)	DAR (%)
$E^1 = -1.1,\ E^2 = -1.6$	34.01	-0.05	-0.11	28.65
$E^1 = -1.2,\ E^2 = -1.7$	31.71	-0.12	0.18	28.71
$E^1 = -1.3,\ E^2 = -1.8$	29.72	0.20	0.47	28.76
$E^1 = -1.4,\ E^2 = -1.9$	27.98	0.39	0.62	28.81
$E^1 = -1.5,\ E^2 = -2.0$	26.45	0.62	0.82	28.90

4.4 The effects of types of price-demand relationship

Based on the instances I1-I5, we used the exponential price-demand function proposed by [11] to assess the effectiveness of the DTP scheme. The exponential price multipliers θ_1 for commuters ranged from -2.0 to -3.0, and θ_2 for leisure travelers varied between -4.0 and -5.0, with a decrement of 0.5. The improvements are presented in Table 6. Form Table 6, similar conclusions as the ones in Sections 4.3 and 4.4 can be obtained, which signals the applicability of the TDP scheme for different user response to trip price variations.

Table 6 Improvements under exponential price-demand relationship

Instance	$\theta_1 = -2.0,\ \theta_2 = -4.0$				$\theta_1 = -2.5,\ \theta_2 = -4.5$				$\theta_1 = -3.0,\ \theta_2 = -5.0$			
	Profit (%)	CUR (%)	SU (%)	DAR (%)	Profit (%)	CUR (%)	SU (%)	DAR (%)	Profit (%)	CUR (%)	SU (%)	DAR (%)
I1	35.52	0.85	1.29	30.71	30.14	2.08	2.45	30.56	26.43	2.76	3.05	30.47
I2	35.74	1.03	1.35	30.31	30.32	2.03	2.26	30.11	26.54	2.50	2.66	30.02
I3	35.57	-0.47	-0.23	29.99	29.83	0.32	0.49	29.96	25.84	0.98	1.10	29.91
I4	35.92	-0.86	-0.52	30.03	29.94	0.05	0.34	29.96	25.81	0.73	1.01	29.88
I5	38.29	0.07	0.21	31.76	32.02	0.98	1.04	31.65	27.72	1.73	1.74	31.58
Average	36.21	0.12	0.42	30.56	30.45	1.09	1.32	30.45	26.47	1.74	1.91	30.37

5 CONCLUSIONS AND FURTHER RESEARCH

This research investigates a DTP problem for one-way station-based carsharing systems. A non-linear programming model is built to formulate the problem and a PSO is used to solve the model. The proposed methods are validated and evaluated based on a serious of instances.

Results demonstrate that the DTP scheme can help enhance system profit and service level by adjusting potential car demand patterns. What's more, the TDP scheme can be applied to different carsharing systems with different user-response types for trip-price variations.

Primary limitations are as follows. Firstly, the trip classification is relatively coarse, which leads to our plan on more accurate trip classification in further research. Secondly, we relaxed the limitation of inadequate parking spaces in each station, reckoning that when a car arrives at any station, there is always a parking space to occupy it.

The research could be extended in several aspects. Firstly, trip prices can be subdivided into several categories subtly in different time periods, and real-time trip prices can be set up based on current system states and unforthcoming car demand. Secondly, for that unmet demand, what influences it will generate on users' carsharing usage utilities and further potential demand?

REFERENCES

[1] X. Li, J. Ma, J. Cui, A. Ghiasi, F. Zhou, Design framework of large-scale one-way electric vehicle sharing systems: A continuum approximation model. Transportation Research Part B: Methodological, Vol. 88, 21-45, 2016.

[2] D. Jorge, G. H. de Almeida Correia, Carsharing systems demand estimation and defined operations: A literature review. European Journal of Transport & Infrastructure Research, Vol. 13, No. 3, 201-220, 2013.

[3] R. Nair, E. Miller-Hooks, Fleet management for vehicle sharing operations. Transportation Science, Vol. 45, No. 4, 524-540, 2011.

[4] B. Boyaci, K. G. Zografos, N. Geroliminis, An optimization framework for the development of efficient one-way car-sharing systems. European Journal of Operational Research, Vol. 240, No. 3, 718-733, 2015.

[5] M. Nourinejad, S. Zhu, S. Bahrami, M. J. Roorda, Vehicle relocation and staff rebalancing in one-way carsharing systems. Transportation Research Part E: Logistics and Transportation Review, Vol. 81, 98-113, 2015.

[6] M. Zhao, X. Li, J. Yin, J. Cui, L. Yang, S. An, An integrated framework for electric vehicle rebalancing and staff relocation in one-way carsharing systems: Model formulation and Lagrangian relaxation-based solution approach. Transportation Research Part B: Methodological, Vol. 117, 542-572, 2018.

[7] G. H. de Almeida Correia, D. R. Jorge, D. M. Antunes, The added value of accounting for users' flexibility and information on the potential of a station-based one-way car-sharing system: An application in Lisbon, Portugal. Journal of Intelligent Transportation Systems, Vol. 18, No. 3, 299-308, 2014.

[8] H. R. Sayarshad, J. Y. J. Chow, Non-myopic relocation of idle mobility-on-demand vehicles as a dynamic location-allocation-queueing problem. Transportation Research Part E: Logistics and Transportation Review, Vol. 106, 60-77, 2017.

[9] P. Ströhle, C. M. Flath, J. Gärttner, Leveraging customer flexibility for car-sharing fleet optimization. Transportation Science, Vol. 53, No. 1, 42-61, 2019.

[10] D. Jorge, G. Molnar, G. H. de Almeida Correia, Trip pricing of one-way station-based carsharing networks with zone and time of day price variations. Transportation Research Part B: Methodological, Vol. 81, 461-482, 2015.

[11] M. Xu, Q. Meng, Z. Liu, Electric vehicle fleet size and trip pricing for one-way carsharing services considering vehicle relocation and personnel assignment. Transportation Research Part B: Methodological, Vol. 111, 60-82, 2018.

[12] S. Ren, F. Luo, L. Lin, S.-C. Hsu, X. I. Li, A novel dynamic pricing scheme for a large-scale electric vehicle sharing network considering vehicle relocation and vehicle-grid-integration. International Journal of Production Economics, Vol. 218, 339-351, 2019.

[13] L. Li, M. Shan, Bidirectional incentive model for bicycle redistribution of a bicycle sharing system during rush hour. Sustainability, Vol. 8, No. 12, 1299-1313, 2016.

[14] L. Wang, Q. Liu, W. Ma, Optimization of dynamic relocation operations for one-way electric carsharing systems. Transportation Research Part C: Emerging Technologies, Vol. 101, 55-69, 2019.

[15] A. Ratnaweera, S. K. Halgamuge, H. C. Watson, Self-organizing hierarchical particle swarm optimizer with time-varying acceleration coefficients. IEEE Transactions on Evolutionary Computation, Vol. 8, No. 3, 240-255, 200