Optimization-based analysis of last-mile one-way
mobility sharing

by

Masaki YAMADA, Masashi KIMURA, Naoki TAKAHASHI, and Akiko YO SHISE

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UNIVERSITY OF TSUKUBA
Tsukuba, Ibaraki 305-8573
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Masaki YAMADA, Masashi KIMURA, Naoki TAKAHASHI, and Akiko YOSHISE

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Abstract
One-way carsharing is becoming increasingly popular because it is more convenient for users than conventional round-trip carsharing. However, a one-way service suffers from a mismatch between user demand and the distribution of vehicles (supply). A number of methods have been studied in attempts to resolve this issue. In particular, “last-mile mobility”, a type of one-way carsharing providing short trips between stations at public transport hubs and origins/destinations in local areas, reserves destination parking spaces in addition to vehicles at origins, and it needs to control both resources carefully.

Here, we develop a mixed integer linear programming (MILP) model of an existing short-trip last-mile mobility service (Ha:mo RIDE) in Japan and optimize the vehicle distribution and relocations to maximize the operator’s profit. The optimal solution indicates that the operator should reduce relocations disproportionately because of the low revenue per short trip. However, a low satisfied demand rate would result in customer defection and lead to a long-term loss. As a solution, we propose autonomous relocation by low-speed automated driving and show that slow but frequent relocations would yield both a benefit to the user (high satisfied demand) and profit for the operator as well as a virtual increase in parking capacity for last-mile-mobility operations with many small stations.

Keyword: one-way carsharing; last-mile mobility; Ha:mo; autonomous vehicle relocation; Mobility as a Service; MaaS; optimization-based analysis; mixed integer linear programming

1 Introduction

The Japanese government is promoting “Society 5.0”, a “super smart” society as a successor to hunter-gatherer, agricultural, industrial, and information societies that came before it. Society 5.0 is described in the 5th Science and Technology Basic Plan; one of its pillars is MaaS, mobility as a service, including carsharing and ridesharing.
Carsharing has become a popular means of transportation in the 21st century. For instance, Zipcar, founded in 2000 in the US, has expanded to Canada and Europe: it provided services to more than 1 million members in 2017. Members can find and reserve vehicles with a smartphone app and get access to vehicles simply by using their member’s cards as entry badges. In 2007, car2go started as a free-floating one-way carsharing experiment in Ulm, Germany, and it is now the world’s largest carsharing company with operations all over the globe. Car2go has a convenient one-way service which allows users to return vehicles anywhere within the service area, while a round-trip service requires vehicles to be returned to their original points. Autolib', initiated in Paris in 2011, is a one-way carsharing scheme that provides electric vehicles (EVs). Autolib' is a non-floating (station-base) system and EVs have to be returned to Autolib' stations to be recharged.

Station-base one-way carsharing using ultra-compact EVs started in Japan in 2012. Yokohama city and Nissan launched “Choimobi Yokohama”, a two-person EV sharing service, whose main objectives are to encourage low-carbon emission transport and promote tourism. One-way service was available for the first two years, and round-trip service is currently available. In the same year, Toyota launched “Ha:mo RIDE”[36], a new type of mobility service for last-mile transport. Providing one-way sharing service with ultra-compact EVs such as i-ROAD[37] and COMS[10], Ha:mo is intended to be a stress-free and eco-friendly “Harmonious Mobility Network” that utilizes both personal and public transport. Since its launch in Toyota city, Ha:mo RIDE has expanded to Tokyo, Okinawa, and Okayama in Japan, Grenoble in France, and Chulalongkorn University in Thailand.

One-way carsharing provides more flexibility for users, but has an issue of imbalanced user demand and vehicle supply. To increase satisfied demand, many carsharing operators hire personnel to relocate vehicles from lower demand areas to higher demand areas in a time-dependent manner, but the labor cost of the relocation staff puts pressure on their profitability. Another approach to ease the imbalance is adaptive pricing, which controls user demand by placing premiums on trips from high-demand areas (or giving discounts for trips to high-demand areas). There are several studies on adaptive pricing for on-demand mobility, such as that of Drwal, Gerding, Stein, Hayakawa, and Kitaoka[16]. Ridesharing services such as Uber and Lyft use dynamic pricing to control both demand and supply[32]. To increase both the number of demands served and revenue, companies have placed premiums on attracting drivers (increasing supply) as well as discouraging potential users (decreasing demand). By allying with car makers, ridesharing companies are developing self-driving vehicles[38] to maximize vehicle utilization.

In this paper, we focus on last-mile mobility, one-way carsharing designated for short trips within a city, and develop an optimization model for making optimal operation decisions. The next section 2 reviews previous research related to one-way carsharing optimization. Section 3 explains the characteristics of last-mile mobility and develops an optimization model for Ha:mo RIDE. Section 4 describes our application and the developed model for Ha:mo RIDE in Toyota city (Ha:mo RIDE Toyota), and it compares the optimal solution with the actual operation. It also describes several case studies involving modifications to the model: (1) a “premium service” guaranteeing reservations in return for price premiums and (2) autonomous relocation by slow-speed automated self-driving. The last section 5 provides conclusions and ideas for future research.

2 Recent research on optimization-based analysis of carsharing

There is a growing body of research on optimization-based analysis of carsharing and other kinds of mobility sharing. Jorge and Correia[25] reviewed the history of carsharing, from its beginnings as a cooperative initiative to recent one-way services and related research. Boyaci, Zografos, and Gerolimi-
nis classified models related to planning and operation of carsharing systems into two categories: (i) models addressing strategic planning decisions and (ii) models supporting operational decisions. In order to maximize performance metrics such as the number of uses, strategic planning decides the locations and sizes of stations and the number of vehicles assigned to each station, while operational decisions relocate the vehicles among the stations.

Correia and Antunes presented an optimization approach for determining the locations of stations to maximize the profit of the one-way carsharing operator. The approach included determining locations that would maximize revenues from users and reduce the costs of maintaining vehicles, parking spaces, and relocating vehicles. The interest of the study was strategic decision making, and neither detailed relocation operations nor constraints on the maximum parking space per station or total number of vehicles were considered. Later, Jorge and Correia incorporated a relocation operation into their optimization models for maximizing profit and examined relocation policies in simulations. They found that a dynamic (frequent) relocation policy significantly improved profitability.

Correia, Jorge, and Antunes introduced a notion of user flexibility by offering a choice of disembarking at the second- or third-closest stations. When exploited in combination with real-time information about vehicle availability, such user flexibility increases the number of demands served and raises the operator’s profit. Although this notion reflects the situation of actual carsharing services that provide information on nearby vehicles, an actual user’s willingness to use alternative stations can only be supposed until he or she states it.

Kek, Cheu, Meng, and Fung proposed a three-phase optimization-trend-simulation (OTS) decision support system for dealing with the staff-based vehicle relocation problem. Phase one of the OTS the Optimizer returns the lowest-cost resource allocation, phase two the Trend Filter filters the output through a series of heuristics, and phase three the Simulator evaluates the performance of the result. In the optimization, the problem is modeled as a mixed integer linear programming (MILP) on a time-space network in which nodes represent staff behaviors. It was found that an increase in variables such as the number of stations and time steps increased the computational complexity of the model, and no effective solution was presented in their paper.

Boyaci, Zografos, and Geroliminis proposed an integrated multi-objective mixed integer linear programming (MMILP) optimization and discrete event simulation framework for vehicle and personnel relocation in a one-way carsharing system with reservations. By clustering stations, the number of variables is reduced and the computational complexity of the optimization decreases as result. The optimization model was developed on a time-augmented network, using time intervals (15 minutes) during which each vehicle and each staff member had only one status. This network contributes to a clear formulation including the flow conservations of the vehicles and relocation staff. Our optimization modeling for last-mile mobility in section uses the same network structure.

He, Mak, Rong, and Shen provided a robust optimization problem for designing a geographical service region in which to operate the service based on the second-order cone optimization model presented in Ghaoui, Oks, and Oustry and usage data of the car sharing service car 2go.

Wang considered a last-mile transportation system which supports movement from the nearest public transportation system (train, bus, etc.) to home or another destination. The author formulated an MILP model for finding optimal routes and operation schedules to minimize the user’s waiting and boarding times.

Braverman, Dai, Liu, and Ying performed optimization to make empty-car relocation schedules by using the usage data of a ride-sharing service in China. Their optimization model includes a ride-sharing network and Markov chain analysis of space-time networks.
Linag, Correia, Arem [29] considered last-mile self-driving taxi services and proposed two MILP models for examining the quality of services expected to be implemented in the future: a model that maximizes profit by determining the acceptable trip demand and a more restrictive model with the constraint that the demand for a specified zone must be satisfied.

Several other recent studies were conducted on robust optimization analysis of car sharing service (Naoum-Sawaya et al. [30], Brandstatter, Kahr, and Leitner [5], Deng, Cardin [14], Erera, Morales, and Savelbergh [17], etc.), on ride-sharing service (Agatz et al. [1], Stiglic et al. [35], Xu, Yin, and Zha [43], Dong et al. [15], etc.), on bicycle-sharing service (Chardon, Caruso [7], Forma, Raviv, and Tzur [20], Celebi, Yorusun, and Isik [6], Wang et al. [41], etc.), on autonomous car-sharing service Fagnant, Kockelman, and Bansal [18], Chen, Kockelman, and Hanna [8], Hanna et al. [23], Farhan, and Chen [19], etc.), and on pricing of car-sharing service (Jorge, Molnar, and Correia [26], Schwieterman, Bieszczat [33], Chen, Wang [9], Xu, Meng, and Liu [42], etc.).

As shown above, there has been substantial research pursuing optimal vehicle distributions and relocation operations for one-way carsharing. However, the developed models are inappropriate for last-mile mobility because of the characteristics described in section 3.1.

### 3 Framework and modeling

#### 3.1 Last-mile mobility sharing

Last-mile mobility sharing has different aspects from the usual one-way carsharing. Here, taking Ha:mo RIDE as an example, we describe the characteristics of last-mile mobility. To be used as last-mile transport, vehicles are parked at stations close to public transport stations, bus stops, and other points of interest such as shopping malls, office, and homes (Fig. 1). Users of last-mile mobility typically travel from the origin to the destination without taking any detours, as in the case of other kinds of last-mile transportation such as bus or taxi. Round-trips account for only a few rides, and most last-mile one-way trips end in a shorter time than other kinds of one-way carsharing. The actual data on use of Ha:mo RIDE Toyota clearly reflects these features.

![Fig. 1: Last-mile mobility network - Ha:mo RIDE](image)
A characteristic of last-mile mobility is that users reserve parking spaces at destinations as well as vehicles at origins. Assigning parking spaces before departure allows users to end their trips on arrival, just as other last-mile transports, such as bus and taxi, do. This feature is necessary for last-mile mobility: while it is frustrating if it takes 10 minutes to find a parking space after driving for 1 hour, it is nearly intolerable if it takes 10 minutes to park after driving for only 10 minutes. On the other hand, users cannot make reservations if they cannot find available parking spaces at the destinations, even if they find vehicles at the origin station (Fig. 2). In last-mile mobility with parking assignments, both vehicles and parking spaces need to be managed more carefully than in carsharing without parking assignments in order to meet demand.

![Fig. 2: No parking, no reservation. Users reserve parking spaces as well as vehicles. Users don’t need to look for available parking spaces when they arrive, but parking spaces have to be available when they make reservations.](image)

Ha:mo RIDE is operated by local operators in each area under common service procedure, as follows. First, users reserve vehicles with smartphone apps or through a web page by registering both origin and destination stations. If there is no “free” (available) vehicle at the origin or no “free” parking space at the destination, the applications fail (vanish). Once made, reservations are valid for 20 to 30 minutes depending on each service, and both vehicles and parking spaces become “assigned”, i.e., not available to other users. When a registered user departs from an origin station, a parking space becomes “free”, i.e., available to other users and vehicles. When the user arrives at the destination station, the driven vehicle becomes “free” again. Fig. 3 shows this process together with the changes in state of the resources.

![Fig. 3: Service procedure and changes in resource status. Note that optimization modeling assumes that users depart the origin station immediately after making a reservation; i.e., the resource state transitions reflecting reservation and departure occur at the same time.](image)
To avoid imbalances between supply and demand and at the same time increase the number of uses, operators set vehicle distribution targets (relocation thresholds at each station) based on use-history analyses and experience. In practice though, actual operations depend on the on-site relocation staff. Despite the operators’ efforts and costs, there still remains customer dissatisfaction due to imbalances, which means lost business and if, not corrected, long-term reductions in the number of customers. In the next section [3.2] we develop a mixed integer linear programming (MILP) model that optimizes the vehicle distribution and relocations to maximize the operator’s profit.

3.2 Optimization modeling

Our optimization model is based on the idea described in Boyaci et al. [4], but it is more restrictive than theirs [4]. In particular, it puts specific assumptions on last-mile mobility sharing, as follows.

1. Last-mile mobility is modeled on a time-augmented network, which consists of stations and time intervals. Note that each time interval is 5 minutes, shorter than in previous research (e.g., 15 minutes), because last-mile mobility is used for relatively short trips.
2. The demand for the whole day is given at once, though actual reservations are made 30 minutes before rides. There is no time gap between reservation and departure, and there are no cancellations.
3. For a trip to occur, there have to be vehicles at the origin and parking spaces at the destination at the time of departure.
4. Travel time is the trip duration plus a constant period, assuming one-way short trips without making any detours. The constant period is thus a margin for departure and arrival that includes the time spent getting into and out of the vehicle and getting the vehicle ready to move. The travel time of moving staff and relocating vehicles is calculated in the same way.
5. The trip duration is expressed in terms of parameters depending on the traffic conditions as well as the distance between stations. Travel times between the same stations at different times of the day can be different.
6. Every trip or relocation takes at least 1 time interval.
7. Each node of the network is represented as (j, t), where j identifies the station and t the time interval, is a state including the number of parked vehicles, number of assigned parking spaces, and number of relocation staff.
8. In each time interval, each vehicle can have only one status: “free” or “assigned”. “Assigned” includes rides of users and relocation of staff.
9. In each time interval, each parking space can have only one status: “free” (available) or “assigned” or “parked” (both unavailable).
10. In each time interval, each relocation staff can have only one status: “idle”, “moving”, or “relocating”.
11. Relocation staff work for one shift, and each shift has a beginning time and a finishing time. The manager must work a specific shift (the shift in dark green in Fig. 4), while other staff work when relocation becomes necessary.

![Fig. 4: Staff shift](image)

12. The relocation staff move on a staff vehicle as a team (a two-man team), and they relocate vehicles
by one driving the vehicle that was used and the other driving the staff vehicle (Fig. 5). Previous research did not clearly define how the staff moves or otherwise assumed they did so by bicycle over a long distance. Instead, we followed the actual operation procedure of Ha:mo RIDE Toyota*1. In this setting, there is only one staff vehicle, but in section 4.4 we discuss a model with more staff vehicles and the effect of increasing the number of vehicles.

Fig. 5: Moving and relocating using staff vehicle

13. The state of charge (SOC) of the vehicle’s battery is not considered. Last-mile mobility is mostly intended for one-way short trips, and electricity consumption is low enough for the battery to be recharged in the time between one trip and the next. In the Ha:mo RIDE Toyota case study, we ran simulations on a simulator (updated by Shimazaki, Kuwahara, Yoshioka, Homma, Yamada, and Matsui [34]) and found that no vehicles became unavailable because of a low SOC.

14. The number of vehicles and the number, capacity (number of parking spaces), and locations of stations are given as parameters.

Assumptions 2, 3, 4, 5, 9, 12, 13, 14 are different from previous research.

Fig. 6 shows the time-augmented network and arcs representing trips and relocations.

Fig. 6: Time-augmented network and arcs representing vehicle movements

- The arcs represent movements of vehicles between nodes. There are four vehicle movements, three for trips and one for relocation: three vehicles driven by users from node (2, 2) to (j, t) (from station 2 at time interval 2 to station j at time interval t), from (2, t - 1) to (1, t + 1), from (j, t + 1) to (1, t + 2), and one vehicle driven by relocation staff from (1, t + 2) to (2, t + 3).
- Because each vehicle can have only one status during each time interval, a vehicle starting at station j in time interval t must be ready by the end of the previous time interval t – 1. Moreover,
a vehicle arriving at station \( j \) in time interval \( t \) must be ready starting from the next time interval \( t + 1 \). The same is true for parking spaces and relocation staff.

- Parking spaces must be assigned to each trip from the beginning of the trip. For example, for a trip from \((2, 2)\) to \((j, t)\), a parking space at station \( j \) must be assigned from the beginning of time interval \( 2 \). The reservation of parking spaces at destinations is important for actual smooth Ha:mo RIDE Toyota operation. However, it may place severe constraints on the optimization settings. In section 4.5, we consider a case in which there is no parking space reservation constraint and discuss its effect.

- Relocation staff are needed to relocate vehicles. During the relocation from \((1, t + 2)\) to \((2, t + 3)\), the relocation staff move just the same as the vehicle.

- Besides using the staff vehicle for relocation, staff also use it to move between stations, as described in section 3.2. The operation is limited to serial relocation from a station where the staff start working when only one member is working. For example, after relocation to \((2, t + 3)\), the staff cannot move from station \( 2 \) without the staff vehicle.

For moving staff and relocating vehicles, stations are clustered in order to decrease the number of variables and reduce computational complexity. Fig. 7 shows the moving and relocating arcs on the time-augmented network with clusters of stations.

- The moving and relocating operations are divided into three parts. Taking relocation from node \((j, t)\) to \((l, t + 2)\) as an example, part (i) is from origin station \( j \) to the origin station’s cluster \( b \) in time interval \( t \), part (ii) is from cluster \( b \) at time interval \( t \) to the destination station’s cluster \( d \) in time interval \( t + 2 \), while part (iii) is from cluster \( d \) to destination station \( l \) in time interval \( t + 2 \).

- Stations are clustered by using an algorithm based on the one in Boyaci et al. [1]. The station clustering algorithm is described in section 3.3.

3.2.1 Sets and indices

- \( i \in I \): trips
- \( j, l \in J \): stations
- \( t \in T \): time interval
- \( s \in S \): relocation staff shift
- \( b, d \in B \): station clusters
- \( J_b \): set of stations in cluster \( b \), i.e. \( J = \bigcup_{b \in B} J_b \)
3.2.2 Parameters

- begin<sub>s</sub>, fin<sub>s</sub> ∈ T: beginning and finishing time intervals of shift s
- start<sub>i</sub>, end<sub>i</sub> ∈ T: start and end time intervals of trip i
- origin<sub>i</sub>, dest<sub>i</sub> ∈ J: origin and destination stations of trip i
- travel<sub>b,d</sub> ∈ N: travel time starting at time interval t from cluster b to cluster d
- t.end<sub>b,d</sub> ∈ T: set of departing time intervals of driving or relocating from cluster b to cluster d arriving during time interval t
- P<sub>i</sub>: price for trip i
- PC<sub><i,j</sub>: personnel cost of relocation staff for shift s
- RC<sub>b,d</sub>: relocating cost from cluster b to cluster d (fuel cost)
- MC<sub>b,d</sub>: moving cost from cluster b to cluster d (fuel cost of staff vehicle)
- Lcost: maximum acceptable labor cost per day in the service
- cap<sub>j</sub>: maximum number of vehicles available in the service
- cap<sub>j</sub>: number of parking spaces (capacity) at station j
- NW: total number of relocation staff able to work in the service

3.2.3 Variables

The decision variables are as follows.

- z<sub>i</sub> ∈ {0, 1}, ∀i ∈ I: binary variables, if trip i is served 1, otherwise 0.
- v<sub>s</sub> ∈ Z<sup>+</sup>, ∀s ∈ S: number of staff in shift s.
- n<sub>j,t</sub> ∈ Z<sup>+</sup>, ∀j ∈ J, t ∈ T: number of vehicles at station j at the beginning of time interval t.
- * n<sub>j,t</sub> ∈ Z<sup>+</sup>, ∀j ∈ J, t ∈ T: number of parking spaces at station j at the beginning of time interval t that are assigned to vehicles coming to the stations.
- m<sub><i,s</sub> ∈ Z<sup>+</sup>, ∀s ∈ S, j ∈ J, t ∈ {begin<sub>s</sub>, ..., fin<sub>s</sub>}: number of staff in shift s at station j at the beginning of time interval t.
- r<sub><i,s</sub> ∈ Z<sup>+</sup>, ∀s ∈ S, j ∈ J, t ∈ {begin<sub>s</sub>, ..., fin<sub>s</sub>}: number of staff of shift s relocating vehicle(s) from station j during time interval t.
- r<sub><i,s</sub> ∈ Z<sup>+</sup>, ∀s ∈ S, j ∈ J, t ∈ {begin<sub>s</sub>, ..., fin<sub>s</sub>}: number of staff of shift s relocating vehicle(s) to station j during time interval t.
- p<sub><i,s</sub> ∈ Z<sup>+</sup>, ∀s ∈ S, j ∈ J, t ∈ {begin<sub>s</sub>, ..., fin<sub>s</sub>}: number of staff of shift s moving from station j during time interval t.
- p<sub><i,s</sub> ∈ Z<sup>+</sup>, ∀s ∈ S, j ∈ J, t ∈ {begin<sub>s</sub>, ..., fin<sub>s</sub>}: number of staff of shift s moving to station j during time interval t.
- r<sub>s,b,d</sub> ∈ Z<sup>+</sup>, ∀s ∈ S, b, d ∈ B, t ∈ {begin<sub>s</sub>, ..., fin<sub>s</sub>}: number of staff of shift s relocating vehicle(s) from cluster b to cluster d during time interval t.
- p<sub>s,b,d</sub> ∈ Z<sup>+</sup>, ∀s ∈ S, b, d ∈ B, t ∈ {begin<sub>s</sub>, ..., fin<sub>s</sub>}: number of staff in shift s moving from cluster b to cluster d during time interval t.
- l<sub>j,t</sub> ∈ {0, 1}, ∀j ∈ J, t ∈ T: binary variables, 1 if relocation staff vehicle exists at station j during time interval t, 0 otherwise.
- u<sub>j,t</sub> ∈ {0, 1}, ∀j ∈ J, t ∈ T: binary variables, 1 if relocation staff vehicle moves out from station j during time interval t, 0 otherwise.
- u<sub>j,t</sub> ∈ {0, 1}, ∀j ∈ J, t ∈ T: binary variables, 1 if relocation staff vehicle moves to station j during

*2 Travel time depends not only on OD (origin b and destination d) but also on time of departure t. For example, suppose that each time interval duration is 1, travel<sub>b,d</sub> = 4 and travel<sub>b,d</sub> = 3; then t.end<sub>b,d</sub> is {1, 2}.
time interval $t$, 0 otherwise.

### 3.2.4 Formulation

The mixed integer linear programming problem is formulated as follows.

\[
\text{maximize } \sum_{i \in I} P_i z_i - \sum_{s \in S} PC_s v_s - \sum_{s \in S, b \in B, t \in \{\text{begin}, \ldots, \text{fin}_s\}} (R_{bd}^s v_{sbdt} + M_{bd}^s p_{sbdt}) \tag{1}
\]

such that

\[
n_{jt+1} = n_{jt} - \sum_{i: \text{origin}_i = j, \text{start}_i = t} z_i - \sum_{s: \text{begin}_s \leq t \leq \text{fin}_s} r_{sjt}' + \sum_{i: \text{dest}_i = j, \text{end}_i = t} z_i + \sum_{s: \text{begin}_s \leq t \leq \text{fin}_s} r_{sjt} \quad \forall j \in J, t \in \{0, \ldots, t_{\text{last}} - 1\} \tag{2}
\]

\[
n_{jt} \geq \sum_{i: \text{origin}_i = j, \text{start}_i = t} z_i + \sum_{s: \text{begin}_s \leq t \leq \text{fin}_s} r_{sjt}' \quad \forall j \in J, t \in T \tag{3}
\]

\[
\sum_{j \in J} m_{sjbegin_s} = v_s
\]

\[
\sum_{j \in J} m_{sj\text{fin}_s} + r_{sj\text{fin}_s} + p_{sj\text{fin}_s} = v_s \quad \forall s \in S \tag{4}
\]

\[
m_{sjt+1} = m_{sjt} - p_{sjt}' - r_{sjt}' + p_{sjt} + r_{sjt} \quad \forall s \in S, j \in J, t \in \{\text{begin}_s, \ldots, \text{fin}_s - 1\} \tag{5}
\]

\[
m_{sjt} \geq p_{sjt}' + r_{sjt}' \quad \forall s \in S, j \in J, t \in \{\text{begin}_s, \ldots, \text{fin}_s\} \tag{6}
\]

\[
\sum_{d \in B} \tilde{r}_{sbdt} = \sum_{j \in J} r_{sjt}'
\]

\[
\sum_{d \in B, t' \in \text{end}_db \cap \{\text{begin}_s, \ldots, \text{fin}_s\}} \tilde{r}_{sbdt'} = \sum_{j \in J} r_{sjt} \quad \forall s \in S, b \in B, t \in \{\text{begin}_s, \ldots, \text{fin}_s\} \tag{7}
\]

\[
\sum_{d \in B} \tilde{p}_{sbdt} = \sum_{j \in J} p_{sjt}'
\]

\[
\sum_{d \in B, t' \in \text{end}_db \cap \{\text{begin}_s, \ldots, \text{fin}_s\}} \tilde{p}_{sbdt'} = \sum_{j \in J} p_{sjt} \quad \forall s \in S, b \in B, t \in \{\text{begin}_s, \ldots, \text{fin}_s\} \tag{8}
\]

\[
\sum_{j \in J} n_{j0} \leq NV \tag{9}
\]
\[ n_{jt} \leq \text{cap}_j \] 
\[ n'_{jt+1} = n'_{jt} - \sum_{i: \text{dest}_i = j \land \text{end}_i = t} z_i + \sum_{i: \text{start}_i = t} z_i \quad \forall j \in J, t \in T \]  
(10)
\[ n_{jt} + n'_{jt} \leq \text{cap}_j \quad \forall j \in J, t \in T \]  
(11)
\[ \sum_{s \in S} v_s \leq \text{NW} \]  
(12)
\[ \sum_{s \in S} (\text{fin}_s - \text{begin}_s) v_s \leq \text{Lcost} \]  
(13)
\[ v_0 \geq 1 \]  
(14)
\[ \sum_{s: \text{begin}_s \leq t \leq \text{fin}_s} p'_{sjt} \leq \text{NW} u'_{jt} \quad \forall j \in J, t \in T \]  
(15)
\[ \sum_{s: \text{begin}_s \leq t \leq \text{fin}_s} p_{sjt} \leq \text{NW} u_{jt} \quad \forall j \in J, t \in T \]  
(16)
\[ \sum_{s: \text{begin}_s \leq t \leq \text{fin}_s} p'_{sjt} \geq u'_{jt} \]  
(17)
\[ \sum_{s: \text{begin}_s \leq t \leq \text{fin}_s} p_{sjt} \geq u_{jt} \quad \forall j \in J, t \in T \]  
(18)
\[ l_{jt+1} = l_{jt} - u'_{jt} + u_{jt} \quad \forall j \in J, t \in T \]  
(19)

The objective function (11) maximizes the total daily profit including revenues from users’ served trips, personnel costs of relocation staff, and relocating and moving costs (cost of fueling the staff vehicle) between clusters. While carsharing operators want to increase the number of trips, relocation costs put pressure on their profitability (an easy but unprofitable way to increase the number of trips is to hire hundreds of relocation staff). We propose to find a way to maximize profits under certain costs restrictions.

Constraints (2) are the flow conservation equations for vehicles for each station and each time interval. The number of vehicles at station \( j \) at the beginning of time interval \( t + 1 \) \( (n_{jt+1}) \) is equal to the number of vehicles at the beginning of the previous time interval \( (n_{jt}) \) minus the number of vehicles departing from station \( j \) during time interval \( t \) on trips \( (\sum_{i: \text{dest}_i = j \land \text{end}_i = t} z_i) \) and relocations \( (\sum_{s: \text{begin}_s \leq t \leq \text{fin}_s} r_{sjt}) \) plus the number of vehicles arriving at \( j \) during \( t \) on trips \( (\sum_{i: \text{dest}_i = j \land \text{end}_i = t} z_i + \sum_{i: \text{dest}_i = j \land \text{start}_i = t} z_i) \) and relocations \( (\sum_{s: \text{begin}_s \leq t \leq \text{fin}_s} r_{sjt}) \). This flow is shown in Fig. 8.

Constraints (3) represent that there are enough vehicles for trips and relocations at each station during each time interval. Vehicles arriving at station \( j \) during \( t \) \( (\sum_{i: \text{dest}_i = j \land \text{end}_i = t} z_i + \sum_{s: \text{begin}_s \leq t \leq \text{fin}_s} r_{sjt}) \) cannot be counted during the same time interval \( t \). Because of these constraints, every vehicle can have one and only one status (“free”, “assigned”) during each time interval.

Constraints (4) show the boundary of the number of staff at the beginning shift and finishing shift time.
The sum of staff in shift $s$ over all stations at the beginning shift time interval $t_{\text{begin}}$ must equal the number of staff from shift $v_s$. Moreover, at the finishing shift time interval $t_{\text{finish}}$ as well, the total number of staff in shift $s$ at all stations must equal the number of staff from shift $v_s$.

Constraints (4) are the flow conservations of staff for each shift, each station, and each time interval. The number of staff from shift $s$ at station $j$ at the beginning of time interval $t + 1$ ($m_{sjt+1}$) is equal to the number of staff at the beginning of the previous time interval $t$ ($m_{sjt}$) minus the number of staff departing from station $j$ during time interval $t$ for moving ($p'_{sjt}$) and relocating ($r'_{sjt}$) plus the number of staff arriving at station $j$ during time interval $t$ for trips ($p_{sjt}$) and relocations ($r_{sjt}$). This flow is shown in Fig. 9.

Similar to the constraints (3) on vehicles, constraints (5) on the number of staff represent whether there are enough staff for moving and relocating operations at each station during each time interval. Staff arriving at station $j$ in time interval $t$ ($p_{sjt} + r_{sjt}$) cannot be counted during the same time interval $t$. Because of these constraints, every staff can have one and only one status (“idle”, “moving”, or “relocating”) during each time interval.

Constraints (7) and (8) are respectively the relocating and moving staff flow conservations between clusters and stations in the clusters. The left equations indicate that the number of staff in shift $s$ starting to relocate/move from cluster $b$ during time interval $t$ must be equal to the sum of staff from shift $s$ relocating/moving from all stations in cluster ($J_b$) during $t$. Likewise, the right equations represent that the number of staff in shift $s$ starting to relocate/move into cluster $b$ during $t$ must be equal to the
sum of staff in shift $s$ relocating/moving to all stations in cluster $(J_b)$ during $t$.

Constraint (9) indicates that the total number of vehicles at all stations at the beginning of the day must be equal to or less than the maximum number of vehicles available in the service.

Constraints (10) show the parking capacity restriction at each station during each time interval $t$. The number of vehicles at station $j$ during $t$ must be equal to or less than the number of parking spaces at station $j$.

Constraints (11) are the flow conservation equations for assigned (unavailable) parking spaces at each station and each time interval. The number of assigned parking spaces at station $j$ at the beginning of time interval $t + 1$ ($n^t_{jt+1}$) is equal to the number of assigned parking spaces in the previous time interval $t$ ($n^t_j$) minus the number of (parking spaces assigned for) vehicles arriving at station $j$ during time interval $t$ on trips ($\sum_{i: \text{dest}_i=j} z_i$) plus the number of (parking spaces assigned for) vehicles departing from station $j$ during $t$ on trips ($\sum_{i: \text{origin}_i=j} z_i$). Note that parking spaces are only assigned to user trips and not for staff relocation, so the equations don’t include the number of relocations ($r^t_{s,jt}$ or $r^t_{s,jt}$), unlike constraints (2).

Constraints (12) show the parking capacity restrictions, including assigned parking spaces at each station in each time interval $t$. The sum of vehicles and assigned parking spaces at station $j$ during $t$ must be equal to or less than the number of parking spaces at station $j$.

Constraint (13) represents that the total number of staff in all shifts must be equal to or less than the total number of relocation staff able to work in the service.

Constraint (14) represents the maximum labor cost per day.

Constraint (15) indicates that at least a manager must work in shift 0, which is the full-time shift.

Constraint (16) indicates that if $u_{jt}$ or $u^t_{jt}$ is equal to 0, no staff move from/to station $j$ during time interval $t$. On the contrary, constraint (17) represents that if $u_{jt}$ or $u^t_{jt}$ equals 1, there must be staff moving from/to station $j$ during $t$. These constraints mean that relocation staff can only move by using the staff vehicle.

Constraint (18) is the flow conservation of staff vehicles at each station during each time interval. Finally, constraint (19) is the maximum number of staff vehicles. In this study, it is assumed there is only one staff vehicle.

Note that the objective function (1) is different from that of Boyaci et al. [4], and the constraints (9), (10), (11), (12), (13), (14), (15), (16), (17), (18), and (19) are not used in [4].
3.3 Station clustering

The stations used for moving staff and relocating vehicles are clustered to decrease the number of variables and reduce the computational complexity.

Without clustering, the number of variables for moving and relocating is on the order of $O(|S||J|^2|T|)$, where $S$ is the set of relocation staff shifts, $J$ is the set of stations, and $T$ is the set of time intervals (the number of variables for trip $|I|$ is ignored here). As described in section 3.2 by clustering stations and dividing staff moving and relocation operations into intra-cluster and inter-cluster parts (Fig. 7), the number of variables changes to on the order of $O(|S||J||T| + |B|^2|T|)$. By setting the number of clusters as $|B| \leq \sqrt{|J|}$, the number of variables decreases to on the order of $O(|S||J||T|)$.

As a result of clustering, the travel time from station $j$ to station $l$ ($\delta t_{jl}$) is replaced with the travel time from cluster $b$ of station $j$ to cluster $d$ of station $l$ (travel$_{bd}$), whose difference remains as a clustering error ($dev_{tjl}$).

$$dev_{tjl} = travel_{bd} - \delta t_{jl} \quad \forall j \in J_b, l \in J_d$$ (20)

To minimize the sum of clustering errors $dev_{tjl}$, we developed an algorithm based on the one in Boyaci et al. [4]. The algorithm is similar to the $k$-Medoid algorithm, which minimizes the sum of dissimilarities within clusters. We define the travel time from cluster $b$ to cluster $d$ (travel$_{bd}$) as the maximum travel time between any stations in each cluster as (21) and set the objective function as (22), the sum of the clustering errors to be minimized. Because of the definition (21), the clustering algorithm always returns feasible solutions (travel$_{bd}$ is always equal to or larger than the actual travel time).

$$travel_{bd} = \max\{\delta t_{jl} \mid j \in J_b, l \in J_d\}$$ (21)

$$F_B = \sum_{b,d \in B} \sum_{j \in J_b} \sum_{l \in J_d} dev_{jl}$$ (22)

In the objective function (22), the clustering error $dev_{tjl}$ is replaced with $dev_{jl}$ (without $t$). Because the set of clusters $B$ is unique in the optimization formulation, the station clustering requires time-independent representatives of $dev_{tjl}$. We set $dev_{jl}$ as the median of $dev_{tjl}$ in the case studies described later in section 4.

The station clustering algorithm [1] is based on the one in Boyaci et al. [4].

1. Create an initial solution (lines from 1 to 15). For all $N_k$ stations, assign each station to each cluster one by one, and add the station to a cluster which gives the best (minimum) objective function (22). Note that the initial solution depends on the order of stations added.
2. Iteratively search for a better solution by exchanging stations between clusters (line 16 below).
   (a) Find a station to be removed (lines 21 to 31). For all stations, temporarily remove each station from its cluster one by one, and find the removal which improves the objective function the most. We avoid selecting the same stations repeatedly by remembering the stations selected to be removed in variable $C$ and excluding them from subsequent searches.
   (b) Find a cluster to which the removed station can be added (lines 32 to 40). For all clusters except the one the station was removed from, assign the station to each cluster one by one, and find an addition which gives the minimum objective function.
   (c) If the new solution has a better (smaller) objective function than the best solution, replace the best solution with the new solution (line 41). If the best solution is not updated after every station has been checked to see if it is to be put in a different cluster, run the algorithm for swapping stations between any two clusters to seek a new set of clusters with the smallest objective function (Algorithm 2). If the new solution has a better (smaller) objective function than the best solution, replace the best solution with the new solution.
Algorithm 1 Clustering stations

Input: $J, N, n, F_B$
Output: $B^*, Z^*$

1: for $k \leftarrow 1$ to $N_k$ do
2:   $B_b \leftarrow \emptyset$
3: end for
4: for $j \leftarrow 1$ to $|J|$ do
5:   $Z \leftarrow \infty$
6:   for $b \leftarrow 1$ to $N_k$ do
7:     $B_b \leftarrow B_b \cup \{j\}$
8:     if $F_B < Z$ then
9:       $b^* \leftarrow b; Z \leftarrow F_B$
10:   end if
11:   $B_b \leftarrow B_b \setminus \{j\}$
12: end for
13: $B_b^* \leftarrow B_b \cup \{j\}$
14: end for
15: $B^* \leftarrow B; Z^* \leftarrow F_B$
16: $C \leftarrow \emptyset$
17: for $i \leftarrow 1$ to $N$ do
18:   if $C = J$ then
19:     break
20: end if
21: $Z \leftarrow \infty$
22: for $b \leftarrow 1$ to $N_k$ do
23:   for $j \in J_b \setminus C$ do
24:     $B_b \leftarrow B_b \setminus \{j\}$
25:     if $F_B < Z$ then
26:       $j^* \leftarrow j; b^* \leftarrow b; Z \leftarrow F_B$
27:     end if
28:     $B_b \leftarrow B_b \cup \{j\}$
29:   end for
30: $B_b^* \leftarrow B_b \setminus \{j^*\}; C \leftarrow C \cup \{j^*\}$
31: $Z \leftarrow \infty$
32: for $b \leftarrow 1$ to $N_k$ do
33:   $B_b \leftarrow B_b \cup \{j^*\}$
34:   if $F_B < Z^*$ then
35:     $b^* \leftarrow b; Z^* \leftarrow F_B; C \leftarrow \emptyset$
36:   end if
37: $B_b \leftarrow B_b \setminus \{j^*\}$
38: end for
39: $B_b^* \leftarrow B_b \cup \{j^*\}$
40: if $F_B < Z^*$ then
41:   $B^* \leftarrow B; Z^* \leftarrow F_B; C \leftarrow \emptyset$
42: else if $C = J$ then
43:   $B \leftarrow \text{Swapping stations}(B, Z)$
44:   if $Z < Z^*$ then
45:     $B^* \leftarrow B; Z^* \leftarrow F_B; C \leftarrow \emptyset$
46:   end if
47: end if
48: end if
49: end for
Algorithm 2 Swapping stations

Input: $B$, $Z$
Output: $B$

1: $Z_0 \leftarrow Z$
2: for $b \leftarrow 1$ to $N_k - 1$ do
3: for $d \leftarrow b + 1$ to $N_k$ do
4: for $j \in J_b$ do
5: for $l \in J_d$ do
6: $B_b \leftarrow B_b \setminus \{j\}; B_d \leftarrow B_d \setminus \{l\}; B_b \leftarrow B_b \cup \{l\}; B_d \leftarrow B_d \cup \{j\}$
7: if $F_B < Z$ then
8: $b^* \leftarrow b; d^* \leftarrow d; j^* \leftarrow j; l^* \leftarrow l; Z \leftarrow F_B$
9: end if
10: $B_b \leftarrow B_b \setminus \{l\}; B_d \leftarrow B_d \setminus \{j\}; B_b \leftarrow B_b \cup \{j\}; B_d \leftarrow B_d \cup \{l\}$
11: end for
12: end for
13: end for
14: if $Z < Z_0$ then
15: $B_b^* \leftarrow B_b^* \setminus \{j^*\}; B_d^* \leftarrow B_d^* \setminus \{l^*\}; B_b^* \leftarrow B_b^* \cup \{l^*\}; B_d^* \leftarrow B_d^* \cup \{j^*\}$
16: end if
17: return $B$

4 Case studies

This section describes case studies on applying the framework developed in section 3 to Ha:mo RIDE Toyota, which has been operating in Toyota, Japan since 2012. The models were implemented in an E5-1630 v3 (3.70GHz), 64GB computer running a Windows 8.1 Pro OS and the Gurobi Optimizer 7.0.2 tool.

4.1 Ha:mo RIDE (current service)

The use history for one year from April 1st, 2016 to March 31st, 2017 and station data were provided by Toyota Motor Corporation.\textsuperscript{3}

4.1.1 Station clustering

There were 55 stations operating during the period when the use data was acquired, including one depot that was off-limits to users. The travel time $\delta_{tjl}$, starting from time interval $t$ between station $j$ and station $l$, was estimated using the Google Maps Distance Matrix API.\textsuperscript{22} By setting the travel mode option to “driving” and specifying the departure time $t$, the API returns a route distance and trip duration between two points, taking traffic conditions into account. Deviations in trip duration of up to a maximum of 20 minutes were observed in an OD (origin $b$ and destination $d$) throughout the day, and we used the travel time at $h:30$ as a representative departure time $t$ during $[h:00, (h+1):00)$. We added a 3 minute margin (described in 3.2) to the trip durations to make the travel time $\delta_{tjl}$. These travel

\textsuperscript{3} Not allowed to be publicly shared.
times were applied to the user as well as relocation staff travels. Note that the travel times between the same stations but in opposite directions are generally not the same ($\delta_{tjl} \neq \delta_{tlj}$). Fig. 10 shows histograms of route distances and trip durations returned by the Google Maps Matrix API.

Fig. 10: Distribution of (a) distance and (b) trip duration returned by Google Maps Distance Matrix API

As described in section 3.3, we set the number of clusters so that $|B| \leq \sqrt{|J|}$ holds, where $B$ is the set of clusters and $J$ is the set of stations. For the 55 stations, the number of clusters turned out to be equal to or less than $\sqrt{55}$, or around 7.4 to reduce computational complexity. Fewer clusters would result in more errors in the travel time for moving or relocating.

We varied the number of clusters to see how it would affect the objective function. Because clustering results depend on the initial solutions, i.e. on the order of stations added, we shuffled the stations randomly and ran the clustering algorithm 25 times per condition and picked the best result. The maximum number of iterations $n$ was 1,000. As shown in Fig. 11, the objective function was sharply worse at less than five clusters. As a result, we decided to use seven clusters, shown as different colors in Fig. 12.

Fig. 11: Aggregate error of different numbers of clusters
4.1.2 Optimization settings

As mentioned above, the number of stations was 55, and the total number of parking spaces $\sum_{j \in J} \text{cap}_j$ was 266. The maximum number of vehicles $N_V$ was 90. The time period for optimization was 6 am to 12 am, when demand was relatively high and all stations were open. Fig. 13 shows trip data taken from a 2011 person-trip survey conducted in Toyota city, which have a similar distribution to the Ha:mo RIDE Toyota use data.

The relocation staff shifts are shown in Fig. 14a. It was necessary to set the number of shifts to 2 or less in order to avoid excessive computational time. Shift 0 is a full-time shift in which a manager has to work, and shift 1 is a part-time shift that covers high-demand hours in the evening. The total number of relocation staff $N_W$ was 5, the personnel costs of relocation staff $P_{CS}$ was ¥900 per hour for any shift $s$, and the maximum labor cost $L_{cost}$ was ¥27,000 per day (equivalent to 30 man-hours per day).

Instead of estimating potential demand, we generated demand values from the use history according to a Poisson distribution to run the optimization many times. From the use history, we aggregated

\[^4\text{For events with an expected occurrence rate of } \lambda, \text{ the Poisson distribution describes the probability of } x \text{ events}\]
**Fig. 13:** Number of trips from/to Toyota City: data from 2011 person-trip survey

![Graph showing the number of trips from/to Toyota City.]

(a) staff shift #1

(b) staff shift #2

(only high-demand hours)

**Fig. 14:** Staff shift

The one-way use data except the data gathered on holidays and calculated the average number of uses per hour $h$ per OD from station $j$ to $l$, $\lambda_{jl}^h$. The number of trips departing on $h:m$ ($h \in [6,23]$, $m \in [0,5,10,\ldots,55]$) from station $j$ to $l$ was given by a Poisson distribution with an average $\lambda_{jl}^h \times \frac{5}{60}$. The end time of the trip was determined by adding $\delta_{jl}$ to the departing time and rounding up to the nearest five-minute interval.

The price for trip $i$ ($P_i$) was taken to be the actual price: fare of ¥200 for up to 10 minutes and ¥20 per minute after that. The price for a trip from station $j$ to $l$ was calculated as follows:

$$P_{jl} = \max\{P_0, P_0 + (\delta_{jl} - t_0) \times dP\}$$

$P_0 = 200, t_0 = 10, P_0 = 20$

---

occurring within a fixed interval of time.

$$P(x) = \frac{\lambda^x e^{-\lambda}}{x!}$$

Thus, for demands with an average $\lambda^h$ in 1 hour (60 minutes), the Poisson distribution with an average $\lambda = \lambda^h \times \frac{5}{60}$ gives the number of demands in 5 minutes.
Finally, the relocating costs and moving costs $\tilde{K}_{bd} (1.0)$ and $\tilde{M}_{bd} (1.1)$ reflected the use of fuel-efficient compact cars.

### 4.1.3 Optimization results

Table 1 shows the results of the optimization compared with data gathered during actual operation. The numbers are averages of 50 runs with different demand samples (satisfied demand and profit related numbers are shown as ratios of the optimization results to the data gathered during actual operation).

<table>
<thead>
<tr>
<th>Shift #1</th>
<th>Shift #2</th>
<th>1.5×demand</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Satisfied demand ratio [%]</td>
<td>83.5</td>
<td>81.3</td>
<td>105.9</td>
</tr>
<tr>
<td>Number of staff working</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>Number of vehicles used</td>
<td>66.8</td>
<td>68.6</td>
<td>72.5</td>
</tr>
<tr>
<td>Number of relocations</td>
<td>4.5</td>
<td>2.0</td>
<td>5.5</td>
</tr>
<tr>
<td>Optimized profit compared with actual</td>
<td>1.97</td>
<td>2.54</td>
<td>2.98</td>
</tr>
<tr>
<td>Revenue ratio</td>
<td>0.84</td>
<td>0.82</td>
<td>1.14</td>
</tr>
<tr>
<td>Personnel costs ratio</td>
<td>0.37</td>
<td>0.10</td>
<td>0.37</td>
</tr>
<tr>
<td>Relocation and moving costs ratio</td>
<td>0.22</td>
<td>0.10</td>
<td>0.29</td>
</tr>
</tbody>
</table>

In spite of using a demand generated from the actual history, the satisfied demand was only 83.5%. While the actual operation relocated vehicles with 5 staff in total, the optimal solution had only 1 staff (manager, forced to work by constraint (15)), thereby cutting personnel costs to maximize profit. The average revenue was a little over ¥300 because of the average approximate 15-minute travel time. One set of relocations often consisted of two trips: moving to a station from which a vehicle was to be removed and the actual relocation, as shown in Fig. 5. The number of relocations per hour was 2 on average. A two-man team relocated 2 vehicles and cost ¥1,800 per hour, i.e., ¥900 per relocation, a three-man team relocated 4 vehicles and cost ¥2,700 per hour, i.e., ¥675 per relocation, and so on. The larger the team was, the less expensive each relocation became, decreasing the driver staff cost per relocation by ¥450 (¥900 per two sets of relocations).

To confirm the above results, we added another case “staff shift #2” (Fig. 14b) with a staff shift focusing only on high-demand hours and a case with a staff shift and 1.5 times the demand (“Shift #2” and “1.5×demand” in Table 1). Both cases had only 1 staff and infrequent relocations, which indicates that staff-based relocation does not lead to additional revenue.

In “staff shift #1,” the number of vehicles used was 66.8, about 2/3rds of the maximum number of available vehicles. This result suggests that there is a best ratio of the number of vehicles to the number of parking spaces depending on the relocation frequency. Obviously, the more frequently vehicles are relocated, the more vehicles should be added, but when vehicles are relocated often, it is better for fewer vehicles to leave parking spaces available for incoming trips. We will discuss the parking-to-vehicle ratio in section 4.3.

The optimal solution maximizing profit indicates that the operator should reduce relocation staff. Additional revenues from the short trips of last-mile mobility are too low to cover relocation personnel costs, and the best operation policy is distributing an appropriate number of vehicles to stations and leaving

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*5 60 minutes / (15 minutes × 2) = 2.
*6 Note that one of the team has to drive the staff vehicle and cannot relocate vehicles.
them there. However, in doing so, the low satisfied demand rate would result in customer dissatisfaction and long-term defection. The operator must relocate vehicles not to increase profit but to maintain certain levels of satisfied demand and retain users.

4.2 Premium Service

Here, in an attempt to cover the costs of relocating personnel, we introduced a “Premium Service” guaranteeing reservations in return for price premiums. As mentioned in section 4.1.1, ridesharing companies such as Uber and Lyft are implementing special pricing for high-demand hours, called “surge pricing” and “Premium Time” [32], respectively.

4.2.1 Settings

Here the idea is that demand for premium service must be satisfied before demand for the standard service is satisfied. Vehicles are relocated if necessary.

Although premium service should be more popular during high-demand hours and ODs, it is quite challenging to estimate the potential demand accurately, as it depends on pricing. Instead, we assumed a 1.5 times total demand and regenerated trips from the average $1.5 \times \lambda_{h}$ in the same manner as in section 4.1.2. From these trips, we picked trips randomly at a uniform rate of $p$ per hour and OD, and formed a premium service trip set $I_p$ ($I_p \subseteq I$). As for pricing, we set the starting fare higher than the standard and lower than that of a taxi, ¥300. We ran the optimization at different selection ratios $p$: 1/6 and 1/3.

The premium service formulation added the following constraints to those in section 3.2.

\[ z_i = 1 \quad \forall i \in I_p \]  \hspace{1cm} (23)

Constraints (23) represent that every premium service demand must be satisfied.

![Demand assumption](image1.png)  \hspace{1cm} ![Price setting](image2.png)

Fig. 15: Assumptions of Premium Service
4.2.2 Results

Table 2 shows the results of premium service optimization. The numbers for the 1/6 and standard-only cases are averages of 50 runs with different demand samples. The numbers for the 1/3 case are averages of 39 runs out of 50, terminated by a 5,000-second timeout; the remaining 11 runs are infeasible, as described later. (The satisfied demand and profit related numbers are the ratios of the results of the Premium Service to those of the standard service for the 1.5-times demand.)

<table>
<thead>
<tr>
<th>Premium service demand ratio $p$</th>
<th>Standard only</th>
<th>1/6</th>
<th>1/3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Satisfied demand ratio [%]</td>
<td>72.4</td>
<td>72.0</td>
<td>73.4</td>
</tr>
<tr>
<td>Premium service</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td>Standard service</td>
<td>72.4</td>
<td>66.4</td>
<td>59.9</td>
</tr>
<tr>
<td>Number of staff working</td>
<td>1.0</td>
<td>1.0</td>
<td>1.7</td>
</tr>
<tr>
<td>Number of vehicles used</td>
<td>72.5</td>
<td>75.4</td>
<td>72.2</td>
</tr>
<tr>
<td>Number of relocations</td>
<td>5.5</td>
<td>5.3</td>
<td>6.8</td>
</tr>
<tr>
<td>Profit ratio compared with standard only</td>
<td>1.000</td>
<td>1.059</td>
<td>1.024</td>
</tr>
<tr>
<td>Revenue ratio</td>
<td>1.00</td>
<td>1.05</td>
<td>1.10</td>
</tr>
<tr>
<td>Personnel costs ratio</td>
<td>1.00</td>
<td>1.01</td>
<td>1.37</td>
</tr>
<tr>
<td>Relocation and moving costs ratio</td>
<td>1.00</td>
<td>0.96</td>
<td>1.29</td>
</tr>
</tbody>
</table>

In the case of $p = 1/6$, no big differences from the standard service were observed. The number of staff remained 1 (manager only).

In the case of $p = 1/3$, the total satisfied demand ratio was almost the same as in the standard case, but the satisfied demand ratio of the standard service decreased by 12.5%, which means standard service users were pushed out by premium service users, though some runs returned solutions with 2 or 3 relocation staff working to meet the demand. Also, 11 out of 50 runs (22%) were infeasible because of constraints (23), i.e., the requirement of satisfying the premium service demand, and other constraints about vehicles, parking spaces, and relocation staff. In other words, premium service could not guarantee rides because of the shortage of resources such as vehicles, parking, and staff, even under assumption (2) that the demand for the whole day is given in advance.

Although the profit might increase in the short term, this service would result in a long term loss or become infeasible. We conclude that premium service is not worth implementing in our setting.

4.3 Autonomous relocation

In the previous section 4.2, we investigated premium pricing to cover relocation costs. In this section, we consider self-driving as a way of low-cost relocation. The majority of the relocation costs consist of personnel costs, which exceed additional revenues from trips afforded by the staff-based relocation. We supposed that unstaffed autonomous relocation could increase the number of trips and cover the relocation costs (Note that we did not consider fixed costs of self-driving such as vehicle remodeling or infrastructure investments).
4.3.1 Settings

Although car makers and ridesharing providers are developing self-driving systems for drivers (Advanced Driver Assistance Systems or ADAS) and passengers (so-called “robot taxis”), we assumed that self-driving would only be for autonomous relocation, not for providing rides for users.

Because of it being a not-for-passenger kind of transport, vehicles being relocated do not need to drive as fast as a human would drive them. Moreover, the vehicles would be required to drive on designated paths at low speed. Assuming a 10 km/h speed limit for automatically commanded steering functions or 6 km/h walking speed, low-speed automated relocation would take approximately five times longer than manual driving. (Fig. 16 shows the “walking” trip duration calculated from the Google Maps Distance Matrix API).

![Fig. 16: Trip duration on foot, approx. five times longer than by car in Fig. 10](image)

We called a trip duration of five times the duration of driving (with the same margin of 3 minutes) “walking speed” and a trip duration of 50 times that of driving “super slow”. Although automated driving might actually be allowed only at limited times and in limited areas, we did not limit the autonomous relocation time or placement of stations in this case study. We set three levels of potential demand, 1.2, 1.5, 2.0 times higher than actual demand (equal to the number of uses), in the expectation that autonomous relocation would increase demand. Vehicle equipment or infrastructure for autonomous relocation were not included in the formulations, as they were considered to be sunk.

The transformed objective function shown below does not include terms related to personnel costs.

$$\text{maximize } \sum_{i \in I} P_i z_i - \sum_{b,d \in B} \sum_{t \in T} \tilde{R}C_{bd} \tilde{r}_{bdt}$$

(24)

In addition, constraints on shifting relocation staff (4), (5), (6), (13), (14), (15) and moving relocation staff (3), (10), (11), (12) are omitted, and the flow conservation equations (2) for vehicles and (7) for

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*7 Currently under discussion to be modified in the UNECE World Forum for Harmonization of Vehicle Regulations (WP29).

*8 The Cabinet Office Ordinance specifies the speed of walking assist vehicles to be at most 6 km/h in Japan.
relocation are replaced with \((25)\) and \((26)\), respectively. Note that the suffix \(s\) indicating the staff shift is omitted from variables \(r', r, \tilde{r}\).

\[
n_{jt+1} = n_{jt} - \sum_{i: \text{origin}_i = j} z_i - r'_{jt} + \sum_{i: \text{dest}_i = j} z_i + r_{jt} \quad \forall j \in J, t \in \{0, ..., t_{last-1}\} \tag{25}
\]

\[
\sum_{d \in B} \tilde{r}_{bdt} = \sum_{j \in J_b} r'_{jt}
\]

\[
\sum_{d \in B} \sum_{t' \in t.\text{end}_{i,ab}} \tilde{r}_{dbt'} = \sum_{j \in J_b} r_{jt} \quad \forall b \in B, t \in T \tag{26}
\]

### 4.3.2 Results

Table 3 and Fig. 17 compare the results of optimization with staff-based relocation. The numbers are averages of 50 runs with different demand samples (satisfied demand and profit related numbers are shown as ratios of the results of the optimization to the ones of staff-based relocation).

**Table. 3:** Autonomous drive relocation compared with base case

(a) 5-times trip duration (walking speed)

<table>
<thead>
<tr>
<th>Total demand</th>
<th>(\times 1.2)</th>
<th>(\times 1.5)</th>
<th>(\times 2.0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Satisfied demand ratio [%]</td>
<td>99.8%</td>
<td>99.7%</td>
<td>99.4%</td>
</tr>
<tr>
<td>Number of vehicles used</td>
<td>69.9</td>
<td>79.2</td>
<td>89.1</td>
</tr>
<tr>
<td>Number of relocations</td>
<td>33.8</td>
<td>53.0</td>
<td>83.4</td>
</tr>
<tr>
<td>Relocation / Vehicle</td>
<td>0.48</td>
<td>0.67</td>
<td>0.94</td>
</tr>
<tr>
<td>(Parking + 2(\times)Relocation) / Vehicle</td>
<td>4.77</td>
<td>4.69</td>
<td>4.86</td>
</tr>
<tr>
<td>Profit ratio compared with base case</td>
<td>1.6</td>
<td>1.6</td>
<td>1.7</td>
</tr>
<tr>
<td>Revenue ratio</td>
<td>1.2</td>
<td>1.3</td>
<td>1.4</td>
</tr>
<tr>
<td>Relocation and moving costs ratio</td>
<td>6.0</td>
<td>9.7</td>
<td>13.6</td>
</tr>
</tbody>
</table>

(b) 50-times trip duration (super slow)

<table>
<thead>
<tr>
<th>Total demand</th>
<th>(\times 1.2)</th>
<th>(\times 1.5)</th>
<th>(\times 2.0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Satisfied demand ratio [%]</td>
<td>94.7%</td>
<td>90.9%</td>
<td>84.1%</td>
</tr>
<tr>
<td>Number of vehicles used</td>
<td>73.9</td>
<td>85.5</td>
<td>89.9</td>
</tr>
<tr>
<td>Number of relocations</td>
<td>24.2</td>
<td>34.1</td>
<td>44.1</td>
</tr>
<tr>
<td>Relocation / Vehicle</td>
<td>0.33</td>
<td>0.40</td>
<td>0.49</td>
</tr>
<tr>
<td>(Parking + 2(\times)Relocation) / Vehicle</td>
<td>4.25</td>
<td>3.91</td>
<td>3.94</td>
</tr>
<tr>
<td>Profit ratio compared with base case</td>
<td>1.6</td>
<td>1.5</td>
<td>1.5</td>
</tr>
<tr>
<td>Revenue ratio</td>
<td>1.2</td>
<td>1.2</td>
<td>1.2</td>
</tr>
<tr>
<td>Relocation and moving costs ratio</td>
<td>3.9</td>
<td>5.2</td>
<td>6.4</td>
</tr>
</tbody>
</table>
In the walking speed case, the satisfied demand ratio is over 99% for all demand cases, including 2.0 times higher than actual (Table 3a). The super slow case is a bit worse, 90% for 1.5 times demand and 84% for 2.0 times demand, but the number of satisfied demands is two times more compared with the no-relocation solution. The relocation cost increases in either case, but its proportion remains a small fraction of the of revenue, and the profit improves to over 1.5 times that of the base case. In the walking speed case, along with the increase in potential demand, the number of vehicles used increases and almost reaches the maximum number of vehicles available at 2.0 times demand. Not only the number of relocations but also the number of relocations per vehicle increases. The frequent vehicle relocation is considered to increase the per per-parking parking-space operation ratio as well as the per per-vehicle one and avoids a situation where there is a lack of parking spaces caused by an increase in vehicles. We found the ratio of (parking + 2×relocation) to vehicle rate gives almost the same value (a little under 5) as the ratio of the parking to vehicle rate described in section 4.1.3. We conjecture that the additional term “2×relocation” for parking spaces comes from that one relocation has two effects on increasing parking capacity: one relocation obviously leaves open a parking space at a station the vehicle is relocated from and virtually adds a parking space at a station that the vehicle is to be relocated to during the period in which it is being dispatched.

In the super slow case, the number of relocations per vehicle does not increase as much as in the walking speed case. Relocation operations cannot meet the increase in demand, because super-slow driving takes too long to relocate vehicles (for example, driving a distance that usually takes 15 minutes takes 12.5 hours with super-slow driving, $15 \times 50 = 750$ minutes). In addition, because of station clustering, relocation between adjacent stations in actuality are replaced to the longest travels among the station clusters.

To check how clustering the stations affects the results, we developed another low-speed autonomous relocation model without station clustering. Because of the absence of relocation staff variables, the without-clustering model would be not as computationally expensive as the original model.

We replaced the variable $\tilde{r}$ representing relocation between clusters with $\bar{r}$ between stations and modified the parameter $\tilde{RC}$ for the relocating costs between clusters to $\bar{RC}$ between stations.

- $\bar{RC}_{jl}$: relocating costs from station $j$ to station $l$

*(The number of satisfied demands) / (the number of vehicles used + the number of relocations) stays at almost the same level, which indicates that the relocating vehicles works efficiently in high high-demand situations.
\[ \hat{r}_{jlt} \in \mathbb{Z}^+, \ j, l \in J, j \neq l, \ t \in T : \text{number of vehicle(s) relocating from station} \ j \ \text{to station} \ l \ \text{departing during time interval} \ t \]

The reformulation is as follows.

\[
\text{maximize} \quad \sum_{i \in I} P_i z_i - \sum_{\substack{j, l \in J \ t \in T}} R_{C_{jlt}} \hat{r}_{jlt}
\]

\[ n_{jt+1} = n_{jt} - \sum_{\substack{i: \text{origin}_i = j \ \text{start}_i = t}} z_i - \sum_{\substack{j \neq l \ i \in J \ \{j\}}} r_{jlt} + \sum_{\substack{i: \text{dest}_i = j \ \text{end}_i = t}} z_i + \sum_{\substack{j \neq l \ i \in J \ \{j\}}} r_{ljt} \]

\[ n_{jt} \geq \sum_{\substack{i: \text{origin}_i = j \ \text{start}_i = t}} z_i + \sum_{\substack{i \in J \ \{j\}}} \hat{r}_{jlt} \quad \forall j \in J, \ t \in \{0, \ldots, t_{\text{last}} - 1\} \]

\[ \forall j \in J, t \in T \]

The objective function (27) maximizes the profit, i.e., the revenue from satisfied trips minus the cost of autonomous relocation. The flow conservation equations for vehicles (28) replace (25), and constraints for vehicle status (29) replace (3). Constraints (26) are removed because relocation is represented by \( \hat{r} \) without clusters.

Table 4 and Fig. 18 show the optimization results for with- and without-clustering models at 1.5-times potential demand. The numbers are averages of 50 runs with different demand samples. Each calculation took less than 10 seconds per 50 runs, as fast as expected.

For super super-slow relocation, the without-clustering cases have more relocations than the with-clustering cases, which supports the assumption conclusion that the station clustering prevents relocation between adjacent stations. Even in this case, removing station clustering increases the satisfied demand ratio to almost 99% by exploiting vehicles as much as in the walking speed case. In addition, the ratio of (parking + 2 × relocation) to vehicle rate increased to the same level as in the walking speed case, which suggests that autonomous relocation sufficiently expands the parking capacity. This feature, virtual parking increase, especially suits the last-mile mobility scenario with many small stations scattered all over a city. Finally, Fig. 19 shows the results for one-day operation of autonomous relocation at 50 times the trip duration (super slow) without station clustering.
Table 4: Autonomous relocation with and without clustering at 1.5-times demand

(a) Five-times trip duration (walking speed)

<table>
<thead>
<tr>
<th>clustering</th>
<th>Yes</th>
<th>No</th>
</tr>
</thead>
<tbody>
<tr>
<td>Satisfied demand ratio [%]</td>
<td>99.7%</td>
<td>99.9%</td>
</tr>
<tr>
<td>Number of vehicles used</td>
<td>79.2</td>
<td>85.5</td>
</tr>
<tr>
<td>Number of relocations</td>
<td>53.0</td>
<td>68.3</td>
</tr>
<tr>
<td>Relocation / Vehicle</td>
<td>0.67</td>
<td>0.80</td>
</tr>
<tr>
<td>(Parking + 2×Relocation) / Vehicle</td>
<td>4.69</td>
<td>4.71</td>
</tr>
<tr>
<td>Computation time [sec]</td>
<td>0.53</td>
<td>7.44</td>
</tr>
</tbody>
</table>

(b) Trip duration 50 times (super slow)

<table>
<thead>
<tr>
<th>clustering</th>
<th>Yes</th>
<th>No</th>
</tr>
</thead>
<tbody>
<tr>
<td>Satisfied demand ratio [%]</td>
<td>90.9%</td>
<td>98.8%</td>
</tr>
<tr>
<td>Number of vehicles used</td>
<td>85.5</td>
<td>87.4</td>
</tr>
<tr>
<td>Number of relocations</td>
<td>34.1</td>
<td>69.7</td>
</tr>
<tr>
<td>Relocation / Vehicle</td>
<td>0.40</td>
<td>0.80</td>
</tr>
<tr>
<td>(Parking + 2×Relocation) / Vehicle</td>
<td>3.91</td>
<td>4.64</td>
</tr>
<tr>
<td>Computation time [sec]</td>
<td>0.31</td>
<td>6.32</td>
</tr>
</tbody>
</table>

Fig. 18: Autonomous relocation with and without station clustering at 1.5-times demand

4.4 Adding more staff vehicles

As modeled in section 3, the current Ha:mo RIDE service uses only one staff vehicle. In this section, we assume that multiple staff vehicles can be used and discuss the effect of increasing the number of staff vehicles on the models described in section 4.2.
4.4.1 Settings

To model this situation, we introduce the following additional sets and variables.

- \( v \in \mathcal{NSV} \): staff vehicles.
- \( p_{svjt} \in \mathbb{Z}^+, \forall s \in \mathcal{S}, v \in \mathcal{NSV}, j \in \mathcal{J}, t \in \{\text{begin}_s, \ldots, \text{fin}_s\} \): number of staff of shift \( s \) moving from station \( j \) during time interval \( t \) by staff vehicle \( v \).
- \( p_{svjt} \in \mathbb{Z}^+, \forall s \in \mathcal{S}, v \in \mathcal{NSV}, j \in \mathcal{J}, t \in \{\text{begin}_s, \ldots, \text{fin}_s\} \): number of staff of shift \( s \) moving to station \( j \) during time interval \( t \) by staff vehicle \( v \).
- \( \tilde{p}_{svbdt} \in \mathbb{Z}^+, \forall s \in \mathcal{S}, v \in \mathcal{NSV}, b, d \in \mathcal{B}, t \in \{\text{begin}_s, \ldots, \text{fin}_s\} \): number of staff in shift \( s \) moving from cluster \( b \) to cluster \( d \) during time interval \( t \) by staff vehicle \( v \).
- \( l_{vj} \in \{0,1\}, \forall v \in \mathcal{NSV}, j \in \mathcal{J}, t \in \mathcal{T} \): binary variables, 1 if relocation staff and staff vehicle \( v \) exist at station \( j \) during time interval \( t \), 0 otherwise.
- \( u'_{vj} \in \{0,1\}, \forall v \in \mathcal{NSV}, j \in \mathcal{J}, t \in \mathcal{T} \): binary variables, 1 if relocation staff moves out from station \( j \) during time interval \( t \) by staff vehicle \( v \), 0 otherwise.
- \( u_{vj} \in \{0,1\}, \forall v \in \mathcal{NSV}, j \in \mathcal{J}, t \in \mathcal{T} \): binary variables, 1 if relocation staff moves to station \( j \) during time interval \( t \) by staff vehicle \( v \), 0 otherwise.

Using the above set and variables, constraints (4), (5), (6), (8), (16), (17), (18) and (19) are replaced by (30), (31), (32), (33), (34), (35), (36) and (37), respectively.

\[
\sum_{j \in \mathcal{J}} m_{sj\text{fin}_s} + r_{sj\text{fin}_s} + \sum_{v \in \mathcal{NSV}} p_{svj\text{fin}_s} = v_s \forall s \in \mathcal{S} \tag{30}
\]
According to the situation, we also modify the objective function (1) which maximizes the total daily profit including revenues from users’ served trips, personnel costs of relocation staff, and relocating and moving costs (cost of fueling the staff vehicle) between clusters, as follows:

\[
\max \sum_{i \in I} P_i z_i - \sum_{s \in S} PC_s v_s - \sum_{s \in S} \sum_{b \in B} \sum_{t \in \{\text{begin}_s, \ldots, \text{fin}_s\}} R\bar{C}_{btd} \bar{p}_{svbdt} - \sum_{s \in S} \sum_{b \in B} \sum_{t \in \{\text{begin}_s, \ldots, \text{fin}_s\}} \sum_{v \in NSV} MC_{btd} \bar{p}_{svbdt}
\]

(38)

4.4.2 Results

As in section 4.2.1, we assumed a 1.5 times total demand and regenerated trips from the average 1.5 \times \lambda^h_j.

We set the premium service demand ratio \( p \) for randomly picking the trips as 1/6, the starting fare as ¥300, and the total number of relocation staff to 5.

As the number of staff vehicles increased, the calculation time to obtain an optimal solution became quite long, and we terminated each run at 5000 seconds. Table 5 shows the results for the cases of one,
two, and three vehicles. Profit, personnel costs, relocation and moving costs are indicated by the ratio when the actual operation result is 1. For one vehicle, each number is the average of 49 runs excluding 1 run for which a feasible solution was not obtained within 5000 seconds. For the cases of two (three) vehicles, each number is the average of 47 (48) times excluding 3 (2) runs.

We also performed runs with a premium service demand ratio of \( p = \frac{1}{3} \) and two staff vehicles, but for 17 runs, no feasible solution could be obtained within 5000 seconds and for the remaining seven runs, no reasonable objective function values were found. Therefore, we will not discuss those results here.

<table>
<thead>
<tr>
<th>Table. 5: Increase in the number of staff vehicles for premium service demand ratio of ( p = 1/6 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of staff vehicles</td>
</tr>
<tr>
<td>Satisfied demand ratio [%]</td>
</tr>
<tr>
<td>Premium service</td>
</tr>
<tr>
<td>Standard service</td>
</tr>
<tr>
<td>Number of staff working</td>
</tr>
<tr>
<td>Number of vehicles used</td>
</tr>
<tr>
<td>Number of relocations</td>
</tr>
<tr>
<td>Profit ratio compared with actual</td>
</tr>
<tr>
<td>Revenue ratio</td>
</tr>
<tr>
<td>Personnel costs ratio</td>
</tr>
<tr>
<td>Relocation and moving costs ratio</td>
</tr>
<tr>
<td>Computation time [sec]</td>
</tr>
<tr>
<td>Number of variables</td>
</tr>
</tbody>
</table>

The number of relocation operations increases with the number of staff vehicles. As a result, the number of satisfied trip demands increases. Taken alone, this result would allow us to conclude that increasing the number of staff vehicles is effective, but personnel costs and relocation and moving costs would also increase. Thus, we could not confirm a significant increase in profit.

Fig. 20a, 20b, and 20c show diagrams of one-day relocation operations for the cases of one, two, and three staff. The relocation range is almost the same when there are one or two vehicles and the relocations concentrate where demand is the highest (see Fig. 19a). For three vehicles, the range of the relocations is expanded.

### 4.5 Absence of parking-space reservation

As mentioned on page 8 in section 3, parking spaces must be assigned to each trip from the beginning of the trip. The reservation of parking spaces at destinations is important for actual smooth Ha:mo RIDE Toyota operation. However, so far in this study, we have assumed that all users’ trip data for one day are given and that the start and end time intervals of each trip are known. In other words, even if there is no "free" parking space at the arrival station at the start time, there are cases where "free" parking space is available at the end time and which can be computed exactly through optimization. Here, we modify the premium service model in section 4.2 and the autonomous relocation model in 4.3 to omit the constraint for reserving parking spaces at destinations and discuss the effect.

If there is no need for reserving parking spaces at destinations, we can remove constraints (11) and the variable \( n'_{jt} \) for the number of parking spaces at station \( j \) at the beginning of time interval \( t \) from
Fig. 20: Diagram of one-day relocation operation with station clustering

(a) One staff vehicle
(b) Two staff vehicles
(c) Three staff vehicles
constraints (12) as follows:

\[ n_{jt} \leq \text{cap}_j \quad \forall j \in J, t \in T \]  \hspace{1cm} (39)

By making these two modifications to each model, we obtain a modified premium service and autonomous relocation model where the destination parking space is not reserved at the beginning of trips.

### 4.5.1 Results: Premium service

As in section 4.2.1, we assumed a 1.5 times total demand and regenerated trips from the average 1.5 \( \lambda^h_j \). We also set the premium service demand ratio \( p \) for randomly picking the trips as 1/6 and 1/3. The starting fare was ¥300, the total number of relocation staff was 5, and the number of staff vehicles was 1.

We terminated each run at 5000 seconds since the calculation time to obtain an optimal solution became quite long in some cases. Table 6 compares the cases with- and without- parking space reservation constraints when the premium service demand ratio is set to 1/6. Profit, personnel costs, relocation and moving costs are indicated by the ratio when the actual operation result is 1. Each number is the average value of 49 runs excluding 1 run for which a feasible solution was not obtained within 5000 seconds for the case with the parking space reservation constraint.

<table>
<thead>
<tr>
<th>parking space reservation</th>
<th>Yes</th>
<th>No</th>
</tr>
</thead>
<tbody>
<tr>
<td>Satisfied demand ratio [%]</td>
<td>72.0</td>
<td>72.3</td>
</tr>
<tr>
<td>Premium service</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td>Standard service</td>
<td>66.4</td>
<td>66.7</td>
</tr>
<tr>
<td>Number of staff working</td>
<td>1.02</td>
<td>1.04</td>
</tr>
<tr>
<td>Number of vehicles used</td>
<td>75.4</td>
<td>75.2</td>
</tr>
<tr>
<td>Number of relocations</td>
<td>5.30</td>
<td>5.50</td>
</tr>
<tr>
<td>Profit ratio compared with actual</td>
<td>3.16</td>
<td>3.17</td>
</tr>
<tr>
<td>Revenue ratio</td>
<td>1.19</td>
<td>1.20</td>
</tr>
<tr>
<td>Personnel costs ratio</td>
<td>0.370</td>
<td>0.374</td>
</tr>
<tr>
<td>Relocation and moving costs ratio</td>
<td>0.278</td>
<td>0.285</td>
</tr>
<tr>
<td>Computation time [sec]</td>
<td>1071.8</td>
<td>891.3</td>
</tr>
<tr>
<td>Number of variables</td>
<td>126366.5</td>
<td>114452.7</td>
</tr>
</tbody>
</table>

Table 7 compares results for cases with- and without- parking space reservation constraints when the premium service demand ratio is set to 1/3. Each number is the average of 39 runs, excluding 11 runs for which a feasible solution was not obtained within 5000 seconds for the case with a parking space reservation constraint.

In both cases, removing the parking space reservation constraints slightly increased the satisfied demand ratio of the premium service to that of the standard service and the profit ratio compared with the cases in which a parking space reservation is required. The changes were small, although significant decreases (about 15%) in calculation time were observed. These results suggest that the parking space reservation constraint is not so severe a restriction in terms of profit, but that it does have a severe effect on the optimization calculation under our settings.
### Table 7: Premium service without parking space reservation requirement ($p = 1/3$)

<table>
<thead>
<tr>
<th>parking space reservation</th>
<th>Yes</th>
<th>No</th>
</tr>
</thead>
<tbody>
<tr>
<td>Satisfied demand ratio [%]</td>
<td>73.4</td>
<td>73.5</td>
</tr>
<tr>
<td>Premium service</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td>Standard service</td>
<td>60.0</td>
<td>60.2</td>
</tr>
<tr>
<td>Number of staff working</td>
<td>1.69</td>
<td>1.56</td>
</tr>
<tr>
<td>Number of vehicles used</td>
<td>72.2</td>
<td>75.3</td>
</tr>
<tr>
<td>Number of relocations</td>
<td>6.80</td>
<td>6.70</td>
</tr>
<tr>
<td>Profit ratio compared with actual</td>
<td>3.06</td>
<td>3.14</td>
</tr>
<tr>
<td>Revenue ratio</td>
<td>1.26</td>
<td>1.26</td>
</tr>
<tr>
<td>Personnel costs ratio</td>
<td>0.500</td>
<td>0.474</td>
</tr>
<tr>
<td>Relocation and moving costs ratio</td>
<td>0.376</td>
<td>0.367</td>
</tr>
<tr>
<td>Computational time [sec]</td>
<td>3112.9</td>
<td>2627.6</td>
</tr>
<tr>
<td>Number of variables</td>
<td>126330.3</td>
<td>114450.3</td>
</tr>
</tbody>
</table>

#### 4.5.2 Results: Autonomous relocation

Here, we discuss the results for when parking space reservation constraints are removed from the autonomous relocation model in section 4.3. We assumed a 1.5 times total demand and regenerated trips from the average $1.5 \times \lambda h^k$.

Tables 8a and 8 compares results for cases with- and without- parking space reservation constraints when the trip duration is five times (walking speed) and fifty times (super slow), respectively. Profit, personnel costs, relocation and moving costs are indicated by the ratio when the actual operation result is 1. Each number is the average value of 50 runs.

For both cases, removing the parking space reservation constraint increased the satisfied demand ratio slightly. The changes were small, but there were significant decreases (about 16%) in calculation time. Similarly to the case of the premium service, the parking space reservation constraint may be not so severe a restriction in terms of profit, but it may have severe effects on the optimization calculation in our autonomous relocation settings.

#### 5 Conclusion

We developed an optimization model specialized for last-mile mobility, short-trip one-way carsharing. The model reflected the characteristics of last-mile mobility that requires both vehicles and parking spaces to be reserved and vehicles to be relocated by using a team in staff vehicles. In addition, we improved the station clustering algorithm by reducing its computational complexity.

We applied the developed model to five different cases, in combination with the improved station clustering. The first case, Ha:mo RIDE, revealed that the characteristic short trips did not generate enough additional revenue to cover relocation costs. The optimal solution to maximize the operator’s profit was cutting relocation personnel costs, which would result in dissatisfaction and long-term customer defection. The operator must relocate vehicles not for profit, but for customer retention. The second case, “Premium Service,” which guarantees rides in return for price premiums, could not resolve the

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issue; low demand for the new service led to not enough premiums to cover relocation costs, while high demand was infeasible due to shortage of resources, even when assuming that the whole-day demand was given in advance. The third case, autonomous relocation by low-speed self-driving, showed the prospect for low-cost operation together with high demand satisfaction. Even driving at 1/10th of walking speed satisfied almost 1.5 times the demand that can be expected in actual use. The workforce case, i.e., increasing the number of staff vehicles, showed that by increasing the number of staff vehicles, the satisfied demand ratio increased, but personnel costs and relocation and moving costs also increased. Thus, we could not confirm a significant increase in profit in this case. The results for the fifth case, removing the parking space reservation requirement, implied that, in both premium service and autonomous relocation settings, removing parking space constraints may not be so severe from the viewpoint of raising profit, but it may be rather severe from the viewpoint of the optimization calculation.

Although we assumed that autonomous relocation was available at all stations, this assumption would face challenges, due to regulations, different road environments, etc., in an actual implementation. To demonstrate the effect of autonomous relocation, the first step should be a small-scale field test in a limited area, like a small valet parking. The 5th Science and Technology Basic Plan of the Japanese government \[13\] calls for implementations in specific areas such as the Tsukuba Mobility Robot Experimental Zone.

We assumed the demand for the whole day was given at the beginning of the day, but actual demand is at the earliest 30 minutes before a ride. In addition, we generated demand samples from the 1-year average demand and ignored the deviations. Incorporating a mechanism for dealing with short-notice demand with deviations will be one of the biggest challenges facing an actual implementation. One idea to deal with it is combining long-term estimation and short-term modification. We observed substantial deviations in seasonal demand. Perhaps previous uses such as commuting in the morning can explain the trend. Or perhaps weather, day of the week, or other events can be explanatory variables.
Another research idea is adaptive pricing, which has been studied in Ha:mo RIDE but is not implemented yet. Appropriate pricing in combination with autonomous relocation can balance demand for vehicles and parking space supply and increase profit.

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