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RESEARCH ARTICLE

Simulation Analysis on Benefits of Introducing Meeting Points Into On-Demand Shared Mobility Services

RYO NISHIDA^{1,3}, RYO KANAMORI², MASAKI ONISHI³, ITSUKI NODA⁴, AND KOICHI HASHIMOTO¹, (Senior Member, IEEE)

¹Graduate School of Information Sciences, Tohoku University, Sendai 980-8579, Japan

²Institutes of Innovation for Future Society, Nagoya University, Nagoya 464-8601, Japan

³Artificial Intelligence Research Center, National Institute of Advanced Industrial Science and Technology, Tokyo 100-8921, Japan

⁴Graduate School/Faculty of Information Science and Technology, Hokkaido University, Sapporo 060-0808, Japan

Corresponding author: Ryo Nishida (ryo.nishida.t4@dc.tohoku.ac.jp)

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ABSTRACT We investigate the benefits of introducing meeting points (MPs) into on-demand shared mobility services (OSMS). OSMS generally provide door-to-door transportation between passengers' origins and destinations. In addition, services using specific pick-up/drop-off locations, which are called as MPs, are also deployed. The operational efficiency of OSMS could be improved by asking passengers to walk to an MP. Previous studies have found that the introduction of MPs can improve operational efficiency in terms of the number of vehicles, the vehicle kilometers traveled (VKT), and the rejection rate of passengers' requests. However, the travel time of passengers (i.e. passenger convenience) has not been sufficiently explored. The introduction of MPs may reduce the average travel time of passengers by reducing the number of detours. We conduct a static analysis under simple settings, and a simulation analysis using actual road network data. The effects of the introducing MPs are evaluated via various configurations such as MP locations, the number of passengers' requests, the number of vehicles, and vehicle capacity. Results showed that the introduction of MPs reduces VKT as well as average travel time of passengers when the number of demands is greater than 200 per hour in the same conditions on service provider.

INDEX TERMS Agent-based simulation, meeting points, on-demand shared mobility services, ride-sourcing.

I. INTRODUCTION

As smartphones are becoming prevalent and the accuracy of location-information data improves, on-demand mobility services, such as Uber, Lyft, and DiDi, are becoming more common. On-demand mobility services allow passengers to move from their current locations to their destinations. They make trips of passengers more convenient than conventional public transportation such as railways and buses. Furthermore, the population of elderly people is increasing in some countries, and the elderly are required to return their driver's

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licenses. Therefore, the number of people who are unable to travel conveniently is likely to increase in the near future, and on-demand mobility services are expected to provide for their mobility. However, the shift to on-demand mobility services by former public transit users and private vehicle users has increased the number of service vehicles and caused congestion. [11], [22].

On-demand shared mobility services (OSMS), such as UberPOOL (recently, called UberX Share), Lyft Shared, and Via, are viewed as more appropriate than others. OSMS can be operated with a small number of vehicles, thereby mitigating congestion caused by on-demand mobility services. In 2017, UberPOOL operated in 36 cities, and Lyft Shared

was used in 16 cities in the United States [19]. OSMS can transport multiple passengers who move to similar destinations and routes at a time. OSMS serve as both a “bus” that can carry many passengers and a “taxi” that can move flexibly. It may take a longer travel time than for a regular taxi due to the detours of shared passengers. On the other hand, the fare is cheaper than a regular taxi. One vehicle can carry multiple passengers, so operating costs can be reduced as well as congestion.

Researchers have analyzed the effects of OSMS, that is, the effectiveness of sharing, but only few studies have used actual usage data. Generally, a small amount of OSMS data is available, and the specific impact of OSMS cannot be quantified [16], [19]. The only research in which actual data were used was that of Li et al. who analyzed DiDi’s operation data [13]. From their findings, OSMS saved an average of 22% on vehicle hours traveled compared with regular taxis. However, passengers’ average travel time and travel distance increased by 30% (10 [min]) and 15% (1.5 [km]), respectively. They stated that the usage rate of OSMS was as low as 6%-7% due to reduced passenger convenience. Other studies based on simulations suggested that OSMS improve operational efficiency. For example, Sun et al. used taxi-usage data in Washington, D.C. to compare taxi trips with simulated OSMS trips [21]. From their findings, total vehicle hours traveled decreased by 18% if passengers were willing to increase their travel time by an average of 25% and four passengers share a vehicle.

OSMS improve operational efficiency but increase the travel time of passengers. Because OSMS are generally door-to-door (D2D) services that transports passengers from their current locations to their destinations. It causes detours, one-way streets, traffic jams, and so on, extending the travel time of passengers [5], [10]. This is undesirable for both the operator and passengers.

Recently, meeting points (MPs)-based OSMS have been developed. MPs-based OSMS allow passengers to walk near specific pick-up/drop-off points (MPs), as shown in Fig. 1. The benefits of introducing MPs are as follows [5].

- *Operational efficiency*: Services can be established with fewer vehicles and shorter VKT by reducing the number of extra detours. More passengers’ requests (hereafter, passengers’ requests are termed as demands) can be handled under the same setting.
- *Passengers convenience*: When multiple passengers are riding simultaneously, the total travel time may be reduced because fewer stops are required.
- *Safety*: Pick-up and drop-off on residential roads can cause accidents. Placing MPs on arterial roads and parking lots makes pick-up and drop-off safe.
- *Health*: Incorporating walking into a trip can be seen as a healthier and more sustainable mobility service.
- *Privacy*: Because passengers are not picked up and dropped off at their actual origin and destination, their home or workplace addresses are not revealed.

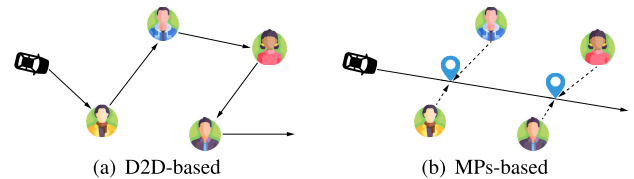


FIGURE 1. Illustration of the differences between D2D-based and MPs-based OSMS.

- *Easier rendezvous*: In D2D, the driver and passengers cannot identify each other’s location easily. By clearly defining the meeting place, drivers can easily recognize passengers’ boarding and destination and passengers can easily recognize the location of the vehicle.

Previous studies have demonstrated that the introduction of MPs into OSMS can improve operational efficiency from the perspectives of the number of vehicles, VKT, and the rejection rate of demands [5], [8]. However, the benefits in terms of passenger convenience have not been thoroughly investigated. OSMS increase the travel time of passengers more than non-shared services, and the introduction of MPs mandates passengers to walk. Therefore, some companies have attempted to address these issues by discounting the fare. For example, Uber offers MPs-based OSMS, called Uber ExpressPOOL, which is 25% lower than UberPOOL [7].

In this study, we examine the impact of the introducing MPs into OSMS on the travel time of passengers by asking the question: “Is there any possibility that the introduction of MPs will shorten the travel time of passengers?” Intuitively, as the number of passengers increases, the average travel time of passengers will be shorter if passengers are picked up and dropped off at MPs rather than using D2D-based services. It is crucial to determine whether there is an advantage in terms of the travel time of passengers, and if so, under what conditions can it be achieved.

We evaluate the introduction of MPs in terms of operational efficiency and passenger convenience through agent-based simulations. First, we compare D2D-based OSMS with MPs-based one, which mandates passengers to walk to MPs. Moreover, we analyze the benefits of introducing MPs and the conditions under which those benefits occur in synthetic and static situations. This is called static analysis because all requests are generated at the same time and no sequential route optimization. Then, we conduct a simulation analysis on the basis of the hypotheses obtained from the static analysis. This is an agent-based simulation, where requests are generated each time, and vehicle allocation route optimization is performed dynamically. In the simulation analysis, we use actual road network and demand data to verify the benefits of introducing MPs. Simulations were performed by varying parameter combinations such as MP locations, the number of demands, the number of vehicles, and vehicle capacity.

The remainder of this paper is organized as follows. Section II reviews the literature related to MPs; Section III describes the static analysis; Section IV explains the configuration of the simulator used in our simulation analysis and a

vehicle assignment algorithms; Section V describes the setup and results of the simulation analysis; finally, Section VI summarizes the study, along with future works.

II. LITERATURE REVIEW

In this section, we review the literature related to MPs-based OSMS (on-demand shared mobility services).

According to Czioska et al. [5], most studies on MPs assumed a ride-sharing case. Each driver has their origin and destination and does not act as a service provider. The popular study by Stiglic et al. have reported that introducing MPs in a setting with one driver and multiple passengers improves the number of matches and reduces the total VKT [20]. Subsequently, many variations have been studied, such as the recommendation of MP locations in long-distance ride-sharing [6], allocation-route optimization when MPs are included in ride-sharing [4], and optimization of MP locations in ride-sharing situations when passengers do not reveal their origin and destination for privacy reasons [2].

Zheng et al. analyzed the effect of introducing MPs on Flex-route buses [24], where routes between bus stops are not fixed and can be changed flexibly within the constraints of the timetable at bus stops. Timetable constraints of bus stops sometimes reject some demands. Zheng et al. attempted to solve this problem by introducing MPs into Flex-route buses. MPs are installed in the area between bus stops. Passengers are picked up and dropped off at either bus stops or MPs. They formulated this problem as a two-stage optimization problem. First, demand rejection is determined, and then, the route is optimized. An experiment using an artificial map shows that the demand rejection rate decreases with the introduction of MPs. In other words, the number of detours and stops can be reduced by introducing MPs, and more demand can be handled within the time schedule constraints. However, the travel time of passengers is increased. It is noted that the total travel time of rejected passengers was excluded, so there was no direct comparison with D2D-based services.

Few studies have investigated the effects of introducing MPs on OSMS. Czioska et al. proposed bi-level optimization for MP-based OSMS in a setting in which all demands are known in advance [5]. First, demands are clustered on the basis of the origin, destination, and departure time. Then, the demands in each cluster are further divided into subgroups on the basis of the walking distance to MPs and assigned to MPs. Candidate MPs are located at parking lots, train stations, and other locations for easy pick-up and drop-off. In an experiment using a map of the city of Braunschweig, Germany, MPs-based OSMS improved operational efficiency in terms of the number of vehicles, vehicle hours traveled and VKT; however, the travel time of passengers was increased. This is consistent with the results of Stiglic et al. for simple ride-sharing. The reason for the increase in passenger travel time is that passengers have to walk to an MP and wait for other passengers to arrive at the MP.

Czioska et al. assumed a static situation in which the demand is known in advance, but Fielbaum et al. investigated

the optimization of routes for MP-based OSMS in dynamic situations [8]. Passengers can move to their desired pick-up and drop-off locations or MPs. The waiting time, walking time, in-vehicle time, and additional waiting and in-vehicle time due to the acceptance of new demands are defined as passenger travel costs. Moreover, the cost of demand rejection is also considered a cost that should minimize. Demand acceptance and routing are optimized to minimize these costs. Experiments using actual maps and demands in Manhattan have shown that introducing MPs improves VKT and reduces the number of rejected trips. The experiment results also show that the passenger cost (including demand rejection) is less in MPs-based OSMS than in D2D-based OSMS. However, since these results depend on the cost definition of demand rejection, it is necessary to compare the travel time of passengers in D2D-based OSMS with that in MPs-based OSMS in a setting where all demands are accepted. In addition to reducing VKT, it has also been reported that the introduction of MPs can reduce congestion at curbsides [9] and noise [25].

In summary, studies on introducing MPs into OSMS and similar studies have confirmed operational efficiency improvement in terms of the number of vehicles, VKT, and demand rejection rate. However, the benefits to passengers are unclear. Therefore, the purpose of this study is to investigate the benefits of introducing MPs from the perspective of not only operational efficiency but also passenger convenience, especially travel time.

III. STATIC ANALYSIS

This section analyzes the effect of introducing MPs in a static situation.

A. SETTING

As shown in Fig. 2, we consider a trip between two areas. There is only one vehicle and no capacity constraint. All passengers request a trip simultaneously, and they go in the same direction (from left to right). In D2D-based OSMS, a vehicle moves through the origin and destination of each passenger. In MPs-based OSMS, passengers walk to an MP, board and alight a vehicle at an MP, and then walk to their respective destinations. The passengers' travel time is equal to the time it takes to arrive at their respective destinations because they call a vehicle simultaneously. In this analysis, we compare the average travel time of passengers in D2D-based OSMS with that in MPs-based OSMS and examine the effect of introducing MPs. In the case of a three-area trip, passengers board a vehicle at the first MP and alight at the second or third one.

D2D-based OSMS route is calculated by solving an optimization problem formulated as a 0-1 integer programming problem similar to the traveling salesman problem. Let $G = (V, E)$ be a graph consisting of a node set V and an edge set E connecting each node. Let the number of passengers be n . Let V be a node set of node 0 representing the initial position of the vehicle and nodes $\{1, 2, \dots, 2n\}$ representing the pick-up and drop-off locations of each passenger. The

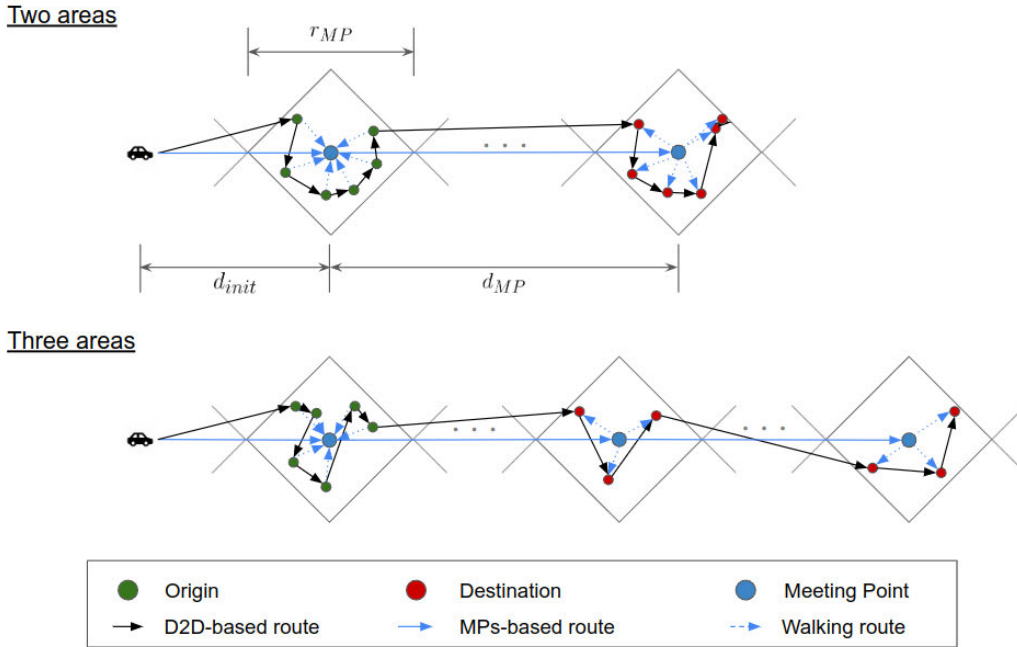


FIGURE 2. Static analysis situations.

edge-connecting nodes i and j are denoted as $e_{ij} \in E$. The travel cost between nodes i and j is c_{ij} , where the Manhattan distance is used to account for the structure of the road. Let x_{ij} be the decision variable to be optimized. It is set to 1 if the vehicle passes through the edge e_{ij} ; otherwise, it is set to 0. From the above explanation, the optimization problem formulation to search for D2D-based OSMS route is as follows.

$$\min \sum_{(i,j) \in E} c_{ij} x_{ij} \quad (1)$$

subject to

$$\sum_{i \in V, i \neq j} x_{ij} = 1 \quad \forall j \in V \setminus \{0\} \quad (2)$$

$$\sum_{j \in V \setminus \{0\}} x_{0j} = 1 \quad (3)$$

$$\sum_{i \in V, i \neq j} x_{ij} - \sum_{i \in V} x_{ji} = 0 \quad \forall j \in V \quad (4)$$

$$\sum_{(i,j) \in E, i \neq j} x_{ij} \leq |S| - 1 \quad S \subseteq V \setminus \{0\} \quad (5)$$

$$x_{ij} \in \{0, 1\} \quad \forall (i, j) \in E \quad (6)$$

where Eq. 1 represents the objective function to minimize the travel cost of a vehicle. Eq. 2 is the constraint that the vehicle visits each passenger location only once. Eq. 3 is the constraint that the vehicle starts from an initial location. Eq. 4 is the constraint that the number of vehicle coming to a passenger location is the same as that leaving that location. Eq. 5 is a sub-tour elimination constraint. The sub-tour S is a round tour that returns to where the vehicle starts without visiting all the points, and is a set consisting of combinations

of nodes that do not contain a depot. Eq. 6 is a constraint on the decision variables. Note that a constraint to remove routes such that the vehicle goes to drop-off locations before the passenger's pick-up locations is excluded in the formulation. Such routes are removed from the candidate solutions automatically during the optimization process because they do not minimize the cost.

Furthermore, we describe the specific setup. The number of passengers is $n = \{1, 2, \dots, 15\}$. In the three-area trip, $n = 1$ is the same as in the two-area case, so $n = \{2, \dots, 15\}$. We define a walking speed of 3 [km/h] as assumed for elderly users because OSMS is assumed to replace private cars as transportation for the elderly. Additionally, let the vehicle speed be 30 [km/h]. The size of the rhombus determines how far passengers should walk to/from an MP and is $r_{MP} = \{200, 400\}$ [m]. The r_{MP} is also the interval between MPs. We chose this setting because bus stops are generally 300-500 [m] apart. In other words, if $r_{MP} = 200$ [m], passengers will walk up to 100 [m] to the MP. The distance d_{init} from the initial position of the vehicle to the first MP is set to $\{1, 2\}$ [km], depending on r_{MP} . This is the same distance that a vehicle can travel in the time it takes a passenger to walk $\{100, 200\}$ [m], and it is set to prevent the vehicle from departing before the passengers farthest from the MP in the rhombus arrive. In the two-area trip, the distance d_{MP} between the first and second MPs is set to 2 [km], and in the three-area trip, it is set to 1.5 [km].

The vehicle stop time includes the acceleration/deceleration time and passenger pick-up/drop-off time. Since the acceleration/deceleration time is 11 [s] in a previous study [12], we assume that it takes an additional 5.5 [s] each to stop and start the vehicle at the pick-up/drop-off point. In addition,

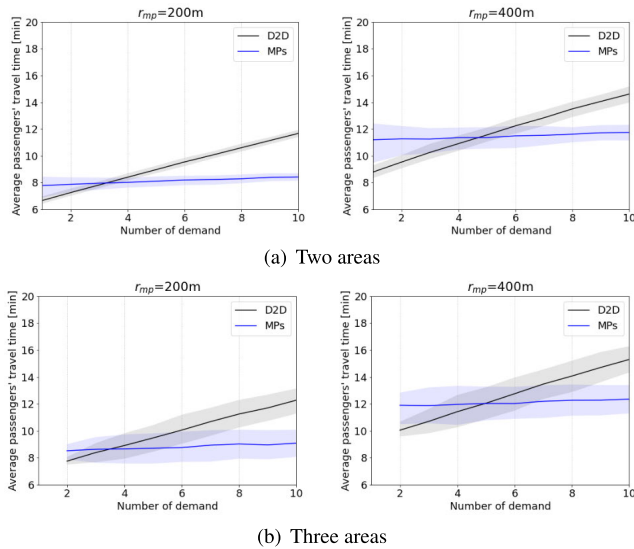


FIGURE 3. Average travel time of passengers in D2D-based and MPs-based OSMS.

according to the same study [12], the passenger pick-up and drop-off times are proportional to the number of passengers, n_{ba} , and each is assumed to be $5 + 2.75n_{ba}$ [s].

From the above information, we compare the average travel time of passengers in D2D-based and MPs-based OSMS using varying n and r_{MP} . Passengers' origin and destination locations are generated randomly within the rhombus, and an average of 200 calculations are performed for the comparison. D2D-based OSMS route optimization is modeled using PuLP, a Python optimization library, and the CBC solver is used for optimization.

B. RESULTS

The results for the two-area trip are displayed in Fig. 3(a). Each graph corresponds to $r_{MP} = \{200, 400\}$ [m], respectively. The solid line represents the average value, and the widths represent the maximum and minimum values in 200 trials. Specifically, when $r_{MP} = 200$ [m], four or more passengers are picked up and dropped off at the MP; when $r_{MP} = 400$ [m], five or more passengers are picked up and dropped off at the MP, the average travel time of passengers becomes shorter in MPs-based OSMS than in D2D-based one. The same results are obtained for the three-area trip (Fig. 3(b)). The VKT is reduced when the pick-up and drop-off locations are aggregated at one MP.

We found that the introduction of MPs reduces the VKT and, if the number of demands n exceeds a certain number, the average travel time of passengers in MPs-based OSMS is shorter than that in D2D-based OSMS. Since, in this static analysis, there is one vehicle and all passengers ride together, n represents the number of shared passengers. Therefore, in other words, the introduction of MPs reduces the average travel time of passengers if the number of shared passengers is greater than a certain number.

However, there are limitations to this static analysis.

- Demands are generated in the same one direction simultaneously. However, in the real world, trips are requested from various directions at various times, so it is difficult to share rides.
- Passengers wait for other to arrive. In this static analysis, passengers are assumed to wait until other passengers arrive at the aggregation MP. However, waiting for other passengers is not typically considered in a case without a timetable because it would negatively affect convenience.
- The capacity of a vehicle. Although more passengers boarding/alighting a vehicle at an MP simultaneously reduces their average travel time, depending on the vehicle capacity, the effect may not be seen.

In the real world, MPs-based OSMS charge a smaller fare than D2D-based OSMS because of reduced passenger convenience caused by the condition requiring passengers to walk to MPs. For example, Uber charges 25% less for UberExpressPOOL (i.e. MPs-based OSMS) than for UberPOOL (i.e. a regular D2D-based OSMS). Therefore, when evaluating the effect of MPs introduction on passenger convenience, it is better to include the fare in the analysis.

IV. SIMULATION ANALYSIS METHOD

The static analysis shows that the introduction of MPs shortens the VKT and, reduces the average travel time of passengers more in MPs-based OSMS than in D2D-based OSMS if the number of shared passengers exceeds a certain number. However, the static analysis has the above-mentioned limitations, thus further analysis in a more realistic setting is needed. In addition, several configurations such as the locations of MPs, the number of vehicles, and vehicle capacity, should be adjusted to create conditions under which the average travel time of passengers can be reduced. Among the combinations of these configurations, we want to determine conditions that improve operational efficiency and passenger convenience. Therefore, we perform agent-based simulation analysis.

A. SIMULATOR CONFIGURATION

The configuration of the simulator is shown in Fig. 4. Passengers and vehicles are treated as agents, and the simulator represents the traffic conditions of the day. It consists of network data, passenger models, and vehicle models. The network data consist of nodes and links. Nodes are intersections and links are roads connecting nodes. The passenger model is used to calculate the utility (convenience) of trips.¹ The utility calculation method is described in Appendix A. The vehicle movement is simulated using the traffic simulator Simulation of Urban Mobility (SUMO) [14].

B. ALLOCATION METHOD

The vehicle agent moves in accordance with the optimized route by using the successive best insertion method proposed

¹In the future, we plan to incorporate the choice model of transportation modes or D2D- and MPs-based OSMS.

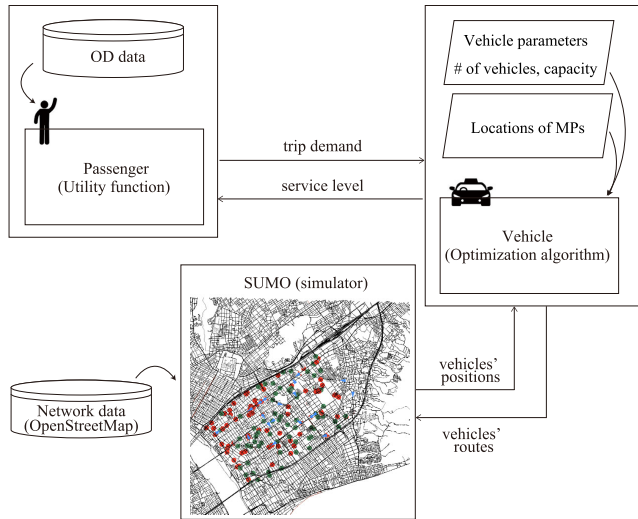


FIGURE 4. Configuration of our simulator.

by Noda et al. [18]. This algorithm is adopted in SAVS (Smart Access Vehicle Service) [1], which is one of the OSMS provided in Japanese cities. Although many optimization algorithms have been proposed, such as [3], the object of this study is not to validate optimization algorithms. Moreover, this algorithm leads to a quasi-optimum, and we believe that the tendency of the simulation is not different from that of using an algorithm that leads to a fully optimal solution.

The centralized system has information on the current demand and the location of vehicles and performs vehicle allocation and route optimization each time a demand generates, based on the following constraints. An illustration of the successive best insertion method is shown in Fig. 5.

- The vehicle v that accepts the new demand d does not change the order of pick-up and drop-off of the already accepted demand $d' \in D_v$ but inserts the pick-up and drop-off of the new demand.
- Each demand has a time constraint for pick-up and drop-off, and vehicles are allocated to satisfy the time constraint. When a new demand is generated, the vehicle shall be allocated so that the time constraints of the existing demand are not exceeded.
- The allocation of vehicles v is determined in such a way that for each new demand d accepted, the travel time of the new demand $t_{travel}^{d,v}$ and the total delay time for the existing demand $t_{delay}^{d',v}$ are minimized (Eq. 7).

$$\arg \min_v t_{travel}^{d,v} + \sum_{d' \in D_v} t_{delay}^{d',v} \quad (7)$$

Note that for t_{travel} and t_{delay} , the travel time is obtained by dividing the Manhattan distance between two points in the pick-up and drop-off sequence by the average vehicle speed, in this study, it is 30 [km/h]. To account for the structure of the road, we use the Manhattan distance.

Each demand has a time constraint for pick-up and drop-off, and the time constraint is calculated at the time the

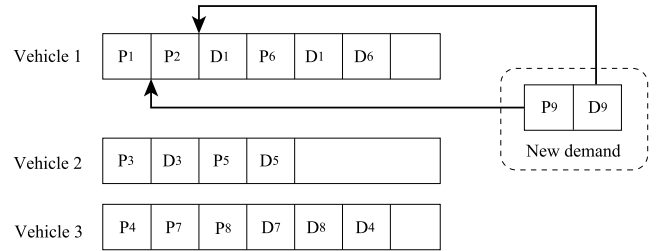


FIGURE 5. Illustration of the successive best insertion method for real-time OSMS.

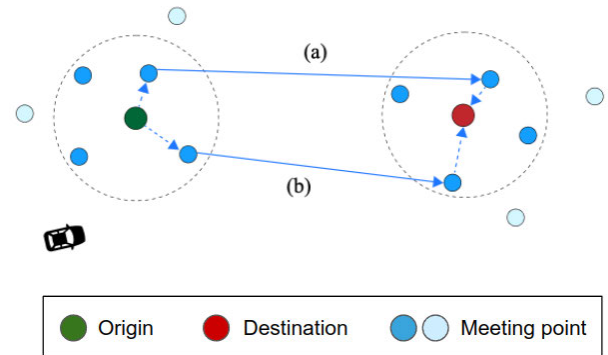


FIGURE 6. Illustration of MP selection.

demand is generated. In D2D-based OSMS, a time constraint is set for drop-off so that it is not faster to travel on foot. In MPs-based OSMS, it is assumed that passengers are picked up and dropped off at MPs. Moreover, as a pick-up time constraint, the vehicle does not arrive at an MP before passengers arrive at that MP. The constraint on the drop-off time is the same as in D2D-based OSMS.

In addition, the selection of MPs also affects operational efficiency and passenger convenience. For example, in the case shown in Fig. 6, if the nearest MP is used, the passenger would take route (a) every time. However, depending on the location of the vehicle, it may be better to use route (b) even though it may require a longer walk. Therefore, in MPs-based OSMS, when a demand is generated, four MPs around the origin or destination are searched, and the successive best insertion method is used to optimize the allocation for each of the 16 route patterns (4×4). The pattern with the lowest cost among the 16 patterns is selected. This MP selection is expected to improve vehicle operating efficiency and passenger convenience. A comparison of the case with the closest MP and the case with MP selection is mentioned in the Appendix B.

C. SIMULATION FLOW

The simulation flow is as follows.

- 1) Input service configurations such as the locations of MPs, the number of vehicles, and vehicle capacity.
- 2) A passenger requests a trip (a demand) following the OD data representing the passenger's origin, destination, and departure time.

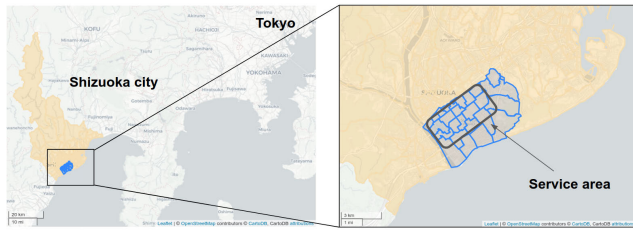


FIGURE 7. Map of Shizuoka City. The service area is highlighted in the gray square. The zones delimited by the blue line are the aggregation zones used in the Person Trip Survey.

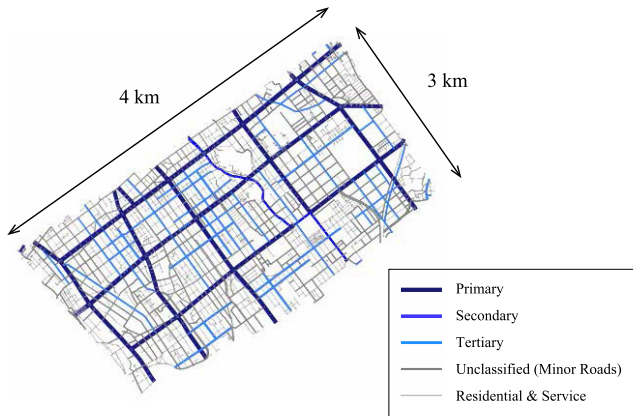


FIGURE 8. Network and road types (Source: OpenStreetMap).

- 3) The current vehicle location is obtained from SUMO, and the vehicle allocation is optimized.
- 4) The vehicle agent moves on SUMO following the optimized route.
- 5) Steps 2 to 4 are repeated until all passenger demands have been attended to.
- 6) Return various indices related to operational efficiency and passenger convenience.

V. EXPERIMENT

We examine the effects of MPs introduction on operational efficiency and passenger convenience using real maps and demand data. We explain the actual data, service configurations, and the results.

A. DATA

We focus on the area south of central station (Shizuoka Station), Shizuoka City, shown in gray in Fig. 7.² Fig. 8 shows the road network in the service area, consisting of 4,045 nodes and 9,257 links. The average link length is 43.8 [m]. The area is 3 [km] long and 4 [km] wide. The edge colors in Fig. 8 correspond OpenStreetMap way tags.

We use the Person Trip Survey (a kind of Household Travel Survey) conducted in 2012 as source data to generate passenger demands. The survey asked citizens to respond to a questionnaire, which included their characteristics (e.g., age

²In this area, the local government and some companies have frequently conducted demonstration tests of new mobility services such as OSMS and MaaS (Mobility as a Service).

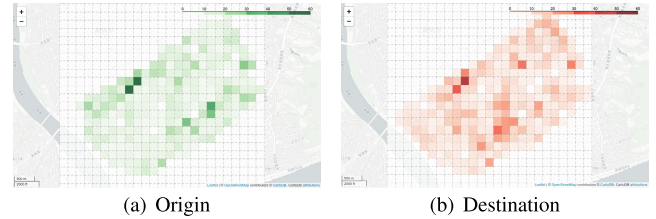


FIGURE 9. Origin and destination distributions of peak time (4 P.M.) demand.

and gender), the purpose of travel, places of origin and destination, time of travel, and travel mode. The origin and destination points were aggregated by the zones shown in Fig. 7. We select travels by public transportation (bus, taxi) and/or private cars as potential candidates of OSMS users. We also omit trips within the same zone and trips of less than 1 [km] travel distance.

From the Survey, the most frequently traveled hour was 4 P.M. The total number of demands at 4 P.M. is 2,038. Fig. 9 shows the distributions of origin (a) and destination (b) at 4 P.M. The color intensity indicates the number of origins and destinations within a 200 [m] mesh; the mesh with the highest concentration of origins is located at the central station. The same mesh is also a highly concentrated area on the destination map. Another highly concentrated mesh in the destination map is located southeast of the station, which is a shopping mall zone.

To verify the result of the static analysis, we perform simulations with varying the numbers of demands. The static analysis indicates that the average travel time of passengers is shorter in MPs-based OSMS than in D2D-based OSMS when the demand exceeds a certain level. we define the number of minutes of starting the travel for each demand by uniformly sampling between 0 ~ 59 because the Person Trip Survey does not record the start time of the travel in minutes. Then, from the 2,038 demands at 4 P.M., we randomly sample 50, 100, 200, 500, and 1,000 demands. To obtain robust results, we sample the demand and run a simulation with it for 100 times for each demand pattern. Note that the demand for travel by taxi, bus, and private cars for elderly persons aged 65 and over at 4:00 p.m. is approximately 500.

B. SETTINGS

To demonstrate the effects of MP in real-world scenarios, we need to carefully select the parameters of MPs and OSMS. Especially, the locations of MPs, the number of vehicles, and vehicle capacity are three key parameters reflecting the real features of the OSMS with MPs.

Locations of MPs depend on two parameters: the average interval between MPs and the categories of road edges where MPs are located. For the average interval, we use 200 [m] and 400 [m] in the experiments. The value 400 [m] reflects a setting similar to typical bus services with stops spaced 300 to 500 [m] apart. The value 200 [m] is the case that OSMS with MPs provide more convenient services than the bus services. We suppose that shorter MP intervals will

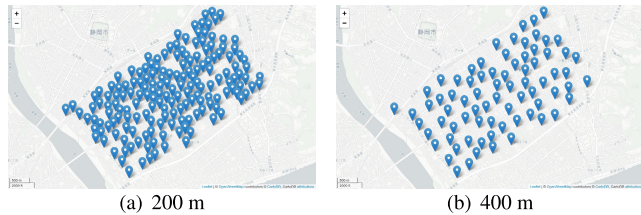


FIGURE 10. Locations of MPs.

reduce the cost of walking for passengers. For the categories of road edges, we choose only “primary,” “secondary,” and “tertiary” edges in OpenStreetMap data, excluding residential and minor edges, because frequent traffic on such minor roads tends to cause accidents. It has also been reported that on-demand services often travel on residential roads [11]. Finally, we determine the MPs as follows: Collect midpoints of the primary/secondary/tertiary edges and choose a subset of them as MPs with their intervals greater than 200 [m] and 400 [m]. Fig. 10 shows MP locations. The number of MPs for 200 [m] and 400 [m] intervals is 175 and 77, respectively.

We find the minimum fleet sizes that avoid any rejections. In other words, find the minimum number of vehicles needed to ensure that travels of all demands are faster than walking. Since the actual minimum number of vehicles depends on the number of demands and the size of the area, we perform 100 simulations for different combinations of the number of vehicles and other parameters and determine the minimum number.

Vehicle capacity affects operational efficiency and passenger convenience. It can be assumed that the VKT and, by extension, the travel time of passengers is reduced by picking up and dropping off passengers at the same MP because D2D detours are avoided. The reduction will be greater as more passengers are picked up and dropped off at the same MP. Larger vehicle capacity will improve the possibility of accepting more passengers at the same MP. In the experiment, 1, 2, 4, and 8 vehicle capacities are tested. A vehicle capacity of 1 assumes an operation of a regular taxi in which passengers don’t share their trip. A vehicle capacity of 2 or 4 indicates the number of passengers that can be accommodated in a regular taxi vehicle. A capacity of 8 assumes the case of a minibus.

The parameters in the simulation, along with other parameters are shown in Table 1. The stop time for pick-up and drop-off is 15 [s], regardless of the number of passengers, and the acceleration/deceleration time uses the default value of SUMO. And the initial locations of all vehicles are Shizuoka Station.

C. RESULTS

The number of vehicles affects operational efficiency and passenger convenience. The number of vehicles required for each demand pattern is shown in Table 2. This table shows that the vehicle capacity has the largest impact on the number of vehicles, followed by MPs introduction. The number of

TABLE 1. Simulation parameters.

Parameter	Value
Number of demands (1 hour)	50, 100, 200, 500, 1000
MP location interval	200, 400 [m]
Vehicle capacity	1, 2, 4, 8 passengers
Stop time for boarding and alighting	15 [s]
Average vehicle speed	30 [km/h]
Maximum vehicle speed	60 [km/h]
Walking speed	3 [km/h]

TABLE 2. Number of vehicles.

Capacity	Type	Number of demands				
		50	100	200	500	1000
1	D2D	6	10	20	40	77
	MPs (200m)	5	9	16	37	70
	MPs (400m)	5	8	15	32	64
2	D2D	5	8	15	34	61
	MPs (200m)	5	7	14	29	56
	MPs (400m)	5	7	12	25	50
4	D2D	4	7	12	26	50
	MPs (200m)	4	7	11	23	41
	MPs (400m)	4	6	10	21	36
8	D2D	4	7	12	26	48
	MPs (200m)	4	7	11	22	38
	MPs (400m)	4	6	10	20	32

vehicles in D2D-based OSMS is reduced by increasing the vehicle capacity from 1 to 2 and from 2 to 4. When demand is low, there is no difference between vehicle capacities of 4 and 8, but when demand is high (1000 demands), there is a difference. The results also show that as the number of demands increases, the reduction in the number of vehicles due to the introduction of MPs becomes more significant.

Here, we discuss the results of D2D- and MPs-based OSMS with the adjusted number of vehicles required for each service (Case 1) and the results of MPs-based OSMS with the same number of vehicles as in D2D-based OSMS (Case 2) (Number of vehicles of D2D-based OSMS in Table 2).

1) VKT

Fig. 11 shows the VKT for each vehicle capacity and demand. The solid line indicates the mean value of 100 simulations, and the width indicates the standard deviation. Since the number of vehicles required is reduced by capacity expansion and the MPs introduction, the VKT is also reduced. The VKT reduction in Case 2 is smaller than in Case 1 because the number of vehicles is the same. However, even when the number of vehicles is the same, the MPs introduction can reduce the VKT.

The larger vehicle capacity and MPs intervals mean that more passengers can be picked up and dropped off at a single MP, leading to fewer detours than in D2D-based OSMS, which is thought to reduce the VKT. In addition, fewer stops due to pick-up and drop-off reduce the demand processing time, allowing for more efficient operation with fewer vehicles. The VKT is also reduced when the vehicle capacity is 1, i.e., when MPs are introduced in a normal taxi operation. This is because passengers walk part of the way between ODS, and

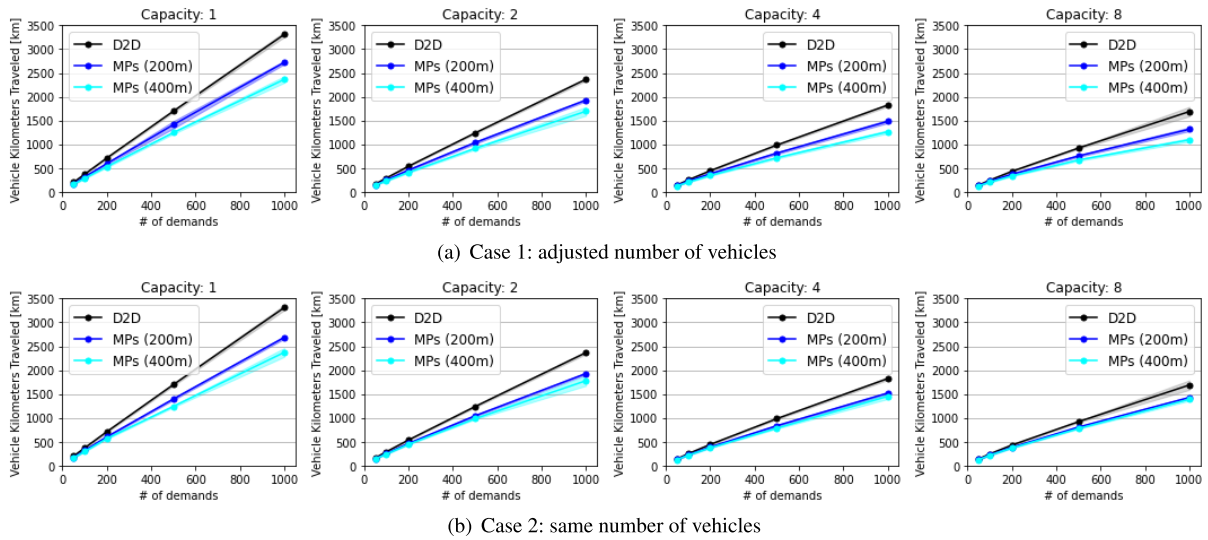


FIGURE 11. Total vehicle kilometers traveled (VKT).

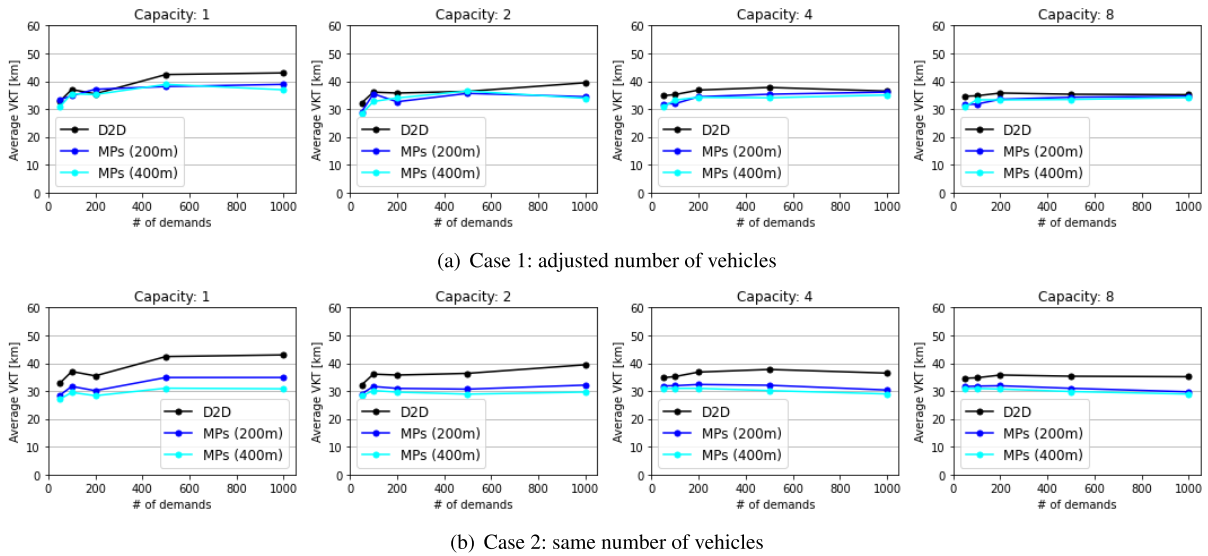


FIGURE 12. Vehicle kilometers traveled (VKT) per vehicle.

since the detour is reduced by passengers are picked up and dropped off at the MPs.

Fig. 12 shows the VKT per vehicle. This figure shows that VKT per vehicle remains the same even as the number of vehicles (number of demand) increases. In addition, the results of Case 2 show that the VKT per vehicle decreases with the introduction of MP. Since there is a trade-off between the number of vehicles and VKT per vehicle, Fig. 11 and Fig. 12 show an inverse relationship.

2) TRAVEL TIME OF PASSENGERS

We define passenger travel time as shown in Fig. 13. In the case of D2D-based OSMS, after passengers request a trip, they wait at the point of departure until a vehicle arrives. They then board the vehicle and travel to their destination.

Therefore, the travel time consists of waiting time and in-vehicle time. In the case of MP-based OSMS, after passengers request a trip, they walk from the departure point to the MP and wait until a vehicle arrives at the MP. Then, after boarding the vehicle and traveling to the MP, the passenger walks to the destination. Therefore, the travel time consists of waiting time, in-vehicle time, and walking time. Fig. 14 shows the average travel time of passengers. This figures show that in Case 1, the travel time is longer in MPs-based OSMS than in D2D-based OSMS, even when the number of demands is increased. On the other hand, in Case 2, the travel time is shorter in MPs-based OSMS than in D2D-based OSMS when the number of demands is increased. Note that from Welch’s test, it was statistically found that MPs-based OSMS has shorter travel time of passengers than D2D-based OSMS when the number of demands is greater than 100 for

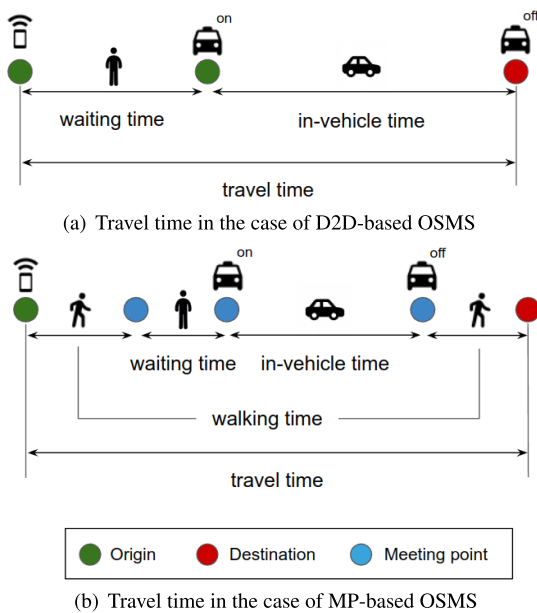


FIGURE 13. The definition of travel time of passengers.

capacity 1, and when the number of demands is greater than 200 for capacities 2, 4, and 8.

Fig. 15 and Fig. 16 show the in-vehicle and waiting time, respectively. Incidentally, the walking time is approximately 6 [min] when the MPs interval is 200 [m] and approximately 10 [min] when MPs interval is 400 [m] for all conditions. Fig. 15 shows that as vehicle capacity increases, the in-vehicle time increases. This is due to the increase in the number of shared passengers. However, the introduction of MPs reduces the in-vehicle compared with D2D-based OSMS for all conditions. In addition, Fig. 16 shows that the introduction of MPs reduces waiting time. However, the walking time to use MPs is greater than the reduction in in-vehicle and waiting time, increasing the travel time in Case1. On the other hand, in Case 2, the MPs introduction significantly reduces the waiting time compared to Case 1, resulting in a shorter travel time than D2D-based OSMS.

Fig. 17 shows the average number of pick-up passengers at an MP. For a vehicle capacity of 1, the number of pick-up passengers per MP is 1, even for an MPs-based OSMS. As the vehicle capacity is increased, the average number of passengers per MP increases. The larger the MP interval, the larger the number of pick-up passengers per MP. This is because the larger the MP interval, the fewer the number of MPs, and thus, the greater the probability of passengers being concentrated into a single MP. This tendency is stronger when the number of demand is larger. In Case 2, the number of vehicles in MPs-based OSMS is larger than in Case 1, so the average number of passengers per MP is smaller, but this trend is consistent. Fig. 16(b) shows that the waiting time in MPs-based OSMS decreases as the number of demands increases when vehicle capacities of 4 or 8. This is because the average number of pick-up passengers per MP increases as the demand increases. The introduction of MPs allows

passengers to board a vehicle and alight at the same MP, even if the number of passengers increases, thus reducing the number of detours and the time spent waiting for other passengers. The reduction in VKT also shows that the introduction of MPs reduces the number of detours, allowing demand to be processed more quickly, thus reducing the waiting time. Therefore, the average travel time of passengers is shorter in MPs-based OSMS than in D2D-based OSMS when the demand is increased.

3) ILLUSTRATIVE RESULTS

For a more intuitive understanding, we focus on a certain OD set to explain the effects of introducing MPs. Based on the results for the 1000 demands, the number of vehicles is 48, and the vehicle capacity is 8, we focus on the five ODs moving from east to west, as shown in Fig. 18. Fig. 18 shows the trajectory of the vehicle for these five ODs.

We can see that in the D2D- and MPs-based (200 [m]) cases, the demand is handled by four and three vehicles, respectively. Whereas, in the MPs-based (400 [m]) case, it is handled by one vehicle. In the D2D-based case, the vehicles detour to process other demands as well. The dispatch and routing are optimized under a time constraint such that the travel time between the pick-up and drop-off points is shorter than the time required for walking. In the MPs-based case, the time constraint is tighter than in the D2D-based case because the distance between the pick-up and drop-off points is shorter. Therefore, the routing optimization is performed to minimize the number of detours in the MPs-based case. This can be clearly seen in Fig. 18.

Table 3 shows the results for this sample OD. As shown in Fig. 18, the introduction of MPs significantly reduces the VKT. The effect is further improved by increasing the MPs intervals, i.e., by aggregating more passengers to a single MP. The travel time is 68% of D2D at 200 [m] intervals and almost the same at 400 [m] intervals. Note that the results for this sample represent the most effective example of aggregation, so the improvement in VKT is large, while the reduction in travel time is small.

4) SUMMARY OF RESULTS

The introduction of MPs reduce the number of vehicles required to maintain a certain level of service quality. If the number of vehicles is reduced in response to the introduction of MPs, the travel time of passengers will increase, but only by a maximum of 5 [min]. The static analysis results that the introduction of MPs into OSMS shortens the VKT and reduces the average travel time of passenger in MPs-based OSMS more than in D2D-based service if the number of demands are above a certain number, are also verified by simulation analysis. Although not conducted in our experiment, if the number of demand is further increased, the travel time by MPs-based OSMS is expected to be more shorter than that by D2D-based OSMS.

Czioska et al. stated that the introduction of MPs increases passenger travel time, but this is a result of using the

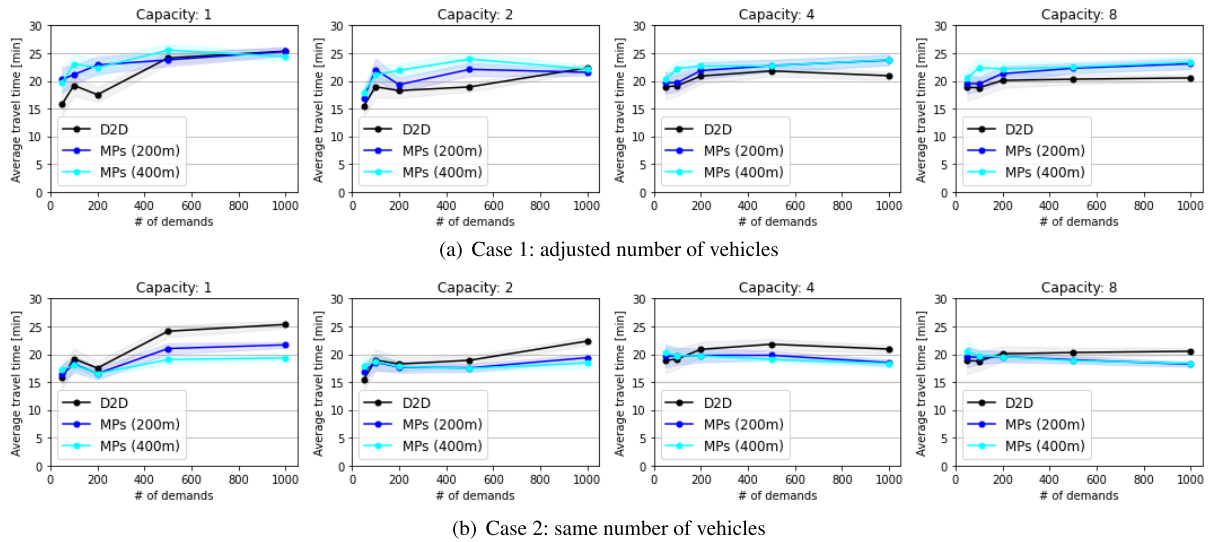


FIGURE 14. Average travel time of passengers.

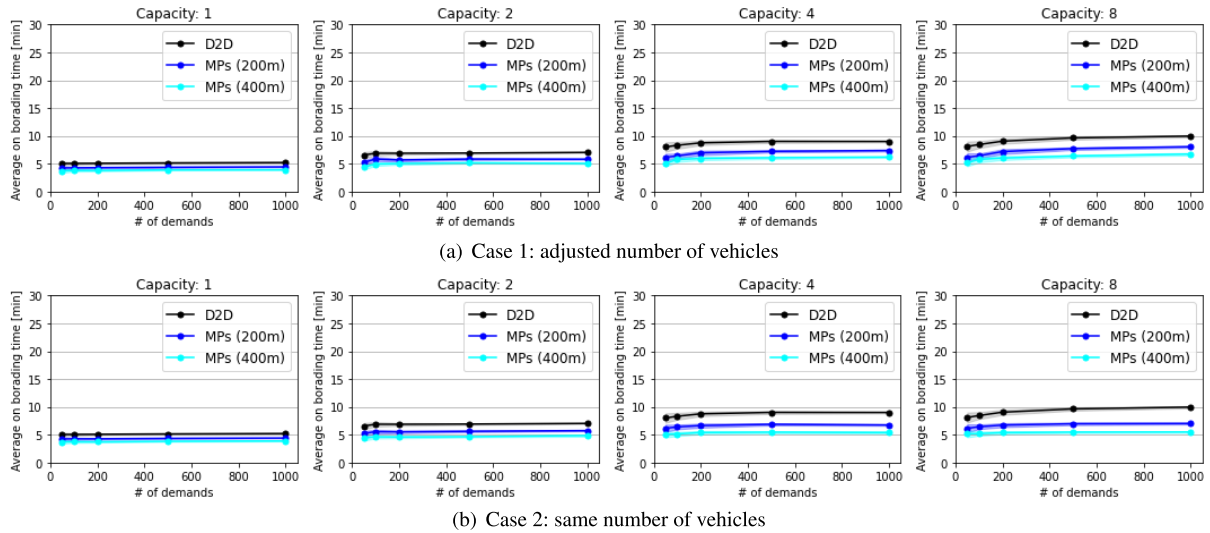


FIGURE 15. Average in-vehicle time.

TABLE 3. Results of sample OD.

	D2D	MPs (200 [m])	MPs (400 [m])
Number of vehicles that handle the sample OD	4	3	1
Total VKT [km]	16.8	9.1	3.5
Average travel Time [min]	22.1	15.2	21.5
Average in-vehicle Time [min]	10.3	7.5	6.8
Average waiting Time [min]	11.8	2.2	4.4
Average walking Time [min]	0	5.6	10.2

minimum required number of vehicles for D2D- and MPs-based OSMS, respectively. We have conducted a similar experiment, with the same results as Czioska et al., as shown in Case 1. In addition, unlike Fielbaum et al., we simply compare travel times in D2D- and MPs-based OSMS under no demand rejection conditions.

MP-based OSMS was evaluated in two cases, Case 1 and Case 2. In Case 1, the MP-based OSMS was evaluated

with fewer vehicles than the D2D-based OSMS. The results showed that the introduction of MP did not reduce passenger travel time. On the other hand, in Case 2, the MP-based OSMS was evaluated with the same number of vehicles as the D2D-based OSMS, and it was confirmed that the MP-based OSMS reduced passenger travel time. This means that there is a trade-off between reducing the number of vehicles (Case 1) and reducing passenger travel time (Case 2). Note that in

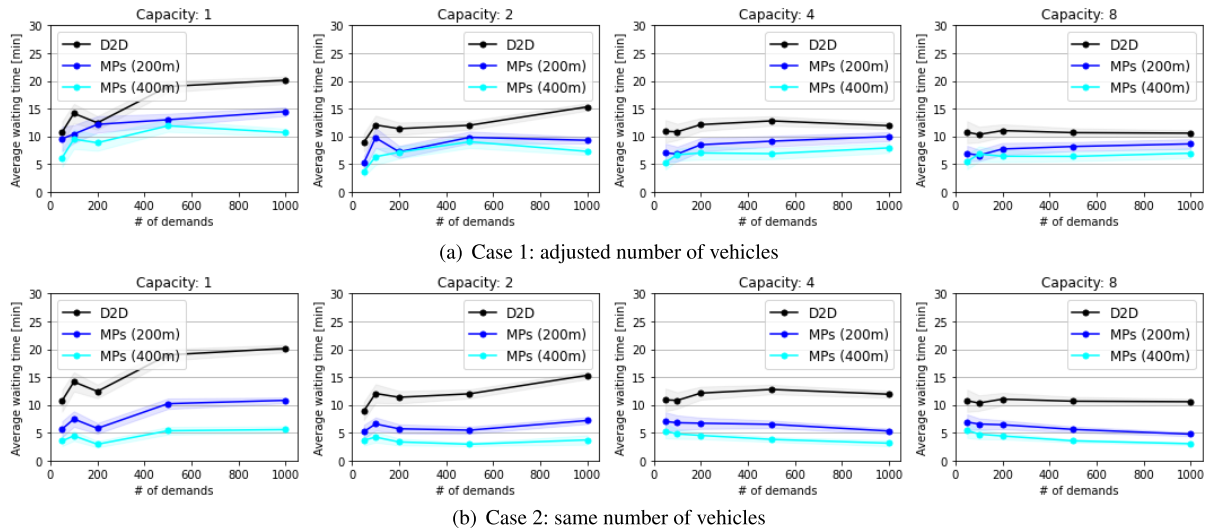


FIGURE 16. Average waiting time.

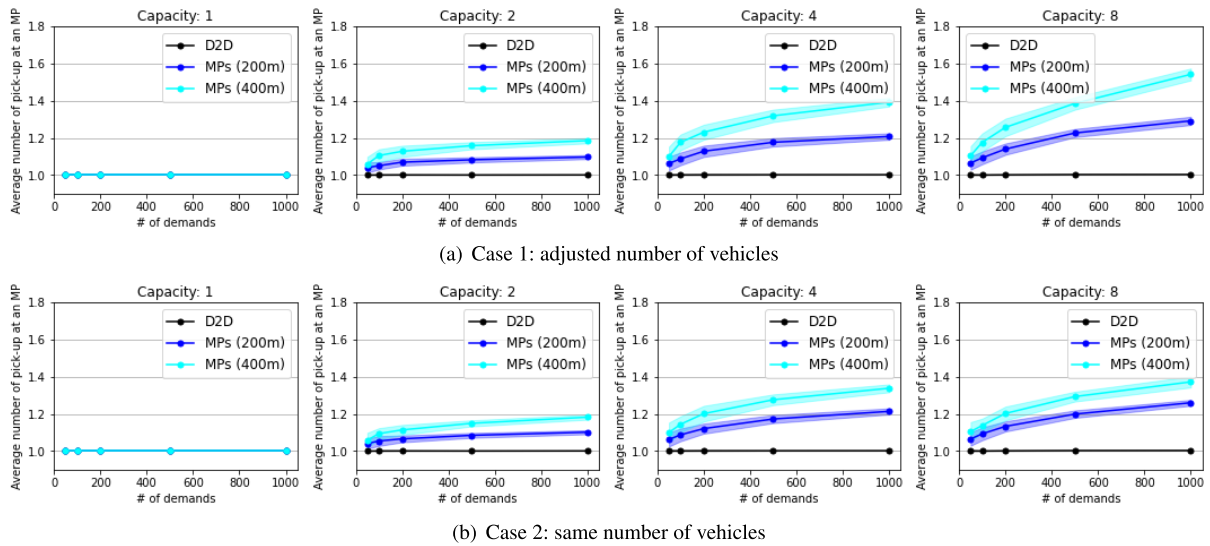


FIGURE 17. Average number of pick-up passengers at an MP.



FIGURE 18. Examples of D2D-based and MPs-based OSMS routes. The green circle indicates the origin and the red circle indicates the destination. The gray circles indicate the pick-up/drop-off points of the other demands handled by the vehicle in addition to the five ODs. The light blue markers are MPs. The black solid lines indicate vehicle trajectories and the dotted lines indicate passenger walkways.

both cases, the total VKT decreased with the introduction of MP.

According to the result in this study, the introducing MPs can reduce not only the efficiency of vehicle operation but also the travel time of passengers if the number of vehicles required for D2D-based OSMS is sufficient to prevent a constraint (i.e., it is not faster to walk) and if the number of demands is above a certain level. Furthermore, the introduction of MPs is effective in improving operational efficiency and travel time not only for shared services such as OSMS but also for conventional one-vehicle, one-passenger services such as a taxi and on-demand mobility services.

VI. CONCLUSION

We analyzed the benefits of introducing MPs into OSMS in terms of operational efficiency and passenger convenience, especially travel time. Previous studies have shown that the introduction of MPs into OSMS can improve operational efficiency. However, the benefits in terms of passenger convenience have not been sufficiently investigated. The static analysis and the simulation analysis using actual maps and demands show that the introduction of MPs shortens the VKT and, if the number of demands exceed a certain number and the number of vehicles is equivalent to D2D-based OSMS, reduces the average travel time of passengers compared with D2D-based OSMS.

Some limitations of this study must be addressed. The first is to optimize the location of the MPs. In this study, MPs were placed at equal intervals on major roads, but adjusting the location of MPs based on the spatial distribution of demand can be expected to further improve operational efficiency and passenger convenience. In addition, this study was limited to an investigation of one-hour demand. Analysis for longer periods, including peak and off-peak periods, is required for a more detailed understanding of the advantages and disadvantages of MP-based OSMS.

One interesting future issue will be how to encourage passengers to use MPs. Based on the simulation analysis, there are tradeoffs between the number of vehicles, VKT, passenger travel time, and walking time. For example, the introduction of MP can reduce passenger travel time only when the number of vehicles is not reduced. Therefore, the trade-off exists between reducing the number of vehicles and reducing passenger travel time. Operators would prefer a smaller number of vehicles and passengers would prefer shorter travel times. When designing a service, it is important to deal with this trade-off. To better understand these trade-offs, a topic to study is the use of multi-objective optimization in the vehicle allocation algorithm to optimize all indicators simultaneously. Once the tradeoffs are known, it is possible to determine how much of a fee discount is best for both the service provider and the passenger.

Another important topic is how to integrate various types of mobility services. The service design could be based on demand, for instance, D2D-based OSMS could be used when demand is low and MP-based OSMS could be used when

demand is high. Recently, on-demand services have become popular; however, despite their convenience, on-demand services have negative effects, such as congestion. Therefore, OSMS has been developed, and MPs-based services, which are the subject of this study, are being considered. There is a sense that the time is reversing from on-demand to conventional fixed-route transport. Railways and buses are the largest sharing services. The development and research of tools to support service design based on demand and regional characteristics, such as the extent to which services should be on-demand and the extent to which they should be fixed, will also be an issue in the future.

APPENDIX A FURTHER EVALUATION

The introduction of MPs may reduce travel time, but only if passengers are willing to walk. Walking is probably more inconvenient for passengers; so it is difficult to argue that simply shortening travel time will improve passenger convenience. Therefore, we evaluate passenger convenience using a generalized cost. The generalized cost is an index that changes the advantages and disadvantages of travel, such as travel time, into monetary values.

To calculate the generalized cost, the modeling of choice behavior is described. Discrete choice models are often used to model choice behavior such as transportation. This model assumes that people choose the option with the highest utility. By converting this utility into an economic value, a generalized cost is obtained. In other words, modeling of transportation choices is necessary to calculate generalized costs.

We use the transportation mode choice data obtained from the MaaS demonstration experiment that was conducted in the same area as the simulation analysis in November 2019, to estimate the transportation choice model. In this experiment, OSMS were introduced in addition to railways and local buses. We constructed a transportation mode choice dataset using the route search smartphone App's usage history and estimated the parameters of the transportation mode choice model.

We applied a Nested logit model as the transportation mode choice model, which is one of the discrete choice model. The estimated parameters are listed in Table 4. From the estimated parameters, we know, for example, that a transportation mode that requires a longer in-vehicle time is less likely to be chosen. $\bar{\rho}^2$ is the pseudo-determination coefficient, which indicates the fitness of the model, and 0.2 or higher indicates that the model is valid [15]. For more details on models and estimation methods, we refer the readers to [17].

We define the generalized cost for a trip other than fare, GC w/o fare, as the following Eq. A.1. This represents the monetary equivalent of the utility of travel, consisting of in-vehicle time, waiting time, and walking time.

$$GC \text{ w/o fare} = -\frac{1}{\beta_{Fare}}(\beta_{On_boarding_time} \times x_{In_vehicle_time} + \beta_{Walking_time} \times x_{Walking_time} + \beta_{Waiting_time} \times x_{Waiting_time}) \quad (A.1)$$

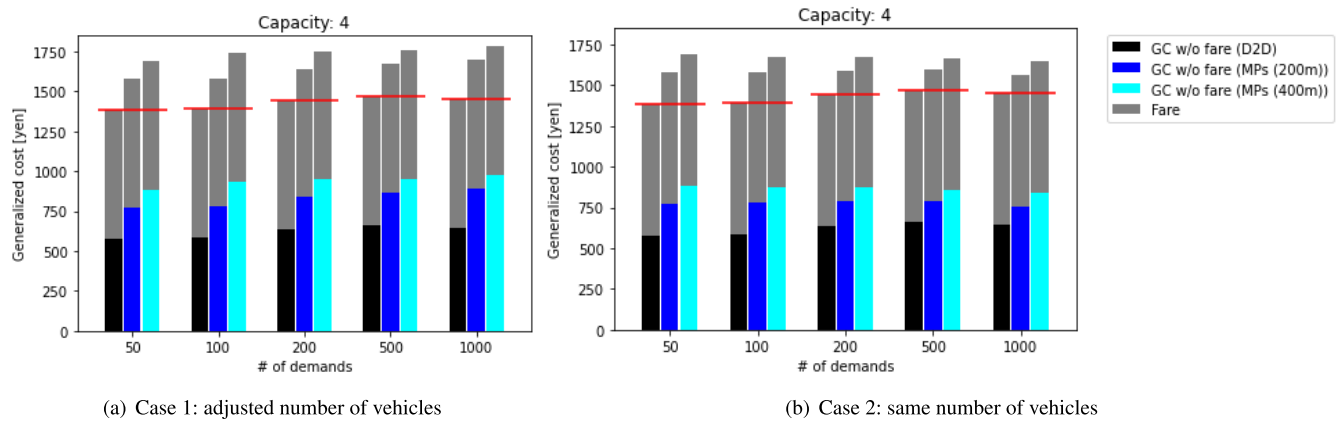


FIGURE 19. Generalized cost calculated using the Nested logit model parameters (Vehicle capacity is 4).

TABLE 4. Estimated parameters of the the Nested logit model.

	estimated parameters	t-value
$\beta_{In_vehicle_time}$	-23.90	-1.99
$\beta_{Walking_time}$	-32.89	-4.17
$\beta_{Waiting_time}$	-13.65	-2.61
β_{Fare}	-0.59	-2.79
ρ^2	0.25	

Based on the above, we obtain the generalized cost in the D2D-based and MP-based OSMS. Fig. 19 shows the average generalized cost for a vehicle capacity of four passengers. The generalized cost comprised *GC w/o fare* and *fare* for taxi services. The taxi fare calculation is 420 [yen] up to 1.052 [km], and 80 [yen] is added for every 233 [m] beyond that. This taxi fare calculation is based on Tokyo area [23].

For example, in Case 1, the generalized cost of D2D-based OSMS is 31% (200 [m]) and 42% (400 [m]) less than that of MPs-based OSMS for a vehicle capacity of four passengers and 1000 demands.³ On the other hand, in Case 2, the generalized cost for a D2D-based OSMS is 14% (200 [m]) and 25% (400 [m]) less than that of MPs-based OSMS for a vehicle capacity of four passengers and 1000 demands. In the case of a conventional taxi-like operation with a predetermined number of vehicles or drivers, the same convenience as in D2D-based OSMS can be achieved at a lower discount rate than in Case 1.

APPENDIX B EFFECTS OF MP SELECTION

We have confirmed that the introduction of MPs reduces travel time when the number of vehicles is approximately the same as the number of vehicles in D2D-based OSMS (Case 2) and when the number of demands is above a certain level. Here, we discuss the effect of the MP selection on the vehicle allocation algorithm. As described in Section IV-B, when a

³Case 1 can be viewed as a type of work in which drivers work when they want to work, such as Uber. Uber offers its OSMS, UberPOOL, at half the price of its regular on-demand service, UberX, and its MPs-based OSMS, UberExpressPOOL is reportedly offered at a further 25% off. Our results indicate that the discount rate is excessive.

new demand is generated, MPs at four locations around the origin and destination of that demand are listed. The MPs combination that minimizes the cost is determined. At this time, there is a possibility that passengers may be asked to walk to a slightly more distant MP depending on the situation.

To verify the difference between dynamic MP selection and simply assigning the closest MP, we perform simulations for 1000 demands with the same number of vehicles as for D2D-based OSMS. The MPs intervals is 200 [m]. Vehicle capacity is 4 and 8.

Fig. 20 shows the VKT, passenger travel time, walking time, and waiting time for D2D- and MPs-based OSMS when using the closest MP and MP-based OSMS with dynamic MP selection. Fig. 20(a) shows that the case with MP selection reduces the VKT more than that without the MP selection. Note that simply using the nearest MP increases the travel time, whereas MP selection reduces the travel time, as shown in Fig. 20(b). These results show that the travel time can be reduced by introducing MPs only when an MP is dynamically determined. On the other hand, since MPs are determined according to the situation, the closest MP is not always selected, increasing the walking time. This means that there is a tradeoff between walking time and vehicle operating efficiency or the travel time of passengers.

APPENDIX C COMPUTATIONAL TIME FOR SIMULATION

We discuss the computation time of the simulation. We use Intel(R) Core(TM) i9-9900K CPU (3.60GHz) to run the simulation. Fig. 21 shows the computation time of one simulation for each demand in the case of that the vehicle capacity is four. The number of vehicles in the simulation for each demand is 4, 7, 12, 26, and 50 for the number of demands 50, 100, 200, 500, and 1000, respectively. Since the vehicle allocation optimization is performed when a demand is generated, the number of calculations increases with the number of demands. The computational cost also increases with the number of vehicles because the cost of inserting the demand process in each vehicle is calculated. When the number of demands is large, the number of vehicles required inevitably

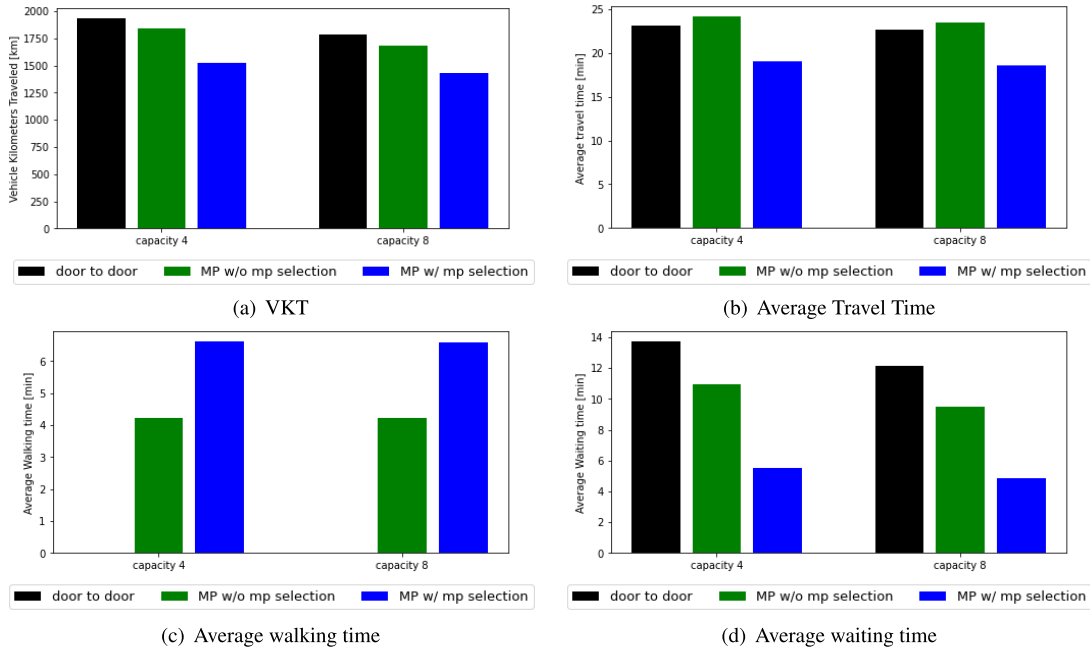


FIGURE 20. Effects of MP selection.

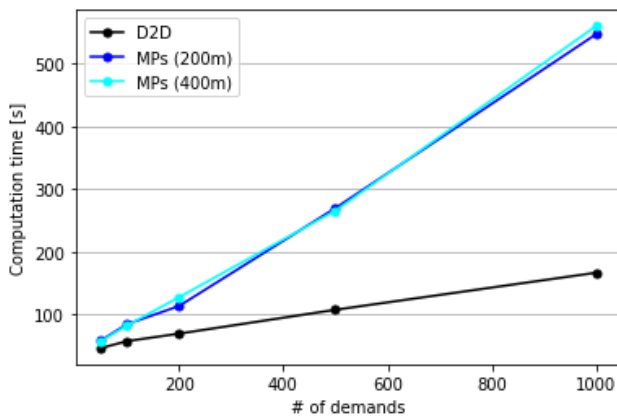


FIGURE 21. Computational time for simulation (Vehicle capacity is 4).

increases, so the calculation time increases with the number of demands.

In the case of MP-based OSMS, additional calculations are required for MP selection. MP selection is performed for each demand and computes the travel cost in each vehicle for each MP pattern, so the computation time increases with the number of demands and vehicles. Therefore, MP-based OSMS requires more computation time than D2D-based OSMS, and the increase is larger for each additional demand.

Note that this study required the simulation of several hundred thousand patterns that including the five demand patterns, four vehicle capacity patterns, the presence or absence of MPs, the location of MPs, 100 simulations to account for randomness, and the simulations needed to determine the number of vehicles required, which could be performed by parallel computation on a supercomputer.

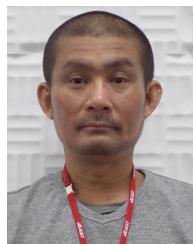
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MASAKI ONISHI received the B.S., M.S., and Ph.D. degrees from Osaka Prefecture University, in 1997, 1999, and 2002, respectively. From 2002 to 2006, he was a Research Scientist at the Bio-Mimetic Control Research Center, RIKEN. Since 2006, he has been a Researcher with the National Institute of Advanced Industrial Science and Technology (AIST). His research interests include computer vision, video surveillance, multi-agent simulation, and optimization.



ITSUKI NODA received the B.E., M.E., and Ph.D. degrees in engineering from Kyoto University, Kyoto, Japan, in 1987, 1989, and 1995, respectively. He has been a Researcher with the Electrotechnical Laboratory (ETL), since 1992, a Senior Researcher with the National Institute of Advanced Industrial Science and Technology, since 2000, and a Professor with Hokkaido University, since 2021. His main research interests include multiagent social simulation, machine learning, RoboCup, and disaster mitigation information. He has been a Founding Member of RoboCup and promoted Soccer Simulation League, since 1995. He was the President of RoboCup Federation, from 2014 to 2017. He was the President of the Japanese Society of Artificial Intelligence, from 2020 to 2022. He is also one of founders of a venture company, Mirai Share, for taxi-share system, which is a result of the social simulation research.



RYO NISHIDA received the B.E. degree in engineering and the M.S. degree in information science from Tohoku University, Sendai, Japan, in 2018 and 2020, respectively, where he is currently pursuing the Ph.D. degree in information science. Since 2019, he has been a Research Assistant with the National Institute of Advanced Industrial Science and Technology. His research interests include choice modeling, agent-based simulation, and reinforcement learning for mobility service design and crowd management.



RYO KANAMORI received the D.E. degree from Nagoya University, Japan, in 2007. He has been a Research Associate Professor with Nagoya University, since 2014. His research interests include the evaluation of transportation policies with travel demand forecasting models and travel behavior analysis. He currently evaluates the impacts of mobility services using ride-sharing systems and automated driving systems in urban area.



KOICHI HASHIMOTO (Senior Member, IEEE) received the B.S., M.S., and Ph.D. degrees in engineering from Osaka University, Osaka, Japan, in 1985, 1987, and 1990, respectively. From 2000 to 2004, he was an Associate Professor at the Department of Mathematical Engineering and Information Physics, Graduate School of Engineering, The University of Tokyo. He is currently a Professor with the Graduate School of Information Sciences, Tohoku University. His major research interests include visual servoing, parallel processing, and biological systems. He is a fellow of RSJ and SICE, and a member of ISCI, IPSJ, and JSME. He received the Best Mechatronics Paper Award from the IEEE International Conference on Mechatronics and Information Technology, in 2005, the Best Biomimetics Paper Award from the IEEE ROBIO, in 2006, the Best Paper Award from the IEEE ICMA, in 2009, and the two Best Paper Finalists at IEEE ROBIO 2019.