Developing an Agent-based Simulator Combining Mesoscopic Traffic Simulator with Dynamic Vehicle Allocation System to Evaluate a Ride-Sharing Service in Urban Area

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Abstract In this study, we developed an advanced agent-based simulator which allows an agent-based mesoscopic traffic simulator to cooperate with a dynamic vehicle allocation system. this simulator can reproduce a dynamic vehicle allocation service in real world through its Web API (Application Programming Interface). We implemented this simulator to evaluate ride-sharing taxi services in Kumamoto City compared with the conventional taxi service (without sharing). From simulation results, the ride-sharing taxi service is more effective. The average time from booking a ride to arriving at the intended destination was significantly reduced as the number of vehicles increased. However, the average occupancy rate of vehicles decreased.

Keywords *Ride-sharing taxi service, Mesoscopic traffic-simulation model, Dynamic on-demand vehicle allocation system, Web API interaction.*

1 Introduction

The over-reliance on private vehicles could cause some issues such as air pollution, traffic congestion, and road accidents in cities. To achieve sustainable urban mobility, classical public transportation systems (services with fixed timetable and route) have been considered as an important means [1]. However, the operation conditions for classical public transportation systems, especially bus, have exasperated over the past years. Classical public transportation services should not be the only option because in some cities there are no services in the areas of low density or low transport demand [2], [3]. Moreover, public transportation operators face a shortage of drivers due to a reducing workforce in Japan [4]. Therefore, to resolve the problems above, Demand Responsive Transport (DRT) services, which operate according to the demand of users, have caused widespread concern in the last years [5].

One example of DRT is the paratransit, also called community transport, for transporting elderly people and disabled people [6]. It is a service that does not follow fixed timetable and fixed-route which could contribute to mobility support in areas where public transportation is inconvenient. However, there are also some customer service problems. Toland [7] indicated that paratransit services charge higher fares than classical public transportation. Furthermore, most of the services are not real-time as customers need to make an advance reservation for more than 24 hours [8]. The main function of this service could be emphasized as a social service rather than an option to make sustainable mobility [9].

One interesting option of DRT is carsharing, which typically can be often rented by hours among different customers [10]. Carsharing services could be regarded as an important tool to achieve sustainable urban mobility by decreasing the requirement for private vehicles [11]. However, the carsharing systems still have uncertainty problems, such as vehicle availability problems and available parking space problems. [12].

Ride sharing services are another type of DRT, which includes carpooling and taxi sharing [5]. By allowing more people to use one vehicle, ride sharing could increase occupancy rate and reduce total travel distance, traffic congestion, and carbon emissions [13]. However, unregulated carpooling for transporting paying customers is illegal in Japan now, unless there is a green plate on the vehicle and an appropriate driver license. The taxi sharing services (pick up customers not traveling together) in Japan were also illegal till the transportation ministry approved taxi sharing services nationwide in 2021 [14]. After this introduction, it could allow strangers with similar destinations to ride in the same vehicle to offer greater convenience for customers. Enhancing taxi sharing services is also one way to address the increase in elderly population, especially those who are unable to drive [15]. There, each customer of taxi sharing services could pay a lower fare compared with a regular taxi [16]. For all these benefits, demonstrations of taxi sharing systems have been conducted across Japan. Two separate verification tests were conducted in Arao City, Kumamoto Prefecture [17], and a full-scale introduction is planned.

This paper focuses on the effect of introducing taxi sharing service on the current demand for taxis. Using a shared taxi such as this, users can set the boarding points and destinations with a smartphone or other device. And users who want to travel in the same direction can use the same taxi, which could enhance mobility and efficient of taxi service and reduce the need for private vehicles [18]. When introducing new shared services, it is important to evaluate the efficiency and level of the service in advance. The stated preference experiment has been used to investigate the potential acceptability of introducing new shared services [19]–[21]. However, the implementation scale is not large enough because of the lack of budget and labour. Recently, the simulation models have been proposed to analyse the new shared services [22]–[24]. Simulations models are useful to better comprehend the impact of new shared services in future scenarios [25]. In these simulation models, agent-based model (ABM) is very suitable for testing different mobility services [26].

Inturri et al. [5] used ABM to evaluate different system configurations for new shared services in Italy. They explored scheduling strategies and found suitable variables to improve the level of service. Oh et al. [27] studied the impact of Automated Mobility-on-Demand in Singapore through ABM and high-fidelity activity. They indicated that the introduction of automated mobility may increase congestion. ABM also has been used to test car sharing services. Martínez et al. [12] developed a detailed ABM to simulate car sharing services in Lisbon, Portugal. Their simulation incorporated a car-sharing demand model with discrete spatiotemporal alternatives to analyse the superiority of car sharing services for other traffic modes. Their results showed that car sharing performs better than public transportation in travel time. Combined with the analysis on behaviours of taxi drivers using GPS data, Cheng and Nguyen [28] developed an agent-based simulation platform, TaxiSim, that allows researchers to assess interactions between taxis.

Several agent-based simulators also have been developed by researchers, such as MATSim and SUMO, have been proven sufficient for transport simulation [29]. Ciari et al. [30] analysed the effects of various policies on one-way car-sharing services in Zurich, Switzerland, using MATSim. Consequently, it was clarified that the number of usage increases with the number of vehicles, and the occupancy rate of parking spaces varies with the price. However, MATSim and SUMO are insufficient for a wider variety of DRT systems [31]. In addition, it is not possible to directly visualize the traffic conditions and the behaviour of agents during the simulation process without a separately developed visualizing system. Even though it is open source, the structure of the model is quite complicated; hence, it is difficult to master it.

Therefore, the authors developed a new agent-based traffic simulator, Kumamoto Multi-Agent-based Traffic Simulator (K-MATSim), which is mesoscopic in an attempt to describe the behaviour of each traveller. We linked K-MATSim with an on-demand ride sharing taxi-allocation system, Smart Access Vehicle System (SAVS), described in Nakashima et al. [32], to evaluate the effect of introducing a ride sharing taxi service on the current demand for taxis in the central part of Kumamoto City. In this research, the authors investigated a taxi sharing service, which is a dynamic on-demand sharing service up to the taxi capacity. The main innovation of our model is that: (1) K-MATSim has all the standard features that a meso-scale traffic simulation model should have, (2) can explicitly model daily demand-supply interaction in mode and route chosen by individuals, and (3) the simulator is interfaced with a real-world real-time on-demand vehicle allocation system (SAVS) by Web-API which is a novel aspect compared with other studies.

This paper consists of four sections. The second section describes the verification method, the third section describes the simulation analysis, and the fourth section draws conclusions from the present study and discusses possible future research directions.

2 Materials and Methods

When introducing a new mobility service, deciding on the extent of the service and its area of operation is necessary. However, in the case of a new type of service, such as a ride-sharing taxi service, the effects of introducing the service cannot be predicted. From January 22 to March 11, 2018, a social experiment involving ride-sharing taxis and based on vehicle allocation software was conducted in cooperation with two major taxi companies in 23 Tokyo wards and two neighboring cities. Thus, there was some testing of the system in the real world before its introduction. However, the scope of this test was limited because of the small number of registered participants and the cost and effort involved. Thus, using social experiments such as this to fully examine the effect of introducing mobility services is not easy.

An analytical tool that could simulate the process of reserving ride-sharing taxis by users and vehicle allocation by operators under actual traffic conditions in place of experiments in the real world would enable demand forecasting and impact assessments to be made under different conditions in an area where the introduction of such a service was planned. We, therefore, developed a computer-simulation system that linked the on-demand optimal taxi-allocation system, SAVS, with the mesoscopic traffic flow simulation model, K-MATSim. Using this system, we analyzed the impact of a ride-sharing taxi service from the perspectives of both users and operators. The area used for this simulation was limited to the center of Kumamoto City but could be expanded to the entire Kumamoto metropolitan area. The details of K-MATSim and SAVS and how they were linked together is explained below.

2.1 Overview of K-MATSim

K-MATSim is an agent-based mesoscale traffic flow simulator originally developed by Kumamoto University. K-MATSim generates the traffic environment in the target area based on input data, as shown in Fig. 1, and simulates the travel behavior of individual users and the dynamic traffic flow that results from the combined behavior of all users. The parameters of the system can be adjusted, and the impact of different transportation policies can be evaluated from an analysis of the results of the simulation.

In the simulator, an individual who departs from a certain point at a given time becomes an agent moving toward a chosen destination. Each agent decides on their own travel mode and route on the basis of discrete modal-choice and route choice models, respectively, both of which are built into K-MATSim. The travel mode with the greatest utility is selected from among multiple alternatives, including walking, bicycle, motorcycle, automobile, bus, train, and taxi. The route with the lowest cost is selected from the available alternatives corresponding to the selected transport mode. The route cost is the sum of the expected times for the different links that constitute the route. The concept of the expected time is discussed further on.

The traffic flow simulation model expresses the traffic flow as an aggregation of the behaviors of all the agents in the transportation network. This type of model constitutes a mesoscopic traffic flow simulation model. The movement of each vehicle on the road is determined by the Fundamental Diagram, which shows the relationships among the traffic density, traffic volume, and mean speed. Traffic congestion is described by the Physical Queue model, which allows for an increase or reduction in traffic congestion on a particular link. Information regarding the transportation network, such as link travel time, which is based on previous agent experience, is used to determine subsequent expected travel time. Thus, the model has a loop structure that includes agent-based simulation and mesoscopic transport-flow simulation. As these processes are repeated day by day, the different travel behaviors of all agents and the traffic conditions on the network change simultaneously. However, these changes gradually converge after a certain number of iterations, until, finally, the behaviors of the agents and traffic conditions become stable. K-MATSim has been verified to meet the performance standards of the standard verification process for traffic flow simulation contained in the verification manual formulated by the Japan Society for Traffic Engineering [33].

2.2 Abbreviation and acronyms

SAVS is a real-time on-demand taxi-allocation system developed by Public Hakodate Mirai University, Nagoya University, the National Institute of Advanced Industrial Science and Technology, and Mirai Share Co., Ltd. A ride-sharing taxi is a service that combines the advantages of a taxi—that is, on-demand and responsive— and a bus route—that is, ride-sharing—without fixing the route between departure point and destination in advance. This way, SAVS can be characterized as a door-to-door DRT optimum-allocation platform that can provide mobility services in real time to users who need it [34], [35].

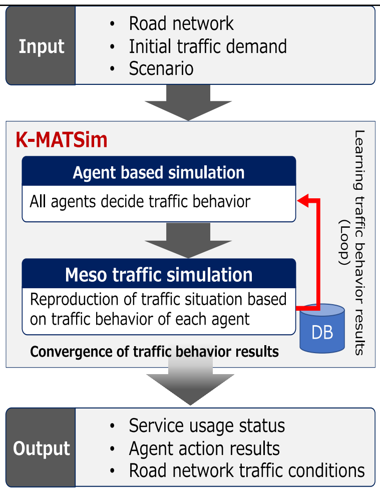


Figure 1. K-MATSim analysis process

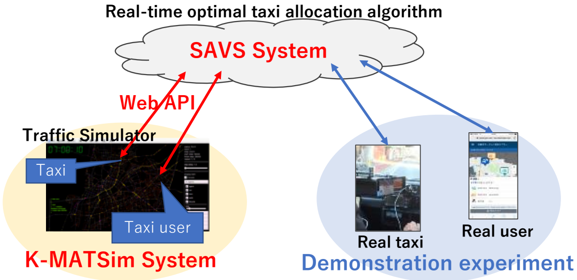


Figure 2. Cooperation between K-MATSim and SAVS

Unlike conventional demand-based transportation systems, SAVS does not require reservations made several hours in advance. There is, thus, no need to coordinate the activity schedule with the plan of operation, which is highly convenient for users. In addition, because it is possible for one user to begin and complete a journey while another user is being transported, it is expected that SAVS can help to compensate for taxi driver shortages and improve the occupancy rate of vehicles.

SAVS users access the system from a device, such as a smartphone, and select the number of passengers, their current location, and their destination using a map. If the reservation is successful, the number of allocated taxis, estimated journey time, estimated arrival time at the destination, and number of passengers will be displayed on the terminal screen. SAVS vehicles are equipped with a tablet terminal that communicates with the SAVS cloud system. On the tablet, the route that the driver should take is displayed on a map. As instructed by SAVS, the driver arrives at the correct location to pick up the user and drives the user to the destination.

2.3 Coordination between K-MATSIM and SAVS

In this research study, demand forecasting and impact assessment for a ride-sharing taxi service were conducted for the Kumamoto metropolitan area. We developed a combined system that linked K-MATSim and SAVS on a computer in which the traffic flow based on the behavior of different agents was reproduced in K-MATSim. At the same time, optimal allocation of taxis was carried out by the SAVS algorithm. In this study, SAVS incorporated a cloud system that worked exactly as it does in actual operation. In this combined system, SAVS replaced the communication between real ride-sharing taxi users and taxis with the communication between the user agents and taxis in K-MATSim. As a result, as shown in Fig. 2, SAVS performed the same processes as those done for real situations.

K-MATSim and SAVS were linked using a web Application Programming Interface (API). In SAVS, communication between the user's smartphone, PC, vehicle-mounted device, and cloud system is carried out by the web API. A Web API is an interface between applications that is called over the network using the HTTP protocol, which is a communication protocol used by web browsers to access websites. A web API is, thus, a standard communication method that can be used on web browsers, and it is highly compatible with applications run on web browsers. Using the agents in K-MATSim to simulate the communication by a web API on a user's smartphone, PC, or in-vehicle device, the accessing of SAVS by humans or in-vehicle devices can be simulated. This system makes it possible to conduct verification in situations involving tens of thousands of users and hundreds of vehicles, which is difficult to do in real-world experiments.

2.4 Simulation model combing K-MATSIM and SAVS

K-MATSim can generate trips by itself, including choosing the travel mode and the route based on the characteristics of the individual agent, level of service required, and expected travel time. However, in the case of this simulation, no suitable model for choosing the mode of travel was available, so it was impossible to predict trips for which there would be a change from the currently used travel mode to a ride-sharing taxi. Therefore, it was assumed that for all trips undertaken using conventional taxis that were recorded in the Kumamoto metropolitan area household travel survey conducted in 2012, the user would use a ride-sharing taxi. The locations of the departure and arrival points of all taxi trips were coded as zones rather than as points in this survey. Therefore, in the simulation, we set the locations of the departure points and destinations to correspond to randomly-distributed points within the appropriate zones. It was assumed that each agent would choose the route with the minimum expected travel time from the departure point to the arrival point. Seven modes of travel those are walking, bicycle, scooter, motorcycle, light car, automobile, and taxi- were used in the initial input to K-MATSim.

SAVS can only operate optimally under certain conditions: if the taxi is unable to reach the user 120 minutes before the desired departure time or if the distance between the boarding and alighting locations is less than 100 meters, a reservation will not be made. The taxis that are used are sedans and have a passenger capacity of four. Further details of the models used for taxis and users in the simulation are given below.

2.4.1 taxi behavior model. The flowchart of the taxi is described in Fig. 3 (left). The rules of behavior used for taxis are:
(1) Initial position: At the beginning of the simulation, all taxis are randomly placed on main roads within the target area.
(2) Send current position: The locations of taxis could be sent to SAVS every 10 seconds.
(3) Acquisition of route information: Each time the optimal route is updated by SAVS, the taxi obtains the latest route information.
(4) Action without reservation: If there are no current reservations, the taxis continue cruising.
(5) Action at the time of reservation acceptance: A taxi will move to the boarding point specified by SAVS. After the user boards, the taxi will move to the destination specified by SAVS, and the user will be dropped off there.

2.4.2 Taxi-user behavior model. The flowchart of the taxi-user is described in Fig. 3 (right). The rules of behavior used for taxi-users are:
(1) Initial position: Users are randomly placed on roads within their departure zones as recorded in the household travel survey.
(2) Time of reservation: Users make a reservation by specifying their departure point and destination. The point at which they leave the taxi corresponds to a node arbitrarily selected from the nodes within the destination zone.

3 Analysis of the simulation

The analytical system linking K-MATSim and SAVS with the web API developed in this study was just the prototype of a full-scale application that could be applied to an entire metropolitan area. The first aim of the analysis of the simulation was to verify the applicability of this system and the overall effect of introducing ride-sharing taxi services. Therefore, the conditions under which the simulation was run represented a considerable simplification: for example, the possibility that a user would change from another mode of transport to a ride-

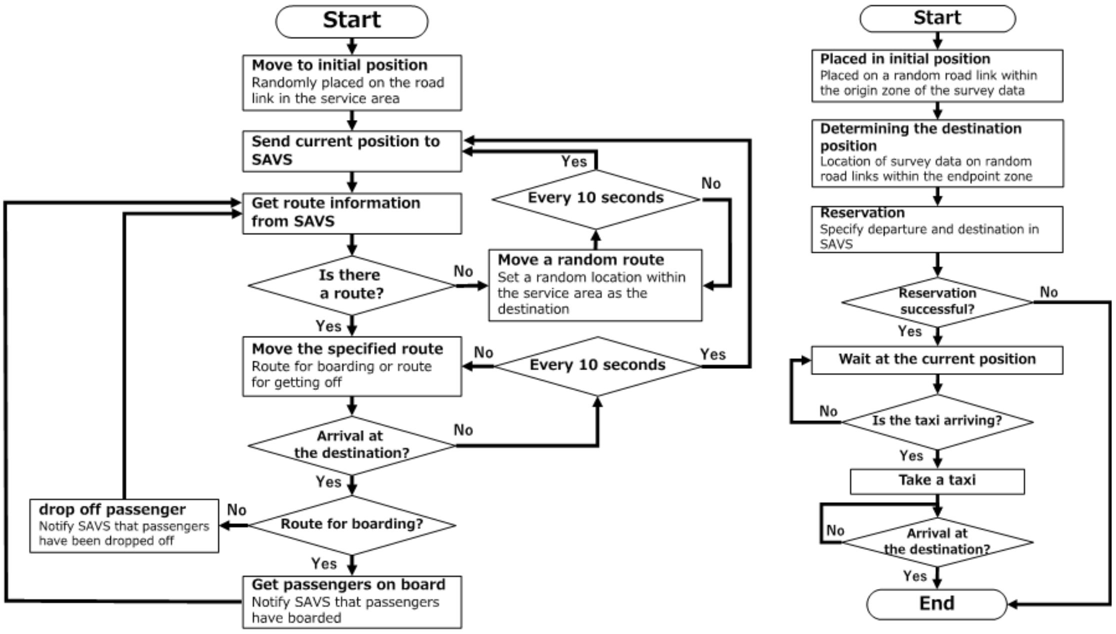


Figure 3. Flowchart of taxi driver (left) and taxi user (right)

Table 1. Simulation scenario

Scenario	Number of vehicles	Evaluation indices
Conventional taxi	5	Number of reservations Average waiting time Average distance traveled Average journey time Average total travel time Number of rideshares Number of failed reservations Average occupancy rate
	10	
	20	
	30	
Ride-sharing taxi	5	
	10	
	20	
	30	

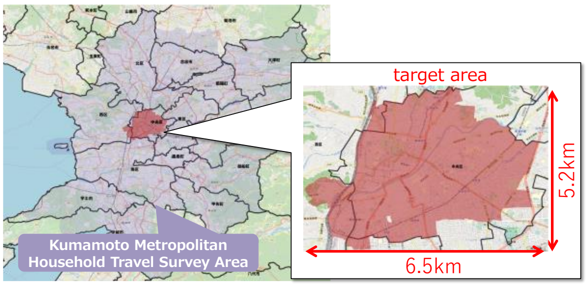


Figure 4. Simulation target area

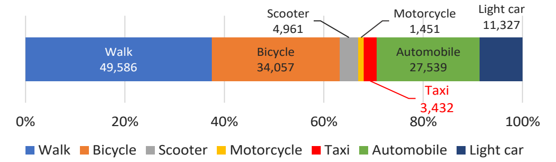


Figure 5. Transportation modal shares for trips in the target area

sharing taxi was not considered, and the target trips were limited to trips within the test area. However, these conditions can all be made broader within K-MATSim. Here, we analyze how the introduction of a ride-sharing taxi service would affect businesses and users.

3.1 Comparison scenarios

The introduction of ride-sharing taxis is expected to compensate for the shortage of drivers, improve profits for businesses, and improve convenience for users. To test our model, we aimed to analyze the impact on businesses and users when a shared taxi service is introduced. Simulations were performed to study the effect of sharing service with different numbers of vehicles. To this end, we increased the number of vehicles one step at a time and analyzed the changes in demand and other effects.

The simulations were performed for twelve different scenarios shown in Table 1. The effects between different scenarios are evaluated, including the number of reservations, average waiting time, average distance, average on-board time, average total travel time, number of rideshares, number of failed reservations, and average occupancy rate. It was assumed that the conventional taxi service and the ride-sharing taxi service could not operate at the same time. Under each of the different scenarios, 5, 10, 15, 20, 25, and 30 vehicles were provided by each service. In addition, in both cases, the conventional taxi service and the ride-sharing service, optimal vehicle allocation was carried out using the SAVS vehicle allocation algorithm.

3.1.1 Target area and road network. To verify the performance of the prototype analysis model and to reduce the computational cost, we decided to limit the study area to the central part of Kumamoto City, as shown in Fig. 4. The road network data in the target area was obtained from "Open Street Map," which allows free access.

3.1.2. Target trips. The agents used in the simulation of the ride-sharing taxi service consisted of current taxi users inside the target area as extracted from data contained in the 4th Kumamoto Metropolitan Area Household Travel Survey conducted in 2012. As shown in Fig. 5, the total number of trips in the study area was 132,353, with current taxi trips accounting for 3,432 of them, or a share of 2.6%. In addition, background car trips on the road network were limited to trips within the study area.

3.1.3 Simulation parameters. The values of the various parameters required to execute the simulation were set as follows.

(1) Number of trials: K-MATSim includes a mechanism by which the expected cost, which is determined by repeating the daily behavior of each agent, affects the choice of the travel mode as well as the route. However, in this study, only the choice of route changed on different days. The simulation was run for 50 days, and the results were then evaluated.

(2) Target time of day: The scan time used in the simulation was 1 second, and the simulation was run for 24 hours from 0:00:00 to 24:00:00. Because taxi trips that ran into the next day were not included in the simulation, the number of trips available for a ride-sharing taxi may have differed from the number of reservations described below, depending on the scenario.

3.1.4. Evaluation indices. The evaluation indices shown in Tables 1 and Table 2 are described below.

(1) Number of reservations: This is the total number of times that users tried to make a reservation. All trips made using a taxi had been reserved; however, trips that ran past 24:00 were excluded from the evaluation of the simulation.

(2) Average waiting time: This is the average time from the completion of a reservation to boarding for users who have completed a reservation.

(3) Average distance: This is the average distance traveled from boarding to leaving the taxi for users who have a completed reservation.

(4) Average on-board time: This is the average time from boarding to leaving the taxi for users who have taken a ride-sharing taxi.

(5) Average total travel time: This is the average length of time from the completion of the reservation to leaving the taxi for all ride-sharing users. It is equal to the sum of the average waiting time and average on-board time.

(6) Number of rideshares: This is the number of trips that resulted in ride-sharing. If there is more than one person in the vehicle at the time of boarding, this is counted as one rideshare.

(7) Number of failed reservations: This is the total number of times users' reservations failed. A reservation is not made if SAVS determines that it is impossible to board the taxi within 120 and 60 minutes of the desired boarding time at the time of reservation or if the distance between the point of boarding and the destination is less than 100 meters.

(8) Average occupancy rate: This is the average value of the ratio of the total travel time to the time that the vehicle is in operation. It is assumed that taxis cruise randomly except when picking up or transporting passengers.

(9) Average occupancy rate (Only while riding): This is the average value of the ratio of on-board time to the time that the vehicle is in operation.

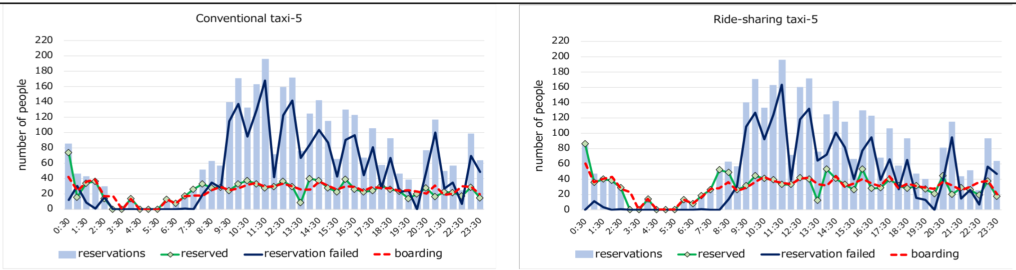
3.2 Comparative analysis

The results of the evaluation indices obtained for each scenario are shown in Table 2. The main results are analyzed below.

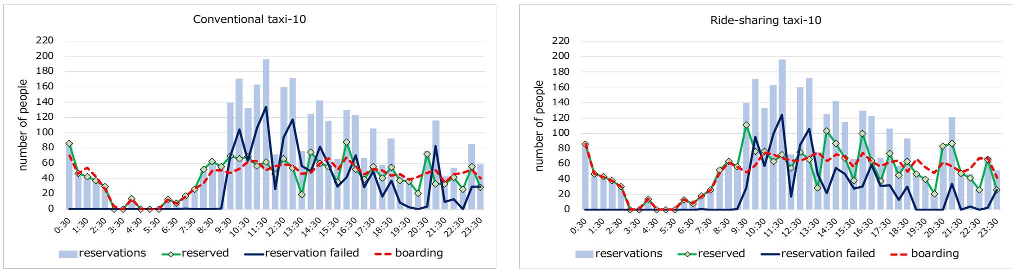
3.2.1 The average of distance and on-board time. For the conventional taxi services, was low, ranging from 1.9km to 2.3km. The average on-board time was also low, ranging from 2.8min to 3.5min. This is because the target area was limited to the central area of Kumamoto City, which is a small area of approximately 5.2 km x 6.2 km, and only trips completed within the target area were analyzed. The situations are similar for the ride-sharing taxis, the average distance and the average on-board time are both low. However, the average distance and average on-board time are considerable increases over the results for conventional taxis. The average distance was ranging from 3.4 km to 3.8 km, and the average on-board time was

Table 2. Results of simulation analysis

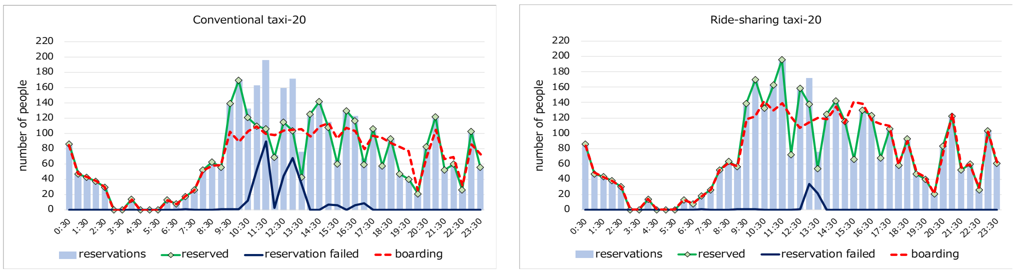
Reservation limit time [min]	taxi type	Number of vehicles	Number of reservations [times]	Number of reservation failed [times]	Average waiting time [min]	Average distance [m]	Average boarding time [min]	Average total travel time [min]	Number of ride-sharing [times]	Average operation rate [%]	Average operation rate [%] (Only while riding)
120	Conventional taxi	5	3,400	2,284	31.1	1.9	2.8	33.94	0	86.7%	43.9%
		10	3,374	1,426	29.5	2.1	3.1	32.67	0	81.3%	42.3%
		15	3,369	755	28.9	2.2	3.3	32.23	0	75.4%	40.3%
		20	3,415	336	24.5	2.3	3.4	27.97	0	67.4%	36.7%
		25	3,425	72	18.3	2.3	3.5	21.79	0	58.4%	32.6%
		30	3,426	5	5.5	2.3	3.5	9.05	0	48.0%	27.9%
	Ride-sharing taxi	5	3,388	2,005	30.1	3.5	5.6	35.68	842	85.5%	62.5%
		10	3,358	1,076	28.8	3.8	5.9	34.69	1,337	75.4%	54.7%
		15	3,420	412	23.9	3.5	5.6	29.51	1,713	63.8%	45.4%
		20	3,420	61	16.5	3.4	5.4	21.81	1,815	52.5%	36.7%
		25	3,422	5	3.5	3.5	5.7	9.16	2,172	38.7%	29.0%
		30	3,422	5	2.6	3.5	5.7	8.26	2,238	30.5%	23.8%



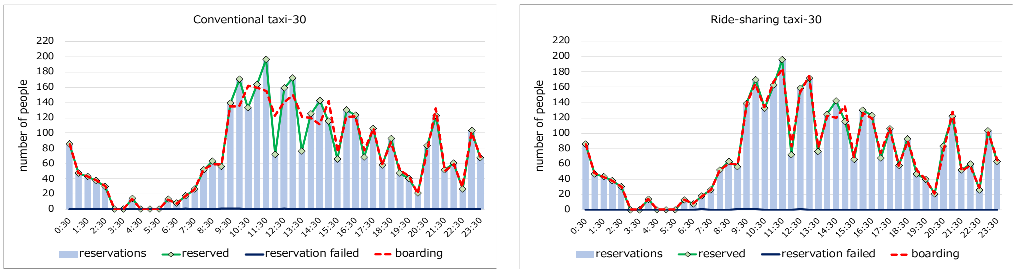
(a) in case of 5 vehicles



(b) in case of 10 vehicles



(c) in case of 20 vehicles



(d) in case of 30 vehicles

Figure 6. Reservation and boarding status by time of each case

from 5.4 min to 5.9 min. This is because the ride-sharing taxis have to take a detour to pick up different passengers.

3.2.2 The average total travel time. The average total travel time varies considerably depending on whether the taxi service is acting in a "sharing" mode. However, regardless of whether the service was provided by ride-sharing taxis or a conventional one, the average total travel time decreased as the number of allocated vehicles increased.

3.2.3 The average waiting time and the number of failed reservations. For the ride-sharing taxi service, the reduction in average travel time with the increasing number of vehicles was very large. That is because the average waiting time greatly decreased when the number of allocated vehicles increased. In all of the tested scenarios, the waiting times for 60%-70% of users were 10 minutes or less.

3.2.4 The average occupancy rate. The average occupancy rate decreases as the number of vehicles increases, regardless of the service type. Besides, the occupancy rate of ride-sharing taxis decreased more significantly. To find the reason for this, we calculated the total number of reservations, the number of successful or failed reservations, and the number of passengers under each scenario. The results are shown in Fig. 6. For the scenario with five conventional taxis, there were very few successful reservations even when the total number of reservations was very small, such as between 0:00 and 3:00 (Fig. 6 (a) left). However, when the number of

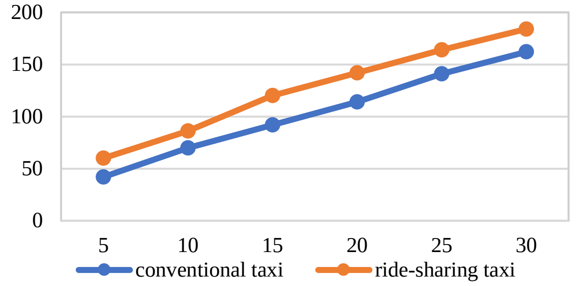


Figure 7. The maximum-number of passengers in each scenario

vehicles increased to more than 10, almost all reservations made at these times (0:00~3:00) were successful (Fig. 6 (b)~(d) left).

In the period from 10:00 to 14:00, when reservations were made, many reservations were unsuccessful in most of the scenarios (Fig. 6 (a), (b)). However, in the scenario with 20 ride-sharing taxis, the number of unsuccessful reservations was small (Fig. 6 (c) right). Moreover, in the scenario with 30 ride-sharing taxis, there were no unsuccessful reservations (Fig. 6 (d) right). These findings indicate that there is an upper limit on the transportation capacity for each scenario, and if the number of reservations exceeds that capacity, many reservations will not be successful

If the number of ride-sharing taxis is increased, the transportation capacity improves and the service can cope with more demand. However, the occupancy rate then falls. As shown in Fig. 7, since the transportation capacity of a ride-sharing taxi service increases with the number of vehicles, excesses of capacity occurred in the off-peak period (see 3.2.5). A decrease in the occupancy rate leads to lower business profits. To reduce this surplus capacity and improve occupancy rate, it will be necessary for operators to predict demand within each period in advance and adjust the number of allocated vehicles appropriately.

3.2.5 The average occupancy rate (only while riding).

The average vehicle occupancy rates throughout a day for conventional taxis and ride-sharing taxis are shown in Fig. 8. The average occupancy rate (Only while riding) refers to the ratio of on-board time to the time that the vehicle is in operation. In the scenario with 10 vehicles, the largest occupancy rate of conventional taxis is 57.3%, while the largest occupancy rate of ride-sharing taxis is 81.1%, 1.5 times that of conventional taxis. This is because the ride-sharing taxi is shared by multiple passengers in the same taxi route to reduce the waiting time. In both scenarios, the vehicle occupancy rate peaks for conventional taxis and shared taxis are around 55% and 80%, respectively.

3.2.6 The seat occupancy rate

The average seat occupancy rates throughout a day for conventional taxis and ride-sharing taxis are shown in Fig. 9. Seat occupancy rate refers to the ratio of the number of passengers to the maximum number of passengers (four passengers) per vehicle. In the scenario with 10 vehicles, the largest occupancy rate of conventional taxis is 14.3%. The largest occupancy rate of ride-sharing taxis is 36.9%, about 2.5 times that of conventional taxis, which indicates that sharing mode is used more effectively. In terms of ride-sharing taxis, when the number of dispatch vehicles is 25, the vehicle occupancy rate and seat occupancy rate are both high during off-peak (0:00 to 5:00) and peak (8:00 to 18:00) periods. This finding indicates that ride-sharing taxis could operate efficiently in the study area.

3.2.7 The maximum number of passengers

According to the number of applications and the ratio of successful reservations, 30 conventional taxis or 25 ride-sharing taxis could accept almost all reservations in the study area. As described above, there is an upper limit on the transportation capacity for each scenario. Fig. 10 shows the maximum number of passengers (upper limit) in each scenario (different vehicle number) per unit time. The maximum number of passengers increases linearly by increasing the number of dispatch taxis in both the conventional taxi and the ride-sharing taxi. In addition, since conventional taxis and ride-sharing taxis are growing in tandem, the difference in transportation efficiency between the conventional taxi and the ride-sharing taxi becomes smaller as the number of dispatch vehicles increases.

4 Conclusions

The results obtained from this research, together with topics for possible future investigation, are briefly described below.

(1) A simulated environment was constructed wherein K-MATSim and SAVS were linked together by a web API. K-MATSim describes user behavior and vehicle movements; SAVS allocates ride-sharing taxis using an optimal vehicle allocation algorithm.

(2) Six scenarios consisting of three scenarios with different numbers of both conventional and ride-sharing taxis were established. For both the traditional and ride-sharing taxis, the average total travel time, which was taken to be the sum of the average waiting time and the average journey time, decreased as the number of allocated vehicles increased. In particular, in the case of the ride-sharing taxi service, the greater the number of vehicles the shorter the waiting time from the completion of reservation to boarding. Similarly, for both the conventional and ride-sharing taxis, the number of reservations that failed decreased as the number of allocated vehicles increased. The reduction in the number of failed reservations was greater in the case of the ride-sharing taxis than that for the conventional taxi service.

(3) For both service types, the average occupancy rate decreased as the number of allocated vehicles increased. This decrease was particularly large in the case of the ride-sharing taxi service. This was because as the number of allocated vehicles and the transportation capacity increased, a surplus in transportation capacity was

produced at times when the demand was less than the capacity. Operators should predict the demand within each time period in advance and adjust the number of allocated vehicles accordingly so as not to produce such a surplus.

These findings related to both user convenience and businesses profitability are useful benchmarks for designing the areas of operation and the number of vehicles to be allocated to ride-sharing services. However, this case study omitted some important factors that should be considered. For example, in this study, existing taxi usage was simply replaced by journeys using ride-sharing taxis without considering the choices that might be made by users. Possible future areas for study are listed below.

(1) Incorporating a modal-choice model in K-MATSim

A mode-conversion model that converts from current use to ride-sharing taxi use or one of the other available modes should be included in K-MATSim. Data are needed to make estimates of the choices that might be made by users or to construct conversion models. However, as previously explained, at present, there are no ride-sharing taxi services actually operating in Japan, which means that obtaining data that include ride-sharing taxis as possible alternative modes of travel is difficult. These data may, therefore, have to be obtained by drawing up suitable questionnaires and conducting surveys.

(2) Expanding the target area

The target area in this case study consisted only of the central area of Kumamoto City. In addition, as was the case with taxis, car trips in K-MATSim were also limited to car trips inside the area of interest. However, the effect on traffic congestion in the target area due to traffic originating outside the area should also be considered. In addition, improving the computability so that this simulated system can be made applicable to larger urban areas is necessary.

(3) Application to areas with different travel patterns and demand characteristics

In this study, the focus was on the center of Kumamoto City, which is an urban area, where high demand can be expected. Ride-sharing taxi services are expected to be a useful mobility service for vulnerable people who live in less densely populated areas, where the demand for movement is low, and where there is a shortage of drivers. Subsequent case studies should be conducted in various different areas that have different demand patterns and socioeconomic characteristics.

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