Evaluating the Impact of Autonomous Vehicles on Short-Term Travel Behavior and Accessibility Changes using Agent-Based Simulation: A Case Study of Gunma Prefecture
エージェントベースシミュレーションを用いた自動運転車導入による交通行動とアクセシビリティへの短期影響の評価：群馬県を例に

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The emergence of autonomous vehicles is expected to shape the urban transportation system in various ways. In this study, a large-scale agent-based disaggregate simulation model, MATSim, is employed to measure the impact of autonomous vehicles on accessibility changes. This study used disaggregate spatial data from the Gunma Prefecture Person Trip Survey as the initial travel demand input for the model. Two new autonomous transport modes, shared autonomous vehicle (SAV) and private autonomous vehicle (PAV), are included in the simulation, in addition to the existing human-driven private vehicles. A scenario analysis is conducted using fleet size of SAV, ownership of PAV, operation cost, value of time changes as the key variables in the scenario setting. Based on the final travel demand results, a Hansen-type accessibility analysis is conducted, providing quantitative evidence to measure the potential impact of autonomous vehicles on accessibility changes in the context of Japanese regional cities. This research found a considerable market share of AVs in scenarios with positive assumptions, and an overall accessibility increase in the scenario where PAVs were introduced. Particularly suburban areas seemed to enjoy more accessibility gains which might result in further urban sprawl in future.

1. Introduction

With the rapid development of vehicle to infrastructure communication and infrastructure to vehicle communication technologies nowadays, the automobile industry has high expectations regarding autonomous vehicles (AVs). Although fully autonomous vehicles (SAE Level 5[1)]) are not yet operational, automobile manufacturers are committed to this task and many have publicized plans to introduce fully autonomous vehicle by 2020.

As an extensive research field nowadays, many academic papers on the implication of AVs have been published, with most research efforts focusing on the effects of the new technology on both vehicle characteristics and users' travel behavior. Such changes include more efficient use of road capacity and level-of-service with smoother acceleration and deceleration, a shift from human driven vehicle ownership to AV ownership, higher tolerance to distance traveled, shorter in-vehicle times, but also an increase in vehicle kilometers traveled, and also economical saving as drivers aren't needed anymore.

Given the benefits listed above, AVs have been hailed as the future daily mobility tool, and thus it is expected that it will not only impact transportation systems but also shape the urban land-use system in various ways. From a regional perspective, impacts on accessibility might influence people's travel pattern and even residential choice in a longer time span[2)].

In considering the concerns above, this research aims to evaluate AV implications on short-term travel behaviors and regional accessibility changes via simulation method.

2. Methodology & Data

(1) Agent-based Simulation: MATSim

In this paper, an activity-based agent-based disaggregated simulation model, considered one of the most behaviorally realistic simulation models nowadays, is used. Specifically, a the large-scale open-source simulation platform, MATSim[3)] is employed.

This toolkit adopts an activity-based agent-based iterative loop to solve the traffic assignment problem, as shown in **Fig.1**.

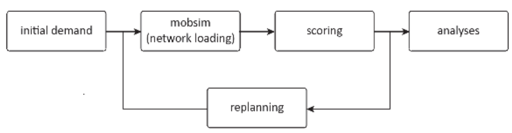

Fig.1 MATSim iterative loop

The loop starts with an initial travel demand in the form of daily activity chains for every individual. Later in the mobsim phase, the activity chain is loaded and assigned to the road network. After the end of one simulation day, a score is calculated for each agent's activity chains (plans). Then in the replanning phase, every agent has to choose one plan to execute for the next iteration. The collection of plans is generated (mutated) from their previous plans.

To be specific, the scoring function is formulated following Charypar and Nagel[4], where the utility of a plan S_{plan} is computed as the sum of the utility of all activities $S_{act,q}$ plus the sum of all travel (dis)utilities $S_{trav,mode(q)}$:

$$S_{plan} = \sum_{q0}^{N-1} S_{act,q} + \sum_{q=0}^{N-1} S_{trav,mode(q)} \quad (1)$$

Where N denotes the number of activities. q is the activity and *mode*(q) refers to the travel mode using by the agent following activity q.

This algorithm makes it more authentic to simulate traffic assignment and people's choice process, which is important to improve prediction validity. A more detailed description of the mechanics refers to Nagel et al.[5]:

(2) Data collection

Several data sources are used in this study. The Gunma Person Trip Survey data in 2015 (PT data) is used as the initial travel demand input in MATSim.

The survey provides one-day activity chains including trip purpose, location, mode and departure times. Sample size is 64,500 households in Gunma prefecture plus Ashikaga City in Tochigi prefecture.

Train and bus are excluded from the choice set because of their low modal share and intractability. The effective sample size was 53,814, which is around 2.53% of the whole target population.

TelPOINT Pack DB 2016 is used to get facilities data used as the input for the accessibility computation. The data records facility types and geographical coordinates for 23 million facilities across Japan.

Network data is extracted from OpenStreetMap[6]. The study area bounding box covers totally 13,680km^2.

(3) Simulation settings

a) Network loading settings and traffic behavior

This study adopts with the MATSim's default traffic flow model: QSim[7] to simulate network loading part in the iterative loop. Basically, when vehicles enter a road segment, they are inserted into the tail of the queue of the road. The outflow speed is distinctive to each road and being specified by the capacity attribution.

In this study, both private autonomous vehicle (PAV) and shared autonomous vehicle (SAV) are added as new transport mode alternatives, competing with human-driven private vehicles.

HVs and PAVs are exclusive to one certain agent, namely they will not be shared with other agents. SAVs basically follow the behavior of current taxis where ride-sharing is not considered.

The SAV dispatching follows a rule-based heuristic, namely, demand-supply balancing. It is a strategy that dispatches the nearest idle taxi in oversupply situations and dispatches the taxi that just became idle, to the nearest request in undersupply situations. Refer to Maciejewski et al.[8] for more details.

b) Scoring settings and mode choice set

In this work, the travel disutility for leg q is given as:

$$S_{trav,mode(q)} = C_{mode(q)} + \beta_m \times m_q + \beta_{trav,mode(q)} \times t_{trav,q} \quad (2)$$

Where, $C_{mode(q)}$ is a mode-specific constant. β_m is the marginal utility of money. m_q is the change in monetary budget caused by fares, or tolls for the complete leg. $\beta_{trav,mode(q)}$ is the direct marginal utility of time spent traveling by mode. $t_{trav,q}$ is the travel time between activity locations q and $q+1$. In SAV's case, the waiting time is included in $t_{trav,q}$.

The parameters are calibrated using the PT data for a more realistic representation for the replanning and also accessibility computation.

Driver and passenger mode are separated for the car mode in the PT data since these two are assumed to differ in marginal utility of time. And on the basis of the separation, passenger mode is further divided into two types: "passenger with car ∩ with license" and "passenger with no car ∪ no license" in attempt to distinguish whether the agent chooses to be a passenger because he or she has to or not.

SAV and PAV parameters defined in the simulation are modified on the basis of the Car (passenger with car ∩ with license) coefficients for value of time variable. The constant is reference to Car (passenger with car ∩ with license) and car (driver) mode, respectively.

The basic idea behind this ad-hoc approach is that given no observational data is available, parameters of AV must be proxied with an existing mode. The willingness to choose the car (passenger with car ∩ with license) resembles the most with AV, because the trip-maker most likely chooses to be a passenger on his or her own initiative (not because he or she doesn't own a car or license), to avoid the driving burden in both of these two modes presumably.

On the basis of the rules set above, the marginal utility of each mode is calibrated on the basis of a Multinomial logit mode choice model. Travel time of car and walk mode are calculated using Google Distance Matrix API, with the input of coordinates of OD pairs, where time of day is set following the reported departure time in the PT survey; travel time of bike mode is calculated from the ratio of walk distance and bike speed, which is set to 9km/h; travel cost of car is set to 6.8yen/km, considering the average fuel consumption in Japan is 21.9 km/L[9)], and average gasoline price (regular) in Gunma is 150 yen/L[10)]. The calibration results are shown in **Table 1**.

Table 1 Multinomial Logit model calibration results for mode choices

Variable name	Coefficient	t statistic
Car (passenger with no car ∪ no license) constant	-3.453	-129.96
Car (passenger with car ∩ with license) constant	-4.599	-153.75
Bike constant	-1.416	-55.27
Walk constant	-0.708	-28.33
Travel cost/yen	-0.00424	-6.93
Travel time of car (driver)/h	-2.824	-7.65
Travel time of car (passenger with no car ∪ no license)/h	-5.631	-14.70
Travel time of car (passenger with car ∩ with license)/h	-2.548	-6.64
Travel time of bike/h	-3.221	-22.18
Travel time of walk/h	-8.058	-68.417
Goodness of fit		
LL(0)	-156087.7	
LL(β)	-57356.3	
-2[LL(0)- LL(β)]	197462.8	
ρ^2	0.633	
Adjusted ρ^2	0.632	

c) Replanning settings

In application, the plan in the next iteration is generated with two operators: mutation and selection. Mutation operator modifies a certain component in previously executed plan, and adopted this modified (mutated) plan for the next iteration. Three types of mutation operator, namely Reroute Mutator, Time Allocation Mutator, Subtour Mode Choice Mutator, are used in this study. The mutators suggest a mutation in route choice, departure time choice and mode choice, respectively.

As for the selector part, to account for stochasticity in variations in agents' behavior, this study uses MNL model as the plan selection approach.

In this study, the share of agents to execute Reroute mutator, Time allocation mutator, Subtour mode mutator and MNL selector is 0.05, 0.1, 0.15 and 0.7, respectively.

(4) Accessibility computation

In this study, an economically interpretable accessibility assessment based on Hansen[11)] is adopted as follows:

$$A_l = ln \sum_k e^{V_{lk}} \tag{3}$$

Where k denotes all possible destinations and V_{lk} equals the disutility (marginal utility × travel time + constant) of traveling from location l to destination k. The logsum term of exponentials can be interpreted as the expected maximum utility[12)]. The marginal utility is exactly the aforementioned $\beta_{trav,mode(q)}$, and the travel time of each link is acquired after simulation converges.

(5) Scenario settings

Given the uncertainty associated with the future, a scenario analysis with different degrees in vehicle characteristics and travel behavior changes is used in this research. Fleet size of PAV and SAV, operation cost, value of time change is considered key variables in the scenario setting.

There are several studies providing insights on the setting of these key variables. Johnson and Walker[13)] predict that shared, electric autonomous vehicles will cost around 35 eurocents per mile (29yen/km) in 2035. And Stephens et al.[14)] argue a $0.40-$0.60 per mile (27-41yen/km) in the American context. Compared to the human-driven cost to date of about $2.00 per mile (136yen/km, NY), a discount around 20%-40% with current taxi fare in Japan is assumed for the operation cost of SAV. In terms of fleet size of autonomous vehicles, there are few references available, especially for SAV: Fagnant et al[15),16)] employed MATSim to test the optimized fleet size with a rule that generates a new SAV for every traveler who has been waiting for at least 10 min after sending the request in their warming-up simulation. They found that 1,977 SAVs meet the demand of 56,324 agents (3.51% of the demand size) and 1,688 SAV meet it for the 60,551 case (2.78% of the demand size), respectively. More generally, Bansal and Kockelman[17)] forecast Level-4 automation market penetration would be 28.6% in 2035, using a binary logit model and Monte-Carlo simulation based on a state preference (SP) survey. As for the change of in-vehicle value of time, to the best of our knowledge there is no quantified evidence so far.

Based on the above, the scenarios are set as below (**Table 2**):

Table 2 Scenario definitions

Scenario	**PAV ownership** (of agents' number)	**SAV fleet size** (of agents' number)	**Value of travel time for AV** (of current passengers')	**Fare of SAV** (of current taxi's fare)
base	*Only HV, bike and walk applied, where parameters are set exactly as the calibration results.*			
1	10%	2%	70%	60%
2	30%	5%	40%	20%
3	40%	8%	10%	10%
4	50%	10%	10%	5%
5	None	5%	40%	20%

Note: the current taxi fare refers to Gunma Prefecture taxi pricing pattern (small car), with start fare of 710yen for the first 2000m and 90yen per 301m hereafter.

3. Simulation result

After 70 iterations for each scenario, converged simulation results are derived from data processing as below:

(1) Modal split result

As **Fig. 2** shows, the base scenario approximates the observed mode share in the Gunma PT data.

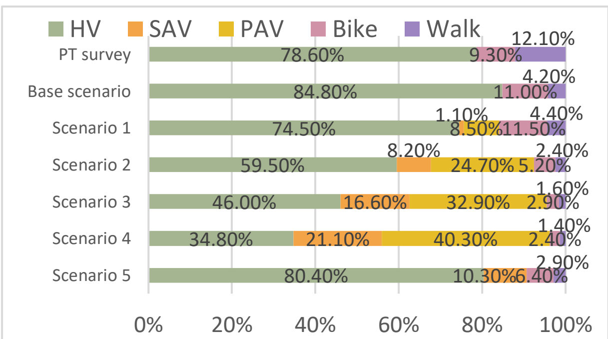

Fig.2 Mode shift result

For the PAV mode, in Scenarios 1-4, nearly all the people who own a PAV prefer to use it in their daily activities, showing that only the acquisition cost behind the PAV ownership choice might be the largest barrier against usage. The lower travel time parameter and no tour constraint might explain this tendency.

Value of travel time and SAV fare compositely affect the SAV share along with the fleet size. A potential extra cost of waiting time and distance-based fare discourage the agents for using SAV presumably.

Nevertheless, as a whole, the results of Scenarios 2-5 still indicate a considerable market penetration for SAV given relatively optimistic settings, and hence a promising potential niche market.

(2) Travel distance

Total daily travel distance (or Vehicle Kilometer Traveled, VKT) for each scenario is shown in **Table 4**.

Table 4 Total daily travel distance

Scenario	**Total daily travel distance**	**Ratio change versus the base**
Base	8.340×10^5km	-
1	8.369×10^5km	+0.35%
2	8.779×10^5km	+5.26%
3	9.001×10^5km	+7.93%
4	9.123×10^5km	+9.39%
5	8.756×10^5km	+4.99%

An increase of total VKT is observed with the SAV introduction. Hence it might result in more traffic congestion in the future all else equal. Nevertheless, the level of increase seems to be not that high considering the potential AV benefits upon road capacity. Further studies could make more credible results in this issue.

(3) Accessibility analysis

The accessibility analysis simulation area is shown in **Fig.3**. **Fig.4** shows the HV accessibility result of the base scenario. It can be observed that the result matches the developing level of Gunma. In large cities such as Takasaki and Maebashi, the accessibility is clearly higher than other remote places.

Fig.5-Fig.8 depict the PAV accessibility changes against the base scenario (HV) for the 4 scenarios with PAV applied. For these scenarios, they are deliberately plotted in the exact same scale so as to be comparable. The black box in the legend in the left indicates the value range for each scenario.

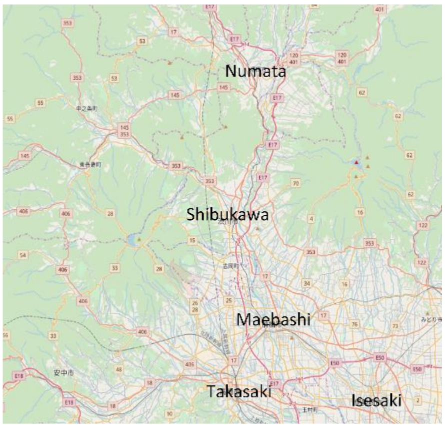

Fig.3 Accessibility analysis area (Source: OpenStreetMap)

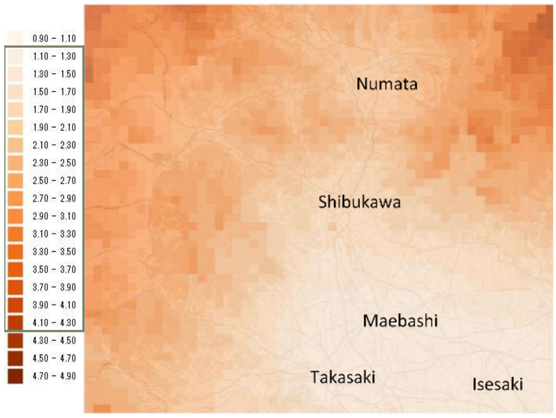

Fig.6 Accessibility changes plot of Scenario 2 (PAV)

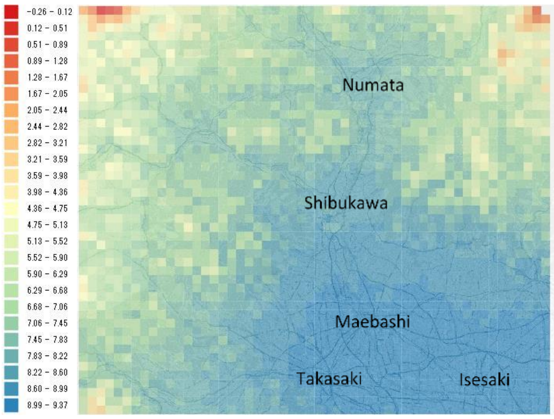

Fig.4 Accessibility plot of base scenario (HV)

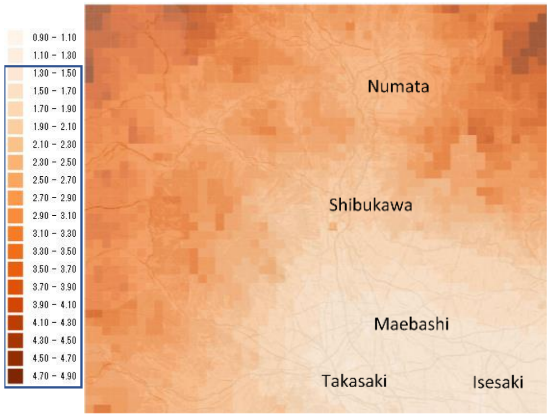

Fig.7 Accessibility changes plot of Scenario 3 (PAV)

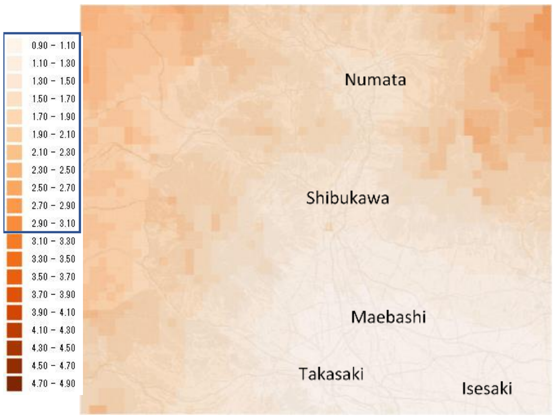

Fig.5 Accessibility changes plot of Scenario 1 (PAV)

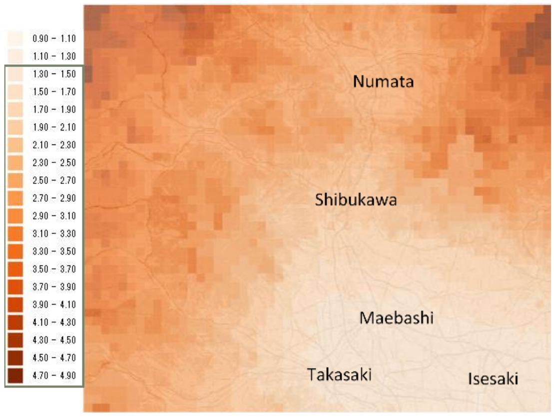

Fig.8 Accessibility changes plot of Scenario 4 (PAV)

It is assumed here that the decrease of value of travel time mainly accounts for the accessibility gains. The accessibility increases in particularly remote areas will likely encourage people to travel further and might promote further suburbanization in the future. Every evolution of mobility in human history resulted into an expansion of human activity area. The spreading of automobiles 100 years ago sparked aggressive urban sprawl in the subsequent decades.

As such, the findings presented here should serve as a warning among planners and governments of potential risks of these new technologies and further offer some insights in specific urban policies.

4.Limitation & Future work

Some limitations need to be highlighted: first of all, this study uses the current travel demand data as the input for the simulation and does not consider new travel demand generation or destination choice changes in the replanning. In this case, the induced trips and potentially longer distance with AVs cannot be captured, which is probably another important factor to influence modal shift. In order to address this limitation, generating a synthetic population and building a model to simulate travel patterns and OD matrix altogether is necessary. Besides, modeling of vehicle ownership is necessary to improve the simulation interpretability and forecast reliability.

In addition, the mode choice calibration is based on current choice preferences and might be a source of error as well. Conducting a SP survey to capture attitudes on the unexisting modes would be helpful.

Also, the method for computing accessibility of shared mobility modes is of significance in order that a more comprehensive assessment could be conducted thus providing more substantive evidence. Other activity type such as employment are pending to be involved in accessibility analysis.

Finally, as a forecast research, the author is fully aware that due to not only the uncertainty of future development but also those procedures aimed to adapt the simulation model into the AV context, any attempt to predict future implications of AVs should be understood as mapping potential outcomes to further inform design and implementation.

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