Evaluating the Impact of Autonomous Vehicles on Accessibility using Agent-Based Simulation—A Case Study of Gunma Prefecture

Lichen LUO[1], Giancarlos TRONCOSO PARADY[2], Kiyoshi TAKAMI[3] and Noboru HARATA[4]

[1]Dept. of Urban Eng., The University of Tokyo
(Hongo 7-3-1, Bunkyo-ku, Tokyo 113-8656, Japan)
E-mail:lichen.l@ut.t.u-tokyo.ac.jp
[2]Member of JSCE, Assistant Professor, Dept. of Urban Eng., The University of Tokyo
(Hongo 7-3-1, Bunkyo-ku, Tokyo 113-8656, Japan)
E-mail:gtroncoso@ut.t.u-tokyo.ac.jp
[3]Member of JSCE, Associate Professor, Dept. of Urban Eng, The University of Tokyo
(Hongo 7-3-1, Bunkyo-ku, Tokyo 113-8656, Japan)
E-mail:takami@ut.t.u-tokyo.ac.jp
[4]Member of JSCE, Professor, Dept. of Urban Eng, The University of Tokyo
(Hongo 7-3-1, Bunkyo-ku, Tokyo 113-8656, Japan)
E-mail:nhara@ut.t.u-tokyo.ac.jp

The emergence of autonomous vehicles is expected to shape the urban transportation system in various way. 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 traditional private cars. 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, an Hansen-type accessibility analysis is conducted, providing a quantitative evidence to measure the potential impact of autonomous vehicles' in the context of Japan.

Key Words : *autonomous vehicles, agent-based simulation, travel behavior, accessibility, person trip survey,.*

1. INTRODUCTION

With the rapid development of V2V (vehicle to vehicle communication), V2I (vehicle to infrastructure communication) and I2V (infrastructure to vehicle communication) technologies nowadays, the automobile industry has high expectations regarding a new mobility type: autonomous vehicles (hereinafter AVs). Although fully autonomous vehicles (SAE Level 5[1)]) are not yet operational, automobile manufacturers are commited to to this task and many have publicized plans to introduce fully autonomous vehicle by 2020[2)].

As an extensive research field nowadays, many of 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[3,4)], a modal shift that influences private car ownership[5,6,7)], higher tolerance to distance traveled[8,9)], shorter in-vehicle times, but also an increase in vehicle kilometers traveled[10,11)], and also economical saving as no driver are needed anymore[12,13)].

Given the benefits listed above, AVs have been hailed as the future daily mobility tool, and thus it will not only impact transportation systems but also shape the urban land-use system in various way. From a regional prespective, an impact on accessibility is expected which might influence people's travel pattern and even residential choice in a longer time span[14)].

Some studies have been conducted to evaluate accessibility changes resulting from AV introduction. Meyer et al.[15)] studied the impact of AVs on accessibility in the Swiss municipalities based on the Swiss National Transport Model data. Three nation-wide scenarios that differ in AV deployment strategies (i.e. type of roads or areas AVs can operate) and ownership were examined and the induced travel demand identified. Their findings suggest overall considerable accessibility gains in all the scenarios while large cities suffer a small decrease in the fully shared autonomous scenario. For example, a 10% increase in accessibility is found in the scenario with induced demand and optimistic capacity change settings. However, the absence of a detailed individual network loading model, but rather using BPR function[16)] to calculate congested travel time limits their results since few traffic interactions are concerned. In addition, the reduction of the driving burden is not considered in this study.

Childress et al.[17)] also conducted an accessibility analysis in the context of AVs for the Puget Sound area, Washington State, USA. The study applied an activity-based travel model, SoundCast, which simulates individual travel choices across a day and long-term choices like residential and work location. Four scenaios concerning capacity change, parking cost change, and value of time changes were evaluated using indicators such as VKT (vehicle kilometers traveled) and delay.Accessibility changes were also evaluated for the most aggressive AV scenario. The Puget Sound Regional Council researchers founded that due to the convenience of AVs, VKT and total traveled distances increase 19.6% and 14.5%, respectively in their most optimistic scenario, a finding that is consistent with the concerns of some scholars. In the same scenario, aggregate logsum accessibility increased from 8.5% to 8.9% for the whole Seattle area, with considerable higher increases in more remote areas. Nevertheless, the study does not consider the effect of AVs empty trips, and has a very simplistic representation of the shared AVs.

While aiming to address some of the limitations stated above, this study offers insights into the implications of AVs in the Japanese context. By using the disaggregate spatial data and an activity-based agent-based simulation model, several AVs evaluation criteria such as passengers' waiting time and AV empty driving ratio are used to measure whether the scenario is feasible or not. Furthermore, A Hansen-type accessibility analysis is conducted, providing a quantitative evidence on the potential impact of autonomous vehicles in a longer term.

To the best of our knowledge, this is the first research addressing via agent-based simulation the effects of AVs on accessibility in Japan. As a developed country, Japan shares some similarities with European countries and the United States, while also possesing some distinct characteristics like high transit modal share and the ageing society problem. To what degree will AVs impact this nation is definitely of significance from the authors' perspective.

It is also worth noticing that with the uncertainty about technology development, governmental policies, customers' attitudes, economic growth and environmental issues in the future[18)], any attempt to predict future implications of AVs should be understood as mapping potential outcomes to futher inform policy design an implemetations, while acknowledging the limitations of this approach.

2. METHODOLOGY & DATA

(1) Agent-based Simulation —MATSim

In this paper, an agent-based disaggregated simulation model, considered one of the most behaviorally realistic simulation model nowadays,is used. Specifically, a large-scale open-source simulation platform, MATSim[19)] is employed.

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

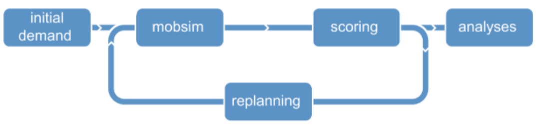

Fig.1 MATSim iterative loop

The loop starts with an initial travel demand in the form of daily activity chains for every individual. Later in the iterations, 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). The score can be interpreted as econometric utility[20)]. Every agent possesses a collection of plans generated from their previous plans, and have to choose one to execute in the next iteration.

The basic logic behind the iteration process is extending the route assignment loop in classical Stochastic User Equilibrium[21)] to other choice dimensions like mode departure time choice, at the individual (agent) level.

It is believed by the authors that this algorithm makes it more authentic to simulate traffic assignment and people's choice process, which is important to improve the validity of the prediction. A more detailed description of the mechanics of the simulator is provided below borrowing from Nagel et al[22)]:

First, the incorporation of agent-based simulation rather than continuous flow allows for capturing travel demand heterogeneity efficiently. Second, switching towards daily plans from "route swapping" renders a more authentic simulation with all choice dimensions jointly equilibrated. However, even given many constraints like Hägerstrand's space-time prisms[23], the attempt to identify the optimal all-day plan is computationally unmanageable. Meanwhile, the criticism of lack of behavioral realism has always been raised as well since real travelers might not able to compute the best responses[24] ,which is similar with the case in pure route assignment model. Therefore, the agent's daily planning problem is approached with a population-based search algorithm (i.e. evolutionary algorithm), where each agent maintains and improves multiple candidate solutions. Thus, "a population of persons where every person has a population of plans", the so-called co-evolutionary algorithm, is applied in MATSim.

Clearly, in order to account for the effects of additional choice dimensions, it is necessary to use generalized utility functions in the scoring part. In MATSim, the scoring function is formulated according to Charypar and Nagel[25], where utility of a plan S_{plan} is computed as the sum of all activity utilities $S_{act,q}$ plus the sum of all travel (dis)utilities $S_{trav,mode(q)}$:

$$S_{plan} = \sum_{q=0}^{N-1} S_{act,q} + \sum_{q=0}^{N-1} S_{trav,mode(q)} \quad (2a)$$

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.

(2) Accessibility computation

Accessibility can be defined as "the potential for interaction and exchange"[26] or "people's overall ability to reach services and activities, and therefore the time and money that people and businesses must devote to transportation."[27] Being different with classical mobility-based planning performance indicators such as automobile travel speed, delay and travel cost, accessibility-based analysis concerns the ultimate goal of transportation activity, access; thus measuring the transport system in a more comprehensive way.

In this work, an economically interpretable accessibility assessment that based on Hansen[27] is adopted as follows:

$$A_l = ln \sum_k e^{V_{lk}} \qquad (2b)$$

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[25,28].

The procedure quantifies "how accessible a given location l is to certain services"[29], called outgoing accessibility. In application, the computation procedure is highly disaggregated and coordinate-based with single facility considered as the activity opportunity (destinantion k). However, the location to be evaluated is tessellated in the form of 1km×1km cells. For each pair of cell l and service k, a Least Cost Path Tree is applied[30] that determines the route with the least travel disutility.

In this study, the measurement of the time-dependent travel times is based in the morning peak on the mode of PAV and/or Human-drived vehicles. Facility type is limited to leisure and shopping and 246,918 facilities are concerned in this research finally.

(3) Data collection

Severa data sources are used in this study. Gunma Person Trip Survey data in 2015[31] (hereinafter 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.

The scoring parameters is calibrated from the PT data. After eliminating data with missing values, excluding persons who used bus at least once during the survey period, and trips either starting or ending outside the study area, the effective sample size was 59,249, which is around 2.79% 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 the Open Street Map. The study area bounding box covers totally 13,680km^2. Road capacity was scaled down by a 2.79% factor to match the sample/population ratio.

(4) Simulation settings

a) Mode choice set.

In this simulation, both private autonomous vehicle(PAV) and shared autonomous vehicle(SAV) are added as new transport mode alternatives, competing with traditional private vehicles. Altogether, there are 5 travel modes involved: human-drived vehicle(HV), SAV, PAV, bicycle and walking. Private ownership is only considered for PAVs. As such, everyone can choose HV and bicycle in the mode choice (as well as walk and taxi mode), but PAV could only be choosed by those who are assigned to own one.

Train and bus are excluded from the choice set because of their low modal share (2.5% and 0.3%[30]), and uncertainty in future. Current mode share of Gunma is showed in Fig.2.

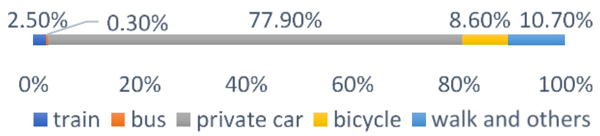

Fig.2 Mode share in Gunma and Ashikaga city in 2016[30]

In the plan selection part, to account for stochasticity in variations in agents behavior, this research uses Multinomial Logit model[31] as the plan selection approach:

$$\mathrm{P(i)} = \frac{e^{\mu S_i}}{\sum_j e^{\mu S_j}} \qquad (2c)$$

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

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

Where, $C_{mode(q)}$ is a mode-specific constant. β_m is the marginal utility of money. Δm_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 $q+1$.

The parameters are calibrated with PT data for a more realistic representation for the replanning and also accessibility computation. The calibtration uses the same sample size, 59,246 with the effective agent size in the simulation, where totally 169,992 trips are included. And 5 modes, HV(car), taxi, bike, walk and train are included as the mode choice set, accounting for car and bike ownership.

In application, It is worth noticing that the train choice is included in the calibration but it will not be used in the simulation hereafter. Parameters of SAV and PAV will be modified on the basis of the car coefficients for value of time variable. But the constant is reference to taxi and car mode, respectively.

b) Network loading and traffic mode behavior

This research adopts with the MATSim's default traffic flow model: QSim[32] to simulate network loading part in the iterative loop. The QSim applies with a computationally efficient queue-based approach but at the compromise of reduced resolution. 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.
Specifically, HVs and PAVs are following the similar rule that is exclusive to one certain agent.

Table 1 Multinomial Logit model calibration results for mode choices.

Variable name	**Coefficient**	**t statistic**
Taxi constant	-6.078	-64.687
Bike constant	-1.259	-67.549
Walk constant	-0.903	-44.589
Train constant	-4.886	-87.841
Travel cost/yen	-0.000982	-99.005
Travel time of car, taxi/h	-6.325	-56.545
Travel time of bike/h	-4.355	-71.061
Travel time of walk/h	-6.829	-93.732
Travel time of train/h	-1.226	-27.401
Goodness of fit		
LL(0)		-224930.8
LL(β)		-48777.3
-2[LL(0)- LL(β)]		352307.0
ρ^2		0.783
Adjusted ρ^2		0.783

HVs are restrained with the subtours: a consecutive subset of a plan which starts and ends at the same link, in the mode choice replanning part. In other word, an agent cannot choose other mode than HV given the last activity is fulfilled by HV. To be noticed, the passenger car unit (PCU) factor of AVs is assumed unchanged in this research.

The SAV behavior follows rule-based heurisics, namely, demand-supply balancing. It is a strategy that dispatchs the nearest idle taxi in oversupply situation while dispatchs the taxi that just become idle, to the nearest request in undersupply situation. Please refer to Maciejewski et al[33] for more details. In addition, each SAV trip is imposed with a pick-up and drop-off time of 120s together and no roaming behavior.

As for bicycle and walking modes, the former follows the so-called Seepage behavior[34] that mixed with vehicles. The latter is performed via teleportation, where the distance is calculated as the beeline distance imposed with a 1.3 factor and the speed is set as 4km/h.

(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. Among them, fleet size of PAV and SAV, operation cost, value of time change are considered as the key variables in the scenario setting.

Modifying parameters in both simulation initial input and choice model renders the realization of different scenarios in MATSim.

There are several academic studies providing insights on the setting of these key variables. Johnson and Walker[35] predict that shared, electric autonomous vehicles will cost around 35 eurocents per mile(29yen/km) in 2035. And Stephens et al[36] argue a $0.40-$0.60 per mile(27-41yen/km) in the American context. Comparing with the human-drived cost to date about $2.00 per mile(136yen/km, NY), a discount around 20%-40% with current taxi fare in Japan is assumed to be imposed to the operation cost of shared autonomous vehicles. For the fleet size of autonomous vehicles, there is few general references available especially for SAV: Fagnant et al[12,13] employed MATSim to test the optimized fleet size with a rule that generate 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[6] forecasted a Level-4 automation market penetration would be 28.6% in 2035, using binary logit model and Monte-Carlo simulation based on an internet survey. As for the change of in-vehicle value of time, there is no quantified suggestion published with evidence.On the reference of the review, the scenarios are set as below (Table 2):

a) Scenario 1: Exclusive sharing autonomy

“*Fast, cheap, comfortable, sharing autonomous units everywhere.*”

It is assumed that in 2030, both the technology and economy grows at a considerable pace. The government finds it a great way to improve people’s mobility and safety by franchising a fleet of SAVs with almost full control of them. People are very willing to use the,. and have got accustomed to this novel transport of mode.

This scenario corresponds to the suggestion that no private ownership is allowed in future, as thus make it more convenient to manage the fleets.

b) Scenario 2: Skeptical market

“Can those computers really be trusted?”

In this scenario, the assumption is that in 2030, the technology is still not fully trusted, some lethal accidents in trial occured, people are holding a wait-and-see attitude and only those innovators buy some PAVs. The government is also suspicious and restrains in the regulations and subsidies of AVs.

This scenario shows a pessimistic view in future and is a counterpoint for other scenarios.

Table 2 Scenario definitions.

	PAV ownership	SAV fleet size	Value of travel time for AVs	Fare of SAV
Scenario 1	None	6% of agents’ number	40% of current cars’	20% of current taxi’s fare
Scenario 2	10% of agents’ number	2% of agents’ number	70% of current cars’	60% of current taxi’s fare
Scenario 3	30% of agents’ number	4% of agents’ number	40% of current cars’	20% of current taxi’s fare

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.

c) Scenario 3: Booming market

“Booming sales performance and satisfied governments”

A situation is observed with exciting sales performance of autonomous vehicles in both vehicle manufacturers and SAV operation companies thanks to rapid technology development, positive customers’ attitudes as well as supportive governmental policies.

Similar to Scenario 1, this scenario offers relatively optimistic prediction of the future with bloom in both PAVs and SAVs. The same settings in value of travel time and operation cost as Scenario 1 provides convenience in the analysis part.

In addition to Scenario 1-3, a base scenario where only HVs, bicycle and walk compose as the choice set is conducted as well. Other settings are set the same with other scenarios.

3. SIMULATION RESULT

After 50 iterations for each scenario, simulation results are derived from data processing as below:

(1) Modal split result

As the Table 3 shows, the base scenario resembles the current mode share (Fig.2). Bicycle and HV mode takes a higher share possibly because vehicle ownership as well as the fact that parking issues are not considered in this study.

For Scenario 1-3, It is found that the bicycle and walk maintain similar shared compared to the base scenario despite the introduction of AVs. The result suggests that traditional HV trips, have higher tendency to be fulfilled by AVs in future, while trips with short distance probably will not

Table 3 Modal split result.

	HV	SAV	PAV	Bike	Walk
Base	86.3%	-	-	10.2%	3.5%
Scenario 1	81.4%	2.5%	-	12.1%	4.0%
Scenario 2	73.3%	1.5%	9.3%	12.1%	3.8%
Scenario 3	55.7%	2.3%	28.0%	10.7%	3.3%

In detail, the share of SAV is found to be unexpectedly low in all three scenarios. Some speculations can be drawn. First, it is possibly that the fleet size is not adequate to serve the requests in time. Although the network capacity is reduced as to match the sample/population ratio, the overall size and road length remain as it is. In this case, the sparse distribution of both SAV fleet and requests impose a negative effect in SAV performance and thus decrease its choice probability in following iterations. Secondly, the constant in the SAV utility function that was calibrated from the current taxi mode is fairly low. The SAV mode might share less similarity with the current taxi mode and some amendment might be supposed to apply to the mode choice model. Still, the share of Scenario 2 is the least among the three, which confirms the relative disadvantage of SAVs in the scenario settings.

As for the PAV, in Scenario 2 and 3, it is observed that nearly all the people who own a PAV prefer to use it in their daily activities. The lower travel time parameter and no subtour constraint might explain this tendency.

(2) SAV metrics

For the three scenarios introducing SAVs, we picked two typical metrics for evaluating the service from both the user side and operation side: the passenger average waiting time and average empty driving ratio (Table 4). The higher waiting time and empty driving ratio in Scenario 2 account for the relatively disadvantage of SAVs compared to Scenarios 1 and 3. Particularly, the lowest waiting time of Scenario 1 could be explained with the larger fleet size.

It is also worth noticing that the no-roaming behavior of SAVs probably results low waiting times here.

(3) Travel distance

Total daily travel distance for each scenario is shown in Table 5.

Differing from previous findings[12,13,17], it was found that the total daily travel distance of all three scenarios barely changes versus base scenario in this research. Given that this research is using the existing travel patterns and OD matrix, induced travel cannot be evaluated. As such we can only attribute the change to the empty driving of SAVs. Hence, the low SAV share also probably accounts for the reason that distance does not change much here.

Table 4 SAV metrics.

	Passenger average waiting time	Average empty driving ratio
Base	-	-
Scenario 1	58.2s	6.1%
Scenario 2	80.1s	10.9%
Scenario 3	72.6s	6.2%

Table 5 Travel distance comparation

	Total daily travel distance	Change versus base
Base	$9.84*10^8$m	-
Scenario 1	$9.80*10^8$m	-0.41%
Scenario 2	$9.73*10^8$m	-1.12%
Scenario 3	$9.88*10^8$m	0.41%

(4) Accessibility analysis

The accessibility analysis simulation area is showed in Fig.4, where the place of three representative cities are pointed. Fig.5 shows the HV accessibility result of the base scenario. It can be observed that the result matchs the convenience degree of Gunma spatially. In large cities such as Takasaki and Maebashi, the accessibility is clearly higher than other remote places where transportation infrastructures possess lower quality and quantity.

Fig.6-Fig.8 depict the accessibility changes against the base scenario for the three AV scenarios. It is worth noticing that the accessibility of scenario 1 is computed based on HV since no PAV is applied in this specific scenario. For these three scenarios, they are deliberately plotted in the exact same scale so as to be sensible in comparsion. The black box in the scale part refers to the value range of the certain scenario.

After the introduction of AVs, several changes could be observed. Clearly, Scenario 1 barely changes in the comparison of the base scenario while Scenario 2 and 3 increase by a considerable extent.

Totally, the sum of accessibility for all cells increases by 0.12%, 19.9% and 36.8% for three scenarios respectively. It is assumed here that the decrease of value of travel time mainly accounts for the accessibility gains.

Spatially, in both scenarios 2 and 3, we can find higher accessibility gains in remote areas than the cities. This observation is consistent with the basic assumption of this research and the findings of Meyer et al[15] and Childress et al[17], even with the condition of the low SAVs share.

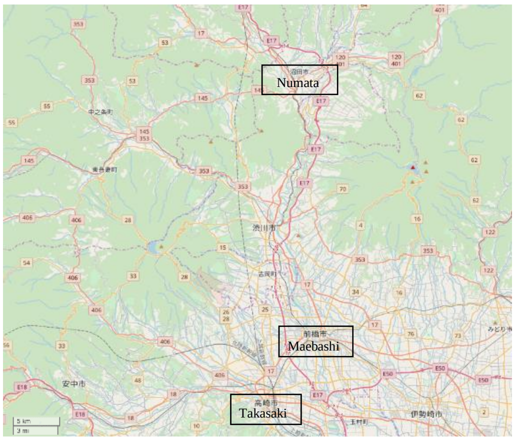

Fig.4 Accessibility analysis area

Source: Open Street Map

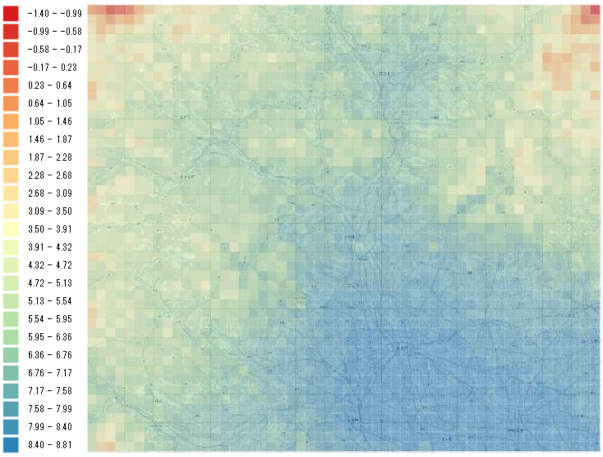

Fig.5 Accessibility plot of base scenario

The accessibility increases in particularly remote areas will likely encourage people to travel further and might promote suburbanization in the future. Every evolution of mobility in human history resulted into a expansion of humans' activity area: the spreading of automobiles in 100 years ago sparked aggressive urban sprawl in the following decades. We believe that this finding ought to arouse some alerts among planners and govenments in order to prevent further sprawl.

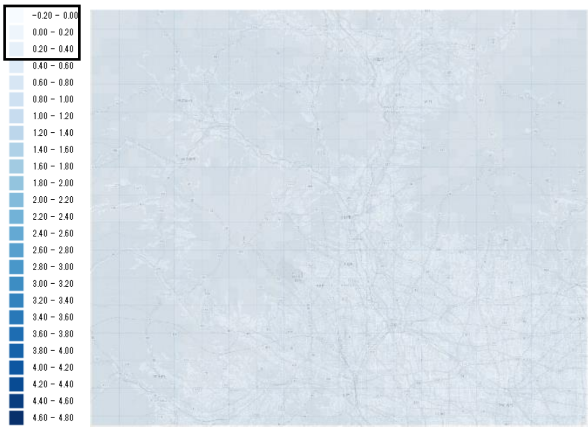

Fig.6 Accessibility changes plot of Scenario 1 (versus the base scenario)

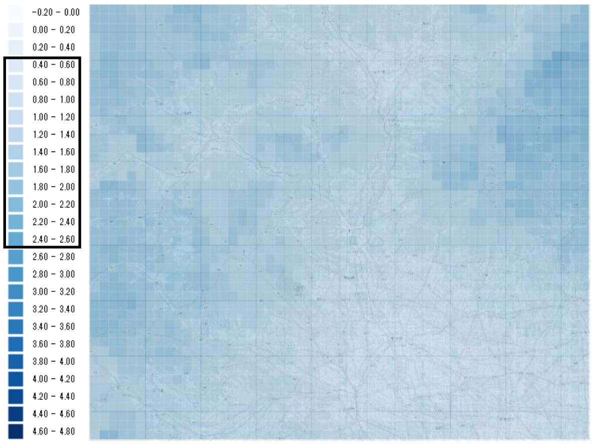

Fig.7 Accessibility changes plot of Scenario 2 (versus the base scenario)

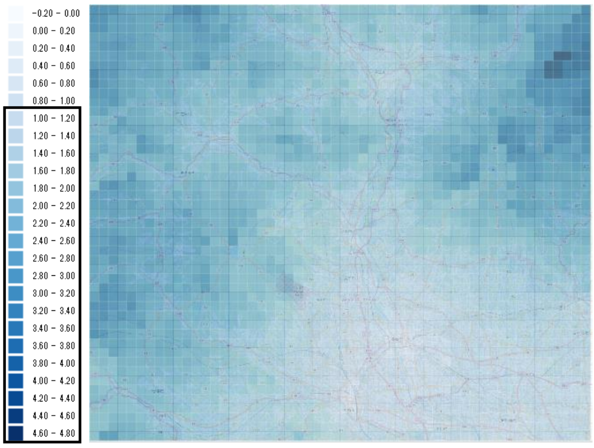

Fig.8 Accessibility changes plot of Scenario 3 (versus the base scenario)

4.LIMITATIONS & FUTURE WORK

Although the findings in terms of accessibility changes support our basic assumptions, there are still many limitations to be indicated. First of all, the research 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 the modal shifts. In order to address the limitation, generating a synthetic population and building a model to simulate travel patterns and OD matrix altogether is pending.

Apart from that, the mode choice calibration is based in the current choice preference might be a source of error as well. Some amendment could be implemented such as build an outer loop to recalibrate the model with the output of warming-up simulations.

Finally, 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.

5. CONCLUSION

This research used MATSim, an agent-based simulation model to forecast the implications of AVs in the Japanese context. With two new modes, shared AVs and private AVs added to the agents' mode choices, first a modal shift prediction was given. On the basis of predicted modal split, an accessibility analysis was conducted within the Gunma area. This research found an overall accessibility increase in the scenario were PAVs were introduced. Particularly the suburban area seemed to enjoy more accessibility gains which might cause further urban sprawl in future.

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