Car following model of mixed traffic flow with autonomous vehicles on urban expressway in Japan

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This study proposes a workflow to construct car following model of mixed traffic flow with autonomous vehicles based on the observation data on urban expressways in Japan. Based on Wiedemann model, this study cleans and reconstructs a vehicle trajectory dataset to calibrate car following models for human-driven vehicles and validates the capability of the model to reproduce observed traffic patterns in simulation. Then the autonomous vehicles are modeled in a way considering the current regulation in Japan. VISSIM simulation is utilized to validate the impact of autonomous vehicles. It is found that the increase of AV penetration rate results in a shorter travel time and higher capacity, but the strict autonomous driving speed regulation will reduce the advantages of AV.

Key Words: *urban expressway, car following model, autonomous vehicles*

1. INTRODUCTION

With the development and popularization of advanced driving assistant system (ADAS) and vehicle-to-vehicle (V2V) communication technology, the vehicles are moving towards autonomy. There are increased manufacturers participating in the development of autonomous vehicles (AV). Recently in Japan, with the revision of the Road Traffic Act in 2020, SAE level 3 AV can drive on expressway, but autonomous driving system can be only used when speed is under 60km/h (Ministry of Land, Infrastructure, Transport and Tourism, 2020).

There have been several studies on impact of AV on traffic flow, but most of them are based on the road traffic data in Europe or America. Thus, it is necessary to look into the impact of AV under the road condition and law regulation of Japan. This study proposes a complete workflow to calibrate CF models using field observation data from urban expressway in Japan, and construct microscopic simulation scenarios to simulate mix traffic flow with AV.

2. DATASET AND TRAJECTORY RECONSTRUCTION

(1) Introduction of Zen Traffic Data (ZTD)

Zen Traffic Data (ZTD) is a trajectory database observed on the urban parts of Hanshin Expressway, providing high resolution, wide range, and long time period of vehicle trajectory information.

There have been several studies utilizing ZTD in analysis of CF behavior. Yoshida et al. (2021) studied the variation of Newell model parameters on different road sections and time periods. Igaki et al. (2021) also consider the variation of reaction time, using a multiple linear regression CF model, while the detail simulation is not explained. Sano et al. (2021) analyzed the sensitivity in car following and validated the impact of Wiedemann parameter CC2 (range of gap between vehicles in the following regime).

These studies either use a simplified CF model, or do not explain the calibrated parameters. Besides, Montanino et al. (2013) proposed the problem of measurement noise of NGSIM database, and studies on ZTD did not consider such problems. In this study, the CF model parameters are calibrated considering the noise of the measurement.

(2) Data and study area

The ZTD dataset provides vehicle position and speed at every 0.1s with the vehicle length and type. It was collected at two different sites: I) Route 11, Ikeda Line (bound for Osaka), with five different time periods in September 2018; Ⅱ) Route 4, Wangan line (bound for Osaka), with five different time periods in 2017. data was collected at two different sites: I) Route 11, Ikeda Line (bound for Osaka), in September 2018, with five different time periods, II) Route 4, Wangan Line (bound for Osaka), in 2017, with five different time periods.

The data from site-I is utilized in this study. This site is 2-km expressway with two lanes. There is a S-shaped curve and an on-ramp entrance at 3.8 kilometer-post (kp). Lane changing is prohibited from 4.2 to 3.5kp. The speed limit is 60 km/h. The map of site I is shown in **Fig.1**.

(3) Trajectory reconstruction

a) Problem of raw data

According to the description of ZTD, the speed information in the dataset (to be convenient, it is referred as observed speed below) is calculated from observed position data. However, the position data itself contains noise and the speed directly calculated from position (referred as calculated speed) shows large fluctuation different from the smooth observed speed.

That is, there is inconsistency between observed position (furtherly, the spacing between to vehicles) and speed data, and this makes it difficult to utilize both location and speed to furtherly calibrate car following model.

b) Trajectory reconstruction methodology

In order to keep the consistency of speed and position, position data is used, and a workflow to filter the position data is proposed.

Step1: Remove outliers

In this step, the outliers with unreliable value of acceleration are removed by locally filtering the trajectory. Based on several times of test, a threshold of [-50,30] m/s2 is adopted, such a threshold should be set appropriately high to capture only the measurement errors (i.e., the outliers), and not the random disturbances that affect the observations. Then the outlier points are replaced by natural cubic spline interpolation with 10 reference points (1 sec of data points) before and after the outliers. The average number of outliers is 342 for a trajectory.

Step2: Filter high frequency noise

The objective of this step is to remove the noise (i.e., the random error component) from the signal. Kalman filtering is applied to the trajectory in order to filter high frequency noise.

Step3: Remove residual outliers

After step1 and step2, among several trajectories, there are still isolated abnormal points with sudden change to 0 in speed. For these points, natural cubic spline with 10 reference points (1 sec of data points) before and after the point is applied to speed.

Fig.2 shows an example of filtering result after each step, and **Table 1** shows the improvement of MAPE comparing calculated speed and observed speed for all 3 time periods of observation. The MAPE is reduced to about 10% and we got relatively smooth trajectories, indicating it is usable for next step.

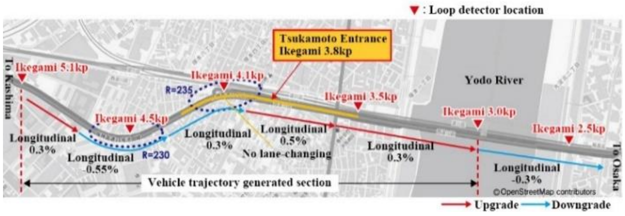
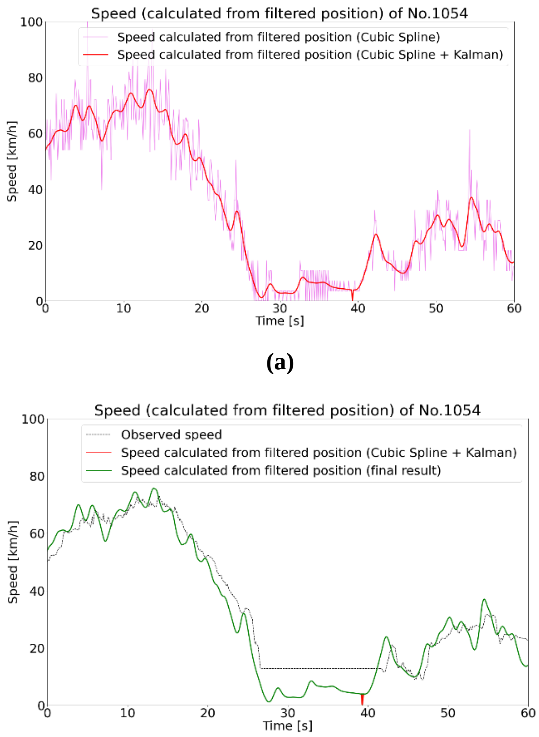


Fig.1 Map of site I: Ikeda Line



(a)

(b)

Fig.2 1-minute clip of vehicle No.1054 after reconstruction: (a) Speed profile after step 1 and 2, the arrow indicates the isolated outlier; (b) speed profile after step3

Table 1 MAPE against calculated and observed speed

Average MAPE	**7:00-8:00**	**10:00-11:00**	**15:00-16:00**
Raw position calculated speed	0.217	0.223	0.192
Filtered position calculated speed	0.101	0.114	0.098

3. CAR FOLLOWING MODEL OF MIXED TRAFFIC FLOW

(1) Modelling human driven vehicles

a) Wiedemann car following (CF) model

Wiedemann 99 (W99) model is a state-based model, supposing that drivers change their response state (regime) at specific threshold of spacing/relative speed. The 4 regimes of Wiedemann model, free-flow, closing-in, following and emergency bake, are determined by several thresholds determined by speed, speed difference and spacing gap. The detailed definition of W99 parameters is listed in the appendix

b) Calibration methodology

First, it's necessary to extract the actual car-following pair from the trajectories, in which the spacing between two vehicles should be in the following regime. Two criteria are set when extracting car-following pairs: 1) spacing less than 30m is approximately considered as following regime based on the reference value of parameters, 2) the following time should be longer than 5s. A total of 3006 valid pairs satisfying the two criteria are obtained.

The process of parameters calibration is described as follows, and **Fig.3** shows the framework of calibration:

For each parameter combination, 150 car-following trajectories are randomly selected from the extracted results as the calculation sample, in order to avoid over-fitting.

Step1: for each time step t of trajectory i, predict acceleration using observed inputs. For W99 the acceleration is calculated after calculating perpetual threshold and determining the following regimes.

Step2: calculate the speed and position for next time step $t+1$. This process is numerical integration of differential equations. Here the Euler method is adopted.

$$v(t+1) = v(t) + a(t)dt$$

$$x(t+1) = x(t) + v(t+1)dt$$

Step3: repeat step 1-2 to calculate the complete following trajectory of vehicle i, and the measure of performance (MoP) is calculated from the normalized root-mean-square deviation (NRMSE) of speed and spacing as follows, based on the findings of Punzo and Zheng (2015):

$$MoP = \sqrt{(\sum(v_{predicted} - v_{obs})^2)/n} + 0.5 * \sqrt{(\sum(s_{predicted} - s_{obs})^2)/n}$$

Where v is the speed of following vehicle, s is gross spacing to leader, and n is number of time steps in the trajectory.

Step4: repeat step 1-3 for all vehicle trajectory i and calculate the average MoP of all vehicles as the

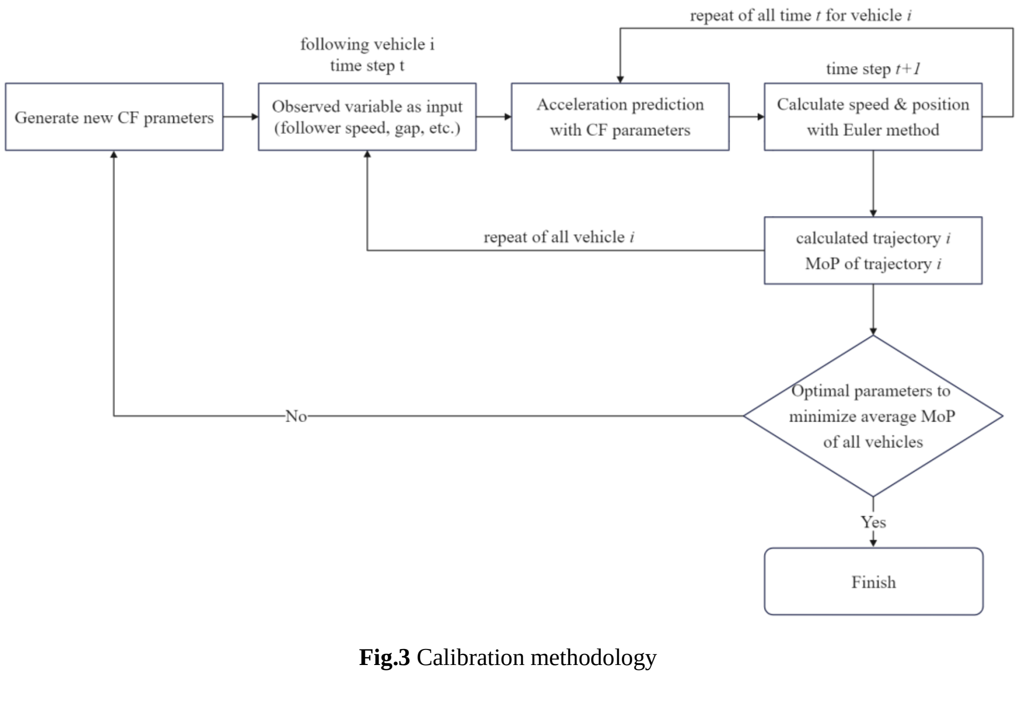


Fig.3 Calibration methodology

fitness f of current CF parameter combination.

In this study, in order to improve computing efficiency, differential evolution (DE) algorithm is adopted to estimate the optimal parameter combination.

c) Calibration result and discussion

The parameters for inner lane and outer lane are calibrated separately. The parameters CC0-5 and CC9 of W99 are calibrated.

The number of DE iteration is 300 times. **Table 2** presents the calibration results. **Fig.4** shows an iteration process of DE when calibrating W99 outer lane.

From the results, we can find some unique characteristics of Hanshin Expressway data comparing with the reference values based on European studies

Larger CC0 (standstill distance) and smaller CC1 (following headway) indicate that drivers tend to keep larger gap when stopped but smaller gap when moving. When driving on outer lane with lower speed and potential of merging vehicles, drivers tend to keep a larger gap than inner lane.

Larger CC4 (speed differences during the opening process) and CC5 (speed differences in the closing process) indicate that drivers are less sensitive to changes in leader's speed. This should be related to the findings about reaction delay and synchronization failure (Sano et al., 2021)

Besides, the desired free-flow speed is extracted from the free flow part of observation with a density less than 25veh/km, which is shown in **Fig.5**. The average desired speed of both lane is much higher than the 60km/h limit.

(2) Modelling AV

a) Assumptions of AV

As for the current regulations, the road speed limit of studied site is 60 km/h, and the allowed top speed for activating autonomous driving is also 60km/h. However, as shown in previous section, the desired free speed and actual free flow speed of HV are much higher. So, there will be a question, whether these "slow" and well-behaved AV can contribute in the faster traffic.

Based on such conditions, 2 types of AV usage scenarios are set in this study.

AV strict: The driver activates autonomous driving under the regulated 60km/h and doesn't drive over the 60km/h speed limit.

AV fully functional: It is supposed that the speed regulation of autonomous driving is canceled and the driver activates AV at all speed range.

b) CF model of AV

As mentioned in chapter 2, the car following behavior of AV can be simulated in VISSIM with specific W99 parameter combinations or using other models. In this study, AV are supposed to be able to communicate with other AV to form a platoon, as well as obey several rules related to the actual regulation in Japan, which is difficult to directly control when using W99 method. Thus, an ACC/CACC model based on the study of Arem et al. (2006) is adopted.

The acceleration demand of AV is defined as follows:

$$a_{ref} = min\,(a_{ref\_v}, a_{ref\_d})$$

The free flow acceleration a_{ref_v} is determined by the speed difference between intended speed and current speed. Let v_{set} and k denote the set speed of AV and a cruising factor, respectively, the acceleration is:

$$a_{ref\_v} = k_c \cdot (v_{set} - v)$$

The car-following acceleration a_{ref_d} is determined by spacing and speed difference between subject vehicle and leading vehicle. Let s_{ref} denote the reference spacing of CACC system, k_a, k_v, k_d denote constant sensitivity factors, a_l denotes the acceleration of leading vehicle transferred through V2V. The acceleration is:

$$a_{ref\_d} = k_a \cdot a_l + k_v \cdot (v_l - v) + k_d \cdot \left(s - s_{ref}\right)$$

Table 2 Calibration methodology

Parameter	Calibrated (inner lane)	Calibrated (outer lane)	Reference value
CC0	2.51m	2.40m	1.5m
CC1	0.71s	1.02s	0.9s
CC2	11.65m	13.40m	4m
CC3	-12.81s	-13.90s	-8s
CC4	-0.50m/s	-1.27m/s	-0.35m/s
CC5	1.52m/s	2.04m/s	0.35m/s
CC9	0.50 m/s^2	0.51m/s^2	1.5m/s^2
MoP	0.40	0.42	0.68

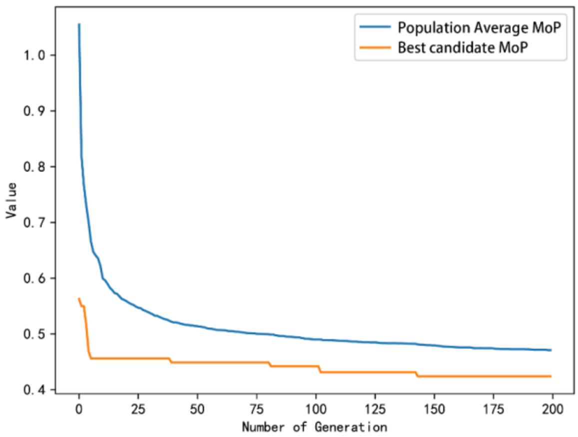


Fig.4 MoP vs iteration process

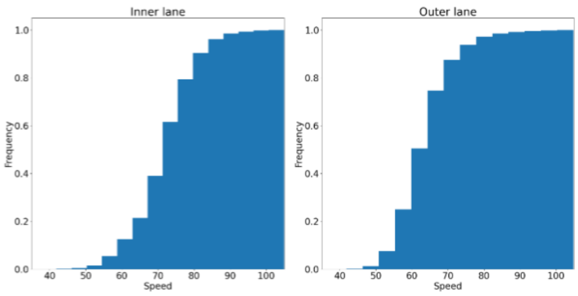


Fig.5 Desired speed distribution

For non-AV leading vehicles, a_l is set as 0, representing that AV cannot get the leading acceleration through V2V and only ACC is activated.

The reference spacing s_{ref} is defined as the maximum among safe following distance (s_{safe}), following distance according to the system headway setting (s_{system}), and the minimum allowed spacing (s_{min}).

The safe following distance s_{safe} is determined by the deceleration capability of leading vehicle d_l and subject vehicle d. AV is supposed to avoid hard brake, so the deceleration capability is usually set as an allowed maximum comfortable deceleration.

$$s_{safe} = \frac{v^2}{2}\left(\frac{1}{d_l} - \frac{1}{d}\right)$$

The system spacing setting s_{system} is determined by the system-target headway of car following. Unlike the definition in W99, there is supposed to be no standstill distance for AV following.

$$s_{system} = v \cdot t_{system}$$

The t_{system} is set as a smaller value HW_{short} for platoon followers, representing the CACC mode is activated inside the platoon. And a larger value HW_{long} for platoon leader and the situation where leading vehicle is not an AV, representing only ACC is activated.

Finally, the executed acceleration of AV is limited to the capability of the vehicle itself.

$$a_{AV} = max\left(min\left(a_{ref}, a_{max}\right), d\right)$$

Besides, AV have a limited detect range and can only response to vehicles or obstacle located within the detection range (DR) of sensors. Based on such characteristics, the top speed of AV is assumed to be low enough so that the vehicle can be completely stopped within the DR (Ye et al. 2018) even there is no speed limit for the road. The maximum allowed speed of AV v_{max}^{AV} is defined as follows:

$$v_{max}^{AV} = \sqrt{2d \cdot DR}$$

Due to the lack of field test data of AV in this study, the parameters required for the CACC process follow the results of MIXIC (1997) and the study by Kerner (2016). The parameters are summarized in **Table 3**. Thus $v_{max}^{AV} = \sqrt{2d \cdot DR} = 27$m/s in this case.

c) Lane changing of AV

The lane change behavior is not studied in detail. Besides, due to the MILT regulations, autonomous driving can be only used in lane car-following, and lane change should be taken over by drivers. Thus, the default lane change settings of VISSIM are adopted in the simulation for both human driven vehicle and AV.

4. SIMULATION AND RESULTS

(1) AV platooning settings

As mentioned in Chapter 3, AV are assumed to form a platoon spontaneously, and CACC is activated inside the platoon to keep a shorter following head way. In this case, it is assumed that the length of a platoon is 6 vehicles.

Table 3 AV model parameters

Parameter	Description	Value
DR	Maximum detection range	120m
k	Cruising factor in free flow condition	0.3
k_a	Following sensitivity factor for leader's acceleration	0.9s
k_v	Following sensitivity factor for speed difference	0.58
k_d	Following sensitivity factor for spacing error	0.1
HW_{long}	System headway in ACC mode	1.4s
HW_{short}	System headway in CACC mode	0.5s
a_{max}	Maximum acceleration	3m/s2
d	Declaration capability	-3m/s2

(2) Traffic demand

The real-world traffic demand is directly obtained from the dataset as the vehicle inputs of VISSIM. The number of vehicles passing the 5.0kp cross-section is counted and summed up with an interval of 5 min. In order to check the performance of mixed traffic under different demand conditions, an off-peak simulation (20% less than observed volume) is also conducted. **Fig.6** presents the aggregated traffic volumes.

For each demand settings, 2 AV usage scenarios are simulated separately, the AV penetration rate is changed from 0% to 100% in a step of 10%.

(3) VISSIM settings

A simulation network of site I is built in VISSIM with desired speed decision using the result in **Fig.5**, and the calibrated W99 model is imported into VISSIM. The COM interface of VISSIM is utilized to change other microscopic simulation setting.

Data collectors are set in VISSIM to record the average speed and travel time, the vehicle records are also directly outputted to get the trajectories of each simulated car. Time interval is 5min which is the same as traffic inputs.

The whole simulation time is 4200s, while the first 600s of simulation is used as warm-up time and the collected data is ignored. For each input volume and AV rate combination, simulation is repeated for 10 times, and the average result is used.

(4) Discussion of results

The proportions of AV play major roles in mixed traffic, which can be seen in traffic performances such as travel time, speed and delay time. A total of 44 combinations (11 AV penetration rates, 2 traffic volume condition, 2 AV usage scenarios) have been investigated for this section. **Fig.7** presents the changes of average travel time under different combinations.

In both traffic volume settings and AV usage scenarios, higher AV penetration rate will result in shorter travel time. However, the magnitude of change is not the same. Under actual traffic volume settings, AV strict and AV full-functional have similar performance in reducing travel time. But under off-peak traffic volume settings, AV strict contributes very small reduction because HV at free flow condition can drive at a higher speed than AV strict. With fewer interactions between vehicles, the stable following features of AV does not show significant advantage.

The similar trend can be found in from **Fig.8** showing the flow-density plot of inner lane. AV full-functional significant contributes to higher average speed

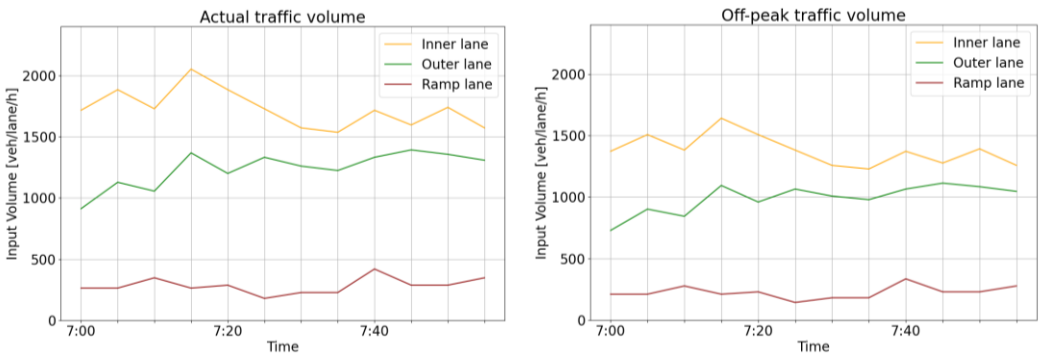


Fig.6 Input traffic volume

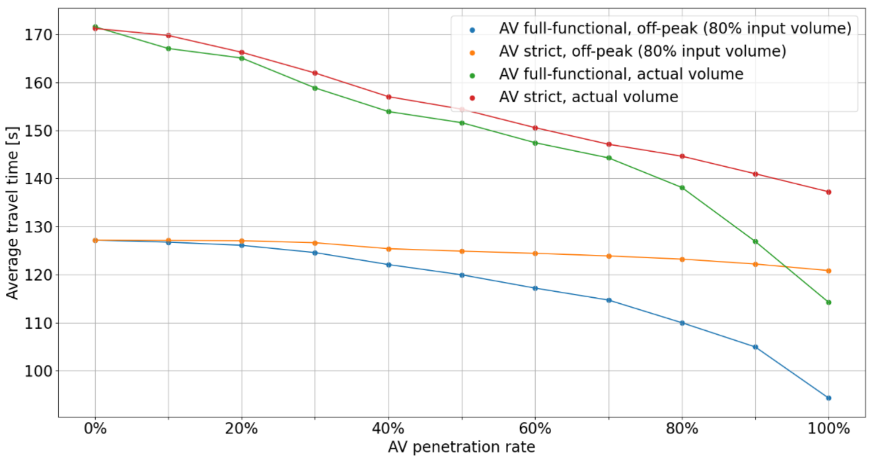
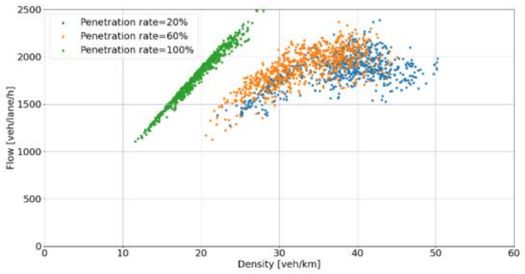
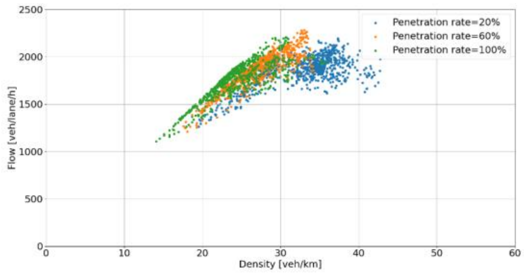


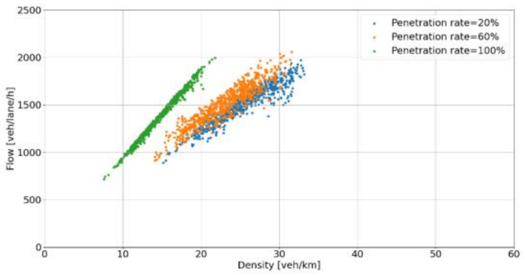
Fig.7 Average travel time under conditions



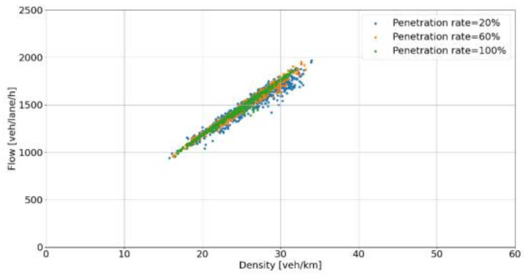
(a) AV full-functional, actual volume



(b) AV strict, actual volume



(c) AV full-functional, off-peak volume



(d) AV strict, off-peak volume

Fig.8 Flow-density plot under conditions

and capacity, while AV strict makes almost no difference under off-peak traffic volume settings.

5. SUMMARY

The first objective of this study is to calibrate a CF model reflecting the unique characteristics of urban expressway in Japan. The second objective is to model the CF behavior of AV and construct a microscopic simulation platform in VISSIM to check the impact of AV in mixed traffic flow.

For the first objective, the field observed traffic trajectory dataset of urban expressway in Japan, the Zen traffic data is utilized in this study. The observation data with noise is cleaned and reconstructed to be suitable for car following model calibration. Differential evolution algorithm is adopted in calibration. The regime-based Wiedemann 99 model is calibrated. The two models share some similar definition in terms of minimum following headway and standstill distance, in the calibrated result, the parameters related to these parts are also similar, demonstrating the reliability of calibration framework. Due to the capability of representing both car-following dynamics and the macroscopic traffic characteristics, the calibrated W99 is adopted for the next step.

For the second objective, an ACC&CACC model is adopted to model the car following behavior of AV. Two usage scenarios, AV strict representing the current condition of use for autonomous driving under Japan's regulation, and AV full-functional representing the ideal condition of use for AV, are assumed and set in the simulation. A simulation network representing the road shape and traffic demand of ZTD observation site is setup in VISSIM. Two traffic demand scenarios, the actual volume and off-peak volume are simulated under different AV penetration rates. The initial simulation results show the capability of AV in improving traffic performance. And it is also found that the AV strict scenario makes less improvement dur to the lower speed restrictions.

APPENDIX

The VISSIM parameters are explained in this appendix

1) The perception thresholds

AX: the desired standstill distance between two stationary vehicles

BX: the minimum safe following distance as the lower limit of following regime

CLDV: the points at short distances where drivers perceive that their speeds are higher than leader

SDV: the points at long distances where drivers perceive speed differences when they are approaching slower leaders

OPDV: the points at short distances where drivers perceive that their speeds are lower than leader

SDX: The maximum following distance as the upper limit of following regime

2) The 10 car following parameters are explained in the **Table 4** below

Table 4 Wiedemann-99 parameters

Parameter	Description	Reference value
CC0	The desired gap between two vehicles in a stopped condition (standstill distance)	1.5m
CC1	Time gap following the driver keeps in for a safety in moving state (minimum headway)	0.9s
CC2	Range of gap between vehicles in the following regime	4m
CC3	The time between the beginning of deceleration after perceiving of slow-moving leader to start the unconscious-following behavior	-8s
CC4	Speed difference during the following process. CC4 controls speed differences during the opening process	-0.35m/s
CC5	Speed difference during the following process. CC5 controls speed differences in the closing process	0.35m/s
CC6	Influence of distance on speed oscillation during the following condition	11.44/(m· s)
CC7	Actual acceleration during oscillation in the unconscious following regime	0.25m/s^2
CC8	Desired acceleration when the vehicle starting from the standing condition	3.5m/s^2
CC9	Desired acceleration at 80km/h, limited by maximum acceleration capability of vehicle	1.5m/s^2

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