Traffic Flow Prediction Using Micro-Simulator with Multiple Information

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Abstract: There are numerous prediction methods used in the transportation engineering field. Among those, micro-simulation is becoming a more widely used tool due to its advantages. Utilizing accuracy and relevance real world input data- OD matrices, drivers' behaviors, route choice are essential for developing a reliable large scale traffic simulation models. This research describes a procedure to adjust the micro simulation parameters depending on the observation traffic state. Traffic network of Kofu city, Japan is used in AIMSUN micro-simulator. Considering driving behaviors and route choice parameters, six parameters of micro simulator are considered to calibrate one hour interval by data assimilation between observation travel time and simulation travel time. Continuously, current traffic flow is predicted by micro simulator, and parameters of the simulator are calibrated considering real world observation. Utilizing observation data, this calibration process improves prediction accuracy in the network.

Keywords: Assimilation, Calibration, Micro-simulation, Traffic flow, Prediction

1. INTRODUCTION

The purpose of this study is to improve the traffic state accuracy in micro-simulator as a tool of forecasting, as the fluctuation of traffic flow behavior is one of the major sources of error generation. To reduce the gap between simulated traffic state and observation traffic state, parameters of micro-simulator are calibrated each time slice interval considering observation traffic state. The rapid progress of urbanization has modernized many people's lives but also brought challenges like traffic congestion. It cost road users extra hours of sitting in traffic that can lead to increase energy/fuel consumption and enormous emission of pollutants. Intelligent management systems can help overcome or significantly reduce the impact of such negative effects on city-dwellers by providing information about traffic conditions before and during their trips. Additionally, this information can be applied to provide alternatives to users so that they may make an informed decision about their trips. Advanced Traffic Management Systems (ATMSs) and Intelligent Transportation Systems (ITSs) integrate information, communication, and other technologies and apply them in the field of transportation to build an integrated system of people, roads, and vehicles. These systems consist of a large, fully-functioning, real-time, accurate, and efficient transportation management framework. In ATMSs and ITSs, it is a fundamental challenge to predict the next possible states of traffic with high precision, because this information helps to prevent unfortunate events like traffic jams or other anomalies on roads (Nagy *et al.*, 2018).

There are numerous prediction methods used in Transportation engineering. Among these, micro-simulation is becoming a more widely used tool in transportation researches and studies. The advantage of micro-simulation is that it can reproduce the traffic flows with simulating the behavior of the individual vehicles, this not only enables them to capture the dynamics of time dependent traffic phenomena but also deals with the behavioral models according to drivers' reactions. The availability, accurate and relevant input data- OD matrices, drivers' behaviors, route choice are essential for developing a reliable large scale traffic simulation models. Even with today's enhanced computational power, the calibration process of the simulation models is a major challenge because of uncertainty in the modeled systems.

Micro-simulation is applied for traffic signal optimization, studying route choice behavior and travel time estimation. Park *et al.* (2003) showed that simulation models under default calibration parameters may not accurately represent field conditions and produce unreliable results. There are numerous optimization techniques which are used for calibration of parameter to reflect real world conditions in simulator. Calibration is the process in which the input parameters are refined so that the model accuracy replicates observed traffic conditions (Yu *et al.,* 2006). Genetic algorithm (Cheu *et al*., 1998) is used to find a suitable combination of parameter values for a real network. Other techniques are Monte Carlo (Park *et al*., 2006), OptQuest/Multisart algorithm (Kim *et al.,* 2003), Simplex algorithm (Kunde *et al.,* 2002), Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm (Ding *et al*., 2003). Different approaches focused on the calibration of the different types of parameters considering the different measures of performance for a small network. But none of the studies focuses on the recalibration process. However, traffic flow has highly fluctuation property throughout the day. Traffic flow is differed between off peak and on peak time. Rather than traffic flow and driving behavior are also affected by weather conditions (Maze *et al*., 2006). For example, due to snowfall, the speed of vehicles is significantly reduced as well as during heavy rainfall, the speed of vehicles is also reduced. Those would cause difficulty in traffic management in the network. Other traffic related incidents can affect traffic flow as well as driving behavior and route choice.

Sasaki *et al*. (2016) used the state space model and data assimilation technique for calibration purposes in the expressway. As parameters are recalibrated after a specific time interval considering observation traffic state. It can make the simulator to adjust with dynamic and fluctuation property of traffic flow.

The objective of this research is to predict accurate traffic flow in micro-simulator using multiple information in a large traffic network. OD matrices are used as the given condition to predict traffic flow in simulator. 15 minute interval OD matrices are incorporated into simulator. For achieving accurate simulation, driving behavior and route choice parameters of simulator are calibrated using observation traffic state. 24 hours of simulations are done in this study.

From numerous parameters of simulator, six parameters are considered to calibrate after one hour interval.

- Four parameters of desire speed of vehicles in network- Mean, Max. Min. and standard deviation of speed which can reflect the driving behavior of each vehicle in the network.
- Maximum section speed which can reflect the driving behavior of vehicles in a section.
- User defined link cost parameter which is used as a surcharge value in route choice model in network.

These parameters are calibrated into one hour interval by data assimilation the simulated travel time into the observed. Continuously, current traffic flow is predicted by the micro simulator for time t, then parameters of simulator are calibrated considering real world observation at time t. AIMSUN micro-simulator is used in this study which is equipped with an API that invokes the external program. The API allows us to incorporate additional algorithms into the simulator.

2. NETWORK AND DATA

Kofu city traffic network, the major city of Yamanashi prefecture, Japan is used in micro-simulator. There are 33,135 numbers of sections and 1,272 nodes exist in this network shown in Figure 1. The total area is divided into 100 zones. 100 by 100 OD matrices are used for traffic generation. Four sections in the network are selected for the observation link of traffic state. They are sections of route-20, route-358, route-411 and route-140 which are major routes in this network. Observation sections are shown in figure 1. Route 20 is one of the national trunk roads which connected to Tokyo city. It is well-known that traffic network signal timing is essential for accurate simulation, especially for a large network. Providing signal timing in simulator, it helps to create real world scenario into the simulator. Signal timing for 14 intersections of this network are collected from JARTIC (Japan Road Traffic Information Center). And others 213 intersection signal timing are fixed with using two hypotheses- neighboring intersection will be the same signal timing and the same characteristic intersection will be the same signal timing. In simulator, full network is divided into two parts, micro- simulation area and macro-simulation area, to get individual car driving behaviors' information from micro simulation area only.

In the microscopic view, every individual vehicle on the roads and their interactions are modeled in a multi-agent system where every agent keeps a record of its trip including basic information or behavior such as lane changing, gap acceptance, acceleration and speed of each vehicle. In macroscopic simulation, only global variables of a road network are considered- such as density, speed or traffic count- where these variables are determined for each road segment of the road network.

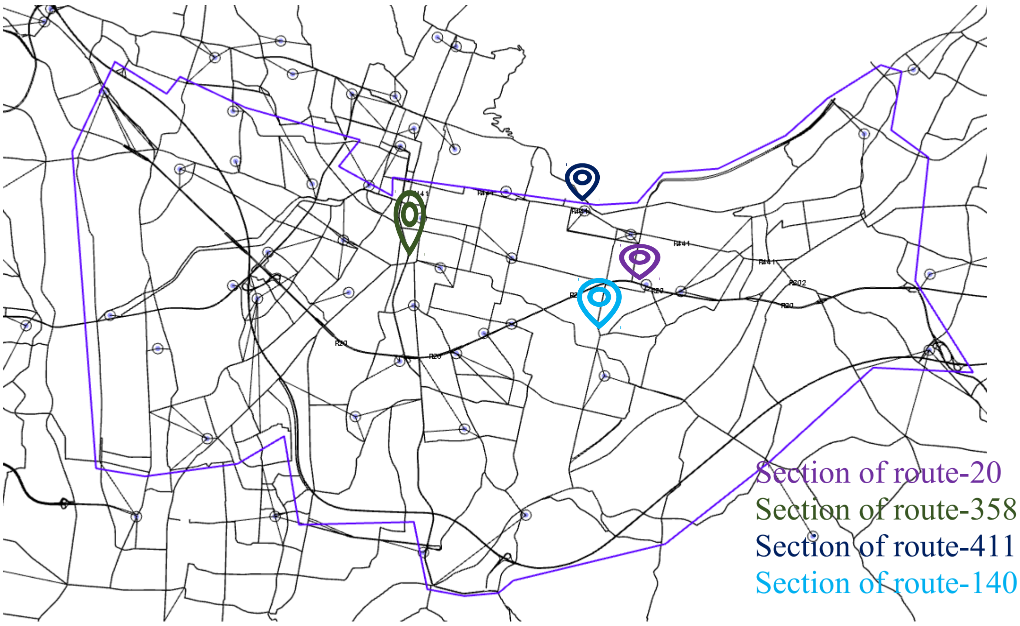

Figure 1. Traffic flow observation location in the network

It is convenient to apply QV diagram for converting traffic flow, density and speed of vehicle, as the indices of the traffic state. One hour interval of one day traffic flow is the common data which are collected from road traffic detector. In this research, QV diagram is used for converting observation traffic flow to travel speed for a specific section and using distance = speed x time (s=vt) equation travel time for specific section is calculated which is used as observation travel time. For creating QV diagram, formula are used-

If, $v_0 > v_p$

Then,

$$v_t = \frac{v_p - v_0}{q_p} x\, q_t + v_0$$

(1)

Otherwise, $v_0 \le v_p$

Then,

$$v_t = v_0$$

(2)

Where,

v_t: Travel speed of vehicle at time t [km/h]

v_p: Travel speed of vehicle during congestion time/peak time [km/h]

v_0: Free flow travel speed [km/h]

q_p: Peak time traffic flow [PCU/h]

q_t: Traffic flow at time t [PCU/h]

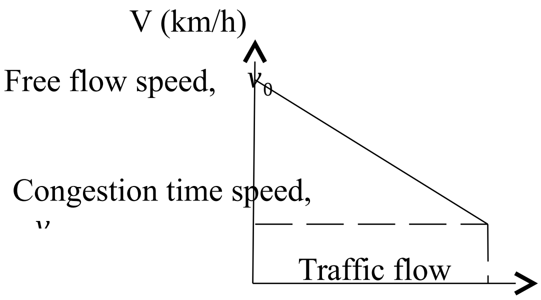

Figure 2. QV diagram

QV diagram is shown in Figure 2. Which data are required for drawing QV diagram are collected from Yamanashi prefecture traffic survey data, shown in Table 1. Those data are collected for specific section from where traffic flow data are collected.

Table 1. Traffic survey data used for drawing QV diagram

Section of route	Peak time traffic flow (PCU/hour)	Peak time vehicle speed (km/h)	Free flow Speed (km/h)	Length of section (meters)
Section of route-20	986	22	50	255.811
Section of route-358	1174	24.7	50	656.832
Section of route-411	599	22.8	40	431.780
Section of route-140	751	17	40	942.380

Figure 3 indicates the observed travel time of each observation section of route 20, 358, 411 and 140 of downstream direction. Those observed travel time are used in data assimilation with simulated travel time for parameters calibration.

From our four observation sections, downstream direction traffic flow of section of route 20, 358, 411 and 140 are used as observation data for parameter calibration and simulation traffic flow are compare with observation traffic flow for determining the prediction accuracy of our proposed calibration process. Upstream direction traffic flow of section of route 20, 358, 411 and 140 are used as validation purpose of this simulation. Simulation traffic flow of section of route 20, 358, 411 and 140 are compared with upstream direction observation traffic flow of those routes. It can indicate the prediction accuracy of the network in which parts are not directly connected to calibration purpose.

Figure 3. Observation Travel time of downstream direction for section of route-20, 358, 411 and 140

3. DATA ASSIMILATION

Data assimilation is the art of combining information from different sources in an optimal way. Generally, these sources are models and observations.

Data Assimilation has two main objectives:

1) To improve the forecast of the simulation by incorporating observation
2) To interpolate the state of coarse-grained observation by simulation

By data assimilation, it is possible to get a better estimation of the state of a system. To maintain the relationship between observation and state variable, state space model has two main equation.

a) State equation: $x_t = f_{t-1}(x_{t-1}, w_{t-1})$ (3)

where,

x_t : *system state at time t* , certain state of the traffic, travel time

f_{t-1} : *state transition function*

w_{t-1} : *system noise*

b) Measurement equation: $y_t = h_t(x_t, v_t)$ (4)

where,

y_t : observation at time t

h_t : observation function, average velocity $\cong$ *travel time*

v_t : observation noise

State equation works as transition of the traffic state between time t and time t+1 and measurement equation works as to maintain relation of the state of the system with observation. Simulation model can be applied as the state equation of the state space model, because the function of the state equation is to predict traffic state of the next period. When we execute micro-simulator for a certain period as the transition model of the state-space model, traffic state such as travel time of each vehicle can be collected from simulator. At the same time, we can observe the actual traffic state in a certain format such as average travel time. If we can treat the relationship between those two traffic states by the state space model, the simulated variables will be assimilated to the observation. In this study, particle filter algorithm is used for data assimilation. When Monte Carlo sampling technique is recursive Bayesian filter, it called particle filter. It is perfect to deal with non-linearity and non-Gaussian distribution to estimate state base on noisy observation. Particle filter implements the updates in an approximate manner. The samples from the distribution are represented by a set of particles, each particle has a likelihood weight assigned to it that represents the probability of that particle being sampled from the probability density function.

Particle filter result will be the posterior distribution of the state space model. State space model is shown in figure 4. Simulated travel time distribution is regarded as the prior distribution $p(x_t \vee x_{t-1})^i$ of the traffic state of this study in i^{th} step. The re-sampled distribution of travel time is used as posterior probability distribution $p(x_t \vee y_t)$ of travel time. The parameters of simulator are estimated to fit the posterior distribution and used for the next time slice. For data assimilation observation travel time and simulation travel time are considered as normal distribution.

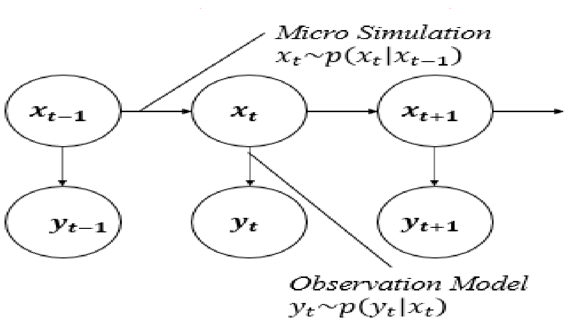

Figure 4. State-space model

4. PARAMETERS CALIBRATION

Typically, traffic simulator has many parameters to represent a simulation. Those parameters are related to creating a perfect simulation. If we can perfectly coordinate those parameters value, accurate simulation can be possible. However, it is not possible to do that practically, because many of them are difficult to estimate in real world. Using data assimilation technique, parameters of simulator can be calibrated according to the observation of the traffic state. By this calibration process, real world dynamic properties of traffic flow can be approximated to the actual them in simulator.

From previous research (Punzo *et al.,* 2015) it has found that vehicle speed is one of the most sensitive parameters in simulator which can directly control the car following and route choice model in AIMSUN. The car following model used in AIMSUN is based on the model developed by Gipps, 1981, which considers the speed of the following vehicle to be either free or constrained by the leading vehicle. The speed of the following vehicle during the time interval [$n,t+\tau$] is calculated by equation 5.

$$V(n,t)+2.5a_n\tau*\left(1-\frac{V(n,t)}{V^{¿}(n)}\sqrt{0.025+\frac{V(n,t)}{V^{¿}(n)}},b_n\tau+\sqrt{b_n^2\tau^2-b_n\left[2\left[x_{n-1}(t)-s_{n-1}-x_n(t)\right]-v_n(t)\tau-v_{n-1}(t)^2b_n\right]}\right)$$

$$V_a(n,t+\tau)=min\ ¿$$

(5)

where,

$V_a(n,t)$: the speed of n[th] vehicle

$V^{¿}(n)$: the desire speed of n[th] vehicle

a_n : the maximum acceleration of vehicle *n*

b_n : the most severe breaking that the driver of vehicle *n*

τ : the apparent reaction time

Section speed of a vehicle is determined by equation

$$V_{max}(n,s)=Minimum[Max.Section\,Speed.\theta(n),V_a(n,t+\tau)]$$

(6)

where,

$\theta(n)$: the speed acceptance limit

From equation 5 and 6, it is noted that driving behavior of vehicles are highly controlled by speed. $V_a(n,t+\tau)$ is the desire speed which is applicable for all sections in the network. But, speed of vehicle $v_{max}(n,s)$ is ultimately defined by the minimum value between maximum section speed and desire speed of network. The simulated travel time are assimilated into the observed travel time by particle filter. For each observation section, we get different particle filter result, which is an approximate travel time distribution for next simulation for this observation section. From this distribution- mean, max., min. and Std. of speed are calculated. As we consider four observation locations, we get four different particle filter results. Considering those four distributions- four parameters of desired speed- mean, max., min. and standard deviation of speed of network are calibrated as followed-

Mean desire speed of network = max. (mean $speed_{20}$, mean $speed_{358}$, mean $speed_{411}$, mean $speed_{140}$) (7)

Max. desire speed of network = max. (max. $speed_{20}$, max. $speed_{358}$, max. $speed_{411}$, max. $speed_{140}$)

(8)

Min. desire speed of network = min. (min. $speed_{20}$, min. $speed_{358}$, min. $speed_{411}$, min. $speed_{140}$)

(9)

Network standard deviation of desire speed = max. (standard deviation of $speed_{20}$, standard deviation of $speed_{358}$, standard deviation of $speed_{411}$, standard deviation of $speed_{140}$) (10)

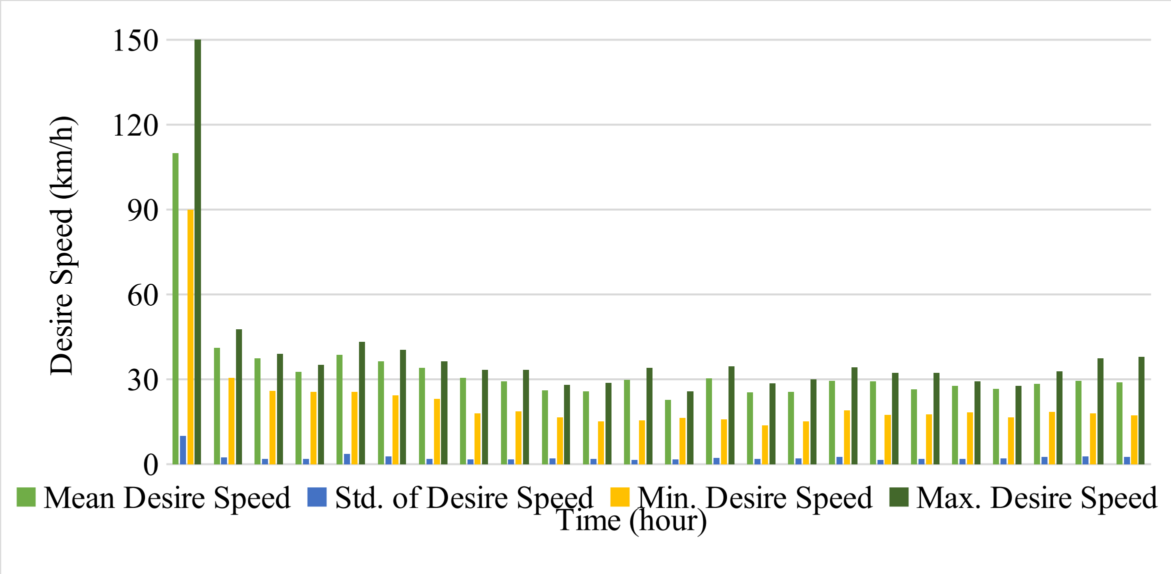

Figure 5. Desire speed calibration of network (one hour interval)

Using the equation 7, 8, 9 and 10, four parameters of desire speed are calculated at one hour interval. First one hour simulation is done with default parameter of AIMSUN. Where, max., mean, min. and STD of speed are 150 km/h, 110 km/h, 90 km/h and 10 km/h respectively. The calibration value of desire speed on every hour is shown in Figure 5. Those values are applicable to all sections of the network. As simulation progress, errors generate in micro simulator results due to fixed parameters for long time simulation. Incorporating real time observation to revise the parameters of simulator, can make a contribution to answering this problem.

For calibrating Maximum section speed, considering the same distribution which is used for desired speed calibration, but in this case, Maximum value of speed from distribution is considered for Maximum section speed of that route. This maximum section value is considered for all sections of route-20, 358, 411 and 140 in the network. Maximum Section speeds for four observation sections are shown in Figure 6. Travel speed of vehicles are changed with time of day as well as off-peak and peak travel speed of network are not same. First one hour simulation is done considering max. section speed 50 km/h, 50 km/h, 40 km/h, 40 km/h of section of route-20, 358, 411 and 140 respectively. If we consider same desire speed and maximum section speed for all time, it can be the cause of the errors in the simulation. If one section travel time change due to congestion or other factors, other sections are also affected by this occurrence. In our study, four observation locations are used for calibrating network desired speed. Same as maximum section speed is changed for route-20,358,411 and 140 considering the observation section.

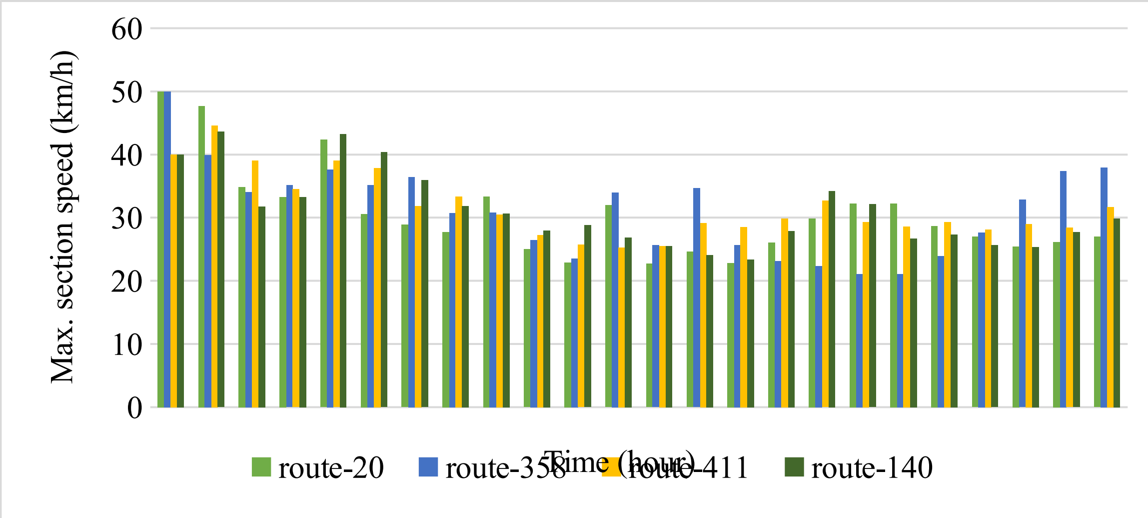

Figure 6. Maximum section speed calibration (one hour interval)

In our study, four observation locations are used for calibrating full network desired speed. Same as maximum section speed is changed for route. For route choice, c-logit model is used in AIMSUN. The advantage of this model is that it considers overlapping of the route that means it holds the independence of irrelevant alternatives (IIA) theory. The probability of route choice is directly influenced by the link cost of the routes.

$$DynCost_j = EstimatedTravelTime_j + UserDefCost \tag{11}$$

Each time interval, dynamic links cost are calculated by considering estimated travel time which is the travel time for previous time slice and user defined cost. User defined cost is used as a surcharge value in this study to adjust the simulation travel time with observation travel time. User defined cost value represents the route choice due to human behavior, route condition. Doing data assimilation between observation travel time and simulated travel time, we get the result of particle filter which is the approximate travel time distribution for current simulation time. User defined cost (parameter of link cost) is estimated from the difference between the distribution of particle filter result and previous simulation estimated travel time.

Traffic flow and link costs are related to each other. It is considered that the number of traffic flow in the section will increase with the decrease of link cost. This value is negative, when observation traffic flow is less than simulation traffic flow in a section and this value is positive, when observation traffic flow is higher than simulation traffic flow. Each time interval by recalibrating user defined cost in simulator, real time route choice scenario of the real world can be possible to represent in simulator. Considering observation section of route-20, user define cost of route-20 in the network is calibrated each time interval. Same procedure is considered for route-358, route-411 and route-140. Calibration results are shown in Figure 7.

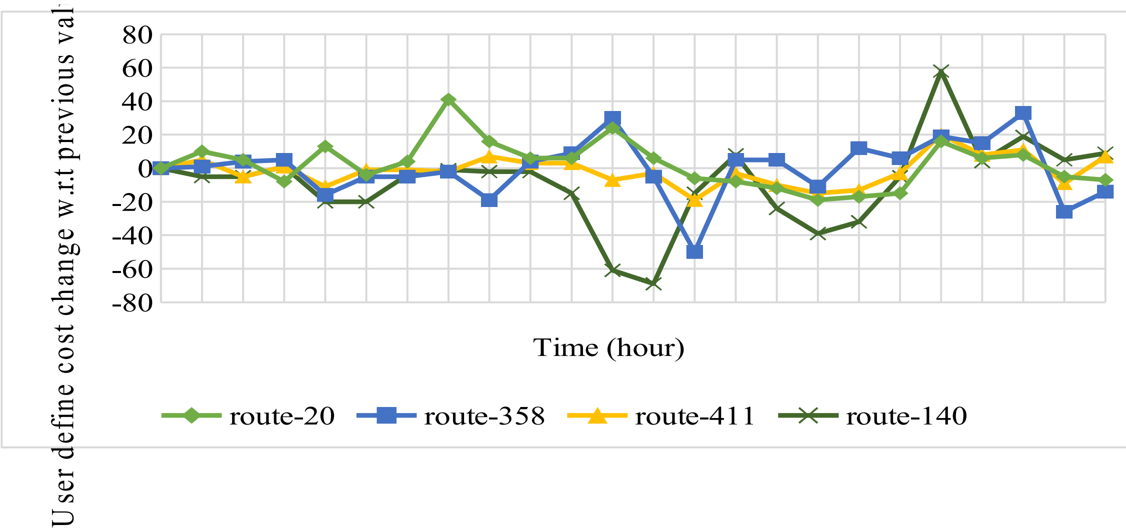

Figure 7. User define cost parameter calibration (one hour interval)

5. SIMULATION RESULTS

Data assimilation technique is utilized to determine the best set of parameters to make the model output match the observations. Calibration of medium/large scale networks have several difficulties and challenges. Because, we need to focus on OD matrix, driving behavior and route choice parameters. Utilizing only OD matrices information in simulator with default parameters, traffic flow prediction is not accurately done by simulator due to imperfect parameters. Default parameters used in AIMSUN simulator are shown in Table 2.

Table 2. Default parameters used in AIMSUN simulator

Parameters	Value
Mean desire speed	110 km/h
Max. desire speed	150 km/h
Min. desire speed	90 km/h
STD of desire speed	10 km/h
Max. section speed of route-20	50 km/h
Max. section speed of route-358	50 km/h
Max. section speed of route-411	40 km/h
Max. section speed of route-140	40 km/h
Reaction time at stop	1.35 sec
Reaction time at traffic light	1.35 sec
Reaction time	0.75 sec

With default parameters and without parameters calibration, simulation results do not represent the accurate traffic scenario in simulation due to irregularity property of traffic flow. On the other hand, traffic flow are fluctuated throughout the day. The parameters of simulator are calibrated by the assimilation of real time observation data in order to incorporate the dynamic properties of traffic flow. 24 hours' simulations are done in this study. Driving behaviors (Desire speed and max. section speed) and route choice (user define cost) parameters are calibrated every one hour interval. Four parameters related with desire speed, maximum section speed and user define cost, total six parameters are calibrated by data assimilation of the simulated travel time and observation travel time. Traffic flow is used as measure of performance in this study. Observation traffic flow data of entire day are collected at specific section of route-20, 358, 411 and 140 in every one hour. Then those observation traffic flow data are compared with simulation traffic flow result without parameters calibration and with parameters calibration. It is found that with repeatedly calibrated parameters, simulation results provide more actual scenario precisely comparing with fixed default parameters. Figure 8 shows the simulation traffic flow without parameters calibration and with calibration compare with observation traffic flow for observation section of route-20 downstream direction.

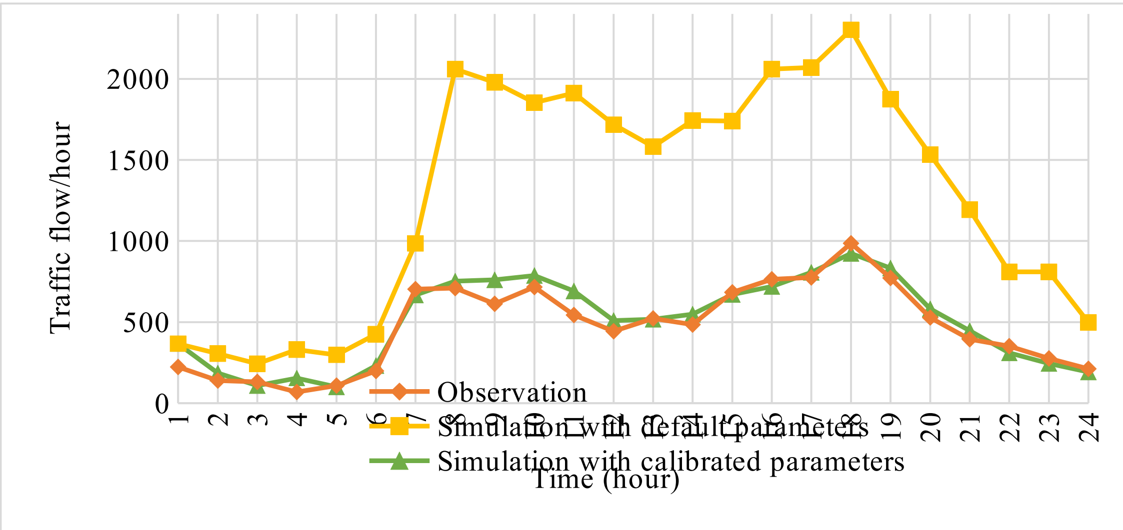

Figure 8. Compare traffic flow among observation and simulation with & without calibrated parameters, downstream direction of section of route-20

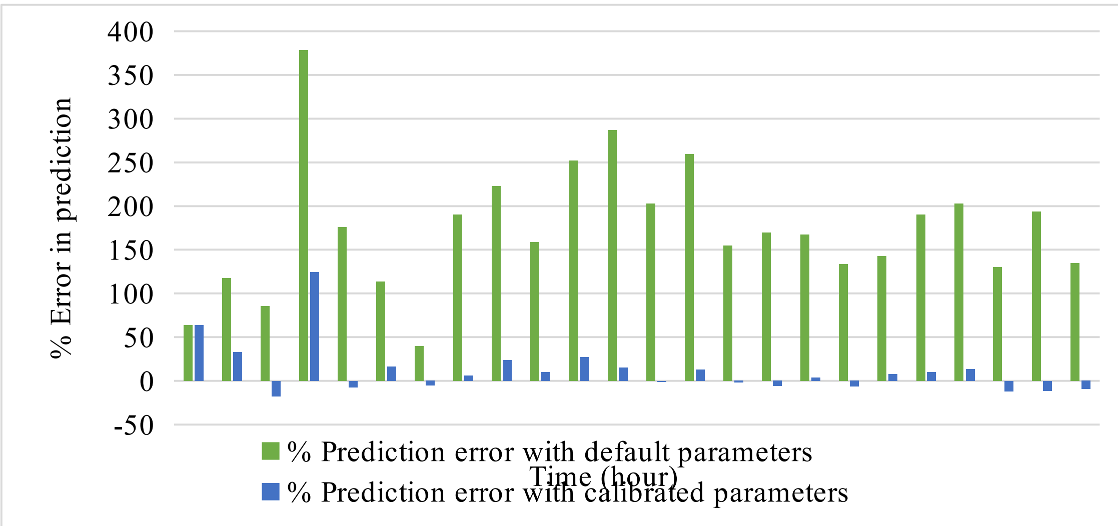

Figure 9. Prediction error with & without calibrated parameters in simulator, downstream direction of section of route-20

It is found that most of the time, defaults parameters provide more than 100% error for section of route-20 downstream direction shown in Figure 9. When, parameters calibration are done in one hour interval, simulation gave better result compare with default parameters.

Same things are also happened for section of route-358, 411 and 140, shown in Figure 10, 11 and 12.

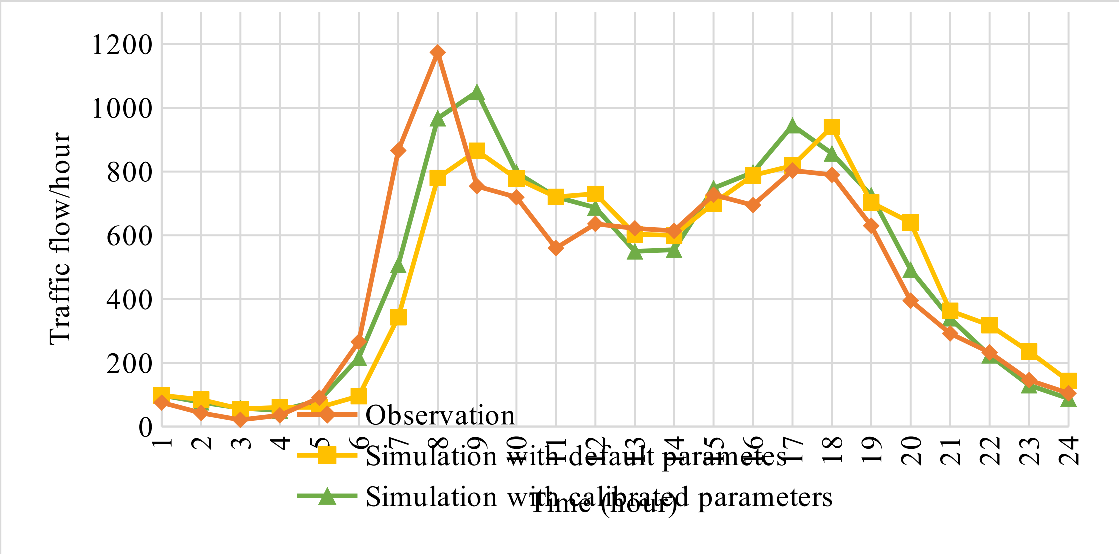

Figure 10. Compare traffic flow among observation and simulation with & without calibrated parameters, downstream direction section of route-358

With default parameters, section of route 20 and section of route 140 occupied with large gap between the simulated traffic flow and the observation traffic flow. In simulation, large amount of car choose section of route 20 due to its large capacity. This route is one of the nationwide trunk route in Japan. Other hand, observation section location of route-20 and route 140 are very close and it is also found that most of the car used section of route 20 rather than section of route 140 in simulator. During parameters calibration along with driving behaviors parameters, user define cost plays a significant effect to reduce this error in simulator.

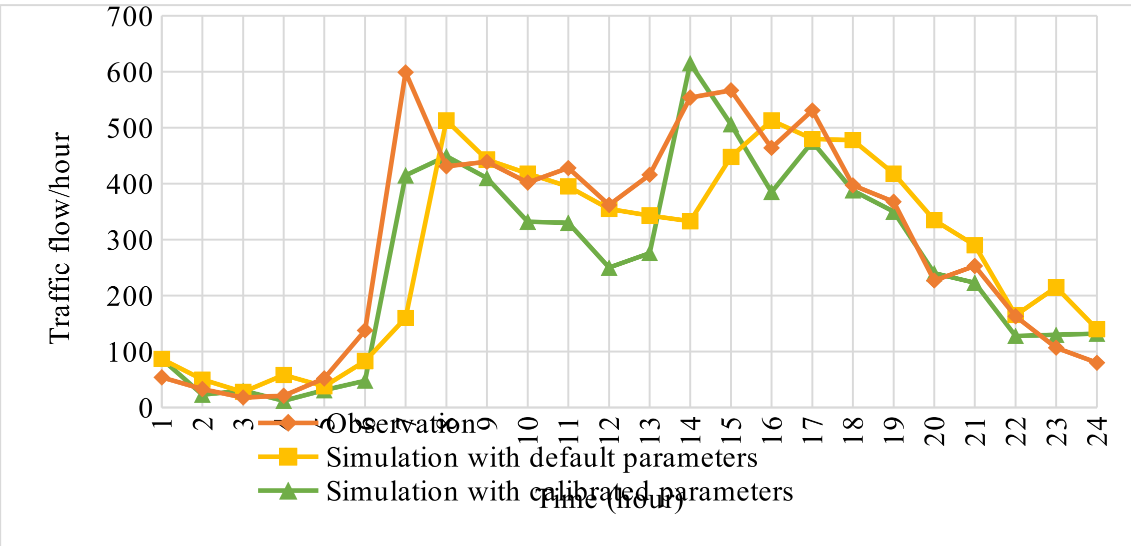

Figure 11. Compare traffic flow among observation and simulation with & without calibrated parameters, downstream direction section of route-411

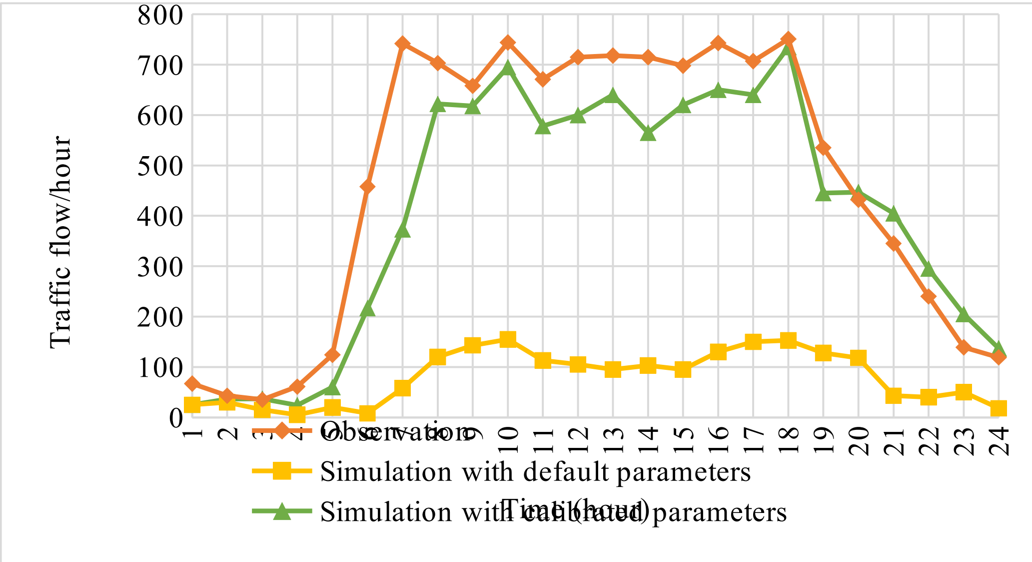

Figure 12. Compare traffic flow among observation and simulation with & without calibrated parameters, downstream direction section of route-140

This study focuses on establish a methodology of the parameters calibration utilizing observation data for the purpose of short term traffic prediction of the next time slice. Traffic flow are predicted by micro simulator for time t, then parameters of simulator are calibrated considering real world observation at time t. And traffic flow is predicted for next time slice t+1 by micro simulator again. Figure 8, 10, 11 and 12 indicate that our proposed methodology can give significantly effect on improve the simulation performance. R-square value also is used to determine the prediction accuracy due to its simplicity. Section of route 358 and route 140 satisfy certain level as 0.752 and 0.650 R-square value without parameters calibration. Prediction accuracy increased with parameters calibration from 0.752 to 0.866 for section of route 358 and from 0.650 to 0.907 for section of route 140. Table 3 give the evidence of the simulation with parameters calibration perform better comparing with default and without parameters calibration.

Table 3. R-square value for prediction accuracy

Observation section	Downstream direction		Upstream direction	
	With calibration	Without calibration	With calibration	Without calibration
Route-20	0.945	0.835	0.910	0.701
Route-358	0.866	0.752	0.838	0.762
Route-411	0.907	0.650	0.893	0.799
Route-140	0.891	0.691	0.871	0.760

6. VALIDATION

The purpose of model validation here is to compare the output of the calibrated model to real life measures that were not used in the calibration. As downstream direction observation traffic flow of section of route-20, 358, 411 and 140 are used for calibration purpose. Upstream direction observation traffic flow of section of route-20, 358, 411 and 140 are used for validation purpose. It can indicate what will be the simulation performance of other parts of network. Upstream direction, R-square values (Table 3) indicate that the simulation with parameters calibration perform well comparing with default or without parameters calibration. Figure 13 showed the simulation traffic flow without parameters calibration and that with calibration compare with observation traffic flow of section of route 20 upstream direction. It is found that most of the time, defaults parameters cannot represent real world scenario in simulator. When, parameter calibration is done in one hour interval, simulation give better result comparing with default parameters. The same things are also observed in the results of section of route-358, 411 and 140, shown in Figure 14, 15 and 16.

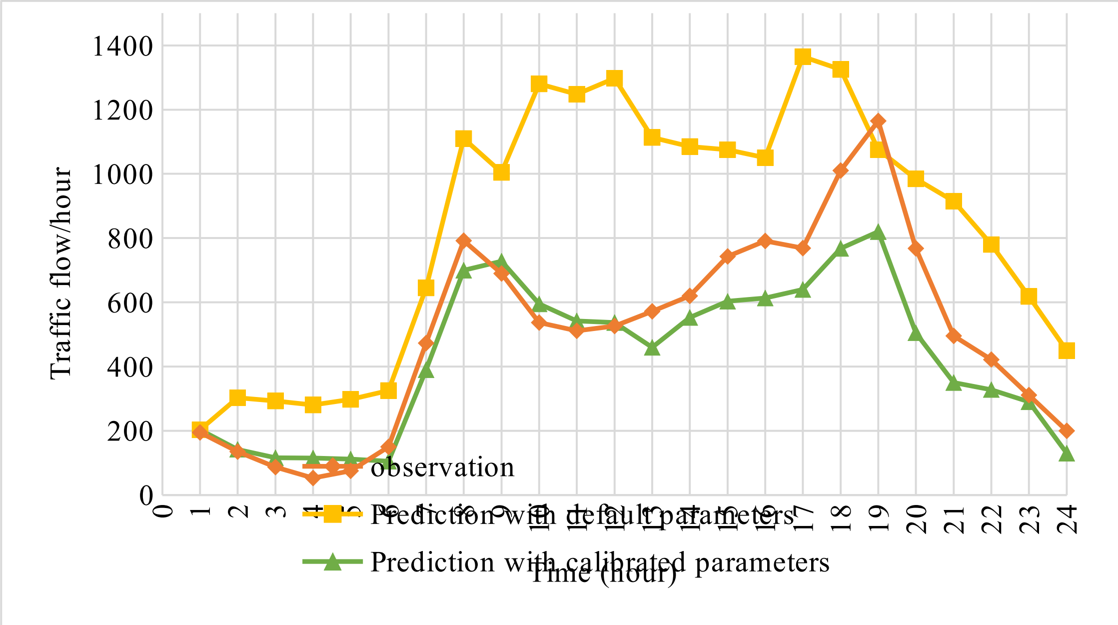

Figure 13. Compare traffic flow among observation and simulation with & without calibrated parameters, upstream direction of section of route-20

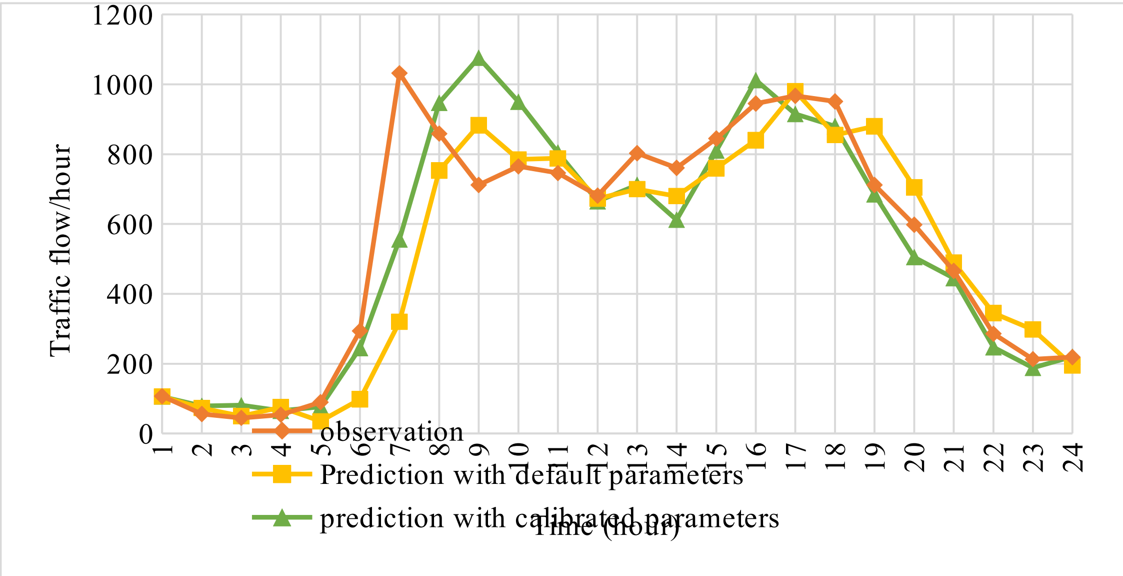

Figure 14. Compare traffic flow among observation and simulation with & without calibrated parameters, upstream direction of section of route-358

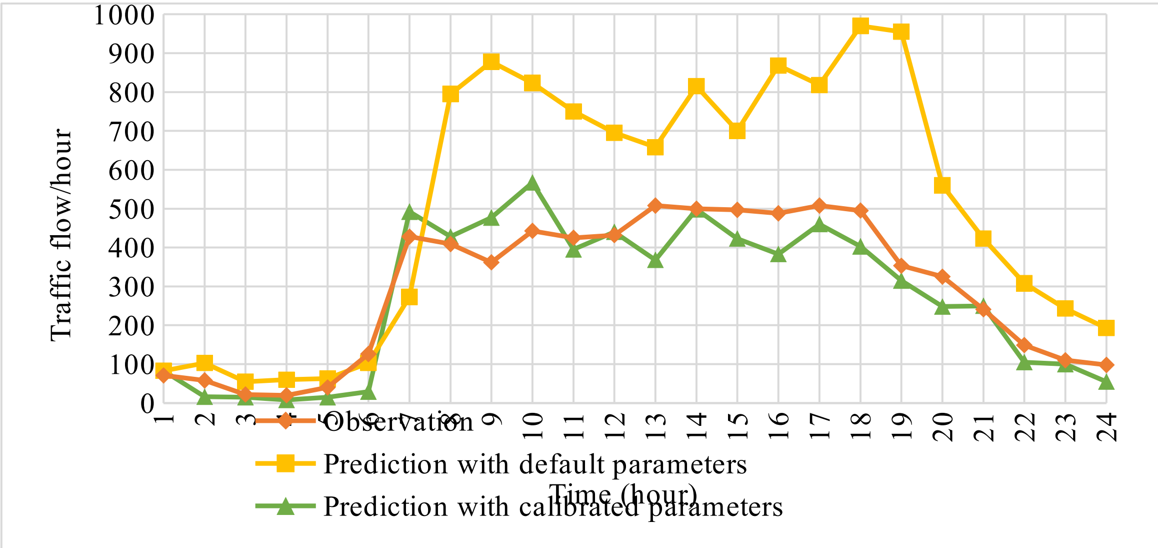

Figure 15. Compare traffic flow among observation and simulation with & without calibrated parameters, upstream direction of section of route-411

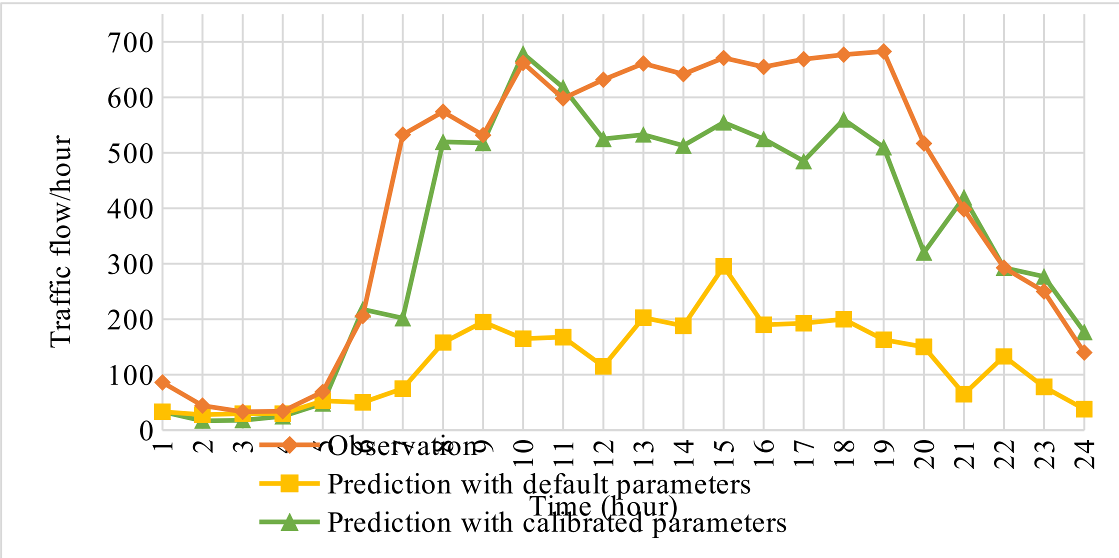

Figure 16. Compare traffic flow among observation and simulation with & without calibrated parameters, upstream direction of section of route-140

This study can improve the accuracy of traffic state forecasting for big scale traffic network. By incorporating the observation data into micro-simulator, our proposed methodology can adjust the simulation parameters considering traffic network condition. With simulation progress, parameters maladaptation is one of the key source of errors generation due to fluctuation property of traffic flow. Parameters recalibration can give the answer to reduce this error. Assimilation is done between simulated traffic state and observation traffic state. Parameters of micro-simulator are calibrated to fit the posterior distribution of the traffic state. So that, this methodology can coup with fluctuation property of traffic flow in a network.

Observed travel time which is considered for parameter calibration are also compared with the mean of simulated travel time. Figure 17 shows the comparison between the mean of the simulated travel time and the observed section travel time of section of route 20 downstream direction.

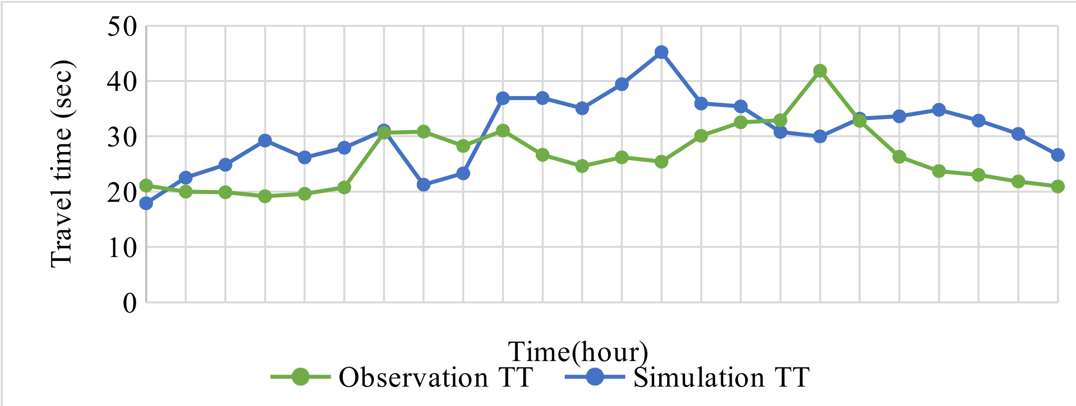

Figure 17. Compare between observed travel time and simulated travel time with parameters calibration, downstream direction of section of route-20

Figure 18, 19 and 20 shows the comparison between simulated travel time and observed section travel time of section of route-358, 411 and 140 downstream direction respectively. Those comparisons can be treated as validation of the proposed methodology to represent the real world scenario in micro-simulator, as observation travel time is not directly involved in parameters calibration purpose.

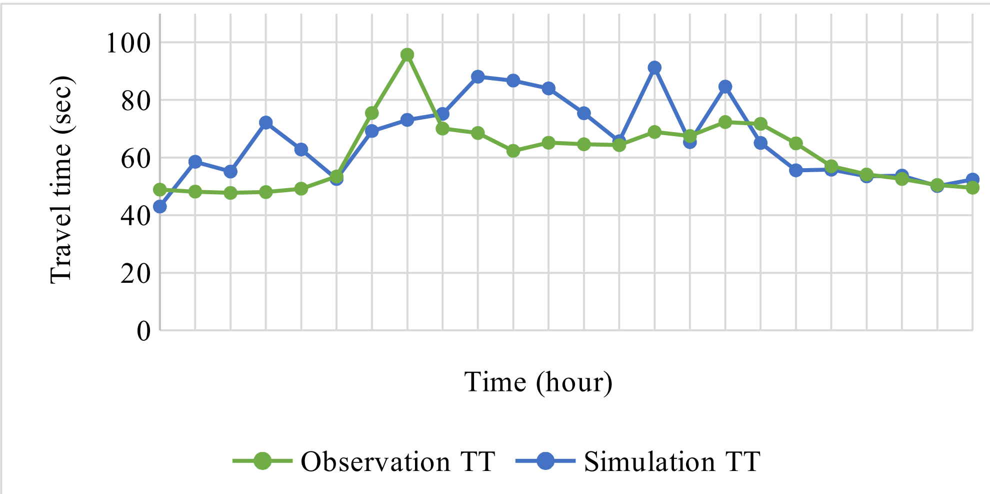

Figure 18. Compare between observed travel time and simulated travel time with parameters calibration, downstream direction of section of route-358

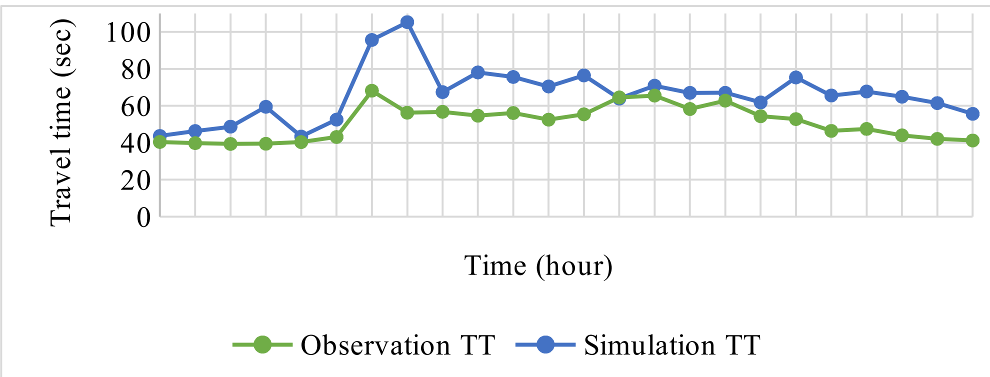

Figure 19. Compare between observed travel time and simulated travel time with parameters calibration, downstream direction of section of route-411

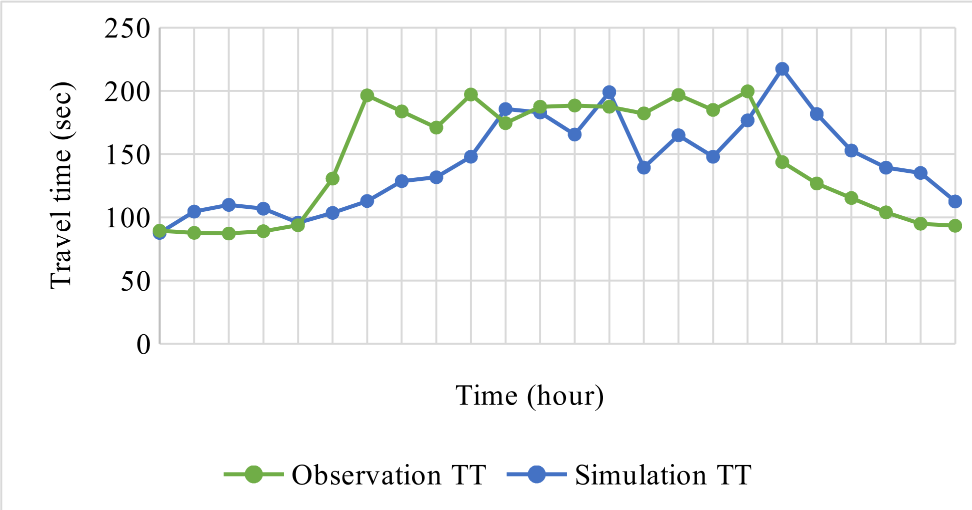

Figure 20. Compare between observed travel time and simulated travel time with parameters calibration, downstream direction of section of route-140

From observation validation result, it is indicated that our proposed methodology can perform well to represent the real world scenario in simulator for traffic network. In this study, we only consider four observation location for parameters calibration. With the increase of observation locations, the performance of simulator can be more accurate.

7. CONCLUSION AND DISCUSSION

Nowadays, the data on the traffic state can collect through various device and system. On the other hand, the short time prediction is getting important for the coming new device and management of the traffic. Traffic state are affected by the various condition, through the traffic simulator modeled the ideal state. So, utilizing real time observation of the traffic state into micro simulation is important for the precise simulation of the short time traffic prediction. Variation of traffic flow is one of the major source of errors generation in micro simulation. This study can contribute to answer this problem by incorporating the real time observation to revise the parameters of simulator through the data assimilation algorithms. So that, real world traffic conditions such as drivers' behavior and route choice behaviors changes due to congestion, weather effect or accident in network can be possible to represent in simulator. Real time traffic prediction can be possible considering those factors.

Our methodology contains continuous traffic prediction and calibration based on the state space modeling frame. In our empirical study, four observation locations are considered to calibrate parameters. Traffic prediction is done by micro simulator, and parameters are re-calibrated to fit observation data. The calibration process included four parameters of desire speed which can represent the driving behavior of each car in the network. The maximum section speed can control the driving behavior of a section. As the route choice related parameters, we calibrated user defined cost which can be treated as surcharge to estimate link cost.

Simulation of large scale traffic network is a challenging task for researchers, because of its dynamic properties. This study also gives the solution for this purpose by calibrating link cost using surcharge value of user define cost as well as calibrating desire speed and maximum section speed parameters. With this study accuracy of large scale traffic simulation is improved, and real time simulation is possible. The short term traffic prediction is expected to become accurate by the calibrating the parameters along with driving behavior and route choice. Utilizing those predictions, it is possible to improve the traffic management system by controlling the traffic. Besides, the short term forecasting in the network would be useful for autonomous vehicle management. This study focused on establishing a methodology, where sequentially traffic flow prediction and parameters of simulator are calibrated by utilizing observation data. Traffic flow is predicted by micro simulator for time t, then parameters of simulator are calibrated considering real world observation at time t. And traffic flow is predicted for next time slice t+1 by micro simulator again. This study can open the door for utilizing available real time information in incorporation in micro simulator for parameters calibration and predict short term traffic state. This study is done only considering car traffic flow in the network. With the increase of observation sections, prediction accuracy will be increased in the network.

REFERENCES

Cheu, R. L., X., Jin, K. C., Ng, Y. L. Ng, Srinivasan, D. (1998) Calibration of FRESIM for a Singapore expressway using genetic algorithm. *Journal of Transportation Engineering, Vol. 124, No. 6, pp. 526-535*.

Ding, L. (2003) Evaluation of ITS Technologies In South Jersey Priority Corridor Project. *Master Thesis, Rutgers, The State University of New Jersey*.

Kim, K. O., Rilett, L. R. (2003) Simplex-based Calibration of Traffic Microsimulation Models with Intelligent Transportation Systems Data. *Transportation Research Record: Journal of Transportation Research Board, No. 1855, pp.80-89*.

Kundé, K. K. (2002) Calibration of Mesoscopic Traffic Simulation Models for Dynamic Traffic Assignment. *Master Thesis, Massachusetts Institute of Technology*.

Maze, T., Agarwai, M., Burchett, G. (2006) Whether Weather Matters to Traffic Demand, Traffic Safety, and Traffic Operations and Flow. *Transportation Research Record: Journal of the Transportation Research Board, Vol. 1948, pp. 170-176.*

Nagy, A. M., Simon, V. (2018) Survey on traffic prediction in smart cities. *Pervasive and Mobile Computing, Vol. 50, pp. 148-163.*

Park, B., Schneeberger, J. D. (2003) Microscopic Simulation Model Calibration and Validation: A Case Study of VISSIM for a Coordinated Actuated Signal System. *Transportation Research Record 1856, TRB, National Research Council, Washington, D.C., pp. 185-192.*

Park, B., Won, J., Yin, I. (2006) Application of Microscopic Simulation Mode Calibration and Validation Procedure: A Case Study of Coordinated Actuated Signal System. *Transportation Research Record: journal of the Transportation Research Board, no. 1978, pp. 113-122.*

Punzo, V., Montanino, M., Ciuffo, B. (2015) Do we really need to calibrate all the parameters? Variance-based sensitivity analysis to simplify microscopic traffic flow models. *IEEE Transactions on Intelligent Transportation Systems 16(1), 184-193.*

Sasaki, K., JSCE, M. (2016) Improvement of short Term Prediction of Micro-Simulation though Parameter Adjustment using Observation Traffic State. *The 7th Civil Engineering Conference in the Asian Region (CECAR 7).*

Yu, L., Chen, X.M., Wan, T., Guo, J. F. (2006) Calibration of VISSIM for Bus Rapid Transit Systems in Beijing 23 Using GPS Data. *Journal of Public Transportation, Vol. 9, No. 3, pp. 239 - 257.*