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TRIP-CHAIN ESTIMATION FOR ELECTRIC VEHICLE (EV) TRAFFIC SIMULATION USING ENTROPY MODEL

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ABSTRACT

Electric vehicles (EVs) are expected to be used widely because of its energy efficiency in the future, then a methodology to evaluate traffic situation holding significant amount of EVs using traffic simulation model is also desired. However, traffic simulation models generally do not consider trip-chains of individual vehicles even though they use hourly OD demand tables. It means EV's battery status change by multiple trips during a day cannot be described appropriately. This paper proposed a methodology to estimate trip-chains of individual vehicles comprising hourly OD demand tables in a day from simple OD distribution information so that traffic simulation models can analyze EV movements throughout a day.

Keywords: Trip-chain, Entropy model, Traffic simulation, Electric vehicle (EV)

BACKGROUND

Electric vehicle (EV) has a great advantage in energy use efficiency and it is expected to be used widely for road traffic in the future. However, one of the issues to promote EV use is its shorter range of travel distance. Typical EV's travel range is approximately 160 - 200 km, which is much shorter compared with internal combustion engine vehicle (ICV). The performance of battery would become improved gradually in the future, but it is necessary to prepare enough number of battery charging stations for the time being. Then, we need a methodology to decide how to arrange charging stations in a focus area under a certain budget constraint. Then, if we can see the picture of EVs' movement in this process, it is very helpful to determine the location of charging stations because the potential needs of charging demand is clarified.

Traffic simulation is an effective tool to analyze vehicles' movement in a road network which has a nature of dynamic changes over time. However, most of the traffic simulation models do not consider trip-chains of individual vehicles in a day even though they use hourly OD tables, that is, a trip cannot be connected to the next trip in later hours. This is not convenient to analyze EV's battery status (State of charge, SOC) because vehicles usually make more than one trips during a day and low SOC of an EV may occur in the second or third trip of that day. Thus, a methodology to estimate trip-chains from the existing OD table is necessary to apply traffic simulation for EVs' movement evaluation.
This paper aims at proposing a simplified methodology to estimate trip-chains of individual vehicles comprising hourly OD demand tables in a day from simple OD distribution information so that traffic simulation models can analyze EV movements throughout a day. To consider trip-chains in the context of transportation planning and engineering would be more and more important as advanced traffic control and demand management become available. This study can contribute not only EV traffic simulation but also overall transportation planning that deals with multiple trips during a day.

ESTIMATION OF TRIP-CHAINS

Previous researches

Researches on trip-chain began in 1960s and there were several researches that tried to describe trip-chains using Markov chain model. Sasaki (1974) proposed a vehicle OD distribution forecasting model applying absorbing Markov chain process. These models calculated transition probability matrix and applied it to the generated trips from a base zone. Markov chain approach had advantages in simple model structure, however, it had some difficulty in obtaining the base unit value of the trip generation etc. to apply it for practical use.
Then, activity-based approach became popular in 1980s that regards trip as a part of living activities and includes the concept of trip-chains by nature. Fujii et al (1997) proposed an activity simulator to describe individual's all living activities in a day considering his/her time and space constraints. The type of activities was selected by disaggregate choice model and the activity duration was determined by hazard-based duration model etc. Activity-based approach had rich expressive ability, however, it required a lot of detailed input variables that leaded to inconvenience for implementation.
The review results show that the previous researches have some difficulties in setting initial conditions or obtaining necessary data for the proposed models. Therefore, to develop a trip-chain estimation methodology that requires only simple information would have advantage in practice.

Entropy model

Entropy model (Sasaki (1967)) is one of the mathematical models that is used in four stage demand forecasting to estimate trip distribution from trip generation / attraction. The concept

of entropy model is that a certain OD pattern which maximizes the occurrence probability under prior choice probability of destinations is most likely to be realized.
Now, occurrence probability of a certain OD pattern $\{x_{ij}\}$ is described as follows.

$$F = \frac{X!}{\prod_i \prod_j x_{ij}!} \prod_i \prod_j (q_{ij})^{x_{ij}} \tag{1}$$

where, X: total trip production, x_{ij}: element of OD table $\{x_{ij}\}$, q_{ij}: prior probability of OD table$\{x_{ij}\}$. Here, probability of trip generation, trip attraction and destination choice are written as f_i, g_j and h_{ij}, respectively.

$$f_i = \frac{X_i}{X} \quad \left(\sum_i f_i = 1\right), \quad g_j = \frac{Y_j}{X} \quad \left(\sum_j g_j = 1\right), \quad h_{ij} = \frac{X_{ij}}{X_i} \quad \left(\sum_j h_{ij} = 1\right) \tag{2}$$

where, X_i: trip generation of zone i, Y_i; trip attraction of zone i, X_{ij}: trip distribution between zone i and j, X: total trip production. Using these probabilities, trip end conditions of generation and attraction are,

$$\sum_j h_{ij} = 1 \quad , \quad \sum_i f_i h_{ij} = g_j \tag{3}$$

Then, prior probability of trip distribution q_{ij} (between zone i and j), whch is a form of a gravity model, is written as follows.

$$q_{ij} = \alpha f_i g_j t_{ij}^{-\gamma} \tag{4}$$

where, t_{ij}: travel time, α, γ: regression coefficient.
To determine a plausible OD pattern, Equation (1) should be maximized. By taking natural logarithm,

$$\begin{aligned} G &= \ln X! - \sum_i \sum_j \ln X_{ij}! + \sum_i \sum_j \ln X_{ij} \ln q_{ij} \\ &= X \ln X - X - \sum_i \sum_j \left(f_i h_{ij} \ln f_i h_{ij} - f_i h_{ij}\right) - \gamma \sum_i \sum_j f_i h_{ij} \ln\left(\alpha f_i g_j t_{ij}\right) \\ &= -\sum_i \sum_j f_i h_{ij} \ln f_i h_{ij} - \gamma \sum_i \sum_j f_i h_{ij} \ln t_{ij} + const \end{aligned} \tag{5}$$

Now f_i is given as exogenous variable, then h_{ij} can be obtained to maximize G under the condition (3), that is,

$$h_{ij} = e^{-1} a_i b_j t_{ij}^{-\gamma} \quad \text{where, } a_i = \exp\left(\frac{\mu_i}{f_i}\right), \quad b_j = \exp\left(\lambda_j\right) \tag{6}$$

Here μ_i and λ_j are Lagrangian multiplier for the condition (3). Thus, OD pattern can be estimated in a unit of single trips by the entropy model. However, these trips are not connected as trip-chains, so the above mentioned entropy model is extended to trip-chain estimation in the next section.

Extension of entropy model

This study tries to estimate trip-chains by utilizing only simple information of given OD trip distribution. We deal with trip-chains that start from their origins, go through one or multiple destinations and return back to their origins. This is called as perfect trip-chain. This section explains the proposed methodology to estimate perfect trip-chains by extending the entropy model.

First, we assume the number of trip-chains from zone i that includes L+1 trips (zone i -> zone k_1 -> zone k_2 -> ... -> zone k_L -> zone i) and denote it by $t_{i\mathbf{k}}$. Here, $\mathbf{k}$ is L-dimension vector and defined as $\mathbf{k}=[k_1, k_2, \dots, k_L]$. Then $t_{i\mathbf{k}}$ should hold generation condition as follows.

$$X_i = \sum_{\mathbf{k}\in\phi} t_{i\mathbf{k}} + \sum_{j=1}^{N}\sum_{l=1}^{L}\sum_{\{\mathbf{k}\in\phi | k_l=i\}} t_{j\mathbf{k}} \tag{7}$$

Here, the first term of the right side is the number of trip-chains whose first trip starts from zone i, and the second term is the number of trip-chains whose second or later trips start from zone i. The total number of trip-chains is described as follows.

$$T\left(=\sum_{i=1}^{N}\sum_{\mathbf{k}\in\phi} t_{i\mathbf{k}}\right) \tag{8}$$

Now we define $p_{i\mathbf{k}}$ as occurrence probability of a trip-chain (zone i -> zone k_1 -> zone k_2 -> ... -> zone k_L -> zone i) as follows.

$$p_{i\mathbf{k}} = \alpha \times \left(x_{ik_1} \times \prod_{l=1}^{L-1} x_{k_l k_{l+1}} \times x_{k_L i} \right), \qquad \sum_{i=1}^{N}\sum_{\mathbf{k}\in\phi} p_{i\mathbf{k}} = 1 \tag{9}$$

Then, the occurrence probability of the trip-chain { $t_{i\mathbf{k}}$ } is defined similarly to the form of (1) as follows.

$$F = \frac{T!}{\prod_{i=1}^{N}\prod_{\mathbf{k}\in\phi} t_{i\mathbf{k}}!} \prod_{i=1}^{N}\prod_{\mathbf{k}\in\phi} \left(p_{i\mathbf{k}}\right)^{t_{i\mathbf{k}}} \tag{10}$$

The trip-chain { $t_{i\mathbf{k}}$ } that maximize (10) is regarded as the most plausible one. By making Lagrange function,

$$\begin{aligned} L &= \ln(F) + \sum_{i=1}^{N}\lambda_i \left(X_i - \sum_{\mathbf{k}\in\phi} t_{i\mathbf{k}} - \sum_{j=1}^{N}\sum_{l=1}^{L}\sum_{\{\mathbf{k}\in\phi | k_l=i\}} t_{j\mathbf{k}} \right) \\ &= (T\ln T - T) - \left\{ \sum_{i=1}^{N}\sum_{\mathbf{k}\in\phi} \left(t_{i\mathbf{k}} \ln t_{i\mathbf{k}} - t_{i\mathbf{k}} \right) \right\} + \sum_{i=1}^{N}\sum_{\mathbf{k}\in\phi} t_{i\mathbf{k}} \ln p_{i\mathbf{k}} \\ &\quad + \sum_{i=1}^{N}\lambda_i \left(X_i - \sum_{\mathbf{k}\in\phi} t_{i\mathbf{k}} - \sum_{j=1}^{N}\sum_{l=1}^{L}\sum_{\{\mathbf{k}\in\phi | k_l=i\}} t_{j\mathbf{k}} \right) \\ &= (T\ln T - T) - \left\{ \sum_{i=1}^{N}\sum_{\mathbf{k}\in\phi} \left(t_{i\mathbf{k}} \ln t_{i\mathbf{k}} - t_{i\mathbf{k}} \right) \right\} + \sum_{i=1}^{N}\sum_{\mathbf{k}\in\phi} t_{i\mathbf{k}} \ln p_{i\mathbf{k}} \\ &\quad + \sum_{i=1}^{N}\lambda_i \left(X_i - \sum_{\mathbf{k}\in\phi} t_{i\mathbf{k}} - \sum_{l=1}^{L}\sum_{\{\mathbf{k}\in\phi | k_l=i\}} t_{j\mathbf{k}} - \sum_{j\neq i}^{N}\sum_{l=1}^{L}\sum_{\{\mathbf{k}\in\phi | k_l=i\}} t_{j\mathbf{k}} \right) \end{aligned} \tag{11}$$

To maximize (11), the following has to hold

$$\begin{aligned}
&\frac{\partial L}{\partial t_{i\mathbf{k}}} = 0 \quad \forall i, \mathbf{k} \\
&\Leftrightarrow -\ln t_{i\mathbf{k}} + \ln p_{i\mathbf{k}} - \lambda_i - \sum_{l=1}^{L} \lambda_{k_l} = 0 \quad \forall i, \mathbf{k} \\
&\Leftrightarrow t_{i\mathbf{k}} = p_{i\mathbf{k}} \exp(-\lambda_i) \prod_{l=1}^{L} \exp(-\lambda_{k_l}) = 0 \quad \forall i, \mathbf{k}
\end{aligned} \tag{12}$$

$$\begin{aligned}
&\frac{\partial L}{\partial \lambda_i} = 0 \quad \forall i \\
&\Leftrightarrow X_i - \sum_{\mathbf{k}\in\phi} t_{i\mathbf{k}} - \sum_{j=1}^{N} \sum_{l=1}^{L} \sum_{\{\mathbf{k}\in\phi | k_l = i\}} t_{j\mathbf{k}} = 0 \quad \forall i \\
&\Leftrightarrow X_i - \sum_{\mathbf{k}\in\phi} \left[p_{i\mathbf{k}} \exp(-\lambda_i) \prod_{l=1}^{L} \exp(-\lambda_{k_l}) \right] - \sum_{j=1}^{N} \sum_{l=1}^{L} \sum_{\{\mathbf{k}\in\phi | k_l = i\}} \left[p_{i\mathbf{k}} \exp(-\lambda_i) \prod_{l=1}^{L} \exp(-\lambda_{k_l}) \right] = 0 \quad \forall i \\
&\Leftrightarrow X_i - \exp(-\lambda_i) \sum_{\mathbf{k}\in\phi} \left[p_{i\mathbf{k}} \prod_{l=1}^{L} \exp(-\lambda_{k_l}) \right] - \sum_{j=1}^{N} \sum_{l=1}^{L} \sum_{\{\mathbf{k}\in\phi | k_l = i\}} \left[p_{i\mathbf{k}} \exp(-\lambda_i) \prod_{l=1}^{L} \exp(-\lambda_{k_l}) \right] = 0 \quad \forall i
\end{aligned} \tag{13}$$

Therefore, if λ_i (i = 1,.., N) to satisfy (13) are calculated, $t_{i\mathbf{k}}$ can be obtained by (12). Thus, trip-chains which is most likely to occur under a certain OD trip distribution can be estimated.

Verification of the estimation methodology

To verify the proposed methodology, estimated trip-chains and actual trip-chains need to be compared. However, it is very difficult to obtain complete trip-chains data from the actual field. Therefore, this study generated a certain number of hypothetical trip-chains in the study area, and aggregated them to make an OD table. Then, using the proposed methodology, trip-chains were estimated from the information of that OD table, and compared with the original trip-chains. Figure 1 shows the flow of the verification process.

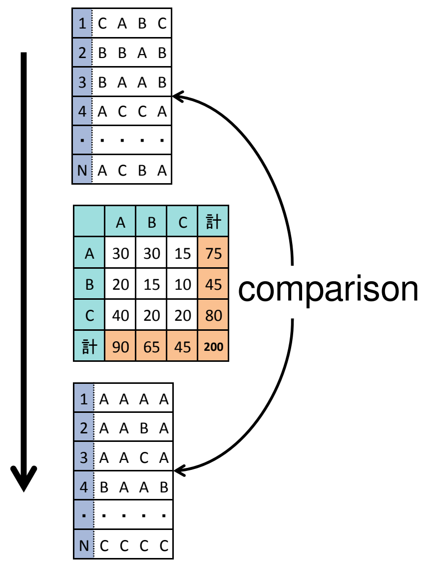

Figure 1 – Flow of the verification process

The number of trips in a trip-chain considered in the estimation was determined referring the existing person trip survey result. Table 1 shows the proportion of the number of trips per day by different travellers. According to this result, more than 90% of travellers make less than 5 trips in a day. Therefore, we estimated trip-chains of 2, 3 and 4 trips in this study.

Table 1 – Number of trips per day by individual travellers (from person trip survey)

num of trips	2	3	4	5	6	7	8	9	10	11	12	13 and more
share [%]	67.05	6.81	16.40	2.86	3.59	1.40	1.48	0.28	0.05	0.04	0.00	0.02

We selected Tokyo metropolis as a study area and set 23 zones. Figure 2 shows the base map of the area and the zone allocation which includes 115 zones originally. These zones were integrated by adjacent 5 zones to comprise 23 zones The number of vehicle trips are 5 million in this area and the average number of trips per day are 2.5 from the person trip survey in Tokyo, then 2 million trip-chains were generated. The generated trip-chains were only perfect ones.

Figure 2 – Zone map of Tokyo metropolis

Figure 3 shows the comparison of the generated trip-chains and the estimated ones. One point means one series of trip-chain. For example, if 800 trip-chains of A -> B -> A were generated and 750 trip-chains of A -> B -> A were estimated, a point is plotted at (800, 750). The number of trip-chains of 3 and 4 trips are much smaller than that of 2 trips, so plots are very much separated. Figure 4 enlarges the part of the trip-chains of 2 trips. Both figures shows that the estimated number of trip-chains suits with the original number of trip-chains well.

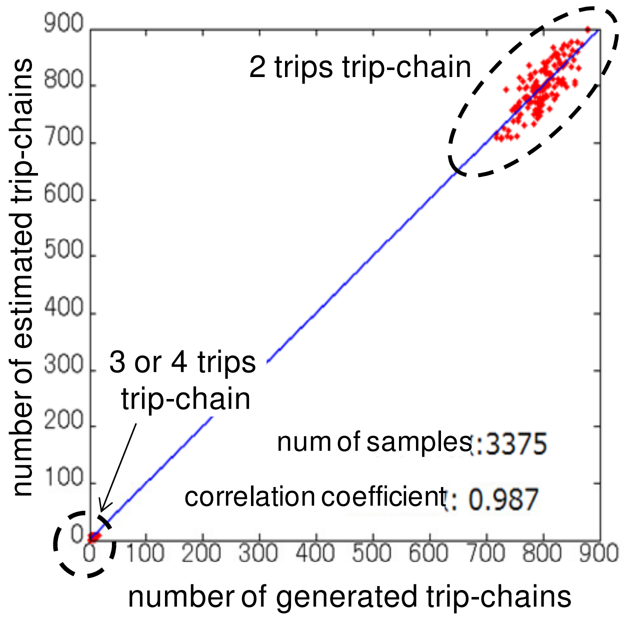

Figure 3 – Scatter diagram of generated and estimated trip-chains

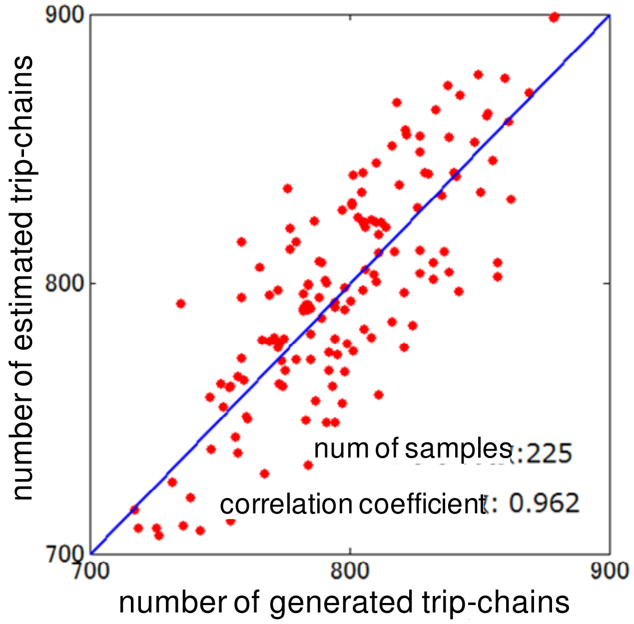

Figure 4 – Scatter diagram of generated and estimated trip-chains (2 trips)

To check the statistical accuracy, RMSE was calculated by trip-chains of 2, 3 and 4 trips separately. The result is shown in Table 2. And Figure 5, 6 and 7 shows histograms of these RMSE distribution.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i}(y_i - x_i)^2} \tag{14}$$

Table 2 – RMSE and Percent RMSE

	number of trips			
	2	3	4	total
RMSE [trip-chains}	42.369	2.641	1.311	31.963
Percent RMSE [%]	4.2	23.2	43.0	12.6

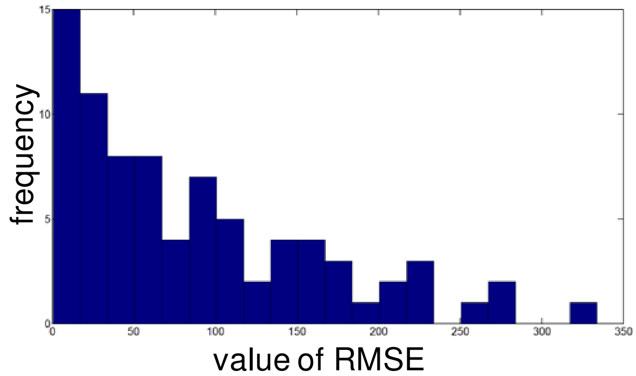

Figure 5 – Histogram of RMSE distribution (2 trips)

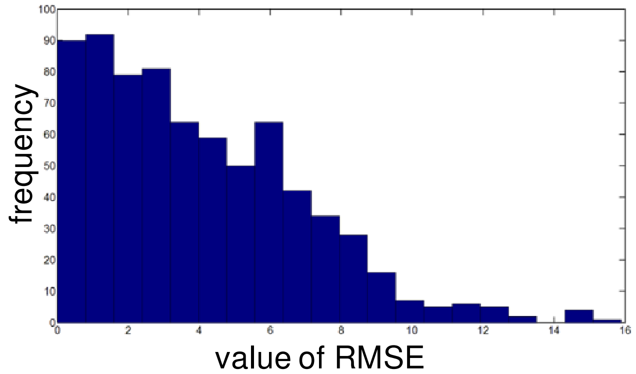

Figure 6 – Histogram of RMSE distribution (3 trips)

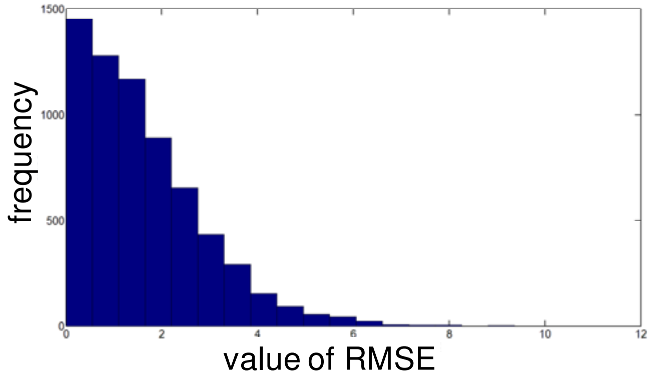

Figure 7 – Histogram of RMSE distribution (4 trips)

We can see as the number of trips increases, the value of percent RMSE also increases. However, the share of 3 or 4 trips trip-chains are much smaller than 2 trips ones, so the total value of the percent RMSE is relatively small, that is, 12.6%.

APPLICATION OF EV SIMULATION IN TOKYO

Using the proposed methodology, traffic demand with trip-chains were estimation and EV traffic simulation were demonstrated considering the conditions in Tokyo road network.

Simulation model

To simulate EVs movements we used a mesoscopic traffic simulation model called SOUND, which was developed by The University of Tokyo. It can manage the traffic flow - density relationship according to the traffic flow theory as well as each vehicle's movement. The route choice behaviour is modelled using Dial's assignment. It can simulate dynamic traffic situation by updating route choice probability in every predefined interval.
EVs' movement was modelled as follows. Every EV holds an attribute of its battery status (SOC) and EV's run is classified into 4 modes, that is, normal run, charging station search, charging and run out of battery. In the normal run, EV's SOC decreases depending on its distance travelled as it moves toward its destination. The SOC at the destination is maintained until its next trip starts from there according to its trip-chain. When the SOC decreases below a certain threshold value such as 20%, then the EV starts the charging station search mode. It looks for charging stations around its location calculating the minimum travel cost and choose one of them unless the destination is nearer than charging stations. While charging mode, EV enters the charging station and recovers the SOC. However, if the charging slots are full, EV lines up in the queue and wait for an available slot. Finally, if the SOC gets to zero before EV reaches a charging station, it stops there by running out of the battery and the simulator records its location. Figure 8 shows the EV's movement in the simulator.

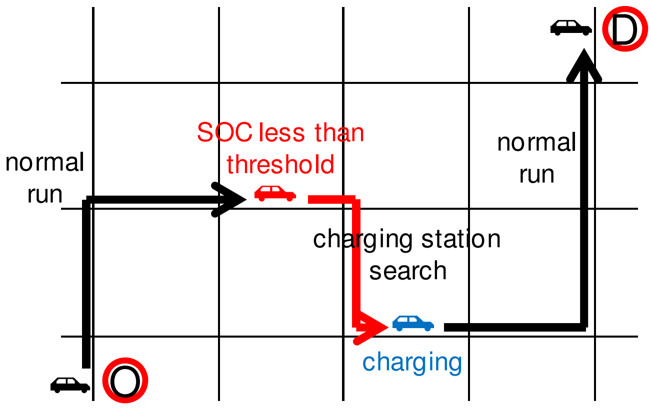

Figure 8 – EV's movement during its trip

Study network

Figure 9 shows the road network which was used in this simulation. This network consists of arterial streets in Tokyo that holds 418 nodes and 1400 links, and each link has information of link length, number of lanes and link capacity.

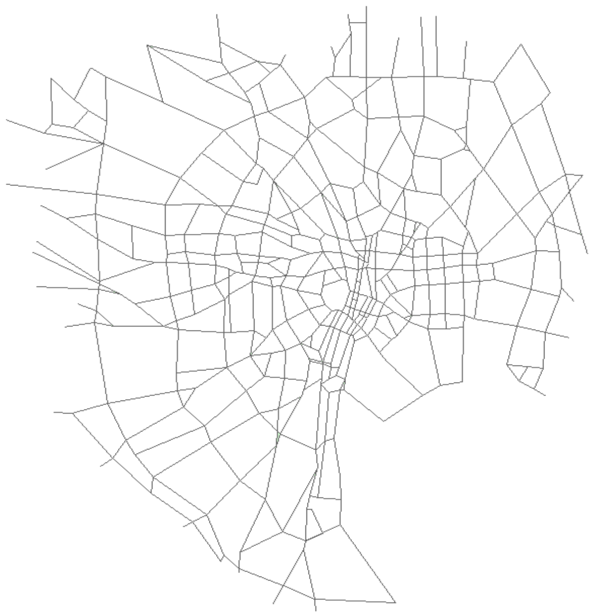

Figure 9 – Study network in Tokyo

Simulation run

In preparing OD traffic demand, we considered only EVs demand as the diffusion rate of EVs among different zones was unclear. Trip-chains of these EVs were estimated by the proposed methodology in the previous chapter, then we ran the simulation.

Figure 10 shows the result of the calculated location where EVs run out of their battery. The height of the bar shows the number of EVs. They are concentrated in the city centre, where a lot of traffic demand is generated and attracted. On the other hand, there are relatively few locations in the surrounding area. This result means that the potential needs of battery charge is not evenly distributed over the network but relatively concentrated depending on the EVs' movement. Therefore, it is meaningful to analyze EVs' movement by appropriate tools such as traffic simulation when we determine the locations of charging stations.

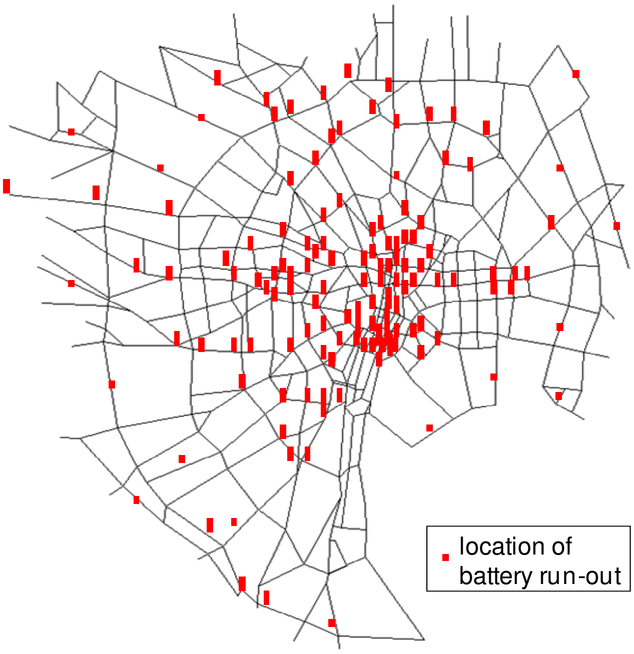

Figure 10 – Location of EVs' battery run-out

CONCLUSION

This study proposed a methodology to estimate a plausible set of trip-chains from OD trip distribution by entropy model that is essential to evaluate EVs' battery charge needs and charging stations arrangement. This methodology requires only simple and limited information of OD pattern, which is very advantageous in practice. The application of the EV traffic simulation in Tokyo showed the potential needs of battery charge on that network.
However, the current methodology estimates trip-chains purely by maximum probability, that means zone or network characteristics are not considered for the estimation. Therefore, such information should be incorporated into this methodology in the next step for better trip-chain estimation.

REFERENCE

Sasaki, T. (1974). Estimation of person trip patterns through Markov chains, Traffic Flow and Transportation, 119-130.

Fujii, S., Otsuka, Y., Kitamura, R., Momma, T. (1997). Development of activity simulator to reproduce living activities considering time-space constraints, Journal of Infrastructure Planning, No.14, 643-562 (in Japanese)

Sasaki, T. (1967). Stochastic method to estimate OD trip distribution, Traffic Engineering, Vol. 2, 12-21 (in Japanese)

Kitamura, R., and Lam, T. N. (1983). A Time Development Markov Renewal model of Trip Chaining, Transportation and Traffic Theory, 376-402

Kitamura, R. (1984). History Dependent Approach to Trip-Chaining Behavior, Transportation Research Record, 944, 13-22