IEEJ TRANSACTIONS ON ELECTRICAL AND ELECTRONIC ENGINEERING
*IEEJ Trans* 2013; **8**: 139–145
Published online in Wiley Online Library (wileyonlinelibrary.com). DOI:10.1002/tee.21833

**Paper**

# An Application of *Q*-Value-Based Dynamic Programming with Boltzmann Distribution to Real-World Road Networks

Shanqing Yu[a], Non-Member
Shingo Mabu, Member
Manoj Kanta Mainali, Non-Member
Kaoru Shimada, Member
Kotaro Hirasawa, Member

In order to alleviate traffic congestion and improve the efficiency of traffic systems from a global perspective, a dynamic traffic management model is proposed in this paper. The proposed model is applied to the large-scale microscopic simulator SOUND/4U based on the real-world road network of Kurosaki, Kitakyushu, Japan. All the vehicles in the simulator follow the direction from the route guidance of the dynamic traffic management model, in which the extended *Q*-value-based dynamic Programming with Boltzmann distribution (QDP-BD) and the time-varying traffic information are used to generate the routes from the origins to the destinations. The simulation results show that the proposed QDP-BD can reduce traffic congestion and improve the efficiency of the whole traffic system effectively compared with the greedy method in the real-world road network.


**Keywords:** dynamic traffic management, *Q*-value-based dynamic programming with Boltzmann distribution, real-world application

*Received 18 March 2011; Revised 26 October 2011*

## 1. Introduction

As the result of increased motorization and urbanization, the frequently occurring traffic congestion brings about much inconvenience for daily lives through increased traveling time and air pollution. Heavy traffic congestions reduce the efficiency of transportation and even disrupt human activities. Therefore, numerous formulations and solutions have been proposed for reducing the traffic congestion.

Recently, as a result of the development of intelligent transportation system (ITS) technologies [1,2], research in the field of traffic assignment has attracted considerable attention. However, most research, which include our previous research [3], carry out traffic planning and evaluation methods in static traffic systems [4]. In these methods, how to deal with the dynamic traffic information and how to do traffic assignment based on time-varying traffic information are not discussed. Actually, the availability of real-time traffic situations in the advanced ITS [5,6] makes dynamic traffic management more attractive for vehicle management than in the static traffic model. The authors of [7] have proposed approaches to manage traffic using time-varying traffic data, but they only provide the optimal routes for a single vehicle or a small number of vehicles in the traffic system by adopting the greedy method. Although these methods will be of some benefit to some vehicles, they may have only a small contribution to alleviate traffic congestion. Indeed, these methods may cause some negative behavioral phenomena such as concentration and overreaction [8,9] if most of the drivers in the traffic systems use the same guiding strategy.

[a] Correspondence to: Kotaro Hirasawa. E-mail: hirasawa@waseda.jp

Graduate School of Information, Production and Systems, Waseda University, Hibikino 2-7, Wakamatsu-ku, Kitakyushu, Fukuoka 808-0135, Japan

There have also been much work [10,11] proposing dynamic traffic management strategies aiming to improve the system performance. However, they only apply their methods to unrealistic, simple road networks, whose results are unpredictable when applied to the real-world road networks. For example, Lee [10] calculates $k$ shortest paths for the drivers at each operational time interval and equally distributes the traffic volume to the generated shortest paths. This method may perform well only in unrealistic grid road networks, and the requirement for the memory space and computation time may become unacceptable as the number of the origin-destination (OD) pairs increases in a real-world traffic systems. Therefore, there is still high interest in dynamic traffic assignment, particularly in large-scale real-time applications [12].

In this paper, a dynamic traffic management model is described in order to alleviate traffic congestion and to improve the efficiency of the traffic systems from a global perspective. For each time interval, the proposed dynamic traffic management model needs only to calculate the *Q*-value and probability of each section using the extended *Q*-value-based dynamic programming with Boltzmann distribution (QDP-BD). The drivers can generate the route solutions based on the *Q*-value and probability. The computation time of each *Q*-value calculation is discussed in Ref. [3].

The proposed traffic management model is applied to the large-scale microscopic simulator SOUND/4U [13] based on the road network of Kurosaki, Kitakyushu, Japan. All the vehicles in the simulator use the results calculated by the extended QDP-BD [14] and the time-varying traffic information to generate the routes from the the origins to the destinations. The simulations compare the proposed method with the conventional greedy routing method, in which the routes with the smallest traveling time are always suggested to the drivers. The results show that the proposed QDP-BD can reduce traffic congestion and improve the efficiency of the whole traffic system effectively compared with the greedy method in real-world road networks.

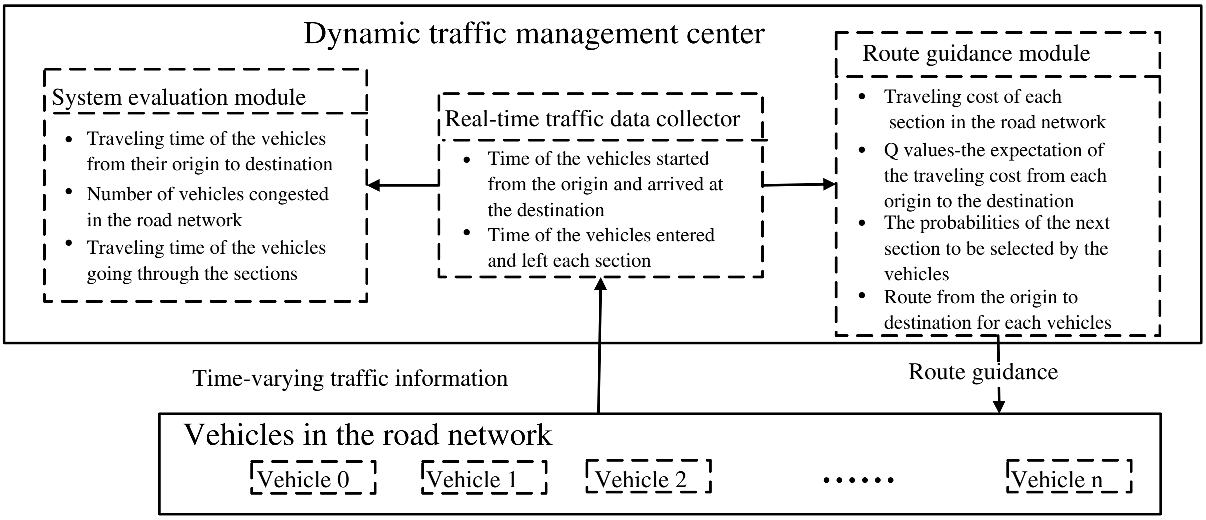



Fig. 1. Structure of the dynamic traffic management model

This paper is organized as follows: In Section 2, the details of the proposed dynamic traffic management model including QDP-BD are explained. In Section 3, the simulations, in which the comparison between the proposed method and greedy method is carried out under dynamically changing traffic situations, are given. Section draws the conclusions.

## 2. Dynamic Traffic Management Model

As shown in Fig. 1, there are three modules, i.e. the real-time traffic data collector, the route guidance module, and the system evaluation module, in the proposed dynamic traffic management model. Each module will be explained in detail in the following subsections.

**2.1. Real-time traffic data collector** In this paper, a large-scale microscopic simulator SOUND/4U is used to replicate the complex traffic flow dynamics and implement different traffic management strategies in the urban-level real-world road networks. The real-time traffic data collector is also implemented based on the SOUND/4U simulator. The traffic data collector gets the traffic information from the vehicles every minute in the simulated traffic system, which includes the vehicles' starting time from the origin, their arrival time at the destination, and the time entered and left each section, which are sent to the route guidance module and system evaluation module.

**2.2. Route guidance module** As shown in Fig. 1, all the vehicles in the traffic systems follow the directions from the route guidance module. The route guidance module first constructs the logistic network based on the geographical road network and then calculates the traveling cost for each section in the logistic network based on the traffic information from the traffic data collector. In addition, the routes from the origin to destination of vehicles are generated using the $Q$-values and probabilities calculated by the QDP-BD.

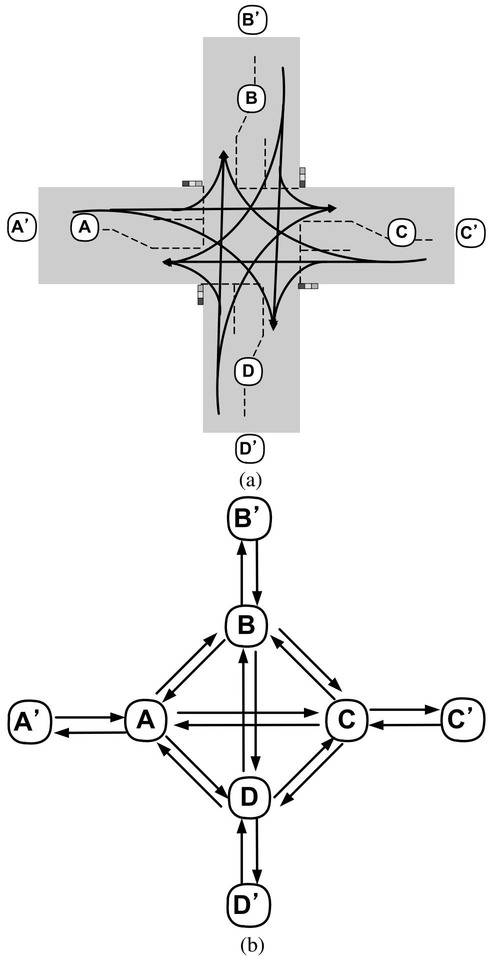



Fig. 2. Example of logistic network construction. (a) Cross in geographical road network. (b) Cross in logistic network

*2.2.1. Logistic network construction* In order to calculate the optimal routes for the vehicles using a Graph-search algorithm, the geographical road network should be transformed into the logistic graph. The simplest way to do this is to consider the crosses in the road network as intersections and the roads as directed sections. However, in the real-world traffic systems, the vehicles decideing to turn left, turn right, or go straight may spend different traveling time to go through intersections even if they are the same intersection because of the signals, traffic rules, and the number of the vehicles in that direction. Therefore, the vehicles going though different directions at intersections are assumed to travel on different sections in the logistic network in this paper. Figure 2 shows an example on how three directions in the intersections are transformed into the logistic network. The traveling time $t_{ij}$ from intersection $i$ to intersection $j$ in the logistic network is dynamically changing depending on the traffic information sent from the traffic data collector according to the following equation:

$$t_{ij} = \begin{cases} \frac{\sum_{v\in V(ij)} (lt_{ij}(v)-et_{ij}(v))}{|V(ij)|}, & \text{if } |V(ij)| \neq 0 \\ \frac{\sum_{v\in V(ij)} t'_{ij}(v)}{|CV(ij)|}, & \text{if } |V(ij)| = 0 \\ t^0_{ij}, & \text{if } |CV(ij)| = 0 \end{cases} \tag{1}$$

where $t'_{ij} = ct - et_{ij}(v)$, if $(ct - et_{ij}(v)) > t^0_{ij}$; $t'_{ij} = t^0_{ij}$, if $(ct - et_{ij}(v)) \leqslant t^0_{ij}$; $s_{ij}$ is section from intersection $i$ to intersection $j$; $lt_{ij}(v)$ is time when vehicle $v$ left section $s_{ij}$; $et_{ij}(v)$ is time when vehicle $v$ entered section $s_{ij}$; $V(ij)$ is set of suffixes of vehicles going through $s_{ij}$ during the last traffic information updating interval; $CV(ij)$ is set of suffixes of vehicles in section $s_{ij}$ at the current traffic information updating interval; $ct$ is the current time; and $t^0_{ij}$ is free flow traveling time of section $s_{ij}$.

The logistic network construction is the foundation of the dynamic traffic management model. Without this part, it is difficult to use dynamic traffic information and carry out realistic simulations. Therefore, it is also used in greedy method in this paper.

*2.2.2. Q-values and the probability calculation* The QDP-BD [15,16], which is a routing algorithm used to calculate the expected traveling time from each origin to the the destination and the probability of the next section to be selected, is adopted in the route guidance module.

The $Q$-value and $P$-value, i.e. $Q_d(i,j)$ and $P_d(i,j)$, which are defined as the expected minimum traveling time to destination $d$ and the probability of selecting the next intersection, respectively, when a vehicle bound for destination $d$ moves to intersection $j$ at intersection $i$ are calculated iteratively based on the following equations:

$$Q_d^{(n)}(i,j) \longleftarrow t_{ij} + \sum_{k\in A(j)} P_d^{(n-1)}(j,k) Q_d^{(n-1)}(j,k), \tag{2}$$

$d \in D,\ i \in I - \{d\} - B(d),\ j \in A(i)$

$$P_d^{(n)}(i,j) \longleftarrow \frac{e^{-\frac{Q_d^{(n)}(i,j)}{\tau EQ_d^{(n)}(i)}}}{\sum_{j\in A(i)} e^{-\frac{Q_d^{(n)}(i,j)}{\tau EQ_d^{(n)}(i)}}} \tag{3}$$

$d \in D,\ i \in I - \{d\} - B(d),\ j \in A(i)$

$$EQ_d^{(n)}(i) = \frac{\sum_{j\in A(i)} Q_d^{(n)}(i,j)}{|A(i)|} \tag{4}$$

$$Q_d^{(n)}(d,j) = 0, \quad d \in D, j \in A(d) \tag{5}$$

$$Q_d^{(n)}(i,d) = t_{id}, \quad d \in D, i \in B(d) \tag{6}$$

$$P_d^{(n)}(d,j) = 0, \quad d \in D, j \in A(d) - d \tag{7}$$

$$P_d^{(n)}(d,d) = 1.0, \quad d \in D \tag{8}$$

where $i,j \in I$ is the suffix of the intersections and their set; $t_{ij}$ is traveling cost of section $s_{ij}$; $d \in D$ is the suffix of thedestinations and their set; $A(i)$ is the set of suffixes of intersections moving directly from intersection $i$; $B(i)$ is the set of suffixes of intersections moving directly to intersection $i$; $Q_d^{(n)}(i,j)$ is $Q_d(i,j)$ in the $n$th iteration; $P_d^{(n)}(i,j)$ is the probability that the vehicle bound for destination $d$ moves to intersection $j$ at intersection $i$ in the $n$th iteration; $EQ_d^{(n)}(i)$ is average $Q$-value of the sections connected from intersection $i$ in the $n$th iteration; and $\tau$ is constant.

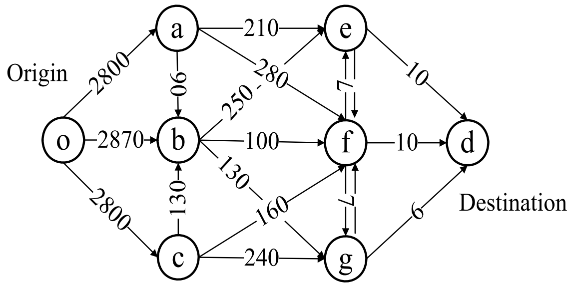



Fig. 3. A simple network

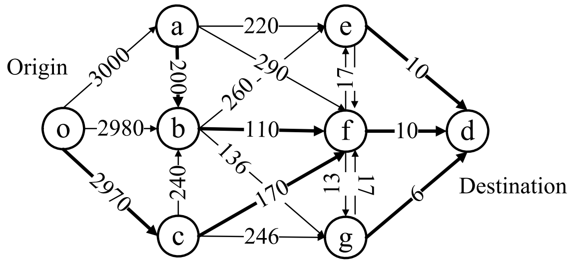



Fig. 4. Optimal routes from each section to the destination with the greedy method

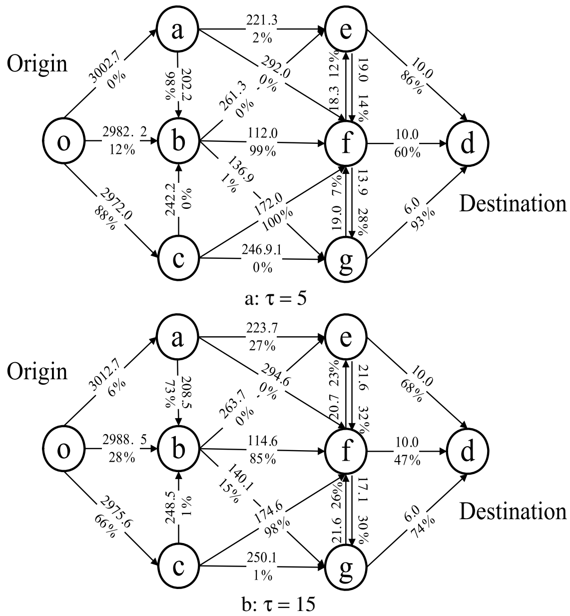



Fig. 5. Conventional $Q$-value-based dynamic programming with Boltzmann distribution

The $Q$-values and probabilities for all pairs of adjacent intersections are initialized as follows:

$$Q_d^{(0)}(i,j) = 0, \quad d \in D,\ i \in I - \{d\} - B(d), j \in A(i) \tag{9}$$

$$Q_d^{(0)}(d,j) = 0, \quad d \in D,\ j \in A(d) \tag{10}$$

$$Q_d^{(0)}(i,d) = t_{id}, \quad d \in D, i \in B(d) \tag{11}$$

$$P_d^{(0)}(i,j) = 0, \quad d \in D,\ i \in I - \{d\} - B(d),\ j \in A(i) \tag{12}$$

$$P_d^{(0)}(d,j) = 0, \quad d \in D,\ j \in A(d) - \{d\} \tag{13}$$

$$P_d^{(0)}(d,d) = 1.0. \quad d \in D \tag{14}$$

Different from the following conventional $P_d^{(n)}(i,j)$ calculation by (15), the new $P_d^{(n)}(i,j)$ and $EQ_d^{(n)}(i)$ in (3) and (4) are

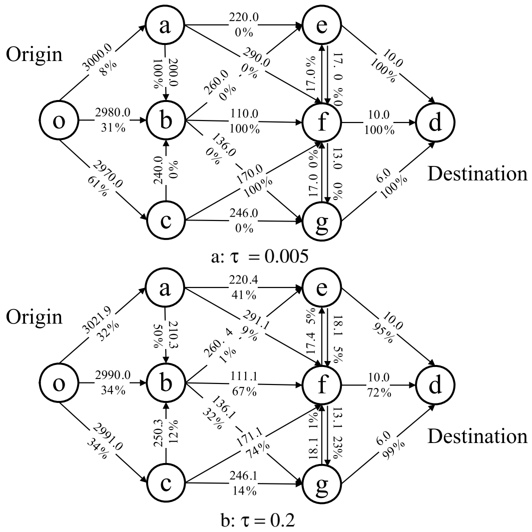



Fig. 6. New $Q$-value-based dynamic programming with Boltzmann distribution

introduced into the $Q$-value calculation in this paper.

$$P_d^{(n)}(i,j) \longleftarrow \frac{e^{-\frac{Q_d^{(n)}(i,\,j)}{\tau}}}{\sum\limits_{j\in A(i)} e^{-\frac{Q_d^{(n)}(i,\,j)}{\tau}}}. \tag{15}$$

The reasons why this modification is necessary is explained below.

In a large-scale road network, the numerical range of $Q$-values are quite different from each other. Generally speaking, the $Q$-values of the intersection pairs near the destinations are much smaller than those the intersection pairs far away from the destinations. In the case where a constant $\tau$ such as (15) is adopted, the conventional QDP-BD may introduce the unexpected greedier strategy for the intersection pairs with large $Q$-values compared to the intersection pairs with small $Q$-values, no mater what the value of $\tau$ is.

Let us see a simple extreme road network in Fig. 3, where the numbers show the traveling time of the sections. Figure 4 shows the optimal routes and the minimum traveling time from each section to the destination when using the greedy method. Figures 5 and 6 show the $Q$-values and the probabilities calculated by the conventional method and new proposed method with different $\tau$, respectively. As shown in Fig. 5(b), although $Q_d(f,e)$ is twice $Q_d(f,d)$, $s_{fe}$ still has the probability of 23% to be selected, while it is only 47% for $s_{fd}$. Contrarily, the probability of selecting $s_{ob}$ is 28% despite $Q_d(o,b)$ being almost the same as $Q_d(o,c)$.

Actually, it is not advisable to select the routes randomly for the intersection pairs with small $Q$-values. Intersection pairs with small numerical ranges of $Q$-values mean not only that their locations are near the destination, but also that the traffic volume on the routes to the destination is not heavy. Therefore, the strategy like the greedier ones should be adopted because it is not necessary to distribute the traffic volume when the traffic does not exceed the route's capacity.

Considering the above reasons, $EQ_d^{(n)}(i)$ is introduced into QDP-BD in this paper, which solves the above problems as shown in Fig. 6.

How to determine a suitable parameter $\tau$ is discussed in the simulation part of this paper.

*2.2.3. Route generation* Based on the probabilities calculated by QDP-BD, the routes from the origin to destination are generated for each vehicle in the traffic system. Let us use the results in Fig. 6(a) to explain how to generate the routes. Suppose there is a driver who wants to drive from origin $o$ to destination $d$; then the probability of this driver to visit section is 8% for $s_{oa}$, 31% for $s_{ob}$, and 61% for $s_{oc}$. If there are 100 vehicles trying to travel from $o$ to $d$, there will be 8 vehicles going through $s_{oa}$, 31 vehicles going through $s_{ob}$, and 61 vehicles traveling from $o$ to $c$ in the ideal case.

In addition, the loops in the generated routes will be forbidden.

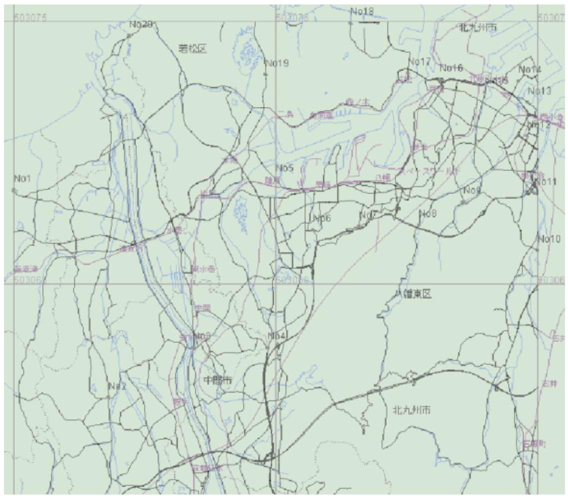


Fig. 7. Simulation road network

**2.3. System evaluation module** In the system evaluation module, three kinds of data are available to evaluate the system performance. All of them are calculated using the traffic information from the real-time traffic data collector. The definitions of these data are as follows:

The first one is the traveling time of the vehicles from the origin to the destination, which is calculated as

$$t_v = \begin{cases} dt(v) - ot(v), & \text{if vehicle } v \text{ arrived at the destination,} \\ ft - ot(v), & \text{if vehicle } v \text{ did not arrived at the} \\ & \text{destination when simulation ended} \end{cases} \tag{16}$$

where $t_v$ is total traveling time of vehicle $v$ during the simulation; $dt(v)$ is time when vehicle $v$ arrived at the destination; $ot(v)$ is time when vehicle $v$ started from the origin; and $ft$ is the time when the simulation ended.

The second one is the number of the vehicles $nv_{ij}$ congested in section $s_{ij}$ in the road network.

$$nv_{ij} = \sum_{v\in V(ij)\cup CV(ij)} J(v) \tag{17}$$

$$J(v) = \begin{cases} 1, & \text{if } v \in V(ij) \text{ and } (lt_{ij}(v) - et_{ij}(v)) > t_{ij}^0 \\ & \text{or } v \in CV(ij) \text{ and } (ct - et_{ij}(v)) > t_{ij}^0, \\ 0, & \text{if } v \in V(ij) \text{ and } (lt_{ij}(v) - et_{ij}(v)) \leqslant t_{ij}^0 \\ & \text{or } v \in CV(ij) \text{and } (ct - et_{ij}(v)) \leqslant t_{ij}^0, \end{cases} \tag{18}$$

The third is the traveling time of the vehicles going through section $s_{ij}$.

$$t_{ij}(v) = lt_{ij}(v) - et_{ij}(v) \tag{19}$$

Table I. Data of road network

| Item | Value |
|---|---|
| Number of intersections | 4243 |
| Number of sections | 7941 |
| Number of OD | 20 |
| Number of OD pairs | 380 |

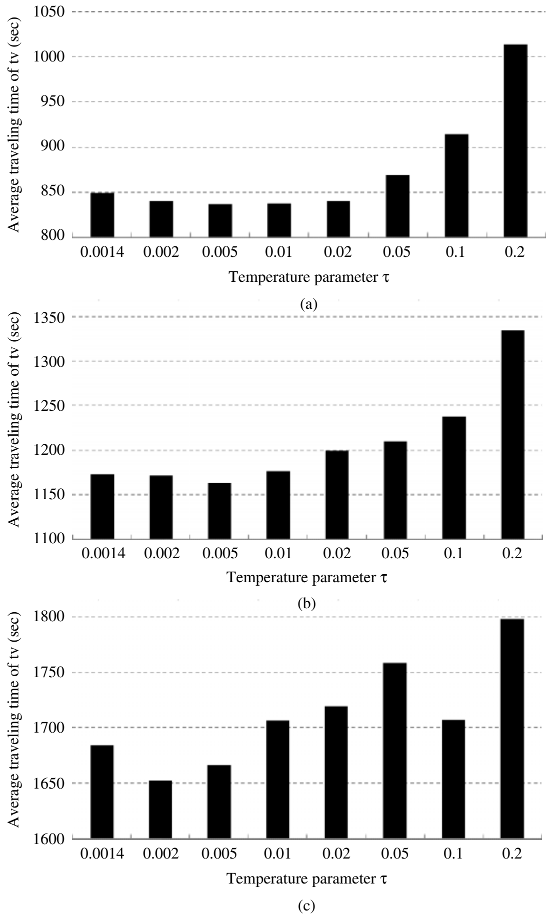



Fig. 8. Comparison of temperature parameters in different traffic situations. (a) $\lambda_{\mathrm{od}} = 0.2$. (b) $\lambda_{\mathrm{od}} = 0.5$. (c) $\lambda_{\mathrm{od}} = 1.0$

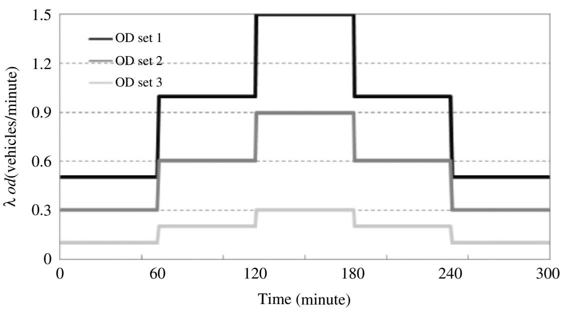



Fig. 9. Average $\lambda_{\mathrm{od}}$ of different OD sets in Experiment 1

## 3. Simulation

**3.1. Simulation condition** The proposed method was applied to the SOUND/4U simulator based on the road network of Kurosaki, Kitakyushu, Japan. The data of the road network is shown in Table ps. As shown in Fig. 7, 20 OD pairs are picked up in the road network. The ODs are mainly located at the center of the city and edges of the road network. Each OD is an area

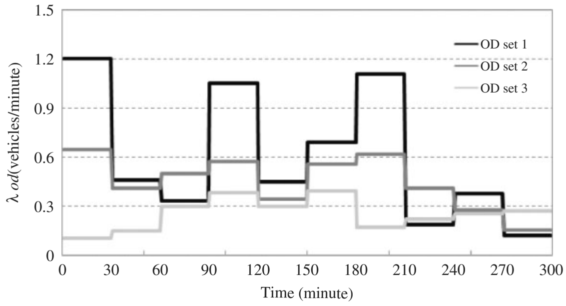



Fig. 10. Comparisons in Experiment 1. (a) Average $t_v$ of the vehicles arrived at the destinations. (b) Total number of $nv_{ij}$ of all the sections. (c) Average $t_{ij}(v)$ of the vehicles going through section $s_{ij}$

related to many sections and intersections. The vehicle occurrence rate of each OD pair is assumed to follow the following Poisson distribution:

$$p_{\mathrm{od}}(n) = \frac{(\lambda_{\mathrm{od}} s)^n \mathrm{e}^{-\lambda_{\mathrm{od}} s}}{n!}, n = 0, 1, \ldots \qquad (20)$$

where $p_{\mathrm{od}}(n)$ is the probability that $n$ vehicles depart from origin $o$ to destination $d$ during time $s$, and $\lambda_{\mathrm{od}}$ is the average rate at which the vehicle departs from The origin $o$ to the destination $d$ in the unit time (the number of vehicles/min).

**3.2. Temperature parameter analysis** The temperature parameter $\tau$ in (3) is a parameter that could affect the relationship between the $Q$-values and probabilities. Basically, the probability distribution $P_d(i, j)$ tends to be random as parameter $\tau$ becomes larger. Adopting too small a $\tau$ is identical to selecting the routes greedily, while too large a $\tau$ may force the vehicles to travel without directions in the road network. In order to distribute the traffic volume effectively, it is crucial to select a reasonable temperature parameter $\tau$ for the QDP-BD.

In this paper, $\tau$ is determined by simulations on different traffic situations, as shown in Fig. 8. For each traffic situation, we simulated three times and the time length for each simulation was 2 h. The real-time traffic data collector sends the time-varying traffic information to the route guidance module every 10 min. The average traveling time $t_v$ from the origin to the destination is used to evaluate the performance of each parameter setting. As is indicated in Fig. 8, the figures have the minimum average traveling time at a certain $\tau$ when the traffic is low or just medium, while the optimal parameter $\tau$ is hard to determine when the traffic is very heavy. Meanwhile, too large a $\tau$ may sacrifice the traveling time a lot in any traffic situation, so forcing the drivers to drive fairly randomly in the traffic system is not an encouraging strategy.

The temperature parameter with the best average performance, i.e. $\tau = 0.002$, is selected in the simulations of the next subsections. It means that the traffic distribution strategy follows the following rules:

- Select the route greedily in the intersections with small average $Q$-values.
- Distribute the traffic volume to each section depending on the $Q$ values for the intersections with comparatively large average $Q$ values.
- Distribute the traffic volume equally to the sections with similar average $Q$-values at any intersection.

**3.3. Comparison between the proposed method and the greedy method** In this subsection, comparison between

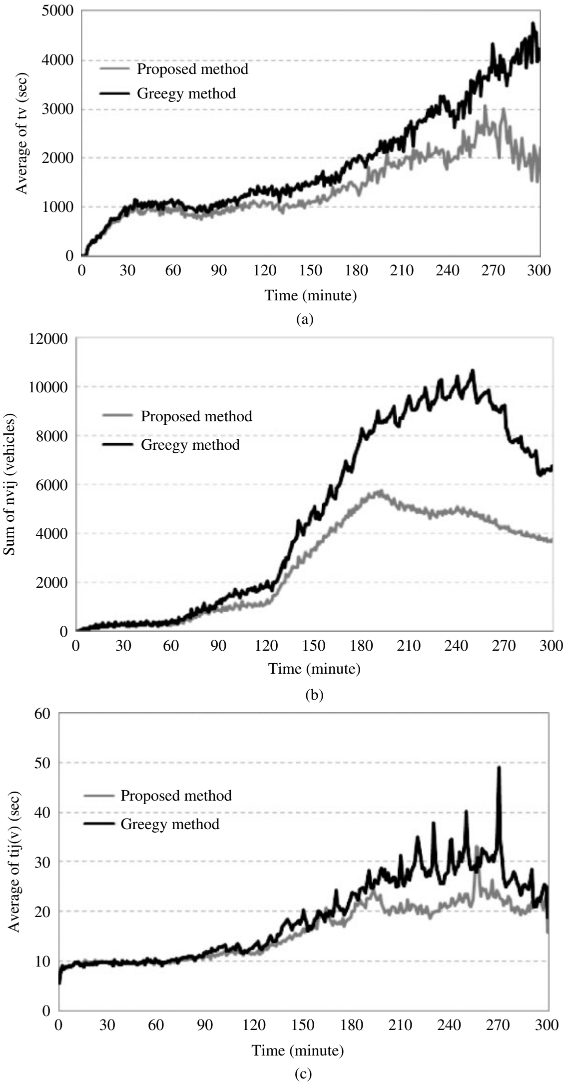



Fig. 11. Average $\lambda_{od}$ of different OD sets in Experiment 2

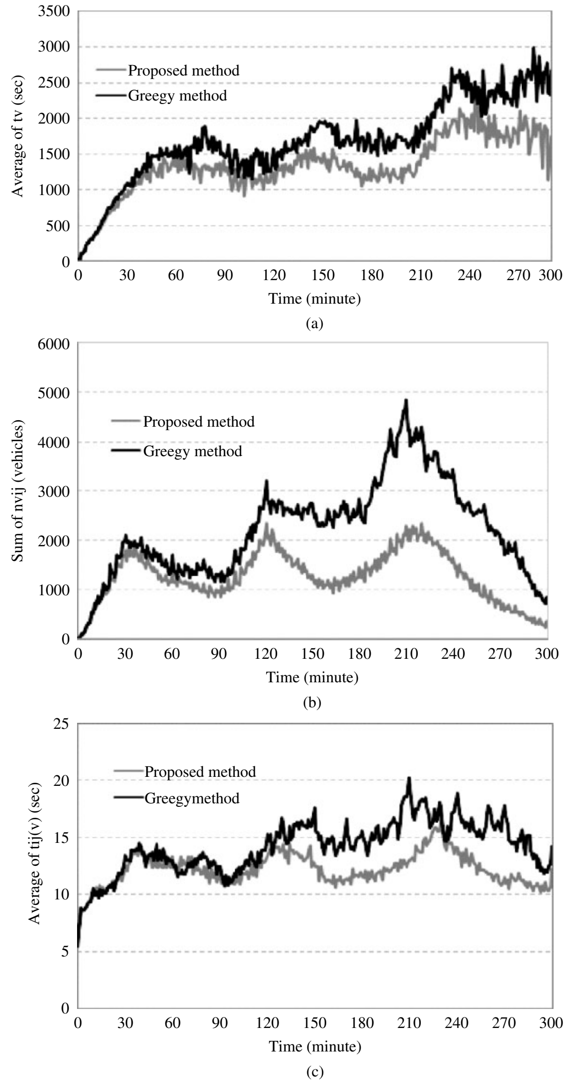



Fig. 12. Comparisons in Experiment 2. (a) Average $t_v$ of the vehicles arrived at the destinations. (b) Total number of $nv_{ij}$ of all the sections. (c) Average $t_{ij}(v)$ of the vehicles going through section $s_{ij}$

Table II. OD sets

| Set | OD |
|---|---|
| OD set 1 | No 2, No 4, No 6, No 13, No 16; |
| OD set 2 | No 1, No 3, No 18, No 19, No 20; |
| OD set 3 | No 5, No 7, No 8, No 9, No 10, No 11, No 12, No 14, No 15, No 17 |

Table III. Comparison between the proposed method and greedy method in two experiments

| Item | Experiment 1 | | Experiment 2 | |
|---|---|---|---|---|
| | Greedy | Proposed | Greedy | Proposed |
| Number of departed vehicles | 59 411 | | 53 302 | |
| Number of arrived vehicles | 49 691 | 53 907 | 51 175 | 52 124 |
| Average $t_v$ of all the vehicles | 2428 s | 1638 s | 1749 s | 1349 s |

the proposed method and greedy method is carried out under two different traffic conditions. One is the hours before and after rush hours, and another is a random set. As shown in Table 2, the 20 ODs have been divided into three different OD sets, and the average $\lambda_{od}$ of each OD set is shown in Figs. 9 and 11 in two experiments, respectively. Each OD pair uses Poisson distribution with $\lambda_{od}$ to decide the number of the vehicles departing from the origin every minute. Each experiment lasts for 5 h, and the real-time traffic data collector sends the time-varying traffic information to the route guidance module every 10 min. The average $t_v$ (16) of the vehicles arrived at the destinations, the total number of $nv_{ij}$ (17) over all the sections, and the average $t_{ij}(v)$ (19) of the vehicles going through the sections, as shown in Figs. 10 and 12, are used to evaluate the two methods. The number of departed vehicles from the origin, the number of arrived vehicles at the destination, and the average $t_v$ of all the vehicles in the two experiments are shown in Table 3. The results indicate that the proposed QDP-BD can reduce the traffic congestion and improve the efficiency of the whole traffic system effectively compared with the greedy strategy in a real-world road network.

## 4. Conclusion

In this paper, a dynamic traffic management model has been proposed that aims at alleviating the traffic congestion and improving the efficiency of the traffic systems from a global perspective. The proposed traffic management model was applied to the large-scale microscopic simulator SOUND/4U based on the road network of Kurosaki, Kitakyushu, Japan. All the vehicles in the simulator followed the direction from the route guidance module of the dynamic traffic management model, in which the extended QDP-BD and the time-varying traffic information were used to generate the routes from the origins to the destinations. The simulation results comparing the proposed method with the conventional greedy routing method showed that the proposed QDP-BD could reduce the traffic congestion and improve the efficiency of the whole traffic system effectively in the real-world road network.

## References


(1) Boyce DE. Route guidance systems for improving urban travel and location choices. *Transportation Research* 1988; **22A**(**4**): 275–282.

(2) Kanninen BJ. Intelligent transportation systems: an economic and environmental policy assessment. *Transportation Research* 1996; **30A**(**1**): 1–10.

(3) Yu S, Xu Y, Mabu S, Mainali M, Shimada K, Hira-sawa K. *Q* value-based dynamic programming with Boltzmann distribution in large scale road network. *SICE Journal of Control, Measurement, and System Integration* 2011; **4**(**2**): 129–136.

(4) Boyles SD, Ukkusuri S, Waller ST, Kockelman K. A Comparison of Static and Dynamic Traffic Assignment under Tolls in the Dallas-Fort Worth Region. *Proceedings of the Transportation Research Board: Innovations in Transportation Modeling Conference*, Austin, Texas, 2006.

(5) Shiose T, Sawaragi T, Katai O. Multiagent model of VICS. *Proceedings of the IEEE SMC Conference* 1999; **4**: 574–579.

(6) Rillings JH, Lewis JW. TravTek. *Proceedings of the Vehicle Navigation and Information Systems Conference*, Vol. 2, 1991, 20–23.

(7) Chen Y, Bell MGH, Bogenberger K. Reliable pretrip multipath planning and dynamic adaptation for a centralized road navigation system. *IEEE Transactions on ITS* 2007; **8**(**1**): 14–20.

(8) Ben-Akiva M. Dynamic network models and driver information systems. *Transportation Research* 1991; **25A**(**5**): 251–266.

(9) Arnott R. Does providing information to drivers reduces traffic congestion ? *Transportation Research* 1991; **25A**(**5**): 309–318.

(10) Lee CK. A multiple-path routing strategy for vehicle route guidance systems. *Transportation Research* 1994; **2**(**3**): 185–195.

(11) Liu HX, Ma W, Ban Jeff X., Mirchandani P. Dynamic equilibrium assignment with microscopic traffic simulation. *Proceedings of the IEEE Conference on Intelligent Transportation Systems*, Vienna, Austria, 2005.

(12) Peeta S, Ziliaskopoulos AK. Foundations of dynamic traffic assignment: the past, the present and the future. *Networks and Spatial Economics* 2001; **1**(**3-4**): 233–265.

(13) i-Transport Lab. Co., Ltd. http://www.i-transportlab. jp/products/sound/. Accessed November 1, 2007.

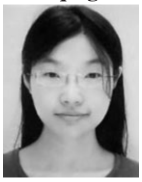
(14) Yu S, Mabu S, Ye F, Wang H, Shimada K, Hirasawa K. *Q* value-based dynamic programming with Boltzmann distribution for global optimal traffic routing strategy. *Journal of Advanced Computational Intelligence and Intelligent Informatics* 2009; **13**(**5**): 581–591.

(15) Mainali MK, Shimada K, Mabu S, Hirasawa K. Optimal route based on dynamic programming for road networks. *Journal of Advanced Computational Intelligence and Intelligent Informatics* 2008; **12**(**4**): 546–553.

(16) Guggenheim EA. *Boltzmann's Distribution Law*. North-Holland Publishing Company: Amsterdam; 1955.



**Shanqing Yu** (Non-Member) received the M.E. degrees both from the Graduate School of Information, Production and Systems, Waseda University, Japan, and the School of Computer Engineering and Science, Shanghai University, China, in 2008. Since October 2008, she has been working toward the Ph.D. degree at the Graduate School of Information, Production and Systems, Waseda University.


**Shingo Mabu** (Member) received the B.E. and M.E. degrees in electrical engineering from Kyushu University, Japan, in 2001 and 2003, respectively, and the Ph.D. degree from Waseda University, Japan, in 2007. Since April 2007, he has been a Assistant Professor with the Graduate School of Information, Production and Systems, Waseda University. Dr. Mabu is a member of the Society of Instrument and Control Engineers and the IEEE.



**Manoj Kanta Mainali** (Non-Member) received the Bachelor's degree from Ritsumeikan Asia Pacific University, Japan, in 2004 and the M.E. degree from the Graduate School of Information, Production and Systems, Waseda University, Japan, in 2009. Since April 2009, he has been workin toward the Ph.D. degree at the Graduate School of Information, Production and Systems, Waseda University.



**Kaoru Shimada** (Member) received the M. Med. Sci. degree from University of Tsukuba, Japan, in 1999 and the Ph.D. degree from the Graduate School of Information, Production and Systems, Waseda University, Japan, in 2007. Since 2007, he has been a Visiting Lecturer at the Graduate School of Information, Production and Systems, Waseda University. Dr. Shimada is a member of the Society of Instrument and Control Engineers, the Information Processing Society of Japan, and the IEEE.



**Kotaro Hirasawa** (Member) He received the B.E. and M.E. degrees from Kyushu University, Japan, in 1964 and 1966, respectively. From 1966 to 1992, he was with Hitachi Ltd., where he worked as a vice president of the Hitachi Research Laboratory. From December 1992 to August 2002, he was a Professor with the Graduate School of In- formation Science and Electrical Engineering, Kyushu University. Since September 2002, he has been a Professor at the Graduate School of Information, Production and Systems, Waseda University. Prof. Hirasawa is a member of the Society of Instrument and Control Engineers, ACM, and IEEE.