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**Paper**

# Dynamic Traffic Management using Temperature Parameter Control in Q value-based Dynamic Programming with Boltzmann Distribution

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In order to improve the efficiency of traffic systems in the global perspective, a traffic control strategy for the dynamic traffic management in the road network has been proposed in this paper. The main idea of the proposed traffic control strategy is based on Q value-based Dynamic Programming with Boltzmann Distribution, and the temperature parameters in Boltzmann Distribution are adjusted by the proposed temperature parameter control strategies, which are Network Method and Intersection Method, depending on the time-varying traffic situations. In the simulation, it is supposed that the route guidance is given to each vehicle and all the vehicles in the traffic system follow the guidance. The simulation results show that temperature parameter control in Q value-based Dynamic Programming with Boltzmann Distribution could improve the performance of the traffic system.

**Keywords:** Dynamic traffic management, Q value-based Dynamic Programming, Boltzmann Distribution, Temperature Parameter

## 1. Introduction

Modern metropolises with overcrowded traffics have been long suffering from the traffic problems such as traffic congestions and traffic accidents. Nowadays, many Intelligent Transportation Systems (ITS) have been developed to improve the efficiency of the traffic systems, such as VICS (Vehicle Information and Communication System) [1] in Japan and TravTek [2] in America. These advanced Intelligent Transportation Systems, which provide users with not only the static traffic information, but also the real time traffic situations, have shown the outstanding performances in keeping the users away from the traffic congestion and saving the traveling cost, while ensuring traffic safety [3]–[5]. Many researchers [6][7] also have contributed to improve the efficiency of the ITS in their own ways.

Meanwhile, it is desirable to develop more effective strategies to manage the traffics in ITS, since the traditional guiding strategy in Navigation Systems, which informs the drivers with similar preferences of the same optimal route, may cause some negative behavioral phenomena like concentration and overreaction [8][9]. Concentration means that the traffic volume centers on the same optimal route which consequently causes the traffic jam, and overreaction means that the vehicles on the optimal route would turn to another route after the update of the information, which results in the unexpected low traffic volume on the previous optimal route.

The multiple-path algorithms like the k-shortest path algorithms [10]–[12] and disjoint path algorithms [13][14] could calculate more than one optional route for the drivers, however how to assign the traffic to these routes effectively for the global optimal of the traffic systems is not discussed. Some researchers [15][16] developed the Ant colony algorithm (ACA) to select optimal routes in transportation systems. Developed ACAs [17][18] are possible to search multiple routes for each OD pair and split the traffics according to the remaining resource of each route. However, it is difficult to apply ACA into complex dynamic traffic systems with time-varying traffic information and multiple OD pairs, since it needs a large number of artificial ants to do the exploration to update the pheromone.

In addition, the length of the real time traffic information updating interval, i.e., three hundred seconds in VICS and one minute in TravTek also could influence on the efficiency of the Intelligent Transportation Systems. Traffic management strategies, which are less influenced by the length of the traffic information updating interval, are more competitive than other strategies.

In order to avoid the disadvantages of the traditional guiding strategy, to minimize the influence of the length of the traffic information updating interval and to improve the efficiency of the traffic systems in global perspective, we have already proposed a static traffic management strategy, that is, Q value-based Dynamic Programming with Boltzmann Distribution [19][20], where Q value-based Dynamic Programming [21] and Boltzmann distribution [22] are combined to calculate the expectation of the traveling time of each Origin-Destination pair and the probability for each intersection to be selected as the next intersection. In this paper, we extend Q value-based Dynamic Programming with Boltzmann Distribution to a dynamic traffic management strategy by adding two temperature control strategies of Boltzmann distribution,

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i.e., Network Method and Intersection Method. Network Method uses the same temperature parameter for the whole road network depending on the global traffic situations, while Intersection Method adopts different temperature parameters intersection by intersection based on the traffic situations of the sections connected to the intersection. The new proposed method could assign the vehicles to different routes depending on the time-varying traffic situations and consequently save the total traveling time of all the vehicles in the traffic system.

The proposed dynamic traffic management strategy has been evaluated using a simple simulator described in the simulation part of the paper. All the vehicles in the simulator determine their routes based on the Q values and the probabilities calculated by Q value-based Dynamic Programming with Boltzmann Distribution. The average traveling time and average waiting time of all vehicles, and the total waiting time of all the sections are observed to evaluate the traffic system performance. The results show the importance of the temperature parameter control depending on the traffic situations and the improvement of the system performance of the proposed method comparing with the conventional Greedy Method and ε-Greedy Method. In addition, the efficiency of the system is less influenced by the length of the real time traffic information updating interval when adopting the proposed method.

This paper is organized as follows: In the next section, the outline of Q value-based Dynamic Programming with Boltzmann distribution is reviewed, while two temperature parameter control strategies, i.e., Network Method and Intersection Method are presented in section 3. In addition, section 4 shows the simulations, in which the comparison among two temperature parameter control strategies, Greedy strategy and ε-Greedy strategy is carried out under dynamically changing traffic situations and different traffic information update interval. Section 5 is devoted to conclusions.

## 2. Q value-based Dynamic Programming with Boltzmann Distribution

Q value-based Dynamic Programming with Boltzmann Distribution is a routing algorithm which is developed based on the principle of probabilistic Dynamic Programming.

The Q value, i.e., $Q_d(i, j)$, which is defined as the expected minimum traveling time to destination $d$, when the vehicle bound for destination $d$ moves to intersection $j$ at intersection $i$, is calculated iteratively using Q value-based Dynamic Programming with Boltzmann Distribution based on the following equations [20].

$$Q_d^{(n)}(i,j) \leftarrow t_{ij} + \sum_{k \in A(j)} P_d^{(n-1)}(j,k) Q_d^{(n-1)}(j,k), \quad \cdots\cdots (1)$$
$$d \in D,\ i \in I - \{d\} - B(d),\ j \in A(i)$$

$$P_d^{(n)}(i,j) \longleftarrow \frac{e^{-\frac{Q_d^{(n)}(i,j)}{\tau}}}{\sum_{j \in A(i)} e^{-\frac{Q_d^{(n)}(i,j)}{\tau}}}, \quad \cdots\cdots (2)$$
$$d \in D,\ i \in I - \{d\},\ j \in A(i)$$

$$Q_d^{(n)}(d,j) = 0, \qquad d \in D,\ j \in A(d) \cdots\cdots (3)$$
$$Q_d^{(n)}(i,d) = t_{id}, \qquad d \in D,\ i \in B(d) \cdots\cdots (4)$$

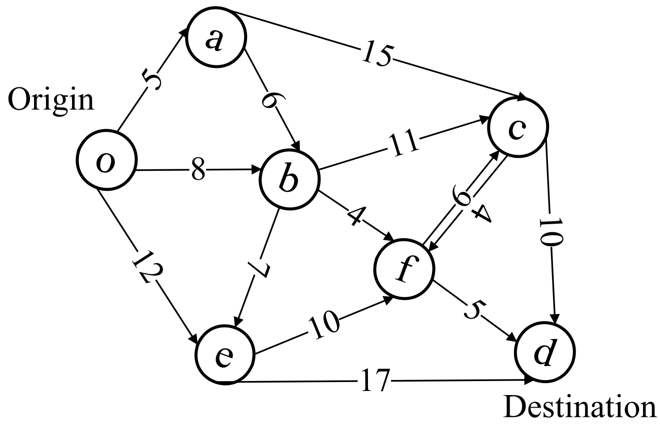



Fig. 1. A simple road network

$$P_d^{(n)}(d,j) = 0, \qquad d \in D,\ j \in A(d) - \{d\} \cdots\cdots (5)$$
$$P_d^{(n)}(d,d) = 1.0, \qquad d \in D \cdots\cdots (6)$$

where,

$i, j \in I$: suffixes of intersections and their set
$d \in D$: suffix of destinations and its set
$t_{ij}$: traveling time from intersection $i$ to intersection $j$
$A(i)$: set of suffixes of intersections moving directly from intersection $i$
$B(i)$: set of suffixes of intersections moving directly to intersection $i$
$Q_d^{(n)}(i,j)$: $Q_d(i,j)$ in the $nth$ iteration
$P_d^{(n)}(i,j)$: the probability that the vehicle bound for destination $d$ moves to intersection $j$ at intersection $i$ in the $n^{th}$ iteration
$\tau$ : parameter called temperature

Q values and probabilities for all the pairs of adjacent intersections are initialized as follows.

$$Q_d^{(0)}(i,j) = 0, \quad \cdots\cdots (7)$$
$$d \in D,\ i \in I - \{d\} - B(d),\ j \in A(i)$$
$$Q_d^{(0)}(d,j) = 0, \qquad d \in D,\ j \in A(d) \cdots\cdots (8)$$
$$Q_d^{(0)}(i,d) = t_{id}, \qquad d \in D,\ i \in B(d) \cdots\cdots (9)$$
$$P_d^{(0)}(i,j) = 0, \quad \cdots\cdots (10)$$
$$d \in D,\ i \in I - \{d\},\ j \in A(i)$$
$$P_d^{(0)}(d,j) = 0, \qquad d \in D,\ j \in A(d) - \{d\} \cdots\cdots (11)$$
$$P_d^{(0)}(d,d) = 1.0. \qquad d \in D \cdots\cdots (12)$$

The optimal routes are produced based on the calculated probabilities. For example, let's take the road network in Fig.1, where the numbers show the traveling time of sections, in order to explain how to determine the traffic assignment based on the probabilities. Fig.2 shows the Q values and the probabilities calculated by Q value-based Dynamic Programming with Boltzmann Distribution when $\tau = 5$. Suppose there is a driver who wants to travel from origin $o$ to destination $d$, the probability for the driver to visit section $s_{oa}$ will be 26%, 63% for $s_{ob}$, and 11% for $s_{oe}$. Then, after the driver traveled from $o$ to $a$, he will have 19% chance to travel from $a$ to $c$ and 81% chance to travel from $a$ to $b$. If there are ten vehicles trying to travel from $o$ to $d$, then there might be three vehicles going through $s_{oa}$, six vehicles going through

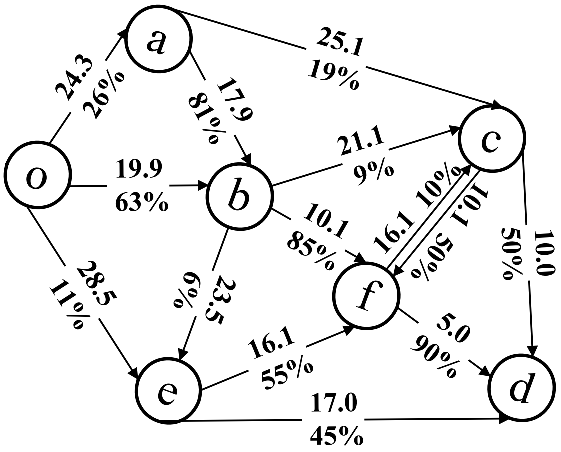



Fig. 2. Q values when temperature parameter = 5

$s_{ob}$ and one vehicle traveling from $o$ to $e$ in ideal case.

## 3. Temperature Parameter Control Strategy

In Q value-based Dynamic Programming with Boltzmann Distribution, the temperature parameter plays a very important role. Basically, the probability in Eq.2 is inversely related to Q values. However, the parameter "temperature" also has its influence. When the "temperature" is very high, Boltzmann Distribution is identical to the random distribution in which each section has equal opportunities to be selected. On the other hand, when the "temperature" approaches 0, only the shortest path is available just like Greedy Strategy. In this sense, it is better to adopt a small temperature parameter when the traffic is light and increase the temperature parameter as the traffic becomes heavier. It is not necessary to distribute the traffic when the number of the vehicles doesn't exceed the capacity of the sections, while the vehicles should be assigned to different routes to avoid the traffic congestion when the number is large. According to the well-known Wardrop equilibrium theory [23], the ideal condition is that the vehicles are assigned to different routes, however, no matter which route the drivers selected, the traveling times of the vehicles from the origin to destination are equal with each other and no vehicles will gain from changing routes. Based on the above concept, two temperature parameter control strategies are proposed in the following subsections, which are Network Method and Intersection Method.

**3.1 Network Method** Network Method is the simplest temperature parameter control strategy, in which the identical temperature parameter is used in all sections for calculating the probability of selecting the next intersection depending on the total number of vehicles in the traffic system in the following.

$$P_d^{(n)}(i,j) \longleftarrow \frac{e^{-\frac{Q_d^{(n)}(i,j)}{\tau}}}{\sum_{j\in A(i)} e^{-\frac{Q_d^{(n)}(i,j)}{\tau}}}, \quad \cdots\cdots (13)$$

$$\tau = \frac{\tau_{max}(N)}{1+e^{-\alpha(NV-\beta)}}, \quad \cdots\cdots (14)$$

where,

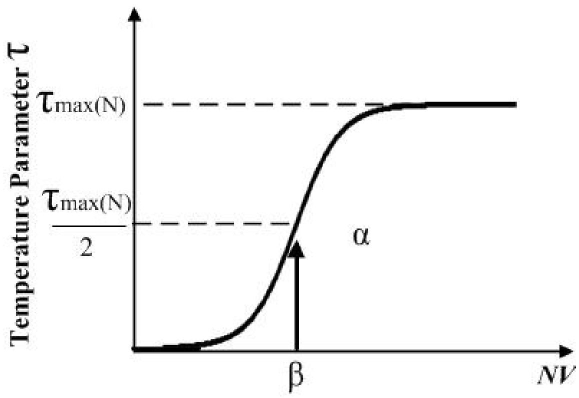



Fig. 3. Network Method

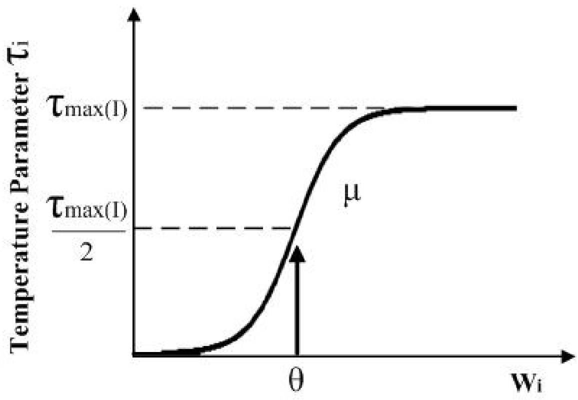



Fig. 4. Intersection Method

$\tau_{max}(N), \alpha$ *and* $\beta$ : constant
$NV$: the number of vehicles in the whole traffic system

The principle of Network Method is to adjust the temperature parameter in global perspective. As shown in Fig.3, the Network Method increases the temperature parameter to provide more optimal routes for drivers when the whole traffic system is crowded, while just the Greedy Strategy is adopted if the total number of vehicles is small.

**3.2 Intersection Method** Intersection Method adopts different temperature parameters for each intersection $i$ based on $W_i$, i.e., the sum of the longest waiting time of the sections connected to intersection $i$, according to the following equations.

$$P_d^{(n)}(i,j) \longleftarrow \frac{e^{-\frac{Q_d^{(n)}(i,j)}{\tau_i}}}{\sum_{j\in A(i)} e^{-\frac{Q_d^{(n)}(i,j)}{\tau_i}}}, \quad \cdots\cdots (15)$$

$$\tau_i = \frac{\tau_{max}(I)}{1+e^{-\mu(W_i-\theta)}}, \quad \cdots\cdots (16)$$

$$W_i = \sum_{j\in B(i)} W_{ji}, \quad \cdots\cdots (17)$$

where,

$\tau_{max}(I), \mu, \theta$: constant
$W_{ji}$: the longest waiting time of the vehicles in section $s_{ji}$ during the last traffic information updating interval

As shown in Fig.4, the principle of Intersection Method is similar to Network Method. The value of the temperature parameter increases as the traffic becomes heavier in order to distribute the traffic volumes. However, Intersection Method only distributes the vehicles at the intersections with overcrowded traffics, while Greedy Strategy is used at low traffic intersections. It enables enhanced routing strategies in the road network since each intersection has its own temperature parameter.

## 4. Simulation

**4.1 Traffic Simulator** In this paper, a traffic simulator for evaluating the proposed method is described. As can be seen from Fig.5, the temperature parameter, Q values and probabilities are calculated for the vehicles every time the traffic information is updated , that is, $t_{ij}$, $W_{ij}$ and $W_i$ are updated depending on the time-varying traffics. The traveling time $t_{ij}$, which is initialized according to the distance of section $s_{ij}$, is updated by calculating the summation of the initialized traveling time and $W_{ij}$.

A $7 \times 11$ road network, where the length of the sections in the road network is set at the range of 9 to 25 as shown in Fig.6, is used in the simulator. Each road in the network is bidirectional and each section has two driveways as shown in Fig.7, in which the vehicles going to turn left choose the left one, and vehicles going to turn right and turn around prefer the right one. The signal control follows the regulation shown in Table 1, in which the time delay between the neighboring intersections is 3 time steps.

The occurrence of the vehicles in each section has the Poisson distribution with different occurrence rate $\lambda_{ij}$.

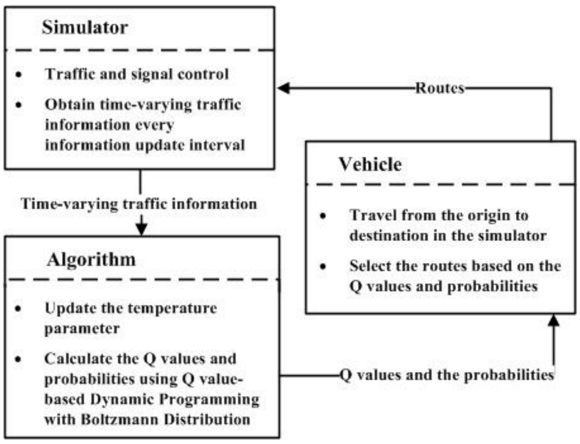



Fig. 5. Flow chart of the simulation model

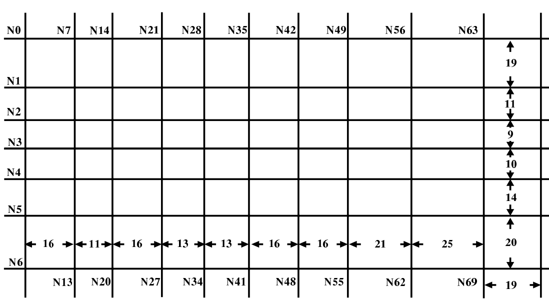



Fig. 6. Road network for simulations

$$p_{ij}(n) = \frac{(\lambda_{ij}s)^n e^{-\lambda_{ij}s}}{n!}, \qquad n = 0, 1, ... \cdots\cdots\cdots\cdots (18)$$

where,

$p_{ij}(n)$: the probability that $n$ vehicles occur in section $s_{ij}$ during $s$ time steps

$\lambda_{ij}$: the rate that vehicles occur at section $s_{ij}$ (the number of vehicle occurrence/time step)

All the vehicles in the simulator determine their routes to their destination based on the Q values and probabilities calculated by Q value-based Dynamic Programming with Boltzmann Distribution when they occurred at the origin. The speed limit for each section and the kind of vehicles are the same, but the vehicles could move one step forward only if there are no other vehicles in front of them. In addition, the loops in the routes are forbidden.

**4.2 Experiments of Greedy Method and ε-Greedy Method** In order to avoid the concentration and overreaction, the traffic should be distributed into different routes. However, simply adopting ε-greedy method, in which the vehicles have (1-ε) probability to take the greedy strategy and ε probability to travel randomly, may not a good way. In this subsection, four different values of ε are tested under three different traffic situations, i.e, Small, Middle and Large, which are defined in Table 2. For each traffic situation, we simulated twenty times using the same vehicle occurrence rate, but different random seeds. The average traveling time from the origin to destination and average waiting time, i.e., average stopping time over all the vehicles during the whole simulation time period are calculated to evaluate the system performance. Other simulation conditions are given in Table 3. It is clear from Fig.8 that adopting ε-greedy method to distribute traffics only reduces the efficiency of the traffic system, and more effective methods are needed.

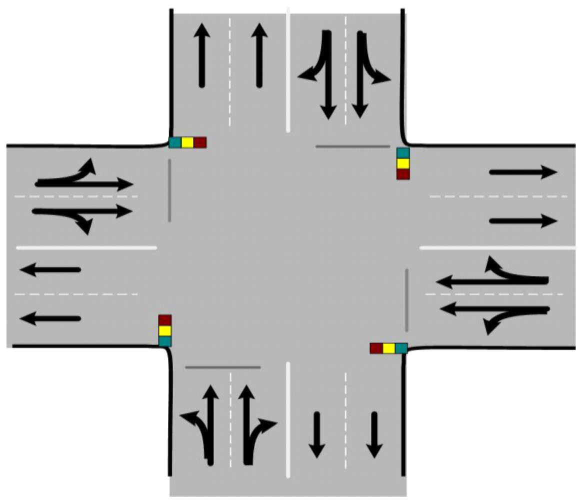


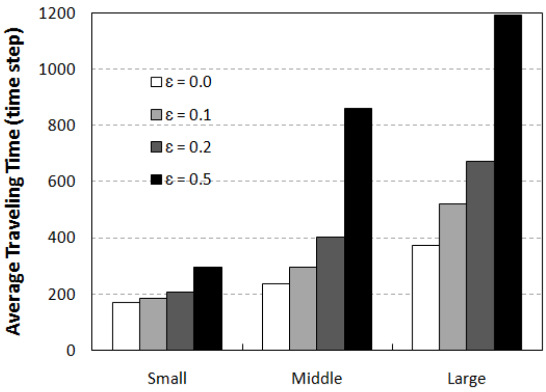
Fig. 7. An example of intersections in the road network

Table 1. Signal control of simulator

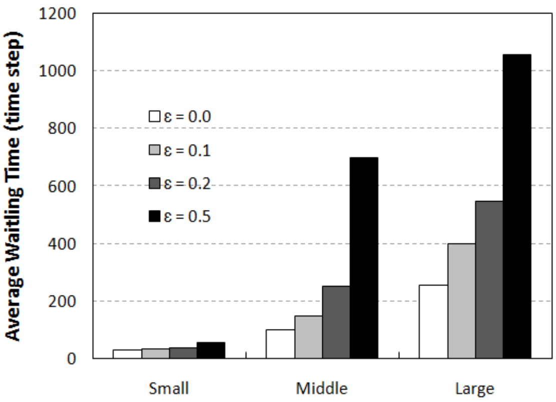
| Direction \ Signal | Red (time steps) | Yellow (time steps) | Green (time steps) |
|---|---|---|---|
| Horizontal | 6 | 1 | 8 |
| Vertical | 9 | 1 | 5 |

Table 2. Traffic situations in simulations

| Traffic situation | Occurrence rate in external sections (vehicles/time step) | Occurrence rate in internal sections (vehicles/time step) | Average of $N$ (vehicle) | Average of $W_{ij}$ (time steps) |
|---|---|---|---|---|
| Small | 0.05 | 0.02 | 200-700 | 1-3 |
| Middle | 0.12 | 0.04 | 701-1500 | 4-11 |
| Large | 0.14 | 0.06 | more than 1501 | more than 12 |




(a) Average traveling time under different traffic situations




(b) Average waiting time under different traffic situations

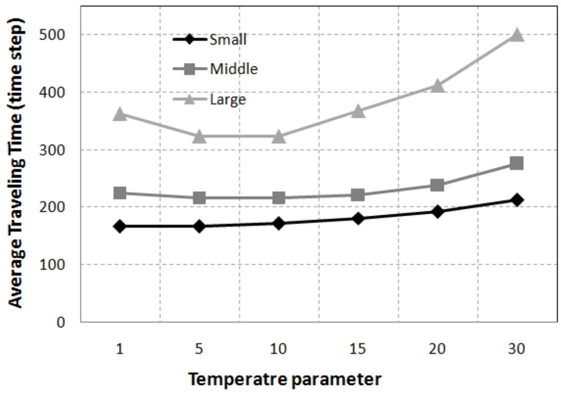
Fig. 8. Comparison of ε-Greedy Method in different ε

Table 3. Parameter setting for simulations

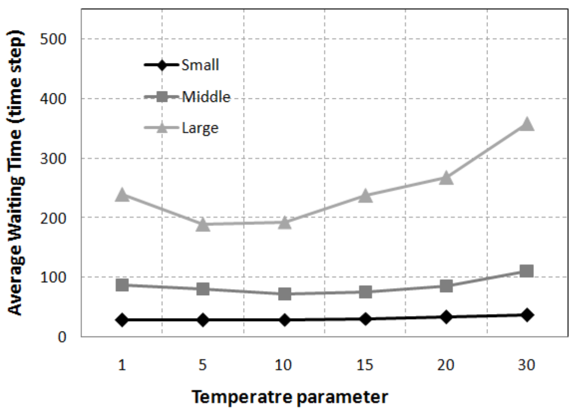
| Item | Value |
|---|---|
| Maximum time step | 3000 |
| Information update interval step | 10 |
| Initial number of vehicles | 200-250 |

**4.3 Experiments with Constant Temperature Parameter** In our previous research, the proposed method was only applied to the static traffic system. In this subsection, six constant temperature parameters are tested under three different traffic situations, i.e, Small, Middle and Large, which are defined in Table 2. For each traffic situation, we simulated twenty times using the same vehicle occurrence rate, but different random seeds. The average traveling time from the origin to destination and average waiting time, i.e., average stopping time over all the vehicles during the whole simulation time period are calculated to evaluate the system performance. Other simulation conditions are given in Table 3. Fig.9 shows the average traveling time and average waiting time with different temperature parameters, but without temperature control in the dynamic traffic system.

It is clear from Fig.9 that the temperauture should be different when traffic condition is different. As is shown in Fig.9, the value of the best temperature parameter is small in the light traffic, in which the distribution of the vehicles is not necessary, while it becomes large as the traffic becomes heavier. Meanwhile, the comparison between Fig.9(a) and Fig.9(b) shows that the temperature parameter with unnecessarily large values increases the traveling time and waiting time a lot since it forces the drivers to drive randomly in the traffic system. Considering the above, it is clear that adjusting the temperature parameter depending on the traffic situations is necessary.



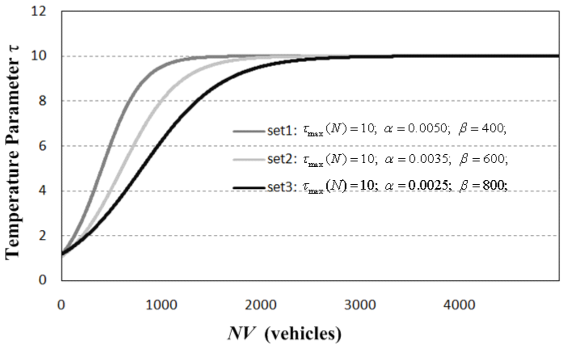

(a) Average traveling time under different traffic situations



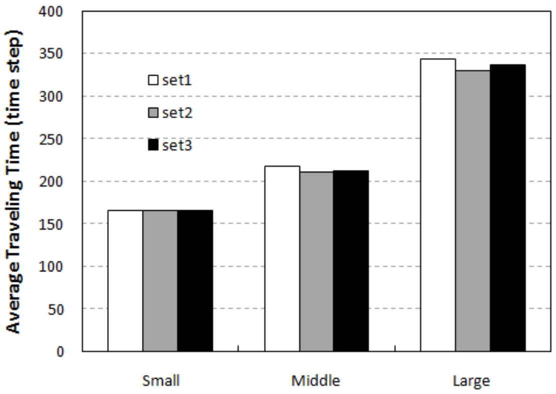

(b) Average waiting time under different traffic situations

Fig. 9. Comparison of different temperature parameters

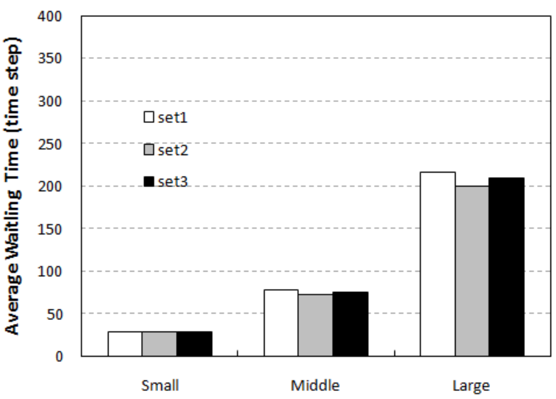
**4.4 Parameter Analysis of Network Method** In the Network Method, all the intersections use the same temperature parameter and are adjusted depending on the total number of vehicles in the traffic system. Based on the results in last subsection, we decided to increase the temperature parameter from one to ten as the number of the vehicles $NV$ changes from 200 to 1500 in Network Method. Some detailed analysis are given in Fig.10. It shows that set 2, in which $\tau_{max}(N) = 10$, $\alpha = 0.0035$ and $\beta = 600$, is the best se-




(a) Different parameter settings in Network Method

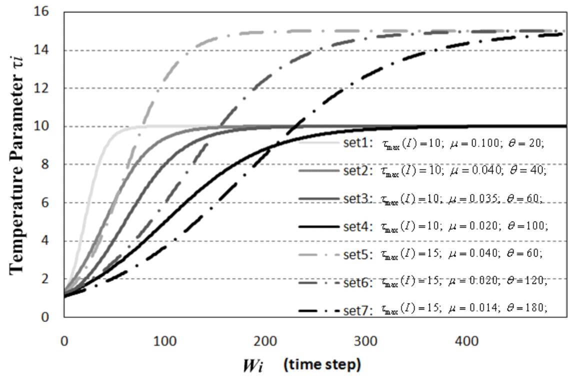



(b) Average traveling time under different traffic situations

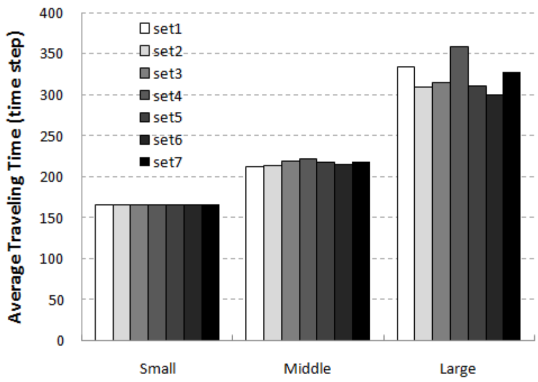



(c) Average waiting time under different traffic situations

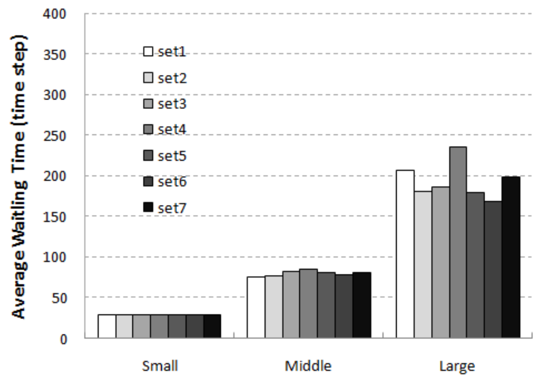
Fig. 10. Comparison of different parameter setting in Network Method




(a) Different parameter settings in Intersection Method




(b) Average traveling time under different traffic situations




(c) Average waiting time under different traffic situations

Fig. 11. Comparison of different parameter setting in Intersection Method

lection for the parameters in Network Method. The proposed method could adopt the suitable parameter for all traffic conditions by using Network Method.

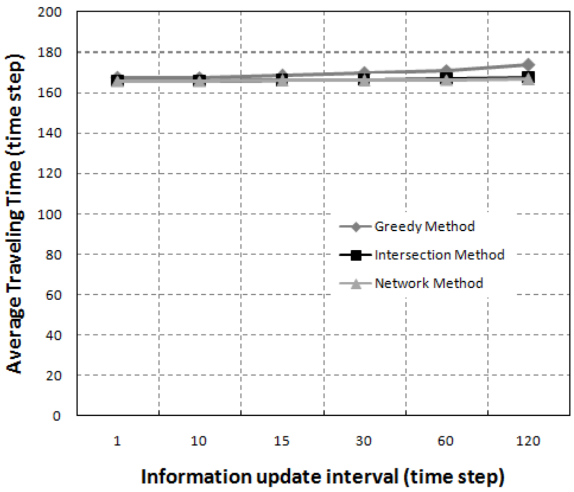
### 4.5 Parameter Analysis of Intersection Method

Since the traffic condition may different in each area of the road network, just using Network Method may not good enough to deal with the complex traffic conditions. Therefore, we developed Intersection Method to adopt different routing strategies intersection by intersection. In order to determine how to adjust the temperature parameters of Intersection Method, seven different sets of parameters of Intersection Method shown in Fig.11(a) are simulated under three different traffic situations in this subsection. For each parameter set, we also simulated twenty times with different random seeds and the average traveling time and waiting time of all the vehicles are calculated to do the evaluation. Fig.11(b) and Fig.11(c) show that set 6, in which $\tau_{max}(I) = 15$, $\mu = 0.020$ and $\theta = 120$, is the best selection for the parameters in Intersection Method. By adopting the reasonable parameter, Intersection Method could save more traveling time than constant temperature parameters and also the Network Method.

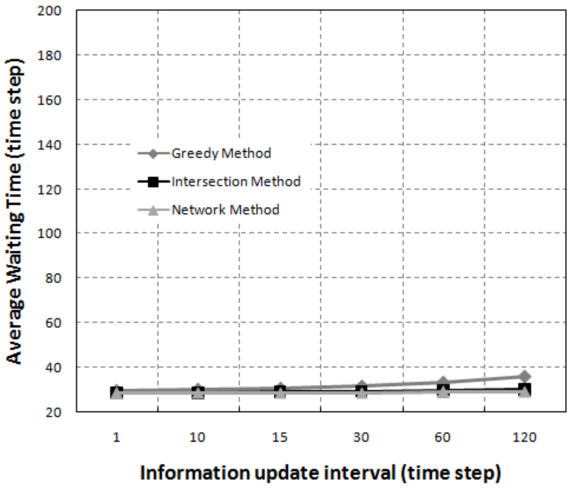
### 4.6 Comparison of Various Temperature Control Strategies

The comparison among Network Method, Intersection Method and Greedy Method is carried out in this subsection.

Firstly, three methods with various traffic information updating intervals is simulated under Small, Middle and Large traffic situations. Each Method is simulated twenty times

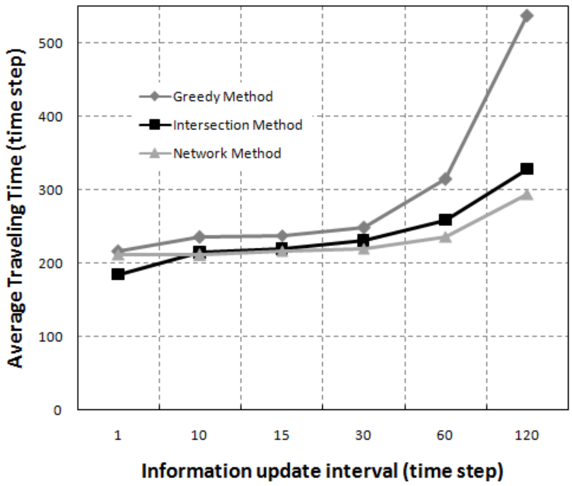



(a) Average traveling time under different information update interval

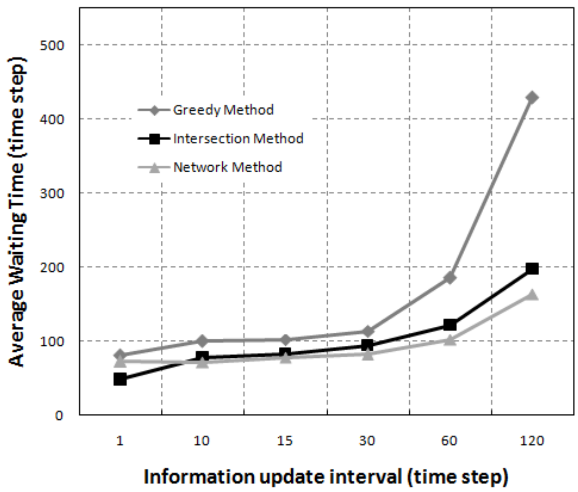



(b) Average waiting time under different information update interval

Fig. 12. Comparison of three methods under different information update interval in Small traffic situation




(a) Average traveling time under different information update interval




(b) Average waiting time under different information update interval

Fig. 13. Comparison of three methods under different information update interval in Middle traffic situation

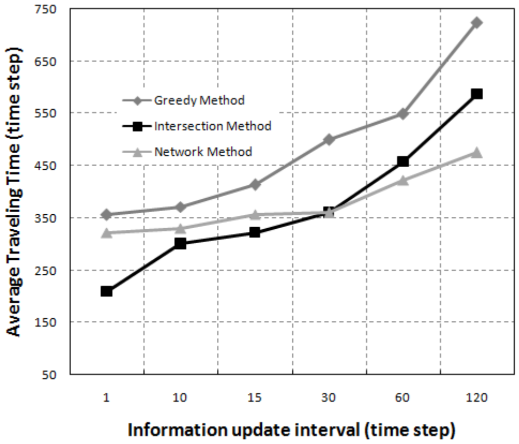
with different random seeds and the average traveling time and waiting time of all the vehicles shown in Fig.12, Fig.13 and Fig.14 are calculated to evaluate the efficiency of the three methods. As we can seen from the results, the average traveling time and waiting time increase as the traffic information updating interval becomes longer, but the degrees of the increase are different. When the ideal traffic information updating interval is adopted, i.e., the update interval is very short, even Greedy Method could perform well, while the proposed methods, especially the Network Method presents their outstanding performance when the traffic information couldn't be updated so often.

Another simulation is carried out for 10000 time steps with dynamically changing traffic situations shown in Fig.15(a). Fig.15(b) shows how the total waiting of all the sections changes as the time step goes when adopting different routing strategies with the information update interval of 10 time steps. In addition, the average traveling time of all the vehicles during the simulation by Greedy Method, Network Method and Intersection Method are equals to 251.1 time steps, 230.8 time steps and 218.7 time steps, respectively. These results indicate that Intersection Method performs the best when dealing with the heavy traffic situations.

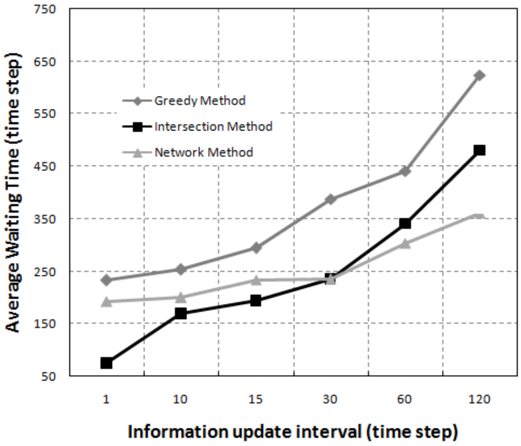
## 5. Conclusion

In this paper, a dynamic traffic management strategy using the temperature parameter control in the Q value-based Dynamic Programming with Boltzmann Distribution has been proposed. Two temperature parameter control strategies, i.e., Network Method and Intersection Method are studied and compared with the conventional Greedy Method in the simulations. As can be seen from the simulation results, it is clarified that the proposed methods are simple, but useful for improving the efficiency of the traffic system and reducing the traffic congestion comparing with the Greedy Method.

As for the application of the proposed method to real traffic systems, the proposed method including the temperature parameter control strategies should be extended in terms of the applicability to large scale real road networks.

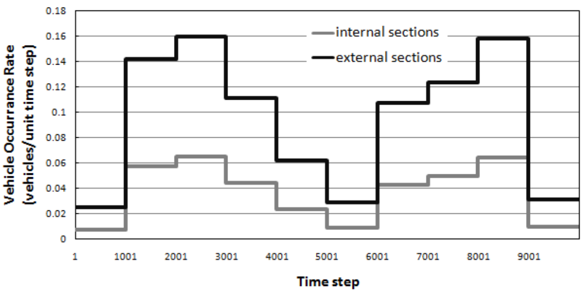



(a) Average traveling time under different information update interval

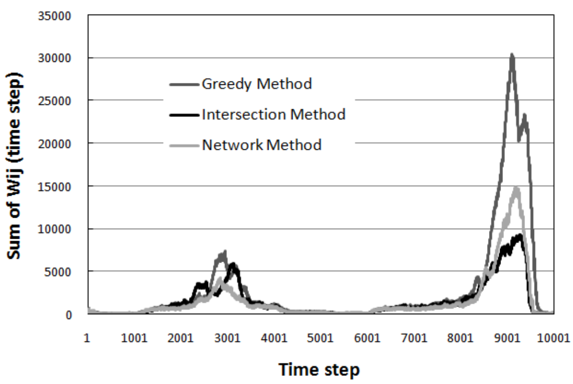



(b) Average waiting time under different information update interval

Fig. 14. Comparison of three methods under different information update interval in High traffic situation




(a) Vehicle occurrence rate $\lambda_{ij}$




(b) Sum of the longest waiting time $Wij$ of all the sections

Fig. 15. Comparison of different strategies

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