A Histogram-Based Model for Road Traffic Characterization in VANET

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Abstract. This paper presents a new route guidance algorithm and a compact road traffic model that can be easily obtained and transmitted in real-time by individual vehicles while they are travelling on streets or queuing in road cross junctions. The proposed algorithm uses histograms as the network traffic model that captures the arrival rate distribution in VANET. In addition, the paper presents an analysis method that works directly with the histogram model to obtain the queue occupancy distribution at cross-junctions or traffic signals using a finite queue model. A microscopic simulation model is utilized to assess the effectiveness of the traffic model in detecting traffic congestion and directing vehicles to choose better paths. Results show that the proposed road traffic model provides a good prediction of road traffic status, and can be used in conjunction with any standard shortest path algorithms to provide an efficient mechanism for selecting fastest road path.

Keywords: VANET, Traffic Modeling, Histograms, Route Guidance.

1 Introduction

Vehicular ad hoc networks (VANETs) are expected to support a large spectrum of distributed applications such as route guidance and navigation, traffic alert dissemination, context-aware advertisement and file sharing. All these applications require an efficient mechanism for selecting shortest road path.

In general, the travel time changes dynamically as the result of interactions between demand, capacity, weather conditions, accidents, work zones and traffic composition [1]. Therefore, the correctness of the fastest or best route plan depends heavily upon the correctness of the cost model of the route. Typical route cost model based on static information cannot entirely be appropriate for determining fastest route, because real-time conditions of routes such as the severity of congestion and the ratio of traffic density on the different streets play an important role. Provision of traffic information to motorists has the potential to influence traffic patterns and thereby reduce congestion and improve network efficiency while also benefiting users in less tangible ways by decreasing uncertainty and reducing stress. Consequently, the

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provision of traffic information to motorists via roadside or in-vehicle systems has become a priority for many road authorities. Moreover, systems for gathering and disseminating traffic data are required to provide drivers with effective fastest route services reflecting on the real-time traffic conditions.

In general, the best predictions of road traffic status can be made using road traffic traces. However, considering the large number of nodes participating in VANET and their high mobility, collecting full traces is not always possible. In addition, the analysis of these road traffic traces may need the support of huge amount of computing power and memories that is impossible in vehicle-to-vehicle network environment. Therefore, there is a pressing need for an efficient mechanism for modeling the real-time traffic information and disseminate it through the transport network to satisfy the throughput and delay requirements of such applications.

Many researches have been proposed in literature to gather traffic information and disseminate it to users, so they can make better-informed decisions regarding their route and improve the quality of driving experience [2-4]. Much work has also been done on the Data Harvesting and Information Dissemination schemes needed to support these types of applications [5]. The problem of efficient data delivery in VANETs has also been studied in literature [6-7]. Furthermore, the design of routing protocols and the computation of shortest or best paths in vehicular networks have been the subject of extensive research for many years. Lee et al. [8] and Lin [9] provided a comprehensive survey of VANET routing protocols and summarized their main characteristics.

In this paper, we do not attempt to propose yet another system for traffic management or another variation of the shortest path problem. We propose a compact road traffic model that can be easily obtained and transmitted in real-time by individual vehicles while they are travelling on streets or queuing in road cross-junctions. The proposed model uses histograms as the network traffic model that captures the arrival rate distribution in VANET. We also present an analysis method that works directly with the histogram models and obtains the queue occupancy distribution at cross-junctions or traffic signals using a finite queue model. With this queue occupancy distribution, we obtain the waiting time delay and congestion probabilities. Furthermore, we have developed a simulation model to study the effectiveness of the traffic model in detecting traffic congestion and directing vehicles to choose better paths. The results showed that the proposed road traffic model provides a good prediction of road traffic status, and can be used in conjunction with of one of the existing shortest path algorithms to provide an efficient mechanism for selecting shortest road path

This paper is structured as follows. Section 2 describes the proposed histogram traffic model. Section 3 describes the queuing models for vehicular road traffic in inter-connected streets. Analysis of the proposed model is presented in Section 4. Section 5 discusses the usage of the proposed models for selecting the best road path. Performance evaluation and simulation results are discussed in Section 6. Conclusion and future work are presented in section 7.

2 Histogram Traffic Model

In this paper, we use traffic histograms to model the road traffic (number of vehicles) on the street during a pre-established equal time periods, called the Observation period O (e.g. 10 minutes per observation period during rush hour on city urban street). During each observation period, we count number of cars entering the road over equal time intervals, called Sampling periods T (e.g. 15 seconds per sampling period during rush hour on city urban street). Therefore, the number of sampling periods N within an observation period is equal to O/T.

Let $V(t)$ be a discrete random variable representing the number of vehicles entering the street during the t^{th} sampling period. Hence, the total number of vehicles entering the street during an observation period $V(t) \mid t \in \{1, 2, ..., N\}$ can be described as a discrete random process with a state space, denoted as I , which is a set of integers between 0 and the maximum number K of vehicles held in the street, that is, $I = \{0,1,..., K\}$.

As the statistical variable $V(t)$ can, in general, varies over a big range of values [0, K]. We divide this range into a limited number of equal width classes and compute the grouped probability distribution (gpd) over each class. For example, Table 1 shows the statistics of number of vehicles on road that has been analyzed using a sampling period of T = 10 seconds by a vehicle to-vehicle network over a total observation period of N = 1000 sampling windows. The range of the number of vehicles during the observation period is [0, 60], which is divided into Nc = 6 classes, with a class length Lc = 10 vehicles, as shown in Table 1. Hence, the statistical histogram based on the observations is given in a grouped probability distribution format as shown in Figure 1.

Table 1. No. of vehicles in road during the observation period

Class number I	Class Interval $\{C_i^-, C_i^+\}$	Midpoint C_i	Probability $P(C_i)$
0	{0, 10}	5	0.2
1	{10,20}	15	0.4
2	{20,30}	25	0.15
3	{30,40}	35	0.15
4	{40,50}	45	0.1
5	{50,60}	55	0

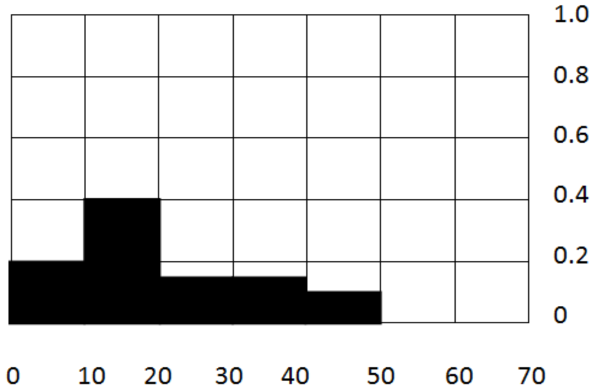

Fig. 1. Statistical histogram of the workload shown in Table 1

In order to ensure that the statistical model of histogram is suitable for practical use, the histogram used in the following analysis is defined as follows. All sampling periods has equal width T. The number of vehicles in a sampling period is stationary and independent from each other. Let C_i^-, C_i^+ and C_i be the lower limit, the upper limit and the middle point of number of vehicles in class i, respectively. The probability $p\ (C_i)$ is defined as follows:

$$P\ (C_i) = \frac{\text{No.of windows with an observation of } \left(C_i^- \le C_t \le C_i^+\right)}{\text{Total No.of windows}} \tag{1}$$

In general, a statistical histogram, denoted as *C*, is presented by two attributes: (1) the set of class midpoints or mean values C_i averaged by $\{C_i^-, C_i^+\}$, denoted as $\overline{C}$ and (2) the set of class probabilities P , also referred as probability mass function (pmf). Hence, a statistical histogram is defined as

$$C = \left(\overline{C}, P\right) = \begin{cases} \overline{C} = [C_i : i = 0, 1, ..., N_c - 1] \\ P = [p(C_i) : i = 0, 1, ..., N_c - 1] \end{cases} \tag{2}$$

Where $\mathrm{N_c}$ is the number of classes

In fact, the histogram defined in this paper is a form of a bar graph representation of a grouped probability distribution (GPD), which is a table representing the number of vehicles in an observation window basis against their corresponding probabilities (or frequencies). This is important, since $C = (\overline{C}, P)$ can be easily obtained by vehicles moving on the road and these statistical information are able to be shared by all other vehicles through an ad hoc based vehicle-to-vehicle network. Here, we note that the arrival process of vehicles into the queuing system is stationary at a uniform rate in a sampling period, and the number of vehicles $V(t) \mid t \in \{1, 2, ..., N\}$ arriving in an observation period is independent and has a distribution modeled by a histogram $C = (\overline{C}, P)$. Therefore, $V(t) \mid t \in \{1, 2, ..., N\}$ is a stochastic process used to characterize variable number of vehicles input into the queue under investigation, which is not a function of time, but it is a discrete statistics of distribution, called histogram, for modeling the number of vehicles on observation window basis.

3 Queuing Models for Vehicular Road Traffic

Figure 2 shows two adjacent road cross-junctions, which are inter-connected by a two-way street of length W. Let $d(t) \mid t \in \{1, 2, ..., N\}$ be the required minimum distance for road safety between consecutive vehicles on the street during a sampling period $t \in \{1, 2, ..., N\}$. According to the 2-second rule for road safety, $d(t) \mid t \in \{1, 2, ..., N\}$ is given by $d(t) = \frac{r(t) \times 1000 \times 2}{3600}$ meter, where $r(t)$ is the vehicle speed during a sampling period t in terms of kilometer per hour. Furthermore, vehicles from the street move into the road cross-junction at a rate of $D(t) = \frac{r(t)}{d(t) + \overline{V}} \times \frac{1000}{3600}$ vehicles per second, where $\overline{V}$ is the average length of vehicle in meters. Hence, the maximum number of vehicles that can be held by the street during a sampling period is given by $K(t) = \frac{W}{d(t) + \overline{V}}$ vehicles, where W is the road length between adjacent road junctions.

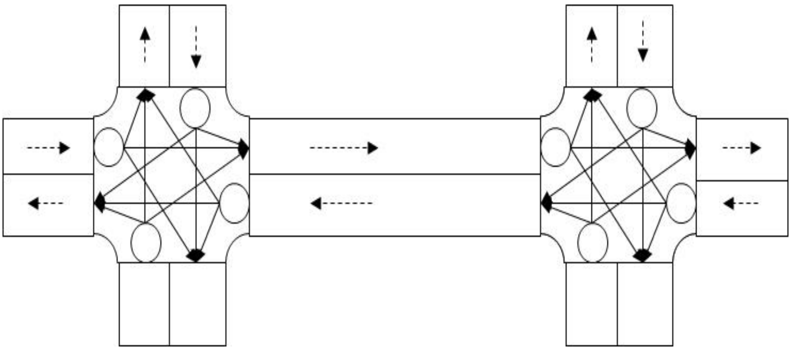

Fig. 2. Streets inter-connected by road junctions

The vehicles entering to the inter-section from the street are controlled by red and green traffic signals (in this case, yellow signal is not taken into account). This process is modeled as a Markov modulated Bernoulli process (MMBP) consisting of ON state and OFF state as shown in Figure 3. The ON state represents the Green signal and the OFF state represents the Red signal. The transition rate from ON state to OFF state is α and the transition rate from OFF state to ON state is β. If vehicles from different directions are equally accessing to the road cross junction, in this case,

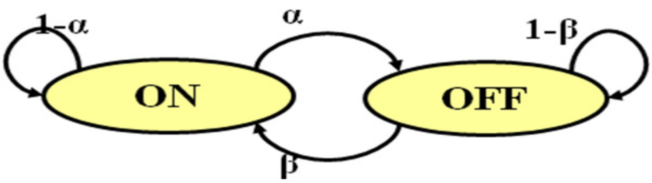

Fig. 3. Markov modulated Bernoulli process model

the transition rate α should to be equal to β. Then vehicles from one direction moves into the inter-section at a rate of D(t)/2 vehicle units per second.

Hence, the process of vehicles entering the inter-section from street is called as MMBP modulated deterministic process. The vehicles traveling on the street and moving to the cross junctions is modeled as finite buffer HD/D/1/K queue as shown in Figure 4. Where HD stands for the Histogram Deterministic Inter-arrival Distribution, which represents vehicle flow in the queue, D represents the deterministic process of vehicles moving from the street into the cross junction at a rate of D(t)/2 and K(t) represents the maximum number of vehicles can be held by the street during a sampling period $t \in \{1, 2, ..., N\}$.

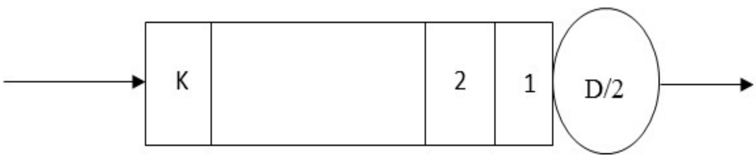

Fig. 4. HD/D/1/K queuing model

Likewise, a road junction with round-about of radius x is modeled as a slotted ring. A road junction with fly-over can be modelled as free-access buffer without traffic control mechanism. Therefore, a roadway in urban city can be modelled as a tandem chain of HD/D/1/K queues, as shown in Figure 5.

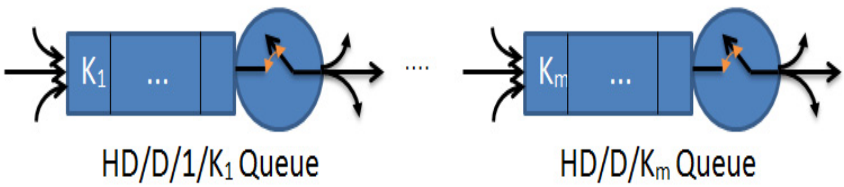

Fig. 5. Urban Roadway Model – A Tandem Queuing Chain

4 Analysis of HD/D/1/K Queuing Chain System

The following analysis of statistics of real-time road traffic histogram is based on the following procedures. Let $V(t) \mid t \in \{1, 2, ..., N\}$ represents the vehicle input flow in the t[th] sampling period, i.e. the number of vehicles entering the street during the t^{th} sampling period. Let $\tau[t]$ is the number of vehicles that have moved out from the queue during the same period. The vehicle input flow is supplied through buffer of finite capacity. The buffer accumulates pending vehicles $Q[t]$ that cannot move from the street and enter the road inter-section during the observation period. The system is assumed to be in stationary if the pending traffic convergences to a finite value. The server discipline is first come first served. Let $Q[t]$ represents the queue length in sampling period $t \in \{1,2,...,N\}$. Then $Q[t]$ can be expressed as follows:

$$Q[t] = \int_0^t \emptyset_0^K(V(t) - \tau[t]\ )\ dt \tag{3}$$

Where, Operator ϕ limits the buffer lengths so that they cannot be either underflow or overflow based on the vehicle speed $\tau[t]$ and the road safety distance d(t) in the tth sampling period. The operator ϕ is defined as

$$\phi_a^b(x) = \begin{cases} 0, & \text{for } x < a \\ x - a & \text{for } a \le x < b + a \\ b & \text{for x} \ge \text{b} + \text{a} \end{cases} \tag{4}$$

Expression (3) can be rewritten using a recurrence equation (known as Lindley's equation [11]) assuming a discrete time space T=t0, t1, t2, etc. Where tn = n * T is a multiple of the sampling period. This way, functions $Q[t]$, $V(t)$ and $\tau[t]$ can be represented by the discrete time functions as follows:

$$Q[n] = \phi_0^K(Q[n-1] + V[n] - \tau[n]) \qquad n \in \{1,2,...,N\} \tag{5}$$

Since the number of vehicles moving from the street into the cross junction during the nth sampling window is given by $\tau(n) = \frac{D(n)}{2} \times T$, where T is the duration of the sampling period. Likewise, if the cross junction is a round-about, then $\tau(n) = \frac{D(n)}{4} \times T$. When $V[n] \le \tau(n)$`, the buffer size is not increased. However, when $V[n] > \tau(n)$, the buffer occupancy increases until queuing buffer is full. Therefore, equation (5) can be expressed as

$$Q[n] = \phi_0^K(Q[n-1] + V[n] - \tau) = \phi_\tau^K(Q[n-1] + V[n]) \tag{7}$$

The foundation of the histogram method basically consists of eliminating the time dependence of V[n] in the previous expression and replacing it by a discrete random variable that describes the arrival process. As our traffic model assumes that traffic is stationary, i.e. $C = V(n)\ \forall\, n \in N$, the previous equation can be transformed into the statistical equation (7):

$$Q[n] = \phi_{\tau}^{K}(Q[n-1] \otimes C) \quad (7)$$

Where C is a statistical histogram defined in Equation (2). The operator $\otimes$ stands for the standard statistical convolution, which is described as follows. If X and Y are two independent random variables with n and m intervals respectively, the convolution X $\otimes$ Y is a new random variable Z with n+m-1 intervals and $P_Z[i] = \sum_{k=0}^{i} P_X(i-k) \times P_Y(k)$

The bound operator ϕ_{τ}^{K} is defined as the statistical generalization of the previously defined ϕ_{a}^{b} operator. If X is a random variable with n intervals then Y = $\phi_{\tau}^{K}(X)$ is a random variable with K+1 intervals where

$$\phi_{\tau}^{K}(X) = [\sum_{i=0}^{\tau} P_X(i), P_X(\tau+1), P_X(\tau+2),..,P_X(\tau+K-1), \sum_{i=\tau+K}^{n-1} P_X(i)] \quad (8)$$

Combining of equation (7) and (8), the buffer length Q[n] is now a discrete time stochastic process whose steady state probability can be calculated through an iterative process as described in [10-11]. The algorithm for calculating the steady state probability of the buffer length is shown below and will be referenced as HBSP (Histogram Based Stochastic Process) algorithm.

```
Algorithm HBSP (C, τ̄ , K̄ ) {
  Q(0) = 1;
  j = 0;

  Do {
      j = j + 1;
      Q(j) = φ_τ^K (Q(j - 1) ⊗ C )
  } While E[Q(j)] - E[Q(j - 1)] > ξ

  Return Q(j)
}
```

Where,

C: the arrival process (Histogram),

$$C = (\overline{C}, P) = \begin{cases} \overline{C} = [C_i : i = 0, 1, ..., N_c - 1] \\ P = [p(C_i) : i = 0, 1, ..., N_c - 1] \end{cases}$$

D: Rate of vehicles moving into the inter-section. $D = \frac{r}{d + \overline{V}} \times \frac{1000}{3600}$, where r is the vehicle speed in terms of kilometer per hour, $\overline{V}$ is the average length of a vehicle

(5 meters), and d the required minimum distance for road safety between consecutive vehicles on the street. According to the 2-second rule for road safety, d is given by $d = \frac{r \times 1000 \times 2}{3600}$ meter

τ : The service rate, or the rate of vehicle moving out of the road junction at an observation period, $\tau = \frac{D}{2} \times T$, where T is the sampling period (10 seconds in our example).

$\bar{\tau}$: The service rate class of τ , $\bar{\tau} = \left\lfloor \frac{\tau}{L_C} \right\rfloor$ where L_C is the class length

K: the maximum buffer length, or the maximum number of vehicles that can be held in the queue. If W is the street length in meters, then $K = \frac{W}{d + \bar{V}}$

$\bar{K}$: The maximum buffer length class, $\bar{K} = \left\lfloor \frac{K}{L_C} \right\rfloor$ where L_C is the class length

$E(X)$: The mean value (or expectation) of gpd X is defined as: $E(X) = \sum_{i=0}^{n-1} P(x_i) * x_i$. Analogously, the mean value of a probability mass function pmf X is defined as $E(X) = \sum_{i=0}^{n-1} P(x_i) * i$

Once the steady state probabilities of the buffer length are calculated, the expected buffer length can be calculated as follows:

$$E(Q) = \sum_{i=0}^{K} P(q_i) * i \tag{9}$$

The queuing delay is the time spent by the car waiting for previous buffered cars to be leave the street and enter the cross junction. In the case of a cross-junction with a output rate of τ , and a buffer length characterized by a gpd Q, the queuing delay W is proportional to Q and has the same pmf. $W = \frac{1}{\tau} \times Q$ Therefore, the expected queuing delay at each intersection can be calculated as follows:

$$E(W) = \frac{1}{\tau} \times E[Q] \tag{10}$$

5 Statistical Histogram Model Usage for Selecting Best Road Path

Figure 6 shows an example of how the statistical histogram model can be used in vehicular network environment. It shows a road map for all possible routes from ingress junction to egress junction with statistical histograms, which are obtained from vehicular network. Based on the information provided by histograms, combined with shortest path algorithm, a driver is able select a best route between the ingress node and egress node and relevant speed and end-to-end delay. Note that since the histograms are updated periodically via vehicle-to-vehicle network, the driver is also able to dynamically change his driving route according to the road traffic conditions obtained from histogram statistics.

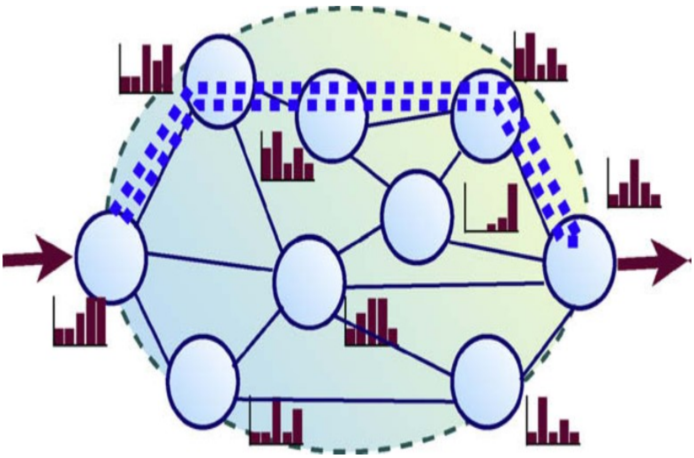

Fig. 6. An example of using the histogram model in VANET

6 Performance Evaluation

In this paper, we compare the performance of the proposed Histogram-Based Algorithm (HBA), with two variations of the standard shortest path algorithm; (i) the shortest path algorithm with static link cost (SPA-Static) and (ii) the optimal shortest path algorithm with dynamic link cost (SPA-Dynamic). The optimal SPA-Dynamic algorithm and the SPA-Static were already embedded in the TSIM microscopic simulator developed by Hawas [12]. However, the HBA algorithm was developed and then embedded in the TSIM microscopic.

The comparative assessment of the three algorithms (HBA, SPA_Static and SPA_Dynamic) is done by comparing various performance measures; namely, number of vehicles entered the network, number of vehicles exited the network and network average travel time (in mins). These attributes are measured under various traffic conditions, such as source volumes, speed, and link length.

Figure 7 shows a grid network of 12 nodes which was used for testing. A summary of the simulation parameters is given below.

- Duration of simulation is 60 minutes
- Maximum vehicle speed along all links is set to 80 km/hour
- Number of source nodes is 6. Each node generates vehicles at a certain rate (ranging from 50 vehicles per hour until 2000 vehicles per hour). The generated vehicles are uniformly distributed in time.

- Number of destination nodes is 14
- Number of intersections is 12 intersections. The length of the links between any two intersections is either 300 m or 150 m long
- Class length of the histogram $L_C = 2$. In other words, the class intervals are $\{\{1,2\},\{3,4\},\{5,6\}, etc.\}$

The total simulation time for any tested scenario is set as 60 minutes. At the beginning of the simulation, details of the network structure, connectivity and characteristics, signal characteristics and settings over the analysis period are provided as input to the simulator. Each vehicle (as it is generated) is assigned an Origin-Destination (OD) pair, in accordance to a pre-specified OD matrix for the entire network. Then, depending on the algorithm used to estimate the expected travel time on the links or link costs, each vehicle is assigned the shortest path to its destination, which does not change during the vehicle trip.

In the optimal SPA-Dynamic algorithm, each link keeps tracks of the maximum travel time reported by every vehicle traveling through the link. Then, the algorithm considers the maximum travel time observed by each link as the link cost. These measured travel times (costs) are then used by the Dijkstra's algorithm to find the shortest path. In this case, the path cost is computed by summing the measured "Maximum Travel Time" per link for all links along the path. The path with the least cost is then chosen as the best path. However, in the SPA-Static algorithm, the travel time along the link, and consequently the cost of the link, does not depend on traffic conditions. The travel time (or link cost) is estimated as the link length divided by the maximum speed along that link. Path cost is also measured by summing the cost of all links along the path.

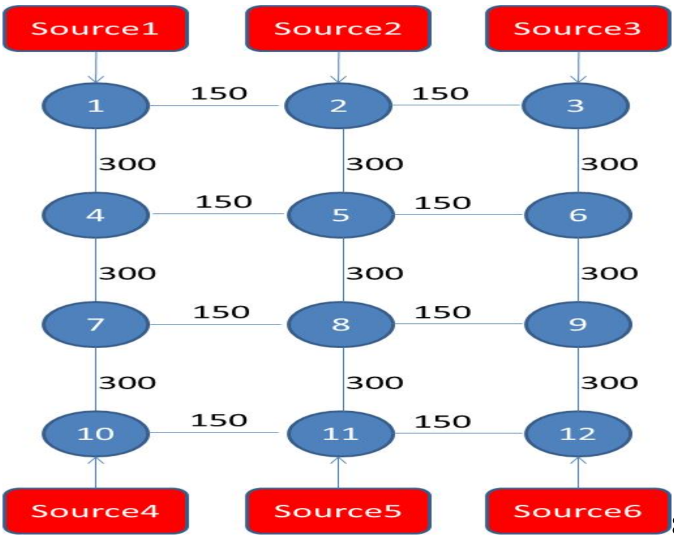

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Fig. 7. The Network Topology used during Simulation

In the HBA algorithm, the expected travel time on any link is estimated by adding the expected queuing delay to enter the link (as calculated by Equation 9 and the HSBSP algorithm discussed in Section 4) and the average travel time through the link (link length/ speed limit on the link). The expected travel times computed on every link is then considered as the link cost and used by a Dijkstra's algorithm to find the shortest path. Each generated vehicle is then assigned this shortest path as a pre-specified path.

During simulation, traffic jam is introduced in some routes to trigger the vehicles to change their route to a less crowded route. This is simulated in our experiments by reducing the green-light period at certain intersections to generate a traffic jam at this intersection. In particular, we simulate a traffic jam along the path between node 5 and node 8 by reducing the green light period at this intersection from 30 seconds to 4 seconds.

6.1 Full Network Monitoring

In this experiment, we use the total travel time metric to compare the performance of the proposed HBA algorithm against the optimal SPA-Dynamic algorithm and the SPA-Static algorithm. We computed the travel time for each vehicle entered the network, which represents the time spent by the vehicle in the network, by calculating the vehicle exit time – the vehicle entry time. The total travel time in the experiment is then computed by summing up the travel times of all vehicles entered the network. Figure 8 shows a summary of the simulation results. We did not see much difference in the performance of the three algorithms. That is because the average of all vehicle travel times across the network conceals the excessive delays along any traffic jams. Please note that in this experiment, we only show the results of the HBA algorithm with a class length $L_C = 2$. The results of the other version of the algorithm (when $L_C = 5$) is omitted for clarity as it shows similar performance.

6.2 Critical Path Monitoring

In this experiment, instead of monitoring all vehicles and compute the total travel time across the network, we monitored only the vehicles which pass through the bottleneck path (i.e. the link between node 5 and node 8), where we introduced the traffic jam. Figure 9 shows a summary of the simulation results. In this experiment, each point in the graph represents the total travel time of all vehicles passed through the bottleneck link between node 5 and node 8. It is clear from Figure 8 that the proposed HBA algorithm adopts well with network conditions and guides vehicles for better routes when some links get congested. It outperforms the performance of the SPA-Static algorithm even when the network was not crowded (i.e. when the source rate = 50 vehicles per hour). Furthermore, the performance of the HBA algorithm is very comparable with that of the optimal SPA-Dynamic algorithm, which assumes that the travel times of each vehicle across all the links are available and known to all other vehicles in the network.

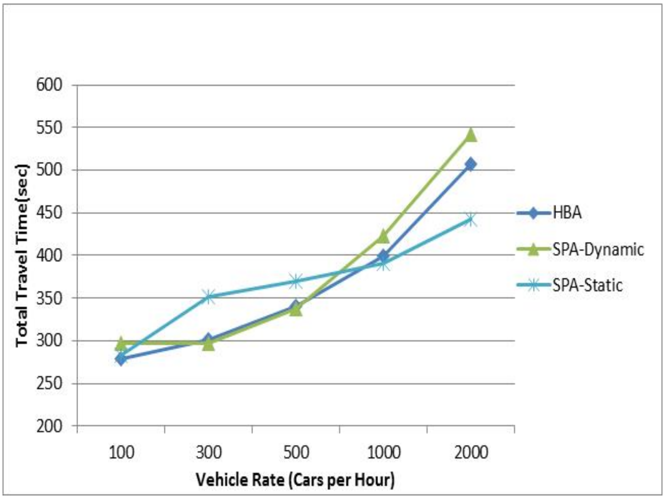

Fig. 8. Full Network Monitoring

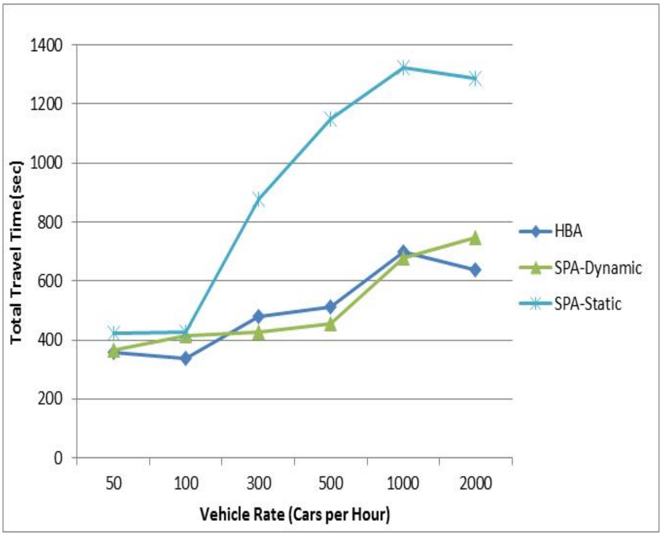

Fig. 9. One Path Monitoring

7 Conclusion

This paper presented a novel histogram-based route guidance algorithm for selecting shortest road path and alerting drivers to potential traffic jams. A microscopic simulation model was developed to assess the effectiveness of the route guidance algorithm against the benchmark shortest path algorithm. Simulation results showed that the proposed road traffic model provides a good prediction of road traffic status, and can be used in conjunction with any standard shortest path algorithms to provide an efficient mechanism for selecting fastest road path.

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