Master's Thesis

Back-Pressure Based Adaptive Traffic Signal Control and Vehicle Routing with Real-Time Control Information Update

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Back-Pressure Based Adaptive Traffic Signal Control and Vehicle Routing with Real-Time Control Information Update *

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Abstract

Back-pressure algorithm has been shown to be effective in reducing traffic congestion. However, available works on back-pressure based traffic control usually ignore the fact that vehicles need time to travel across roads, resulting in inconsistency between controllers' viewpoint of traffic congestion situation and real traffic situation and thus misleading controllers. In this paper, we propose back-pressure based adaptive traffic signal control and vehicle routing with real-time control information update such that controllers always have consistent viewpoint of traffic congestion with real traffic situation and make wise signal control and vehicle routing decisions. As verified by simulations, our algorithm significantly reduces traffic congestion. For example, it reduces average vehicle traveling time by percentage ranging from 67% to 83% under high vehicle arrival rates when compared to other three algorithms.

Keywords:
Back-pressure, traffic signal control, vehicle routing

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List of Figures

Contents

1 Introduction

1.1 Background

Nowadays traffic congestion becomes a serious problem in urban transportation networks, which causes long travel time to drivers [1]. Traffic congestion brings adverse effects and harms to individuals and society. It not only affects the travel mood of individual, but also causes economic losses. It may also endanger personal safety and endanger the physical and mental health of residents. In addition, it also causes overall time loss to society. Air pollution, traffic accidents, fuel costs increase, and economic losses will affect the development of related industries such as automobiles and tourism, and restrict the development of the national economy.

In metropolitan urban road networks, vehicles move according to traffic signals (red means one vehicle must stop, green means one vehicle may go and yellow means one vehicle should be prepared to stop). Traditionally, traffic flows are controlled by traffic lights that change signals in fixed cycles, fixed patterns. which are of low efficiency because they ignore real-time traffic situation. Furthermore, drivers in these networks can hardly have real-time global traffic information, to smartly select routes to avoid future traffic congestion. Surveys showed that traffic congestion can be alleviated by efficient traffic signal control and route selection methods [2]. Thus, it has been of high interest to study these problems over the years.

Some adaptive traffic signal controllers have been implemented in metropolitan cities, such as SCOOT (Split Cycle Offset Optimization Technique) [3], SCATS (Sydney Coordinated Adaptive Traffic System) [4], ROHODES (Real-time Hierarchical Optimizing Distributed Effective System) [5], etc. These systems anticipate vehicle arrivals to adjust signal control parameters, like cycle length and phase, according to real-time traffic situation [6]. Although the feedback of these systems showed some performance improvement, most of the systems cannot provide any performance guarantee [14].

Control theory and game theory have also been applied to design traffic signal control algorithms [7-12] which are more reactive to real-time traffic and have stability guarantees. However, all of these approaches are centralized. It is difficult to use them in large urban road networks, where decentralized algorithm is required.

Recently, researchers proposed decentralized solutions by applying back-pressure algorithm to adaptive traffic control [13-17]. Back-pressure routing is an algorithm originally for routing packets based on queue length differentials (also called pressure gradients) in wireless communication networks [22]. For back-pressure routing in road networks, the pressure of a road is defined as the number of vehicles at that road, then traffic flows from a high-pressure upstream area to a low-pressure downstream area. In other words, the vehicles flow to the roads with more remaining capacity in the network. Back-pressure was firstly applied in traffic signal control in [14]. They allocate the right-of-way for vehicles by controlling traffic signal based on backpressure, which was showed to bring obvious performance gains when compare to fixed cycle signal control. However, all of the above back-pressure based solutions do not provide dynamic route selection and some use fixed shortest path for vehicle routing, which may lead vehicles to congested areas.

Dynamic vehicle routing problems have also been widely studied [25]. The earlier literature only allows vehicles with some minor adjustments of the prior routes [26-29]. With the development of technology, researchers started using Markov Decision Process to route vehicles dynamically without any prior route [30, 31]. Unfortunately, this method failed being applied in relatively large scale road networks which exist most in real-world. To tackle this limitation, an approach based on Approximate Dynamic Programming has been proposed [32, 33], yet all of the solutions above do not integrate with adaptive signal control. Recent researches considered adaptive signal control and dynamic vehicles routing [19, 21, 24]. However, they only focused on providing adaptive route guidance for individual vehicles, not coordinating different vehicles. With the development of self-driving technology, it will be more efficient to coordinate different vehicles to reduce overall traffic congestion.

Back-pressure algorithm has been used to jointly control traffic signals and vehicle routes in [18]. However, the algorithm proposed in [18] applies back-pressure algorithm directly to traffic control without considering the difference between road network and communication network: propagation time of a packet through communication link between two nodes is almost zero, while travel time of a vehicle across a road between two junctions cannot be ignored. According to their algorithm, at a junction, an empty road with 10 vehicles just entering it will be seen as more congested than a road with 5 vehicles already halting and waiting. The inconsistency between controller's viewpoint of traffic congestion situation and real traffic situation misleads controllers in making traffic control decisions.

1.2 Contributions

In this paper, we extend the work [18] and originally propose novel shadow buffers so that shadow queues can update with real-time control information, such that controllers always have a consistent viewpoint of traffic congestion with real traffic situation and wisely do back-pressure based adaptive traffic signal control and vehicle routing. Moreover, we do traffic control by using adaptive rates of vehicles passing through junctions and shortest traveling time between two junctions, instead of constant rates of vehicles passing through junctions and shortest path between two junctions as used in [18]. Finally, we verify the effectiveness of our algorithm with a non-uniform road network while the network used in [18] is uniform.

1.3 Organization

The remainder of this paper is organized as follows. In Section 2, we introduce system model, concerning road network, traffic signal and traffic rules. In Section 3, we describe in details our back-pressure based adaptive traffic signal control and vehicle routing with real-time control information update algorithm. In Section 4, we implement our algorithm with simulator SUMO (Simulation of Urban MObility) [23, 35] using the road network of a real city Stockholm, and show the evaluation results. Section 5 gives the conclusion of the whole paper.

2 Road Network

We model a road network as a directed graph $\mathbb{G} = (\mathbb{J}, \mathbb{R})$, where $\mathbb{J} = \{J_1, J_2, J_3, \cdots, J_{max}\}$ is the set of junctions and $\mathbb{R} = \{R_1, R_2, R_3, \cdots, R_{max}\}$ is the set of roads. Vehicles enter the road network from some origin entry roads and leave the road network from some destination exit roads. Vehicles with the same origin and destination belong to the same flow. Let $\mathbb{F} = \{f_1, f_2, f_3, \cdots, f_{max}\}$ be the set of all flows in the road network. For a vehicle of flow $f \in \mathbb{F}$, let $o(f), d(f)$ be its origin entry road and destination exit road respectively. Let $\mathbb{O} = \{o(f),\ f \in \mathbb{F}\}$ be the set of all origin roads and $\mathbb{D} = \{d(f),\ f \in \mathbb{F}\}$ be the set of all destinations. System time is slotted. Let $\lambda_f(t)$ be the number of vehicles exogenously entering road network from origin $o(f)$ of flow f at slot t.

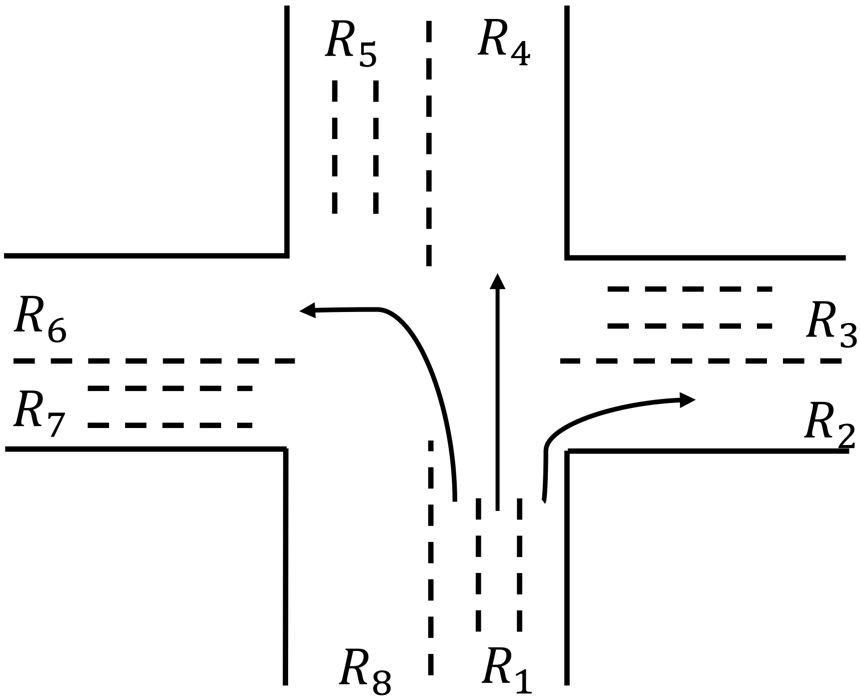

Fig. 1. Possible traffic movement from road R_1 at a junction.

2.1 Traffic Rules

At a junction J_a, vehicles can move from some upstream road R_i to some downstream road R_j, which is called traffic movement (R_i, R_j). For example, Fig. 1 illustrates all possible traffic movements from R_1 at junction J_a: (R_1, R_6), (R_1, R_4), (R_1, R_2). Let $\mathbb{M}_\mathrm{a}$ be the set of all possible traffic movement at junction J_a. A traffic phase p_i^a at junction J_a is defined to be the set of all possible traffic movements that can occur simultaneously. Fig. 2 illustrates four typical traffic phases at a four-way junction. For example, traffic movements (R_3, R_4), (R_3, R_6), (R_7, R_2), (R_7, R_8) belong to the same traffic phase. Let $\mathbb{P}_\mathrm{a} = \{p_1^a, p_2^a, \cdots, p_{max}^a\}$ be the set of all possible traffic phases at junction J_a. Traffic signal control for a junction J_a is executed by activating one selected phase $p_i^a \in \mathbb{P}_\mathrm{a}$ at the beginning of every time slot. Similarly, typical traffic phases at a three-way junction are shown in Fig. 3.

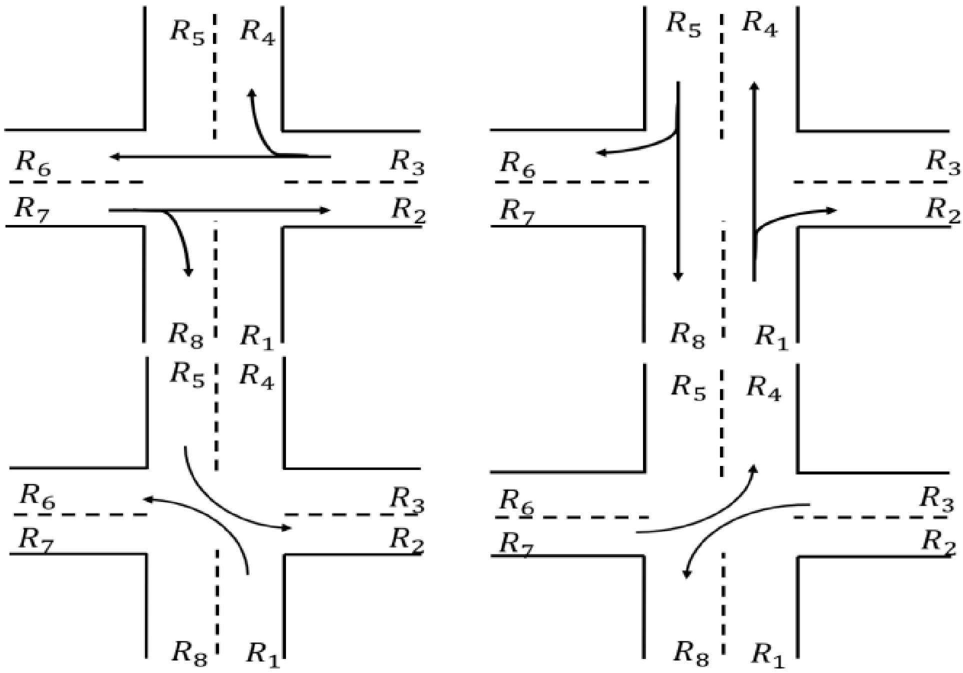

Fig. 2. Four typical phases at a four-way junction.

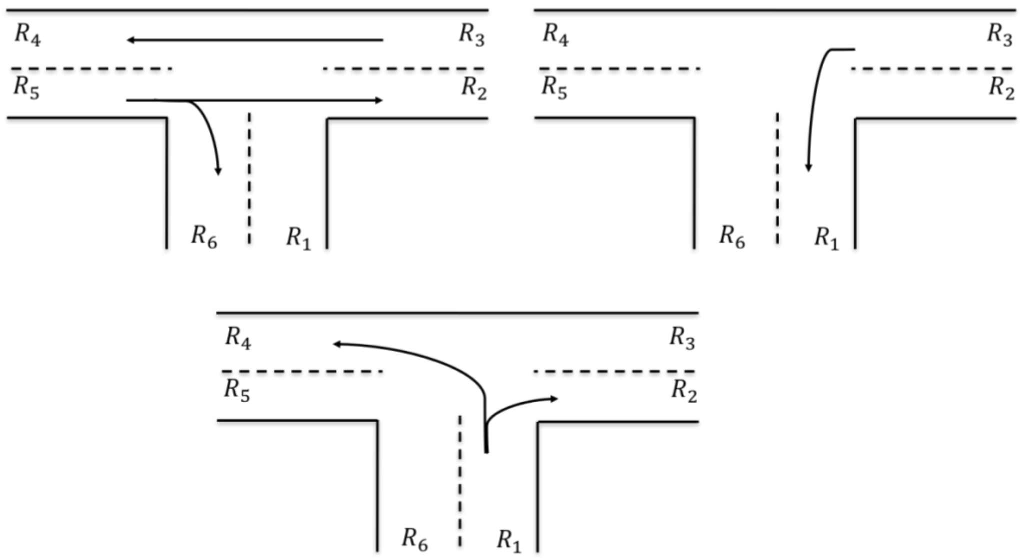

Fig. 3. Three typical phases at a three-way junction.

3 Back-Pressure Based Adaptive Traffic Signal Control and Vehicle Routing

In this section, we describe in details our algorithm: back-pressure based adaptive traffic signal control and vehicle routing with real-time control information update.

The basic idea of our algorithm is as follows. Each junction has a control agent. At each time slot, the control agent at each junction performs two tasks: 1) Firstly, it selects a traffic phase to control traffic signals of the junction. 2) Secondly, when a vehicle enters a road, it determines which direction to turn at the end of this road. Due to this decision is made just when a vehicle enters the road, for manual drivers they have enough time to react for instruction following. Note that for a specific vehicle, the sequence of downstream roads determined by junction agents forms its route. To aid agents to perform the two tasks, we need the following shadow network.

3.1 Shadow Network with Real-Time Control Information Update

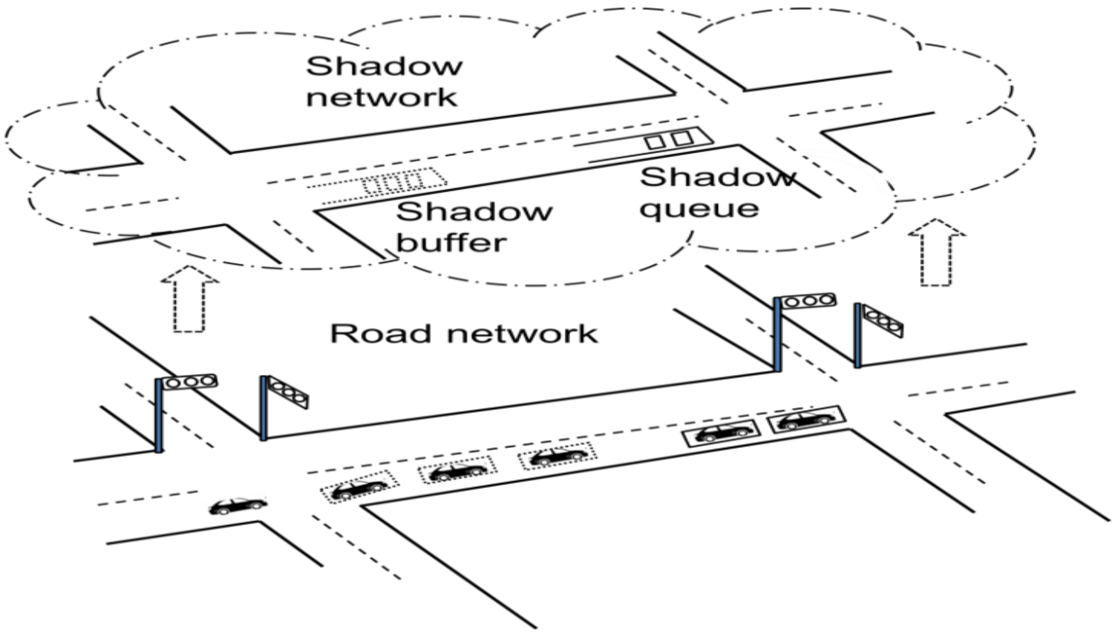

Fig. 4. Illustration of shadow network with shadow buffers and shadow queues.

Based on road network, we construct a shadow network as shown in Fig. 4, which acts as a control network providing control information for agents to perform tasks. In the shadow network, each fictitious shadow vehicle is associated with one real vehicle in road network, each shadow buffer and shadow queue are associated with one real road.

Specifically, the shadow network operates as follows. Once a real vehicle enters an origin entry road in road network, the corresponding junction agent generates a shadow vehicle and further generates another shadow vehicle with probability $\epsilon, 0 < \epsilon < 1$, and let them enter shadow network. Thus, if the vehicle arrival rate of flow $f \in \mathbb{F}$ is λ_f in real road network, then the shadow vehicle arrival rate of flow $f \in \mathbb{F}$ is $(1+\epsilon)\lambda_f$ in shadow network. Here, ϵ is to guarantee network stability [18, 20].

If the exogenous vehicle enters road network from origin road R_i at time slot t and is destined for destination $d \in \mathbb{D}$, then the junction agent let the corresponding generated shadow vehicle/vehicles enter shadow buffer $\tilde{B}_i^d(t)$ associated with destination d and road R_i. After the real vehicle runs on road R_i for a while and meets either of the following two conditions, the junction agent let one shadow vehicle associated with the real vehicle leave shadow buffer $\tilde{B}_i^d(t)$ and join shadow queue $\tilde{Q}_i^d(t)$ associated with destination d and road R_i. One condition is that vehicle speed is less than 5 km/h, the other condition is that the distance between that vehicle and junction is less than 100 meters.

When one real vehicle leaves one road $R_i \in \mathbb{R}$ and enters another road $R_j \in \mathbb{R}$ at slot t, the corresponding junction agent let one associated shadow vehicle leave some shadow queue $\tilde{Q}_i^d(t)$, $d \in \mathbb{D}$, of road R_i and join some shadow buffer $\tilde{B}_j^d(t)$, $d \in \mathbb{D}$, of road R_j as shown in Fig. 3 (Which shadow queue to leave and which shadow buffer to join are specified in Section 3-3.2). After the real vehicle runs on road R_j for a while and meets either of the above two conditions, the junction agent let the associated shadow vehicle leave the shadow buffer $\tilde{B}_j^d(t)$ it joined before and enter the corresponding shadow queue $\tilde{Q}_j^d(t)$ of road R_j.

Movement of fictitious shadow vehicles can be seen as exchange of control information in the shadow network, based on which junction agents perform traffic signal control and vehicle routing tasks. The process of updating shadow vehicle status in real-time, being in shadow buffer or being in shadow queue, mimics the behavior of real vehicles traveling on one road. Like real vehicles first entering road from one road end and then approaching the other road end, shadow vehicles first join shadow buffers and then join shadow queues. This is quite different from work [18], where a vehicle entering road R_j immediately joins some shadow queue $\tilde{Q}_j^d(t)$, ignoring that the vehicle needs time to travel across that road. This results in inconsistency between controllers' viewpoint of traffic congestion and real traffic situation and misleads junction agents in making control decisions.

3.2 Adaptive Traffic Signal Control and Vehicle Routing Algorithm

Our back-pressure based traffic signal control and vehicle routing algorithm is decentralized. Every junction runs the following algorithm independently. At every time slot t, the agent of a junction J_a first selects and activates a phase, then when a vehicle enters a road, determines which downstream of this road to join.

Our algorithm needs to define quantity $s_{ij}(t)$, which is the number of vehicles that can move from road R_{i} to road R_j at slot t given the assumption that traffic light for road R_i changes to green. For example, if traffic light for road R_i changes to green at the beginning of slot t and a vehicle can pass the stop line of road R_i at the end of time slot t with its current location and speed (it may accelerate), then we say the vehicle can move from road R_i to road R_j at slot t. The sum of all these vehicles is equal to $s_{ij}(t)$. Thus, $s_{ij}(t)$ is influenced by factors like previous traffic light status, vehicle location, vehicle speed, acceleration rate, and thus reflects real-time rates of vehicles passing through a junction.

3.2.1 Adaptive Traffic Signal Control

Firstly, the junction agent computes back-pressure $w_{ij}^{d}(t)$ for every destination $d \in \mathbb{D}$ and all possible traffic movement $(R_i, R_j) \in \mathbb{M}_a$ as follows:

$$w_{ij}^{d}(t) = max\{\tilde{Q}_i^d(t) - \tilde{Q}_j^d(t), 0\} \tag{1}$$

And for every traffic movement (R_i, R_j), the agent identifies the destination $d_{ij}^{*}(t)$ that maximizes back-pressure $w_{ij}^{d}(t)$:

$$d_{ij}^{*}(t) = \underset{d}{arg\,max}\, w_{ij}^{d}(t) \tag{2}$$

The agent assigns the maximum back-pressure $w_{ij}^{d_{ij}^{*}(t)}(t)$ as the weight of traffic movement (R_i, R_j). Each traffic movement (R_i, R_j) is associated with one $d_{ij}^{*}(t)$ at slot t.

Then, the agent selects the phase $p^{a*}(t) \in \mathbb{P}_{\mathrm{a}}$ of junction $\mathrm{J_a}$ that maximizes the following and activates the phase $p^{a*}(t)$ for time slot t.

$$p^{a*}(t) = \underset{p_l^a \in \mathbb{P}_a}{arg\,max} \sum\nolimits_{(R_i,R_j)\in p_l^a} w_{ij}^{d_{ij}^{*}(t)}(t)\, s_{ij}(t) \tag{3}$$

Finally, real vehicles move under phase $p^{a*}(t)$ and the agent of junction J_a updates shadow buffers and shadow queues as follows. For traffic movement $(R_i, R_j) \in p^{a*}(t)$ associated with $d_{ij}^{*}(t)$, if a real vehicle moves through junction J_a by leaving upstream road R_i and entering downstream road R_j, then the agent let one associated shadow vehicle leave shadow queue $\tilde{Q}_i^{d_{ij}^{*}(t)}(t)$ of upstream road R_i and join shadow buffer $\tilde{B}_j^{d_{ij}^{*}(t)}(t)$ of downstream road R_j. After the real vehicle runs on road R_j for a while and meets either of the two conditions in Section III-A, the agent let the associated shadow vehicle leave shadow buffer $\tilde{B}_j^{d_{ij}^*(t)}(t)$ and join shadow queue $\tilde{Q}_j^{d_{ij}^*(t)}(t)$. Let $\tilde{V}_j^d(t)$ be the total number of shadow vehicles of destination $d \in \mathbb{D}$ leaving shadow buffer $\tilde{B}_j^d(t)$ and joining shadow queue $\tilde{Q}_j^d(t)$ at slot t.

Shadow buffer evolves as follows:

$$\tilde{B}_j^d(t+1) = \tilde{B}_j^d(t) + \sum_{i:(R_i,R_j)\in\mathbb{M}_a} I_{\{d=d_{ij}^*(t)\}}\widetilde{s_{ij}}(t) - \tilde{V}_j^d(t) + \sum_{f\in\mathbb{F}} I_{\{j=o(f),d=d(f)\}}\widetilde{\lambda_f}(t) \tag{4}$$

where $\widetilde{s_{ij}}(t)$ is the number of actual vehicles (also the number of associated vehicles) that move from road R_i to road R_j in slot t, and $I_{\{x\}}$ is the indicator function: when statement x is true, $I_{\{x\}}$ equals to 1, otherwise $I_{\{x\}}$ equals to 0. $\widetilde{\lambda_f}(t)$ is the number of shadow vehicles entering road R_j at slot t. From (4), we see that only if $d = d_{ij}^*(t)$, then $I_{\{d=d_{ij}^*(t)\}} = 1$, i.e., $\widetilde{s_{ij}}(t)$ shadow vehicles only join the shadow buffer $\tilde{B}_j^{d_{ij}^*(t)}(t)$ under phase $p^{a*}(t)$.

Shadow queue evolves as follows:

$$\tilde{Q}_i^d(t+1) = \tilde{Q}_i^d(t) - \sum_{j:(R_i,R_j)\in\mathbb{M}_a} I_{\{d=d_{ij}^*(t)\}}\widetilde{s_{ij}}(t) + \tilde{V}_i^d(t) \tag{5}$$

3.2.2 Adaptive Vehicle Routing

Let $\sigma_{ij}^d(t)$ be the number of shadow vehicles of destinaiton d moving from shadow queue $\tilde{Q}_i^d(t)$ of road R_i to shadow buffer $\tilde{B}_j^d(t)$ of road R_j at slot t under the above adaptive traffic signal control algorithm. Let $\bar{\sigma}_{ij}^d(t)$ be the expected value of $\sigma_{ij}^d(t)$ and $\hat{\sigma}_{ij}^d(t)$ be the estimated value of $\bar{\sigma}_{ij}^d(t)$. At each time slot t, agent of junction J_a updates the value of $\hat{\sigma}_{ij}^d(t)$ for all $d \in \mathbb{D}$ and traffic movements $(R_i, R_j) \in \mathbb{M}_a$, using exponential averaging:

$$\hat{\sigma}_{ij}^{d}(t) = (1-\beta)\hat{\sigma}_{ij}^{d}(\mathrm{t}-1) + \beta\sigma_{ij}^{d}(\mathrm{t}) \tag{6}$$

where $0 < \beta < 1$.

Then, each agent updates routing probabilities $P_{ij}^{d}(t)$ based on $\hat{\sigma}_{ij}^{d}(t)$ as follows:

$$P_{ij}^{d}(t) = \frac{\hat{\sigma}_{ij}^{d}(\mathrm{t})}{\sum_{h:(R_i,R_h)\in\mathbb{M}_\mathrm{a}} \hat{\sigma}_{ih}^{d}(\mathrm{t})} \tag{7}$$

When a vehicle of destination d enters road R_i at slot t, it will turn to road R_j with routing probability $P_{ij}^{d}(t)$.

For example, if $P_{16}^{d}(t) = 0.4$, $P_{14}^{d}(t) = 0.1$, $P_{12}^{d}(t) = 0.5$, and a vehicle of destination d enters road R_1 in Fig.1, it will turn to road R_6, R_4 and R_2 with probability 0.4, 0.1 and 0.5 respectively.

3.2.3 Further Reducing Vehicle Traveling Time

To encourage traffic flows to follow shorter route to destinations, we introduce a bias L_i^d term in our algorithm. Bias L_i^d is the shortest traveling time from road R_i to destination road d, which is calculated by running shortest path algorithm Floyd–Warshall algorithm on directed graph $\mathbb{G}$, where road weight is calculated by first dividing the length of a road by its speed limit and then normalizing the result to be between 0 and 10.

Specifically, we add bias L_i^d in our algorithm as follows:

$$w_{ij}^{d}(t) = \max\{\tilde{Q}_i^d(t) - \tilde{Q}_j^d(t) + \alpha(L_i^d - L_j^d), 0\} \tag{8}$$

where parameter $\alpha, \alpha > 0$, indicates how much weight we put on encouraging traffic flows to follow the shortest traveling time route. A proper setting of α leads to good algorithm performance and effect of α will be examined by simulations.

3.3 Time Complexity Assessment of our Algorithm

As introduced above, our algorithm is distributed at every junction, every single junction executes the algorithm as follow:

Step 1: for all possible traffic of this junction, calculate shadow queue difference of each destination($T(n) = O(n^2)$).

Step 2: Choose the destination that maximizes the shadow queue difference as each traffic movement pressure($T(n) = O(n)$).

Step 3: Multiply each traffic movement pressure by its corresponding number of vehicles that can move in a time slot, get a value as weight of each traffic movement. Then summation the movement weights of each phase, select the phase has max summation to activate($T(n) = O(n)$).

In summary, the time complexity of our algorithm is equal to $O(n^2)$.

4 Simulations

In this section, we do simulations to evaluate the performance of our algorithm and compare it to other algorithms as follows.

- Fixed-cycle (FC) signal controller: Traffic flows are controlled by traffic lights that change traffic signals in fixed cycle, which is widely used in real world. Vehicles follow fixed shortest paths calculated by Dijkstra's algorithm in the road network.

- Back-pressure based signal controller with shortest path routing (SP-BP): Back-pressure based traffic signal control considers real time traffic situation of each junction as proposed in [14]: at a junction J_a, Q_{ij} denotes the number of vehicles queued at road R_i wait to leave for road R_j. Therefore, $Q_i(t) = \sum_j Q_{ij}$ is the number of vehicles waiting at road R_i. The traffic pressure of all the traffic movements $(R_j, R_k) \in \mathbb{M}_\mathrm{a}$ can be calculated as $W_{jk}(t) = \max\{Q_j - Q_k, 0\}$, then release traffic pressure defined as $p_j(t) = \arg\max_{p_j^a \in \mathbb{P}_\mathrm{a}} \sum_{(R_j,R_k)\in p_j^a} W_{jk}(t)\, s_{jk}(t)$, here $s_{jk}(t)$ is the number of vehicles that can move from road R_j to road R_k at slot t given the assumption that traffic light for road R_j changes to green. Same as our algorithm, $s_{jk}(t)$ of the movement (R_j, R_k) to junction J_a varies from slot to slot influenced by factors like previous traffic light status, vehicle location, vehicle speed, acceleration rate. Traffic phase $p_j(t)$ for junction J_a is activated that maximizes the pressure release. Vehicles follow fixed shortest paths calculated by Dijkstra's algorithm.

- Back-pressure based adaptive traffic signal control and vehicle routing without real-time control information update (AR-BP) proposed in [18]. In order to evaluate our algorithm fairly. $s_{jk}(t)$ in this method also changes from slot to slot which is different with literature [18].

- Back-pressure based adaptive traffic signal control and vehicle routing with real-time control information update (ARD-BP) proposed in this paper.

4.1 Simulation Setup

We have implemented the above algorithms in an open source simulator SUMO (Simulation of Urban MObility) [23, 35].

Topology of a real city Stockholm road network is used for simulation that is outputted from OpenStreetMap, a collaborative project can create an editable map of the world [34, 36]. The road network consists of four-way junctions and three-way junctions as shown in Fig.5. Roads in this network are bi-directional and have different length ranging from 400 meters to 1500 meters and different speed limit ranging from 60 km/h and 120 km/h. Every road has different number of lanes and the shape of each junction is determined by the number of lanes of incoming roads as Fig. 6 and Fig. 7 shows. We generate vehicles of 6 traffic flows with origin and destination pairs $\{(o_1, d_1), (o_2, d_2), \cdots, (o_6, d_6)\}$ as shown in Fig.5. Vehicle arrival rates are set to be the same for all pairs and vary from 0.1 vehicle/second to 0.7 vehicles/second. System time slot is set to be of duration 15 seconds, parameter α of ARD-BP and AR-BP is set to be 2, both of which are proved to be a proper value in following simulation results. Shadow vehicle generating parameter ε is set to be 0.02 and vehicle routing parameter β is set to be 0.02.

We collect the following data: average number of vehicles in road network, number of arrived vehicles and vehicle traveling time. Vehicle traveling time is defined to be the interval from the time a vehicle enters road network to the time it exists road network.

We run simulations of algorithms FC and SP-BP for 7200 + 5000 = 12200 seconds (3.4 hours). We do not collect simulation data of vehicles that enter road network after 7200 seconds, because only 5000 seconds are left for simulation and these vehicles will make us underestimate average vehicle traveling time. We run simulations of algorithms AR-BP and ARD-BP for 6000 + 7200 + 5000 = 18200 seconds (5 hours). We do not collect simulation data of vehicles that enter road network for the first 6000 seconds, because algorithms AR-BP and ARD-BP need time to learn vehicle routing probabilities $P_{ij}^{d}(t)$ and reach a stable routing policy, the first 6000 seconds in simulations constitute a warmup stage. For the same reason as before, we do not collect simulation data of vehicles that enter road network after 6000 + 7200 = 13200 seconds. From the collected vehicle data, we set the number of vehicles that left the network in simulation time as arrived vehicles. In data collecting period, we get the number of vehicles currently running within the scenario every second, then calculate an average as average number of vehicles in road network.

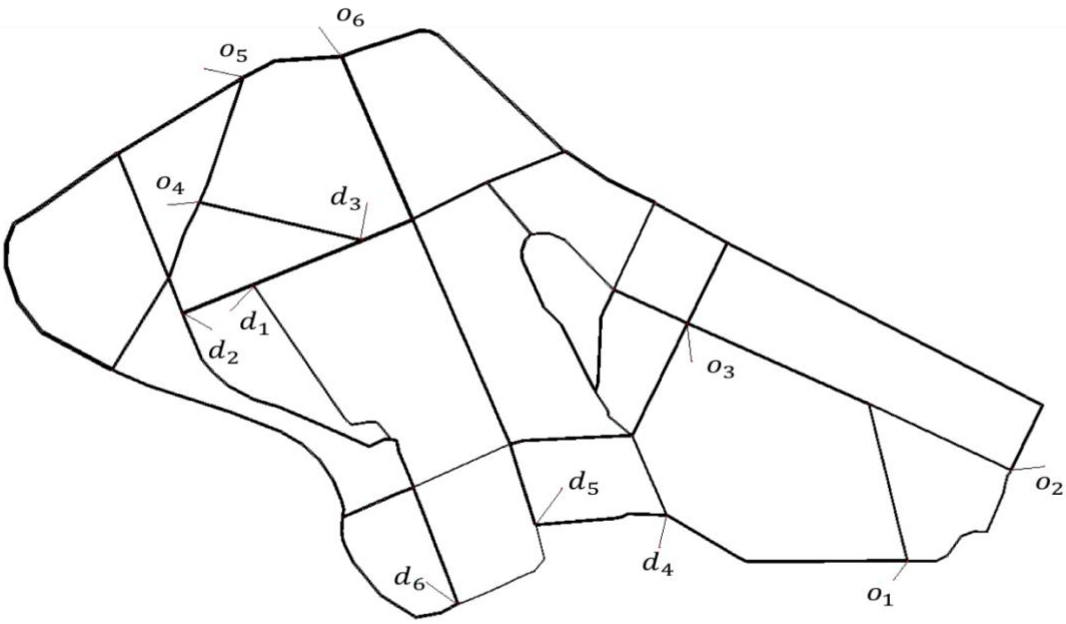

Fig. 5. Road network of city Stockholm

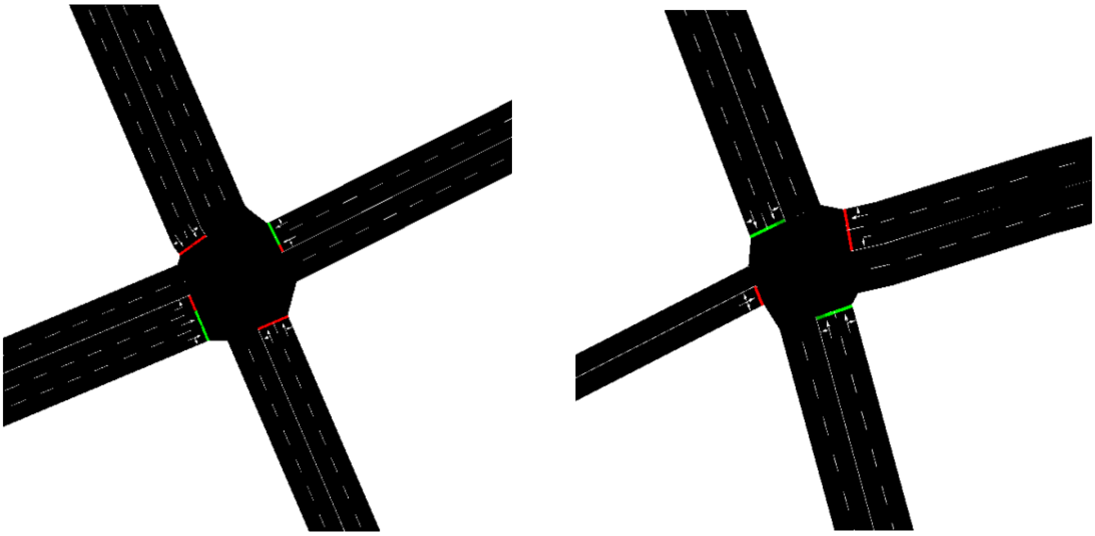

Fig. 6. Two four-way intersection types depending on the number of lanes of incoming roads.

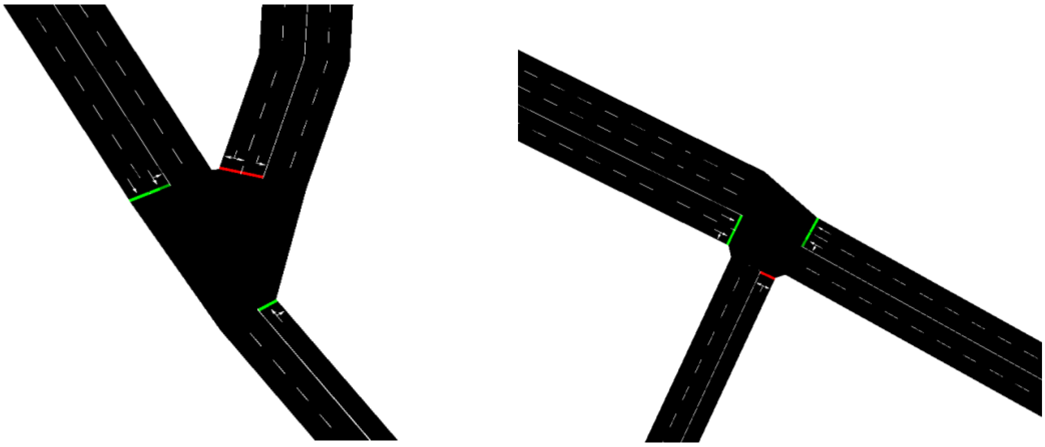

Fig. 7. Two three-way intersection types depending on the number of lanes of incoming roads.

4.2 Simulation Results and Analysis

Simulation results about average vehicle traveling time are summarized in Fig. 8. From Fig. 8., we can see that our algorithm ARD-BP outperforms other algorithms and achieves the lowest average vehicle traveling time for almost all vehicle arrival rates. For example, it reduces average vehicle traveling time by percentage ranging from 67% to 83% under relatively high vehicle arrival rates when compared to other three algorithms. It verifies the effectiveness our algorithm in reducing traffic congestion. Average vehicle traveling time under ARD-BP is slightly larger than that of SP-BP at low vehicle arrival rates. This is because under low vehicle arrival rates, traffic congestion is not a problem, better routing choices may be shortest paths.

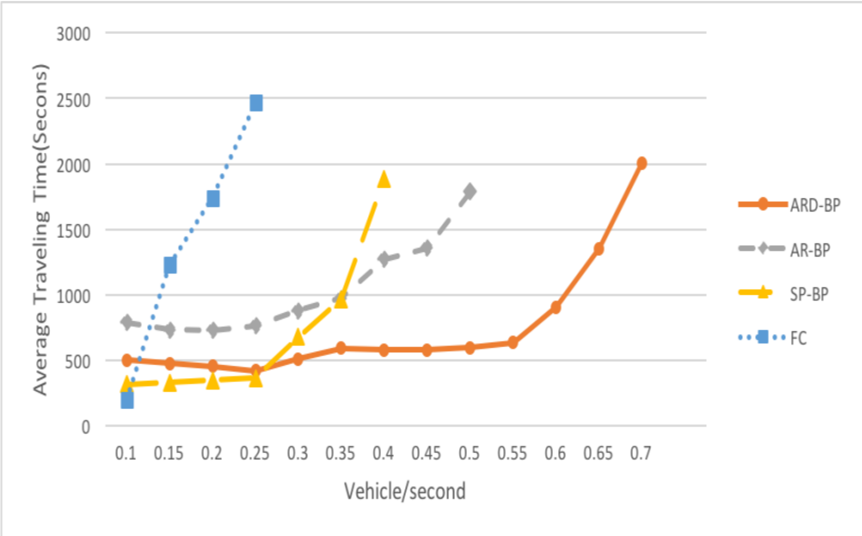

Fig. 8. Average vehicle traveling time with increasing vehicle arrival rate under different algorithms. For AR-BP and ARD-BP, $\alpha = 2$.

Fig. 9 shows simulation results of average number of vehicles in network. This figure directly proves that the number of vehicles in road network under our algorithm is smaller than other algorithms at a same arrival rate, meaning less traffic congestion. Furthermore, in Fig. 9 the average number of vehicles in network of all the other algorithms stop growing at a lower arrival rates when compare to our algorithm, which means they do net allow vehicles enter to the network early. In other words, our algorithm improves the utilization of the road network and expands the network capacity. Fig. 10 shows that more vehicles can arrive at destinations under our algorithm ARD-BP, meaning that vehicles under other algorithms are blocked in road network.

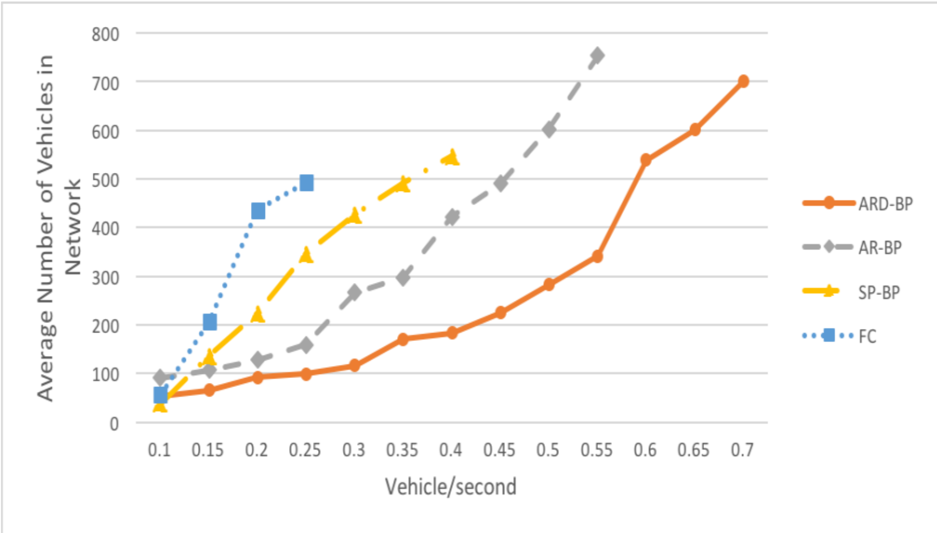

Fig. 9. Average number of vehicles in road network with increasing vehicle arrival rate. For AR-BP and ARD-BP, $\alpha = 2$.

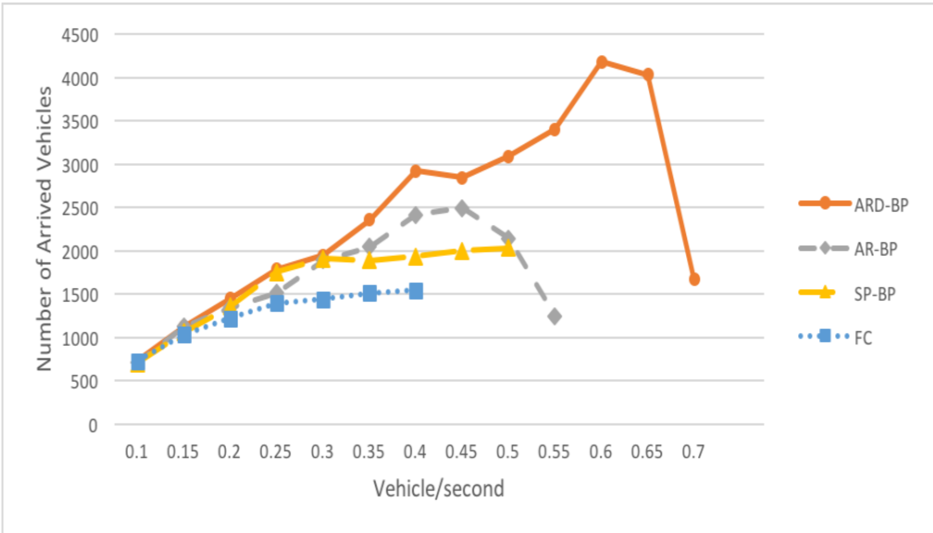

Fig. 10. Number of vehicles arriving at destinations with increasing vehicle arrival rate. For AR-BP and ARD-BP, $\alpha = 2$.

The system time of our algorithm is slotted, we run simulations to investigate the effect of time slot duration on vehicle travelling time. Simulation results are summarized in Fig. 11. Minimum average travelling time is achieved when time slot is set to 15 seconds. Thus, we choose 15 seconds to be the duration of system time slot.

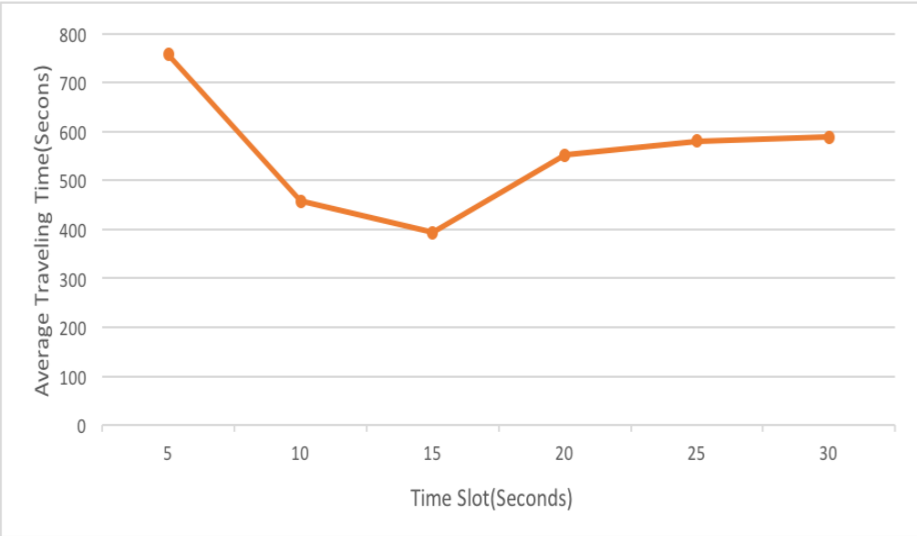

Fig. 11. Average traveling time at different time slot duration. For AR-BP and ARD-BP, $\alpha = 2$, vehicle arrival rate is set to be 0.3 vehicle/second.

Finally, we examine the effect of parameter α on ARD-BP performance. From Fig. 12, we can see that average traveling time under ARD-BP first decreases as α increases and then increases as α further increases. Clearly, there is an optimal value of α such that ARD-BP achieves the lowest average traveling time.

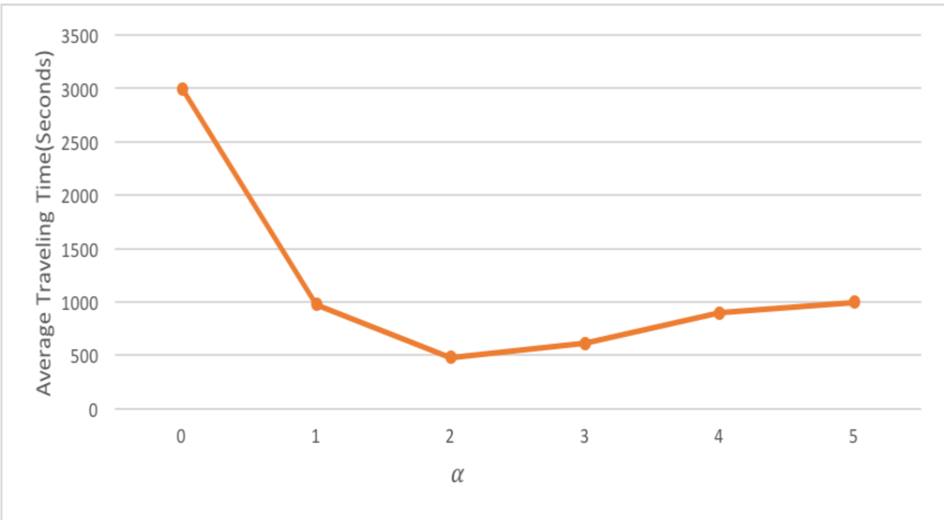

Fig. 12. Effect of parameter α on average traveling time under ARD-BP. Vehicle arrival rate is set to be 0.3 vehicle/hour.

Finally, we evaluate the fairness of our algorithm. Fig.13 shows that most (93%) vehicles arrive at their destination within 900 seconds, which is less than twice the average traveling time (489 seconds). So, our algorithm is fair for most vehicles.

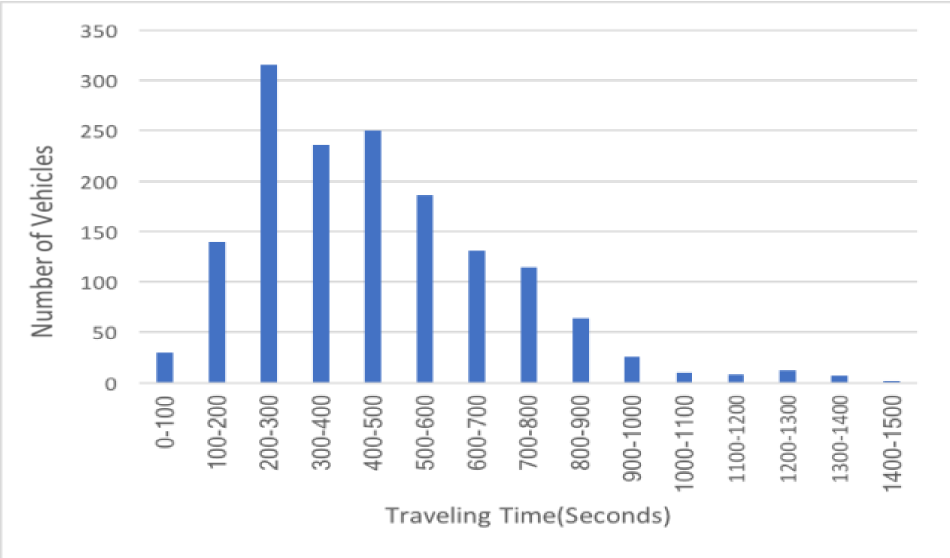

Fig. 13. Histogram of number of vehicles of different travelling time. Vehicle arrival rate is set to be 0.3 vehicle/second and the average traveling time is 489 seconds.

In summary, by introducing novel shadow buffers, shadow queues and real-time control information update, our adaptive traffic signal control and vehicle routing algorithm ARD-BP greatly improves road network utilization, reduces traffic congestion and thus vehicle traveling time. Our algorithm is superior to the one proposed in [18].

5 Conclusion

In this thesis, we proposed a back-pressure based adaptive traffic signal control and vehicle routing algorithm ARD-BP. Our algorithm considers the reality that vehicles need time to travel across roads and achieves consistency between controllers' viewpoint of traffic congestion situation and real traffic situation by using novel mechanism of shadow buffers, shadow queues and real-time control information update. Our algorithm greatly reduces traffic congestion and vehicle traveling time as verified by simulations and is superior to other three algorithms.

As depicted in section 3, our algorithm contains two controls: traffic signal control and vehicle route selection. It is with high operability for self-driving vehicles to accept the execute the instruction. But for manual drivers they may not follow the route selection provided by the system. Thus, it is necessary to consider the situation when some vehicles will not follow the instructions. And for this situation how can the algorithm be improved is the future work of this research.

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