A Simulation Study on Prioritizing Connected Freight Vehicles at Intersections for Traffic Flow Optimization (Industrial Paper)

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Abstract

Due to the importance of road freight, there is a significant cost of delaying freight vehicles on the road. In this work, we focus on freight vehicle optimization by reducing delays at intersections. Our simulation study evaluates the effectiveness of an autonomous intersection management strategy that prioritizes connected freight vehicles using intelligent traffic lights. We simulate a wide range of traffic scenarios on our microscopic traffic simulator. Our results show that the strategy can help reduce the delay of freight vehicles with a minimal impact on other vehicles in a real road network. Our simulations also reveal the scenarios where the strategy works best and where it should be avoided. Effects of individual parameters are also measured through simulations.

CCS Concepts

• **Computing methodologies → Simulation evaluation**; • **Applied computing → Transportation**.

Keywords

traffic simulation, connected vehicle, intelligent transportation, autonomous intersection management

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1 Introduction

Road freight is the most valuable mode in freight shipments [4]. A delay of freight vehicles on the road can lead to significant financial losses [9]. As freight vehicles take a longer time to decelerate and accelerate compared to passenger cars, slowing down at traffic lights can have a detrimental impact on the flow of freight vehicles. Therefore, in this work we focus on the delays caused by slowdown at traffic lights. To mitigate such delays, one needs to reduce the number of red lights on the path of freight vehicles. To achieve this, intelligent transportation systems can apply **autonomous intersection management (AIM)** strategies that prioritize freight vehicles at traffic lights. The AIM strategies are technically feasible thanks to the availability of connected vehicles and adaptive traffic control systems. Several simulation studies have explored the AIM-based freight vehicle prioritization [16, 20, 29]. Implementing the AIM strategies in the real world was also attempted, though at a small scale [28]. All the existing studies show limitations when evaluating the impact of AIM strategies. They either use a small set of parameters or focus on simple networks with a few intersections. There is still a lot to learn before large-scale deployment of the AIM strategies can materialize. We fill the gap and aim to broaden the understanding by simulating a large number of traffic scenarios using road networks at different scales.

Our work is inspired by a recent trial of connected trucks in Wollongong, Australia, where the trucks requested priority to pass intersections by sending certain information to a traffic control system. The information was collected via Telstra mobile network. Telstra is an Australian telecommunication company that supports innovative vehicle-to-infrastructure applications. The trucks participated in the trial used the fleet tracking solution from MTData, a subsidiary of Telstra that provides connected vehicle technology. The area of the trial is shown in Figure 1. The roads travelled by the connected trucks are highlighted in the figure. The trucks requested priority for passing 5 intersections, each of which has a unique ID as shown in the figure. The data collected from the trial shows that the existing traffic control system can accurately track connected

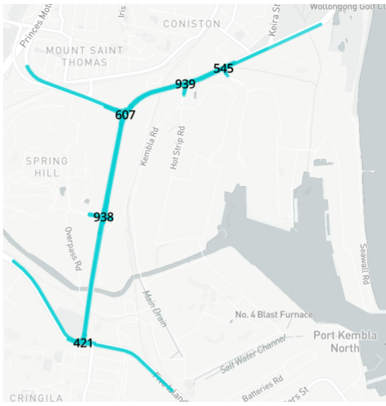


Figure 1: An area in Wollongong, Australia, where a trial of connected trucks was conducted.

trucks that are approaching intersections. The success of the trial proves that there is an actual use case for AIM. However, before the deployment of AIM, which will require significant investments, it is important to have a comprehensive understanding of the impact of AIM on transportation networks. For this reason, Telstra collaborated with us to create an AIM strategy and the experimental setup based on the results from the trial.

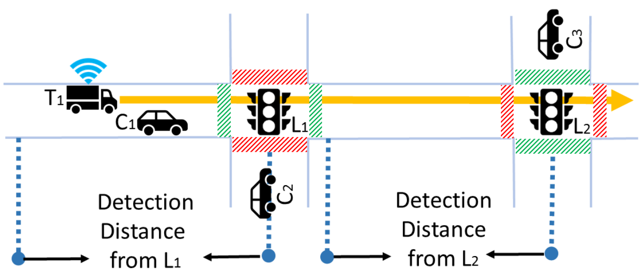


Figure 2: Prioritizing a connected truck using AIM. Traffic lights L_1 and L_2 are along the route of a connected truck T_1. Traffic light color at each entry point to an intersection is shown. T_1 is prioritized at L_1 as the truck is within the detection distance from the light. The three cars (C_1 to C_3) are not connected to the system.

Our AIM strategy assumes that connected freight vehicles can periodically send their GPS position, speed and route to nearby traffic infrastructures. Once a connected freight vehicle has arrived within a certain distance to an intelligent traffic signal, it is detected by the traffic signal, which will then adjust the color phase for the vehicle. A simple example is illustrated in Figure 2, where a connected truck is going to pass two intersections along its route. In the example, traffic light L_1, which has detected the truck, would keep green for the truck until a maximum green light period is reached or when the truck has crossed the intersection. As the truck would not need to stop at L_1, the delay of the truck at the intersection would be minimized. Other vehicles around the truck may also benefit from the traffic light prioritization. In this example, car C_1 would pass the intersection without delay. Traffic light L_2 does not turn green for the truck at this moment because the truck is beyond the detection distance from L_2. Despite the potential benefit of freight vehicle prioritization, traffic in some parts of a road network can be negatively impacted by the dynamic change of traffic lights. For example, in Figure 2, car C_2 may experience a longer delay as it has to stop at L_1 for the truck.

To comprehensively evaluate the impact of the AIM strategy, we first identify a range of parameters that can affect traffic performance in a road network. We then run simulations on a real road network to test the performance of the strategy under realistic settings at a large scale. After that, we perform a multi-dimensional parameter scan by running numerous simulations on a synthetic network with different combinations of settings. The parameter scan reveals the scenarios where the AIM strategy works best and the scenarios where the strategy is detrimental to traffic performance. Finally, we evaluate the effects of individual parameters using further simulations on synthetic networks.

Our simulations are performed on *Scalable Microscopic Adaptive Road Traffic Simulator (SMARTS)* [22]. SMARTS is capable of simulating different driving behaviour, adaptive traffic lights and common traffic rules. It has been used for research in many areas such as autonomous vehicles [27] and dynamic road configurations [12].

A key observation that we made from the study is that the overall performance of a road network is predominantly determined by the performance of non-freight vehicles, which cover a majority of the traffic. Thus, when freight vehicle prioritization has positive effects on non-freight vehicles, the network-level performance improves, and vice versa. We also observe that connected freight vehicles can achieve a significant performance improvement at a small cost of other vehicles in certain scenarios.

The rest of the paper is organized as follows. Section 2 discusses related work. Section 3 describes the key concepts and our approach for studying freight vehicle prioritization. Section 4 details the experimental setup and results. We conclude the paper in Section 5.

2 Related Work

We describe relevant work in three areas, autonomous intersection management, simulation of connected autonomous vehicles and studies on freight vehicle prioritization.

2.1 Autonomous Intersection Management

A large body of research work has been done on autonomous intersection management (AIM). One direction of research focuses on the schedule and order of vehicle arrivals at intersections [25]. For instance, some research work focuses on the least restrictive supervisory control for vehicles at intersections [6, 7], where a traffic control system intervenes when the current actions of vehicles would lead to collisions at intersections. The control system will adjust the schedule of vehicle arrivals for mitigating safety risks. There is a solution that uses linear programming formulation to optimize the order of vehicle arrivals at intersections [1]. The solution considers four types of conflicts between vehicles at intersections and the kinodynamic constraints of vehicles. Carlino et al. propose a solution that uses an auction-based method to manage intersection passing [5]. The solution allows drivers to bid on the order to pass an intersection based on the drivers' value of time. To achieve a certain level of fairness and a good traffic flow, the solution also uses a system-level mechanism to regulate the auction process.

Another research direction focuses on optimizing vehicle trajectories around intersections by adjusting the motion of vehicles [15].

For example, Au et al. develop an optimization procedure that can adjust proportional integral derivative controllers in a real autonomous vehicle [2] . The procedure is tailored for AIM such that the vehicle can arrive at an intersection sooner at a higher velocity while obeying speed limit constraints. The procedure also utilizes a smoothing technique that enables the vehicle to decelerate gracefully. Our recent work [11] develops a machine learning-based solution to control the motion of autonomous vehicles such that the vehicles can arrive at intersections at scheduled times while maintaining a safe gap to their front vehicles. Our solution uses a variation of Q-learning to plan the trajectories of vehicles.

Existing research on AIM generally assumes that vehicles can adjust their schedule and motion frequently [19]. Thus, many existing AIM solutions are suitable for a future generation of traffic environments where the traffic mainly consists of connected autonomous vehicles. Differently, this study focuses on a readily deployable AIM strategy. The two main components involved in the strategy, the connected vehicles and the adaptive traffic signals, are already widely available in the real world [14, 24].

2.2 Simulation of Connected Autonomous Vehicles

Traffic simulations are commonly used in studying connected autonomous vehicles (CAVs). In our previous work, we use the SMARTS simulator to evaluate the impact of automation levels on traffic efficiency and safety in three road networks of different scales [27]. In our simulations, automation levels affect the aggressiveness in car-following and lane-changing models. Our results show that there is a considerable safety risk when highly automated vehicles are mixed with human-driven vehicles. Mattas et al. evaluate the impact of CAVs and autonomous vehicles without connectivity (AVs) by simulating traffic on a ring road without traffic lights [18]. Similar to our previous work, they vary the percentage of autonomous vehicles in different simulation scenarios. Their simulations show that AVs can have a negative impact on traffic speed but CAVs can improve speed by cooperating with other CAVs. Hallé and Chaib-draa study vehicle platooning by simulating autonomous vehicles in a 3D environment [13]. Simulations are done on a straight, one way, hight-way segment. The study compares the effectiveness of centralized platoon coordination where a leader vehicle gives orders to the rest of the platoon, and decentralized coordination where each vehicle in the platoon makes decisions autonomously. Our previous work also simulates autonomous vehicle platooning [21]. The work measures the travel time of vehicles on two corridors that cross each other at a signalled intersection. The simulations are done with our SMARTS simulator [22], and show that the travel time of vehicles can be reduced significantly if some vehicles on the same road can form platoons before reaching the intersection. Gueriau et al. build a simulation framework for studying cooperative driving with connected vehicles [10]. Their simulations consider the unreliability of sensors that can lead to wrong readings of speed and space headway. They find that traffic perturbations caused by unreliable sensors are reduced when the penetration rate of cooperative vehicles increases. Different to the aforementioned studies, the study shown in this paper focuses on the connectivity between freight vehicles and intelligent traffic lights.

2.3 Studies on Freight Vehicle Prioritization

Existing studies on freight vehicle prioritization mostly focus on a limited set of traffic scenarios. Zhao and Ioannou simulate freight vehicle prioritization on a real road network with a number of traffic signals. Their work is based on two truck penetration rates and two types of traffic controllers, one with truck priority and one without truck priority [29]. All the trucks are assumed to be connected trucks. The traffic demand in the simulation area is constant in all the simulations. Different to their work, we simulate various levels of truck connectivity and traffic demand. We also use a number of synthetic road networks for comprehensive testing in addition to a real network in our simulations. Zamanipour et al. simulate prioritization of certain types of vehicles, including trucks and transit vehicles, in an Arizona road network with six intersections [28]. Unlike our study, their work does not show the impact of the cycle length of traffic lights. They also conduct a field test of their AIM strategy at one intersection, where two trucks and two transit vehicles did some round-trips across the intersection. Kari et al. run simulations on a synthetic network with one intersection [16]. Similar to our work, they consider the situation where main street traffic and cross-street traffic have different traffic volumes. However, their road network is relatively simple and their experiments do not test as many parameters as our work does. In addition, we not only test the effects of individual parameters but also perform a parameter scan to find the best cases and the worst cases considering all the combinations of parameter settings. A simulation study done by Park et al. focuses on a short corridor with six traffic lights in Virginia [20]. Their work assumes that truck penetration rate is fixed, whereas we evaluate the effects of different truck penetration rates. As a relevant work, we simulate emergency vehicle prioritization where connected emergency vehicles get more road space and more green lights compared to normal vehicles [26]. Emergency vehicle prioritization is different to freight vehicle prioritization in many aspects. For example, in our previous work, normal vehicles in front of emergency vehicles must give way to the emergency vehicles, whereas vehicles in front of trucks do not have to give way to the trucks in this work. To the best of our knowledge, there is a lack of simulation study that provides a comprehensive view on freight vehicle prioritization using AIM. We fill the research gap in this work.

3 Simulation Study

3.1 AIM Strategy

We study an AIM strategy that helps maximize green light time for freight vehicles. The strategy can be applied to any intersection with adaptive traffic signals that can dynamically change the timing of different color phases. For simplicity, we describe the strategy based on a normal intersection where two roads intersect.

For an adaptive traffic signal, the strategy sets a **maximum cycle length**, which is the longest possible period from when a direction gets a green light to the next time that the same direction gets a green light. The **maximum total green time** is the maximum cycle length minus the total intergreen time. An intergreen period is the period between the end of the green period of one phase and the beginning of the green period of the next phase, which is normally a fixed value. For example, assuming the maximum cycle length is 120 seconds and one intergreen period lasts 10 seconds, the maximum total green time is $120 - 10 \times 2 = 100$ seconds. The maximum total green time can be evenly or unevenly distributed to the crossing roads. Given two roads, r_1 and r_2, the maximum green times for the roads are denoted as **mg1** and **mg2**, respectively. We assume that an incoming connected freight vehicle can be detected by a traffic signal when the vehicle is within a **detection distance** from the intersection. The strategy switches green light between different roads under certain situations. Assuming the current green light is given to road r_1, the strategy will switch green light to r_2 in any of the following circumstances.

- The accumulated green time of r_1 reaches $mg1$.
- There is no detected freight vehicle on r_1 but one or more freight vehicles are detected on r_2. In other words, the strategy grants green light to freight vehicles on a conflicting road when the current green-lighted road is clear of freight vehicles.
- There is no traffic on r_1 but there is traffic on r_2.

As shown in the rules, the AIM strategy can shorten the green time of a road for accommodating incoming trucks on a conflicting road. That is, the actual green light time for a road may be shorter than the maximum green time in some occasions. As a result, the actual cycle length may be shorter than the maximum cycle length.

3.2 Key Parameters

We identify the key parameters that may affect the effectiveness of the AIM strategy. Each parameter is detailed in this section.

Traffic Volume. This is a major factor contributing to traffic performance in the real world. As traffic volume generally depends on road type, our simulations with synthetic networks mainly focus on three common road type combinations at an intersection: major-major, major-minor and minor-minor. The default traffic volume of both road types is extracted from real traffic statistics of Victoria, Australia in the form of annual average daily traffic (AADT) [8]. The major road AADT is based on the records of the top 100 highest-volume non-freeway roads, which is 25000. The minor road AADT is based the records of other non-freeway roads, which is 5000. Based on this, the three aforementioned road type combinations correspond to three traffic volume combinations, {25000,25000}, {25000,5000} and {5000,5000}.

Truck Ratio. The impact of the intersection management strategy may be limited if there are few freight vehicles on the road. Based on the real statistics mentioned above, the percentage of trucks is around 8%. We observe that trucks may only appear on one of the crossing roads at many intersections. For example, in a residential area split by a main road, trucks tend to travel through the main road and they rarely travel through the narrow, minor roads. We consider different combinations of truck ratios at an intersection in the simulations with synthetic networks.

Truck Connectivity. This is the ratio of connected trucks over all trucks. This parameter is important since truck connectivity varies significantly in different scenarios in the real world.

Motion Factor. In many scenarios, the limit of acceleration and deceleration is globally affected by weather, time of day, etc. For example, vehicles tend to accelerate more slowly in wet weather. In this study, the default limit of acceleration and deceleration is based on a work on vehicle mobility models [17]. We apply a motion factor to the limit across different simulation scenarios. The range of the factor is 0.5 to 1.5. A motion factor of 0.5 implies that the limit of acceleration and deceleration is halved, which may reflect traffic characteristics in certain areas [3]. A motion factor of 1.5 may reflect traffic characteristics on the other side of the spectrum.

Look-ahead Distance. The look-ahead distance is the maximum distance from a vehicle to an object that may impede the movement of the vehicle. Drivers normally consider traffic conditions for some distance ahead. When drivers can look further ahead, they have more time to adjust speed based on traffic lights, which can affect traffic performance. The look-ahead distance can vary in different situations. For example, the look-ahead distance is likely to decrease when vehicles enter narrow, bending streets from wide, straight roads.

Max Cycle Length. The maximum cycle length varies significantly across different areas in the real world. A certain cycle length may help mitigate congestion in some areas but cause problems in other areas. Generally a short cycle is considered to be 60 seconds while a long cycle is considered to be 120 seconds. We set intergreen time to 10 seconds based on observation of real intersections.

Green Time Equality. In situations where freight vehicles constantly come from all directions, the green light at a road is likely to last for the maximum green time allocated to the road. The maximum green time for different roads at an intersection can be the same or be different. This parameter controls the level of equality of the maximum green time between different roads. A value of 1 achieves a perfect equality, where each road gets an equal maximum green time. If it is 0, the possible difference of the maximum green time is the highest, where we assume that the time is distributed based on traffic volume. For example, assuming that the volume of one road is 5 times the volume of another road at an intersection, the maximum green time for the former road would be 5 times the maximum green time of the later road. Given a maximum total green time in one cycle mt, the volume of n different roads at an intersection $\{v_1,...,v_n\}$, and the equality parameter e, the maximum green time allocated to a road $i \in n$ is computed as $allocation_i = mt \times \left[\frac{v_i}{\sum_{i=1}^{n} v_i} + e \times \left(\frac{1}{n} - \frac{v_i}{\sum_{i=1}^{n} v_i}\right)\right]$.

Detection Distance. The detection distance is the maximum distance from a connected truck to an intelligent traffic signal that detects the truck. The detection distance can be affected by natural factors such as weather, surrounding buildings, etc. The detection distance may also need to be artificially adjusted in some circumstances, e.g., ignoring connected trucks that are far away from a traffic light.

3.3 Metrics

We evaluate traffic performance based on the following metrics.

Trip Counts. To measure accumulated traffic performance, we count the vehicles that have completed their trips during a simulation. Trips counts are collected for specific types of vehicles and also for all the vehicles.

Average Speed. The average speed is computed for different groups of vehicles, such as trucks on major roads, trucks on all the roads or all the vehicles in the entire network.

Average Number of Stops. We assume that a vehicle is attempting to making a stop if its speed is below 5kph. Vehicles that goes through a number of intersections on a corridor achieve a better performance if their average number of stops is lower.

3.4 Methodology

Our simulation study consists of three parts. The first part tests the effectiveness of the AIM strategy under realistic settings on a real road network. The second part uses a multi-dimensional parameter scan to find the scenarios where the AIM strategy would be most or least beneficial. The last part evaluates the impact of individual parameters across numerous synthetic road network configurations.

3.4.1 *Estimating Performance in Real Environment*

We collect the average speed of cars and trucks with different truck connectivity levels and different traffic volumes in an area east to Melbourne city. The experiment is detailed in Section 4.1.

3.4.2 *Finding Best Cases and Worst Cases*

This part uses a parameter scan to identify the patterns in the scenarios where the AIM strategy would be most beneficial and least beneficial. By comparing the patterns in the best-performing cases and the worst-performing cases, we can gain insight about the performance of freight vehicle prioritization. The study is done in the following way. First, for each parameter described in Section 3.2, we choose several key values within a range. For example, we pick three values for the motion factor parameter, which are 0.5, 1 and 1.5. For each unique combination of parameter values, we run a simulation on a synthetic road network. As the impact of freight vehicle prioritization is maximized when all the trucks are connected (100% connectivity) and is non-existent when all the trucks are not connected (0% connectivity), we compute the change of traffic performance between 100% connectivity and 0% connectivity. If the change is positive, the strategy helps improve traffic performance. Otherwise, the strategy does not help. We rank the simulations based on the change of traffic performance to find the best cases and the worst cases. More details about the parameter scan are shown in Section 4.2.

3.4.3 *Testing Individual Parameters*

Different to the parameter scan, this set of experiments focuses on the effects of individual parameters. Based on the best cases found during the parameter scan, we choose a default setting for each parameter. Then, for each parameter, we run simulations with different values of the parameter while keeping other parameters at their default values. By doing so, the change of traffic performance is only affected by the change of a single parameter. In this part, we use 5 synthetic road networks with different levels of complexity. This part of experiments is detailed in Section 4.3.

4 Experiments

This section presents the setup and results of our experiments. The section has three parts, real network simulations, parameter scan and individual parameter study.

4.1 Simulation of Real Traffic Network

In this part, we first describe the setup of the real network simulations then present our findings from the simulations.

4.1.1 *Simulation Setup*

We observe that the areas most affected by freight vehicles are in large cities where freight vehicles are mixed with passenger cars. In this experiment, we focus on one such area east to Melbourne city. The dimensions of the area are about 12km by 12km. We download a road network of the area from OpenStreetMap. The road network is shown in Figure 3. The total road length in the network is about 650km, where each direction of a two-way road is treated separately. We identify 338 signalled intersections in the area. We keep a constant traffic load in the area during a simulation. Whenever a simulated vehicle reaches its destination, a new vehicle is inserted into the network. The origin and destination of all the vehicles are uniformly distributed in the area at random. A vehicle follows the shortest path from its origin to its destination.

Figure 3: The Melbourne road network used in our simulations.

Due to the limitation of real traffic data, we estimate the total number of vehicles in the area based on traffic statistics for Victoria, Australia [8] and the road types in the area. The normal traffic load in the area is estimated to be between 2000 and 3000. We vary the value between 1000 and 5000 for simulating traffic in different times of the day. For each traffic load, we run 3 simulations with different truck connectivity levels. Each run simulates one-hour traffic.

We set other parameters to fixed values. Max cycle length is set to 90 seconds as it is a common value used in Melbourne [23]. Green time equality is set to 1 as there is no data showing the time distribution at each intersection. Motion factor is set to 1 as we use the default acceleration/deceleration values from an existing work [17]. Truck ratio is set to 0.08 based on real traffic statistics for Victoria [8]. Look-ahead distance is set to 300m based on our experience. Detection distance is set to 300m as we see from real connected vehicle data that the communication range is normally hundreds of metres.

4.1.2 *Results*

Our simulations show that the AIM strategy is beneficial under all the three traffic loads (Figure 4). The speed of trucks improves while the car speed keeps mostly steady when truck connectivity increases from 0% to 100%. The speed improvement is 8.3%, 9.2% and 11.4%, for 1k, 3k and 5k traffic load, respectively. Results show that the percentage improvement is more prominent when the road network is more congested. At 100% connectivity, truck speed reaches car speed under all the three traffic loads.

4.2 Parameter Scan

In this part, we first describe the setup of the parameter scan then present the results.

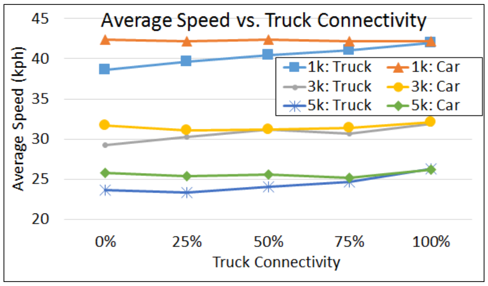


Figure 4: Average speed on the real network under 3 traffic loads, 1k, 3k and 5k.

4.2.1 *Simulation Setup*

We use a 5x5 synthetic road network for all the simulations in the parameter scan. The network consists of 5 western/eastern roads that cross 5 northern/southern roads. As our focus is on intersecting traffic, we create vehicles that do not make turns so that any vehicle needs to pass 5 intersections during its trip. All the roads in this network are two-way roads. There is a traffic signal at each of the 25 intersections. The total intergreen time in a light cycle is 20 seconds. Each road segment is 1km in length. The total length of a road is 6km in each direction. The speed limit of the roads is set to 70km/h, which is a common value for roads in Melbourne, Australia.

The parameter values used in the scan are detailed in Table 1. As mentioned in Section 3.2, we mainly consider three traffic volume combinations at intersections. Given a traffic volume combination $\{v_x, v_y\}$, each western/eastern road will have a traffic volume v_x and each northern/southern road will have a traffic volume v_y. As the values in the combinations are in the form of AADT, we convert the AADT values to the rates that vehicles are injected from the starting point of roads. Similar to traffic volume, the parameter scan considers three combinations of truck ratios at intersections. Given a combination $\{r_x, r_y\}$, the ratio of trucks on each western/eastern road will be r_x and the ratio of trucks on each northern/southern road will be r_y. Based on Table 1, there are 1944 combinations of parameter values. For each combination, we run three simulations with the same settings. Each of them simulates 30-minute traffic on the synthetic road network. The results are averaged from the three runs.

Table 1: Settings for parameter scan.

Parameter	Values
Truck Connectivity	0%, 50%, 100%
Motion Factor	0.5, 1, 1.5
Look-ahead Distance	100m, 300m
Green Time Equality	0, 1
Max Cycle Length	60s, 90s, 120s
Traffic Volume	{25000,25000}, {25000,5000}, {5000,5000}
Truck Ratio	{0.08,0.08}, {0.08,0}, {0,0.08}
Detection Distance	100m, 300m

We are particularly interested in the change of accumulated performance when truck connectivity increases from 0% to 100%. We measure accumulated performance using the percentage change of trip count in this parameter scan. A positive percentage change indicates that the AIM strategy is beneficial at the network level.

4.2.2 *Results*

Table 2 and Table 3 show the best scenarios and the worst scenarios in terms of the percentage change of total trip count (denoted as Total # Change). Each record in the tables also shows percentage changes of truck trip count and car trip count, denoted as Truck # Change and Car # Change, respectively. Key parameter settings of the scenarios are also included in the tables. For example, the top record in Table 2 shows that the throughput of the whole network improves by 4.22% when the AIM strategy is applied to the maximum level, i.e., when all the trucks are connected. We can see that the performance change of trucks and cars are 10.5% and 3.8%, respectively. Table 4 and Table 5 show the best and the worst scenarios in terms of the percentage changes of truck trip counts.

Based on the results, we observe that the change of total trip count is generally tied to the change of car trip count. For example, in Table 3, both types of changes are around -30% while trucks record positive changes. This pattern is due to the fact that the majority of the traffic consists of cars. Therefore, the AIM strategy is not suitable where it has a large negative impact on cars.

The AIM strategy works in the most balanced way when it helps improve the performance for all vehicles, which are the cases shown in Table 2. In these cases, trucks obtain 5.2%-11.5% improvements while cars get 2.2%-3.8% improvements. The overall traffic performance gets 2.7%-4.2% improvements. These best cases have some common characteristics. First, they are all achieved where major roads intersect minor roads. Second, they all use evenly distributed maximum green time in one light cycle. Third, all the major roads have trucks. Based on these characteristics, we believe the reason behind the improvements of accumulated traffic performance is that the AIM strategy increases the ratio of major roads' green time over minor roads' green time. As most of the vehicles in the whole network travel on the major roads, this helps improve the overall traffic performance.

All the worst cases of overall performance change share a different set of characteristics (Table 3). First, all of them are achieved where major roads intersect major roads. Second, trucks come from only one of the major roads at an intersection. Third, vehicles move with a low acceleration rate and a low deceleration rate. The poor performance is due to the fact that prioritizing traffic for only one major road causes significant congestion on the other major road. In addition, when vehicles accelerate and decelerate more slowly, clearing vehicle queue at congested intersections would take a longer time, lowering the overall traffic performance further.

We observe that it is possible to improve truck performance significantly while slightly decreasing the performance of other vehicles. As shown in Table 4, we can achieve 16.4%-31.4% truck improvements while decreasing the car performance by 1.1%-4.8%. All the cases are achieved where trucks only travel on minor roads that cross major roads. And, nearly all the cases use unequal green time distribution that leads to short green time for minor roads. When the trucks are not connected, they tend to wait for a long time at traffic lights because the minor roads tend to only get a small portion of the total green light time. On the contrary, when the trucks are connected, the AIM strategy would frequently lengthen green light time for minor roads, thus allowing more trucks to cross the intersections without delay.

Table 2: Settings for 10 best percentage changes of total trip count when truck connectivity increases from 0% to 100%.

Rank	Total # Change	Truck # Change	Car # Change	Motion Factor	Look-ahead Distance	Green Time Equality	Max Cycle Length	Traffic Volume	Truck Ratio	Detection Distance
1	4.22%	10.5%	3.8%	0.5	300m	1	90s	{25k,5k}	{0.08,0}	300m
2	3.76%	6.5%	3.6%	0.5	300m	1	90s	{25k,5k}	{0.08,0.08}	300m
3	3.73%	5.5%	3.6%	1	300m	1	90s	{25k,5k}	{0.08,0.08}	300m
4	3.58%	6.33%	3.36%	1.5	300m	1	90s	{25k,5k}	{0.08,0.08}	300m
5	3.33%	7.98%	3.03%	1	300m	1	120s	{25k,5k}	{0.08,0}	300m
6	3.18%	8.33%	2.84%	1	300m	1	90s	{25k,5k}	{0.08,0}	300m
7	2.93%	11.31%	2.42%	0.5	300m	1	120s	{25k,5k}	{0.08,0}	300m
8	2.89%	6.09%	2.68%	1	300m	1	90s	{25k,5k}	{0.08,0}	100m
9	2.83%	5.16%	2.64%	1	300m	1	90s	{25k,5k}	{0.08,0.08}	100m
10	2.71%	11.52%	2.2%	0.5	300m	1	60s	{25k,5k}	{0.08,0}	300m

Table 3: Settings for 10 worst percentage changes of total trip count when truck connectivity increases from 0% to 100%.

Rank	Total # Change	Truck # Change	Car # Change	Motion Factor	Look-ahead Distance	Green Time Equality	Max Cycle Length	Traffic Volume	Truck Ratio	Detection Distance
10	-29.95%	13.5%	-31.4%	0.5	300m	1	60s	{25k,25k}	{0,0.08}	300m
9	-30.17%	12.42%	-31.6%	0.5	300m	0	60s	{25k,25k}	{0,0.08}	300m
8	-30.36%	12.53%	-31.89%	0.5	300m	0	90s	{25k,25k}	{0.08,0}	300m
7	-30.59%	11.93%	-32.09%	0.5	300m	1	90s	{25k,25k}	{0,0.08}	300m
6	-30.87%	7.33%	-32.25%	0.5	300m	0	120s	{25k,25k}	{0,0.08}	300m
5	-31.07%	6.98%	-32.45%	0.5	300m	1	120s	{25k,25k}	{0,0.08}	300m
4	-31.31%	11.1%	-32.81%	0.5	300m	0	90s	{25k,25k}	{0,0.08}	300m
3	-31.56%	11.93%	-33.1%	0.5	300m	1	90s	{25k,25k}	{0.08,0}	300m
2	-31.69%	9.06%	-33.16%	0.5	300m	1	120s	{25k,25k}	{0.08,0}	300m
1	-31.93%	7.82%	-33.37%	0.5	300m	0	120s	{25k,25k}	{0.08,0}	300m

Table 4: Settings for 10 best percentage changes of truck trip count when truck connectivity increases from 0% to 100%.

Rank	Truck # Change	Total # Change	Car # Change	Motion Factor	Look-ahead Distance	Green Time Equality	Max Cycle Length	Traffic Volume	Truck Ratio	Detection Distance
1	31.39%	-4.51%	-4.83%	0.5	300m	0	120s	{25k,5k}	{0,0.08}	300m
2	29.96%	-3.09%	-3.4%	0.5	300m	0	90s	{25k,5k}	{0,0.08}	300m
3	24.04%	-4.39%	-4.64%	0.5	300m	0	120s	{25k,5k}	{0,0.08}	100m
4	23.33%	-3.55%	-3.81%	0.5	100m	0	120s	{25k,5k}	{0,0.08}	300m
5	20.85%	-2.21%	-2.45%	0.5	100m	0	90s	{25k,5k}	{0,0.08}	300m
6	18.43%	-1.43%	-1.64%	1	300m	0	90s	{25k,5k}	{0,0.08}	300m
7	16.92%	-1.47%	-1.66%	1	300m	0	60s	{25k,5k}	{0,0.08}	300m
8	16.89%	-1.47%	-1.66%	1	100m	0	120s	{25k,5k}	{0,0.08}	100m
9	16.89%	-0.9%	-1.08%	1	300m	0	90s	{25k,5k}	{0,0.08}	100m
10	16.36%	-2.51%	-2.71%	0.5	100m	1	120s	{25k,5k}	{0,0.08}	300m

Table 5: Settings for 10 worst percentage changes of truck trip count when truck connectivity increases from 0% to 100%.

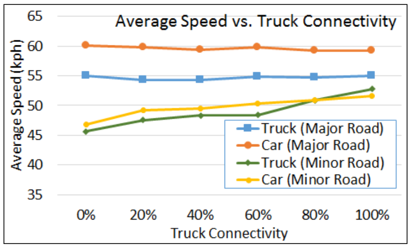
Rank	Truck # Change	Total # Change	Car # Change	Motion Factor	Look-ahead Distance	Green Time Equality	Max Cycle Length	Traffic Volume	Truck Ratio	Detection Distance
10	-5.01%	-5.48%	-5.51%	1	300m	1	60s	{25k,25k}	{0.08,0.08}	100m
9	-5.17%	-4.77%	-4.73%	1.5	300m	1	60s	{25k,25k}	{0.08,0.08}	100m
8	-5.17%	-4.71%	-4.68%	1.5	300m	0	60s	{25k,25k}	{0.08,0.08}	100m
7	-5.55%	-4.86%	-4.81%	1.5	100m	0	60s	{25k,25k}	{0.08,0.08}	100m
6	-5.77%	-4.83%	-4.75%	1	100m	0	120s	{25k,25k}	{0.08,0.08}	100m
5	-6.09%	-6.8%	-6.85%	0.5	300m	0	120s	{25k,25k}	{0.08,0.08}	300m
4	-6.23%	-5.64%	-5.6%	1.5	100m	1	60s	{25k,25k}	{0.08,0.08}	100m
3	-6.26%	-6.6%	-6.62%	0.5	300m	1	120s	{25k,25k}	{0.08,0.08}	300m
2	-6.34%	-8.54%	-8.71%	0.5	300m	0	120s	{25k,25k}	{0.08,0.08}	100m
1	-6.93%	-7.87%	-7.94%	0.5	300m	1	120s	{25k,25k}	{0.08,0.08}	100m

Regarding the worst cases of truck performance change (Table 5), we see that all of them are achieved in major-major scenarios where trucks move on all the roads. Without AIM, the flow of trucks would be similar on different roads. The use of AIM would interrupt the flow of trucks in these cases, leading to a lower truck performance.

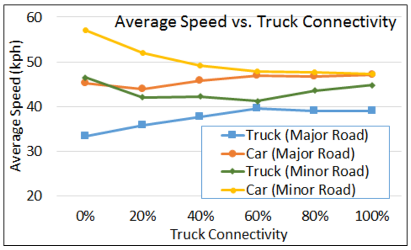
We observe that varying the value of even a small portion of the parameters can lead to significant changes in the results. For example, Figure 5 shows the impact of varying three parameters, motion factor, cycle length and look-ahead distance. For better illustration of the trends in the results, the truck connectivity changes in increments of 20%. The values of other four parameters are the same for the results in both sub-figures (i.e., green time equality is 1, traffic volume is {25000,5000}, truck ratio is {0.08,0.08} and detection distance is 300m). In Figure 5a, trucks and cars on minor roads move faster with higher truck connectivity levels. At the same time, traffic speed on major roads is mostly steady. Differently, in Figure 5b, traffic on major roads moves faster while cars on minor roads slow down when connectivity changes from 0% to 100%. To get a better understanding of the impact of different parameters, we conduct further simulations as shown in Section 4.3.

4.3 Individual Parameter Study

In this part, we first describe the setup of the individual parameter study then show our findings from the tests.



(a) Case 1: 1.5 motion factor, 120s cycle length and 100m look-ahead distance



(b) Case 2: 0.5 motion factor, 60s cycle length and 300m look-ahead distance

Figure 5: Different settings of motion factor, cycle length and look-ahead distance result in different traffic patterns.

4.3.1 Simulation Setup

This part of the experiments uses five synthetic road networks. One of them is the 5x5 synthetic network used in the parameter scan. There are four more synthetic networks with reduced complexity. Same as the 5x5 network, each of the four networks consists of two sets of perpendicular roads. The layouts of the additional networks are 1x1, 1x3, 1x5 and 3x3. For example, the 1x3 network has one western/eastern road that crosses 3 northern/southern roads.

For each road network, we simulate three different scenarios. In **Scenario 1**, western/eastern roads are major roads and northern/southern roads are minor roads. Only the major roads have trucks, i.e., truck ratio parameter does not affect minor roads. **Scenario 2** is similar to the first one except that minor roads also have trucks. In **Scenario 3**, all the roads are major roads with trucks.

Parameter values tested in this part are shown in Table 6. The default parameter values are based on the best cases of overall traffic performance improvements in the earlier parameter scan (Table 2). When testing the impact of a specific parameter, we vary the parameter's value while keeping other parameters at their default values. For each combination of parameter values, we run 5 simulations and average the results. Each simulation lasts 30 minutes. We should note that the traffic volume setting only affects major roads as the volume for minor roads is fixed to 5000.

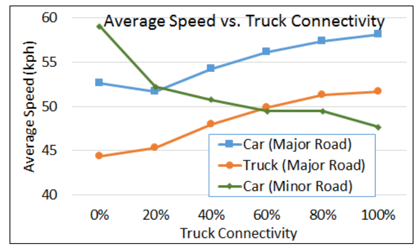
4.3.2 Results

Truck Connectivity. We observe significant differences of traffic performance between the three scenarios on all the road networks. As an example, we show the results on the 3x3 network in Figure 6. In Scenario 1 (Figure 6a), when connectivity changes from 0% to 100%, cars and trucks on major roads move faster by 10.6% and 16.4%, respectively. At the same time, cars on minor roads are slowed down by 19.2%. As minor roads have no trucks in this scenario, they tend to lose green light time to major roads that have connected trucks. In Scenario 2 (Figure 6b), the minor roads gain back some green light time as they have trucks. As a result, the loss of car speed on the minor roads reduces to 13.1%. The trucks on minor roads slow down when only 20% of them are connected. Their speed starts to recover when more of them are connected. In Scenario 3 (Figure 6c), we see that the AIM strategy does not help as the average speed of all vehicles is at the highest at 0% connectivity. In the first two scenarios, we see that the initial speeds on minor roads are higher than that on major roads at 0% connectivity, which indicates that traffic on lower-volume roads move faster in normal situations. But the speeds on minor roads start to deteriorate when some trucks on the major roads are connected.

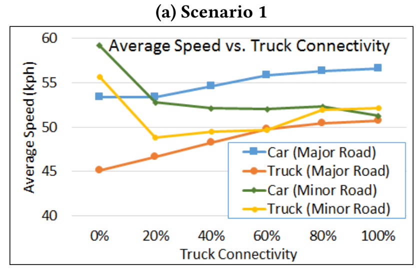
Motion Factor. A higher motion factor leads to a better traffic performance in all the scenarios on all the road maps. Figure 7 shows an example taken from Scenario 2 in the 5x5 network. We see a large improvement of speed for all the vehicles when motion

Table 6: Settings for individual parameter study.

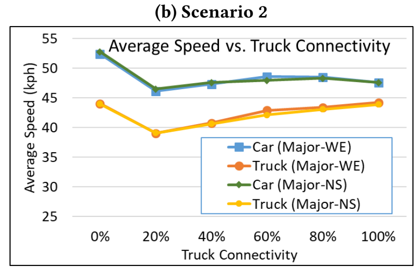
Parameter	Default	Range
Truck Connectivity	100%	0%-100%
Motion Factor	1	0.2-1.8
Look-ahead Distance	300m	100m-300m
Green Time Equality	1	0-1
Max Cycle Length	90s	30s-150s
Traffic Volume (Major)	25k	5k-45k
Truck Ratio	0.08	0-0.16
Detection Distance	300m	10m-300m



(a) Scenario 1



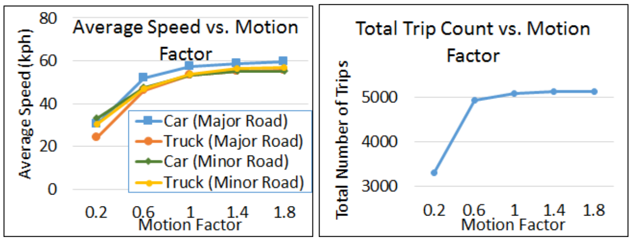
(b) Scenario 2



(c) Scenario 3

Figure 6: Average speed at different connectivity levels on 3x3 network.

factor increases from 0.2 to 0.6 (Figure 7a). The speed increases further after 0.6 motion factor but at a lower rate. Corresponding to the speed improvement, we see a 49.2% increase of total trip count when motion factor changes from 0.2 to 0.6 (Figure 7b).



(a) Average speed **(b) Total trip count**

Figure 7: The effects of motion factor in Scenario 2 on the 5x5 network.

Look-ahead Distance. The impact of look-ahead distance is negligible except for trucks on minor roads in Scenario 2. For example, when look-ahead distance increases from 100m to 300m, the average speed of trucks on minor roads increases by 4.1%, 6.6% and 4.7% in 1x1 network, 1x3 network and 1x5 network, respectively. When truck drivers can look further ahead, the movement of trucks in low-volume roads can be more smooth, resulting in a higher speed. For example, when truck drivers see a red light far ahead, they can gradually slow down the trucks rather than making a sudden stop. As the trucks move closer to the intersection, the traffic light may turn green, at which point the trucks can pick up speed and then cross the intersection without stopping.

Green Time Equality. The effect of this parameter is observable where major roads cross minor roads. For example, Figure 8 shows the change of average speed when this parameter increases from 0 to 1 on the 5x5 network. The results are from Scenario 2 where major roads cross minor roads. In this scenario, truck speed increases by 11.7% and car speed increases by 14.4% on minor roads. At the same time, vehicle speeds on major roads have a slight drop. When green time equality is higher, the minor roads tend to get more green time, resulting in the increased traffic performance on minor roads. Meanwhile, the major roads tend to experience more congestion as there is less time to clear up vehicle queues during a light cycle.

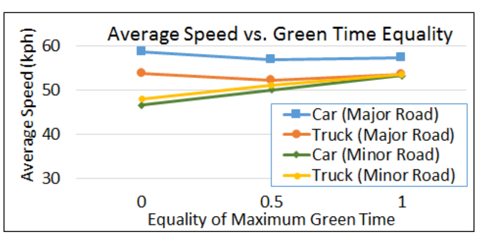


Figure 8: The effects of green time equality in Scenario 2 on the 5x5 network.

Max Cycle Length. The results show that a very short max cycle length has a negative impact on major road traffic. For example, Figure 9 shows the average number of stops with different cycle lengths where major roads cross each other. We can see that the number of stops for all the four vehicle-road combinations drops by around 70% when the max cycle length increases from 30s to 60s. The number of stops does not vary significantly when the cycle length increases further. Due to the high traffic volume on major roads, a very short cycle length can lead to the accumulation of vehicles in a short period, leading to a poor traffic performance.

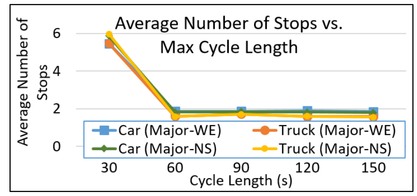
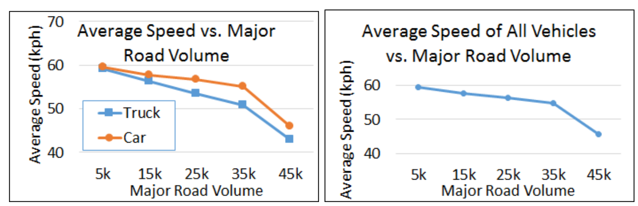


Figure 9: The effects of max cycle length in Scenario 3 on the 1x1 network.

Traffic Volume (Major). When traffic volume on major road increases, there is a drop of average speed for all vehicles in all the scenarios. Figure 10a shows an example taken from Scenario 2 on the 5x5 network. When the volume on major road is the same as the volume on minor road, i.e., 5k, all the vehicles achieve the similar average speed due to negligible traffic congestion at the low volume. As the major road volume grows, we start to see a drop of average speed for both cars and trucks. The rate of drop is smaller for cars as they can accelerate faster than trucks. In Figure 10b, we can see that the average speed of all vehicles decreases gradually when major road volume increases from 5k to 35k. There is a larger speed drop when the volume increases from 35k to 45k. When traffic volume is very high, it would be difficult to clear up vehicle queues at intersections during one light cycle. This can lead to the expansion of vehicle queues as time goes by, lowering the traffic performance further.



(a) Truck speed and car speed **(b) Speed of all vehicles**

Figure 10: The effects of major road volume in Scenario 2 on all the roads in the 5x5 network.

Truck Ratio. Our results show that a higher truck ratio can lead to a higher speed where the traffic volume of a prioritized road is significantly higher than the other road at an intersection. Figure 11 shows the average speed of all vehicles in three scenarios on the 3x3 network. When truck ratio increases from 0% to 16%, we record different levels of speed change in the three scenarios. The best case is achieved in Scenario 1, where freight vehicle prioritization is only applied to major roads effectively as minor roads do not have trucks. There is a speed improvement of 8.8% as major roads get more green time, resulting in faster movements of a majority of traffic in the whole system. In Scenario 2, the average speed of all vehicles varies in a small range. At 16% truck ratio, there is only a 2.2% speed improvement over 0% truck ratio. The reduced improvement is due to the fact green light is switched more frequently between conflicting roads when all the roads have trucks. As the intergreen time for making one switch is fixed, more frequent switching effectively reduces the total green time in a unit of time, resulting in longer vehicle queues at intersections. Similar to our earlier results, we observe that the AIM strategy may not work where high-volume roads intersect. As shown in Scenario 3, the speed change is -10% when truck ratio increases from 0% to 16%. The drop of speed is due to the combinational effects of the increased green-light switching and the higher number of vehicles.

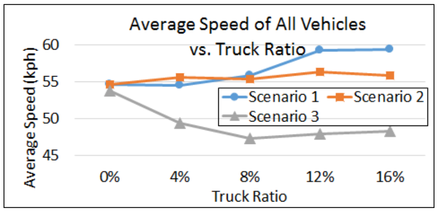


Figure 11: The effects of truck ratio on the 3x3 network.

Detection Distance. Our results show that vehicle speed on the roads that have connected trucks improves when detection distance increases from 10m to 50m. For example, in Scenario 3 on the 5x5 network, cars achieve a speed gain of 5.9% and trucks achieve a speed gain of 14.4% when detection distance increases from 10m to 50m (Figure 12).

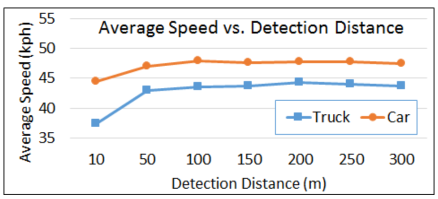


Figure 12: The effects of detection distance in Scenario 3 on the 5x5 network.

5 Conclusions

In this study we evaluated the impact of AIM-based freight vehicle prioritization on the overall traffic. Our simulations showed that AIM can help improve freight vehicle performance with a minimal impact on other vehicles in realistic traffic environments. We have found patterns in the best and worst cases over a wide range of traffic scenarios where the AIM strategy is applied. We also observed that traffic performance can be affected by individual parameters of a traffic system. We hope our results can help traffic engineers in developing effective freight vehicle prioritization solutions. When sufficient real AIM data becomes available in the future, we plan to calibrate simulations further.

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