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The research advances conventional traffic signal control through delay dynamics to design highly efficient network control algorithms. This research focuses on developing a new traffic-responsive network signal control in general, and especially with freight traffic considered. The optimal conditions for the waiting time dynamics are studied, and a new flow-based signal control algorithm is proposed. The derivation process is simple and follows the standard optimization problem-solving path.

The algorithm is implemented by Python and tested in SUMO. The numerical tests are conducted on two types of networks, a single corridor and a local grid network, under three traffic demand scenarios: low, medium, and heavy. The effect of different truck ratios (0%, 10%, 25%, and 40%) on each control algorithm was tested simultaneously for the same major and minor traffic volume scenarios. Compared with existing signal control algorithms, the result shows that the MaxFlow performs better than fixed-time and DORAS-Q in terms of the average vehicle waiting time under varying volumes, in both arterial and grid network cases, with various truck flow ratios.</td></tr>
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FATHOMING THE MAXIMUM POTENTIAL FOR FREIGHT SENSITIVE INTERSECTION CONTROL

Final Report

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DISCLAIMER

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EXCUTIVE SUMMARY

This project primarily studies signal timing with special consideration of freight traffic in urban areas. The rationale is that freight logistics are critical to the quality of life and economies. However, freight mobility, especially along major freight corridors in urban areas, rarely gets special consideration in signal timing. The advent of the Internet of Things (IoT) makes vast information collection a reality. The rich data environment, combined with the boost in computational power, has brought unprecedented opportunities closer to reality than ever for real-time, information-driven intersection traffic control under variants of traffic scenarios.

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1.0 INTRODUCTION

Urban traffic congestion is an increasingly exacerbating societal problem facing today's world. Signal control at intersections plays a vital role in urban life. Millions of travelers experience delays at signalized intersections on a daily basis (Schrank et al., 2015). Signal control is one of the few fundamental challenges in traffic operations. Effective intersection signal control is essential for traffic flow operation since most delay happens at intersections (Srinivasan et al., 2006). Properly designed signal control has one or more advantages: it provides for the orderly movement of traffic, increases the traffic-handling capacity of an intersection, and reduces the frequency and severity of certain types of crashes.

On the other hand, the transportation industry ranks second among sources of atmospheric carbon emissions in the United States. Truck traffic emissions account for over 80% of all petroleum use and generate high unit emissions. Major causes of high emissions include frequent accelerations, complete stops, excess speeds over 60 mph, and slow movements on a congested road. The signals on arterial roads are likely to be one of the causes of such concerns, and inappropriate signal designs will exacerbate these problems. Few people deny the critical role of freight logistics in the quality of life and economies. However, freight mobility, especially along major freight corridors in urban areas, rarely gets special consideration in signal timing. Significant environmental and financial advantages will result from increasing the fuel economy and lowering the emissions of this freight activity by zooming into the signal control policy on the roads.

Signals are intended to better manage traffic flow at level crossings from different approaches, thereby aiding vehicle flow rather than blocking or slowing it down. Although the isolated intersection has been most intensively studied, unfortunately, little research on isolated intersections has revealed its network implications now. In theory, the two shall be inherently consistent. A single intersection is a special example of a network. The research will start by reviewing the history of signal control. The impact of improved traffic control is almost immediately visible and tangible. The advent of the Internet of Things (IoT) makes various information collection means available. The rich data environment, combined with the boost in computation power, has brought unprecedented opportunities closer to reality than ever for real-time, information-driven intersection traffic control.

The signal control is realized by implementing a control policy. A control policy determines the durations and sequences of phases at each intersection to facilitate traffic movement. Here, a signal phase has three time intervals: green, yellow, and red. A phase refers to a time interval in which the traffic right of way under green and yellow does not change for traffic from all approaches. The signal control policy can take the form of a fixed-time control and vehicle actuated control or adaptive control driven by real-time traffic. Isolated intersection control only considers traffic local to the intersection, while network traffic control considers the coordinated effect of signals. Control implementation is through the control box at each intersection. When the intersections communicate with each other through a traffic control center that they are connected to, a network controller may be developed. Many conventional control methods in literature deal with idealistic traffic, such as uniform and constant traffic. Traffic variations should be considered more. Although the isolated intersection has been intensively studied, unfortunately, little research on isolated intersections has revealed its network implications by now.

At a general intersection, how to appropriately and optimally consider freight and passenger vehicles is a problem that needs to be addressed better in literature. Current video cameras popularly used for actuated traffic control have the potential to easily differentiate freight vehicles from passenger cars with today's technology. The video camera can also obtain much real-time vehicular information. In such an information-driven environment, how to conduct signal control by considering relevant factors such as economic values is an interesting and significant problem. This study will examine the optimal mechanism of the general intersection signal control when a mix of freight and passenger traffic is present. A model and according algorithms will be developed to apply to the general urban intersections. Numerical tests via simulation will be conducted to show the benefits of the developed model and algorithms. Discussions with the industry will be taken place for inputs and potential applications. We will reach out to the traffic control center of the City of College Station and deliberate with its in-house consultants about potential implementation. This study aims to deepen the understanding of the tradeoffs for the right of way between the different groups of vehicles and to provide an according mechanism to optimize signal control.

The report is organized as the following:

Section 2 summarizes the literature review. Some investigated research topics include fixed-time control, actuated control, and adaptive control.

Section 3 is about algorithm development. It starts with the waiting time dynamic equation at an intersection. Then, a simplified solution to the dynamic equation will be provided. A flow-based signal control algorithm, MaxFlow, is developed based on the solution.

Section 4 tests the algorithm on the arterial and grid network case via simulation under various traffic volume and truck percentage cases, respectively, and compared with fixed-time algorithms (i.e., PASSER V) and DORAS-Q.

Section 5 summarizes the results and conclusions, briefly discusses the study's limitations and presents directions and potential improvements for future work.

2.0 LITERATURE REVIEW

Trucking freight is ranked first among all the freight modes by both tonnage and value. Efficient trucking contributes to American economic vibrancy. Freight vehicles have significantly different characteristics in kinetic movement, economic values, and environmental effects. However, freight traffic's impact is rarely well-addressed in developing control strategies in the literature for either individual intersections or continuous intersections on arterials. On the other hand, today's technological developments offer unprecedented opportunities for new theories and models for traffic control. Equipment on the intersection or vehicles (e.g., cameras, detectors, GPS, etc.) can identify vehicle types and consider increasing real-time traffic data when adjusting signal timing to real-time traffic.

2.1 FIXED-TIME CONTROL WITH COORDINATION

Under fixed-time control, each controller has a predetermined timing plan. Fixed-time control is based on past traffic surveys and does not timely respond to real-time traffic conditions. Two strategies are generally employed to develop timing plans for an arterial street: progression-based methods (bandwidth maximization) and flow profile methods (delay and stops minimization). Green bandwidth maximization is essentially a geometry problem, which manipulates cycles in time-space diagrams to enable network intersecting coordination (Ficklin, 1969; Petterman, 1947). Morgan and Little et al. first formulate the bandwidth maximization optimization as a mixed-integer linear programming problem. They develop MAXBAND to an arterial and network by adding cycle constraints (Little, 1966; Little et al., 1981; Morgan and Little, 1964). Decades later, many extensions were introduced based on the original method and insights. Gartner considers the specific features of each link and develops MULTIBAND, which optimizes all the signal control variables and bandwidth progressions on each roadway segment (Gartner et al., 1991, 1990). PASSER V, developed by Texas Transportation Institute (TTI), explicitly optimizes over the set of possible phase sequences to maximize progression or minimize total delay. PASSER V works smoothly under both undersaturated and oversaturated traffic conditions (Lopez et al., 2018).

Bandwidth optimization techniques use a portion of traffic data (e.g., traffic flow, signal spacing, and travel speed) to determine the widest progressive band. Still, it lacks consideration of the presence of queues and may result in a relatively long cycle length due to the single objective. The flow profile method generally attempts to minimize the total delay or the total number of stops in the roadway network by delay-offset relationship and then compute the offset required for progression. P.D. Whiting first uses the delay-offset relationship and applies network topology theory to derive the network offsets (Hillier and Holroyd, 1965) The method is further improved by incorporating disaggregate and dynamic programming technique (Allsop, 1968; N.H.Gartner, 1972).

Example of flow profile method includes TRANSYT-7F and Synchro. TRANSYT-7F uses a hill-climbing algorithm to determine the offsets that minimize the network performance index

(PI), which includes delay, progression, stops, fuel consumption, queuing, and throughput. Still, its performance relies significantly on the initial fed, such as initial choice of splits, pre-specified phase, and minimum green time (Robertson, 1969).

Synchro combines the queue length and delay estimates from the Highway Capacity Manual (HCM) with a traffic flow model without modeling platoon dispersion effects to recommend whether signals should be coordinated and to adjust the offset (Trafficware, 2017)

2.2 ACTUATED CONTROL

The controller senses traffic conditions and collects real-time information through detectors. For vehicle-actuated and traffic-actuated control programs, the most used detector is the inductive loop detector (R. T. Van Katwijk, 2008).

If the vehicles' gap is more significant than a pre-determined maximum gap, the control program can decide to terminate the green phase and switch to the next phase. Based on the detector's location, vehicle actuated control can be divided into semi-actuated and fully actuated. The former has loop detectors implemented on the minor approach only and gives the green time when arrivals on the minor approach meet the pre-determined threshold. The latter implements loop detectors on all approaches and serves switch and green extension (Day, 2010).

In networked control, the coordination between actuated controllers follows the same logic as the fixed time controllers. To ensure that traffic-actuated controllers return to the coordination phase in time, either floating or fixed forced off is used to force the termination of the uncoordinated phases. The forced-off point for each non-coordinated phase refers to the point in one cycle where each phase must terminate to ensure coordination at an appropriate time. The main difference between the two depends on whether another uncoordinated phase can use the excess time from the uncoordinated phase. This approach applies to the arterials or networks where there are significant gaps in traffic volumes on major and minor roads and where traffic volumes are below capacity (Sunkari et al., 2004).

2.3 ADAPTIVE CONTROL

In the traffic control field, no universal solution fits all situations. Traffic patterns depend on various external factors such as time, weather, and unpredictable situations such as accidents. These factors used to be indirectly considered in the adaptive traffic control system. However, the emerging artificial intelligence environment in transportation, such as the internet of things (IoT), vehicle-infrastructure communication, and deep learning, make this idea a better implementation in this era. With progressive censoring and data collection techniques, the system can capture real-time situations and adjust the signal timing accordingly. Although there are many ways to do this, achieving optimization control aims to maximize traffic flow through the network, minimize total delay, and maintain the appropriate saturation rate.

Numerous adaptive systems have arisen over the past decades, which have seen varying deployment and coverage levels in the literature. Split Cycle Offset Optimization Technique

(SCOOT) is a centralized system based on data collected from far upstream detectors. It uses the TRANSYT (TRAffic Network StudY Tool) optimization method and prediction algorithm to produce cycles, offsets, and splits e to maintain the saturation rate of the intersection around the "ideal" value (typically 90 %). The changes are gradual and thus less likely to overreact a situation, but it suffers extensive calibration work (Hunt et al., 1981; Stevanovic et al., 2009).

Sydney Coordinated Adaptive Traffic System (SCATS) utilizes a distributed, hierarchical system with central, regional, and local control strata to perform a large-scale network control. It uses detector data to calculate "degrees of saturation" and "link flows" under high volume scenarios and low volume scenarios, respectively, to adjust timing plans in three separate heuristic processes to reduce total delay (Lowrie, 1982; Shelby, 2001).

Optimization Policies for Adaptive Control (OPAC) differs from previous control strategies in eliminating loops, offsets, and split constraints. Instead, OPAC has developed its phase-switching logic for local intersection control. OPAC generally maximizes the number of vehicles passing through an intersection by considering the saturation rate and the space available for storing vehicles on each link. Coordination is achieved by using "virtual cycle lengths." OPAC minimizes performance by continually optimizing the system rather than periodically updating local controller settings (Gartner, 1982; Gartner et al., 2002).

Real-time Hierarchical Optimized Distributed Effective System (RHODES) is a hierarchical traffic control system to optimizes timing plans on a chosen performance measure, such as average delays, stops, and throughput. RHODES uses data collected from upstream and stop-line detectors for each approach to calculate loads on links and predict future platoon sizes and route choices (Abdoos et al., 2014; Mirchandani and Head, 2001).

Then the controller at the intersection uses all the data and constraints to decide whether to change phases (Sen and Head, 1997). Varaiya introduced the max pressure (MP) algorithm to reduce the risk of over-saturation and maximize the network's throughput by minimizing the pressure for a signalized network with multiple intersections. The 'pressure' of a phase is defined as the difference between the total queue length on incoming and outgoing approaches, which indicates the degree of imbalance of inflow and outflow of the corresponding approach through the intersection. The larger pressure is, the more unbalanced the distribution of vehicles is. Green time is given to phases with the most pressure to release (Varaiya, 2013). Although the algorithm requires only queue information at the intersection and has been tested in simulation under various cases, it still relies on assumptions to simplify the traffic condition. It does not guarantee optimal results in the real world (Jennie Lioris et al., 2016; Wei et al., 2019).

Dynamic optimal real-time algorithm for signals, queue-based heuristic (DORAS-Q) is a real-time, traffic responsive control applied to isolated intersections. When making a switch decision, the controller chooses the phase with the highest efficiency, which is calculated based on the existing queues, short-term predictions for the current approach arrivals rates, and average historical arrival rates for other phases. DORAS-Q is much less data demanding but does require knowledge of the existing queues and near-term traffic arrivals (Wang et al., 2017).

2.4 SUMMARY OF OPTIMIZATION OBJECTIVES

As in other mathematical applications, optimization of traffic signal control uses an objective function to determine the optimal solution from a set of feasible groups, thereby maximizing (or minimizing) some metric. Traffic signal control's objective is to facilitate vehicles' efficient movement through the intersection or a roadway network. Various measures have been proposed to quantify the intersection or network's efficiency from different perspectives, such as maximizing the green bandwidth on major arteries. However, most of them fall into the following categories: travel time, delay, queue length, number of stops, and throughput (Hillier and Holroyd, 1965).

Common goals are either to minimize the average travel time of vehicles or to maximize the total number of vehicles through the network. These two correspond to travel time and throughput, respectively. Another similar measurement is the total delay, which is the time a vehicle has traveled within the environment minus the expected travel time. Besides, the number of stops and total queue length is the description of the intersection states.

The typical approach that transportation researchers take is to cast traffic signal control as an optimization problem under certain assumptions about the traffic model, e.g., vehicles come in a uniform and constant rate. In transportation studies, the inaccuracy arises from many assumptions in the models and approximations used to measure critical parameters. While many of the methods and models discussed above may provide the best solution within the defined space, the optimal values are subject to constant change due to the strong assumptions and the traffic flow's non-stationary nature. For simplicity without loss of generality, the research will convert truck to passenger vehicle equivalent by conversion factor in the simulation (Transportation Research Board, 2016). The report will focus on addressing the near-optimal control mechanism and evaluating the effectiveness and robustness of the designed algorithm.

3.0 METHODOLOGY

Traffic is a random process in terms of timing, traffic volume, route choice, vehicle following, etc. therefore, traffic control problem is complex. The early literature often approaches the control problem by assuming a constant and deterministic traffic to develop approximation models. Models gradually progress by explicitly dealing with random traffic. We first introduce the fluid dynamic model and then discuss its solution under various situations.

3.1 FLUID DYNAMIC MODEL

Fluid Dynamic model of the waiting time at general intersections signal control is developed. The recursive model minimizes the total passenger car equivalent vehicle waiting at the intersection. The model captures the effect of signal on vehicle waiting for all approaches and for all successive cycles. In this section, we start from the analytical model of DORAS (Wang et al., 2017).

Assume there is a finite set of signal phases for allocation of traffic right of way (ROW) to avoid vehicular traffic conflict at the intersection and improve intersection performance. Both upcoming vehicle arrivals and the present approach queueing are believed to be known continually. The green signal switches between phases. Each phase grants the ROW to a fixed set of approaches, and traffic from approaches in the same phase concurrently moves through the intersection. For example, a phase may grant green indications to both through and left-turning traffic from a direction. Furthermore, only one signal phase is ever given the right of way via green signals, while all other phases' signal indications are always red. An all-red period is typically required between any two phases for intersection traffic clearance and safety but is not necessarily so, such as in the lagging phase.

All the lost effective green time due to the signal switch is incorporated in the all-red interval. The discharge process is assumed to be known under the queueing and traffic arrival condition with a given signal indication. There are pre-defined rules, such as minimum and maximum green times for each phase or a predetermined order for the stages. In a special case, the set of rules is empty, which implies the maximum potential for intersection efficiency. This predefined set of guidelines considers actual application. A control policy decides on the sequence and durations of the phases. The control objective is to find a policy that minimizes the average vehicle waiting time at the intersection.

Instead of considering queue dynamics, we directly consider the waiting time dynamics in the study. The waiting time of an approach of an intersection can be describe in Equation (1). $\mathrm{w}^{\theta}(\boldsymbol{n}, t)$ the total intersection vehicle waiting time from time t to the end of control time horizon, given green phase π_k at time t and changes to π_{k+1} at $t^{\dagger}$, pivotal point of signal, where $t^{\dagger} \in [t, T]$.

$$\mathrm{w}^{\theta}(\boldsymbol{n},t) = \sum_{\forall i}\int_{T}^{t^{\dagger}}\left(n_i + \int_{t^{\dagger}}^{t}\lambda_i^{\theta}(\tau_1)d\,\tau_1 - \int_{t^{\dagger}}^{t}d_i^{\theta}(\tau_1)d\,\tau_1 + \int_{\tau}^{t^{\dagger}}\lambda_i^{\theta}(\tau_1)d\tau_1 - \int_{\tau}^{t^{\dagger}}d_i^{\theta}(\tau_1)d\,\tau_1\right)d\tau$$
$$+\sum_{i}\int_{t^{\dagger}}^{t}\left(n_i + \int_{\tau}^{t}\lambda_i^{\theta}(\tau_1)d\tau_1 - \int_{\tau}^{t}d_i^{\theta}(\tau_1)d\tau_1\right)d\tau_1 + w^{\theta}\left(\left(\boldsymbol{n_0} + \int_{T}^{t}\lambda^{\theta}(\tau_1)d\tau_1 - \int_{T}^{t}d^{\theta}(\tau_1)d\tau_1\right), T\right) \quad (1)$$

Where (n,t) is the intersection state variable, $\boldsymbol{n} = \{n_i\}$ is a set of vehicle queues for multiple approaches. n_i represents vehicle queue length for approach i. t represents the time before the end of the control horizon.

θ is the control policy that determines signal switch from one approach to another during the entire control horizon., in which $t^{\dagger}$ is a switch point for phase π_k to switch to phase π_{k+1}. The policy allows, but does not require, an all-red interval for a phase change. The logic is illustrated in Figure (1)

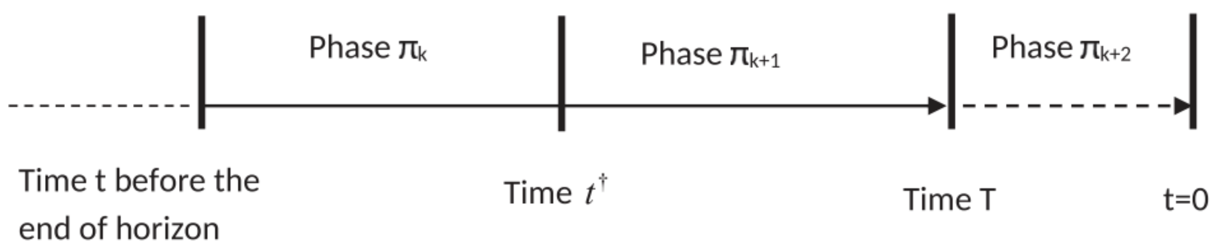


Figure 1 A policy over a control horizon

$\lambda_i^{\theta}(t)$ is the arrival rate from approach i under policy θ.

$d_i^{\theta}(t)$ the discharge rate from approach i under policy θ. The discharge rates are assumed to be continuously monitored and can be known through sensors at the intersection. For approach i, the discharge rate is

$$d_i^{\theta}(t) = \begin{cases} s_i \text{ the saturation flow rate when signal is green and when a queue exists} \\ 0 \text{ when the signal is red} \\ \lambda_i^{\theta}(t) \text{ when signal is green and when no vehicle queue is present} \end{cases} \quad (2)$$

$w^{\theta}(\boldsymbol{n_0},t)$ the salvage waiting time at time T with a resultant state $(\boldsymbol{n_0},t)$. For modeling, we assume t and T are both given.

In Equation (1), the first term is for waiting time after the pivotal point $t^{\dagger}$ till T when green phase switches from π_k to π_{k+1}. The big parenthesis within integral is for the total waiting vehicles at time $\tau \in (t^{\dagger},T)$. The second integral is for waiting time before the pivotal point $t^{\dagger}$ till t. The third term is a salvage value term, which also has to do with the choice of pivotal point $t^{\dagger}$ because $t^{\dagger}$results in the queue $\boldsymbol{n_0}$ at time T.

3.2 MODEL SOLUTION

The original method in the paper Wang et al., 2017 utilize tradition optimization technique trying to solve Equation (1). Specifically, it takes first order derivative of Equation (1) with respect to $t^{\dagger}$ and conduct lots of work on the assumption and estimation, which is much difficult to read or comprehend. The overall process could be more explicit, and the method is worth further investigating. It is questionable to do partial derivation on both sides of the dynamic equation. Such a way assumes the form of the waiting time function stays the same after switching phases. This method only works under the assumption of the same waiting time function. The hypothesis makes the solution of the equation limited. It abandons the multiple possibilities after the signal switch and lacks the consideration of stochasticity. In other words, such a way shrinks the plane to a single line, which could be why DORAS underperforms the OPAC algorithm. Methods from solving dynamics equations or stochastic control may be a better path to work towards the signal control problem. Also, the equation is vector form but such way lacks consideration of the interaction between the intersection. It more like a matrix form of several parallel equations. However, the equation shed light on a new way to look at the signal control problem of a single intersection. This section focuses more on the equation itself instead of solving it. There are other work utilizes advanced techniques and provides solution for the network signal control problem, e.g. (Ma et al., 2022).

3.2.1 Case 1 balanced flow

When $\lambda_i^{\theta}(t) = d_i^{\theta}(t), \forall\, i$, also known as input flow equals the discharge flow for all approach of the intersection. We call such case "balanced flow". We investigate the balanced flow case first. t can be interpreted as any time point before the signal reaches max green time. Equation (1) can be rewritten as

$$\mathrm{w}^{\theta}(\boldsymbol{n}, t) = \sum_{\forall\, i} \int_{T}^{t^{\dagger}} n_i\, d\tau + \sum_{i} \int_{t^{\dagger}}^{t} n_i d\tau_1 + w^{\theta}(\boldsymbol{n_0}, T) \tag{3}$$

$$\mathrm{w}^{\theta}(\boldsymbol{n}, t) = \sum_{\forall\, i} \int_{T}^{t} n_i\, d\tau + w^{\theta}(\boldsymbol{n_0}, T) \tag{4}$$

$$\mathrm{w}^{\theta}(\boldsymbol{n}, t) = \sum_{\forall\, i} n_i\, (t - T) + w^{\theta}(\boldsymbol{n_0}, T) \tag{5}$$

The equation is much simplified. Set $t - T = \Delta T$, we have

$$\mathrm{w}^{\theta}(\boldsymbol{n}, t + \Delta t) - \mathrm{w}^{\theta}(\boldsymbol{n}, t) = \sum_{\forall\, i} n_i\, \Delta t \tag{6}$$

Divide Δt on both sides of the equation and take the limit of $\Delta t \to 0$, we have

$$\lim_{\Delta t \to 0} \frac{\mathrm{w}^{\theta}(\boldsymbol{n}, t+\Delta t) - \mathrm{w}^{\theta}(\boldsymbol{n}, t)}{\Delta t} = \sum_{\forall i} n_i \tag{7}$$

Which is equivalent to

$$\frac{\partial \mathrm{w}^{\theta}(\boldsymbol{n}, t)}{\partial t} = \sum_{\forall i} n_i \tag{8}$$

Equation (8) indicates that the first order derivative is always greater than 0. The waiting is non-decreasing, which meets the common expectation. The second order derivative is

$$\frac{\partial^2 \mathrm{w}^{\theta}(\boldsymbol{n}, t)}{\partial^2 t} = \sum_{\forall i} \frac{\partial n_i}{\partial t} \tag{9}$$

The second order derivative depends on the change rate of the queue. At any time, to decrease the waiting time, we need to make the second order derivative smaller than 0, indicating the maximum waiting time at current time, and the waiting time will decrease in the future. When $\boldsymbol{n_i} = \boldsymbol{0}$, indicating no existing queue at all approach, we can have the policy to maintain the balanced flow $\lambda_i^{\theta}(t) = d_i^{\theta}(t)$ at any time. This policy will work under low volume scenario and share the same idea with actuated control.

3.2.2 Case 2 unbalanced flow

It is uncommon to always have low volume, thus we investigate a common case, medium or high flow in this section. From Equation (1), by eliminating $t^{\dagger}$, we have

$$\begin{aligned}\mathrm{w}^{\theta}(\boldsymbol{n}, t) = \sum_{\forall i} \int_{T}^{t^{\dagger}} \left(n_i + \int_{\tau}^{t} [\lambda_i^{\theta}(\tau_1) - d_i^{\theta}(\tau_1)] d\,\tau_1 \right) d\tau \\ + \sum_{i} \int_{t^{\dagger}}^{t} \left(n_i + \int_{\tau}^{t} \lambda_i^{\theta}(\tau_1) d\tau_1 - \int_{\tau}^{t} d_i^{\theta}(\tau_1) d\tau_1 \right) d\tau_1 + w^{\theta}((\boldsymbol{n_0} + \int_{T}^{t} [\lambda^{\theta}(\tau_1) - d^{\theta}(\tau_1)] d\tau_1, T)\end{aligned} \tag{10}$$

$$\mathrm{w}^{\theta}(\boldsymbol{n}, t) = \sum_{\forall i} \int_{T}^{t} \left(n_i + \int_{\tau}^{t} [\lambda_i^{\theta}(\tau_1) - d_i^{\theta}(\tau_1)] d\,\tau_1 \right) d\tau + w^{\theta}(\boldsymbol{n_0} + \int_{T}^{t} [\lambda^{\theta}(\tau_1) - d^{\theta}(\tau_1)] d\tau_1, T) \tag{11}$$

For connivence, we define the integral of the input flow and discharge flow function, and omit the constant item here

$$L(x) = \int \Lambda(x)dx = \int\int \lambda_i^\theta(x)dx \tag{12}$$

$$A(x) = \int D(x)dx = \int\int d^\theta(x)dx \tag{13}$$

Where $L(x)$, $A(x)$ are the waiting time increase/decrease by the arriving flow and discharged flow, respectively. $\Lambda(x)$, $D(x)$ are the number of arriving vehicles or discharging vehicles, respectively. Then we can rewrite Equation (11) as

$$\begin{aligned} \mathrm{w}^\theta(\boldsymbol{n}, t) &= \sum_{\forall i} \int_T^t (n_i + \Lambda_\mathrm{i}(\mathrm{t}) - \Lambda_\mathrm{i}(\tau) - D_i(t) + D_i(\tau))d\,\tau_1\,)d\tau \\ &+ w^\theta(\boldsymbol{n_0} + \Lambda_\mathrm{i}(\mathrm{t}) - \Lambda_\mathrm{i}(T) - D_i(t) + D_i(T), T) \end{aligned} \tag{14}$$

Reorganize the above equation, we have

$$\begin{aligned} \mathrm{w}^\theta(\boldsymbol{n}, t) &= \sum_{\forall i} (n_i + \Lambda_\mathrm{i}(\mathrm{t}) - D_i(t))(t - T)) - L_\mathrm{i}(t) + L_\mathrm{i}(T) + A_\mathrm{i}(t) - A_\mathrm{i}(T) \\ &+ w^\theta(\boldsymbol{n_0} + \Lambda_\mathrm{i}(\mathrm{t}) - \Lambda_\mathrm{i}(T) - D_i(t) + D_i(T), T) \end{aligned} \tag{15}$$

The existing queue length is also a function of time t. So, the binary function can be transferred to a unary function of variable t. $\mathrm{w}^\theta(\boldsymbol{n}, t)$ equals $\mathrm{w}^\theta(t)$. It can be seen one of the solutions for $\mathrm{w}^\theta(t)$ is

$$\mathrm{w}^\theta(t) = \sum_{\forall i} n_i(\mathrm{t})(t - T) - L_\mathrm{i}(t) + L_\mathrm{i}(T) + A_\mathrm{i}(t) - A_\mathrm{i}(T) \tag{16}$$

Where $n_i(\mathrm{t}) = n_i + \Lambda_\mathrm{i}(\mathrm{t}) - D_i(t)$

Take the explicit form of $\mathrm{w}^\theta(t)$ back to the dynamic Equation (1), we have

$$\begin{aligned} \mathrm{w}^\theta(t) &= \sum_{\forall i} \int_T^{t^\dagger} \left(n_i(t) + \int_{t^\dagger}^t [\lambda_i^\theta(\tau_1) - d_i^\theta(\tau_1)]d\,\tau_1 \right) d\tau + \sum_i \int_{t^\dagger}^t n(t)d\tau \\ &+ \sum_i \int_T^{t^\dagger} [\int_\tau^{t^\dagger} \lambda_i^\theta(\tau_1)\,d\tau - \int_\tau^{t^\dagger} d_i^\theta(\tau_1)d\tau_1]d\tau \\ &+ \sum_i \int_{t^\dagger}^t [\int_\tau^t \lambda_i^\theta(\tau_1)\,d\tau - \int_\tau^t d_i^\theta(\tau_1)d\tau_1]d\tau \ + \mathrm{w}^\theta(T) \end{aligned} \tag{17}$$

We notice that $\mathrm{w}^\theta(T) = 0$, which can be treated as a boundary condition.

Use the definition in Equation (12) and (13), we can see the Equation (16) satisfy the dynamic equation (1).

$$\mathrm{w}^{\theta}(t) = \sum_{\forall\, i} n_i(\mathrm{t})(t-T) - L_{\mathrm{i}}(t) + L_{\mathrm{i}}(T) + A_{\mathrm{i}}(t) - A_{\mathrm{i}}(T) + \ \mathrm{w}^{\theta}(T) \tag{18}$$

$$\mathrm{w}^{\theta}(t) - \mathrm{w}^{\theta}(T) \ = \sum_{\forall\, i} n_i(\mathrm{t})(t-T) - L_{\mathrm{i}}(t) + L_{\mathrm{i}}(T) + A_{\mathrm{i}}(t) - A_{\mathrm{i}}(T) \tag{19}$$

Set $X^{\theta}(t) = \ \mathrm{w}^{\theta}(t) + \sum_i L_i(t) - \sum_i A_i(t)$, we can rewrite Equation (19) as

$$\mathrm{X}^{\theta}(t) - \mathrm{X}^{\theta}(T) \ = \sum_{\forall\, i} n_i(\mathrm{t})(t-T) \tag{20}$$

Take the limit $t \to T$ Then we have the derivative of $\mathrm{X}^{\theta}(t)$

$$\frac{\partial \mathrm{X}^{\theta}(t)}{\partial t} = \sum_{\forall\, i} n_i(\mathrm{t}) \tag{21}$$

We have almost the same but more general results with the result in case 1.

Equation (19) indicates that the first order derivative is always greater than 0. The waiting is non-decreasing, which meets the common expectation. The second order derivative is

$$\frac{\partial^2 \mathrm{w}^{\theta}(\boldsymbol{n}, t)}{\partial^2 t} \ = \sum_{\forall\, i} \frac{\partial n_i(t)}{\partial t} \tag{22}$$

The second order derivative also depends on the change rate of the queue. At any time, to decrease the waiting time, we need to make the second order derivative smaller than 0, indicating the maximum waiting time at current time, and the waiting time will decrease in the future. It is hard to maintain the balanced flow $\lambda_i^{\theta}(t) = \ d_i^{\theta}(t)$ at any time, so we can design a greedy way to push the waiting time function towards desirable direction. The results are consistent with the results in DORAS (Wang et al., 2017). They share the same idea to discharge the flow out the intersection as soon as possible.

3.3 MAXFLOW ALGORITHM DESIGN

At a current state (n, t) and green signal, the decision is whether to switch the green signal to the next phase while continuously satisfying the set of constraints. We no longer follow the fixed sequence of phases and can define similar efficiency of each signal phase in Equation (22) and allocate green time to the phase with max efficiency.

$$\epsilon_i \ = \frac{\partial n_i(t)}{\partial t} = \frac{q_i}{t_0} \tag{23}$$

Where q_i is the estimated queue length in the following time step.

t_0 is incremental time step, which usually takes the minimum green time.

After the minimum green time is reached until the green interval maxes out, at each t_0, the currently active green signal is examined for possible switch by calculation the efficiency in Equation (23). We hoped to reduce the number of estimation parameters and eliminate the green time estimation step in DORAS. The algorithm MaxFlow is described below:

Step 1: Initialization. Define the incremental time step t_0

Step 2: Update the estimated queue length q_i at each approach.

Step 3: Calculate each phase's efficiency by Equation (23).

Step 4: Make switch decision according to the cases below:

If $\epsilon_i < \epsilon_j$, terminate the current phase and switch to all-red interval to transit to the phase j.

Otherwise, do not switch the signal.

The dynamic model representing the waiting time process as a function of traffic control and queue length allows further analytical study of the control process. Optimal control is one at which the waiting time function is minimized at each time step. The discover the sufficient and necessary conditions of the optimal control has general meaning to the signal timing community. Algorithms is developed to code the control in implementation.

4.0 SIMULATION

4.1 SIMULATION SETTINGS

Numerical tests are conducted on two types of networks: a single corridor and a grid network. The reason for separately testing on a single corridor is that single corridors are often the major means of dealing with urban traffic. We have utilized the SUMO 1.8 micro-simulator in conjunction with TraCI (Traffic Control Interface) 1.8 for modeling both the cases. SUMO (Simulation of Urban MObility) is an open-source, microscopic and continuous traffic simulation package designed to handle large traffic networks simulation with a large set of tools for scenario creation (Ma et al., 2022). SUMO allows us to create a traffic simulation environment and track every vehicle. TraCI implements the real-time signal control possible. In this study, the algorithm is realized by Python 3.8.

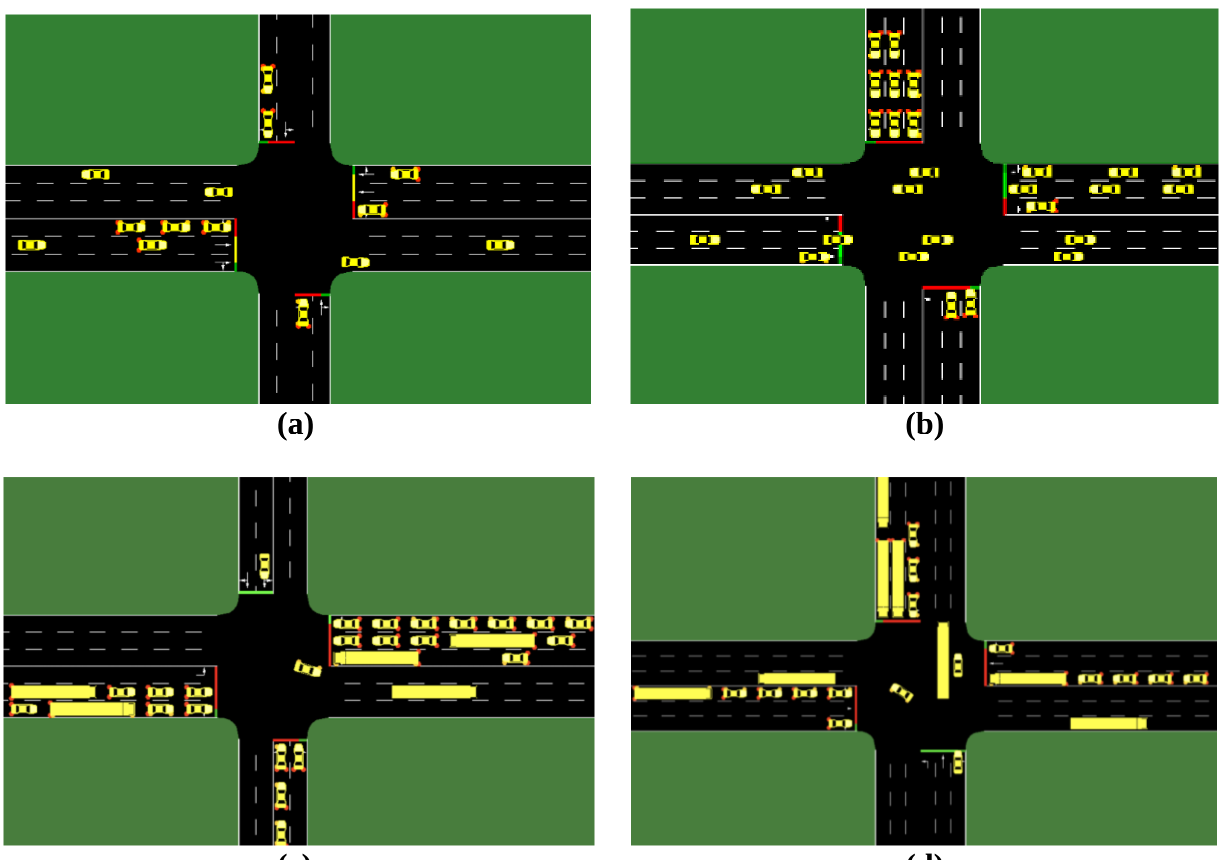
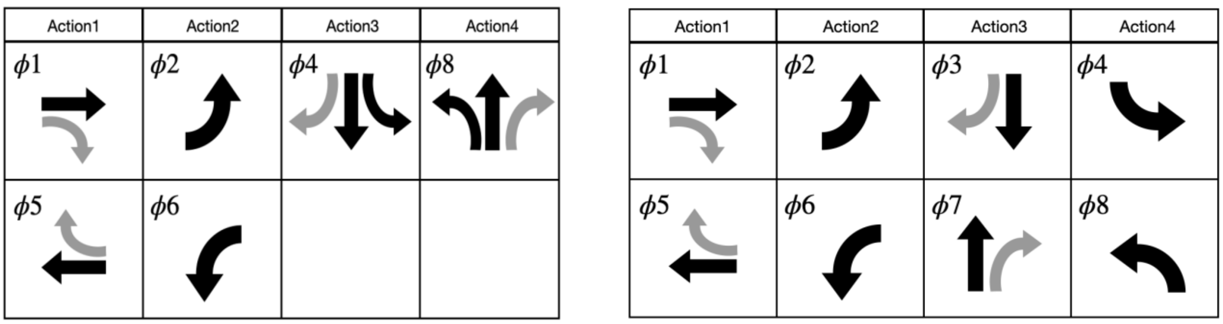


Figure 2: Intersection simulation environment

Figure 2 (a) and **(c)** presents the layout of an individual intersection of major and minor arterial without and with truck volume, respectively, in the simulation network. **Figure 2 (b)** and **(d)** present the intersection of two major arterials, without and with truck volume, respectively. The link on minor arterial at each intersection consists of two through lanes. Each of the through lanes also servers the turning traffic. The link on major arterial at each intersection consists of one left-turn lane and two through lanes. One of the through lanes also servers the right-turning traffic. In reality, there are singular dominating corridors that can be easily identified.

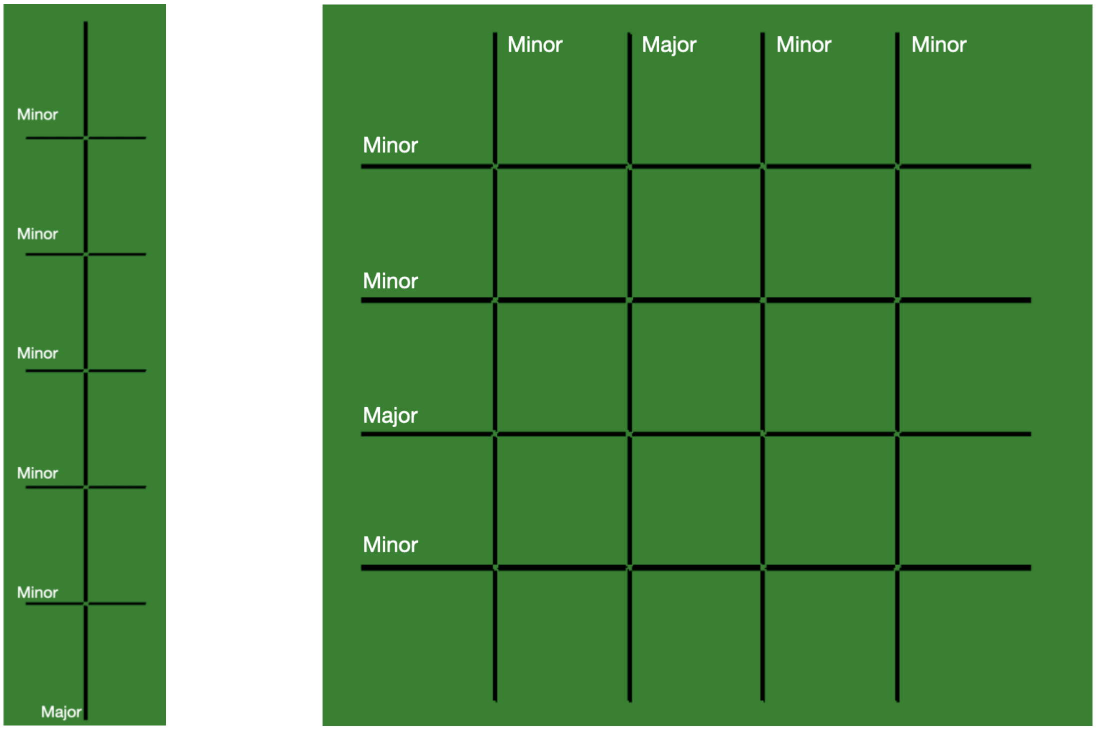
Figure 3 (a) presents the available phase timing plan for the intersection of major and minor arterial, and **(b)** shows the one for the intersection of two major arterials. The phase plan also contains the available action for selecting the phases. The amber interval is set as 5 seconds and represents the time between two consecutive phases to clear the intersection, consisting of 3 seconds yellow and 2 seconds all-red interval. The min green time is 5 seconds, and the max green time is 30 seconds. The ring-and-barrier diagram is for illustrative purposes and presents the phase plan for the simulation. Notice here the phase sequence is used for test purposes. Our algorithm does not require the fixed phase sequence when implementation.



(a) **(b)**

Figure 3: Available phases in traffic signal control of the simulation

Figure 4 illustrates the arterial (a) and grid network (b) used in the simulation. The test arterial consists of five intersections and the grid network contains $4 \times 4 = 16$ intersections. The arterial in the numerical test consists of one major arterial road with higher traffic volumes and five minor roads with lower volumes. The minor street crossings spaced 1640 ft (500 m) along the major arterial with free-flow speed v_f 50 mph. The grid network in the simulation makes of two major arterial roads with higher volumes and three minor roads with lower volumes in each direction. The distance between roads, free-flow speed, and the normal travel times are the same with the arterial. Three traffic scenarios, high, medium, and low, are used for the test, as indicated in Table 1.



(a) (b)

Figure 4: Arterial and grid network environment

Table 1 Traffic volume in the simulation

Traffic Scenario	Major Roads(veh/h)	Minor Roads(veh/h)
Low	500	200
Medium	900	300
High	1300	400

Also, in each scenario, the effect of different truck ratios (0%, 10%, 25%, and 40%) on each control algorithm was tested simultaneously for the same major and minor traffic volume scenarios. The research will convert truck to two passenger vehicle in the simulation (Federal Highway Administration, 2017). The vehicle type defaults are shown in Table 2.

Table 2 Vehicle Type parameter defaults in the simulation

Vehicle Type	Length Width Height	MinGap	Acceleration	Deceleration	Emergency Deceleration
Passenger	5 m 1.8 m 1.5 m	2.5 m	2.6 m/s^2	4.5 m/s^2	9 m/s^2
Truck	16.5 m 2.55 m 4 m	2.5 m	1.1 m/s^2	4 m/s^2	7 m/s^2

4.2 TESTED ALGORITHMS IN SIMULATION

We compare our model with the Fixed timing plan with coordination and DORAS-Q.

Fixed-time: Fixed-timing plan and offsets optimized with PASSER V. Fixed timing plan with green wave progression is the most classical approach achieving coordination on arterial in practice.

DORAS-Q: DORAS-Q is designed for isolated intersection control and may be applied to the network as a distributed control system in which each intersection only optimizes its control and the entire system adapts gradually, it requires the existing queue length, short-term (usually 5 seconds) and the average historical arrival rates for each phase to estimate the switch-to efficiency and phase efficiency. Then decide on changing or keeping the current phase based on the discharge efficiency.

MaxFlow: the algorithm is designed in Section 3.3. It also requires the existing queue length, short-term estimation of input flow rate and discharge rate to calculate the efficiency for each phase and then decide on changing or keeping the current phase based on the discharge efficiency.

4.3 AGENT PERFORMANCE ON SCENARIOS WITH UNIFORM PASSENGER VEHICLE FLOW

We compare our model with Fixed timing plan with coordination, DORAS-Q and Maxflow timing plan with green wave progression is the most classical approach to achieving coordination on the arterial in practice. Fixed-timing plans and offsets are optimized with PASSER V. DORAS-Q (Wang et al., 2017) is designed for isolated intersection control, and may be applied to the network as a distributed control system in which each intersection only optimizes its control and the entire system adapts gradually. MaxFlow defines the efficiency for each phase and select the phase with max efficiency. **Table 3** illustrates the results of the simulation.

Table 3 Average vehicle delay in arterial and grid network case with uniform passenger vehicle flow (in seconds)

	Low Volume		Medium Volume		High Volume	
	Arterial	Network	Arterial	Network	Arterial	Network
Fixed-time	30.93	93.73	38.06	139.87	89.82	191.16
DORAS-Q	23.25	72.77	36.64	84.82	76.64	148.92
MaxFlow	21.49	69.23	33.94	76.65	74.62	143.24

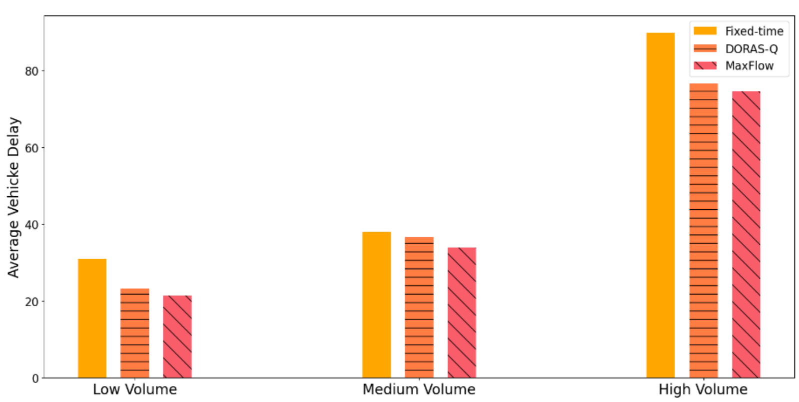


Figure 5: Average vehicle delay in arterial case (in seconds)

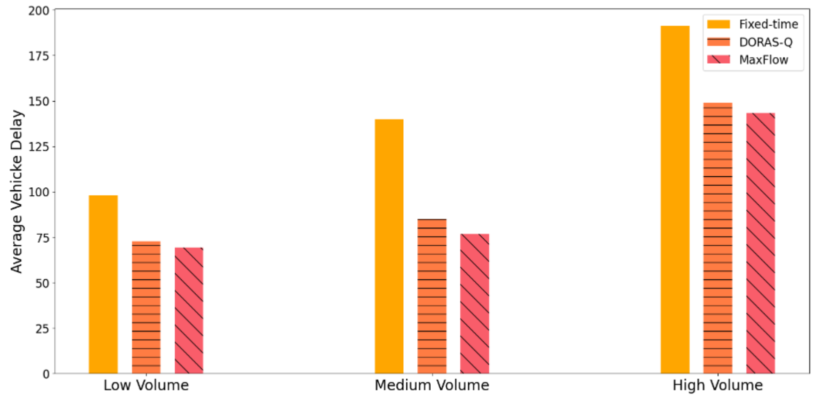


Figure 6: Average vehicle delay in grid network case (in seconds)

Figure 5 and **6** presents MaxFlow outperforms the other two signal control algorithms in most of the scenarios in the arterial and grid network cases. Not surprisingly, fixed-time control performs at the bottom, but it does not stop using it as a benchmark. Under all scenarios, DORAS-Q outperform the fixed time control with coordination. Notice that, DORAS-Q and MaxFlow have similar performance in the high-volume scenario.

4.4 AGENT PERFORMANCE ON SCENARIOS WITH TRUCK FLOW

We also investigate the effect of different truck ratios (0%, 10%, 25%, and 40%) on each control algorithm. All settings are exactly the same as the uniform passenger vehicle flow case except for the different truck ratio. We also conduct the simulation in the low, medium, and high traffic flow scenarios. Specifically, the high traffic volume of 25% truck means that the traffic volume on the major/minor arterials remains at 1300/400 vehicles/hour, with 975/300 trucks/hour on the major/minor arterials and 325/100 vehicles/hour passenger vehicles on major/minor arterials, respectively. When calculating the queue, we assume a truck equal two and half passenger vehicles.

4.4.1 10% truck volume

Table 4 illustrates the results of the simulation under all scenarios with 10% of truck volume.

Table 4 Average vehicle delay in arterial and grid network case with 10% truck volume (in seconds)

	Low Volume		Medium Volume		High Volume	
	Arterial	Network	Arterial	Network	Arterial	Network
Fixed-time	36.96	99.26	52.72	153.79	132.38	226.39
DORAS-Q	28.87	74.82	49.76	96.09	130.47	184.25
MaxFlow	25.92	62.44	41.27	92.43	121.67	171.28

Figure 7 and **8** presents MaxFlow outperforms other signal control algorithms in both arterial and grid network cases. Not surprisingly, fixed-time control performs at the bottom, but it does not stop using it as a benchmark. Under all scenarios, DORAS-Q performs better than the fixed time control with coordination in terms of waiting time per vehicle.

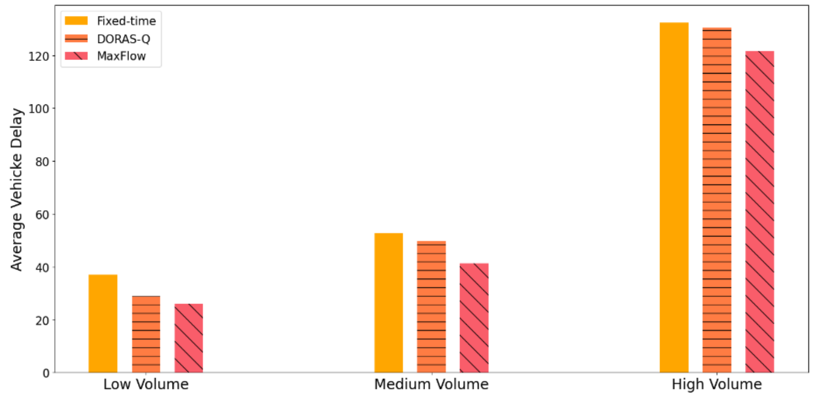


Figure 7 Average vehicle delay through the arterial with 10 % truck volume (in seconds)

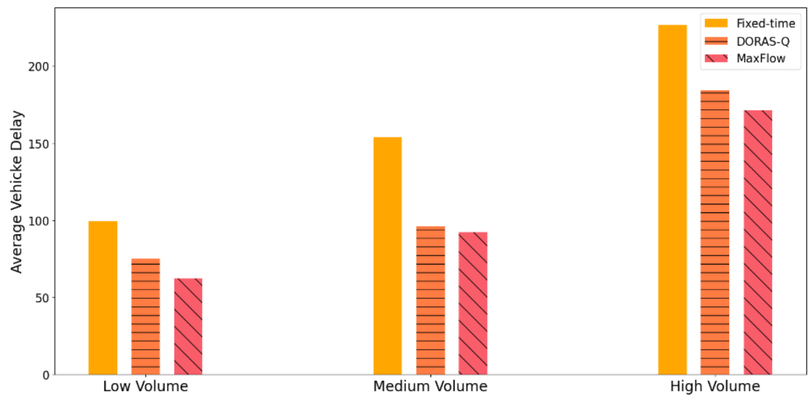


Figure 8 Average vehicle delay through the grid network with 10 % truck volume (in seconds)

4.4.2 25% truck flow

Table 5 illustrates the results of the simulation under all scenarios with 25% of truck volume.

Table 5 Average vehicle delay in arterial and grid network case with 25% truck volume (in seconds)

	Low Volume		Medium Volume		High Volume	
	Arterial	Network	Arterial	Network	Arterial	Network
Fixed-time	42.13	100.62	84.94	181.88	148.03	258.91
DORAS-Q	31.14	75.38	57.52	128.95	118.36	227.39
MaxFlow	30.54	69.89	50.78	119.71	116.27	227.85

Figure 9 9 and 10 present MaxFlow performs the best in both arterial and grid network cases as well. Similar to the 10% truck volume case, DORAS-Q outperform the fixed time control with coordination.

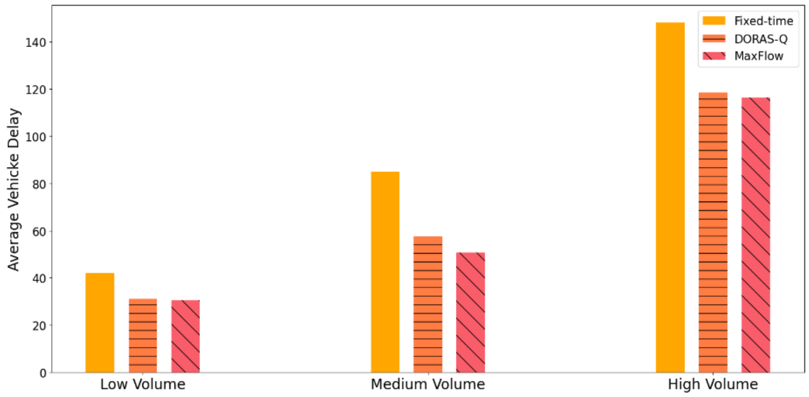


Figure 9 Average vehicle delay through the arterial with 25 % truck volume (in seconds)

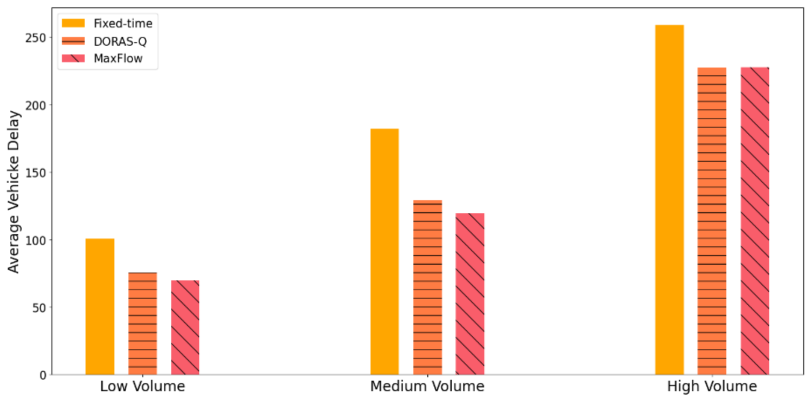


Figure 10 Average vehicle delay through the grid network with 25 % truck volume (in seconds)

4.4.3 40% truck flow

Table 6 illustrates the results of the simulation under all scenarios with 40% of truck volume.

Table 6 Average vehicle delay in arterial and grid network case with 40% truck volume (in seconds)

	Low Volume		Medium Volume		High Volume	
	Arterial	Network	Arterial	Network	Arterial	Network
Fixed-time	69.04	106.25	129.64	192.63	267.68	274.39
DORAS-Q	34.02	76.68	120.33	146.14	225.39	259.32
MaxFlow	31.29	59.80	117.61	128.93	217.78	254.63

Figure 11 and **12** presents MaxFlow outperforms the other four signal control algorithms in both arterial and grid network cases. With higher percentage of truck volume, the algorithm also proves its efficiency.

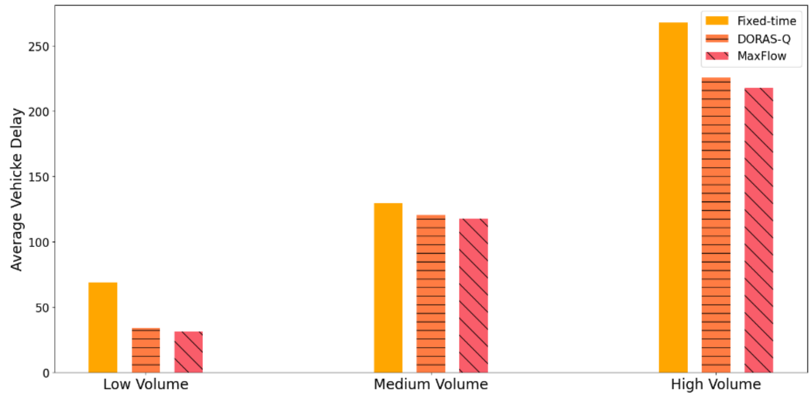


Figure 11 Average vehicle delay through the arterial with 40 % truck volume (in seconds)

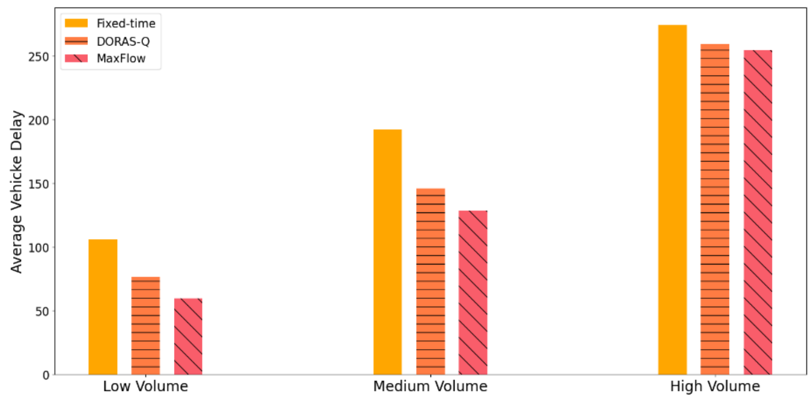


Figure 12 Average vehicle delay through the grid network with 40 % truck volume (in seconds)

4.5 DISCUSSION

We summarize the simulation results in sections 4.3 and 4.4. Considering the truck flow may increase, the simulation may increase the total delay at the intersection. The higher the truck volume percentage, the more delay driver may experience at the intersection with the area. MaxFlow has satisfactory performance in most of the scenarios in the arterial and network case.

The green wave undoubtedly facilitates the vehicle's movement on the arterial and gird network with signalized intersections. However, even though the green wave is added, the fixed timing design does not inherently consider the dynamic changes in traffic flow or responsiveness to the current situation at the intersection. Not surprisingly, fixed-time control performs at the bottom, but it continues using it as a benchmark.

DORAS-Q estimates the intersections' efficiency within a certain period and predicts future arrivals. However, it just focuses on two phases – the current phase and the next switch-to phase- and requires fixed sequences. The MaxFlow algorithm can be interpreted as a generalization of the DORAS algorithm. Also, the theoretical foundation for the MaxFlow algorithm is more solid, which avoid the suspicious process of taking derivative on both sides of the dynamic equation. In most scenarios, the DORAS-Q and MaxFlow outperform the coordinated fixed-time control because each intersection could utilize the arrival steam information from nearby intersections. We can see that the removal of fixed-time sequences significantly improves waiting time.

On the other hand, the truck volume may bring more impact or turbulence on the downstream traffic volume and then decrease the algorithm's performance compared with the uniform passenger vehicle flow case. Using the conversion factor to convert the truck to a passenger vehicle in the queue length estimation may need to be revised in the algorithm. Although the algorithm is based on the queue length estimation, more truck characteristics may need to consider and improve the algorithm's mechanism.

First, a truck is usually longer than a passenger vehicle. A conversion factor or truck coefficient is typically used to convert the truck to a passenger vehicle equivalent in transportation engineering. With the same traffic volume, truck traffic flow will be higher than the equivalent pure passenger vehicle flow. Second, trucks are slower to accelerate and decelerate than passenger vehicles. When trucks approach or leave the intersection, the inhomogeneous may heterogeneity the traffic flow. The conversion factor may be different when the controller decides the phase. Also, the truck volume brings more disturbance to the coverage of the RL baseline algorithms. The results variation is more considerable than the pure passenger vehicle flow case.

5.0 CONCLUSION

Freight logistics in rural and urban areas is essential to supporting life quality and the local economy. Freight mobility, especially in urban areas, has yet to be highlighted in urban traffic control, such as signal timing. As delay mostly happens at intersections, it is, therefore, meaningful to study intersection signal control by explicitly considering freight traffic. A freight vehicle is different from a passenger car. On the other hand, today's technologies (video cameras, GPS, etc.) allow vehicle types identification and more real-time traffic data to be considered in adapting signal timing to real-time traffic. This new situation demands new theories and models for traffic control. The latest theories and models will allow special consideration of freight traffic in signal timing.

In this work, optimal conditions are studied, and a new flow-based signal control algorithm is proposed. The derivation process is easy to understand and avoids debatable methods. The algorithm is tested in SUMO and compared with existing signal control algorithms. The result shows that the MaxFlow performs better than fixed-time and DORAS-Q under varying volumes. Considering the truck flow may increase, the simulation may increase the total delay at the intersection. The addition of truck volume may increase the overall delay compared with the pure passenger flow case. The higher the truck volume percentage, the more delay driver may experience at the intersection with the area. The average travel time in the signal intersection of the grid network is higher than that of the arterial case due to the coordination of surrounding signals.

However, the MaxFlow algorithm is not perfect:

MaxFlow algorithm may also need more accurate estimation or prediction, which may inevitably lead to flawed decisions. The performance still needs to improve due to inaccurate prediction and errors accumulation.

Myopic switching frequently occurs during the signal control cycle, thus defeating the original design intent. More information could be used and kept in the controller to facilitate better decision-making.

Both DORAS-Q and MaxFlow lack consideration between intersections. In the network simulation case, it is more like an additive of several individual intersections instead of a distributed network signal controller. A new measurement correlated with general delay but not heavily dependent on prediction may need to be discovered.

6.0 REFERENCES

Abdoos, M., Mozayani, N., Bazzan, A.L.C., 2014. Hierarchical control of traffic signals using Q-learning with tile coding. Applied Intelligence 40, 201–213. https://doi.org/10.1007/s10489-013-0455-3

Allsop, R.E., 1968. Selection of Offsets to Minimize Delay to Traffic in a Network Controlled by Fixed-Time Signals. Transportation Science 2, 1–13. https://doi.org/10.1287/trsc.2.1.1

Day, C.M., 2010. Performance-based management of arterial traffic signal systems. Theses and Dissertations Available from ProQuest 1–480.

Federal Highway Administration, 2017. Comprehensive Truck Size and Weight Study.

Ficklin, W.E.P., N.C., 1969. The Analog Traffic Signal Model. Traffic Engineering 54–58.

Gartner, N., Assman, S., Lasaga, F., Hou, D., 1991. A multi-band approach to arterial traffic signal optimization. Transportation Research Part B: Methodological 25, 55–74. https://doi.org/10.1016/0191-2615(91)90013-9

Gartner, N.H., 1982. Demand-Responsive Decentralized Urban Traffic Control. Part I: Single-Intersection Policies.

Gartner, N.H., Assmann, S.F., Lasaga, F., Hous, D.L., 1990. MULTIBAND–A VARIABLE-BANDWIDTH ARTERIAL PROGRESSION SCHEME. Transportation Research Record.

Gartner, N.H., Pooran, F.J., Andrews, C.M., 2002. Optimized Policies for Adaptive Control Strategy in Real-Time Traffic Adaptive Control Systems: Implementation and Field Testing. Transportation Research Record 1811, 148–156. https://doi.org/10.3141/1811-18

Hillier, J.A., Holroyd, J., 1965. THE GLASGOW EXPERIMENT IN AREA TRAFFIC CONTROL. Traffic Engineering and Control 7, 569–571.

Hunt, P.B., Robertson, D.I., Bretherton, R.D., Winton, R.I., 1981. SCOOT - A TRAFFIC RESPONSIVE METHOD OF COORDINATING SIGNALS. Publication of: Transport and Road Research Laboratory.

Jennie Lioris, Alex Kurzhanskiy, Pravin Varaiya, 2016. Adaptive Max Pressure Control of Network of Signalized Intersections. IFAC-PapersOnLine 49, 19–24. https://doi.org/10.1016/j.ifacol.2016.10.366

Little, J.D.C., 1966. The Synchronization of Traffic Signals by Mixed-Integer Linear Programming. Operations Research 14, 568–594. https://doi.org/10.1287/opre.14.4.568

Little, J.D.C., Kelson, M.D., Gartner, N.M., 1981. Maxband: a program for setting signals on arteries and triangular networks, in: Transportation Research Record.

Lopez, P.A., Behrisch, M., Bieker-Walz, L., Erdmann, J., Flötteröd, Y., Hilbrich, R., Lücken, L., Rummel, J., Wagner, P., Wiessner, E., 2018. Microscopic Traffic Simulation using SUMO, in: 2018 21st International Conference on Intelligent Transportation Systems (ITSC). pp. 2575–2582. https://doi.org/10.1109/ITSC.2018.8569938

Lowrie, P.R., 1982. The Sydney coordinated adaptive traffic system - principles, methodology, algorithms.

Ma, C., Wang, B., Li, Z., Mahmoudzadeh, A., Zhang, Y., 2022. Lyapunov Function Consistent Adaptive Network Signal Control with Back Pressure and Reinforcement Learning. https://doi.org/10.48550/arXiv.2210.02612

Mirchandani, P., Head, L., 2001. A real-time traffic signal control system: architecture, algorithms, and analysis. Transportation Research Part C: Emerging Technologies 9, 415–432. https://doi.org/10.1016/S0968-090X(00)00047-4

Morgan, J.T., Little, J.D.C., 1964. Synchronizing Traffic Signals for Maximal Bandwidth. Operations Research 12, 896–912. https://doi.org/10.1287/opre.12.6.896

N.H.Gartner, 1972. Optimal synchronization of traffic signal networks by dynamic programming. Traffic Flow and Transportation.

Petterman, J.L., 1947. Timing Progressive Signal Systems. Traffic Engineering 29, 194–199.

R. T. Van Katwijk, 2008. Multi-Agent Look-Ahead Traffic-Adaptive Control (PhD Thesis).

Robertson, D.I., 1969. "TRANSYT" method for area traffic control. Traffic Engineering & Control 11.

Schrank, D., Eisele, B., Lomax, T., Bak, J., 2015. 2015 Urban Mobility Scorecard.

Sen, S., Head, K.L., 1997. Controlled Optimization of Phases at an Intersection. Transportation Science 31, 5–17. https://doi.org/10.1287/trsc.31.1.5

Shelby, S.G., 2001. Design and evaluation of real-time adaptive traffic signal control algorithms (phd). The University of Arizona.

Srinivasan, D., Choy, M.C., Cheu, R.L., 2006. Neural Networks for Real-Time Traffic Signal Control. IEEE Transactions on Intelligent Transportation Systems 7, 261–272. https://doi.org/10.1109/TITS.2006.874716

Stevanovic, A., Kergaye, C., Martin, P.T., 2009. SCOOT and SCATS: Closer Look into Their Operations.

Sunkari, S.R., Engelbrecht, R.J., Kevin N. Balke, 2004. Evaluation of advanced coordination features in traffic signal controllers (No. Report 0-4657-1). Texas Department of Transportation.

Trafficware, 2017. Synchro User Manual [WWW Document]. URL http://www.trafficware.com/resources.html (accessed 10.27.20).

Transportation Research Board, 2016. Highway Capacity Manual 6th Edition: A Guide for Multimodal Mobility Analysis. https://doi.org/10.17226/24798

Varaiya, P., 2013. The Max-Pressure Controller for Arbitrary Networks of Signalized Intersections, in: Ukkusuri, S.V., Ozbay, K. (Eds.), Advances in Dynamic Network Modeling in Complex Transportation Systems, Complex Networks and Dynamic Systems. Springer, New York, NY, pp. 27–66. https://doi.org/10.1007/978-1-4614-6243-9_2

Wang, X.B., Cao, X., Wang, C., 2017. Dynamic optimal real-time algorithm for signals (DORAS): Case of isolated roadway intersections. Transportation Research Part B: Methodological 106, 433–446. https://doi.org/10.1016/j.trb.2017.06.005

Wei, H., Zheng, G., Gayah, V., Li, Z., 2019. A Survey on Traffic Signal Control Methods. arXiv e-prints 1904, arXiv:1904.08117.