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**Development of Agent-Based On-line Adaptive Signal Control (ASC)
Framework Using Connected Vehicle (CV) Technology**

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ABSTRACT

In this study, we developed an adaptive signal control (ASC) framework for connected vehicles (CVs) using agent-based modeling technique. The proposed framework consists of two types of agents: 1) vehicle agents (VAs); and 2) signal controller agents (SCAs) including signal head sub-agent (SH-SA), information processing sub-agent (IP-SA), transition feasibility management sub-agent (TFM-SA) and decision making sub-agent (DM-SA). Within the communication range, each VA communicates with other VAs and SCA and transmits the estimation or prediction of its key statistics, such as position (at the lane level), speed, turning intention and anticipated time-of-arrival (TOA). Then the IP-SA may collect VAs' statistics and aggregate them into some critical metrics (e.g., queue length, delay, and time utilization rate) at the lane or movement level to support the signal control. With the constraints on phase transition feasibility (e.g., minimum green and movement compatibility), the DM-SA can determine in real-time if the current phase should be extended or switch to another phase. In addition, we proposed a new performance measure, called anticipated green utilization rate (GUR), to evaluate the system performance at traffic signals. Preliminary study in simulation validates the proposed ASC framework using an isolated intersection. The results showed that the ASC algorithms with both queue length optimization and anticipated green utilization rate outperformed the fine-tuned fixed signal timings (with knowledge of hourly traffic demands) in terms of mobility and environment sustainability by the range of 9% - 18% and 2% - 7%, respectively.

Keywords:

Agent-based modeling, adaptive signal control (ASC), optimization, connected vehicles (CVs)

I. INTRODUCTION

Uninterrupted growths of travel demands, coupled with limited space for expansion of existing roadway infrastructure, are witnessed in most urban areas. As a result, a variety of social and economic challenges have emerged, including ever-increasing congestion in traffic, more waste in energy consumption and worse air quality. According to the data collected across 471 urban areas in the United States, it is reported that traffic congestion is responsible for an extra 6.9 billion-hours delay and an extra 3.1 billion-gallons of fuel waste for urban Americans in Year 2014 [1]. In addition, the U.S. Environmental Protection Agency (USEPA) estimated that the transportation sector contributed about 30.5% of total U.S. carbon dioxide (CO₂) emissions and 27.1% of total U.S. greenhouse gas (GHG) emissions in 2013 [2].

To cope with aforementioned urban mobility and environment challenges, a variety of strategies have been proposed by policy makers, engineers and researchers, including better urban planning to reduce vehicle-miles-traveled and encouraging environmentally-friendly transportation modes. Developing active traffic and demand management (ATDM) strategies, which may leverage the state-of-the-art information and communication technology (ICT) to maximize the utilization of existing roadway resources, has been proved to be an attractive solution to the problems resulting from traffic congestion in urban areas. For arterial roadways, most ATDM strategies have focused on traffic signal timing optimization at signalized intersections or along signalized corridors. These strategies aim to determine key parameters including optimal cycle lengths, green splits, phase sequence, and offsets of traffic signals in response to the ever-changing traffic demand. It was suggested that signal timing optimization (and coordination) is one of the most cost-effective ways to improve traffic system operation on arterial roads. Previous studies showed that the benefit-to-cost ratio for optimizing signal timing plans in California was estimated to be 17:1 [3].

Since the invention of traffic signals, numerous signal timing optimization methodologies have been introduced over decades. To be mathematically tractable, many of the proposed methods in essence are “off-line” or designed for pre-timed control, which assume that the traffic demand on each intersection approach is constant and known during the analysis period (e.g., one hour or morning peak). However, this is usually not the case in the real world, which has always been a major challenge for traffic operations and management on arterial roadways. In order to accommodate fluctuations in traffic demand and its arrival patterns, traffic responsive signal timing optimization methodologies have been developed, such as TRANSYT [4], PASSER II [5], MAXBAND [6], and MULTIBAND [7, 8]. More recently, adaptive signal control systems, which can continuously adjust signal phases and timings in response to real-time traffic conditions, have received increasing attention [9, 10]. Examples of the existing systems include SCOOT [11], SCAT [12], RHODES [13], MOTION [14], TUC [15], OPAC [16], UTOPIA [17], and PRODYN [18]. However, all the aforementioned signal control systems rely on point detection (e.g., from inductive loop detectors or ILDs), and estimate traffic states based on very limited information. For example, it is non-trivial to differentiate transportation modes, such as transit buses or trucks using conventional ILDs. Even worse, the estimation in some cases (e.g., over-saturated conditions) may greatly deviate from the real-world situation, resulting in degraded system performance.

The introduction of wireless communication among vehicles (V2V) as well as between

vehicles and infrastructure (V2I/I2V), referred to as Connected Vehicle (CV) technology, provides a well-defined platform for continuously monitoring vehicles' characteristics (e.g., vehicle type) and activities (e.g., location and speed), and sharing real-time information among a variety of players (both vehicles and infrastructure) within a transportation network. Given such high resolution information on real-time traffic conditions, many potential problems associated with conventional point detection can be addressed.

Recently, more and more studies have focused on signal control using wireless communication or more specifically CV technology [19]. With the capability to track individual vehicle's activities, CV-based signal control strategies may rely on more accurate detection and more reliable prediction (e.g., using a rolling horizon approach [20]). In addition, unlike conventional adaptive signal control systems that are restricted by the fixed location sensors, the queue spillback issue under over-saturated traffic conditions can be well addressed using CV technology [21]. Some of the existing CV-based strategies formulated the traffic signal control problem into a nonlinear constrained programming [22], which potentially inhibits the on-line implementation of the algorithm. Others used aggregated performance measures (e.g., platoon [23] or passing rate [24]) for computational tractability, without taking full advantage of each individual vehicle's information (e.g., speed trajectory, vehicle type and turning movement) available via vehicular communications. To overcome these limitations, an agent-based online adaptive signal control framework is developed in this study, which is both computationally attractive and flexible enough to accommodate the variation in traffic demands as well as safety constraints (e.g., minimum green). It also has the potential to coordinate among different travel modes (e.g., passenger cars, transit buses and trucks) in order to achieve system-wide optimal solution. In addition, this study can be regarded as an extension of the research team's effort on the development of multi-agent system (MAS) based eco-friendly freight signal priority (Eco-FSP) using CV technology [25].

II. BACKGROUND

Before the presentation of the proposed agent-based on-line adaptive signal control framework, background information on key components or concepts used in this study is discussed in this section.

Agent-Based System (ABS) for Urban Traffic Control

Agent-oriented technology offers a brand-new approach to traffic operation and management. Researchers have designed a variety of agent-based systems ABS to solve traffic congestion problems, some of which have already been effectively applied to traffic controls in real world by improving efficiency, strengthening robustness, increasing scalability and reducing costs [26].

Many studies have explored the use of ABS for cooperative urban traffic networks. Desai et al. [27] reviewed existing congestion management techniques and comprehensively surveyed advantages of existing ABS in the realm of intelligent transportation systems (ITS). Different multi-agent technologies were classified and their suitability in congestion

management was discussed. Wu [28] proposed an urban traffic multi-agent system (MAS) to manage the gradual congestion of a traffic network, where a fuzzy control strategy was developed for the intersection agent. The simulation study showed that the proposed control resulted in better traffic performance than either fixed-time or actuated signal control. In a large-scale traffic network, multi-agent techniques could also coordinate the individual traffic control instruments by modeling various traffic control measures as intelligent agents. van Katwijk et al. [29] developed an integrated block-based look-ahead traffic-adaptive control algorithm with the multi-agent coordination approach and illustrated the benefits of the improved algorithm for an arterial case in simulation.

Metrics for Performance Evaluation at Signals

Based on different detection and communication technologies, a variety of measures of effectiveness (MOEs) have been proposed and used to evaluate traffic operations at intersections controlled by traffic signals. Typical performance measures include travel time and its variance, speed, delay, queue and stops, as detailed in Table 1 below.

Table 1. Commonly Used MOEs for Signalized Intersections [30]

MOE	Typical Usage
Travel Time	Used in long range planning studies at regional or corridor level to evaluate traveler benefits of alternative improvements. Used to evaluate traveler benefits of signal timing improvements for individual facility.
Speed	Used to evaluate alternatives in long range planning studies at regional or corridor level. Used to evaluate benefits of signal timing improvements for individual facility. Used to estimate fuel consumption and air quality impacts.
Delay	Used to evaluate alternatives in long range planning studies at regional or corridor level. Used to evaluate benefits of signal timing improvements for individual intersection or facility. Used to determine the LOS at signalized intersections per HCM Used to estimate fuel consumption and air quality impacts.
Queue	Used to identify hot spots, operations problems at points of facility (left turn bays, blockages, safety)
Stops	Used to evaluate quality of signal timing plans along arterials/networks Used to determine estimates of fuel and air pollution emissions
Travel Time Variance	Used to evaluate benefits of traffic operations improvements that reduce variability but not mean travel time or delay.

A more comprehensive set of performance measures have been proposed in [31] (see Appendix A), which can be classified into three major categories depending on the traffic conditions (either under-saturated or over-saturated):

- **Safety:** this category can be surrogate measures on potential collision risks (e.g., encroachment time) or even statistics related to occurrence of actual accidents, such as number of red light running violators.
- **Mobility:** the system mobility at signals may be measured either directly from vehicles as depicted in Table 1, or indirectly from signal operation status which can include but not limited to percentage of overloaded cycles (or cycle failures) [32], average number phase activations, and average time-to-service.
- **Environment:** the major metrics under this category are energy consumption (or fuel consumption) and emissions of criteria pollutants.

It is noted that the selection of performance measures is limited by the available technology

(e.g., inductive loop detectors). In this study, three key performance measures – queue length, current delay and expected time utilization rate – available via connected vehicle technology will be used for traffic signal control. The definitions of these metrics will be elaborated in Section III.

Simulation Software

To support the modeling and evaluation of proposed adaptive signal control framework, PARAMICS (PARAllel MICroscopic Simulation of road traffic) [33] and the MOVES (MOtor Vehicle Emission Simulator) model [34] were used in this research to conduct simulation study.

PARAMICS

The simulation network was built in PARAMICS traffic micro-simulation software suite version 6.9.3. The software suite consists of six major modules, including Modeler, Processer, Analyzer, Programmer, Monitor, and Estimator. These modules can be used to model behavior of individual vehicle (driver) and interaction between vehicles in a stochastic way, and to evaluate the system performance. Simulation network setup, roadway configuration, and traffic demand coding, among others, are performed in the Modeler module. The inputs to PARAMICS include network geometry, vehicle dynamics, traffic control settings, and traffic demand information, while the typical outputs include statistics at the network level (e.g., total number of vehicles release/arrived, total distance traveled, and overall time spent), on a link basis (e.g., flow, queue length, delay, and average speed), or at specific locations (instantaneous ILD-type information). With a user-defined software plug-in developed through application programming interface (API), statistics can also be reported on a time-step or event basis. For more detailed information about PARAMICS, please refer to [35].

MOVES

The MOVES model developed by the United States Environmental Protection Agency (USEPA) is able to estimate both energy consumption and pollutant emissions from vehicle trajectory data. In MOVES, there are a total of 23 vehicle operating modes (OpMode) for running exhaust emissions, which are defined as a function of vehicle specific power (VSP) and vehicle speed. VSP is defined as the power per unit mass to overcome road grade, rolling and aerodynamic resistance, and inertial acceleration. As a strong descriptor of vehicle fuel consumption and emissions, VSP can be calculated as:

$$VSP = \left(\frac{A}{M}\right) * v + \left(\frac{B}{M}\right) v^2 + \left(\frac{C}{M}\right) v^3 + (a + g * \sin\theta) * v \quad (1)$$

where v is vehicle speed (m/s); a is vehicle acceleration (m/s^2); g is the gravitational acceleration (m/s^2); M is vehicle mass (kg); θ is road grade (degree); and A , B , and C are road load coefficients for rolling, rotating, and drag terms, respectively.

Appendix B presents the procedure for creating vehicle OpMode distribution from second-by-second vehicle trajectories. More specifically, for each second of the vehicle trajectory, the corresponding VSP value is calculated using the equation above. The vehicle OpMode is then determined based on the VSP and speed values. Finally, the vehicle OpMode distribution is created from all of the data points. With the vehicle OpMode distribution, the

energy consumption and pollutant emissions can be estimated using the emission factors from MOVES database.

To integrate the MOVES model into PARAMICS, emission rate tables for different source types were coded as the configuration files for the PARAMICS network model. A dedicated plug-in has been developed to calculate second-by-second OpMode in real-time for each vehicle running in the network. The work flow for MOVE plug-in development is also illustrated in the Appendix B and readers can refer to [36] for more details.

III. PROPOSED AGENT-BASED ADAPTIVE SIGNAL CONTROL FRAMEWORK

The basic idea of the proposed adaptive signal control framework is that a signal controller agent (SCA) can determine the signal head status (i.e., green, yellow or red) of each lane **at the next time step** based on intrinsic constraints (e.g., movement conflicts or minimum greens) as well as information sent from individual vehicle agents (VAs).

Consider a typical four-legged signalized intersection with full capability of Connected Vehicle (CV) technology (see Figure 1). When an equipped VA enters the vehicle-to-infrastructure communication range, it can send associated information, including vehicle type, speed, turning movement and some predicted state (e.g., time-of-arrival), to the SCA to facilitate its decision making on the signal phase and timing (SPaT) at the next time step. On the other hand, the SCA broadcasts the up-to-date SPaT information to any involved VA to assist its state prediction. In addition, each individual VA can communicate its real-time information, such as location and speed, with other VA(s) within the vehicle-to-vehicle communication range to further improve the prediction of vehicle's activities.

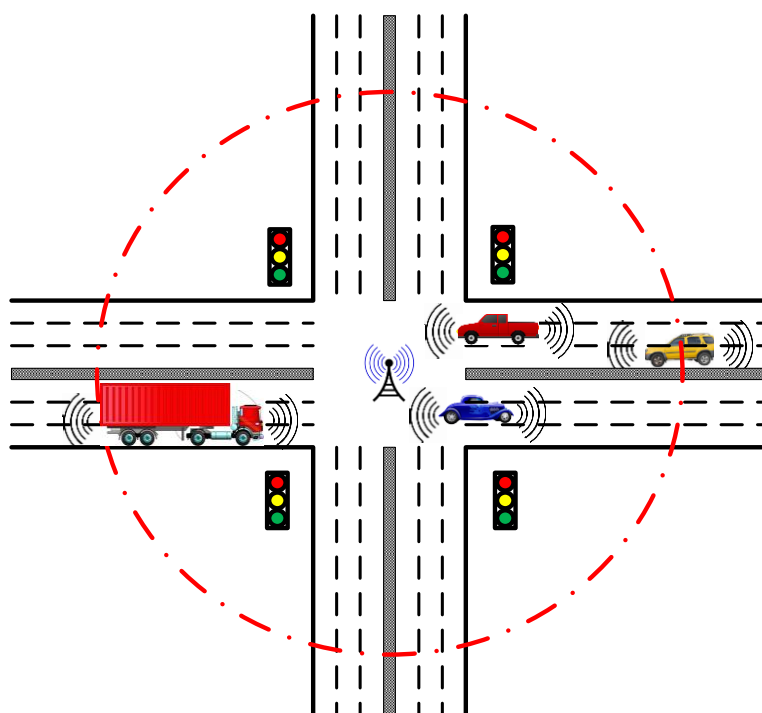


Figure 1. An example signalized intersection with connected vehicle technology.

The Architecture

Figure 2 illustrates the architecture of the proposed system which consists of two major types of agents: 1) vehicle agents (VAs); and 2) signal controller agents (SCAs) including signal head sub-agent (SH-SA), information processing sub-agent (IP-SA), transition feasibility management sub-agent (TFM-SA) and decision making sub-agent (DM-SA). Within the communication range, each VA communicates with other VAs and SCA and transmits the estimation or prediction of its key statistics, such as position (at the lane level), speed, turning intention and anticipated time-of-arrival (TOA). Then the IP-SA may collect VAs' statistics and aggregate them into some critical metrics (e.g., queue length, delay, and time utilization rate) at the lane or movement level to support the signal control. With the constraints on phase transition feasibility (e.g., minimum green and movement compatibility), the DM-SA can determine in real-time if the current phase should be extended or switch to another phase.

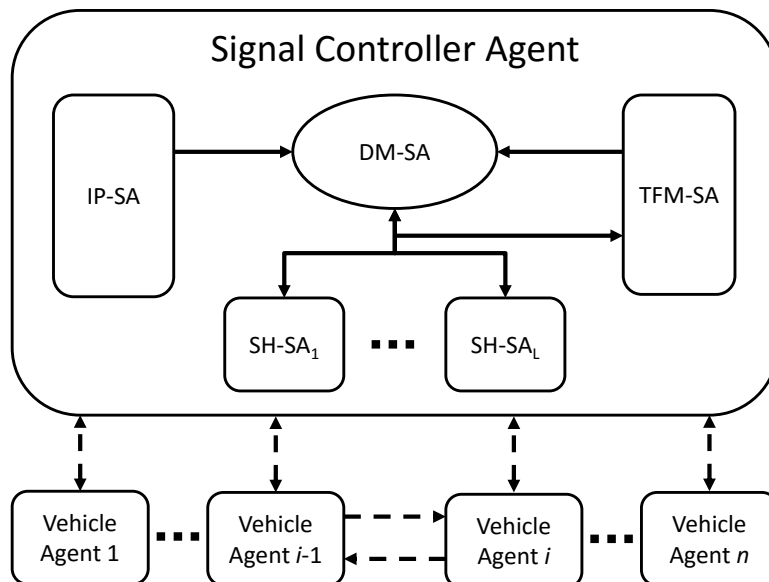


Figure 2. The architecture of proposed agent-based adaptive signal control system.

Vehicle Agent (VA)

As aforementioned, the major functionalities of a VA include communicating with the upcoming SCA and other neighbor VAs, and estimating/predicting its states via CV technology. In this study, the time-of-arrival is the key parameter of each VA for prediction.

Time-Of-Arrival (TOA) Prediction

The time-of-arrival (TOA) in this study is defined as the time instance when the vehicle is about to leave from the stop bar. According to the downstream traffic states at the time stamp when prediction is conducted and the signal status, i.e., green or red (including amber) when the vehicle arrives at the stop bar at free-flow speed, four scenarios can be differentiated as shown in Table 2. If there is no vehicle ahead (before the signal) at prediction, the VA is regarded as a leader VA, otherwise, it is defined as a follower VA. A similar description of the TOA prediction problem may be found in [37].

For the sake of simplicity, the TOA prediction is based on a VA being considered to be either idle or cruising. Additional modes, such as acceleration and deceleration, may be incorporated in the future. Specifically, the predicted TOA for the i -th VA may be expressed as follows:

Table 2. Time-of-arrival Scenario Matrix

Signal Status at FFS	Leader VA	Follower VA
Green	A	C
Red	B	D

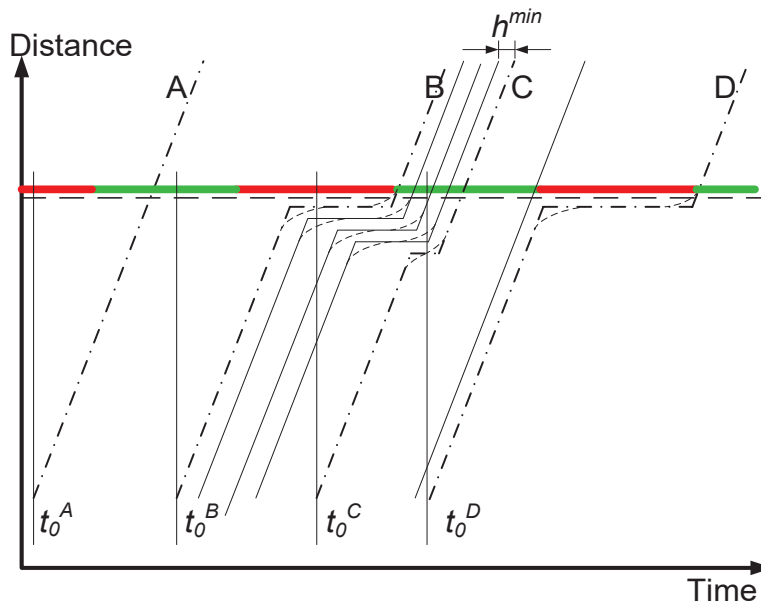


Figure 3. Illustration of scenarios for TOA prediction.

$$T_i^{arr} = \max \left\{ \frac{d_i(t_0)}{v_i^{cruise}} + t_0 + f_1(t_0), T_{i-1}^{arr} + h^{min} + f_2(t_0) \right\} \quad (2)$$

where

$$f_1(t_0) = \begin{cases} 0, & \text{Green at time } \frac{d_i(t_0)}{v_i^{cruise}} + t_0 \text{ (Scenario A)} \\ T_1^{NG}, & \text{Red at time } \frac{d_i(t_0)}{v_i^{cruise}} + t_0 \text{ (Scenario B)} \end{cases} \quad (3)$$

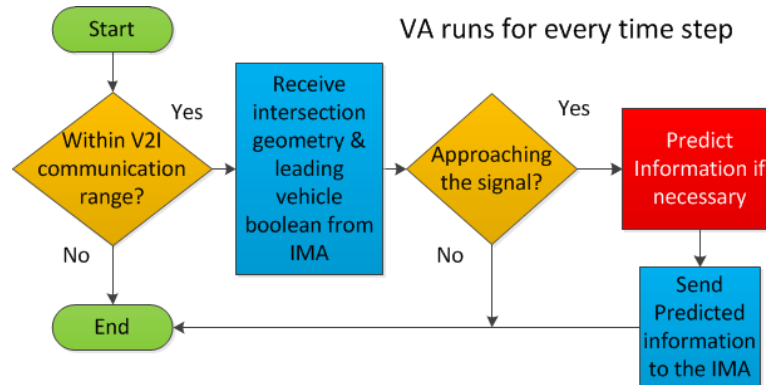
$$f_2(t_0) = \begin{cases} 0, & \text{Green at time } T_{i-1}^{arr} + h^{min} \text{ (Scenario C)} \\ T_2^{NG}, & \text{Red at time } T_{i-1}^{arr} + h^{min} \text{ (Scenario D)} \end{cases} \quad (4)$$

t_0 is the current time, $d_i(t_0)$ is the distance to the stop bar for the i -th VA at time t_0 , v_i^{cruise} is the cruising speed of the i -th VA, h^{min} is the minimum headway between two consecutive VAs, and T_1^{NG} and T_2^{NG} represent the time to the next green with respect to time $\frac{d_i(t_0)}{v_i^{cruise}} + t_0$ and $T_{i-1}^{arr} + h^{min}$, respectively. Note that the algorithm for predicting TOA is recursive in the

sense that a vehicle's TOA is predicted based on the preceding vehicle's predicted TOA.

Flow Chart of Vehicle Agent

Figure 4 presents the flow chart of a vehicle agent, indicating maneuvers that a VA needs to execute at each time step.



Note: IMA (intersection management agent) is SCA in this study

Figure 4. Vehicle agent's flow chart.

Signal Controller Agent (SCA)

As mentioned earlier, the SCA is composed of four sub-agents, i.e., signal head sub-agent (SH-SA), information processing sub-agent (IP-SA), transition feasibility management sub-agent (TFM-SA), and decision making sub-agent (DM-SA). A more detailed description of each sub-agent will be presented below.

Signal Head Sub-Agent (SH-SA)

The function of SH-SA is to display the signal status for each traffic light that is associated with each lane. The display follows a simple pattern of modes, i.e., green – yellow – red – green ... periodically (see Figure 5). Whether or not the mode will transition to another follows either intrinsic constraints (e.g., minimum green) or external command signals from other type of sub-agents.

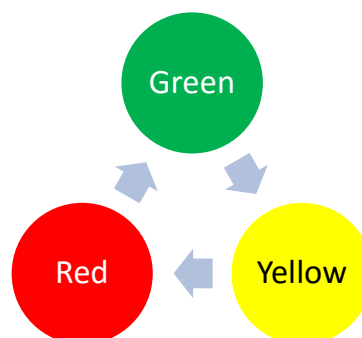


Figure 5. Display pattern for signal head sub-agent.

Information processing sub-agent (IP-SA)

The IP-SA is developed to receive information from incoming VAs, aggregate it into

lane level, and process it into specific performance measure on a movement basis for signal control. In this study, the following two performance measures are estimated to support the decision making of phase transition.

- *Queue length*

The queue length defined in this study is the number of vehicles within the infrastructure-to-vehicle (I2V) communication range. For a movement with multiple lanes, the queue length for the i -th movement, QL_i , is

$$QL_i = \max_{l \in L_i} \{N_l\} \quad (5)$$

where L_i is the set of lanes along the i -th movement; and N_l is the number of vehicles within DSRC range on the l -th lane.

- *Anticipated green utilization rate*

This performance measure is defined to evaluate how well the allocated time (including green intervals and phase transition time) is anticipated to be utilized to discharge vehicles. More specifically, starting from time t_0 , the anticipated green utilization rate for the i -th movement at time t ($t > t_0$), can be written as

$$GUR_i(t, t_0) = \frac{C_i(t, t_0)}{t - t_0} \quad (6)$$

where $C_i(t, t_0)$ represents the number of vehicles whose predicted TOA at time t_0 are not more than t . Figure 6 illustrates the calculation of $GUR_i(t, t_0)$.

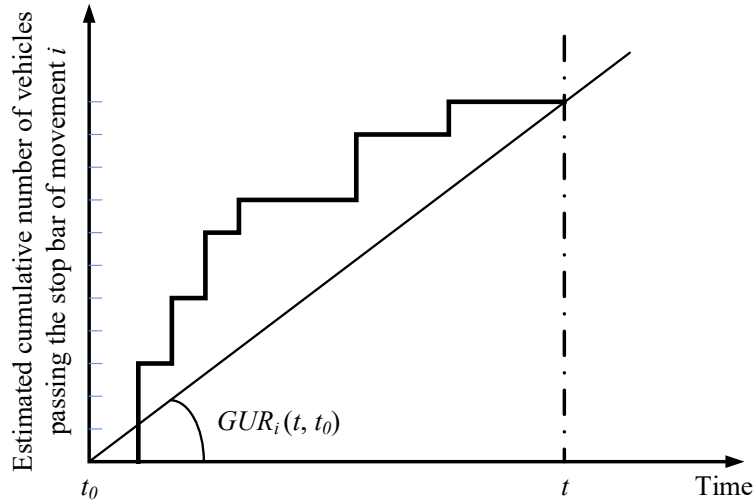


Figure 6. Illustration of GUR calculation.

Transition feasibility management sub-agent (TFM-SA)

The function of this sub-agent is to check the compatibility of movements that occur at the same time and to guarantee the transition from one phase (i.e., combination of movements) to another is feasible. To implement this function, the state machine is coded in application programming interface (API) based on the dual-ring National Electrical Manufacturing Association (NEMA) controller [38] which is commonly used in the United States. Figure 7 includes the dual-ring controller and the corresponding NEMA signal phase diagram. The two “rings” correspond to two sets of self-conflicting phases, phases $\{1, 2, 3, 4\}$ belonging to “Ring 1” and phases $\{5, 6, 7, 8\}$ belonging to “Ring 2.” At any given time instant, at most two signal

phases are active, one from each ring. The two rings operate independently, with the restriction that the selected phases must be on the same side of the barrier (e.g. phases 2 and 7 cannot be active simultaneously). Main street phases are normally numbered as {1, 2, 5, 6}, while side street phases are typically numbered as {3, 4, 7, 8}. A typical background cycle consists of a fixed pairing and sequence of phases, with the main street movements being served prior to the side street movements. For a standard 4-leg intersection, there are four green phases per cycle, separated by appropriate yellow and red phases. Fixed signal timing uses pre-determined durations (splits) for each of the four green phases and uses the fixed sequence and combination of phases prescribed in Figure 7. As shown in the figure, signal operation starts with phases 1 and 5, followed by 2 and 6, 3 and 7, and 4 and 8, before repeating.

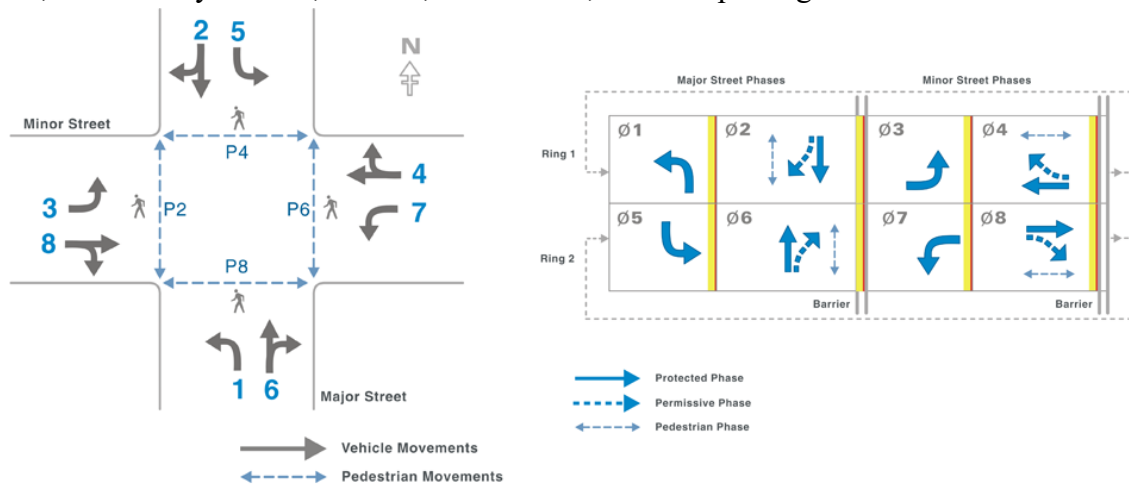


Figure 7. Signal phase diagram & dual-ring controller, adapted from [39].

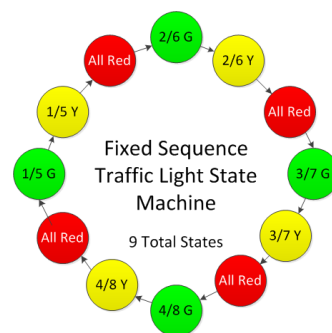


Figure 8. Fixed sequence & coupled phase dual-ring controller, finite state machine representation.

To further illustrate the limitations of the fixed signal timing interpretation of the dual-ring controller, the fixed sequence of traffic signals may be represented using a finite state machine, as shown in Figure 8. Including yellow and red phases, there are a total of 9 unique states, with the “All” red phase repeated in the transition between every phase. Previous work was based on using the fixed sequence of traffic signals as prescribed by the dual-ring controller, and focused on optimizing the duration of each of the green splits [25]. However, a fully adaptive signal control paradigm should also consider optimizing phase sequence in addition to phase duration. Moreover, it is not necessary to have a strict coupling of phases such as 1 and 5, and 2 and 6. In fact, phase 1 may operate with either phase 5 or 6. By permitting the rings to operate independently, the dual-ring controller may be represented with a more

advanced and flexible finite state machine, as shown in Figure 9. The red cylinder, labeled as the “All Red” state, represents the barrier, as well as the only link, between the main street and side street phases. There are four “green” states on each side of the barrier, for a total of eight “green” states. The main street half of the diagram in Figure 9 is shown in Figure 10. The side street half of the diagram is nearly identical to the main street half, and is omitted for the sake of brevity. “Green” colored states occur where two green phases are active. “Yellow” colored states occur where at least one signal phase is yellow. Finally, “Red” colored states occur where all traffic lights are red, or if all but one signal phase is red.

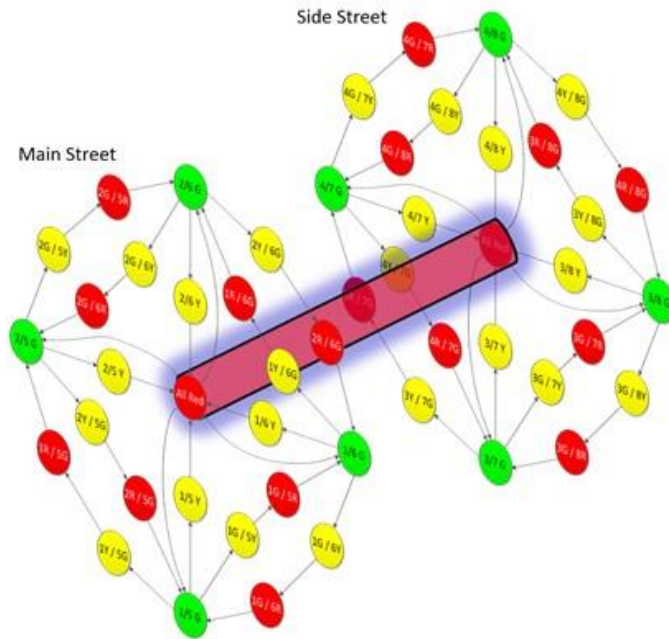


Figure 9. Flexible dual-ring controller, finite state machine representation.

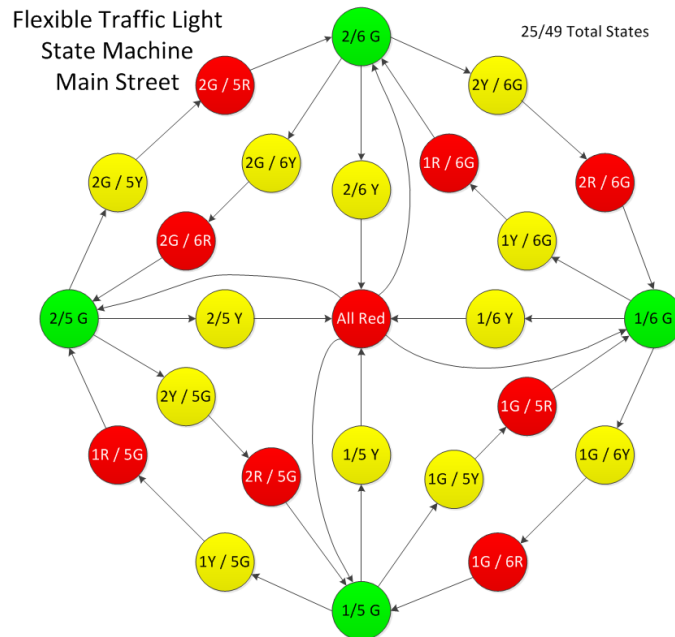


Figure 10. Main street portion of flexible dual-ring controller, finite state machine representation.

The total of 49 states allow for a variety of signal strategies to be implemented by the

signal controller agent, including “green extension,” “early green,” “phase insertion,” and “phase rotation.” Furthermore, the diagram shown in Figure 9 also indicates state transition information. At any given state, the set of possible next states is fully specified. In summary, the proposed flexible traffic light state machine provides a convenient framework for visualizing adaptive signal control and presenting state transition information.

Decision making sub-agent (DM-SA)

Upon receiving the information from the IP-SA, the DM-SA can determine if the current phase should be extended to another time step or not, and which phase should be the next active one, taking into account the feasibility of phase transition. For the anticipated green time utilization rate optimization, the flow chart to govern the decision making process of the DM-SA is illustrated in Figure 11.

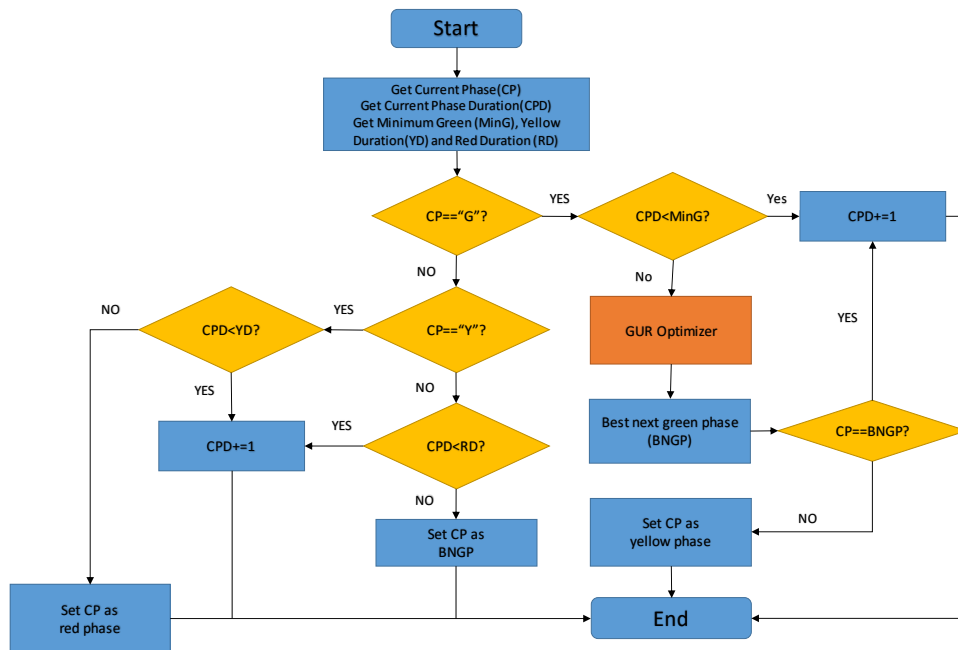


Figure 11(a). Flow chart of the DM-SA.

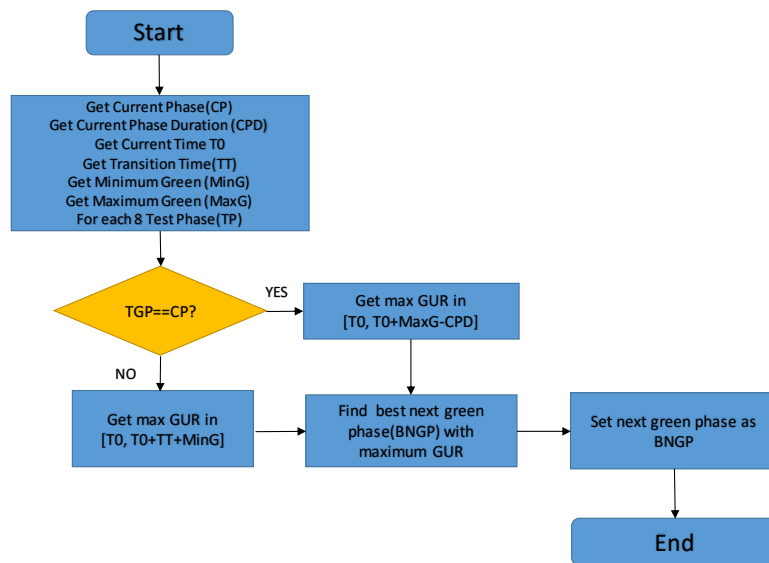


Figure 11(b). Flow chart of the GUR optimizer module.

IV. SIMULATION STUDY

To validate the proposed agent-based on-line adaptive signal control, a preliminary simulation study has been conducted using PARAMICS.

Simulation Setup

An isolated intersection with three lanes in each cardinal direction was constructed in PARAMICS (see Figure 12). The left-most lane is set as a left-turn only lane, the center lane is set as a through lane, and the right-most lane is set as a shared through and right-turn lane with right turn on red (RTOR) functionality. The link length is set to 300 meters and the speed limit is set to 45 mph. The ratio of main street to cross street traffic is set to 3:2 and the ratio of left-turn to through (combined with right-turn) traffic for each approach is set to 1:4. All the vehicles running in the network are passenger cars. The communication radius is set to 300 meters, and packet loss and latency are considered negligible. The experiment is devised as follows:

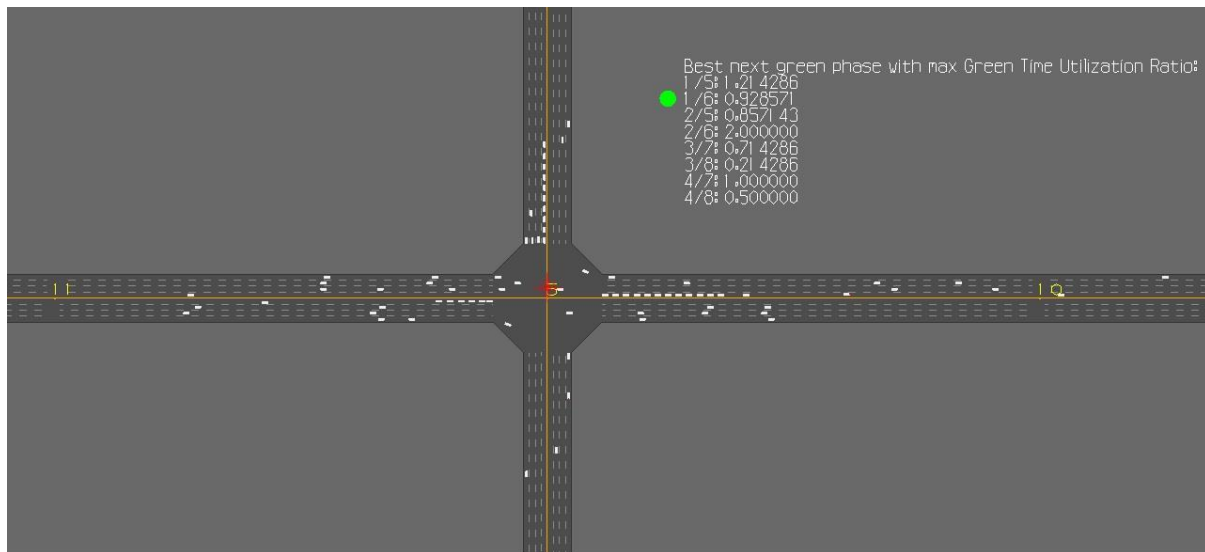


Figure 12. Screenshot of simulation model (an isolated intersection) in PARAMICS.

Vary total volume (1000, 1111, 1250, 1428, and 1666 vph), keeping a *varied* quarter-hourly rate over one hour (as shown in Figure 13).

- Use predetermined Signal Timing Manual (STM) [39] based fixed signal cycle length, phase sequence, and splits;
- Use agent-based online adaptive signal control strategy with queue length optimization;
- Use agent-based online adaptive signal control strategy with GUR optimization.

Traffic demand profile for the experiment is indicated in Figure 13. Note that the integral should be one. The proposed adaptive signal control algorithms with queue length optimization and anticipated green utilization rate are compared against a fixed phase timing baseline in which the total hourly volume for each movement is assumed **to be known a priori**.

As mentioned earlier, the Quick Estimation Method (QEM) is used to determine the green splits [39] under different demand levels, and the HCM method is used to determine the appropriate cycle lengths accordingly [40]. The minimum green and maximum green are 8 seconds and 64 seconds, respectively. The amber is 3 seconds and all red interval is 1 second. Each experiment is conducted for one hour, with the same random generation of VAs used for both the baseline QEM/HCM fixed phase timing and adaptive signal control with both queue length optimization and anticipated green utilization rate optimization.

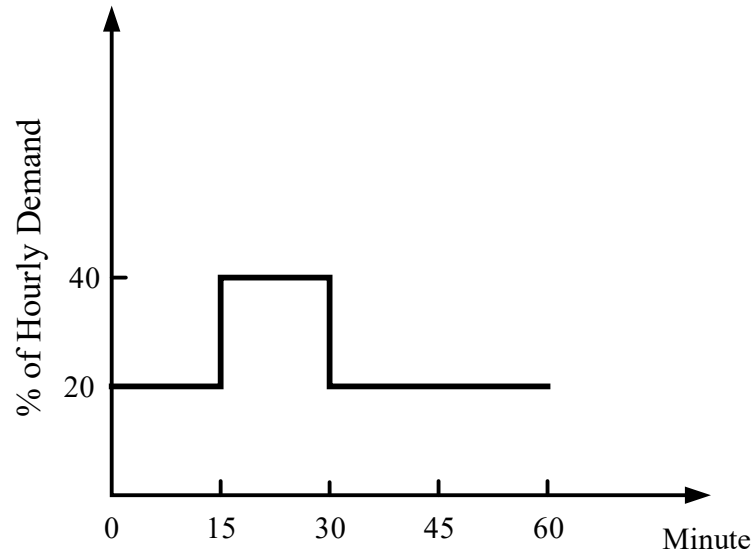


Figure 13. Hourly demand profile for the experiment.

Preliminary Simulation Results

The evaluation of algorithm performance is focused on both mobility and environmental sustainability.

Mobility

In terms of mobility, the average travel time per vehicle is compared among different algorithm. Table 2 and Figure 14 present the simulation results. Compared to the fixed timing signal control which has been tuned under the knowledge of hourly demand, the adaptive signal control with queue length optimization and anticipated green utilization rate optimization may still reduce the average travel time by 9% - 18%, depending on traffic volumes. Interestingly, the adaptive signal control algorithm with queue length optimization, in spite of its simplicity (i.e., count the number of vehicles within the DSRC range), can achieve satisfactory results. One hypothesis is the estimation of queue length is much more robust than the prediction of time-of-arrival.

Table 2. Comparison Results of Average Travel Time (sec/veh)

Control Algorithm	Hourly Volume (vph)				
	1000	1111	1250	1428	1666
Fixed-time	130.9	131.9	131.2	132.2	133.4
ASC with QL	111.4	115.4	109.8	119.7	116.6
ASC with GUR	107.7	111.1	116.2	114.7	117.6

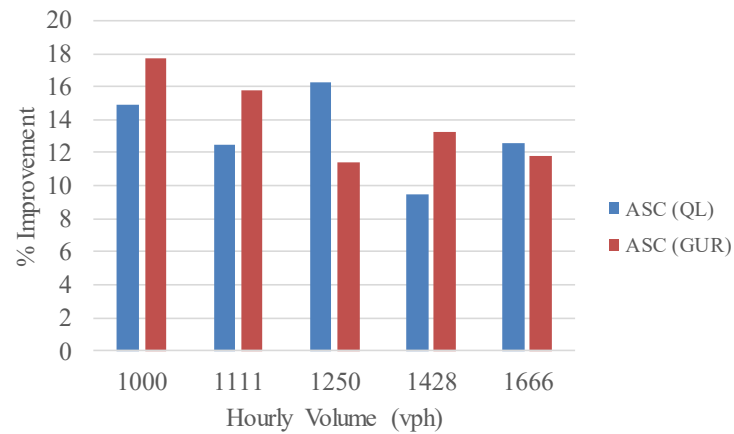


Figure 14. Relative improvement in mobility.

Energy

The simulation results shown in Table 3 and Figure 15 also indicate that the proposed ASC algorithms outperform the fine-tuned fixed-time signal control in the sense of energy consumption. The improvement may range from 2% to 7%, varying with different congestion levels.

Table 3. Comparison Results of Distance-based Energy Consumption (KJ/mi)

Control Algorithm	Hourly Volume (vph)				
	1000	1111	1250	1428	1666
Fixed-time	5069.4	5084.9	5059.4	5074.5	5090.2
ASC with QL	4767.8	4812.6	4762.4	4930.8	4846.0
ASC with GUR	4743.0	4842.2	4871.4	4869.9	4911.2

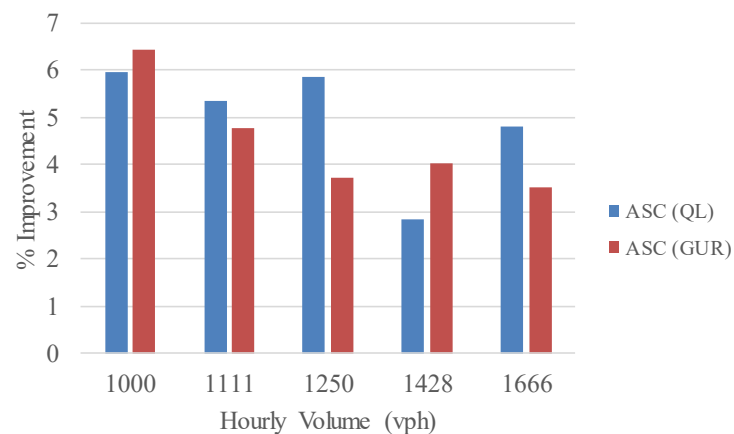


Figure 15. Relative improvement in energy.

V. DISCUSSION

The proposed adaptive signal control framework is designed to be flexible enough to accommodate real-time traffic variation without compromising safety constraints (e.g., minimum green or pedestrian call). Moreover, to guarantee the “fairness” of service, mandatory phase re-activation has been implemented if some phase has not been served for certain time. Regarding each module of the framework, further improvement can be expected as future work. For example, the time-of-arrival prediction is quite simple in this study, which may affect the reliability of green utilization rate estimation, thus downgrade the system performance. More advanced prediction methods and data-driven learning schemes may be developed to reduce the prediction errors and to be resilient to various fleet composition within the traffic stream. In addition, the current framework may be easily extended to a signalized corridor or an urban grid network with signals by considering each junction as an isolated signalized intersection. But adding a coordination layer may potentially enable the entire system to operate in a more cooperative manner.

It is noted that the proposed ASC algorithms cannot be fully implemented due to the constraints in PARAMICS. The provided functions in the signal operation category are not capable of handling such a flexible algorithm. The research team has to resort to an alternative method that relies on dynamically setting the priority types (i.e., major, medium and minor) on a lane basis. It is observed that, however, the way how the vehicles respond to the priority settings are not the same as to the signal settings. By visualization, vehicles’ response is much less sensitive to the dynamic priority settings. This may significantly bias the performance of the proposed ASC algorithms in simulation study. Furthermore, more extensive simulation runs should be conducted in the future to better understand the algorithms’ effectiveness under different scenarios, such as using a more realistic intersection with left-turn bays, various major/minor approach volume ratios, various left-turn/through movement volume ratios, and heterogeneous vehicle types. Besides mobility and energy, safety and reliability (e.g., travel-time index) performance can be evaluated in the next step.

The adaptive signal control framework is proposed herein under the assumption of full penetration rate, i.e., all vehicles are assumed to be connected vehicles. This is a very strong assumption when implemented in the real world. A more realistic scenario would be only a portion of vehicles are equipped. In this case, traffic states or measures of effectiveness have to be estimated or predicted using limited information (like in [41]). An alternative would be to fuse data from other traffic surveillance systems at signals, such as inductive loop detectors (ILDs) and video camera. In the presence of emergency vehicles, the proposed ASC framework should be flexible enough to handle such preemption.

VI. CONCLUSION

In this study, an agent-based online adaptive signal control framework is developed for urban traffic management in the connected vehicle environment. A novel performance measure, called anticipated green utilization rate (GUR), is proposed to support the selection of next active phase. A preliminary simulation study suggests that the proposed ASC algorithms with queue length optimization and GUR optimization are quite promising to accommodate significant traffic demand variations. Compared with a fine-tuned fixed-time signal control, the

proposed algorithms may reduce average travel time by 9% - 18% and reduce energy consumption by 2% - 7%. Further improvements and potential future work have been well discussed in Session V.

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Appendix A

I. MOBILITY

Operating	Operating	Performance Measure	Units	Comments
Intersection	Undersaturated	Average control delay	sec/veh	Difference free-flow travel time and actual travel time
				Average and 95 th % of the max extend of queue
				Proportion of cycles that queue failed to clear during
				Proportion of green utilized by traffic demand served by
	Oversaturated	Throughput	#	# vehicles served at the intersection per time interval
Arterial/ Grid Network	Undersaturated			Average travel time for movements served by
				Average travel speed for movements served by
				st deviation, 80 th or 95 th percentile of travel times served
				Average # of stops (fraction of veh stopped) for
		Total delay	veh-hr	Delay of all vehicles served in the system
				Proportion of platoon arriving during the green time per
				Proportion of the green through bandwidth to the signal
				Proportion of green bandwidth to the min green time for
	Transit delay ¹	sec/bus	average delay to transit vehicles at traffic signals	
	Acceleration noise	ft/sec ²	Standard deviation of veh accelerations	
	Oversaturated	Throughput	#	# veh served
		Extend of queue	#/mi	Distance or # of street segments with queue spillback
		Congestion duration	Hr	Duration of oversaturated conditions
II. SAFETY				
Intersection/ Arterial/	Undersaturated/ Oversaturated	# accidents per type	#/yr	# of accidents by severity and/or traffic movement (e.g.,
		Encroachment time (ET)	# conflicts	Surrogate conflict measure
		# RLR	#	# of red light running violators
				# vehicles in platoon arrive in the yellow clearance
III. ENVIRONMENTAL				
Intersection/ Arterial/	Undersaturated/ Oversaturated	Fuel Consumption	gal	Excess fuel consumption due to delay & stops
		HC/CO/NOx/CO2/PM	/qr/m,	Air pollutant emissions / concentrations
		Noise	[db]	Inceased noise level due to congestion

Appendix A.1: Example performance measures for signalized intersections [31].

Appendix B

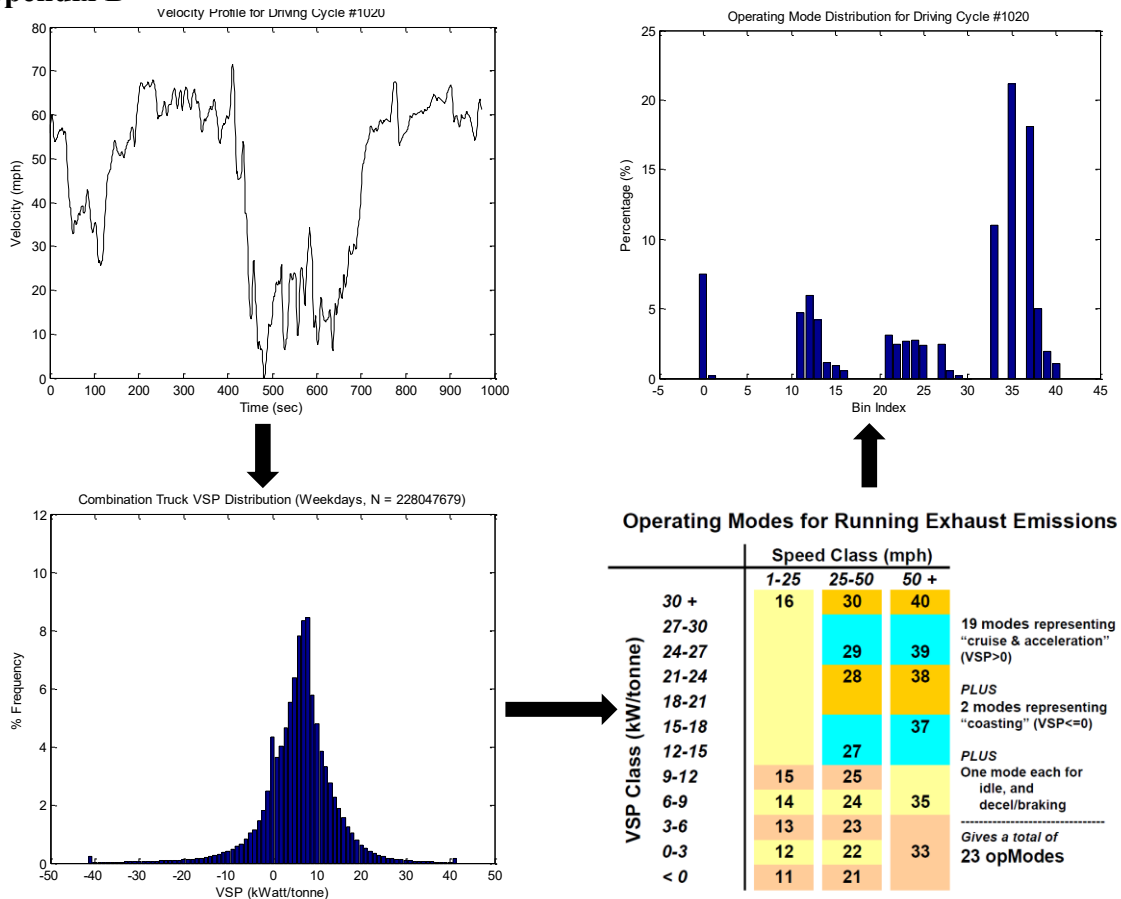


Figure B.1 Calculation of OpMode distribution.

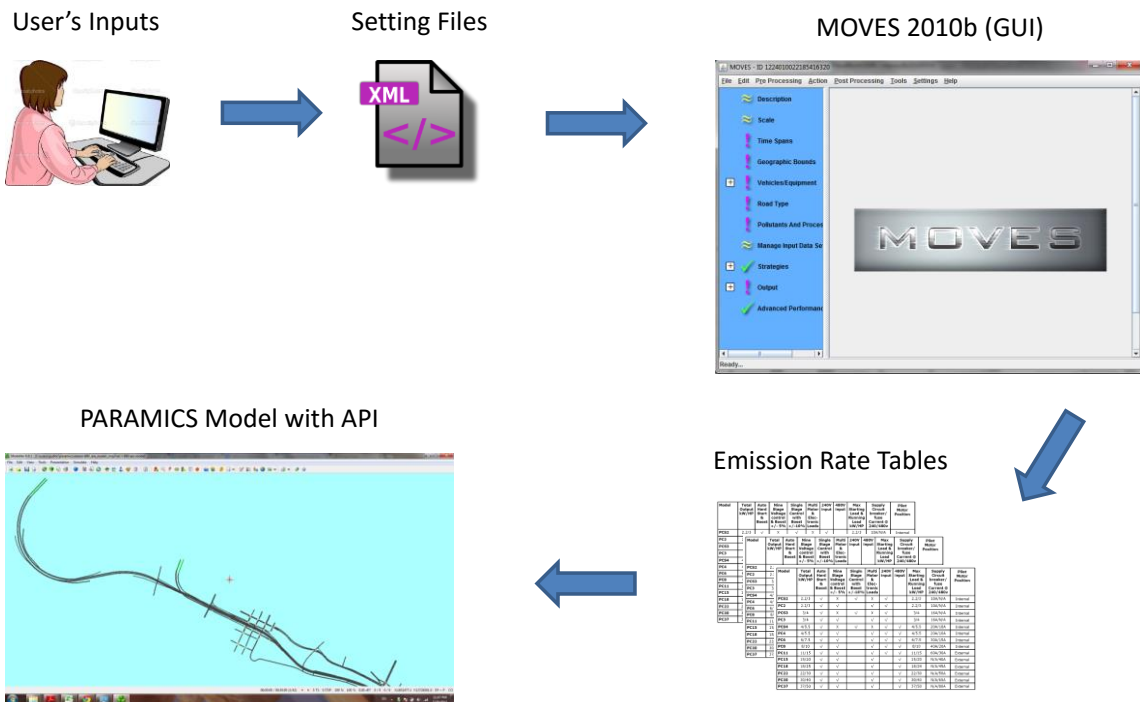


Figure B.2 Work flow of MOVES plug-in development [36].