

ECO-COOPERATIVE ADAPTIVE CRUISE CONTROL AT MULTIPLE SIGNALIZED INTERSECTIONS

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SCHOLARLY ABSTRACT

Consecutive traffic signals produce vehicle stops and acceleration/deceleration maneuvers on arterial roads, which may increase vehicle fuel consumption levels significantly. Eco-cooperative adaptive cruise control (Eco-CACC) systems can improve vehicle energy efficiency using connected vehicle (CV) technology. In this thesis, an Eco-CACC system is proposed to compute a fuel-optimized vehicle trajectory while traversing multiple signalized intersections. The proposed system utilizes signal phasing and timing (SPaT) information together with real-time vehicle dynamics data to compute the optimal acceleration/deceleration levels and cruise speeds for connected-technology-equipped vehicles while approaching and leaving signalized intersections, while considering vehicle queues upstream of the intersections. The INTEGRATION microscopic traffic simulation software was used to conduct a comprehensive sensitivity analysis of a set of variables, including different levels of CV market penetration rates (MPRs), demand levels, phase splits, offsets, and distances between intersections to assess the benefits of the proposed algorithm. Based on the analysis, fuel consumption saving increase with an increase in MPRs and a decrease in the cycle length. At a 100% equipped-vehicle MPR, the fuel consumption is reduced by as much as 13.8% relative to the base no Eco-CACC control. The results demonstrate an existence of optimal values for demand levels and the distance between intersections to reach the maximum fuel consumption reduction. Moreover, if the offset is near the optimal values for that specific approach, the benefits from the algorithm are reduced. The algorithm is limited to under-saturated conditions, so the algorithm should be enhanced to deal with over-saturated conditions.

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GENERAL AUDIENCE ABSTRACT

Consecutive traffic signals produce vehicle stops and acceleration/deceleration maneuvers on arterial roads, increasing vehicle fuel consumption levels. Drivers approaching signals are unaware of the signal status and may accelerate/decelerate aggressively to respond to traffic signal indications and thus increasing their fuel consumption. Research has been conducted to provide the driver with an optimal speed recommendations to reduce fuel consumption. Connected vehicle (CV) technology can be used to create a communication between the vehicle and traffic signals to provide information about the traffic light status and how many vehicles are waiting in the queue. In this thesis, an Eco-cooperative adaptive cruise control (Eco-CACC) system is proposed, which is a system that uses signal information to provide speed advice to the driver. This speed advice will not make the vehicle stop at any intersection, and this will reduce fuel consumption levels. The INTEGRATION software was used to test the effectiveness of the system in many scenarios. These scenarios include how many vehicles are equipped with this system, how many vehicles are in the system, the length of the green interval of the traffic signal, and distance between intersections. If we equip all vehicles with the system, the savings in fuel consumption can reach up to 13.8%. The system is designed for a network that is not extremely congested (over-saturated), implying that queues dissipate in a single traffic light cycle. The system needs to be further developed to deal with over-saturated conditions.

DEDICATION

To my parents,
Ghanima and Farhan,
My Grandparents,
My brothers,
Saud and Abdullah,
My sisters,
Munira and Sarah,
My lovely nephew,
Fawaz,
My uncles, aunt and cousins
Without whom none of my success would be possible

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1 INTRODUCTION

Recently, the volume of passenger cars and trucks has increased rapidly, which has led to a significant increase in energy and vehicle emissions. In 2013, the transportation sector in the U.S. consumed more than 135 billion gallons of fuel, and 70% of that was consumed by passenger cars and trucks [1]. In 2015, about 28% of all the energy consumed by people in the United States went to the transportation sector. Petroleum products accounted for about 92% of the total energy used by the U.S. transportation sector. Gasoline consumption for transportation averaged about 9 million barrels (379 million gallons) per day. Highway vehicles release about 1.7 billion tons of greenhouse gases (GHGs) into the atmosphere each year, contributing to global climate change [2]. This high usage of fuel increases the level of global warming. Many countries are trying to reduce the level of that risk. Reducing this risk is not easy because the number of vehicles and total vehicle miles traveled has increased since the last century. This explains the urgent need for the transportation sector to solve this issue by using fuel reduction strategies.

1.1 Eco-driving

Eco-driving is a cost-effective strategy to improve fuel efficiency. The main goal of eco-driving is to provide real-time driving advice to individual vehicles so that drivers can adjust their driving behavior, thereby reducing fuel consumption and emission rates. Many eco-driving algorithms operate by providing advisory speed limits, acceleration and deceleration levels, and speed alerts to drivers. Recently, several studies have shown that eco-driving can reduce fuel consumption and greenhouse gas emissions by about 10% on average [3]. Stop-and-go waves of traffic result in frequent accelerations, and this is one major cause of fuel inefficiency and greenhouse gas emissions [4]. In addition, high speeds over 60 mph and slow movements on congested roads rapidly increase the emission of air pollutants [5]. Therefore, reducing traffic oscillations and avoiding idling are two strategic methods to increase fuel efficiency.

Technology in vehicles has developed over the years. Vehicles use Cruise Control (CC) systems that automatically maintain user-desired speeds by controlling the vehicle's throttle. After CC, Adaptive Cruise Control (ACC) systems were introduced. These systems enabled intelligent cruising with collision avoidance with lead vehicles and will enact automatic slowdowns, as well as braking and throttle control functions. ACC uses radar sensors in the front of the vehicle to measure time-headway and spacing to avoid forward collisions. Next, the term Cooperative Adaptive Cruise Control (CACC) was introduced. CACC aims to create closely spaced vehicle

platoons using vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communication. Typically these systems are implemented on freeways. Recently, CACC systems have been implemented on arterial using V2I communication to receive signal phasing and timing (SPaT) information to compute the optimum course of action of the vehicle.

1.2 Background

The need to reduce vehicle emissions and fuel consumption has become significant. The U.S. Department of Transportation (USDOT) proposed V2I and V2V initiatives that allow vehicles to receive SPaT data from intersection controllers. CACC systems use this information to prevent vehicles from idling at signalized intersections by smoothing vehicle trajectories. A lot of research was conducted by developing an algorithm that utilized SPaT information in order to reduce the fuel consumption level and vehicle emissions. The Eco-Cooperative Adaptive Cruise Control (Eco-CACC) system was introduced. The Eco-CACC algorithm uses realistic deceleration and acceleration levels. The system also provides time-dependent advisory speed limits for the Eco-CACC equipped vehicle to decelerate to a particular speed and then cruise until it reaches the stop bar or the tail of the queue. After the queue is released, the vehicle accelerates to the free-flow speed at a constant throttle level. As shown in Figure 1-1(a), upstream of the intersection, when the distance between the equipped vehicle and the intersection is less than d , the Eco-CACC algorithm is activated. If there is no control for the vehicle (base) the vehicle will stay at its initial speed v_0 until it has to stop at the end of the queue at deceleration level a_s . For the Eco-CACC algorithm without a queue, the Eco-CACC equipped vehicle decelerates to a cruising speed, with which the vehicle cruises to the stop bar only when the signal turns green. The queue forces the vehicle to stop at the queue tail at deceleration level a_s . Considering the vehicle queue will reduce the speed of an Eco-CACC equipped vehicle at a constant deceleration level in order to arrive to the tail of the queue when it has just been released. Downstream of the intersection, the Eco-CACC algorithm allows the equipped vehicle to accelerate to the free-flow speed at a certain distance. The speed profile is shown as the blue dashed line in Figure 1-1(b). The Eco-CACC algorithm uses an explicit fuel consumption model in which the total fuel consumption is minimized [6]. The details of the Eco-CACC algorithm with queue consideration are described below.

1. For an Eco-CACC equipped vehicle k , once it enters the segment $[x_u, x_0]$, the Eco-CACC algorithm is activated.
2. Upstream of the intersection.

- a. The algorithm provides an advisory speed limit to the Eco-CACC equipped vehicles for the following two scenarios; otherwise, the road speed limit is used as the advisory limit.
 - i. The current signal indication is green, but the traffic signal will turn red when the vehicle arrives at the stop bar if it travels at its current speed.
 - ii. The current signal indication is red and will continue to be red when the vehicle arrives at the stop bar while traveling at its current speed.
 - b. Once either of the above scenarios occurs, we predict the queue length ahead of the Eco-CACC equipped vehicle and estimate the release time of the queue, t_c , based on the speed of the rarefaction wave.
 - c. The algorithm estimates the optimal upstream deceleration level and the downstream acceleration level to minimize vehicle fuel consumption and provides an advisory speed limit to the Eco-CACC equipped vehicle at the next time step $t + \Delta t$, where Δt is the updating interval of the speed advice.
3. Downstream of the intersection, the algorithm searches for the optimal acceleration level based on its current speed to minimize the fuel consumption necessary to reach the free-flow speed v_f at location x_d .
 4. Once the Eco-CACC equipped vehicle arrives at x_d , the Eco-CACC algorithm is deactivated.

traffic conditions; determine the limitations of the algorithm and identify additional areas for improvement of the algorithm.

The Virginia Tech Comprehensive Power-based Fuel Model (VT-CPFM) is used in this study as the microscopic fuel consumption model due to its simplicity, accuracy, and ease of calibration [7]. The fuel consumption model utilizes instantaneous power as an input variable and can be calibrated using publicly available fuel economy data. Thus, the calibration of the model parameters does not require gathering any empirical vehicle-specific data.

1.4 Thesis Contributions

The thesis develops and tests an algorithm that minimizes the vehicle fuel/energy consumption while traveling on signalized arterials. This effort constitutes the first attempt to explicitly optimize the vehicle's energy/fuel consumption while considering multiple signalized intersections and the impact of queues on the signalized approaches within the algorithm.

1.5 Thesis Layout/Attribution

This thesis is divided into five chapters. Chapter one includes background information, thesis objectives, and the thesis layout. Chapter two is a detailed literature review of some previous eco-driving algorithms that deal with relevant issues. Chapter three is based on a paper co-authored by Dr. Hesham Rakha and Dr. Hao Yang that will be presented at the 2017 TRB Annual Meeting. This chapter develops the Eco-CACC-MS algorithm with the consideration of the queue effect. The benefit of this algorithm is presented and compared with the Eco-CACC algorithm. This paper was mainly written by Dr. Hao Yang and Dr. Hesham Rakha and the sensitivity analysis section was conducted by the candidate. Chapter four was co-authored by Dr. Hesham Rakha and Dr. Hao Yang. This chapter conducts a sensitivity analysis of the Eco-CACC-MS algorithm for varying traffic, algorithm, and signal settings in order to test the effectiveness of the algorithm and compare it to the Eco-CACC. The simulations and the first draft paper was done by the candidate and edits by Dr. Hesham Rakha and Dr. Hao Yang. Finally, chapter five summarizes the conclusions of the research and discusses direction for future research.

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2 LITERATURE REVIEW

2.1 Introduction

In this chapter, eco-driving and its benefits will be presented. In addition, previous research about eco-driving will be discussed.

2.2 Eco-driving

Eco-driving is a style of driving designed to reduce fuel consumption levels. It is based on some behaviors that include driving styles, the way the vehicle is used, how often it is used, the configuration of the car, and day-to-day and longer-term vehicle maintenance [1]. Eco-driving has been used as a solution to reduce GHG emissions generated by the transportation sector. Preventing sudden acceleration/deceleration and keeping the velocity constant around the optimal-fuel velocity is correlated with emission and fuel consumption reductions by various fuel models [2, 3]. In order to reduce fuel consumption levels, research was conducted which provided some advice and tips about drivers' behaviors. The recommendations include soft starting with gentle acceleration, driving without excessive accelerating and decelerating, maintaining a steady speed, and driving in the highest gear possible [4-6]. Not only drivers but also vehicles can play a major role in eco-driving and reduced fuel consumption. Eco-driving can include vehicle maintenance measures, such as maintaining optimum tire pressure and the regular changing of air filters [7]. Technology can have an effect on eco-driving with the ACC system, which reduces the use of fuel [8, 9].

Eco-driving was evaluated in many different tests that will be explained in detail in the next section, but overall it decreases the fuel consumption level and reduces GHGs. Fonseca et al. [10] studied the impact of driving style on fuel consumption and pollution emissions and illustrated that eco-driving decreased fuel consumption and carbon dioxide emissions by 14%. In Greece, bus drivers were trained to test eco-driving and the savings reached 10% [11]. Voort et al. [12] used a fuel efficiency support tool which helped drivers to make behavior adjustments. The tools back-calculate the minimal fuel consumption and compare it to the optimal, and then provide advice to the driver on how to change the behavior. The tool was able to provide up to 14 % savings in fuel consumption. Eco-driving can reduce the cost of driving to the individual by saving fuel. It also produces tangible and well-known safety benefits, such as reducing the probability of accidents. It can also increase the efficiency of the road by providing even headway between the vehicles, which may leave space for more vehicles.

2.3 Advanced Eco-driving

The VII initiative proposed by U.S. Department of transportation has at its core, wireless communication of V2I and V2V [13]. This system provides information for the vehicles from intersections, which helps to reduce idling and the waste of fuel. In Canada, if drivers of light-duty vehicles avoided idling by just three minutes a day, over the year they would collectively save 630 million liters of fuel [14]. Many studies were conducted in order to develop an algorithm that utilized the traffic signal information to reduce fuel consumption levels. The goal of utilizing this information is to provide information to the vehicle's driver about signal status. Based on that information, the driver's behavior can be adjusted to prevent unnecessarily stopping at intersections. The aim of this project is to develop an algorithm to focus specifically on controlling the vehicle based on the utilized information coming from the signal. Based on that information, the algorithm provides an advised speed that will prevent the vehicle from stopping at multiple consecutive intersections and reduce fuel consumption.

In general, eco-driving research can be categorized into freeway-based and city-based strategies. On freeways, the traffic is usually uninterrupted and the traffic stream is continuous. Many studies have been conducted on the freeway, and the strategies provide either an advisory speed or speed limit. Barth et al. [15] used a dynamic eco-driving system that provides real-time advice to the driver to change the driving behavior, and the system was able to provide approximately 10–20% in fuel savings without a significant increase in travel time. Yang et al. [16] developed dynamic green driving strategies that basically demonstrate that optimal smoothing effects can be captured when the speed limit is close to, but not less than, the average speed of the road. This guarantees the smoothness of the vehicle profile while following the leader vehicle. Park et al. [17-19] developed a vehicle predictive eco-cruise control system that generates an optimal control plan by using roadway grade information to control vehicle speed in order to achieve fuel savings of up to 27%.

In contrast to the freeway, arterial road traffic streams are frequently interrupted by traffic signals. Vehicles are forced to stop ahead of traffic signals when encountering red indications. This creates shock waves that will result in vehicle acceleration/deceleration maneuvers and idling events, which increase the amount of fuel consumed and the emission levels. Li et al. [20] proposed a signal timing model which optimized the cycle length and green duration by considering the constraint of a minimum green time to allow pedestrians to cross. The objective function of the

model is to reduce vehicle delay and fuel consumption. They concluded that the 200 s cycle is the optimal value corresponding to the performance index function. Stevanovic et al. [21] also studied the effect of optimizing signal timings to minimize fuel consumption and CO₂ emissions. They used seven objective function to optimize the fuel consumption level to find the lowest fuel consumption and CO₂ emissions, which resulted in savings of 1.5%.

Individual vehicles can be controlled to minimize fuel consumption and emission levels by using the development of connected vehicles (CVs). Vehicles using CV technology are enabled to exchange road traffic information and communicate with traffic signals to receive information about SPaT [22]. CV technology appealed to many researchers working to reduce fuel consumption and emissions by providing fuel optimized trajectories. Mandava et al. [23] developed arterial velocity planning algorithms where vehicles receive the signal phase and timing information before approaching a signalized intersection. The algorithm objective is to minimize acceleration/deceleration rates while insuring that the vehicle never exceeds the speed limit and will pass through the intersection without a complete stop. The algorithm provides dynamic speed to the driver so that the vehicle will reach the signal during the green indication. The proposed algorithm was able to save 12-14% in fuel consumption. Xia et al. [24] use a similar algorithm where drivers receive real-time advice to avoid idling. The algorithm was able to reduce the individual vehicle consumption and CO₂ by around 10-15%. Lowering the acceleration/deceleration level does not guarantee a reduction in the fuel consumption level; thus, optimum acceleration/deceleration profiles are computed for probe vehicles to reduce the fuel consumption level [25, 26]. Asadi et al. [27] developed a predictive cruise control system that adjusts cruising speeds to reduce the probability of stopping at intersections. The system did not provide an advisory speed limit to the drivers. The predictive use of signal timing was able to reduce fuel consumption by up to 47%. Rakha et al. [28-30] constructed a dynamic programming based fuel-optimization strategy using a recursive path-finding printable. They evaluated the algorithm with an agent-based model, and savings were up to 19% in fuel and 32% in travel time in the vicinity of intersections. The algorithm was also evaluated using INTEGRATION software, and the average fuel savings per vehicle are in the range of 26 %, and the reduction in total delays reaches 65 % within the vicinity of traffic signalized intersections. De Nunzio et al. [31] used a combination of a velocity pruning algorithm and graph discretizing approach to find the energy-optimal velocity profile, assuming the V2I is used and SPaT information is available. The velocity

pruning algorithm was used to identify the feasible region a vehicle may travel along within the city speed limit. The graph discretizing approach was used to make an advance selection within the feasible region in order to optimize energy consumption. A velocity trajectory is advised to insure that the vehicle will not stop at intersections.

Katsaros et al. [32, 33] developed a Green Light Optimized Speed Advisory (GLOSA) system and the objective function was to minimize average fuel consumption and average stop times behind a traffic light. The system provides the advantage of timely and accurate information about SPaT via V2I communication. Based on that information, the system provides the driver with an optimal advisory speed, which reduces the stopping time at intersections. The GLOSA provides up to an 80% reduction in stop time, 9.85% in total travel time and 7% in fuel consumption. Seredynski et al. [34, 35] improved the GLOSA algorithm to a multi segment GLOSA that takes into consideration several sequences of traffic lights. Results show that the multi segment GLOSA saves up to 12% more fuel than a single segment, and the total travel time was reduced by 6%. Wu et al. [36] studied the behaviors of drivers approaching the signalized intersection and how it could reduce the fuel consumption of vehicles without increasing the total travel time. They used advanced driving alert systems that alert the driver about the time to a red indication so they could adjust their behaviors. They reported up to a 40% reduction in vehicle fuel consumption and CO₂ emissions. Tielert et al. [37] studied the impact of traffic-light-to-vehicle communication on fuel consumption and emissions. The study used a vehicle that followed different speeds and compared the effects of speed adaptation. Gear choice and distance to the intersection play a major role in the study. The savings reach up to 22% in fuel consumption and emissions. Sanchez et al. [38] developed the Intelligent-Driver Model Prediction model. The model used SPaT information to provide speed advice for drivers to reduce idling time, which could save up to 25% of fuel. Li et al. [39] developed an augmented lagrangian genetic algorithm that searches for the optimized speed curve in all possible speed curves based on the minimum fuel consumption and travel time. To calculate the fuel consumption for each vehicle, the VT-Micro model [3] was applied because VT-Micro considers the instantaneous speed and acceleration of each vehicle. Results of simulations show that in free-flow conditions the optimized speed can save up to 69.3% in fuel and 12.2% in total travel time. Alsabaan et al. [40] developed a model that used V2I and V2V communication to receive SPaT information about signals to compute the optimum speed. The objective function is to reduce fuel consumption by providing

the advised speed. They also used the VT-Micro model in estimating fuel consumption. Jin et al. [41] developed a mathematical mode to optimize driving trajectories crossing several intersections. The objective of the model is to reduce fuel consumption and emissions by avoiding idling at intersections, and the model saves up to 12% in CO₂. Wan et al. [42] developed the Speed Advisory System that utilized SPaT information and provided an advisory speed. The system's objective function is to reduce fuel consumption and improve ride comfort by reducing idling at intersections. The model was able to provide savings in overall fuel consumption but caused a slight increase in travel time.

Smart phones are also used as eco-driving tools. Koukoumidis et al. [43] developed SignalGuru, a smart phone application. SignalGuru relies only on a collection of mobile phones to detect and predict the traffic signal schedule by using GLOSA. Feeding the system SPaT information results in savings in fuel consumption of 20.3%. Muñoz-Organero et al. [44] developed an algorithm that uses smart phones in order to reduce fuel consumption by calculating optimal deceleration rates and minimizing the use of braking. The system estimates the distance upstream from the signal that is needed in order to stop without using the brakes. The system provides the driver with advice and feedback to release the brake pedal. However, all the studies above only attempted to reduce idling time and smooth the acceleration/deceleration maneuvers without considering the impact of surrounding traffic. The effect of vehicle queues on idling time was not considered in the above studies, and it is necessary to test the impact of vehicle queues on idling and fuel savings.

In order to test the queue effect and the surrounding traffic, Qian et al. [45, 46] applied a micro-simulation to evaluate eco-driving with moderate and smooth acceleration/deceleration behaviors during queue discharge. The objective function is to minimize the travel time and reduce the fuel consumption and CO₂ emissions. The study found that traffic conditions have a significant impact on the performance of eco-driving. Potentially negative impacts were recorded in the study when using eco-driving; therefore, more investigation is needed to improve eco-driving before implementation. Jin et al. [47] developed a power-based longitudinal control algorithm that reduces the acceleration/deceleration maneuvers when considering queues at intersections. The algorithm provides an optimal speed profile for individual vehicles in order to reduce fuel consumption. The algorithm takes into account the vehicle's brake specific fuel consumption, roadway grade, and traffic conditions while calculating the optimal speed profile in terms of energy

savings and emissions reductions. The algorithm was able to reduce the energy consumption by about 4%. However, these studies only focus on optimizing the speed upstream of the intersection and ignore the downstream part, which results in greater fuel consumption and assumes the queue length to be given. Chen et al. [48, 49] developed an optimization model to determine the optimal eco driving trajectory at a signalized intersection to reduce fuel consumption, emissions, and travel time. The model used the SPaT information and queue discharge time in order to optimize the speed trajectories upstream and downstream of the intersection. In some cases of the sensitivity analysis, the model was able to achieve satisfactory reductions in emissions of up to 50% and 7% in travel time. However, the model assumed that the length of and time to discharge the queue are constant. Hao et al.[50, 51] developed the Eco-Cooperative Adaptive cruise control (Eco-CACC) algorithm, which considers the vehicle queue and speed trajectories downstream of the intersection. Eco-CACC uses V2I communication and SPaT information to provide an advised speed for the individual vehicle to pass through the intersection without the need to stop. The algorithm only minimized fuel consumption for vehicles to pass one intersection independently, which restricted its applications on arterial corridors with multiple consecutive intersections. He et al. [52] developed a multi-stage optimal control system. The system was applied to obtain the optimal vehicle trajectory on signalized arterials while considering the vehicle queue. The system used V2I communication and SPaT information to then provide an advised speed to avoid idling at intersections. The system becomes very complex when more than one intersection is considered. All these research studies attempt to develop an eco-driving system that will provide significant savings in fuel consumption and/or reduction in total travel time. However, not everyone takes into consideration the queue effect and the surrounding traffic for multiple intersections. The objective of this research is to develop an eco-driving system that will provide significant savings in fuel consumption and emissions, but also considers traffic light status and queues for multiple intersections and the surrounding traffic.

2.4 Conclusions

Numerous research efforts have attempted to minimize vehicle energy/fuel consumption at signalized intersections using signal information. These research efforts, however have not considered all aspects of the problem. For example, very limited efforts have considered the vehicle queue upstream a signalized intersection in the optimization algorithm. Furthermore, very limited efforts have considered multiple intersections in the optimization formulation. Using real-time SPaT and queue information

can be used to optimize the vehicle trajectory. The algorithm presented in this thesis fill these gaps by considering multiple intersections, the queues at the signalized approaches and explicitly optimizes the vehicle energy/fuel consumption using a non-linear energy/fuel consumption model.

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3 ECO-COOPERATIVE ADAPTIVE CRUISE CONTROL AT MULTIPLE SIGNALIZED INTERSECTIONS

(Hao Yang, Fawaz Almutairi, and Hesham A Rakha, “Eco-cooperative adaptive cruise control at multiple signalized intersections,” (in-press) *Transportation Research Board 96th Annual Meeting*)

Abstract

Consecutive traffic signals produce continuous vehicle stops and accelerations on arterial roads and increase fuel consumption levels significantly. Eco-cooperative adaptive cruise control (Eco-CACC) systems are one method to improve energy efficiency with the help of connected vehicle technology. In this paper, an Eco-CACC system is proposed to compute a fuel-optimized vehicle trajectory while traversing more than one signalized intersection. The proposed system utilizes the information of signal phasing and timing (SPaT) and real-time vehicle dynamics to find optimal acceleration/deceleration rates and cruise speed for connected-technology-equipped vehicles when approaching intersections. A comprehensive sensitivity analysis of a set of variables, including market penetration rates (MPRs), demand levels, phase splits, offsets and distances between intersections, are applied with the INTEGRATION microscopic simulator to assess the benefits of the proposed algorithm. The analysis shows that at 100% equipped-vehicle MPR, fuel consumption can be reduced as much as 13.8%. Moreover, higher MPRs and smaller phase splits result in larger savings in the overall fuel consumption levels, and there exist optimal values of the demand and the distance between the intersections to maximize the effectiveness of the algorithm. In addition, the study illustrates that the algorithm works less effective when the signal offset is closer to its optimal value. The study also demonstrates that the limitation of the algorithm on over-saturated networks, indicating the need for further work to enhance the algorithm.

Keywords: Eco-CACC, multiple intersections, signal phasing and timing, vehicle queue, fuel consumption, INTEGRATION

3.1 Introduction

Over the past several years, the heavy volume of passenger cars and trucks has led to a significant increase in energy and vehicle emissions. In 2013, the U.S. transportation sector consumed more than 135 billion gallons of fuel, 70% of which was consumed by passenger cars and trucks [1]. Nationwide, more than 60% of oil is consumed by the transportation sector [2]. The urgent need to reduce transportation sector fuel consumption levels requires researchers and policy makers to develop various advanced fuel-reduction strategies. Eco-driving is one viable and cost-effective strategy to improve fuel efficiency in the transportation sector [2]. The main idea of eco-driving is to provide real-time driving advice to individual vehicles so that drivers can adjust their driving behavior or take certain driving actions to reduce fuel consumption and emission levels. Generally, most eco-driving strategies work by providing real-time driving advice, such as advisory speed limits, recommended acceleration or deceleration levels, speed alerts, etc. To date, numerous studies have indicated that eco-driving can reduce fuel consumption and greenhouse gas (GHG) emissions by about 10% on average [3].

The major causes of high fuel consumption levels and air pollutant emissions generated by vehicles have been widely investigated. Frequent accelerations associated with stop-and-go waves [4, 5], excessive speed (over 60 mph), slow movements on congested roads [6], and extra idling time all dramatically increase emissions and fuel consumption levels. Consequently, it is clear that reducing speed and movement fluctuations and reducing idling time are two critical ways to reduce fuel consumption levels.

In general, eco-driving research can be categorized into freeway-based and city-based strategies. On freeways, the traffic stream is continuous, and vehicles are rarely affected by signals (i.e., a vehicle can travel to a particular destination without any extra constraints, with the exception of on and off ramps). Generally, eco-driving strategies on freeways compute advisory speed [7] or speed limits [8-11] for drivers with the help of vehicle-to-infrastructure (V2I) or vehicle-to-vehicle (V2V) communications, and alter driving behavior to minimize emissions and fuel consumption. Unlike freeways, arterial roads have traffic control devices that routinely interrupt the traffic stream. Vehicles are forced to stop ahead of traffic signals when encountering red indications, producing shock waves within the traffic stream. These shock waves in turn result in vehicle acceleration/deceleration maneuvers and idling events, which increase vehicle fuel consumption and emission levels. Most research efforts have focused on optimizing traffic signal timings using traffic volumes and vehicular queue lengths [12, 13]. Recently, with the

development of connected vehicles (CVs), individual vehicles can be controlled to minimize emissions and fuel consumption levels. CV technology enables vehicles to exchange road traffic information, and to communicate with traffic signal controllers to receive signal phasing and timing (SPaT) information [14]. This information can be applied to estimate the fuel-optimized trajectories for vehicles traveling on arterial roads.

In the past decade, environmental CV applications have attracted significant research interest. Most of these efforts assist drivers in their travel along signalized intersections by providing fuel-optimized trajectories. Mandava et al. and Xia et al. proposed a velocity planning algorithm based on traffic signal information to maximize the probability of encountering a green indication when approaching multiple intersections [15, 16]. The algorithm attempted to reduce fuel consumption levels by minimizing acceleration/deceleration levels while avoiding complete stops. It should be noted, however, that lowering acceleration/deceleration levels does not necessarily imply reducing fuel consumption levels. To solve this problem, optimum acceleration/deceleration profiles are computed for probe vehicles to reduce fuel consumption levels [17, 18]. Asadi and Vahidi applied traffic signal information to estimate optimal cruise speeds for probe vehicles to minimize the probability of stopping at signals during red indications [19]. Rakha and Kamalanathsharma constructed a dynamic programming based fuel-optimization strategy using recursive path-finding principles, and evaluated it with an agent-based model [20-22]. De Nunzio et al. used a combination of a pruning algorithm and an optimal control to find the best possible green wave if the vehicles were to receive SPaT information from multiple upcoming intersections [23]. In addition, some practical applications, such as Green Light Optimized Speed Advisory (GLOSA) [24-27] systems and eCoMove [28], are developed to estimate optimal advisory speeds for individual vehicles proceeding through single and multiple traffic signals to minimize delay and fuel consumption levels. Furthermore, various smartphone applications have been developed to provide eco-driving assistance systems for vehicles in the vicinity of signalized intersections [29, 30]. However, the studies above only attempt to minimize idling time and smooth acceleration/deceleration maneuvers without considering the impact of surrounding traffic. While in reality, the idling events are determined not only by the SPaT information, but also by vehicle queues at signals.

To examine the impact of surrounding traffic, Qian, et al. applied micro-simulations to evaluate the effectiveness of eco-driving with moderate acceleration/deceleration during queue discharge [31, 32]. Chen and Jin estimated optimal speed profiles for individual vehicles with the

consideration of vehicle queues and road grade conditions [33, 34] . However, these studies assumed that the queue length are given, which makes them difficult for practical applications without integrating the queue estimation in the algorithm development. Moreover, they only focus on optimizing the speed profiles of probe vehicles upstream of the intersection, but ignoring accelerating behaviors after the signal turns to green, which results in more fuel usage for vehicles passing intersections. In [35, 36], an Eco-Cooperative Adaptive cruise control (Eco-CACC) algorithm was conducted with the consideration of vehicle queue effects and the downstream accelerating behaviors. However, the algorithm only minimized fuel consumption for vehicles to pass one intersection independently, which restricted its applications on arterial corridors with multiple consecutive intersections. In [37], a multi-stage optimal signal control system was applied to obtain the optimal vehicle trajectory to pass multiple intersections with the consideration of vehicle queues. But, the system becomes very complex when more than two intersections are considered.

In this paper, we extend the Eco-CACC algorithm proposed in [35, 36] to multiple intersections. We first develop the algorithm with the consideration of both SPaT and vehicle queue information to compute the optimal trajectories for vehicles to travel in the vicinities of two or more consecutive intersections. Then the algorithm is evaluated with the INTEGRATION microscopic traffic simulator [38]. A comprehensive sensitivity analysis of a set of variables, including market penetration rate (MPR), demand levels, phase splits, offsets, and distance between intersections, is presented to examine the benefits of the proposed algorithm. In addition, a network with four intersections is simulated to illustrate the implementation of the algorithm on large networks. Finally, the limitation of the algorithm on over-saturated networks will be examined.

In terms of the paper's layout, Section 3.2 develops an Eco-CACC algorithm for multiple intersections taking vehicle queues into consideration. Section 3.3 evaluates the algorithm with INTEGRATION in networks with two and four intersections. Section 3.4 includes a comprehensive sensitivity analysis of a set of variables applied in the algorithm. Section 3.5 discuss the 3.5 over-saturated demands condition. Finally, section 3.6 summarizes the entire study.

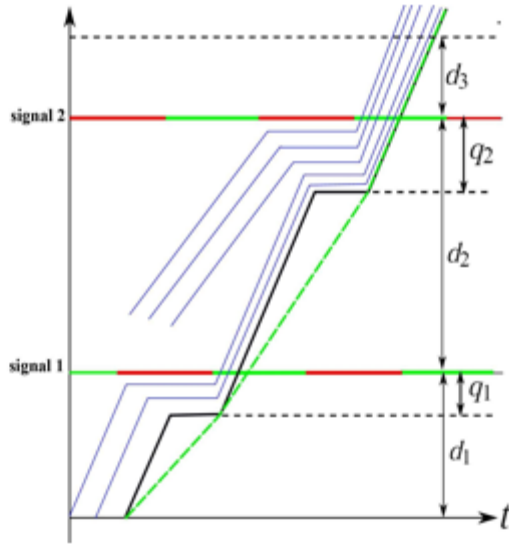
3.2 Eco-CACC at Multiple Intersections

In this section, the Eco-CACC algorithm proposed in [35, 36] is extended for multiple intersections. The Eco-CACC algorithm utilizes SPaT data obtained via V2I communications to compute a fuel-optimized vehicle trajectory in the vicinity of one signalized intersection. The

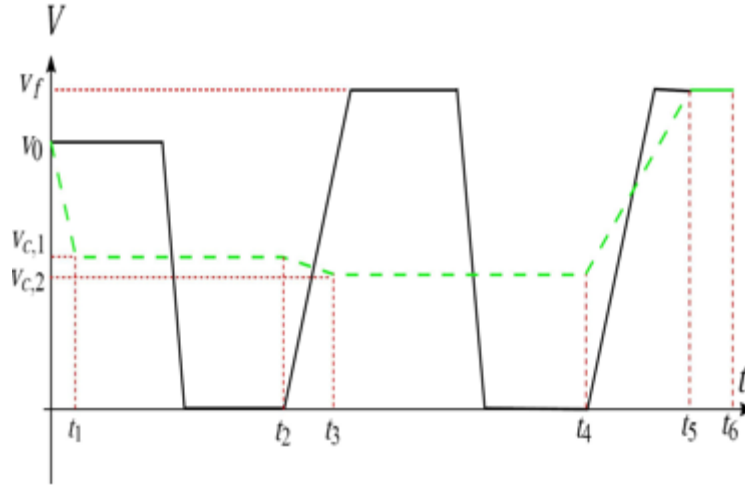
trajectory is optimized by computing an advisory speed limit using the Eco-CACC algorithm, which takes the vehicle queue ahead of the intersection into consideration. However, the trajectory is only optimized for one intersection. When it comes to multiple intersections, the trajectory may not work effectively on minimizing fuel consumption.

Figure 3-1(a) shows the trajectories of vehicles passing two consecutive intersections. The solid black line represents the trajectory of one vehicle experiencing two red lights without control (assume that the vehicle has infinite acceleration/deceleration rates). The vehicle is stopped ahead of both intersections by the red lights and the vehicle queues. Based on the work in [35, 36], applying the Eco-CACC algorithm for multiple intersections (Eco-CACC-MS), the vehicle cruises to each intersection with a constant speed (see the dashed green line in Figure 3-1(a)). However, the assumption that the acceleration/deceleration rates of the equipped vehicle are infinite is not realistic. Figure 3-1(b) compares the speed profiles of the vehicle with (green line) and without (black line) control considering both acceleration and deceleration durations. Without control, the vehicle has to stop completely at the first intersection. Between the two intersections, the vehicle first accelerates to the speed limit and then decelerates to 0 again. The stop-and-go behaviors and the long idling time waste a great deal of energy. However, with control, the vehicle decelerates to a speed, $v_{c,1}$, and cruises to the first intersection. Between the two intersections, it decelerates or accelerates from $v_{c,1}$ to $v_{c,2}$, and cruises to the second intersection. Here, $v_{c,1}$ and $v_{c,2}$ are the cruise speeds to the first and second intersection, respectively. Once the queue at the second intersection is released, the vehicle accelerates to the speed limit. Compared to the base case without control, both the trajectory and the speed profile with Eco-CACC-MS are much smoother.

The objective of developing the Eco-CACC-MS algorithm is to minimize the vehicle fuel consumption level in the vicinity of the two intersections. In addition to the shape of the vehicle speed shown in Figure 3-1(b), the algorithm determines the optimum upstream acceleration/deceleration levels of the controlled speed profile in Figure 3-1(b). The mathematical formulation of the algorithm can be cast as



(a)



(b)

— No Control - - - Eco-CACC-MS

Figure 3-1 Dynamics of the equipped vehicle at two intersections: (a) trajectories, (b) speed profiles.

$$\max_{a_1, a_2, a_3} \int_0^{t_6} F(v(t)) dt, \quad (1a)$$

s.t.

$$v(a_1, a_2, a_3, t) = \begin{cases} v_0 + a_1 t & 0 < t < t_1 \\ v_{c,1} & t_1 < t < t_2 \\ v_{c,1} + a_2(t - t_2) & t_2 < t < t_3 \\ v_{c,2} & t_3 < t < t_4 \\ v_{c,2} + a_3(t - t_4) & t_4 < t < t_5 \\ v_f & t_5 < t < t_6 \end{cases}; \quad (1b)$$

$$v_{c,1} = v_0 + a_1 \cdot t_1; \quad (1c)$$

$$v_0 \cdot t_1 + \frac{1}{2}a_1 t_1^2 + v_{c,1}(t_2 - t_1) = d_1 - q_1; \quad (1d)$$

$$t_2 = t_{g,1} + \frac{q_1}{w_1}; \quad (1e)$$

$$v_{c,2} = v_{c,1} + a_2 \cdot (t_3 - t_2); \quad (1f)$$

$$v_{c,1}(t_3 - t_2) + \frac{1}{2}a_2(t_3 - t_2)^2 + v_{c,2}(t_4 - t_3) = d_2 + q_1 - q_2; \quad (1g)$$

$$t_4 = t_{g,2} + \frac{q_2}{w_2}; \quad (1h)$$

$$v_{c,2} + a_3(t_5 - t_4) = v_f; \quad (1i)$$

$$v_{c,2}(t_5 - t_4) + \frac{1}{2}a_3(t_5 - t_4)^2 + v_f(t_6 - t_5) = d_3 + q_2; \quad (1j)$$

$$a_-^s \leq a_1 \leq a_+^s; \quad (1k)$$

$$a_-^s \leq a_2 \leq a_+^s; \quad (1l)$$

$$0 \leq a_3 \leq a_+^s; \quad (1m)$$

Where

- $F(v(t))$: the vehicle fuel consumption rate at any instant t computed using the Virginia Tech Comprehensive Power-based Fuel Consumption Model (VT-CPFM) [39] (see Eq (2));
- $v(t)$: the advisory speed limit for the equipped vehicle at time t ;
- a_k : the acceleration/deceleration rates for the advisory speed limit, $k = 1, 2, 3$;
- v_0 : the speed of the vehicle when it enters the upstream control segment of the first intersection;
- v_f : the road speed limit;
- d_1 : the length of the upstream control segment of the first intersection;
- d_2 : the distance between the two intersections;
- d_3 : the length of the downstream control segment of the second intersection;
- $t_{g,1}$: the time instant that the indicator of the first signal turns to green;
- $t_{g,2}$: the time instant that the indicator of the second signal turns to green;
- t_k : the time instant defined in Figure 3-1(b), $k = 1, 2, \dots, 6$;
- $v_{c,1}$: the cruise speed to the first intersection;
- $v_{c,2}$: the cruise speed to the second intersection;
- q_1 : the queue length at the first immediate downstream intersection;
- q_2 : the queue length at the second immediate downstream intersection;
- w_1 : the queue dispersion speed at the first immediate downstream intersection;

- w_2 : the queue dispersion speed at the second immediate downstream intersection;
- a_-^s : the saturation deceleration level;
- a_+^s : the saturation acceleration level.

$F(v(t))$ is a function of speed $v(t)$, defined by the VT-CPFM model [39], to estimate the fuel consumption rate based on vehicular speed and acceleration.

$$F(v(t), v'(t)) = \begin{cases} \alpha_0 + \alpha_1 P^2(t) & P(t) \geq 0 \\ \alpha_0 & P(t) < 0 \end{cases}, \quad (2a)$$

where, $\{\alpha_0, \alpha_1, \alpha_2\}$ are the coefficients determined by vehicle types. $P(t)$ is the vehicle power at time t , and is a function of speed and acceleration.

$$P(t) = \frac{R(t) + m \cdot v'(t)(1.04 + 0.0025\xi^2(t))}{3600 \eta_d} \cdot v(t), \quad (2b)$$

$$R(t) = \frac{\rho_a}{25.92} C_D C_h A_f v^2(t) + 9.8066m \frac{c_r}{1000} (c_1 v(t) + c_2) + 9.8066mG(t) \quad (2c)$$

Here, $R(t)$ is the resistance force of the vehicle, and $\xi(t)$ is the gear ratio, and $G(t)$ is the road grade at time t . $m, \rho_a, \eta_d, C_D, C_h, A_f$ represent the vehicle mass, the density of the air, the vehicle drag coefficient, the correction factor of altitude, and the vehicle front area, respectively. C_r, c_1, c_2 are rolling resistance parameters that vary as a function of the road surface type, road condition, and vehicle tire type.

Eq (1b) demonstrates that given the traffic state, including queue lengths, the start and end times of the indicators of the two intersections and the approaching speed of the controlled vehicles, the speed profile varies as a function of a_1, a_2, a_3 . Eq (1)(c-e) defines that the equipped vehicle decelerates to $v_{c,1}$ and passes the first intersection just when the queue is released. Eq (1) (f-h) determines that the vehicle passes the second intersection when the queue is released. Eq (1) (i-j) shows how the vehicle recovers its speed back up to the speed limit. The Eco-CACC-MS algorithm searches for the three acceleration levels to minimize the fuel consumption of the controlled vehicle over the entire control section. The flow chart of the Eco-CACC-MS algorithm is illustrated in Figure 3-2, and the details of the algorithm, including how it is extended to N consecutive intersections (labeled as 1, 2, \dots , N from upstream to downstream), is described below.

1. When an equipped vehicle k that enters the upstream control segment of the first intersection— i.e., the distance between the vehicle and the stop line of the intersection 1 (the first upstream intersection) is less than d_1 , the Eco-CACC-MS algorithm is activated.

2. Upstream of the intersection 1 or the section between the intersection $i - 1$ and i , $i = 2, 3, \dots, N$.

The algorithm estimates the optimal trajectory for the equipped vehicle to pass intersections based on the SPaT and vehicle queue information¹. The algorithm categorizes the traffic condition into three scenarios, and controls the vehicle differently.

a- If the equipped vehicle can pass its immediate downstream intersection, i , with its current speed v_0 or speed limit v_f without complete stops caused by either the red indicator or the vehicle queue, the algorithm does not control the movements of the equipped vehicle, and the vehicle will only apply the road speed limit to pass the intersection.

b- If the equipped vehicle is stopped by the red indicator or the queue at its immediate downstream intersection, i , but it can pass the second intersection, $i + 1$ without stops, or $i = N$, the Eco-CACC algorithm of a single intersection proposed in [35] is applied to the equipped vehicle with the SPaT and the queue information of the intersection i . The optimal trajectory is estimated for the equipped vehicle to pass the intersection.

c- If the equipped vehicle is stopped by the red indicators or the queues at the two immediate downstream intersections, i and $i + 1$, the optimization problem described in Eq (1) is applied to find the optimal trajectory for the vehicle to pass the two intersections. The function estimates three optimal acceleration/deceleration rates $\{a_1^*, a_2^*, a_3^*\}$ of the trajectory for the equipped vehicle to minimize the total fuel consumption to pass two intersections.

3. Downstream of the intersection N ,

The algorithm computes the fuel-optimum acceleration level from its current speed to the speed limit v_f over the distance d_3 .

4. Once the equipped vehicle passes the intersection N , and its distance to the intersection is larger than d_3 , the Eco-CACC-MS algorithm is deactivated.

The Eco-CACC-MS algorithm described above applies vehicle queue information in the estimation of the optimal trajectory (We call the algorithm Eco-CACC-MS-Q.). However, if there is not sufficient information from V2I communications to estimate vehicle queues, the algorithm can be simplified by only using SPaT information. For that case, we developed the Eco-CACC-MS algorithm without the consideration of queue (This algorithm is Eco-CACC-MS-O.), where

¹ The estimation of the queue lengths, $\{q_1, q_2\}$, and the time to release the queue is presented in [35,36]]

the queue lengths are all assumed as 0, i.e., $q_1 = q_2 = 0$ in Eq (1). In the following sections of this paper, the two algorithms will be compared to verify the benefits of introducing queues.

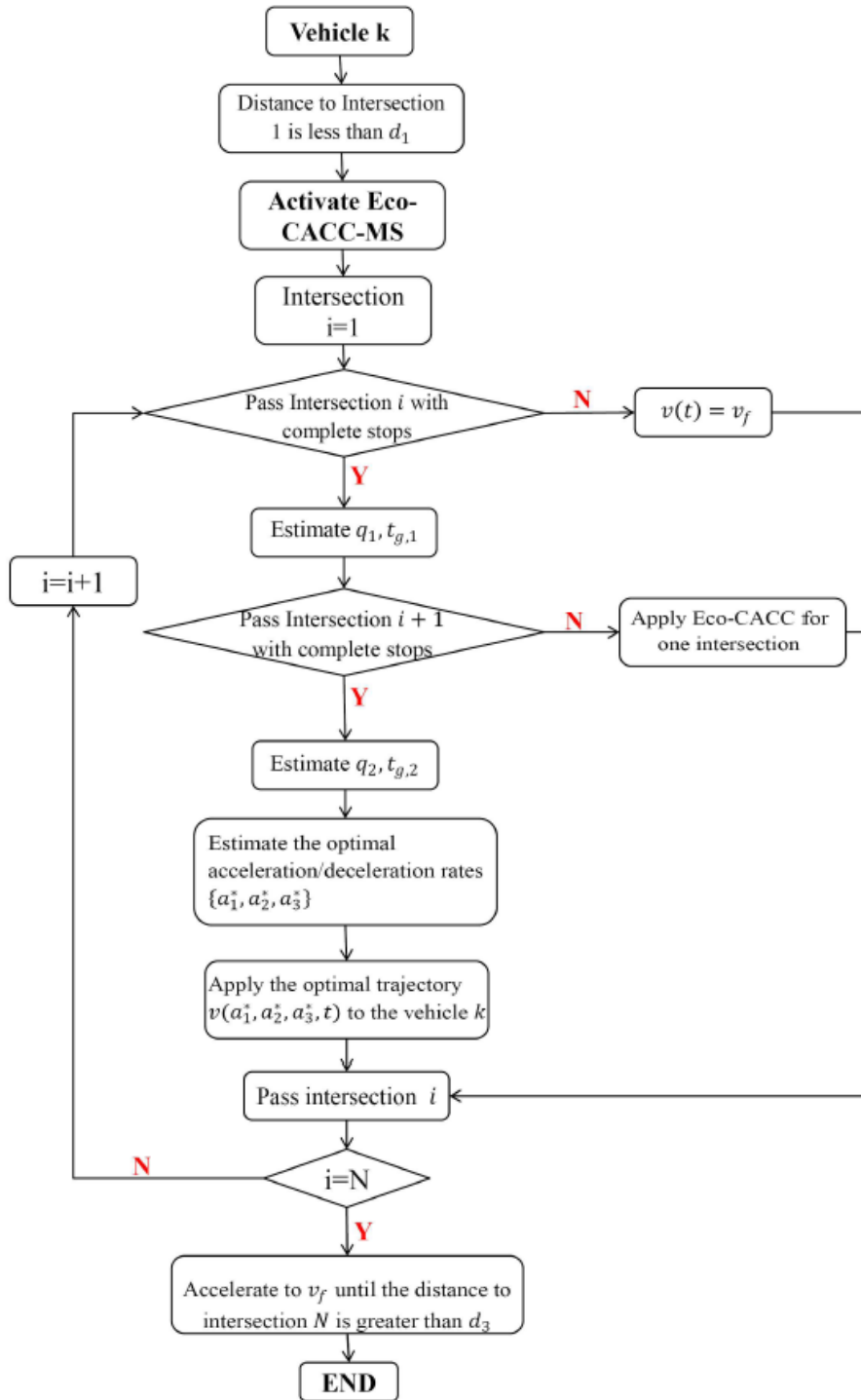


Figure 3-2 Flow chart of the Eco-CACC-MS algorithm.

3.3 Evaluation of the Eco-CACC-MS Algorithm

This section evaluates the benefits of the proposed Eco-CACC-MS algorithm with the INTEGRATION microscopic traffic simulator [38]. The simulator is capable of modeling the traffic signal control system and the movements of individual vehicles. In this section, the proposed algorithm is implemented at networks with two and four intersections to test its impacts on individual vehicle dynamics, to estimate its benefits on vehicle energy, and to check its feasibility in large networks.

3.3.1 Impact on Equipped Vehicles

As a starting point, a simple network of two intersections defined in Figure 3-3 is simulated. The simulation is conducted from one-way movement where vehicles are loaded from one origin to one destination only. In the experiment, the speed limits are 80 km/hr, and the road capacities without considering intersections, i.e., non-interrupted capacities, are $q_c = 1600$ veh/hr/lane (vphpl) for all links.

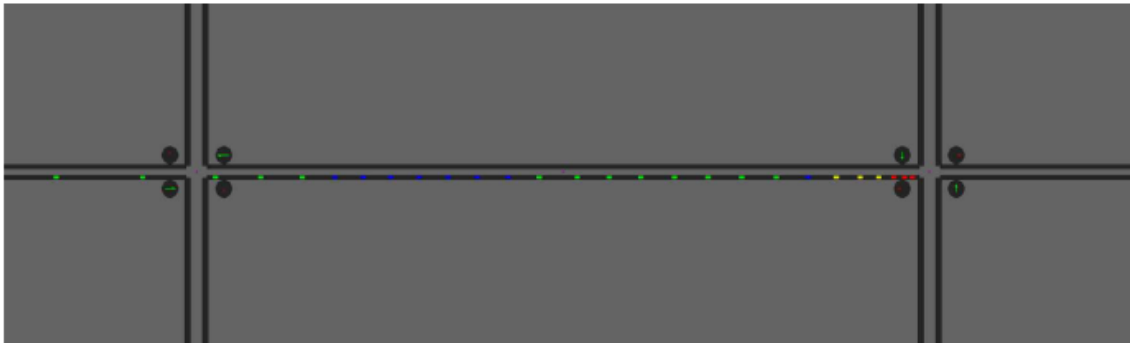


Figure 3-3 Configuration of two consecutive intersections.

Assume that the distance between the two intersections in Figure 3-3 is $d_2 = 1000$ meters, the upstream control segment length of the first intersection is $d_1 = 500$ meters, and the downstream control segment length of the second intersection is $d_3 = 200$ meters. The number of lanes of all links is set as one. In the first simulation, vehicles are only loaded from east (left end) to west (right end) at the rate of 600 vphpl, and 10% of them are equipped with the Eco-CACC-MS-Q algorithm (with the consideration of queues). For the SPaT information, the cycle lengths of both signals are 120 seconds, and the durations of the green and the amber indicators of the through traffic for the first and second signals are all 65 and 2 seconds, respectively. The offset of the second signal with

respect to the first one is 75 seconds². The v/c ration is .7 for that approach. The equipped vehicles receive advisory speed limits from the algorithm, which is updated every second.

Figure 3-4(a) compares the trajectories of one equipped vehicle before and after applying the Eco-CACC-MS-Q algorithm. Compared to the trajectory without control, the trajectory (location between 500 meters and 2200 meters) is much smoother when the algorithm is applied. Figure 3-4(b) compares the speed profiles of the vehicle before and after applying the algorithm. Similar to Figure 3-1(b), the equipped vehicle slows down and cruises to the first intersection with a smaller speed, and passes the intersection without stops. Between the first and second intersections, it accelerates to another cruise speed with a moderate rate and passes the second intersection without stops. The standard deviations of the speed profiles before and after applying the algorithm are 34.2 km/hr and 22.1 km/hr, respectively, i.e., the speed oscillation is reduced as high as 30%. In addition, the fuel consumption levels before and after applying the algorithm are 0.146 liter/km and 0.113 liter/km, indicating that the algorithm reduces fuel consumption by about 22.5%.

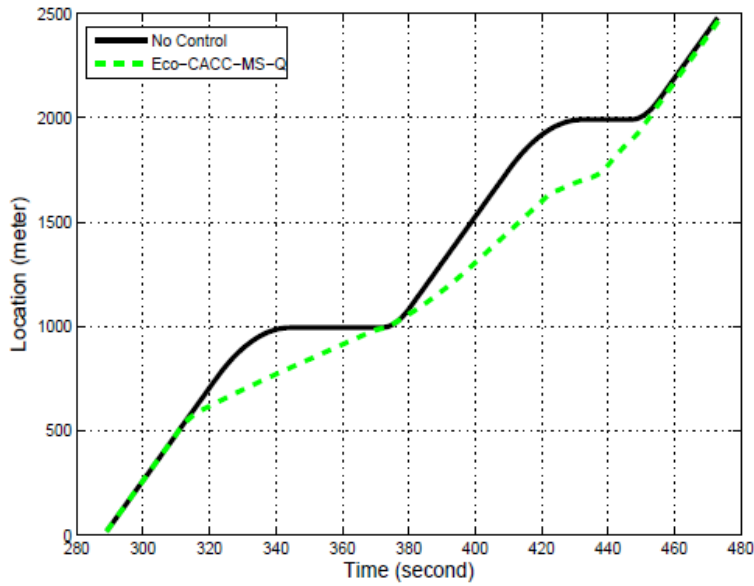
Note that in Figure 3-4(b), after applying the algorithm, the equipped vehicle's speed still drops ahead of the signals and fluctuates a lot, even though the vehicle does not experience complete stops. This fluctuation is caused by the estimation of the vehicle queue lengths, q_1 and q_2 , and the queue dispersion speeds, w_1 and w_2 . In the Eco-CACC-MS-Q algorithm, these variables are estimated with the kinematic wave model using road properties, including road capacity, jam density, and critical density [35]. However, in the microscopic simulations, due to the randomness of vehicle dynamics, the estimation cannot be accurate. Hence, the advisory speed limits calculated by the Eco-CACC-MS-Q algorithm cannot perfectly smooth the movements of equipped vehicles, and the oscillations occur when they travel through the intersections. In the future, with the help of vehicle-to-vehicle communications, queue lengths and queue dispersion speed can be monitored in real time. Then, the estimation of the advisory speed limits will be accurate, and the oscillation can be mitigated.

² The optimal offset of the second signal is 45 seconds. While, to check the benefits of the Eco-CACC-MS-Q algorithm, we try to set the offset to make the equipped vehicles experiencing two stops. The 75-second offset gives a high probability for us to observe two stops for one equipped vehicle.

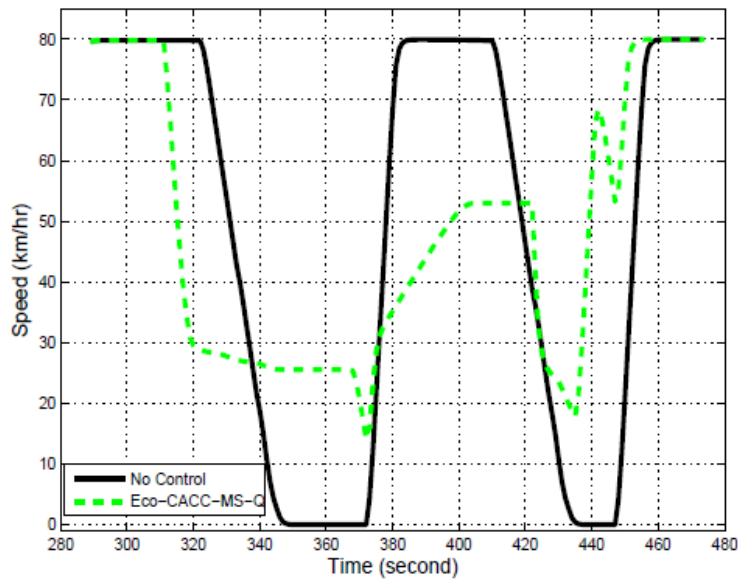
3.3.2 Eco-CACC-MS Algorithm at Two Intersections

In this section, we evaluate the benefit of the proposed algorithm on the network-wide fuel consumption levels, and compare the algorithms with and without the consideration of vehicle queues (Eco-CACC-MS-Q and Eco-CACC-MS-O) under different MPRs of the equipped vehicles. In addition, the algorithms are compared with those proposed in [35, 36] for independent intersections (Eco-CACC-Q and Eco-CACC-O).

The network settings in section 3.3.1 are also applied in this section. For the multiple intersection control algorithms (Eco-CACC-MS-Q and Eco-CACC-MS-O), the equipped vehicles are under control once they are within 500 meters ahead of the first intersection and within 200 meters after the second intersection for the Eco-CACC-MS algorithms. For the single intersection control algorithms (Eco-CACC-Q and Eco-CACC-O), the equipped vehicles are under control once they are within 500 meters before each intersection and 200 meters after each intersection. This simulation was done with a single-lane network, which prevents lane changing or vehicle over-passing behaviors. The demand for the network is still 600 vphpl, and the SPaT plans of the two signals in section 3.3.1 are also applied. The offset of the second signal is set as 0 seconds. To better evaluate performance, the algorithms are tested under different MPRs; only a portion of the vehicles are equipped, while the rest drive normally using car-following models.



(a) Trajectories



(b) Speed profiles

Figure 3-4 Comparison of vehicle movements before and after applying the Eco-CACC-MS-Q algorithm.

Figure 3-5 demonstrates the overall network-wide energy savings of the Eco-CACC and Eco-CACC-MS algorithms considering different MPRs. The figure illustrates that higher MPRs lead to greater savings in all control systems. At 100% MPR, the fuel consumption is reduced about 7% with Eco-CACC-MS-Q and 4.2% with Eco-CACC-Q. In the simulations, the movements

of the equipped vehicles are smoothed by the proposed algorithm, and at the same time due to the car-following behaviors, the trajectories of some non-equipped vehicles are also smoothed, which further reduces the network-wide fuel consumption levels. Figure 3-5 also demonstrates that even without the consideration of vehicle queues, the Eco-CACC-MS-O and Eco-CACC-O algorithms can still produce larger fuel savings as MPRs increase. However, the savings are smaller than those that take queues into consideration. Specifically, without considering queues, the fuel consumption rate is reduced from 7% to 6.1% for the multiple intersection control and from 4.2% to 3.9% for the single intersection control.

In the simulation of the single-lane intersections above, lane changing and over-passing behaviors are not allowed; while in reality, links with two or more lanes are common. Accordingly, the impacts of lane changing and vehicle over-passing need to be considered. In the second example, the same settings used in the previous simulation are applied to the same network with two-lane links. Figure 3-6 compares the fuel consumption savings of Eco-CACC-Q, Eco-CACC-O, Eco-CACC-MS-Q, and Eco-CACC-MS-Q algorithms under different MPRs. Unlike the single-lane network, the savings in fuel consumption are not always observed in the two-lane scenarios, especially when the MPR is less than 30%. When MPRs are less than 30%, all algorithms increase the overall fuel consumption levels. The negative impact of the lower MPRs is a result of the lane changing and over-passing of non-equipped vehicles. As the algorithms only control the equipped vehicles, which are traveling at lower speeds than the non-equipped vehicles, larger gaps will be generated ahead of them. The non-equipped vehicles, traveling at higher speeds, then have a greater likelihood of changing lanes and cutting into the gaps ahead of the equipped vehicles, increasing their speed oscillations and the fuel consumption level for the whole network. With 30% MPRs and above, the number of equipped vehicles increases, making it increasingly possible for equipped vehicles to travel side-by-side for the whole link, preventing lane changing and over-passing movements, and increasing fuel consumption savings. All algorithms provide positive savings with MPRs higher than 30%. At 100% MPR, fuel consumption is reduced by about 6.5% for the Eco-CACC-MS-Q, 5.8% for Eco-CACC-MS-O, 4.2% for Eco-CACC-Q and, and 3.2% for Eco-CACC-O. Similar to the single-lane example, the algorithms taking queue effects into consideration always result in better performance for the network with two-lane links.

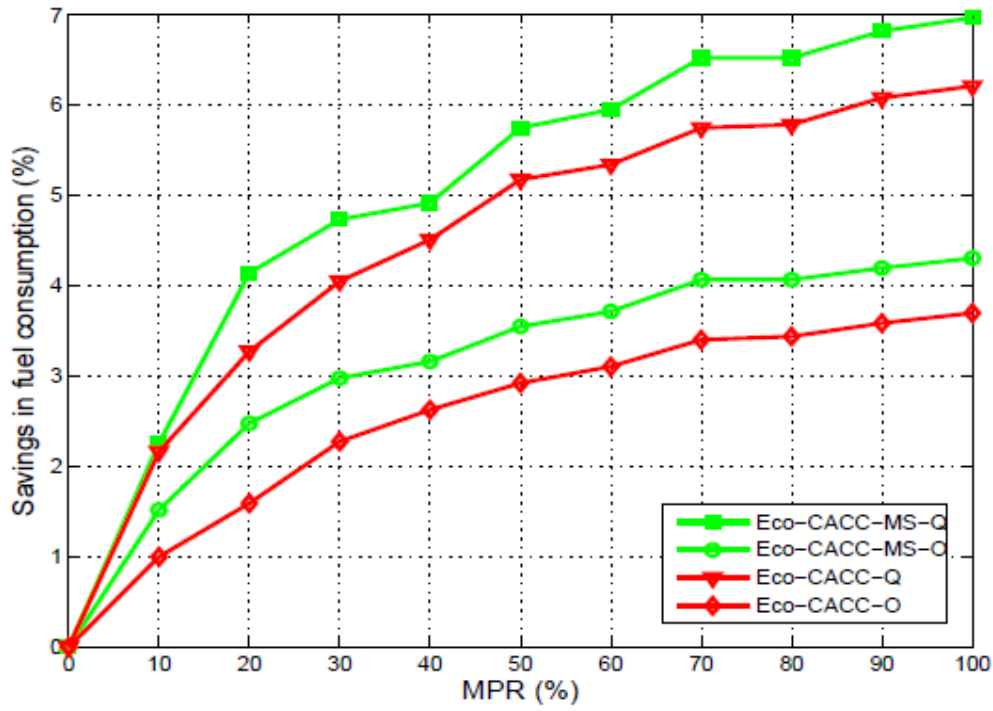


Figure 3-5 Savings in fuel consumption at the single-lane network under different MPRs.

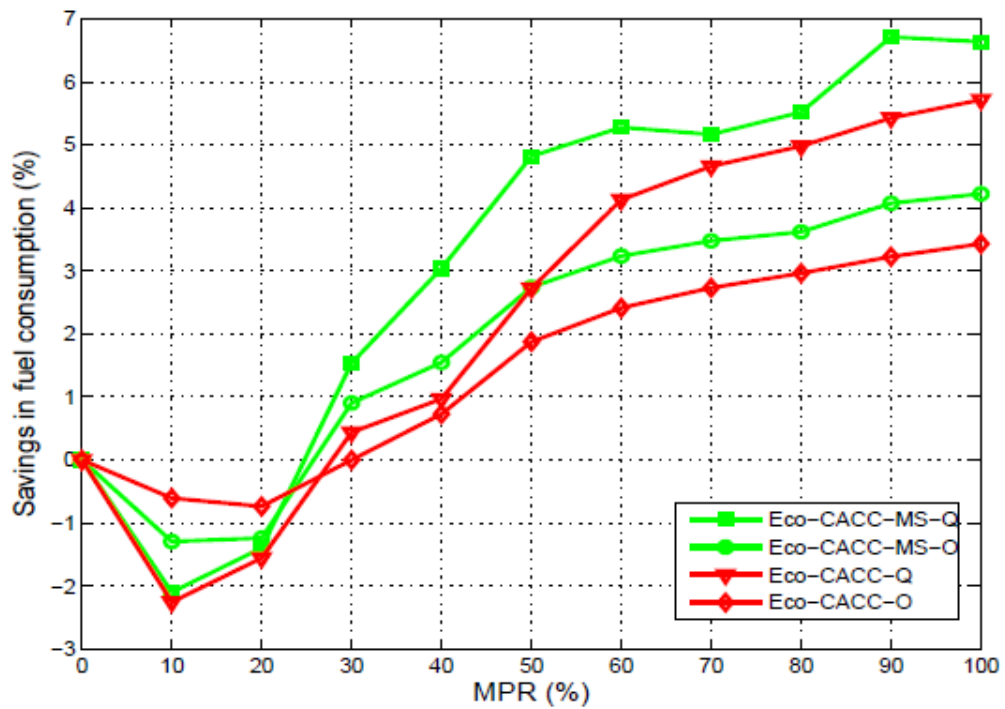
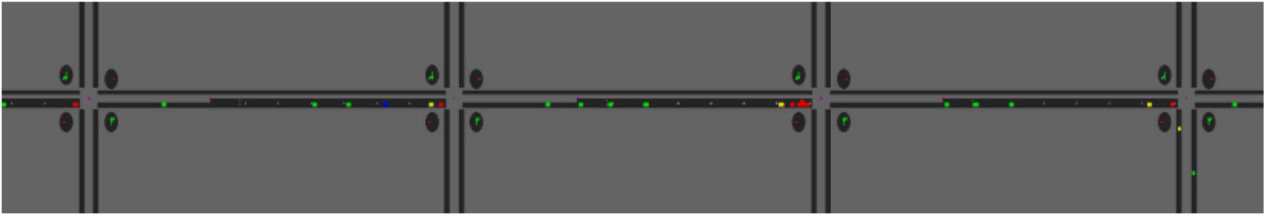


Figure 3-6 Savings in fuel consumption at the two-lane network under different MPRs.

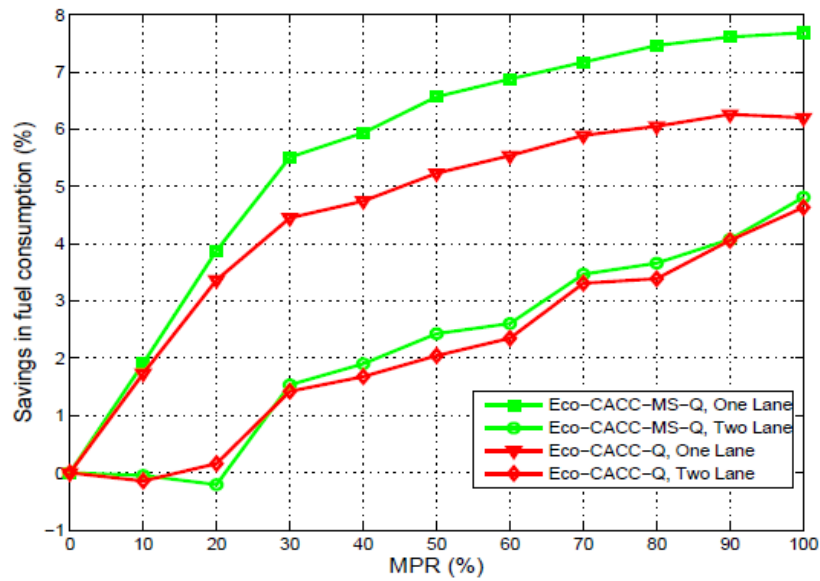
3.3.3 Eco-CACC-MS Algorithm at Four Intersections

In addition to two-intersection networks, the Eco-CACC-MS-Q algorithm is also applied to a larger network with more than two intersections. The network in Figure 3-7(a), which has four consecutive intersections, is simulated. Assume that the distance between any two consecutive intersections is 600 meters. The demand from the west to east is constant at 600 vph. For the SPaT plan, the cycle lengths and phase splits of all intersections are 120 seconds and 50%, respectively, and the offsets of all signals are set as 0.

Figure 3-7(b) illustrates the fuel consumption savings from the Eco-CACC-Q and Eco-CACC-MS-Q algorithms under different MPRs in single-lane and two-lane networks. For the single-lane network, both algorithms have positive benefits to fuel consumption at different MPRs, and higher MPRs result in greater savings for both algorithms. At 100% MPR, fuel consumption is reduced by 7.7% with Eco-CACC-MS-Q, and by 6.2% with the Eco-CACC-Q algorithm. Similar to the results in section 3.3.2, the savings come from both equipped vehicles with the optimal trajectories and non-equipped vehicles following them with car-following models. For the two-lane network, negative effects of the algorithms are still observed when the MPR is low ($< 15\%$ for Eco-CACC-Q and $< 25\%$ for Eco-CACC-MS-Q). When the MPR is larger than 30%, positive savings in fuel consumption can be obtained for both algorithms, and the savings from the multiple intersection control is higher than the single intersection control (even though the difference is not quite large). At 100% MPR, both algorithms can reduce the fuel consumption as high as 4.8%. The two simulations also verify the effectiveness of the proposed algorithm on networks with multiple intersections.



(a)



(b)

Figure 3-7 Eco-CACC-MS at four intersections: (a) configuration, (b) savings.

3.4 Sensitivity Analysis

This section makes a comprehensive sensitivity analysis of variables applied in the proposed Eco-CACC algorithms, including traffic demand levels, phase splits, offsets between two consecutive signals, and distances between intersections. In addition, the impact of over-saturated traffic on the algorithm is assessed. Moreover, the Eco-CACC-Q and the Eco-CACC-MS-Q algorithms are compared to examine the advantage of the multiple intersection control. To complete the analysis, the network in Figure 3-3 with two intersections is simulations, and link properties, including the road speed limits, the road capacities, the jam densities, and the density at capacity, are the same to section 3.3.1.

3.4.1 Sensitivity to Demand Levels

On arterial roads, vehicle demands are directly related to queue lengths ahead of signals and the number of the equipped vehicles in the network, and they play an important role on evaluating the performance of the intersections and assessing the benefits of the Eco-CACC algorithms. In this section, we examine the fuel efficiency of the Eco-CACC-MS-Q and Eco-CACC-Q algorithms under different demand levels. The signal settings of the two intersections are the same to section 3.3.1.³ In addition, we assume that all vehicles are equipped (i.e., the MPR is 100%), and the demand varies from 100 to 700 vphpl for both algorithms.

Figure 3-8 illustrates the fuel consumption savings of both algorithms as a function of the demand. The results show that under the given settings of the signal plans and the offset, positive savings in fuel consumption can be observed for all demand levels. In addition, for the Eco-CACC-MS-Q algorithm, the demand at 400 vphpl results in the best savings for the whole network, about 13.5%. Demands from 400 vphpl to 700 vphpl result in savings of 7% for the Eco-CACC-Q algorithm. The savings are a result of the increase in the number of equipped vehicles in the network. However, this simulation only considers demands below the saturated flow (800 vphpl). The implementation of the algorithm in the over-saturated network will be different, and the details will be analyzed in section 3.5.

³ The 75-second offset is also applied to observed obvious different between the single and multiple intersection control strategies.

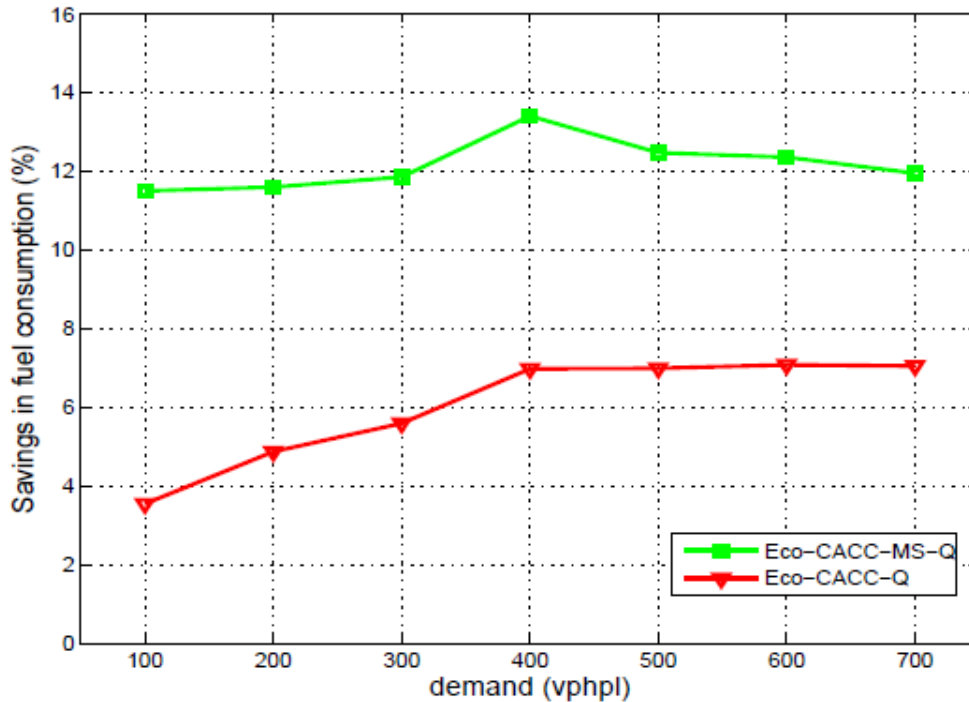


Figure 3-8 Saving in fuel consumption under different traffic demand levels.

3.4.2 Sensitivity to Phase Splits

In this study, both Eco-CACC-MS-Q and Eco-CACC-Q algorithms utilized the SPaT information to compute the optimal trajectories for the equipped vehicles, which indicates the phase splits are highly related to the effectiveness of the algorithms. In this subsection, the impact of the phase splits to the overall network performance is investigated. The simulation settings are the same as those used in the example in section 3.3.1. The demand is constant as 600 vphpl, and the phase split (i.e., the ratio of the total duration of the green and amber indicator to the cycle length) ranges from 35% to 75% for the major road (through traffic from west to east) respect to the total cycle length of 120 seconds.

Figure 3-9 illustrates the fuel consumption savings of both algorithms as a function of the phase split. The figure indicates that with higher phase splits, the savings in fuel consumption will be smaller. With a 35% green split for the major road, the savings reach up to 13.8% for the Eco-CACC-MS-Q and 7.2% for Eco-CACC-Q. This results are intuitively correct. With higher phase splits, the equipped vehicles have less chance of stopping at the signals, resulting in lower fuel consumption savings, as less vehicles have to stop. Consequently, it only needs to control the behaviors of less vehicles at higher phase splits. In addition, the benefits of the proposed algorithms

come from the control of the stopped vehicles. In that sense, the savings of fuel consumption will be smaller.

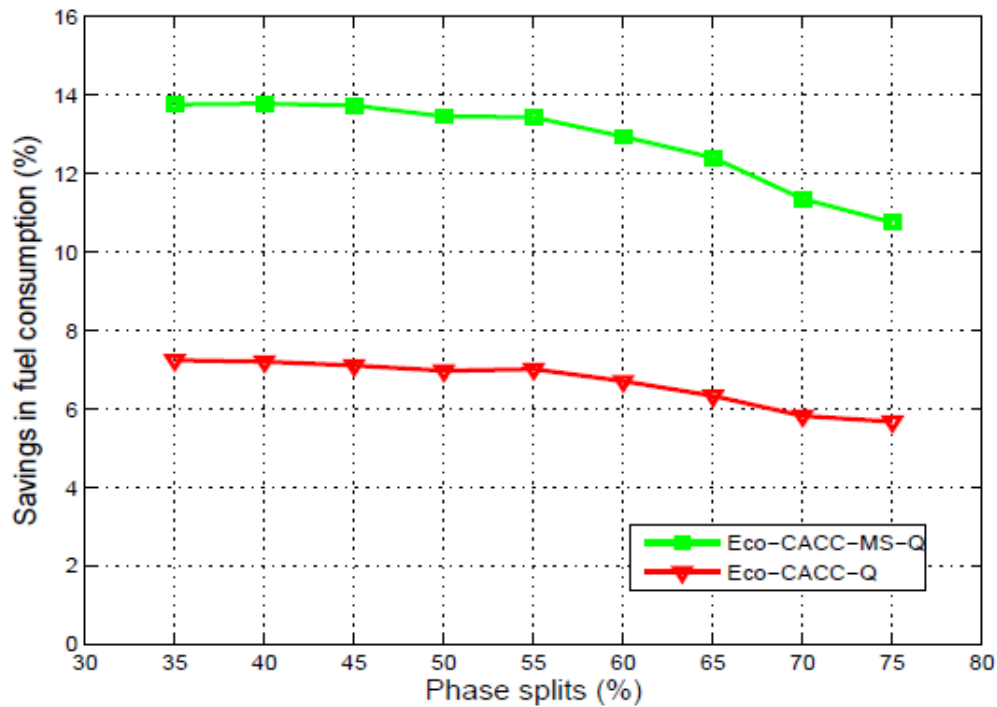


Figure 3-9 Saving in fuel consumption under different phase splits.

3.4.3 Sensitivity to Offsets

The offset is important to coordinate multiple intersections and to improve the performance of the whole network. And, the fluctuations of vehicles' movements through multiple intersections are directly related to the offset. This section investigates the impact of offsets on the performance of the proposed algorithms. The simulation settings are still the same to the example in section 3.4.2, except that the phase split is constant at 55%, and the second signal offset with respect to the first varies from 0 to 120 seconds. In this simulation, the distance between the two intersections is 1000 meters, which can be traveled by equipped vehicles within 45 seconds at the free-flow speed, i.e., the optimal offset of the second signal is about 45-50 seconds (with consideration of lost time).

Figure 3-10 illustrates the fuel consumption savings of both Eco-CACC-MS-Q and Eco-CACC-Q algorithms as a function of the offset. Results indicate that when the offset is closer to the optimal value, the savings of fuel consumption obtained from both algorithms will be smaller. At the optimal offset, the Eco-CACC-MS-Q provides the lowest saving of 2.8%, and the Eco-CACC-Q 2.5%. The highest savings of fuel consumption can be observed at 13.0% with 100-

second offset for Eco-CACC-MS-Q, and 7.3% with 65-second offset for Eco-CACC-Q. This results are valid, as the savings of the algorithms are observed if the equipped vehicles have to stop at both intersections. At the optimal offset, most vehicles only need to stop at the first signal, which results in the least savings for both algorithms.

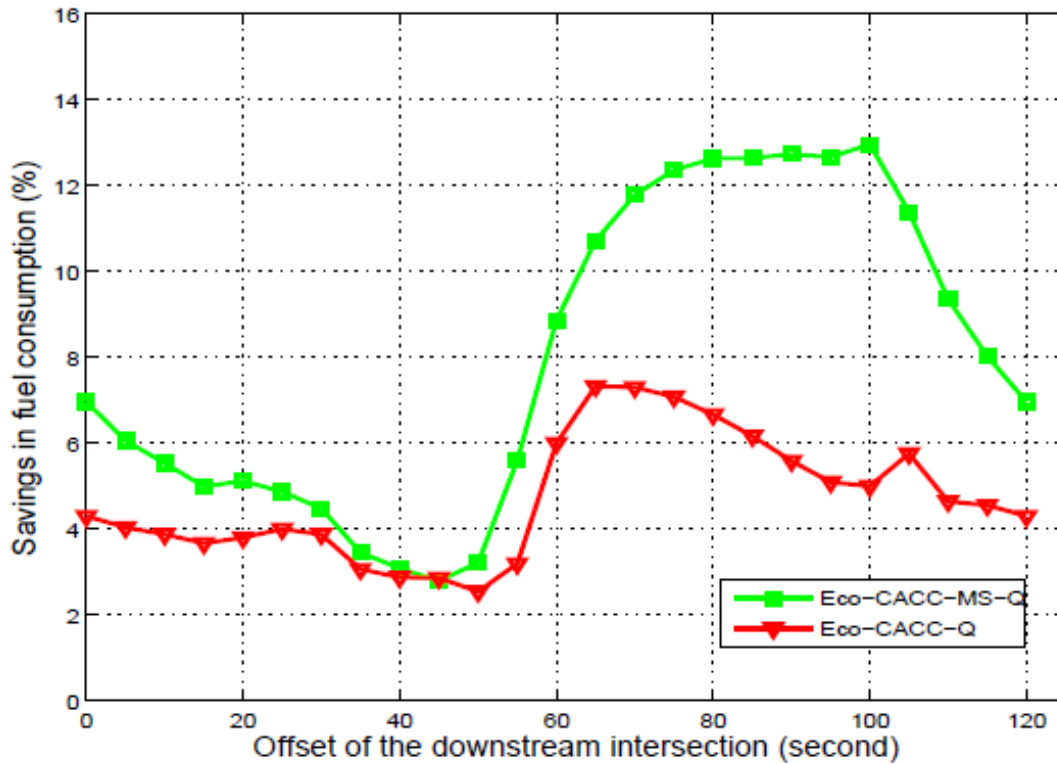


Figure 3-10 Savings in fuel consumption under different offsets.

3.4.4 Sensitivity to the Distance between Intersections

Distance between intersections is another variable affecting the benefits of the proposed algorithm. In this section, the impact of the distance between the intersections is evaluated. The simulation settings are the same section 3.4.3, except that the offset is constant as 75 seconds, and the distance between the two intersections ranges between 200 and 1000 meters.

Figure 3-11 shows the fuel consumption savings for both Eco-CACC-MS-Q and Eco-CACC-Q algorithms as a function of the distance between intersections. Results indicate that under the given signal plans and the demand level, 700 meters is the optimal distance between intersections for both algorithms. The Eco-CACC-MS-Q algorithm provides fuel consumption

savings of 13.1% for the 700-meters distance between intersections, and the Eco-CACC-Q algorithm provides 7.2% savings.

The pattern from the Eco-CACC-MS-Q algorithm is determined by the following two factors. (1) With a longer distance between intersections, equipped vehicles can be controlled for a longer time, allowing the algorithms to provide more fuel-efficient trajectories. However, (2) the longer distance makes the prediction of the queue lengths and queue dispersion times at the downstream intersection less accurately, which reduces the effectiveness of the algorithm. Hence, there exists an optimal value for the distance when the Eco-CACC-MS-Q algorithm is applied. In addition, with the Eco-CACC-Q algorithm, the two intersections are controlled independently. When the distance is large enough, the two intersections can consider to be isolated to each other. Hence, the benefit from the single intersection control will keep constant.

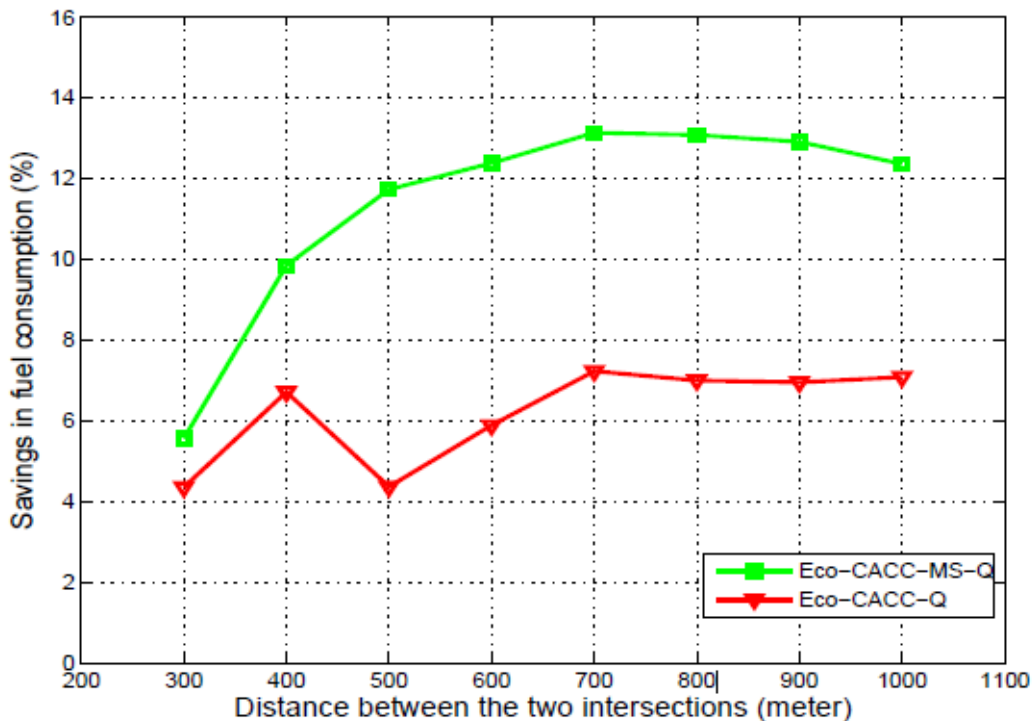


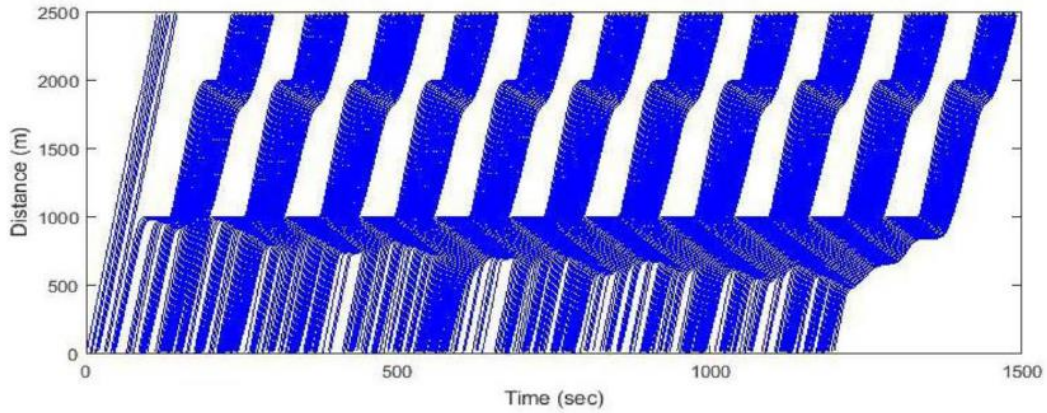
Figure 3-11 Savings in fuel consumption under different distances between intersections.

3.5 Over-Saturated Demands

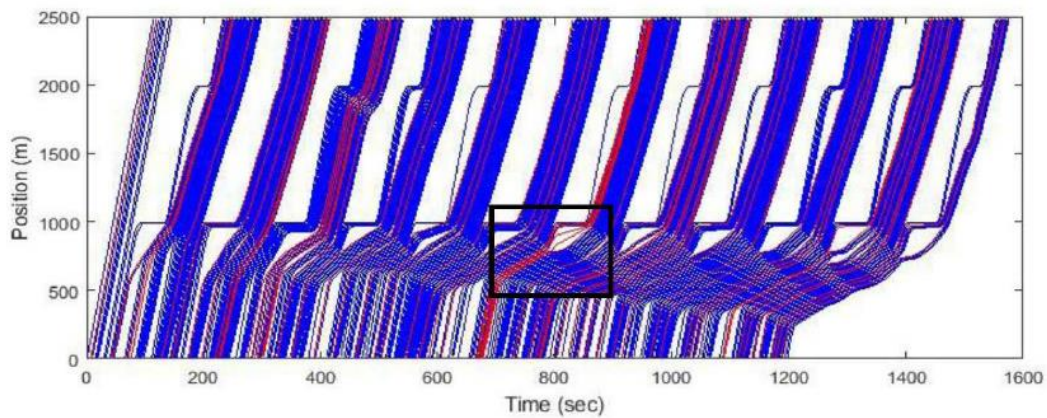
In the development of the Eco-CACC-MS-Q algorithms, one critical assumption is that the network is not over-saturated, and vehicle queues can be released during one cycle. Once the network is over-saturated, rolling queues are generated upstream of the intersections. Then, the

queue estimation method in [35] cannot determine the queue length and the dispersion time accurately. Consequently, the advisory speed limits are not optimized for the equipped vehicles to pass the intersections. [35] showed that the Eco-CACC-Q algorithm was unable to obtain positive savings under over-saturated demands. In this section, we investigate the impact of over-saturated demands on the Eco-CACC-MS-Q algorithm.

The example in section 3.3.1 is applied. The simulation settings maintain the same, except that the demand increases to 1000 vphpl, which is greater than the capacity of the controlled segment. Figure 3-12 compares the trajectories of all vehicles before and after applying the Eco-CACC-MS-Q algorithm. In Figure 3-12(a), most vehicles experience stops at both intersections, and generally the queues at the first intersection cannot be released in one cycle. Figure 3-12(b) shows the trajectories with 10% equipped vehicles. As shown within the black box in the figure, the algorithm fails to provide the optimum speed limits for the equipped vehicles to pass the intersection without stops. The rolling queues caused by the over-saturated demand generate traffic fluctuations and complete stops for the equipped vehicles, reducing the benefits of the algorithm dramatically. However, as the inflow to the second intersection is gated by the first one, over-saturation is averted, and fuel consumption savings can still be observed at the second intersection using the proposed algorithm. In the simulation, a 10% MPR actually reduces fuel consumption by about 2.7%. This implies that compared with Eco-CACC-Q, the Eco-CACC-MS-Q algorithm is more efficient at providing fuel consumption savings under over-saturated demands.



(a)



(b)

Figure 3-12 Vehicle trajectories under over-saturated demands: (a) No control, (b) Eco-CACC-MS-Q.

3.6 Conclusions

This paper developed an Eco-CACC-MS algorithm to minimize fuel consumption for vehicles to pass multiple intersections. The algorithm utilized SPaT and vehicle queue information collected by V2I communications to estimate the optimal trajectories and to provide advisory speed limits for individual vehicles to pass multiple consecutive intersections. The algorithm accelerated/decelerated the equipped vehicles to a constant speed to cruise to the intersections so as to reduce their fuel consumption levels. In addition, the Eco-CACC-MS algorithm was evaluated with the INTEGRATION microscopic simulator. The simulation of the single-lane intersections proved that fuel consumption savings were greater at higher MPRs. The reductions in fuel consumption reached 7% for Eco-CACC-MS-Q and 4.2% for Eco-CACC-Q at 100% MPR. And, taking the vehicle queue into consideration, the Eco-CACC-MS-Q algorithm always performed better than Eco-CACC-O. In the two-lane intersection, due to lane-changing and

passing behaviors, the proposed algorithm increased the total fuel consumption levels when the MPRs were less than 30%. Once the MPRs were larger than 30%, positive savings could be observed. In addition, the Eco-CACC-MS algorithm was implemented in a network with four consecutive intersections, and the fuel consumption savings were also observed to be as high as 7.7% for single-lane roads, and 4.8% for two-lane roads.

The study also included a comprehensive sensitivity analysis of traffic demands, phase splits, offsets, and the distances between intersections. The analysis indicated that under the given offset of 75 seconds, the phase split of 50%, and the 1000-meter segment between the two intersections, loading vehicles at 700 vphpl resulted in the highest fuel consumption savings, at 13.5%. And, given the offset, the demand and the distance between intersections, with a larger percentage of the phase split, the savings from the proposed algorithm were smaller. In addition, when the offset was closer to the optimal offset, fuel consumption savings were smaller. Furthermore, the optimal distance between intersections exists to maximize the savings in fuel consumption. Currently, the proposed algorithm cannot effectively reduce fuel consumption for intersections with over-saturated demands due to the impact of rolling queues. In the future, we plan to apply V2V communications to collect more information from individual vehicles and develop a more accurate prediction model of vehicle queues. We will also introduce a speed harmonization algorithm [40] to restrict traffic entering the intersections to maintain an under-saturated traffic condition at all times. Moreover, we will extend the logic to reduce fuel consumption and delay for large networks and investigate the impact of other variables, such as speed limits, number of lanes, and road grades.

3.7 References

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4 SENSITIVITY ANALYSIS OF ECO-COOPERATIVE ADAPTIVE CRUISE CONTROL AT MULTIPLE SIGNALIZED INTERSECTIONS

(Fawaz Almutairi, Hao Yang, and Hesham A Rakha, “Sensitivity analysis of eco-cooperative adaptive cruise control at multiple signalized intersections.”)

Abstract

Network-wide fuel consumption along arterial roadways increases as the number of vehicle stops caused by traffic signals increase. Eco-Cooperative Adaptive Cruise Control for Multiple Signals (Eco-CACC-MS) systems are being introduced to increase vehicle fuel consumption savings in the vicinity of signalized intersections. These Eco-CACC-MS systems utilize traffic Signal Phasing and Timing (SPaT) data received from vehicle-to-infrastructure (V2I) communication and vehicle queue predictions to compute and transmit fuel-optimum vehicle trajectories to vehicles traveling through the vicinity of the signalized intersections. This study used INTEGRATION microscopic traffic assignment and simulation software to evaluate the Eco-CACC-MS algorithm to assess its network-wide environmental and energy impacts. A simulation sensitivity analysis showed that the Eco-CACC-MS algorithm reduces fuel consumption up to 13% with a 100% market penetration rate compared with Eco-CACC. The analyses also examined multi-lane networks, different demand levels, and different signal offsets. The significance analysis section showed the significance difference in the saving of Eco-CACC-MS and Eco-CACC. However, the algorithm may cause an increase in fuel consumption with oversaturated networks; thus, further work is needed to enhance the algorithm for these conditions.

Keywords: Eco-CACC-MS, eco-driving, connected vehicles, fuel consumption levels, queue length prediction, INTEGRATION software

4.1 INTRODUCTION

In the past few years, passenger car and truck volume has increased rapidly, which has led energy and vehicle emissions to increase significantly. In 2013, the transportation sector in the U.S. consumed more than 135 billion gallons of fuel, and 70% of that was consumed by passenger cars and trucks [1]. Nationwide, transportation used more than 60% of the oil produced. This explains the urgent need for the transportation sector to solve this issue by using fuel reduction strategies. Eco-driving is a cost-effective strategy to improve fuel efficiency [2]. The main idea of eco-driving is to provide real-time driving advice to individual vehicles so drivers can adjust their driving behavior to reduce fuel consumption and emission rates. Many eco-driving algorithms operate by providing advisory speed limits, acceleration and deceleration levels, and speed alerts to drivers. Recently, several studies have shown that eco-driving can reduce fuel consumption and greenhouse gas emissions by about 10% on average [3].

Stop-and-go waves of traffic are one major cause of fuel inefficiency and greenhouse gas emissions because of the frequent accelerations that occur [4]. High speeds over 60 mph and slow movements on congested roads increase the emission of air pollutants rapidly [5]. Therefore, reducing traffic oscillations and avoiding idling are two strategic methods to increase fuel efficiency. Thus, eco-driving can be divided to two categories: freeway-based and city-based. With freeway-based eco-driving, traffic is continuous and rarely disturbed. The strategy to control this is straightforward: provide an advisory speed limit or speed limits based on road conditions to save emissions. Barth and Boriboonsomsin applied vehicle-to-infrastructure (V2I) communications to determine the average link speed and variation, then provided advisory speeds for drivers to reduce emissions [6]. Yang and Jin estimated advisory speed limits for drivers based on the movements of surrounding vehicles with the assistance of vehicle-to-vehicle communication technologies [7]. In addition, a moving-horizon Dynamic Programming (DP) Eco-Adaptive Cruise Control (Eco-ACC) system has demonstrated the benefits of the system [8-10].

In city driving, traffic on arterial roads is typically interrupted by traffic control devices like signals. During a red indication, vehicles are forced to stop ahead of the signal, which generates shockwaves within the traffic stream. The shockwaves produce acceleration and deceleration maneuvers and idling, which increase fuel consumption and emission levels. Researchers have tried to optimize traffic signal timing using approach volumes and queue lengths [11, 12].

Lately, individual vehicles can be controlled to reduce emission levels by using connected vehicle (CV) technologies, for example Eco-Cooperative Adaptive Cruise Control (Eco-CACC). CVs allow vehicles to communicate with signal controllers to receive Signal Phase and Timing (SpaT) data and queue information [13]. Using these data, vehicle speeds can be adjusted to reduce fuel consumption levels.

Recently, many researchers have started developing environmental CV applications. These applications advise drivers to travel at a speed that saves fuel. Mandava et al. and Xia et al. introduced a velocity-planning algorithm built on traffic signal information to maximize the probability of encountering a green indication when approaching many intersections [14, 15]. The algorithm tries to save fuel by minimizing acceleration and deceleration levels by avoiding complete stops, but lowering acceleration and deceleration levels will not necessarily reduce fuel consumption. Asadi and Vahidi utilized traffic signal information to provide optimal cruise speeds for probe vehicles to reduce the probability of having to stop at a signalized intersection during red indications [16]. Malakorn and Park used SPaT information and introduced a cooperative adaptive cruise control system to reduce the absolute acceleration levels of probe vehicles [17]. Barth et al. developed a dynamic eco-driving system for arterial roads that provides the best acceleration and deceleration levels to reduce the total tractive power demand and idling time to save fuel consumption levels [18]. A DP-based fuel-optimization strategy using recursive path-finding principles, which was evaluated using an agent-based model, was proposed by Rakha and Kamalanathsharma [19-21]. A combination of pruning algorithms and optimal controls to identify the best green wave if the vehicles were to receive signal information from many upcoming intersections was used by De Nunzio et al. [22]. A Smartphone application for Android was developed to evaluate the effect of an eco-driving assistant that maintains moderate deceleration and acceleration behavior on fuel consumption levels by Munoz and Magana [23].

Yang, Ala, and Rakha [24], Ala, Yang, and Rakha [25], and Yang, Almutairi, and Rakha [26] proposed Eco-CACC and Eco-CACC-MS algorithms based on V2I communication that optimize vehicle fuel consumption levels in the vicinity of signalized intersections. These algorithms are different from the others discussed above since they consider the impact of surrounding traffic. The algorithms provide an advisory speed limit for probe vehicles upstream and downstream of each intersection to optimize vehicle accelerations downstream of a traffic signal. To test the algorithm, a microscopic simulation model, INTEGRATION [27], was used. The model is open source, and incorporating and testing vehicle or traffic control strategies is easy.

This paper reviews the Eco-CACC-MS algorithm, considering queue effects developed in Yang et al. [24] by using Rakha and Van Aerde [27], and incorporates the algorithm in the INTEGRATION software. In addition, a sensitivity analysis of the algorithm is presented.

4.2 METHODOLOGY

This study evaluates the environmental benefits of the Eco-CACC-MS algorithm proposed in Yang et al. [24] using the INTEGRATION microscopic traffic assignment and simulation model [25, 26].

4.2.1 Eco-CACC-MS Algorithm

The Eco-CACC-MS algorithm proposed in [26] minimizes the fuel consumption rates for vehicles passing multiple intersections. The algorithm utilizes the SPaT data from V2I communications to compute vehicle trajectories optimized to reduce fuel consumption by providing an advisory speed limit. This speed limit takes into consideration the vehicle queue ahead of the intersection.

Figure 4-1(a) demonstrates the trajectories of vehicles passing two consecutive intersections. The solid black line represents the trajectory of one vehicle not under Eco-CACC control experiencing two red lights. It is assumed that the vehicle has infinite acceleration/deceleration rates. The vehicle has to stop ahead of both intersections due to the red light and the vehicle queues. According to the work in [26], the Eco-CACC-MS algorithm allows the vehicle to cruise to each intersection at a constant speed (see the dashed green line in Figure 4-1(a)). But the assumption that the acceleration/deceleration rates of the equipped vehicle are infinite is not realistic.

Figure 4-1(b) compares the speed profiles of the vehicle with Eco-CACC control (green line) to the vehicle without Eco-CACC control (black line), considering both acceleration and deceleration durations. The first intersection is at t_2 and the second intersection is at t_4 . Without Eco-CACC control, the vehicle has to come to a complete stop at both intersections, and between the two stops it accelerates to the free-flow speed. Stop-and-go behaviors and the long idling time waste a great deal of energy. On the other hand, the vehicle under Eco-CACC-MS control decelerates to a speed, $v_{C,1}$, and then cruises to the first intersection. Between the two intersections, it decelerates or accelerates from $v_{C,1}$ to $v_{C,2}$, and cruises to the second intersection. Here, $v_{C,1}$ and $v_{C,2}$ are the cruise speeds to the first and second intersection, respectively. Once the queue at the second intersection is released, the vehicle accelerates to the speed limit. Compared to the base

case without control, both the trajectory and the speed profile with Eco-CACC-MS are much smoother. In addition to the shape of the vehicle speed shown in

Figure 4-1(b), the algorithm determines the optimum upstream acceleration/deceleration levels of the controlled speed profile in

Figure 4-1(b). The mathematical formulation of the algorithm can be cast as follows:

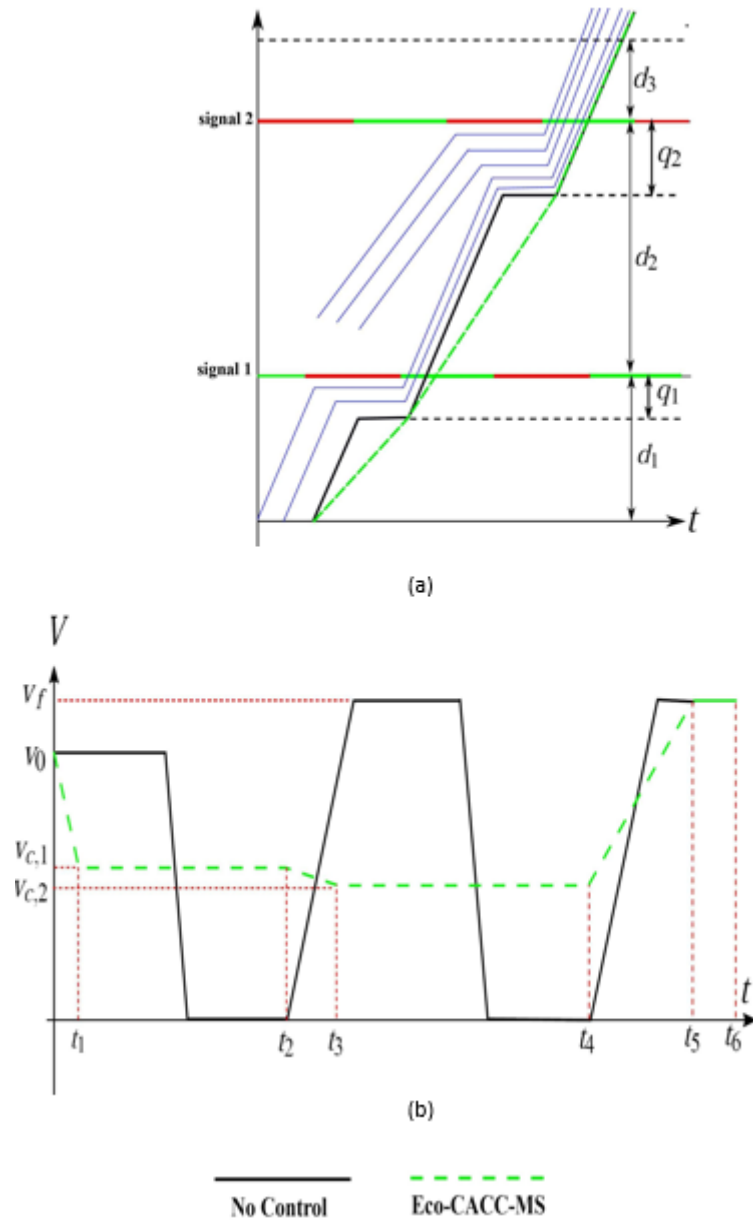


Figure 4-1 Dynamics of the equipped vehicle at two intersections: (a) trajectories, (b) speed profiles.

$$\max_{a_1, a_2, a_3} \int_0^{t_6} F(v(t)) dt, \quad (1a)$$

s.t.

$$v(a_1, a_2, a_3, t) = \begin{cases} v_0 + a_1 t & 0 < t < t_1 \\ v_{c,1} & t_1 < t < t_2 \\ v_{c,1} + a_2(t - t_2) & t_2 < t < t_3 \\ v_{c,2} & t_3 < t < t_4 \\ v_{c,2} + a_3(t - t_4) & t_4 < t < t_5 \\ v_f & t_5 < t < t_4 \end{cases}; \quad (1b)$$

$$v_{c,1} = v_0 + a_1 \cdot t_1; \quad (1c)$$

$$v_0 \cdot t_1 + \frac{1}{2} a_1 t_1^2 + v_{c,1}(t_2 - t_1) = d_1 - q_1; \quad (1d)$$

$$t_2 = t_{g,1} + \frac{q_1}{w_1}; \quad (1e)$$

$$v_{c,2} = v_{c,1} + a_2 \cdot (t_3 - t_2); \quad (1f)$$

$$v_{c,1}(t_3 - t_2) + \frac{1}{2} a_2 (t_3 - t_2)^2 + v_{c,2}(t_4 - t_3) = d_2 + q_1 - q_2; \quad (1g)$$

$$t_4 = t_{g,2} + \frac{q_2}{w_2}; \quad (1h)$$

$$v_{c,2} + a_3(t_5 - t_4) = v_f; \quad (1i)$$

$$v_{c,2}(t_5 - t_4) + \frac{1}{2} a_3 (t_5 - t_4)^2 + v_f(t_6 - t_5) = d_3 + q_2; \quad (1j)$$

$$a_-^s \leq a_1 \leq a_+^s; \quad (1k)$$

$$a_-^s \leq a_2 \leq a_+^s; \quad (1l)$$

$$0 \leq a_3 \leq a_+^s; \quad (1m)$$

- $F(v(t))$: the vehicle fuel consumption rate at any instant t computed using the Virginia Tech Comprehensive Power-based Fuel Consumption Model (VT-CPFM) [28];
- $v(t)$: the advisory speed limit for the equipped vehicle at time t ;
- a_k : the acceleration/deceleration rates for the advisory speed limit, $k = 1, 2, 3$;
- v_0 : the speed of the vehicle when it enters the upstream control segment of the first intersection;

- v_f : the road speed limit;
- d_1 : the length of the upstream control segment of the first intersection;
- d_2 : the distance between the two intersections;
- d_3 : the length of the downstream control segment of the second intersection;
- $t_{g,1}$: the time instant that the indicator of the first signal turns to green;
- $t_{g,2}$: the time instant that the indicator of the second signal turns to green;
- t_k : the time instant defined in Figure 4-1(b), $k=1,2, \dots, 6$;
- $v_{c,1}$: the cruise speed to the first intersection;
- $v_{c,2}$: the cruise speed to the second intersection;
- q_1 : the queue length at the first immediate downstream intersection;
- q_2 : the queue length at the second immediate downstream intersection;
- w_1 : the queue dispersion speed at the first immediate downstream intersection;
- w_2 : the queue dispersion speed at the second immediate downstream intersection;
- a_-^s : the saturation deceleration level;
- a_+^s : the saturation acceleration level.

Eq. (1b) demonstrates that the speed profile varies as a function of a_1 , a_2 , and a_3 , given the traffic state, including queue lengths, the start and end times of the indicators of the two intersections, and the approaching speed of the controlled vehicles. Eq. (1c–e) govern how the equipped vehicle decelerates to $v_{c,1}$ and passes the first intersection just when the queue is released. Eq. (1f–h) determine how the vehicle passes the second intersection when the queue is released. Eq. (1)(i, j) show how the vehicle recovers its speed to return to the speed limit.

The flowchart of the Eco-CACC-MS algorithm is illustrated in Figure 4-2, and the details of the algorithm, including how it is extended to N consecutive intersections (labeled as 1, 2, \dots , N from upstream to downstream), are described below.

1. When an equipped vehicle k enters the upstream control segment of the first intersection (i.e., the distance between the vehicle and the stop line of intersection 1 [the first upstream intersection] is less than d_1), the Eco-CACC-MS algorithm is activated.

2. Upstream of intersection 1 or the section between intersection $i-1$ and i , $i = 2, 3, \dots, N$, the algorithm estimates the optimal trajectory for the equipped vehicle to pass intersections based on the SPaT and vehicle queue information.⁴ The algorithm categorizes the traffic condition into three scenarios, and controls the vehicle differently depending on the scenario.

(a) If the equipped vehicle can pass its immediate downstream intersection, i , at its current speed, v_0 , or the speed limit, v_f , without a complete stop caused by either the red indicator or the vehicle queue, the algorithm does not control the movements of the equipped vehicle, and the vehicle will only apply the road speed limit to pass the intersection.

(b) If the equipped vehicle is stopped by the red indicator or the queue at its immediate downstream intersection, i , but it can pass the second intersection, $i+1$, without stops, or $i = N$, the Eco-CACC algorithm for a single intersection proposed in [24] is applied to the equipped vehicle with the SPaT and the queue information of the intersection i . The optimal trajectory is estimated for the equipped vehicle to pass the intersection.

(c) If the equipped vehicle is stopped by the red indicators or the queues at the two immediate downstream intersections, i and $i+1$, the optimization problem described in Eq. (1) is applied to find the optimal trajectory for the vehicle to pass the two intersections. The function estimates three optimal acceleration/deceleration rates, $\{a^*_1, a^*_2, a^*_3\}$, for the equipped vehicle to minimize the total fuel consumption to pass the two intersections.

3. Downstream of the intersection N , the algorithm computes the fuel-optimum acceleration level from its current speed to the speed limit v_f over the distance d_3 .

4. Once the equipped vehicle passes the intersection N , and its distance to the intersection is larger than d_3 , the Eco-CACC-MS algorithm is deactivated.

The Eco-CACC-MS algorithm described above applies vehicle queue information in the estimation of the optimal trajectory. (We call the algorithm Eco-CACC-MS-Q.) However, if there is insufficient information from V2I communications to estimate vehicle queues, the algorithm can be simplified by only using SPaT information. For that case, we developed an Eco-CACC-MS

⁴The estimation of the queue lengths, $\{q_1, q_2\}$, and the time to release the queue are presented in (24, 25).

algorithm that does not consider the queue (Eco-CACC-MS-O), where the queue lengths are all assumed to be 0, i.e., $q_1 = q_2 = 0$ in Eq. (1).

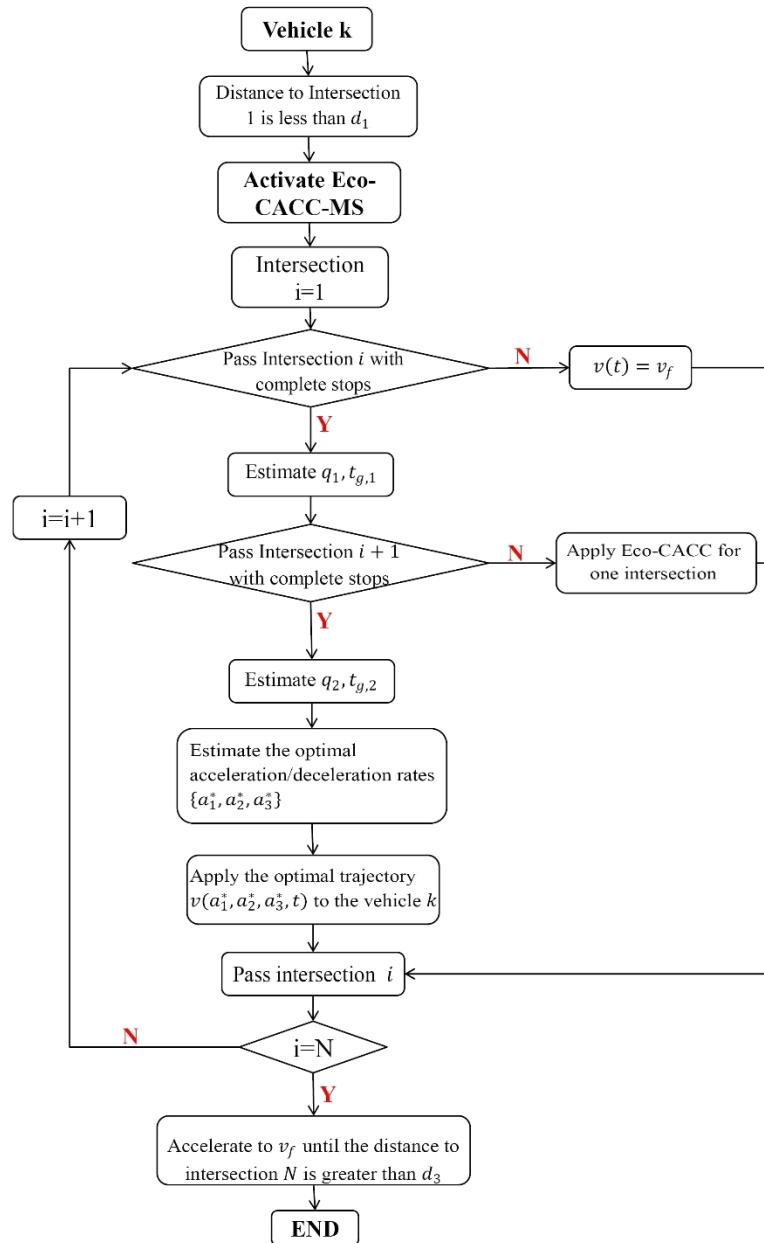


Figure 4-2 Flow chart of the Eco-CACC-MS algorithm.

4.3 SENSITIVITY ANALYSIS

A sensitivity analysis was conducted to verify the proposed algorithm with the INTEGRATION microscopic simulator [27]. The sensitivity analysis considered factors such as the impact of the market penetration rate (MPR) of Eco-CACC-MS-Q and Eco-CACC-Q equipped vehicles, number

of lanes of the controlled segment, traffic demand rates, offset between the traffic signals, and distance between intersections.

INTEGRATION simulation software was used to model the movements of all vehicles individually, which included the control of CACC-equipped vehicles. INTEGRATION provides the ability to test the impact of all vehicle dynamics individually, which helps to estimate the benefit of using Eco-CACC-MS-Q on vehicle dynamics and fuel consumption.

4.3.1 Impact of MPR

The impact of MPR for Eco-CACC-MS-Q equipped vehicles was studied for network-wide fuel consumption. The impact of the Eco-CACC-MS-Q algorithm was compared to the Eco-CACC-Q algorithm under different MPRs for equipped vehicles.

To better evaluate the algorithm, a simple network was simulated same as Figure 4-3 which contains two consecutive intersections. In Figure 4-3, the upstream control segment from the first intersection $d_1 = 500$ m, the distance between intersections $d_2 = 500$ m, and the downstream control segment length of the second intersection $d_3 = 200$ m. The movement in the simulation is one-way only, in which vehicles travel from one origin to one destination only. For all scenarios, the speed limit is 80 km/h and the saturation flow rate, q_c , is 1,600 vehicles per hour per lane (vphpln). The cycle length of both signals is 120 s, the duration of the through traffic for the first and second signals is 65 s of the green indicator and 2 s of the amber indicator, and the offset of the second signal respective to the first is 45 s.⁵ The v/c ration is .35 for that approach. The equipped vehicles receive advisory speed limits from the algorithm, which is updated every second.

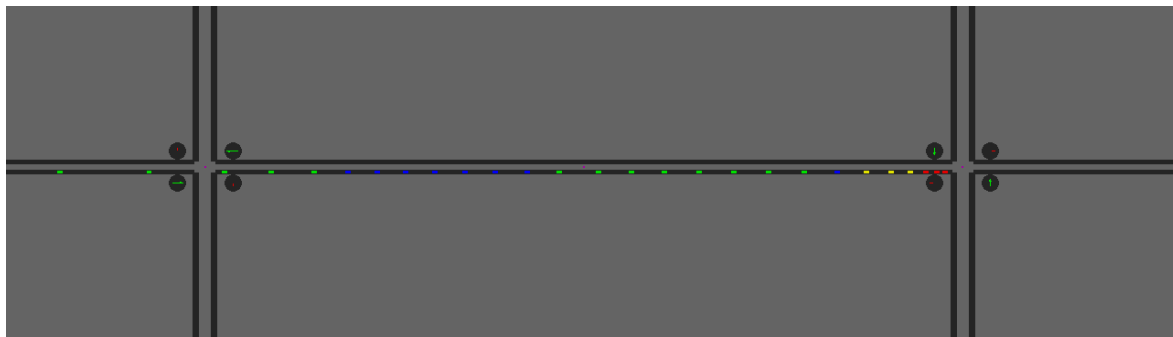


Figure 4-3 Configuration of a simple network of two consecutive intersection.

⁵ The optimal offset of the second signal is 22.5 s. To check the benefits of the Eco-CACC-MS-Q algorithm, we tried to set the offset to make the equipped vehicles experience two stops. The 45-s offset gives a high probability of observing two stops for one equipped vehicle.

For the Eco-CACC-MS-Q algorithm, the vehicles are under control from 500 m ahead of the first intersection to 200 m after the second intersection. The Eco-CACC-Q algorithms activate when the vehicles are 500 m before each intersection and deactivate 200 m after each intersection. The simulation was done for both a single-lane network and a two-lane network. The single-lane network prevented lane changing or passing Eco-CACC-MS-Q equipped vehicles. The demand in the network is 300 vehicles per hour per lane (vphpln). Different MPRs were tested in which only a portion of the vehicles were equipped with the Eco-CACC-MS-Q system and the rest of the vehicles were modeled using standard car-following models.

Figure 4-4 illustrates the overall network-wide fuel savings of the Eco-CACC-Q and Eco-CACC-MS-Q systems with different MPRs for a single-lane network. As the MPR increases, the savings increase for both algorithms. Eco-CACC-MS-Q provides better savings than Eco-CACC-Q in all MPRs for both one- and two-lane networks. For a one-lane network, Eco-CACC-MS-Q had fuel savings of 12.8% compared to 5.5 % in Eco-CACC-Q. In the simulations, the movements of the equipped vehicles are smoothed by the proposed algorithm and due to car-following behavior. The trajectories of the non-equipped vehicles are also smoothed by following the equipped ones. This led to improved network-wide fuel consumption.

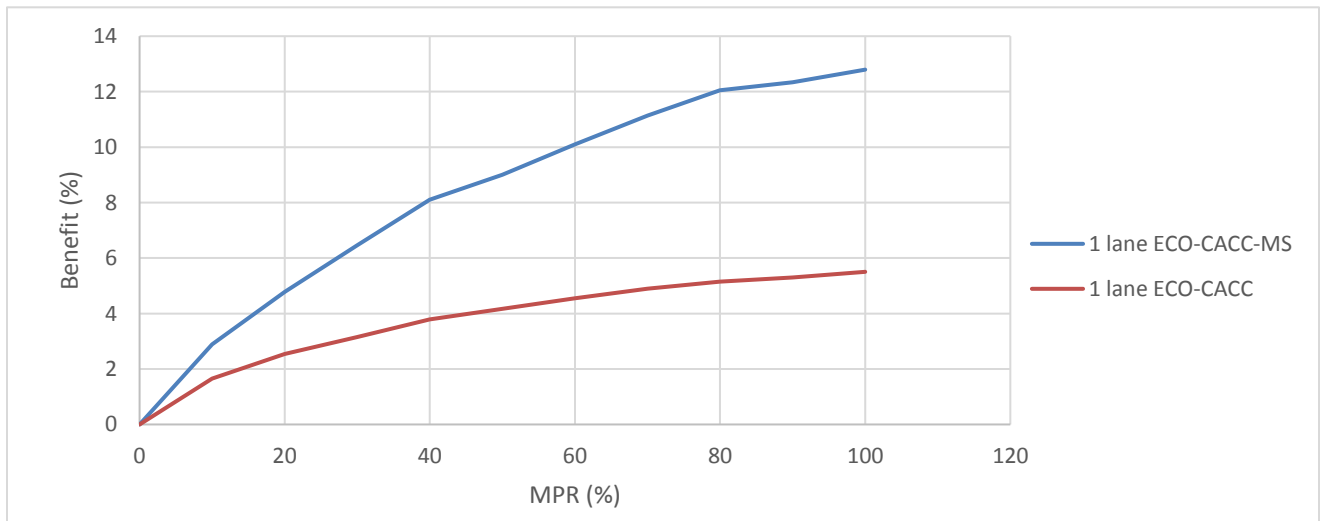


Figure 4-4 Savings in fuel consumption under different MPRs for single-lane network.

The single-lane network configuration prevents lane changing or overtaking behaviors, but in reality more than one lane may exist. To test the effects of lane changing, a two-lane network was set up. The same settings were used. Figure 4-5 demonstrates the overall network-wide fuel savings of the Eco-CACC-Q and Eco-CACC-MS-Q systems. For a two-lane network, Eco-CACC-

MS-Q yielded 13% fuel savings compared to 5.6% in Eco-CACC-Q. The negative impact for the lower MPRs is due to lane-changing movements by non-equipped vehicles in some scenarios. The negative impact or low savings is due to the speed of the equipped vehicles. Since the algorithm-controlled vehicles travel at lower speeds than the non-equipped vehicles, larger gaps form ahead of them. The non-equipped vehicles may use this space to cut into the gap, which causes the increase in the fuel consumption rate for the network. As the MPR increases, it is possible that equipped vehicles may travel side-by-side and block the whole link, which prevents lane changing or overtaking movements.

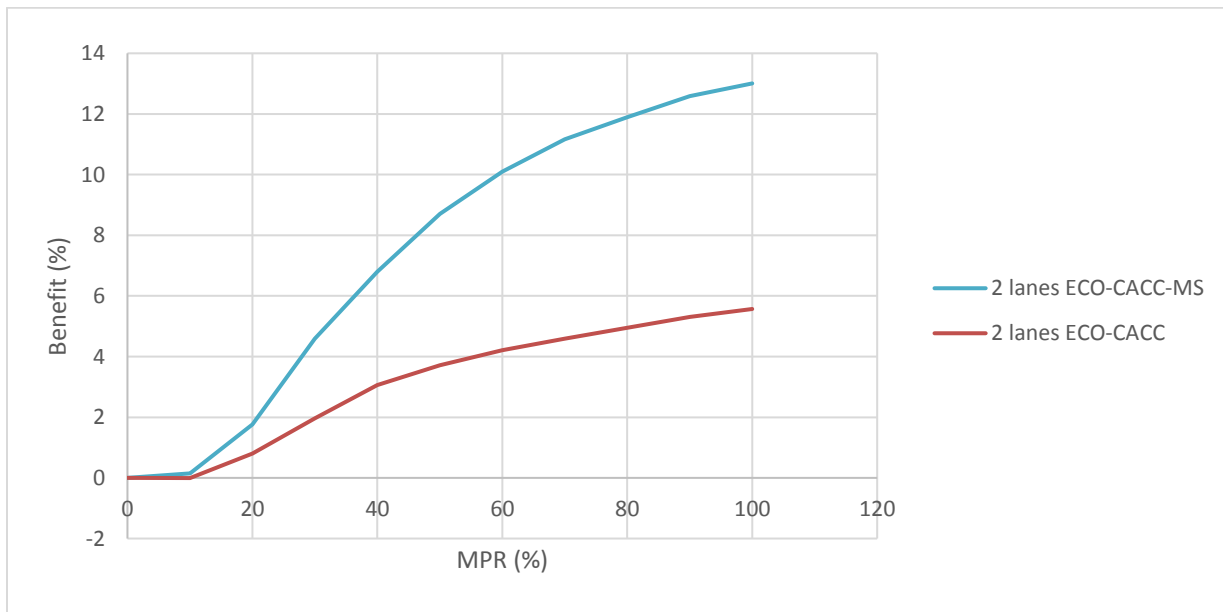


Figure 4-5 Savings in fuel consumption under different MPRs for two-lane network.

The overall saving of the network increases with increasing the MPR. To look at the algorithm effect in more detail, the average fuel consumption of the equipped vehicle need to be studied. The average fuel consumed by the equipped and the non-equipped vehicles is demonstrated in Figure 4-6 for a single lane network and Figure 4-7 for a two-lane network for at flow of 300 veh/h/lane. Both figures show that the Eco-CACC-MS equipped vehicles save fuel consumption for all MPRs and consume less fuel compared to non-equipped vehicles. For single lane approaches, the non-equipped vehicles always consume less fuel as the MPR increases because they are forced to follow the equipped vehicles and cannot pass them. For the two-lane network, the non-equipped vehicles consume more fuel at low MPRs because of lane-changing and over-passing. This increase is very small and the overall saving for the network is close to zero. As the MPR increases the non-equipped vehicles consume less fuel since the number of the

equipped vehicles in the network increases and they are forced to follow the trajectories of the equipped vehicles.

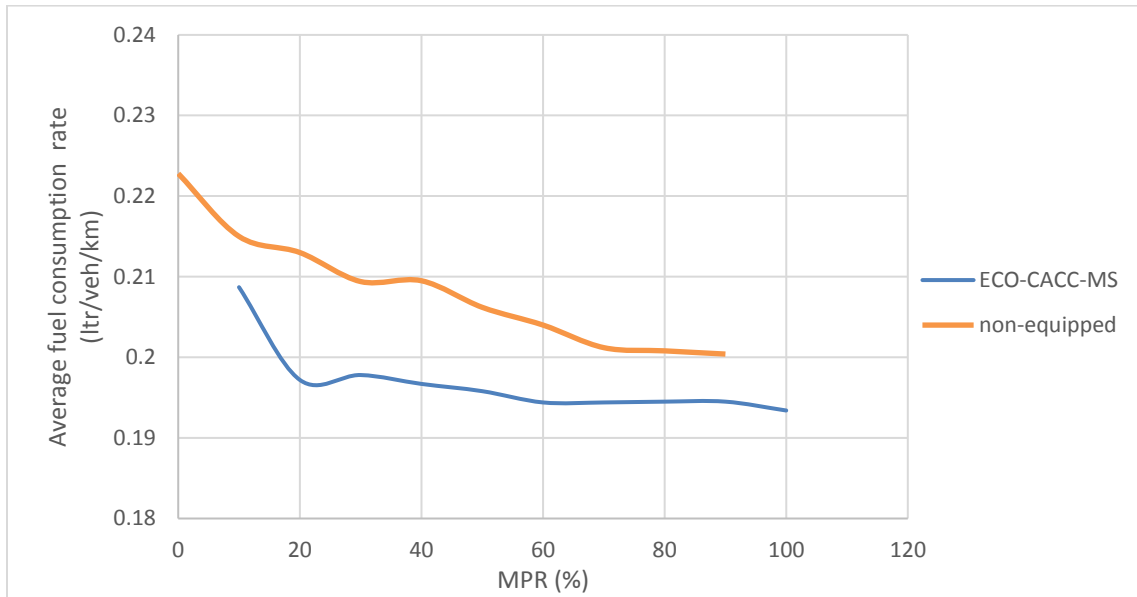


Figure 4-6 Equipped vehicles average fuel consumption for single-lane network at 300 veh/h/lane.

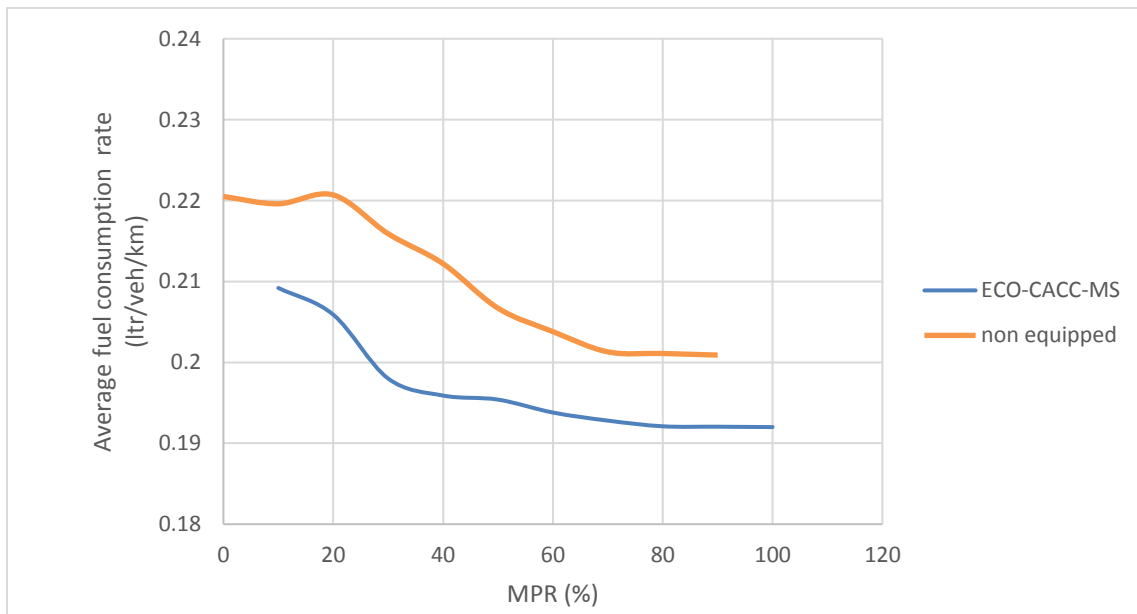


Figure 4-7 Equipped vehicles average fuel consumption for two-lane network at 300 veh/h/lane.

The average fuel consumed by the equipped and non-equipped vehicles is demonstrated in Figure 4-8 for a single lane approach and Figure 4-9 for a two-lane approach for an arrival rate of 700 veh/h/lane. As was the case with the 300 veh/h/lane arrival rate, the Eco-CACC-MS equipped

vehicles save fuel for all MPRs and consume less fuel compared to non-equipped vehicles. The savings, however, are less than the savings for the arrival rate of 300 veh/h/lane. As was the case with the 300 veh/h/lane arrival rate, for the single lane approach, non-equipped vehicles consume less fuel as the MPR increases because they are forced to follow the equipped vehicles. For the two-lane approach, the non-equipped vehicles consume slightly more fuel at low MPRs because of lane changing and over-passing. This slight increase in the average fuel consumption for the non-equipped vehicles did not affect the overall savings for the network. As the MPR increases the non-equipped vehicles consume less fuel since the number of the equipped vehicles in the network increases. This confirms that equipped vehicles save fuel and as the MPR increases the vehicle average fuel consumption is reduced.

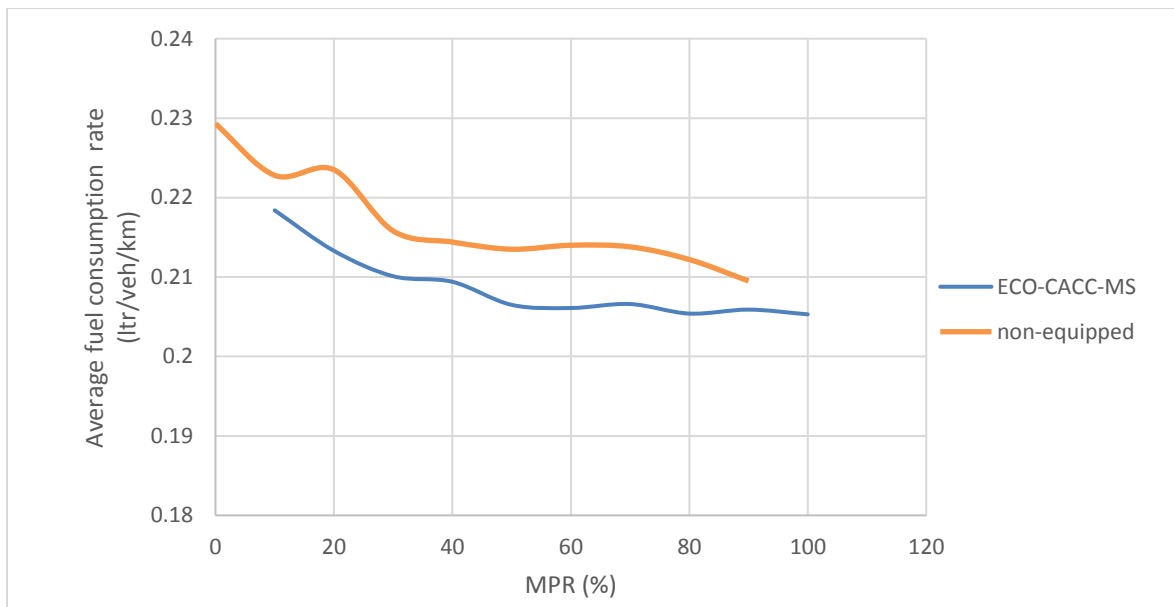


Figure 4-8 Equipped vehicles average fuel consumption for single-lane network at 700 veh/h/lane.

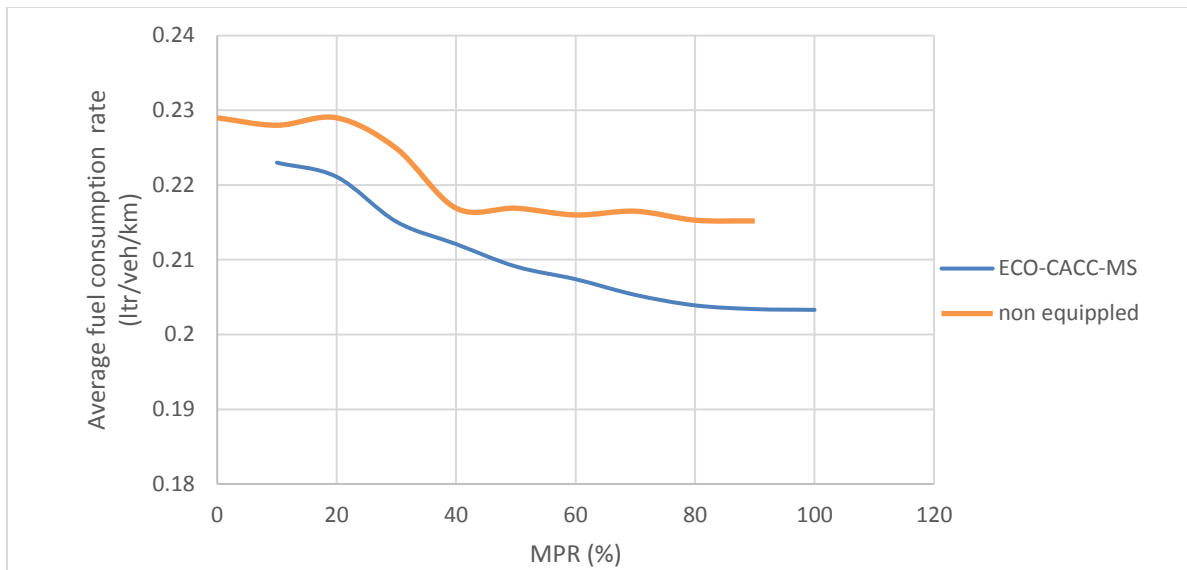


Figure 4-9 Equipped vehicles average fuel consumption for two-lane network at 700 veh/h/lane.

4.3.2 Impact of Traffic Demand Level

As a part of evaluating the Eco-CACC-Q and Eco-CACC-MS-Q algorithms, the traffic demand level should be considered. The demand level has a direct relation to the number of equipped vehicles in the network, which will affect the efficiency of the algorithm.

The first test of the impact of demand level used the same setting as in section 4.3.1 a single-lane scenario with a 45-s offset for the second signal with respect to the first signal, a fixed time plane, and different MPRs at traffic flow demands from 300 to 700 vphpln. Figure 4-10 illustrates the reduction in fuel consumption for Eco-CACC-MS-Q compared to Eco-CACC-Q as a function of the demand level. The results show some savings for all demand levels, but the overall demand of 300 vph has the best savings across the network by 7.7%. These trends are the result of the increase in the number of the probe vehicles in the network. As the network gets close to the oversaturation level, lower-than-optimal results are seen and the network-wide savings decrease.

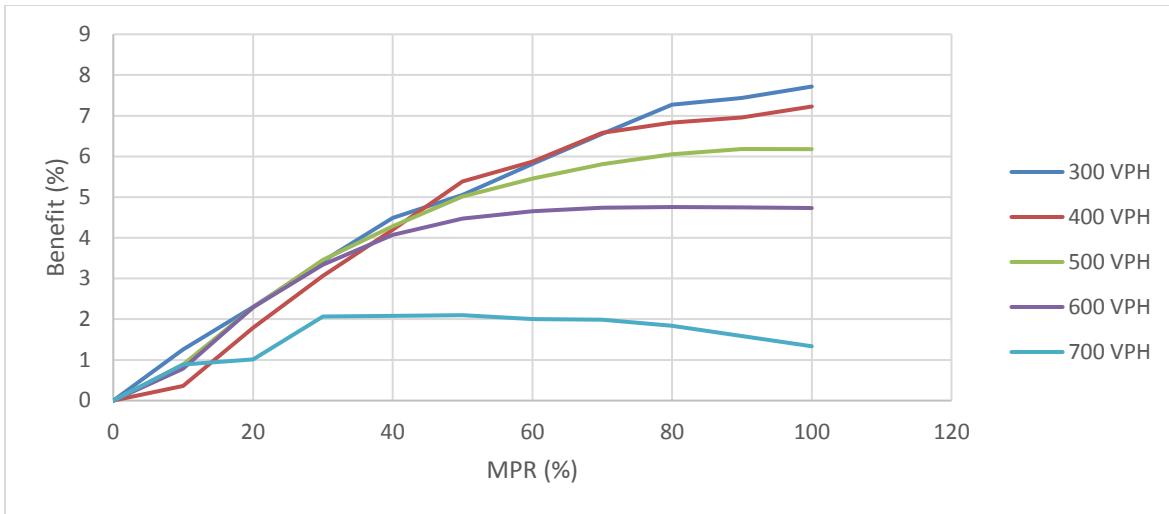


Figure 4-10 Eco-CACC-MS-Q reduction in fuel consumption considering traffic demand level for single-lane network from Eco-CACC-Q.

The setting for the second test was the same as first but with a two-lane network. Different traffic flow demands from 300 to 700 vphpln were tested. Savings for the two-lane network are similar to the single-lane result, as shown in Figure 4-11. Eco-CACC-MS-Q for a demand of 300 vphpln saved 7.9% more fuel than Eco-CACC-Q. Similar to the single-lane network, the network-wide savings in fuel consumption decreased as the demand neared the oversaturation point.

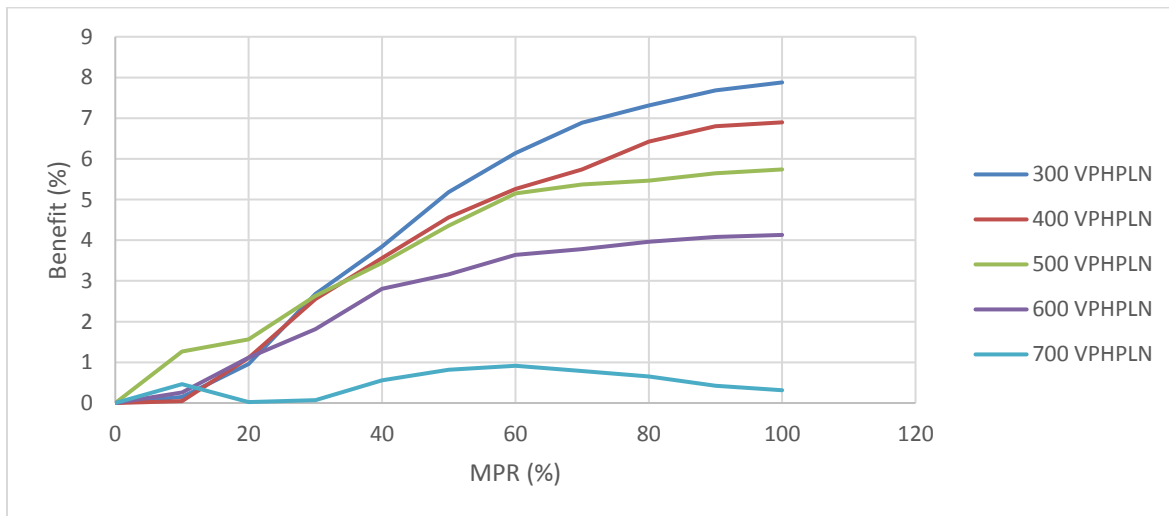


Figure 4-11 Eco-CACC-MS-Q reduction in fuel consumption considering traffic demand level for two-lane network from Eco-CACC-Q.

4.3.3 Impact of Distance between Intersections

Distance between intersections is an important variable that impacts fuel consumption savings. To test the effect of the distance between intersections, the same setting and link characteristics as

section 4.3.1 were used, but the distance between intersections was varied from 400 to 800 m for single-lane networks with 0- and 45-s offsets.

Figure 4-12 illustrates the fuel savings for Eco-CACC-MS-Q compared with Eco-CACC-Q as a function of the distance between intersections for a 45-s offset. The results show that the shorter the distance between the intersections, more savings are achieved by the algorithm, which is 9.9% for 400 m between intersections. The range between the intersections cannot be very small based on the effective distance of the Dedicated Short-Range Communications (DSRC) technology that is implemented in the V2I communications between probe vehicles and signals [29].

Figure 4-13 shows that the fuel savings for Eco-CACC-MS-Q were 0.5% more than Eco-CACC-Q. The offset plays a very important role, and by using a 0-s offset the best savings were captured at a 600-m distance between intersections. Distance between intersections is a variable that plays in the overall savings, but the offset timing also contributes to that effect, as will be discussed in next section.

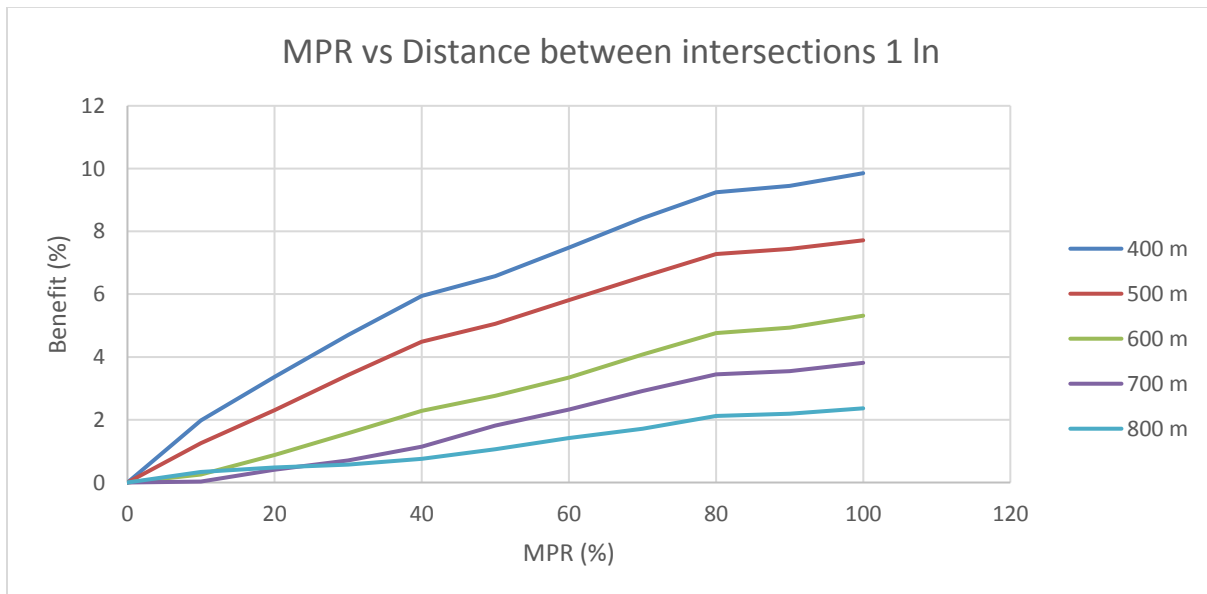


Figure 4-12 Eco-CACC-MS-Q reduction in fuel consumption considering distance between intersections for single-lane network from Eco-CACC-Q for 45-s offset.

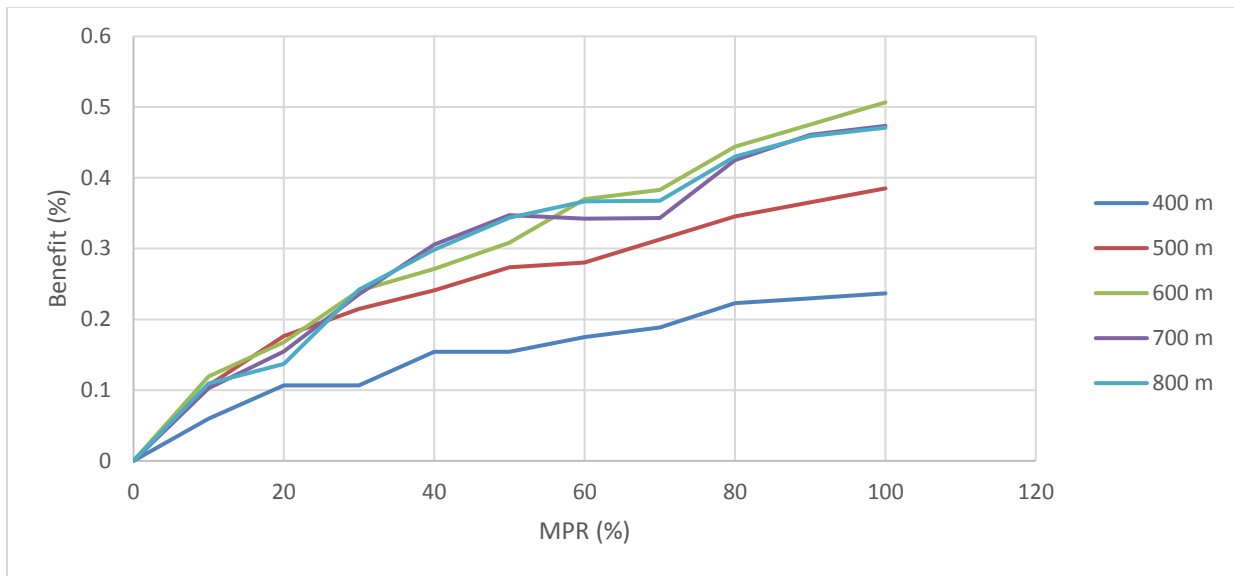


Figure 4-13 Eco-CACC-MS-Q reduction in fuel consumption considering distance between intersections for single-lane network from Eco-CACC-Q for 0-s offset.

4.3.4 Evaluation of Eco-CACC-MS-Q

An overall evaluation of Eco-CACC-MS-Q was conducted by running many scenarios. These scenarios included many of the demand levels, distances between intersections, offsets, and number of lanes. Savings in fuel consumption were observed at all high MPRs for all of the scenarios. Many scenarios were simulated using the same setting as section 4.3.1 but varying the demand and distance between intersections to test the effect on savings. Figure 4-14 demonstrates the savings achieved by Eco-CACC-MS-Q, which were 9.9% more than Eco-CACC-Q at 100% MPR. The result shows that a low-demand level with a small distance between intersections will result in the best savings for the algorithm since the interaction between the intersections is very high for this offset. But, as Figure 4-13 shows, if a different offset is used the result will be different.

The offset between the signals is a major variable in terms of the effectiveness of the algorithm. If the offset is near optimal, the savings will be the least since many cars will pass the intersections without stopping. The most savings for the algorithm will be captured if the offset is not coordinated because vehicles will have a higher chance of having to stop at the intersections. The Eco-CACC-MS-Q algorithm plays a major role in fuel consumption savings in this case. The sensitivity analysis shows that the Eco-CACC-MS-Q algorithm saves fuel consumption by up to 13% with a 100% MPR from the savings observed for Eco-CACC-Q.

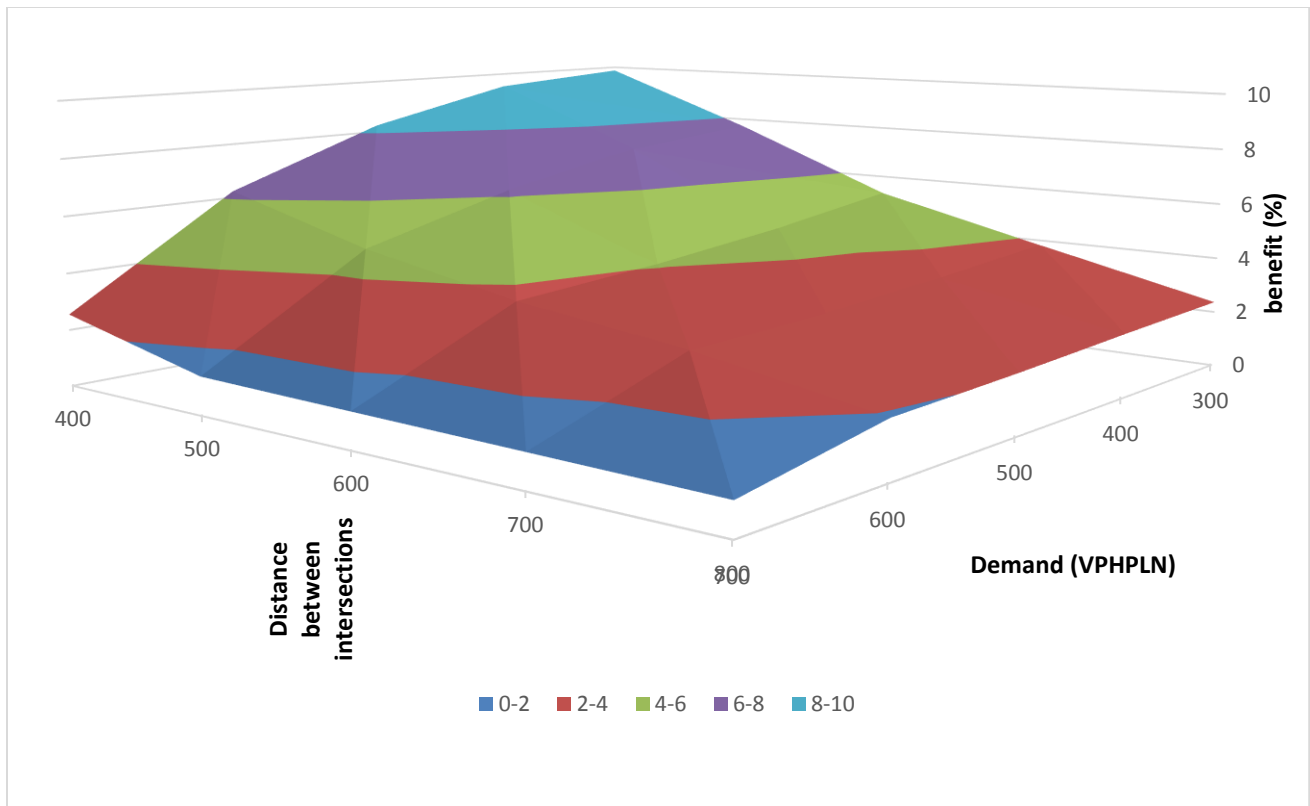


Figure 4-14 ECO-CACC-MS-Q reduction in fuel consumption vs. ECO-CACC-Q considering distance between intersections and demand levels for single-lane network.

4.4 Algorithm Shortcomings

The Eco-CACC-MS algorithm was developed based on the assumption that the network is under the saturation level and that the vehicle queue can be released within one cycle. Once the network is oversaturated, the queues will roll over from previous cycles and a long queue upstream of the intersections will be generated. This will affect the queue estimation method and the accurate determination of queue length and dispersion time [26]. As a result, the advisory speed limit will not let the equipped vehicles pass the intersections. The Eco-CACC-Q algorithm showed that no positive savings were obtained under oversaturated demands; Eco-CACC-MS-Q, however, was able to capture very low savings because the inflow to the second intersection is gated by the first one, and fuel savings can be obtained at the second intersection using the proposed algorithm.

4.5 Significance Analysis

To test the significance of the model all the scenarios were run 20 times with different random seeds. To find out the significant factors, multiple linear regression (MLR) model is used to explain the variability in the fuel saving (response) in terms of the algorithm used, the number of lanes,

demand, offset, the distance between intersection and MPR. All the predictors are continues except the algorithm which is indicator variable. The values of this indicator 1 if the algorithm is Eco-CACC-MS and zero if the algorithm is Eco-CACC. The model has $R_{adj}^2=0.69$.The results are presented in Table 4-1 the p-value of the model is less than 0.0001 which is less than the significance level 0.05. Thus, the relationship between the response and predictors can be described by the MLR model. Table 4-2 show the parameter estimates and the corresponding p-values. As shown in the table all p-values are less than 0.05 and we conclude that:

- 1- All predictors have a significant impact on the fuel saving.
- 2- Switching from Eco-CACC to Eco-CACC-MS while keeping the all predicted unchanged increase the saving by 0.587

Table 4-1 Analysis of variance

Source	Degree of Freedom	Sum of Squares	Mean Square	F Ratio
Model	6	14355.617	2392.60	782.6229
Error	2193	6704.350	3.06	Prob > F
C. Total	2199	21059.967		<.0001*

Table 4-2 Parameter estimates

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	0.1340047	0.223665	0.60	0.5491
algorithm	0.5873201	0.037278	15.76	<.0001*
lane	-1.102335	0.074555	-14.79	<.0001*
flow	0.9948354	0.184515	5.39	<.0001*
offset	2.8228208	0.074555	37.86	<.0001*
dis	-1.479726	0.210874	-7.02	<.0001*
MPR	6.1446317	0.117882	52.13	<.0001*

In addition, each algorithm is compared to the based case (no control) and the fuel saving is compared at different levels of demand and distance between intersection. Then pooled t-test is used to test the significance different in caving between the Eco-CACC and Eco-CACC-MS. Table 4-3 shows the resultant p-value of the pooled t-test and the saving difference between Eco-CACC-MS and Eco-CACC. The hypothesis test that is used in the pooled t-test is:

$$H_0: \text{saving of Eco} - \text{CACC} \geq \text{saving of Eco} - \text{CACC} - \text{MS}$$

$$H_a: \text{saving of Eco} - \text{CACC} < \text{saving of Eco} - \text{CACC} - \text{MS}$$

If p-value is less than 0.05 we reject the H_0 and that mean there is sufficient evidence to conclude that the saving of Eco-CACC-MS is significantly higher than Eco-CACC. Based on the result there was significant larger saving in Eco-CACC-MS from Eco-CACC (in black) in most of the cases.

Except some of the cases where the MPR is less than 30%, there was insufficient evidence to conclude that saving in Eco-CACC-MS is larger from Eco-CACC (in red). This is because the effectiveness of the algorithm saving is higher with higher MPR where the number of the equipped vehicle in the system is higher.

Table 4-3 Pooled t-test between Eco-CACC-MS and Eco-CACC

Demand (vphpln)	MPR		distance between intersection (m)				
			400	500	600	700	800
300	10	saving (%)	1.980	1.254	0.258	0.028	0.332
		p-value	0.0001	0.0039	0.2517	0.466	0.0712
	20	saving (%)	3.369	2.300	0.874	0.409	0.484
		p-value	0.0002	0.0043	0.1184	0.2505	0.3045
	30	saving (%)	4.700	3.426	1.567	0.701	0.570
		p-value	0.0001	0.0001	0.0011	0.0485	0.0085
	40	saving (%)	5.947	4.485	2.283	1.145	0.758
		p-value	0.0001	0.0001	0.0001	0.0005	0.0001
	50	saving (%)	6.579	5.053	2.763	1.813	1.059
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001
	60	saving (%)	7.478	5.813	3.341	2.327	1.419
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001
	70	saving (%)	8.422	6.559	4.080	2.920	1.713
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001
	80	saving (%)	9.241	7.274	4.757	3.443	2.125
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001
	90	saving (%)	9.449	7.439	4.934	3.553	2.191
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001
	100	saving (%)	9.854	7.716	5.315	3.813	2.364
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001
400	10	saving (%)	1.522	0.356	-0.491	-0.277	0.004
		p-value	0.0167	0.3051	0.6624	0.6926	0.4944
	20	saving (%)	3.465	1.789	0.008	-0.244	0.165
		p-value	0.0001	0.0038	0.488	0.7024	0.2902
	30	saving (%)	5.044	3.067	0.846	0.054	0.459
		p-value	0.0001	0.0001	0.045	0.4408	0.0632
	40	saving (%)	6.280	4.199	1.590	0.706	0.611
		p-value	0.0001	0.0001	0.0044	0.0654	0.0531
	50	saving (%)	7.348	5.380	2.627	1.604	1.095
		p-value	0.0001	0.0001	0.0001	0.0006	0.001
	60	saving (%)	7.989	5.872	3.125	2.151	1.379
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001
	70	saving (%)	8.773	6.583	3.757	2.780	1.878
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001
	80	saving (%)	9.024	6.833	4.001	3.047	2.004

		p-value	0.0001	0.0001	0.0001	0.0001	0.0001	
	90	saving (%)	9.247	6.960	4.309	3.267	2.065	
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001	
	100	saving (%)	9.473	7.226	4.600	3.421	2.231	
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001	
500	10	saving (%)	2.198	0.889	-0.469	-0.539	0.201	
		p-value	0.0003	0.0668	0.8076	0.9024	0.2362	
	20	saving (%)	3.907	2.284	0.252	0.020	0.365	
		p-value	0.0001	0.0003	0.3127	0.481	0.1108	
	30	saving (%)	5.002	3.460	1.182	0.679	0.554	
		p-value	0.0001	0.0001	0.0193	0.057	0.0534	
	40	saving (%)	6.091	4.285	1.718	1.261	0.832	
		p-value	0.0001	0.0001	0.003	0.0051	0.0075	
	50	saving (%)	6.694	5.013	2.456	1.797	1.121	
		p-value	0.0001	0.0001	0.0001	0.0001	0.0002	
	60	saving (%)	7.240	5.451	3.010	2.236	1.399	
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001	
	70	saving (%)	7.633	5.806	3.403	2.641	1.665	
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001	
	80	saving (%)	7.972	6.056	3.802	2.930	1.921	
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001	
	90	saving (%)	8.162	6.181	3.948	3.055	2.063	
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001	
	100	saving (%)	8.251	6.178	4.059	3.109	2.061	
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001	
	600	10	saving (%)	1.707	0.788	-0.154	-0.117	-0.014
			p-value	0.0005	0.0612	0.6258	0.6118	0.5255
		20	saving (%)	3.421	2.294	0.740	0.134	0.249
			p-value	0.0001	0.0005	0.1349	0.3983	0.2166
30		saving (%)	4.425	3.339	1.640	0.619	0.491	
		p-value	0.0001	0.0001	0.0045	0.0901	0.0739	
40		saving (%)	5.038	4.069	2.264	1.461	0.762	
		p-value	0.0001	0.0001	0.0001	0.0047	0.0134	
50		saving (%)	5.640	4.469	2.720	1.935	1.023	
		p-value	0.0001	0.0001	0.0001	0.0001	0.001	
60		saving (%)	5.739	4.654	3.060	2.373	1.362	
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001	
70		saving (%)	5.980	4.739	3.256	2.553	1.620	
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001	
80		saving (%)	6.099	4.757	3.547	2.786	1.844	
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001	
90		saving (%)	6.151	4.744	3.587	2.869	1.879	
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001	

	100	saving (%)	6.236	4.731	3.671	2.959	1.937
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001
700	10	saving (%)	0.748	0.885	0.020	0.086	0.204
		p-value	0.0271	0.0842	0.7801	0.436	0.2616
	20	saving (%)	1.338	1.013	0.235	0.570	0.407
		p-value	0.0135	0.0545	0.3569	0.1627	0.0843
	30	saving (%)	1.933	2.062	1.112	1.158	0.787
		p-value	0.0048	0.005	0.0194	0.003	0.0028
	40	saving (%)	1.729	2.081	1.095	1.441	0.949
		p-value	0.0218	0.0022	0.0215	0.0017	0.0005
	50	saving (%)	1.683	2.099	1.426	1.845	1.245
		p-value	0.023	0.0039	0.0103	0.0001	0.0001
	60	saving (%)	1.592	2.001	1.525	1.967	1.342
		p-value	0.029	0.0062	0.0079	0.0001	0.0001
	70	saving (%)	1.523	1.990	1.768	2.223	1.423
		p-value	0.033	0.0039	0.0013	0.0001	0.0001
	80	saving (%)	1.497	1.841	1.652	2.424	1.662
		p-value	0.037	0.0107	0.0041	0.0001	0.0001
	90	saving (%)	1.476	1.587	1.515	2.509	1.766
		p-value	0.04	0.022	0.0059	0.0001	0.0001
	100	saving (%)	1.329	1.331	1.442	2.552	1.862
		p-value	0.047	0.0382	0.0064	0.0001	0.0001

4.6 CONCLUSION

This paper presents the results of an evaluation of the Eco-CACC-MS-Q algorithm using the INTEGRATION microscopic traffic assignment and simulation software. The algorithm uses SPaT data received from each signal controller via V2I communication, to predict the queue and compute the fuel-optimum vehicle trajectory for a controlled vehicle. The algorithm provides an advisory speed that allows the vehicle to pass multiple consecutive intersections without stopping. The objective of this algorithm is to reduce vehicle fuel/energy consumption.

The algorithm was evaluated using the INTEGRATION microscopic simulator. The simulation of the single-lane network concluded that fuel savings are greater at higher MPRs, and that as the MPR increases the savings increase. Reductions in fuel consumption are 7.3% higher for Eco-CACC-MS-Q compared to the Eco-CACC-Q when controlling all vehicles. In the multi-lane network, because of lane-changing behavior, there were small savings in fuel consumption for MPRs lower than 20%. For the two-lane network, reductions in fuel consumption are 7.4%

higher for the Eco-CACC-MS-Q compared to the Eco-CACC-Q system when controlling all vehicles. The results show that considering the queue enhances the algorithm performance.

The study also demonstrated that for different traffic demand levels savings in fuel consumption can be up to 7.7% better for the Eco-CACC-MS-Q compared to the Eco-CACC-Q algorithm for a single-lane network and 7.8% for a two-lane network. Varying the distance between the intersections also affects the savings. By varying the distance, the Eco-CACC-MS-Q algorithm was able to achieve a 10% improvement in fuel savings over Eco-CACC-Q for both single-lane and two-lane networks. The distance of 400 m between intersections produced the highest saving for the specific example used in the sensitivity analysis section, however these findings are not general and need further investigation for different demand levels, signal offsets, and phase splits.

The current algorithms are not applicable for oversaturated conditions due to rolling queues. Possible solutions include using vehicle-to-vehicle (V2V) communication to estimate the queue or to introduce speed harmonization [30] to restrict the traffic entering the intersection to maintain an under-saturated condition at all the times. Future enhancements would extend the logic to reduce the fuel consumption and delay for the overall network and consider the effect of other factors such as speed limit, number of lanes, and road grade.

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5 CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

5.1 Conclusions

In this thesis, an eco-cooperative adaptive cruise control at multiple signalized intersections (Eco-CACC-MS) algorithm was developed to minimize vehicle fuel consumption levels along signalized roadways. The algorithm utilizes SPaT and vehicle queue length information received through V2I communication to compute the fuel-optimum instantaneous advisory speeds for equipped vehicles while traversing signalized intersections. The algorithm predicts the queue length ahead of the Eco-CACC-MS equipped vehicles from the V2I communication to estimate the queue release time. The algorithm computes the optimum vehicle trajectory for equipped vehicles by providing a second-by-second advisory speed limit to reduce the number of vehicle stops and minimize the vehicle fuel/energy consumption level upstream and downstream of each intersection. Analysis of the Eco-CACC-MS indicates that, with longer vehicle queues, the vehicle fuel/energy consumption level increases, but the Eco-CACC-MS algorithm is able to reduce the vehicle fuel/energy consumption level. Eco-CACC-MS was evaluated with and without consideration of the queue; thus, considering queues in the algorithm provides greater reductions in vehicle fuel/energy consumption and emission levels.

In addition, the Eco-CACC-MS algorithm was evaluated using the INTEGRATION microscopic simulator considering through movements in one direction. In the simulation of single-lane intersections at higher MPRs, the vehicle fuel/energy consumption levels consistently decreased. In two two-lane intersections, however, lane-changing maneuvers and passing behavior of non-equipped vehicles passing the equipped vehicles led to a minor increase in the vehicle fuel/energy consumption at low MPRs, but with higher MPRs, similar savings could be observed. Savings in vehicle fuel/energy consumption and emissions when considering the vehicle queue Eco-CACC-MS-Q algorithm was always more successful compared to not considering the vehicle queue, namely Eco-CACC-O. The Eco-CACC-MS algorithm was implemented in a network with four consecutive intersections, and the vehicle fuel/energy consumption savings were also observed to be as high as 7.7% for single-lane roads and 4.8% for two-lane roads relative to no control at the network.

Evaluation of the factors that affect the performance of the algorithm was conducted by considering different traffic demands, phase splits, offsets, and the distances between intersections

for a comprehensive sensitivity analysis. When all the vehicles are equipped with the Eco-CACC-MS-Q algorithm, the overall vehicle fuel/energy consumption is reduced by 13.8% relative to no control at the network. With a larger percentage of the phase split, the savings from the proposed algorithm were smaller given the offset, the demand, and the distance between intersections, but the phase split rarely affects the benefit of the algorithm. For an offset close to the optimal offset, the vehicle fuel/energy consumption savings were smaller given that there were minimal opportunities to improve the vehicle trajectories. In addition, the optimal distance between intersections exists to maximize the savings in vehicle fuel/energy consumption. The proposed algorithm was tested for over-saturation conditions, and the algorithm failed to effectively reduce the vehicle fuel/energy consumption level. The algorithm only utilized loop detector information to estimate the queue length and discharge time ahead of the intersection. If the demand is high producing over-saturated conditions, the queue does not dissipate in a single cycle resulting in rolling queues upstream of the intersections. This will result in an incorrect queue estimation and will cause the Eco-CACC-MS advisory speed to be incorrect as well. Further research is needed to enhance the algorithm for over-saturated conditions.

5.2 Recommendations for Future Work

The algorithm developed in this thesis uses V2I communication and SPaT information to predict the queue upstream of a signalized intersection. However, applying V2V communication to collect information from individual vehicles can be used to develop a more accurate model of vehicle queues at intersections. For over-saturated conditions, we can introduce a speed harmonization algorithm [1] to control the flow of traffic entering the intersections to maintain under-saturated traffic conditions at all times, or a green driving algorithm [2] to reduce the impact of stop-and-go waves when conditions are oversaturated.

To enhance the reduction in the vehicle fuel/energy consumption and reduce the delay for large networks, the logic can be extended to investigate the impact of additional variables such as speed limits, number of lanes, road grade, different weather conditions, and different traffic movements. Lane changing behavior for the non-equipped vehicles should be more thoroughly investigated because it does play a major role in queue production. Furthermore, introducing CV to share individual vehicle information, including location and speed, can help improve the queue prediction algorithm and increase the efficiency of the algorithm. It would also be beneficial to investigate the effect of the algorithm on a large network, such as the downtown area in Blacksburg, Virginia, where there are multiple consecutive signalized intersections with different

traffic movements and some of them are less than 100 meter apart. This will allow for an evaluation of the algorithm if the distance between the intersections is small and considering different traffic movements.

5.3 References

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