Eco-friendly Cooperative Traffic Optimization at Signalized Intersections

February 2023

A Research Report from the National Center for Sustainable Transportation

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16. Abstract
Surface transportation systems (e.g., arterial roadways with signalized intersections) are inherently inefficient, particularly at higher traffic volumes. In general, both the infrastructure (e.g., traffic signals) and the vehicles operate independently, with little coordination between them. Previous research has shown that implementing strategies that take advantage of infrastructure-to-vehicle communication can improve overall mobility and reduce environmental impacts, e.g., the Eco-Approach and Departure (EAD) application that takes advantage of communicating signal phase and timing information to the vehicles. In this paper, the authors build upon this past research to develop a new cooperative traffic operation approach that takes advantage of not only infrastructure-to-vehicle communications, but also vehicle-to-infrastructure communications. This effort integrates a dynamic traffic signalization algorithm together with EAD algorithm to achieve even greater traffic efficiency. The research was carried out in a high-fidelity simulation environment and shows upwards of 15% fuel savings and 85% reductions in waiting time.

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EXECUTIVE SUMMARY

Surface transportation systems, such as arterial roadways with signalized intersections, suffer from efficiency degradations due to high levels of traffic demand and the lack of coordination in overall system operation. Previous research has shown that implementing strategies that take advantage of infrastructure-to-vehicle communication can improve overall efficiency and reduce environmental impacts, e.g., an Eco-Approach and Departure (EAD) application that takes advantage of communicating signal phase and timing information to the vehicles. In this research, the researchers developed an Eco-friendly Cooperative Traffic Operation (ECoTOp) system for signalized intersections where equipped Connected and Automated Vehicles (CAVs) are proactively managed and traverse the intersection in coordination with traffic signal optimization to minimize energy consumption. The proposed system integrates the dynamic traffic signal optimization module and the multi-vehicle multi-lane connected eco-driving system to achieve the optimal overall performance in a mixed connected traffic environment. As vehicles approach the intersection, they can send messages to the downstream traffic signal controller, with information on arrival time and intended turning movement. Considering surrounding traffic conditions, the traffic controller will calculate the optimal signal phase and timing (SPaT), and communicate them with the vehicles. Based on the confirmed SPaT information, vehicle will perform cooperative eco-driving operation where the selection of target arrival time depends on the downstream lane-specific traffic states and vehicle energy consumption for the passage.

The co-optimization of traffic signal and vehicle dynamics is conducted in a bi-level way. At signal level, we formulate the optimization problem which aims to maximize the throughput from all phases in the cycle, while minimizing the variance of oversaturated vehicle number from all phases to ensure fairness. At the vehicle level, we minimize the total energy consumption of each CAV in all the time steps, considering constraints from the signal, roadway and traffic. The research was carried out in a high-fidelity simulation environment in SUMO platform and shows upwards of 15.4% fuel savings and 85.7% reductions in waiting time. Under lower penetration rate, the fuel saving benefit is degraded, e.g., 11.8% reduction under 80% penetration, 8.4% under 60% penetration and 4.6% under 40% penetration. The simulation results also show that the ECoTOp outperforms the other scenarios including signal optimization only and EAD only cases.

1. Introduction

It is well known that contemporary surface transportation systems suffer from efficiency degradations due to high levels of traffic demand and the lack of coordination in overall system operation. According to 2019 Urban Mobility Report (Schrank et al., 2019), by 2025 the average commuter will waste 62 hours and 23 gallons of fuel because of delay in traffic congestion. Traffic congestion is not only a problem for commuters, but can become a drain on economic growth, as it is predicted that by 2025 the national congestion cost will be $237 billion. Transportation also accounts for a large percentage of greenhouse gas (GHG) and air pollutant emissions in the United States. According to the United States Environmental Protection Agency (EPA), mobile sources, such as cars, buses, planes, trucks, and trains, account for 29% of greenhouse gases and over half of all air pollution in the country (US Environmental Protection Agency, 2022; National Park Service, 2018). Advanced approaches have to be developed to improve the overall efficiency of transportation systems and encourage eco-friendly driving styles that can lower fuel consumptions and emissions (Boriboonsomsin at al., 2010).

Driven by emerging technologies (e.g., wireless communications, advanced control, and data analytics), Connected and Automated Vehicles (CAVs) can help enable cooperative traffic operations, particularly for urban signalized arterial roadways, to achieve improvements in safety, mobility, and the environment. As a popular CAV application that can improve overall efficiency, the Eco-Approach and Departure (EAD) application takes advantage of receiving Signal Phase and Timing (SPaT) information along the arterial corridor, along with traffic and roadway conditions, and calculates the most energy-efficient velocity profile when traveling on the corridor (U.S. Department of Transportation, 2014). Because of its potential to improve throughput and significantly reduce energy consumption and tailpipe emissions, numerous studies have been conducted on the development and modeling of this connected vehicle application. Real-world test was also conducted in prototyping and demonstrating this type of system (Xia et al., 2012; Altan et al., 2017; Hao et al., 2019). Li et al. (2009) proposed an advanced driving alert system that provides traffic signal status information to help drivers avoid hard braking at intersections. Asadi and Vahidi (2011) developed an algorithm that uses Signal Phase and Timing (SPaT) information and short-range radar to reduce idling times at signalized intersections and fuel consumption. He et al. (2015) proposed an optimization for speed trajectory on signalized arterials that considers the impacts of surrounding traffic. Altan et al. (2017) ran field experiments testing the benefits of Eco-Approach and Departure (EAD) using a partially automated vehicle as part of the Glidepath project. Thus far, the generic EAD application is somewhat limited, since it only relies on infrastructure-to-vehicle communications (I2V i.e., the connected vehicles receive traffic signal and roadway geometry information). There is much more that can be gained by also enabling vehicle-to-infrastructure communications (V2I), where traffic signal timing can be dynamically updated in harmony with the connected vehicles' longitudinal dynamics. This cooperative traffic operations approach can improve the system performance for all traffic, including vehicles without this communications technology (Yu et al., 2018).

The concept of optimizing traffic signal control from connected vehicles has been around for over 30 years in attempts to increase traffic flow and safety at intersections. An early attempt at improving signal control is the RHODES system in 1992, which was a real-time traffic-adaptive signal control system (Michandani and Head, 2001). RHODES was an early version of the Multi-Modal Intelligent Traffic Signal System (MMITSS) which seeks to provide a comprehensive traffic information framework to service all modes of transportation, including general vehicles, transit, emergency vehicles, freight fleets, and pedestrians and bicyclists in a connected vehicle environment. MMITSS was developed by the University of Arizona in collaboration with Econolite Group, Inc., Savari, Inc., and the University of California, Berkeley PATH program in 2014 (Duncan et al., 2014). Feng et al. (2015) developed a real-time adaptive signal phase allocation algorithm. The algorithm utilizes vehicle location and speed data to optimize phase sequence and duration. In order to estimate the vehicle states of non-connected vehicles, an algorithm that uses connected vehicle data was developed. A real-world intersection was modeled in VISSIM with CAV penetration rates of 100%, 75%, 50% and 25%. With 100% CAV penetration rate, total delay was decreased by up to 14.67% when minimizing total vehicle delay, and 16.33% when minimizing queue length. Sun et al. (2015) developed a quasi-optimal decentralized queue-based feedback control strategy for a system of oversaturated intersections. This strategy is applied cycle-by-cycle based on measurement of current queue sizes, but its overall result is able to approximate the optimal one derived from off-line studies.

A natural progression from optimizing signal control and optimizing vehicle trajectories at intersections is to combine the two and co-optimize signal control and vehicle trajectories at intersections. As V2X technology continues to advance, the possibility of vehicles receiving information from surrounding vehicles and from the signal infrastructure allows for more advanced algorithms for optimizing vehicles at intersections. In the past five years, more and more studies focused on the co-optimizing signal control and vehicle trajectories under CAV environment. Jiang et al. (2017) developed a platform to improve fuel efficiency for vehicles approaching an intersection while having no adverse effect on throughput. The platform puts vehicles into platoons, and is designed for mixed traffic conditions, meaning CAVs and non-CAVs. The platform requires an upstream loop detector. The authors used the traffic simulation software PTV-VISSIM for traffic simulations and MATLAB and Excel for data analysis. The platform showed fuel savings of up to 58% and improved throughput by 11%. Yu et al. (2018) presented a mixed integer linear program (MILP) model for optimizing traffic signals and vehicle trajectories at intersections in a unified framework. This model assumes all vehicles are controllable, and has an optimal control model to generate optimal trajectories for platoon leading vehicles. The authors performed numerical examples for a typical four-arm intersection with different traffic volumes. The model decreased vehicle delay by about 40% in low traffic demand and 80% under high demand. CO_2 emissions decreased by about 7.5% and about 50%. Guo et al. (2019) proposed a platform that integrates automated vehicle control with infrastructure-based control to improve overall system performance. The platform uses a dynamic programming with shooting heuristic as a subroutine algorithm. The authors set out to solve the joint optimal design of signal timing and vehicle trajectory planning in mixed traffic conditions. Numerical experiments were done with different traffic conditions and CAV market penetration rates for a four-phase signal timing intersection. The platform reduced average travel time by up to about 36% and had fuel savings up to 31.5%. The platform performance improved with increased CAV penetration rates. Niroumand et al. (2020) introduced a system to help prepare for transition from human-driven vehicles to self-driving vehicles. The system uses a mixed-integer non-linear program (MINLP) to determine the optimal signal indications and continuously optimizes vehicle trajectory. The system assumes that all vehicles are connected where some are human-driven and some are self-driving, and puts vehicles into platoons led by the self-driving vehicles. The system uses a white phase to enforce human-driven vehicles follow their immediate front vehicles. The authors performed numerical experiments as well as traffic simulations using PTV-VISSIM, and found the system reduced total delay by 20-96% compared to actuated signal control. Ma et al. (2020) developed a hierarchical multi-objective optimization framework to optimized fixed-time traffic signals based on sampled vehicle trajectories at signalized intersections. The objective is to minimized the number of over-saturated phases, and also to minimize the total vehicle delay. The authors used an MINLP model with a hierarchical multi-objective structure. Simulations were done with PTV-VISSIM and reduced delay by up to 19%. In general, many co-optimization studies used mixed integer linear programs (MILP) or mixed integer non-linear programs (MINLP) to determine the optimal signal designations and continuously optimize vehicle trajectory (Han et al., 2016; Ma et al., 2020; Niroumand et al., 2020). A common objective is to minimize traffic delay (Yu et al., 2018; Guo et al., 2019; Xu et al., 2019; Niroumand et al., 2020), or to maximize throughput (Han et al., 2016; Ma et al., 2020). Many often require all vehicles to be either connected or connected and automated (Zhao et al., 2016; Guo et al., 2019; Xu et al., 2019; Niroumand et al., 2020, Tajalli and Hajbabaie, 2021).

To date, very few studies have been conducted to develop a full-scale cooperative traffic operation system for signalized intersections, allowing for two-way communications between vehicles and the traffic signals. Even fewer studies have been focused on real-world deployment. Du et al. (2021) developed a coupled vehicle-signal control (CVSC) method to optimize traffic signal timing and vehicle trajectories of CAVs at the same time. The method uses a sequential least squares programming (SLSQP) and assumes the intelligent traffic signal controllers (I-TSC) can obtain the location information of all non-connected proximate vehicles through cameras. Simulations showed fuel savings of 14%, and up to 13% improved efficiency of the intersection. However, this paper used over-saturation delay as the measure to evaluate the performance of signal control, which may not achieve good results at under-saturated conditions. Another limitation of Du et al. (2021) is that the eco-driving algorithm adapt from the GlidePath algorithm (Altan et al., 2017) does not take energy or emission as the optimization goal directly, which may degrade the performance in trajectory planning.

To address these research gaps, we have developed an Eco-friendly Cooperative Traffic Operation (ECoTOp) system for signalized intersections where equipped CAVs are proactively managed and traverse the intersection in coordination with traffic signal optimization to minimize energy consumption. The EcoTOp framework is developed on the open source and freely available traffic simulation platform Simulation of Urban Mobility (SUMO, Lopez et al., 2019). The fuel consumption and emission analysis of the results was done using the

Comprehensive Model Emissions Model (CMEM, Barth et al., 2000). The objectives of the proposed research include:

1. Develop a full-scale cooperative traffic operation system for signalized intersections, allowing for two-way communications between vehicles and the traffic signals.

2. Design algorithms to achieve co-optimization of traffic signal operation and vehicle dynamics in terms of system efficiency for all traffic, including vehicles without the communication technology.

3. Implement the proposed models in micro-simulation software SUMO, and test it under different penetration rate for both through and turning movement with various queue conditions.

The rest of this report is organized as follows. In Section 2, we introduce the assumptions and algorithms of the proposed model. We then discuss the simulation setup in Section 3 and evaluation results in Section 4. In Section 5 we conclude the report with discussions on future research.

2. Methodology

2.1. Problem Statement

The proposed Eco-friendly Cooperative Traffic Operation (ECoTOp) system integrate two major modules as illustrated in Figure 1:

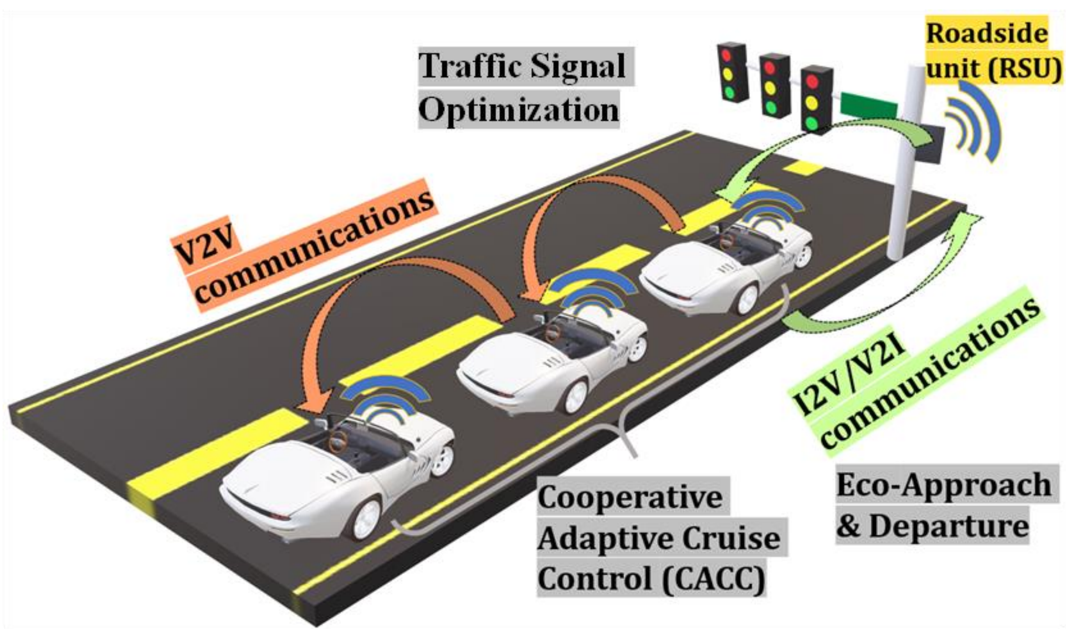


Figure 1. Illustration of the proposed ECoTOp system

1. Dynamic Traffic Signal Optimization. As vehicles approach the intersection, they can send messages to the downstream traffic signal controller, with information on arrival

time and intended turning movement. Taking into account surrounding traffic conditions, the traffic controller will calculate the optimal signal phase and timing (SPaT), and communicate them with the vehicles.

2. Cooperative Eco-Driving Operation. Based on the confirmed SPaT information, each vehicle will perform Eco-Approach and Departure (EAD) where the selection of target arrival time depends on a) downstream traffic states (e.g., queue length); b) vehicle type; and c) vehicle energy consumption for the passage.

The traffic signal optimization module and cooperative eco-driving module are mutually interacted and have some inherent conflict when pursuing their own optimality in operation. The traffic signal optimization system prefers reliable information from all the incoming vehicles, including current dynamic state and future movement, at the earliest convenience. It also prefers the flexibility to adjust the signal timing plan at any time to adapt the dynamic traffic conditions. For the cooperative eco-driving module, it needs reliable signal timing information ahead of time to make a good trajectory plan that saves fuels and emissions. Meanwhile, the vehicle travelling under the eco-driving plan still wants and needs to retain some flexibility in operation to improve the safety, mobility and energy performance when there are better options at some situations, such as emergency braking and lane changing. Although it is possible to build an ideal co-optimized system in a fully-sensed and fully-controlled traffic network, it is not realistic in an isolated intersection with mixed traffic for two reasons: 1) the unconnected vehicles with human drivers have personalized and diverse driving style, which is a unpredictable factor in the system; 2) due to the limitation in the coverage in sensing and control, the time and state when each vehicle enters the system is not predictable, even for CAVs. Table 1 shows the conflict between signal optimization module and cooperative eco-driving module.

Table 1. Conflict between signal optimization and cooperative eco-driving

	Reliability in Input	Flexibility in Output
Signal Optimization	Reliable current dynamic state and future movement of all incoming vehicles as early as possible	Adjust the signal timing to adapt the dynamic situations at any time
Cooperative Eco-driving	Reliable signal timing information for trajectory planning as early as possible	Adjust the original trajectory plan for safety or mobility reasons at any time

To solve this problem in the mixed traffic environment, each module has to make some trade-off to achieve an integrated optimization. In the rest of this section, we will present the methodology assumptions and algorithms on both modules.

2.2. Dynamic Traffic Signal Optimization

In the signal optimization module of the ECoTOp system, we made three basic assumptions to guarantee a certain level of reliability for the CAVs for their trajectory planning and to adapt common senses from human drivers: 1) constant cycle length *C*; 2) same phase orders in every cycle, and the corresponding phases in upper and lower rings in the phase diagram have the same signal timing, and 3) the signal optimization is made at the beginning of each cycle and does not change during that cycle. Under those basic assumptions, we design a scenario for isolated signalized intersection that is capable to receive the real time locations from all proximate CAVs and detect the locations of all proximate non-connected vehicles through cameras (similar as [18]). Then, at the beginning of each cycle, the proposed ECoTOp system collected the total number of vehicles to be served at each lane within the detection zone, i.e., $N_{i,j}$ for lane *j* in phase *i*. We then define N_i as the max $N_{i,j}$ value among all associated lanes in in phase *i*, so N_i is used in the optimization problem to represent the vehicle number to be served in phase *i*. Note that only vehicles can arrive at the stop line before the end of phase *i* can be counted into $N_{i,j}$ or N_i. Assume the green time of phase *i* is G_i and the yellow and all-red time right after phase *i* is Y_i, $N_{i,j}$ is counted based on the number of vehicles along the distance from the stop line of lane *j* of phase *i* to $X_{i,j}$ in the downstream,

$$X_{i,j} = v * \left(G_i + \sum_{ii=1}^{i-1} G_{ii} + Y_{ii}\right) \tag{1}$$

where *v* is the free flow speed and $\sum_{ii=1}^{i-1} G_{ii} + Y_{ii}$ is actually the red time ahead of phase *i*. Figure 2 illustrates the key variables in an example intersection, including $X_{i,j}$, the maximum counting distance for a vehicle at lane *j* of phase *i* to reach the stop line in this cycle, and $N_{i,j}$ the number of vehicles along the distance from the stop line to $X_{i,j}$ of each lane.

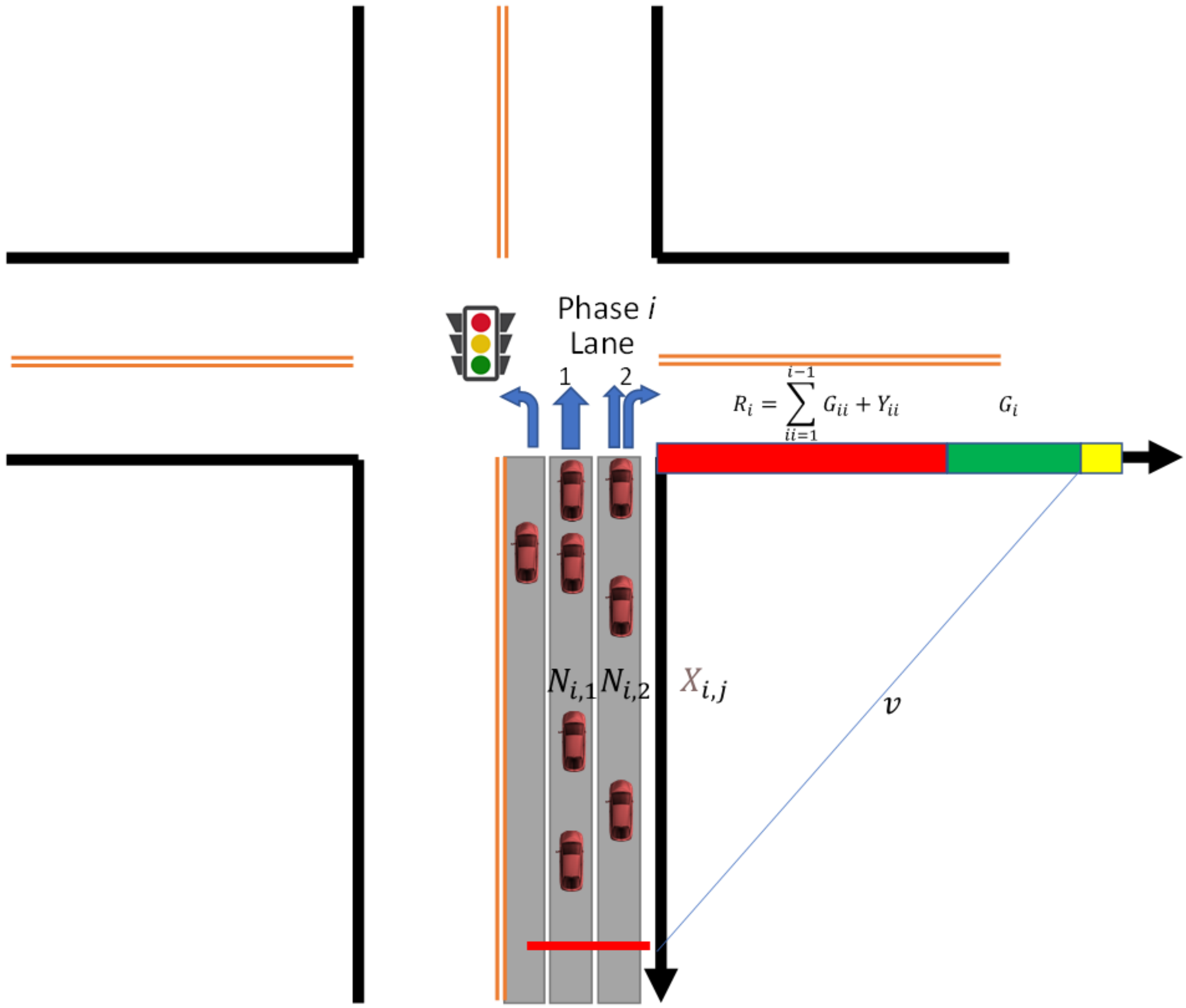


Figure 2. Key variables for ECoTOp system in an example intersection

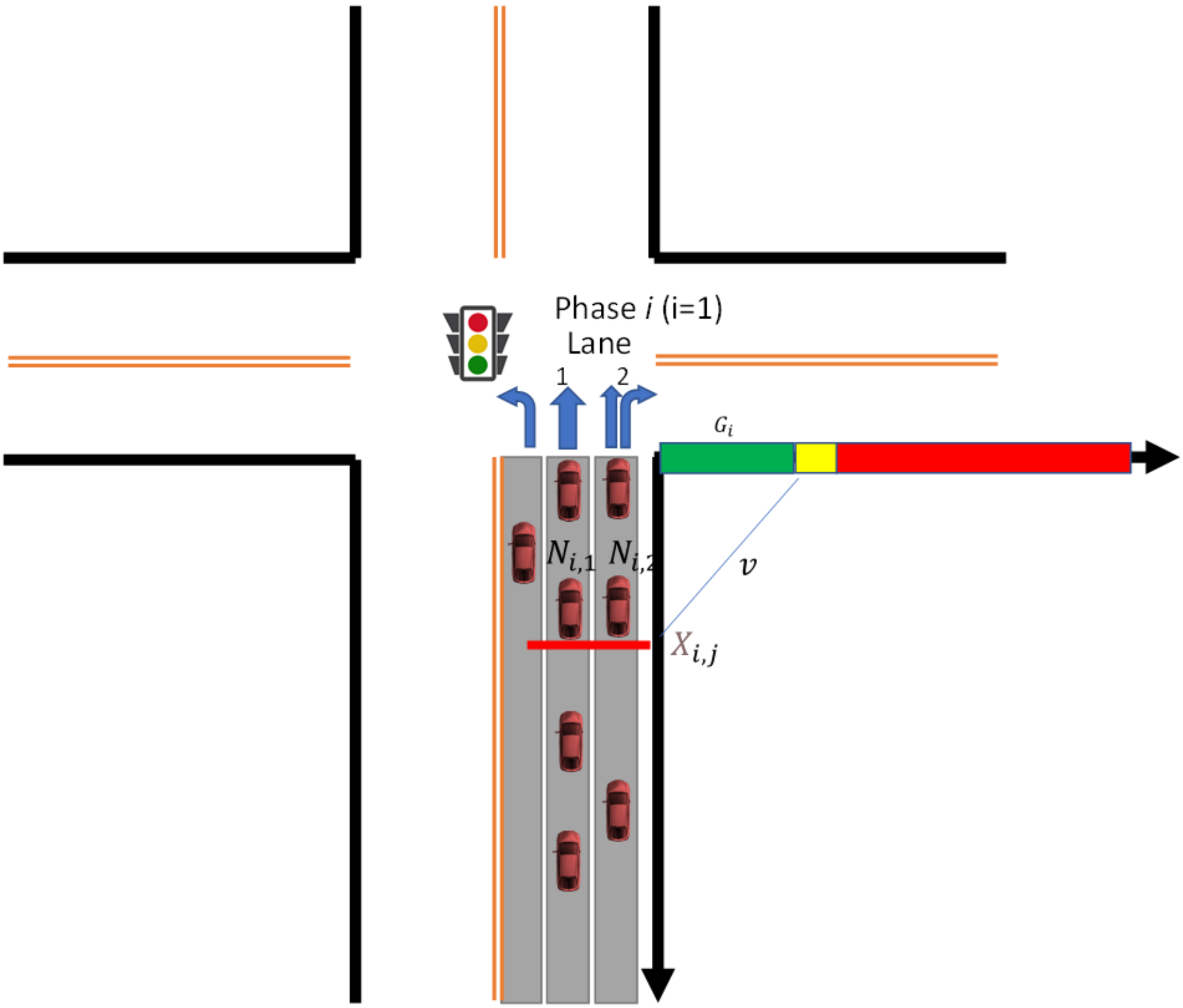


Figure 3. Key variables for ECoTOp system for the first phase in a cycle

Note that for the first phase in a cycle, i.e., *i* =1, there is no red time or yellow time before the start of the green phase. The maximum counting distance is then calculated as $X_{i,j} = v * G_i$ as illustrated in Figure 3, and and $N_{i,j}$ is measured based on the number of vehicles along the distance from the stop line to $X_{i,j}$ accordingly.

We then assume M_i as the discharge capacity per lane in phase *i* in this cycle, which can be computed as

$$M_i = G_i * \frac{1}{h} \tag{2}$$

where G_i is the green time of phase *i* and *h* is the saturated time headway in the discharge process. The expected maximum number of oversaturated vehicles in phase *i* is then calculated as $N_i - M_i$. We then formulate the optimization problem which aims to maximize the throughput from all phases in the cycle, while minimizing the variance of oversaturated vehicle number from all phases to ensure fairness, as follows:

$$\max_{G_i} z = w_1 * \frac{1}{k}\sum_{i=1}^{k} N_i - w_2 * \frac{1}{k}\sum_{i=1}^{k}(N_i - M_i)^2$$

$$\begin{aligned} s.t. \quad & \textstyle\sum_{i=1}^{k} G_i = C - \sum_{i=1}^{k} Y_{ii} \\ & N_i \geq N_{i,j}, \ \forall i,j \\ & M_i = G_i * \frac{1}{h}, \ \forall i \\ & N_{i,j} = \mathrm{count}_{i,j}(X_{i,j}), \ \forall i,j \\ & X_{i,j} = v * \left(G_i + \textstyle\sum_{ii=1}^{i-1} G_{ii} + Y_{ii}\right) \quad \forall i,j \end{aligned} \tag{3}$$

In equation (3), there are 5 constraints in total. The meaning of each constraint is shown as follows:

Constraint 1: assume there are *k* phases in a cycle, the total duration of the green times of all phases is a constant, which is calculated by subtracting all the yellow and all red times from the entire cycle length *C*.

Constraint 2: as N_i is the maximum value of $N_{i,j}$ among all associated lanes in in phase *i*, N_i is then greater or equal to all $N_{i,j}$ values among all associated lanes in in this phase.

Constraint 3: the definition of discharge capacity M_i as shown in equation (2).

Constraint 4: the function $\mathrm{count}_{i,j}(X_{i,j})$ is defined as the current number of vehicles at lane *j* of phase *i* at the beginning of the cycle, measured from the stop line to $X_{i,j}$ in the upstream.

Constraint 5: as defined in equation (1), $X_{i,j}$ is the maximum distance for a vehicle at lane *j* of phase *i* to reach the stop line in this cycle. It is calculated by multiplying the free flow speed *v* by the time span from the start of the cycle to the end of the green time of phase *i*.

In the optimization problem (3), the optimal phase timing G_i is the key variable to optimize. w_1, w_2, h, Y, v, and k are predefined constants. $X_{i,j}$, M_i

We then apply sequential least squares programming (SLSQP) algorithms to solve this problem to obtain the optimal phase timing G_i, and then give update to the signal controller for real time control.

2.3. Cooperative Eco-Driving Operation Module

EAD applications using SPaT information have been developed to calculate an energy-efficient vehicle speed profile for passing through intersections. Unlike driving on freeways, the frequent stop-and-go maneuvers and associated accelerations due to the signal control and traffic result in excessive fuel consumption and air pollutant emissions. Taking advantage of communication and sensing technology, the knowledge of SPaT information, map information and preceding vehicle's state are integrated design the most fuel-efficient speed trajectory, even for complex situations such as actuated signal and congested traffic. In a previous study (Hao et al., 2021), we proposed a graph-based trajectory planning algorithm (GBTPA) for EAD application that computes the minimum cost speed trajectory to cross an intersection legally. GBTPA finds the theoretical optimal speed profile for crossing an intersection legally but suffers from high computation cost and the risk to miss feasible solutions due to the discretized solution space.

The cooperative eco-driving module of the proposed system is developed based on the authors' previous work on single vehicle connected eco-driving strategies (Hao et al., 2021; Wu et al., 2021). Essentially, we discretize the time into fixed time steps Δt, then *T* is the total number of time steps. The objective of the connected eco-driving problem is then to minimize the total energy of the vehicle in all the time steps, considering constraints from total travel distance *X*, and other constraints on speed *v* and acceleration rate *a*. The problem is then formulated in equation (4), where v_t and a_t are the speed and acceleration rate of the vehicle at time step *t*. v_t is bounded by 0 and speed limit v_l, and a_t is also bounded by its minimum and maximum values. $P(v_t, a_t)$ represent the energy cost given the vehicle's state at certain time step.

$$\begin{aligned}
&\min_{a_0, a_1, \dots a_T} \sum_{t=0}^{T} P(v_t, a_t)\, \Delta t \\
s.t. \quad &\sum_{t=0}^{T} v_t = X \\
&v_t = v_{t-1} + a_{t-1}, \forall\, t \in [1, T] \\
&a_{min} \le a_t \le a_{max} \\
&0 \le v_t \le v_l \\
&v_0 = v_s, v_T = v_d
\end{aligned} \tag{4}$$

The model in equation (4) can be reshaped into a graph-based model, using a unique 3-D coordinate (*t*, *x*, *v*) as the node to describe the dynamic state of the vehicle. There is an edge from V_1 (t_1, x_1, v_1) to V_2 (t_2, x_2, v_2) if and only if the following rules are satisfied:

1) Time consistency: $t_2 = t_1 + \Delta t$;
2) Distance consistency: $x_2 = x_1 + v_1 \Delta t$;
3) Speed consistency: $v_2 = v_1 + a_1 \Delta t$ and $0 \le v_2 \le v_l$;
4) Acceleration/deceleration constraint: $a_{min} \le a_1 \le a_{max}$, where $a_{min}$and $a_{max}$are the maximum deceleration and maximum acceleration rates at speed v_1 for the host vehicle, respectively.

We further define the cost on edge $V_1 \rightarrow V_2$ as the tractive power during this state transition process. At this point, the trajectory planning problem for energy minimization is converted into a problem to find the shortest path from the source node $V_s(0, X, v_s)$ to the destination node $V_d\ (T, 0, v_d)$ in the directed graph.

The solution of this model at each time step corresponds to the optimal speed (or acceleration) for the driver or vehicle controller to follow. We then use $M(t, D, V)$ to represent the minimum total cost at state (*t, D, V*), which corresponds to a series of optimal valid action from the initial state to the final state. This problem is then formulated in an iterative way as follows:

$$\begin{aligned} &M(t, D, V) = \min_x \big(H(V, x, \Delta t) + M(D - V\Delta t, V + x\Delta t, t + \Delta t)\big) \\ &\quad s.t.\ \ a_{min} \le x \le a_{max} \\ &\quad\qquad V_{min} \le V + x \le V_{max} \end{aligned} \tag{5}$$

We also define the values of the boundary states at or beyond the stop line. If the vehicle arrives at the stop line at the target time with target speed, $M(T, 0, V') = 0$. For other cases, e.g., 1) if the vehicle exceeds the stop line ($\mathrm{d} < 0$); 2) if the vehicle arrives at the stop line at other time ($\mathrm{d} = 0, t \neq T$); or 3) the vehicle arrives at the stop line with other speed ($\mathrm{d} = 0, V \neq V'$), the total cost function is set to infinity, i.e., $M(t, D, V) = +\infty$.

Based on all the assumptions above, this problem is formulated into a multiple-source single-destination shortest path problem. It can be solved using a variation Dijkstra algorithm in which two nodes are linked only if their time sates are consecutive. The pseudo codes below describe the algorithm. Here we use $X(t, D, V)$ to record the optimal acceleration rate at state (t, D, V).

Initialize the M values of all states with $+\infty$, i.e., $M(t, D, V) = +\infty, X(t, D, V) = 0, \forall t, D, V$.

Set $M(T, 0, V') = 0$.

For $t = T{:} -\Delta t{:}\, T_{min} + \Delta t$

  For each (t, D, V)

    Find all the valid parent states of (t, D, V), i.e., $(t - \Delta t, D + V\Delta t - x\Delta t, V - x), \forall x$

      For each valid action *x*

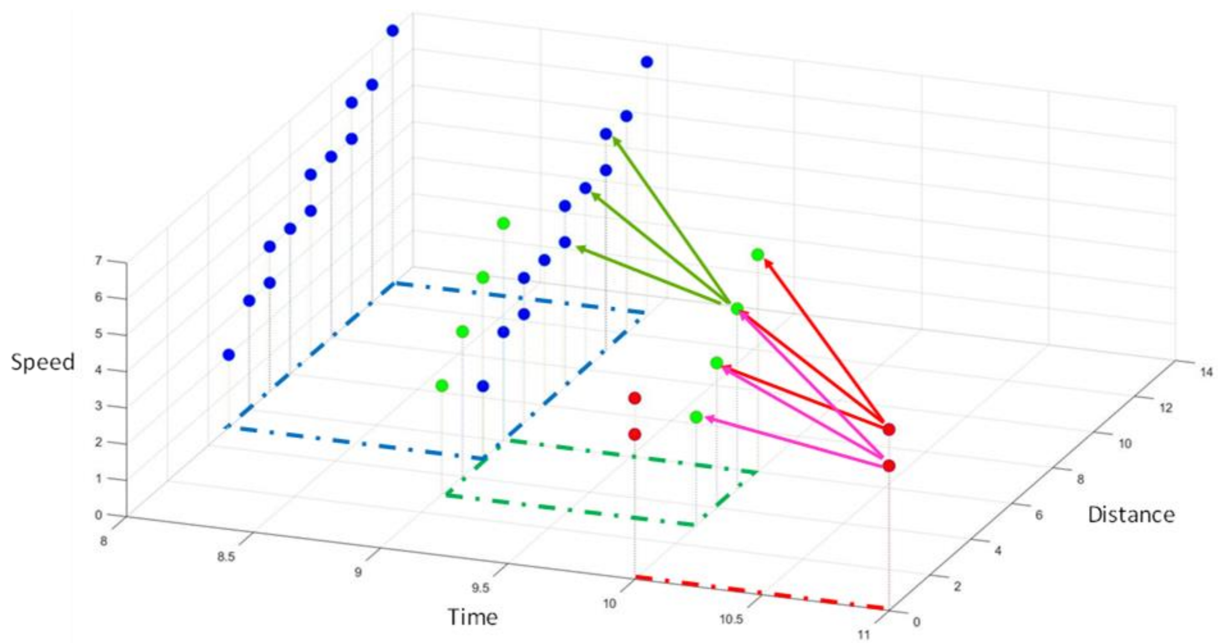
        If $M(t, D, V) + H(V - x, x, \Delta t) < M(\tau - \Delta t, D + V\Delta t - x\Delta t, V - x)$

          Update $M(t - \Delta t, D + V\Delta t - x\Delta t, V - x) = M(t, D, V) + H(V - x, x, \Delta t)$

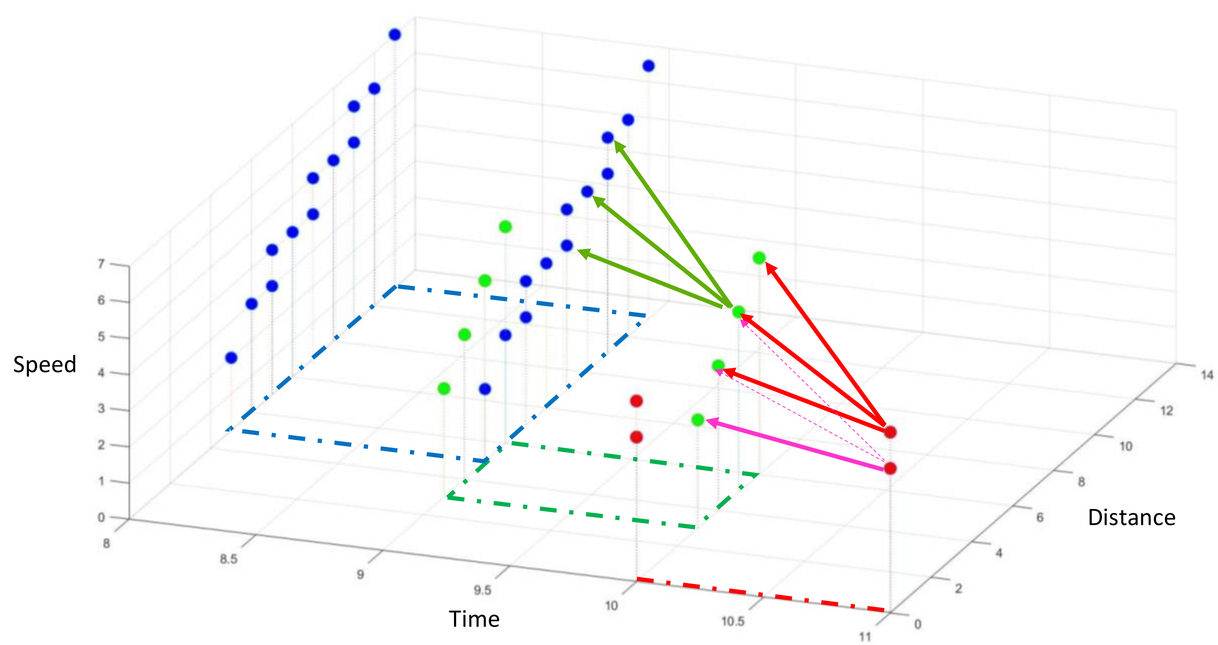
          Update $X(t - \Delta t, D + V\Delta t - x\Delta t, V - x) = x$

Return $M(t, D, V)$ and $x(t, D, V)$

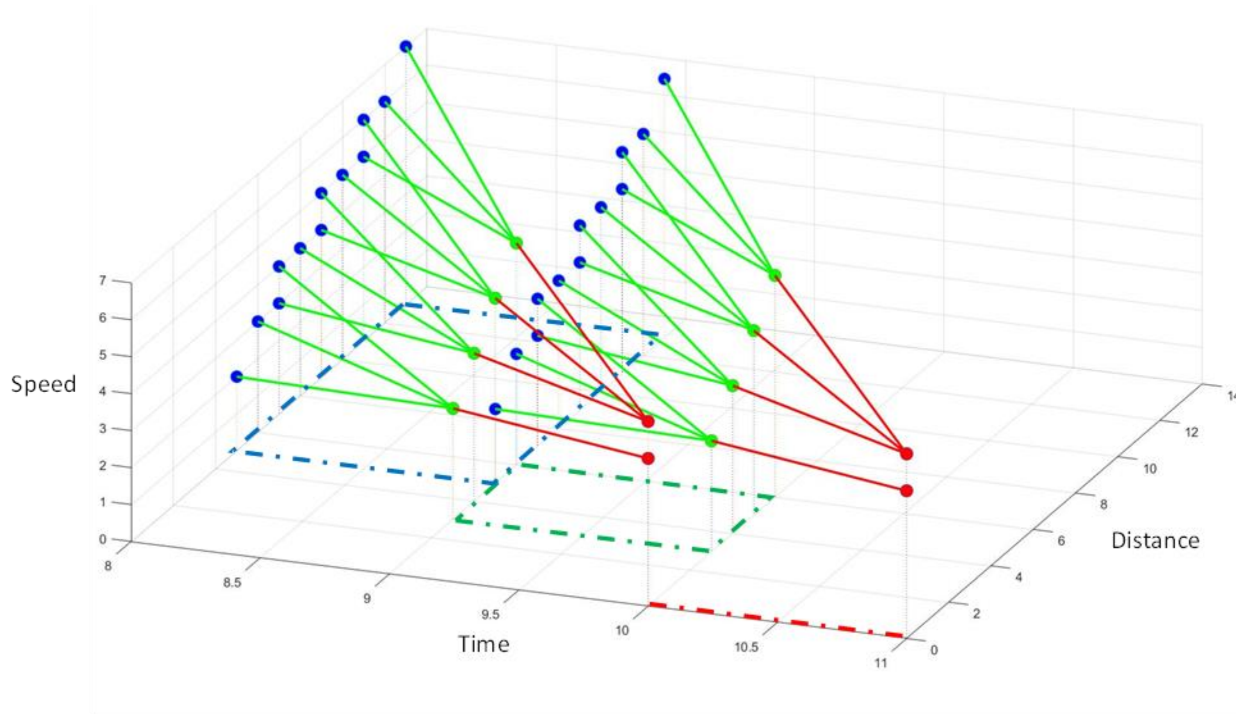
Figure 4 illustrates a simple example of this algorithm. We use blue, green and red dots to show the states in three consecutive time stamps. Figure 4(a) shows the process to find all the valid parent states of each state, using two red states and one green states as examples. Figure 4(b) shows that if one state has two or more valid child states, the optimal valid action corresponds to the one with lower M value. Figure 4(c) illustrates all the optimal valid actions for the blue and green states based on the proposed algorithm.



(a) The process to find all the valid parent states



(b) The process to identify the optimal valid actions



(c) All the optimal valid actions

Figure 4. A graph-based illustration of the eco-driving algorithm

The trajectory planning algorithm described above improves the computation efficiency over conventional optimization techniques by introducing dynamic programming framework. However, we can further reduce the computation time using an innovative algorithm, named Machine Learning-based Trajectory Planning Algorithm (MLTPA) (Esaid et al., 2021). In contrast to the end-to-end model, MLTPA uses training data generated by Graph-Based Trajectory Planning Algorithm (GBTPA) on a range of representative unique inputs. Using the GBTPA-generated data, MLTPA is trained to predict the next target state for the host vehicle. We compare the prediction accuracy of five types of machine learning techniques, including linear regression, k-nearest-neighbors, decision tree, random forest, and multi-layer perceptron neural network. The random forest method has the best performance in terms of root mean square error (RMSE). After being trained offline, MLTPA is then applied in Eco-Drive online to yield both computation efficiency for the system and energy efficiency for the host vehicle. The proposed MLTPA enables the Eco-Drive system to work in real time, in both traffic microsimulation real-world environment.

Based on the single vehicle connected eco-driving model, we further extend it to multiple vehicle case by adding Adaptive Cruise Control (ACC) logic when the host CAV is following a non-connected vehicle, and Cooperative Adaptive Cruise Control (CACC) when following another CAV. We also implemented smart lane changing and queue-aware cooperative eco-driving in the system. The detailed control logic in micro-simulation test is presented in the next section.

3. Model Implementation

3.1. Experiment Design

In order to evaluate the ECoTOp algorithm, the traffic simulation platform Simulation of Urban Mobility (SUMO) was utilized (Lopez et al., 2019). SUMO is an open source and freely available traffic simulator. It was initially developed by the German Aerospace Center in 2001, and open source released in 2002 (Krajzewicz et al., 2012). SUMO has been used for such projects as iTeris, COLUMBO, and Amitran (Krajzewicz et al., 2012; Lazaro et al., 2008; Jonkers et al., 2013).

Figure 5 shows an example of the intersection in SUMO. The network intersection is a typical 4-leg intersection with two through lanes and a left-turn lane for each direction. The signal control for the intersection has 4 phases: East-West through, East and West left-turn, North-South through, North and South left-turn. The initial timing plan uses fixed timing. Based on the SUMO platform, we implemented the ECoTOp system using Python.

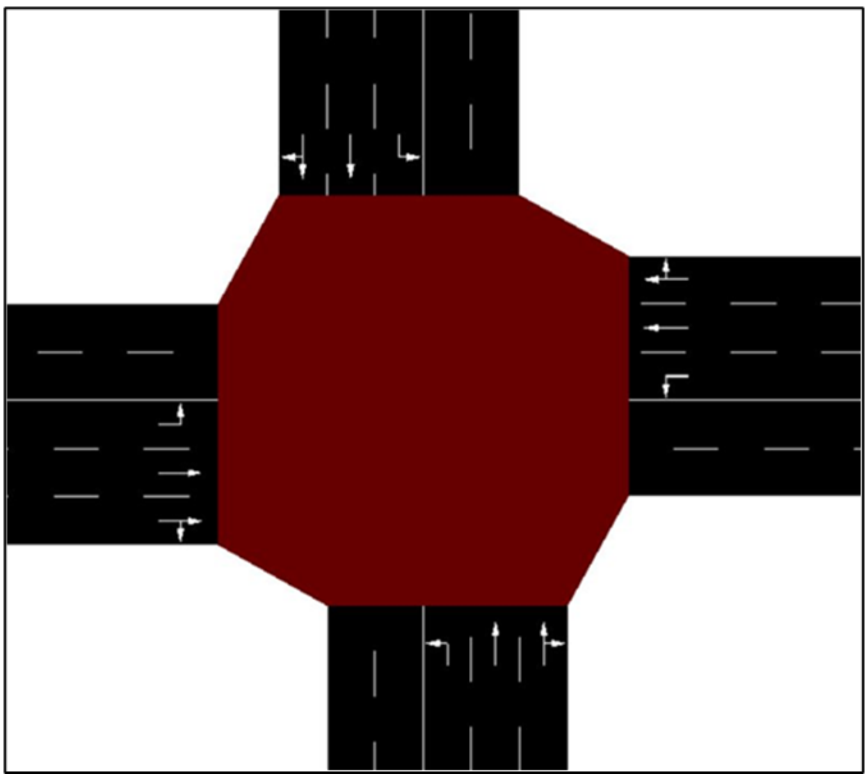


Figure 5. Sample Intersection in SUMO

Under SUMO, the signal phase and timing (SPaT) information for each signal phase was acquired using the Traffic Control Interface (TraCI) tool. The TraCI tool allows the user to retrieve and manipulate values for the simulated objects in the network. The vehicle position data around the study information was also obtained in the system, as a digital mirror of a real world GridSmart fisheye camera system installed at the Iowa-University intersection of the Innovation Corridor in Riverside, CA (Oswald et al., 2019). As shown in Figure 6, the GridSmart camera system uses a single (or two for big intersections) bell shaped cameras for signal actuation and traffic data collection (GridSmart, 2022). The traffic volume generated in this network was also calibrated using the historical data collected from the GRIDSMART system. This surveillance system can not only provide object-level trajectory information, accurate vehicular counts or turning movements for different modes, but also detect and track other road users such as pedestrians, bicyclists, and micro-mobility users.

(a) At Traffic Controller Cabinet

(b) Installing Camera on Street Lamp Post

(c) GridSmart User Interface

Figure 6. Installation and User Interface of GridSmart Fisheye Cameras

The cooperative eco-driving algorithms was then implemented in three steps in SUMO. First, we apply smart lane changing algorithms for CAVs that can receive lane-by-lane traffic condition information from the ECoTOp system, so that they are able to change to the adjacent lane with the least number of vehicles queued. Second, we implement the queue-aware Eco-Approach and Departure (EAD) algorithm to accommodate the dynamic queues in front of the host CAVs. We add a buffer to the time for the phase in the EAD algorithm if there are vehicles queued in the lane, so that the CAV can consider the queue when passing the intersection without having to come to a complete stop. The length of the buffer depends on the number of vehicles queued and can be updated dynamically based on the real time traffic conditions. In the last step, ACC algorithm is applied when the host CAV is following a non-connected vehicle, and CACC is applied when following another CAV. Both algorithms are embedded in SUMO as functions.

For the co-optimization of signal control and vehicle trajectory, Figure 7 shows a flowchart of how the ECoTOp code works. First the number of vehicles for each lane in the network within the communication range are counted. Then the number of vehicles that can be served within the current green time for each lane are counted. These are used to get the time required for the delayed vehicles controlled by the phase for that lane to pass through the intersection. These are also used to get the time required for maximum throughput. These are used in the cost function and put into a Sequential Least Squares Programming (SLSQP) optimizer to get the new phase times. Then each CAV receives the SPaT information and queue information. The queue information is used to possibly change lanes and add a queue buffer to timing. The new time and the current vehicle velocity is sent to a Random Forest based trajectory optimizer to get the new trajectory (Esaid et al., 2021).

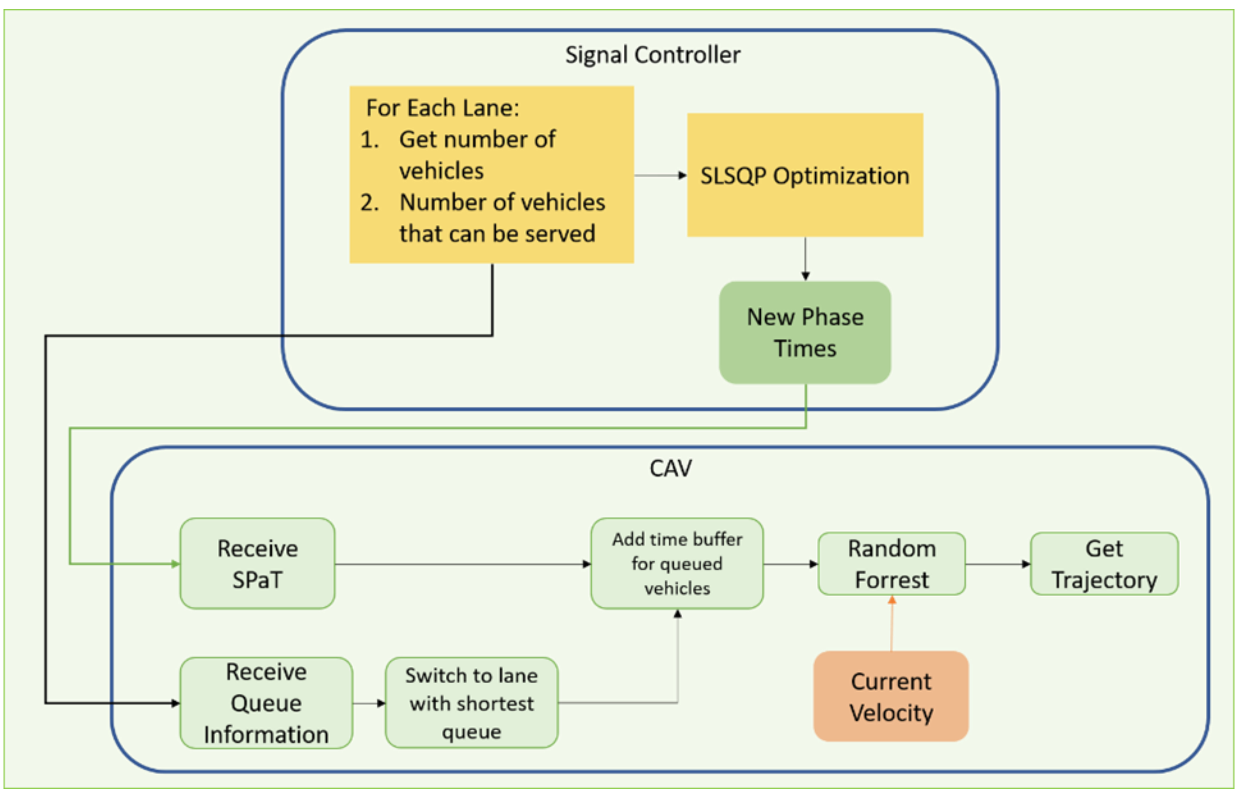
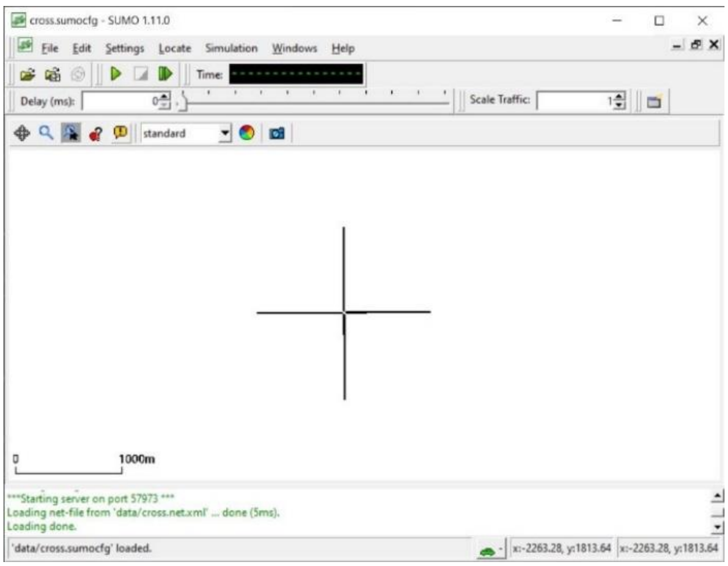


Figure 7. Simulation Flow Chart

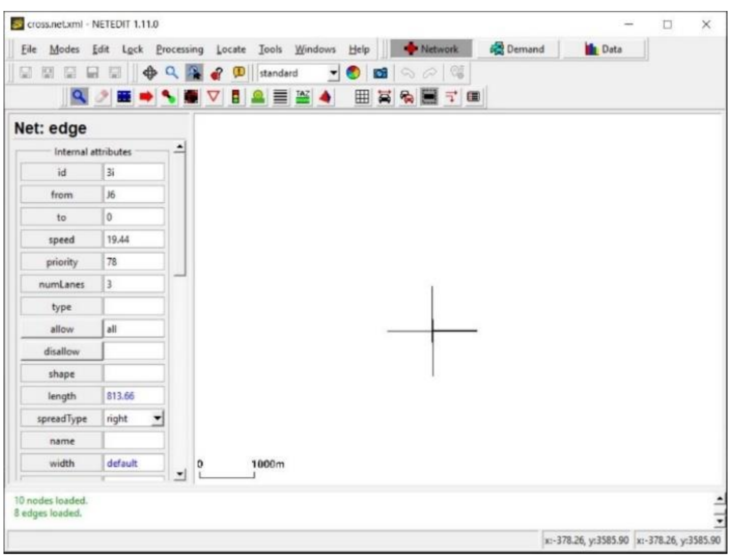
3.2. Simulation Implementation

This section shows more technical details on simulation implementation, including the procedure to code and calibrate the network, and the solutions to some issues when conducting the micro-simulation in SUMO.

As the first step, we coded the simulation network and calibrate the traffic volumes from all directions using GridSmart data. Figure 8(a) shows an example of the SUMO platform visual interface, sumo-gui. Figure 8(b) shows an example of the software to edit the SUMO traffic network, Netedit. For this project the Python programming language was used to interface with SUMO while MATLAB and excel were used to process the data.



(a) Graphical Interface for SUMO Traffic Simulator



(b) SUMO Network Editor

Figure 8. Network coding in SUMO

The first version of ECoTOp did not include turns, only throughs, in order to test the signal optimization portion of the platform. Having no turns in the network made it easier for quick testing. The results from the simple network were encouraging. The next step was to add turns to the network. Adding turns did not affect the traffic signal control coding, but did affect the coding for the vehicle trajectory. The signal phase and timing (SPaT) for the left turn signals needs to be considered. It should be mentioned that the SPaT in this SUMO code for each signal phase was acquired using the Traffic Control Interface (TraCI) tool in SUMO. The TraCI tool allows the user to retrieve and manipulate values for the simulated objects in the network (Lopez et al., 2019) The results after adding in turns were less promising. After watching the simulation, it appeared that the average time headway calculation was resulting in not enough green time for left-turns. Figure 9 shows an example of a left-turn queue after the green time ends. The figure shows the left-turn signal changed to yellow while still having four vehicles in the left-turn lane.

The first attempt to fix the average time headway calculation was to make it constant throughout the simulation. The problem persisted so the constant average time headway for vehicles turning left was made larger than other vehicles in the network. This led to more favorable results, but still not what was expected. After more examination of the simulation, and looking through the Python code, two observations were made: first, sometimes vehicles will get stuck in the wrong lane due to different settings and attributes in SUMO, and second, instead of minimizing vehicle delay in the optimization, total through-put should be maximized. Figure 10 shows an example of a long queue forming behind a vehicle stuck in the wrong lane while the signal is green. Some vehicles will change lanes and go around the stuck vehicle but only when there are no vehicles in the adjacent lane.

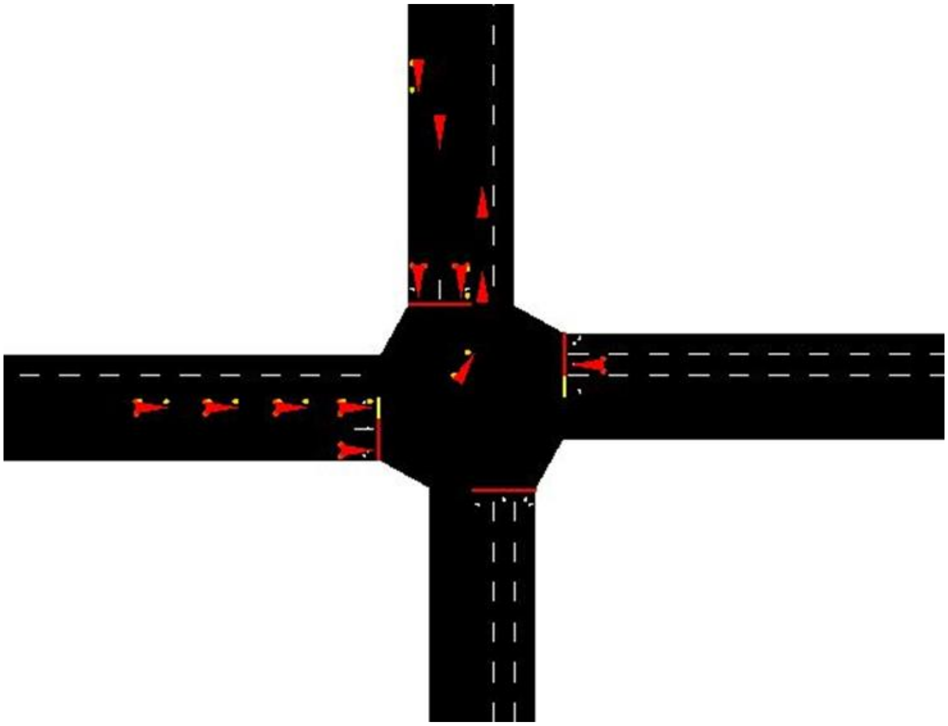


Figure 9. An Example of a Left-turn Queue Running Out of Green Time.

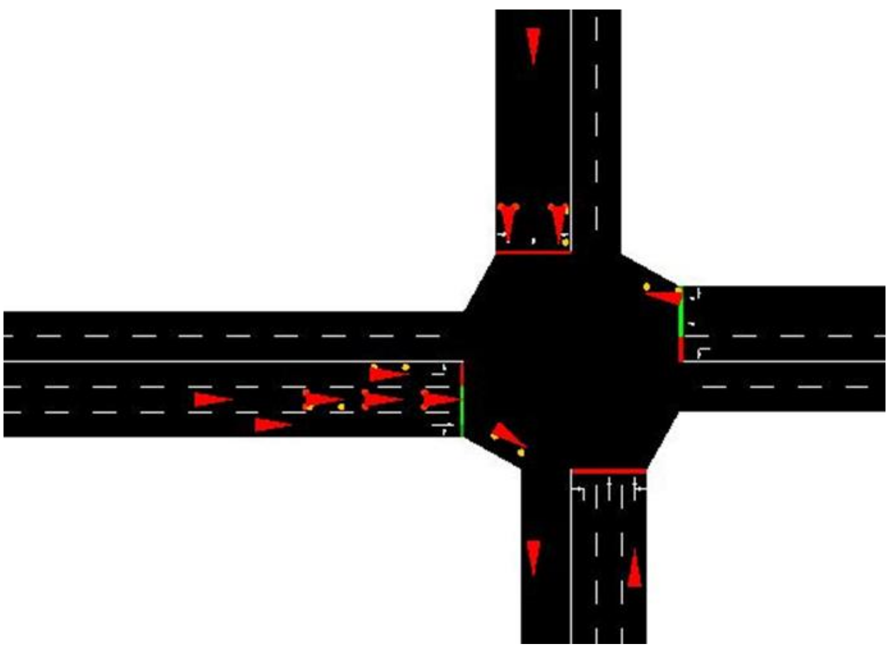


Figure 10. An Example of a Vehicle Stuck in the Wrong Lane.

To address the problem of vehicles getting stuck in the wrong lane it was changed so that the left-turn vehicles will enter the network in the left-turn lane and the right-turn vehicles will enter the network in the right most lane. These changes improved the problem but did not stop the problem completely so the decision was made to force these vehicles to stay in the lane throughout the network. To maximize total through-put, the cost function was changed so that through-put was maximized instead of minimizing delay.

While the traffic signal optimization was being adjusted, simultaneously the vehicle trajectory portion of the ECoTOp platform was changed from the Eco-Approach and Departure (EAD) include information about the vehicles queued at the intersection. As mentioned previously, it is assumed that the CAVs receive information about all vehicles near the intersection.

The idea for adding queue information to EAD is to, first, have the CAV change to the lane with the least number of vehicles queued. Second, add a buffer to the time for the phase in the EAD algorithm if there are vehicles queued in the lane. On a red phase EAD algorithm tries to make the CAV reach the stop bar as the green phase starts, but if there is a vehicle waiting at the stop bar the CAV will be forced to stop rather than continuing and passing on green. Adding a buffer will allow the CAV to continue to the intersection without having to come to a complete stop. The length of the buffer depends on the number of vehicles queued.

4. Numerical Results

In order to analyze the performance of the ECoTOp platform three metrics are considered: fuel consumption, average speed, and average waiting time. SUMO allows users to choose different metrics to write to files automatically. For this analysis, the trajectory output, which gives the name, position, speed, and acceleration for each vehicle, and trip information, which gives aggregated information about each vehicle. SUMO also has an emission output option that uses the Handbook Emission Factors for road transport (HBEFA), but for this analysis the Comprehensive Model Emissions Model (CMEM) was used as CMEM can catch the nuances of traffic smoothing techniques (Barth et al., 2000). The vehicle trajectories from the trajectory output files were used as input for CMEM. CMEM is a microscopic, physical emissions model that estimates the emissions of individual vehicles. CMEM was developed to capture the physical relationships between vehicle characteristics, operating conditions, and the emission/fuel consumption rates. One prominent advantage of this approach is that it is possible to tailor many of the physical parameters to fit a very specific type of vehicle (i.e., down to make and model) (Scora et al., 2011).

The results in this section are shown for an ECoTOp platform with using a traffic signal control cycle length of 66 seconds and a communication range of 750 meters. The SUMO network for this project has lanes of 800 meters before the intersection and 200 meters after the intersection. The simulation timestep is 100 milliseconds. All non-CAV vehicles use the Intelligent Driver Model (IDM) SUMO setting for car-following which is based on the model created by Treiber et al. (2010).

Table 2 shows a comparison of baseline, signal optimization only, EAD only and ECoTOp for different CAV penetrations. As CAV penetration increases the average fuel consumption savings increase and average waiting time savings increase significantly, while the average speed slightly decreased. At high penetration rate, the fuel saving can reach up to 15.4% and the waiting time, defined as the stop time in the queue, can be reduced by 85.7%. Under lower penetration rate, the fuel saving benefit is degraded, e.g., 11.8% reduction under 80% penetration, 84% under 60% penetration and 4.6% under 40% penetration. This table also shows that the ECoTOp outperforms the other scenarios including signal optimization only and EAD only cases. The travel time increase is mainly caused by the signal plan update in each cycle, as EAD vehicles may found the planned trajectories planned in previous cycle may make the vehicle miss the green light in its original plan.

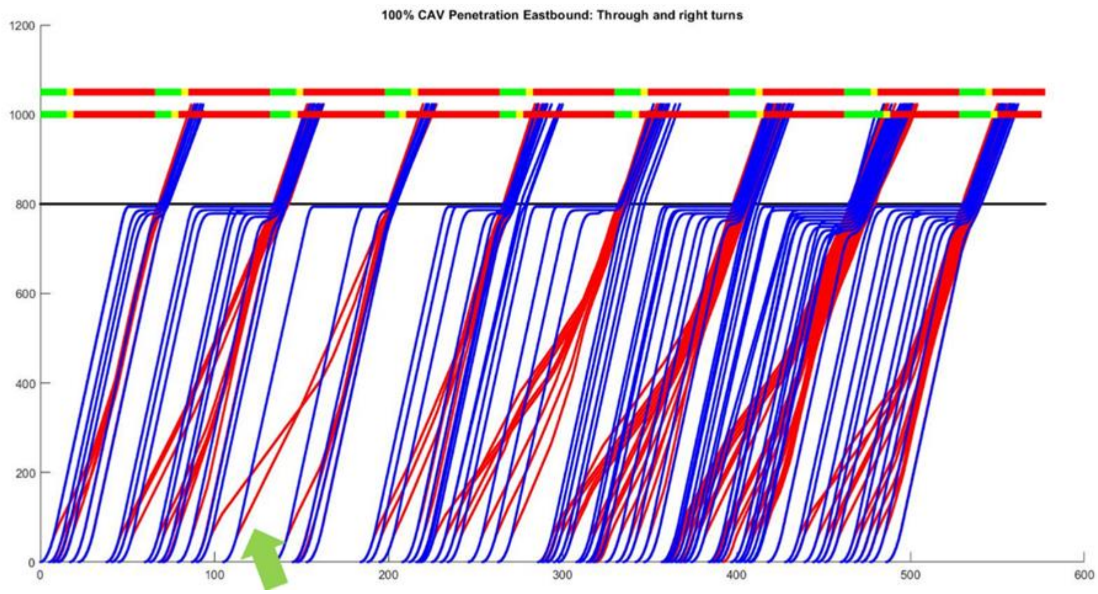
Table 2. Performance comparison at different CAV penetrations

Fuel Consumption Comparison							
CAV Pene-tration	**Tech**	**Fuel g/mile (CMEM)**	**Benefit (%)**	**Speed (mph)**	**Benefit (%)**	**Waiting time (s)**	**Benefit (%)**
-	**Base**	135.57	-	24.02	-	16.8	-
-	**Signal Only**	136.59	-0.7%	23.6	-1.75%	18.1	-7.7%
20%	**EAD only**	131.09	3.3%	23.5	-2.16%	12	28.5%
	ECoTOp	133.24	1.7%	23.36	-2.75%	13.3	20.8%
40%	**EAD only**	126.64	6.6%	22.9	-4.66%	9.1	45.8%
	ECoTOp	129.35	4.6%	23.02	-4.16%	9.4	44.05%
60%	**EAD only**	126.34	6.8%	21.4	-10.9%	9.7	42.2%
	ECoTOp	124.14	8.4%	22.5	-6.3%	7.15	57.4%
80%	**EAD only**	121.39	10.4%	21.15	-11.9%	6.7	60.1%
	ECoTOp	119.6	11.8%	22.53	-6.2%	3.76	77.6%
100%	**EAD only**	116.77	13.8%	21.17	-11.87%	4.31	74.3%
	ECoTOp	114.65	15.4%	22.2	-7.6%	2.39	85.7%

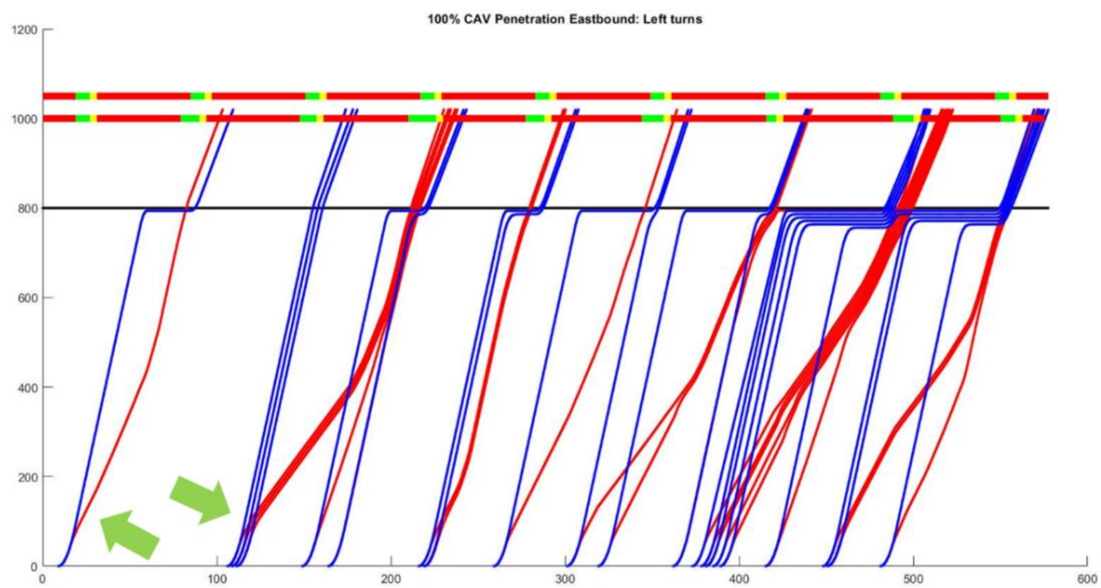
Figure 11-Figure 13 shows the traffic trajectories compared to baselines for different CAV penetration rates: 100%, 60%, and 20%. Baseline here is considered to be no signal control optimization and no trajectory optimization, and the vehicles only use the IDM car-following. In order to make the plots less crowded, trajectories were split up depending on direction. Figure 11 shows traffic trajectories for Eastbound Through direction (a) and Eastbound Left-turn (b) for traffic with that is 100% CAVs. In the figure, the vertical axis is the distance the vehicle has travelled in meters and the horizontal axis is the simulation time in seconds. The figure has a cyan color bar at 800 meters to mark the stop-bar of the intersections. The bar at 1000 meters represents the signal light over time for the ECoTOp platform and the bar above that represents

the baseline signal light over time. The ECoTOp vehicles are colored red for CAV. The baseline vehicles are colored blue.

The green arrow shows an example of when a CAV changes the trajectory plan in order to pass through the intersection on a green light. The figure shows that the baseline vehicles stop and have to wait at almost each traffic signal cycle. For the ECoTOp vehicles, the CAVs have a high non-stop ratio, and when the non-CAVs are following a CAV, they continue following the optimized trajectory of the CAV.



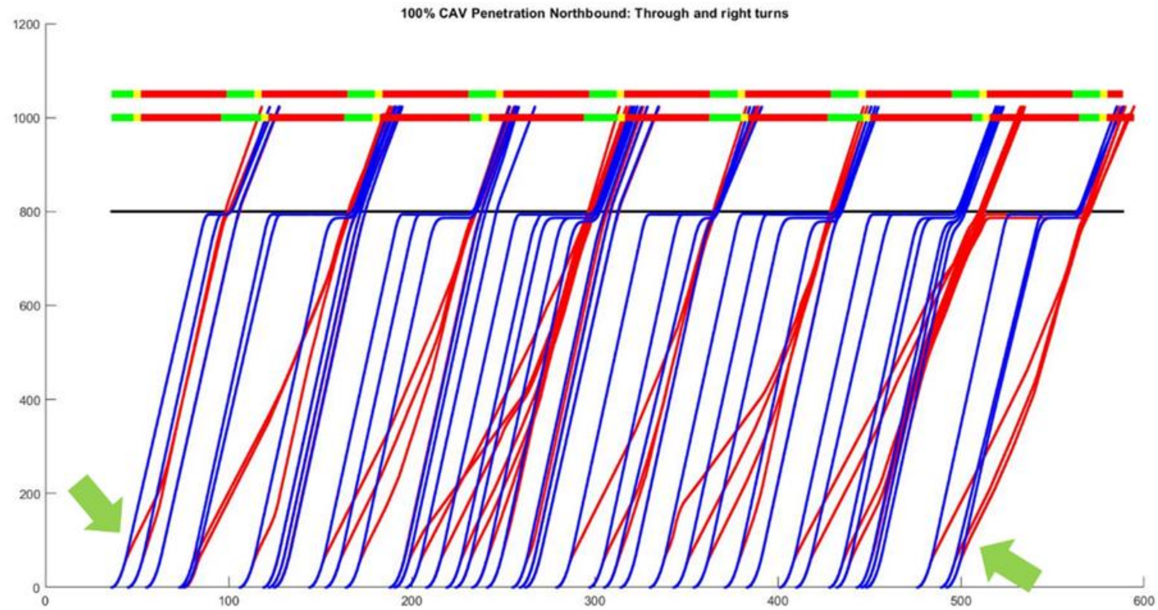
(a) Through and Right Turn



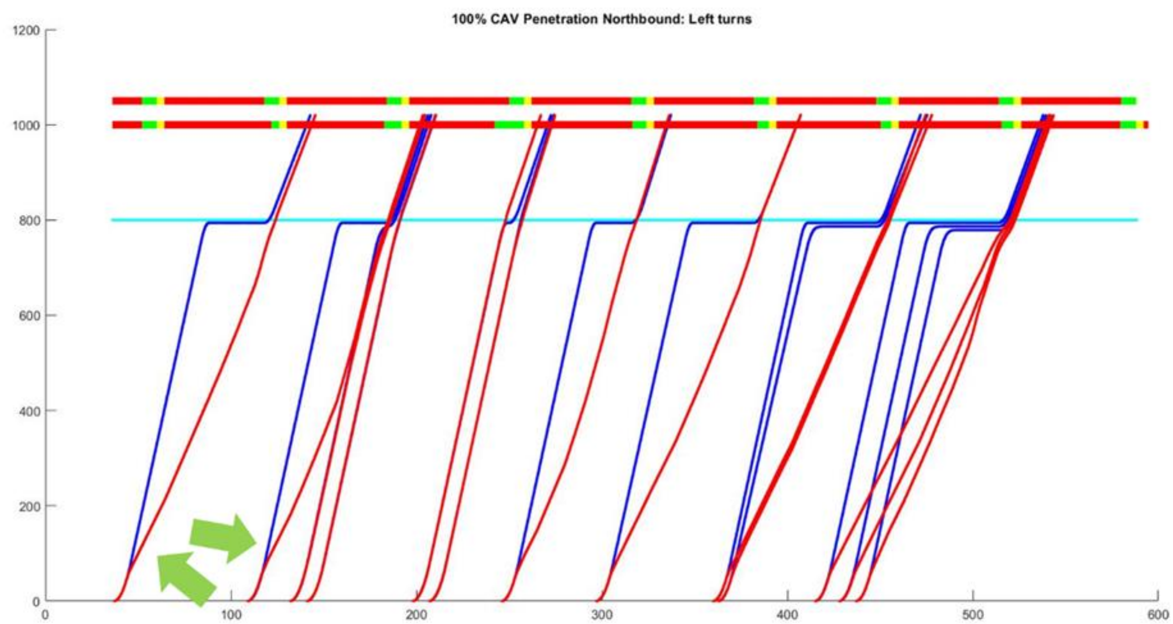
(b) Left Turn

Figure 11. Trajectory Plots for ECoTOp with 100% CAV penetration compared to Baseline in the Eastbound direction.

Figure 12 shows traffic trajectories for Northbound Through direction (a) and Northbound Left-turn (b) for traffic with that is 100% CAVs. The green arrows show examples of when a CAV changes its trajectory plan in order to pass through the intersection on a green light. The figure shows that the baseline vehicles stop and have to wait at almost each traffic signal cycle. For the ECoTOp vehicles, the CAVs have very a high non-stop ratio.



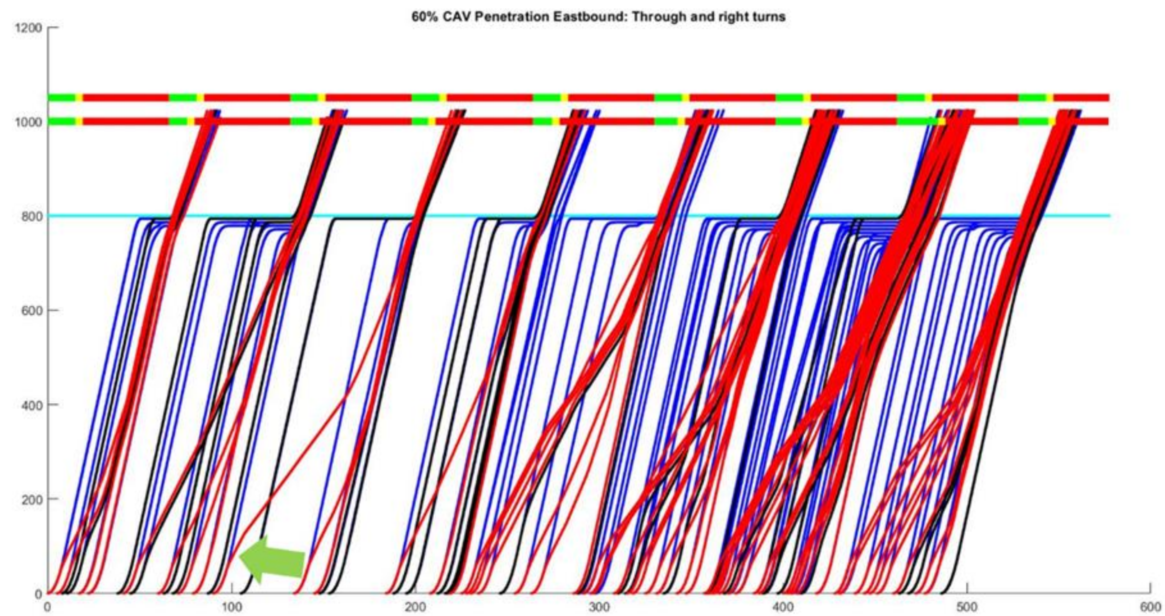
(a) Through and Right Turn



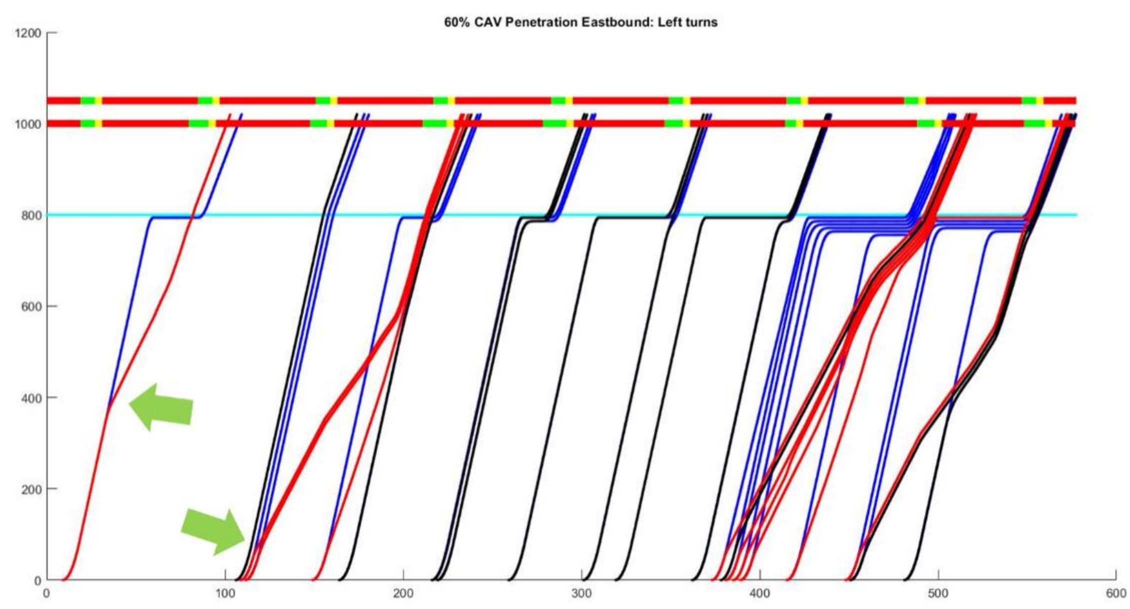
(b) Left Turn

Figure 12. Trajectory Plots for ECoTOp with 100% CAV penetration compared to Baseline in the Northbound direction.

Figure 13 shows traffic trajectories for Eastbound Through direction (a) and Eastbound Left-turn (b) for traffic with that is 60% CAVs. The green arrows show examples of when a CAV changes its trajectory plan in order to pass through the intersection on a green light. The figure shows that the baseline vehicles stop and have to wait at almost each traffic signal cycle. For the ECoTOp vehicles, the CAVs have very a high non-stop ratio.



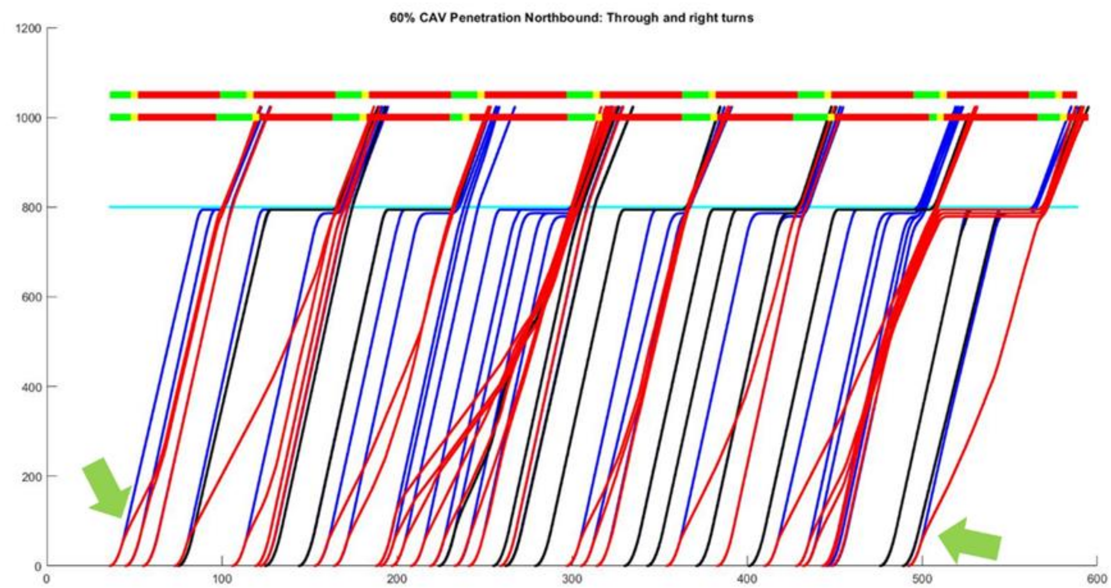
(a) Through and Right Turn



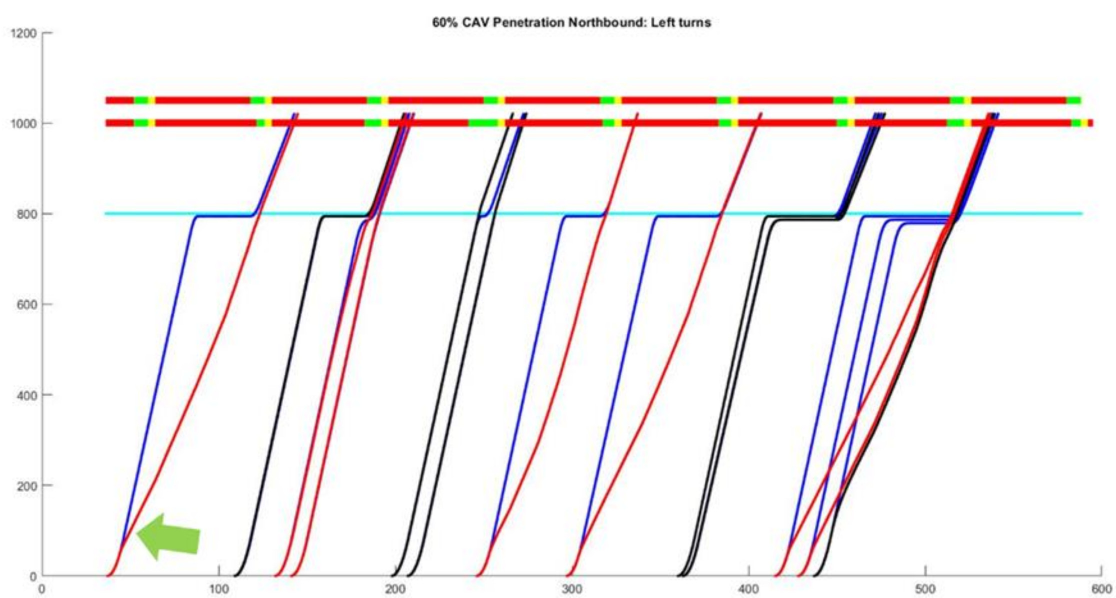
b) Left Turn

Figure 13. Trajectory Plots for ECoTOp with 60% CAV penetration compared to Baseline in the Eastbound direction.

Figure 14 shows traffic trajectories for Northbound Through direction (a) and Northbound Left-turn (b) for traffic with that is 60% CAVs. The green arrows show examples of when a CAV changes its trajectory plan in order to pass through the intersection on a green light. The figure shows that the baseline vehicles stop and have to wait at almost each traffic signal cycle. For the ECoTOp vehicles, the CAVs have very a high non-stop ratio.



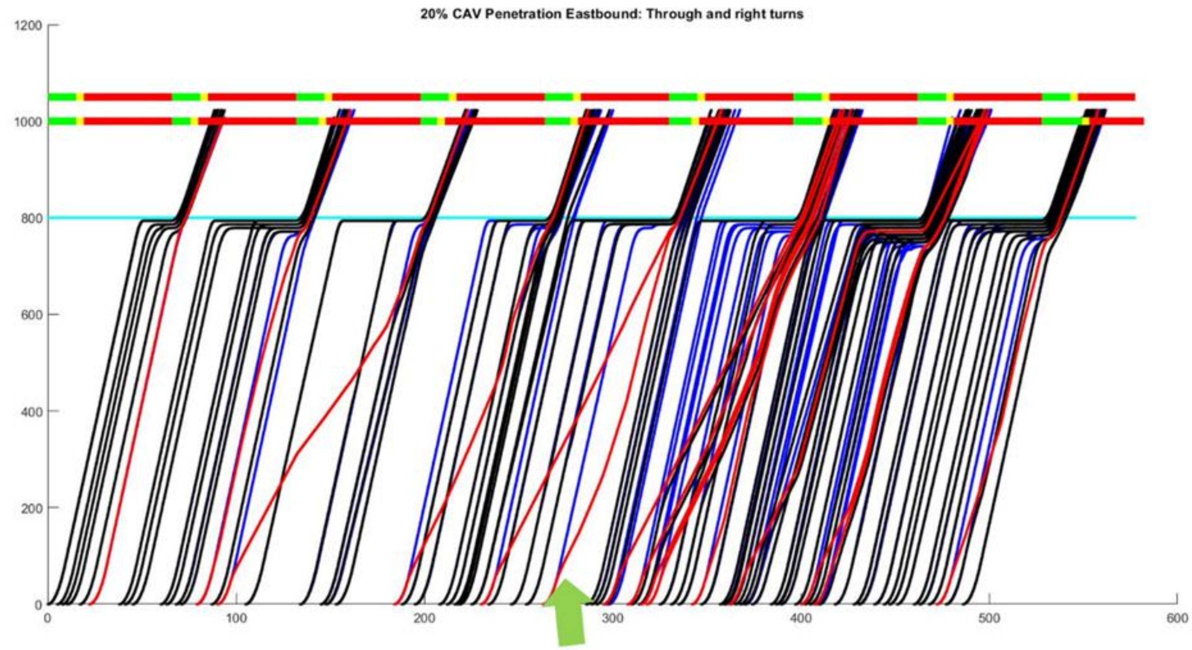
(a) Through and Right Turn



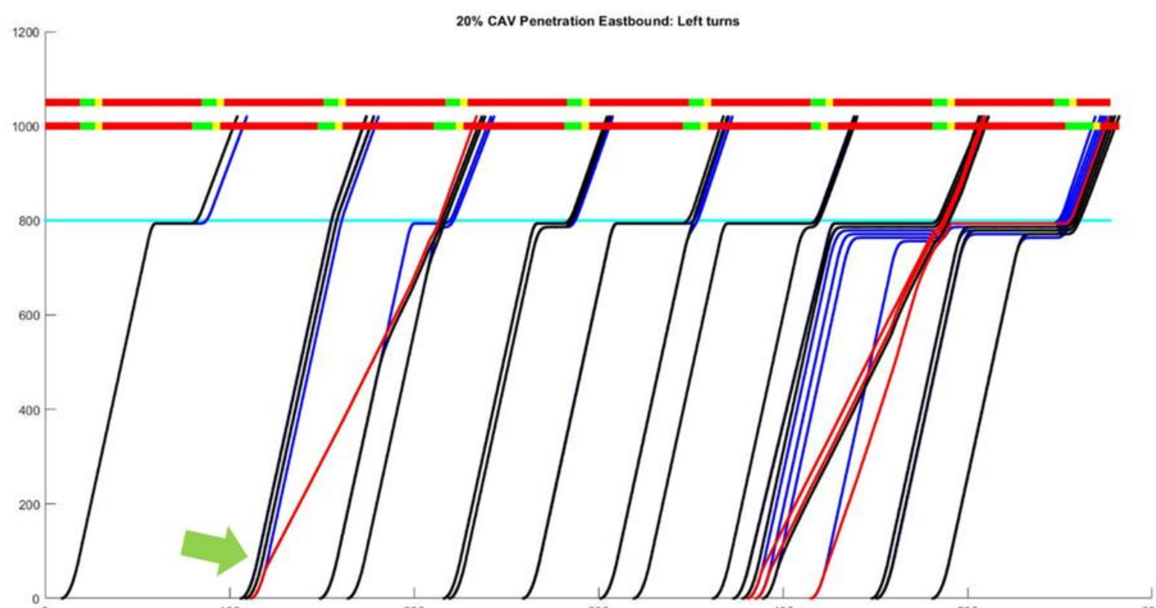
(b) Left Turn

Figure 14. Trajectory Plots for ECoTOp with 60% CAV penetration compared to Baseline in the Northbound direction.

Figure 15 shows traffic trajectories for Eastbound Through direction (a) and Eastbound Left-turn (b) for traffic with that is 20% CAVs. The green arrows show examples of when a CAV changes its trajectory plan in order to pass through the intersection on a green light. The figure shows that the baseline vehicles stop and have to wait at almost each traffic signal cycle. For the ECoTOp vehicles, the CAVs have very a high non-stop ratio.



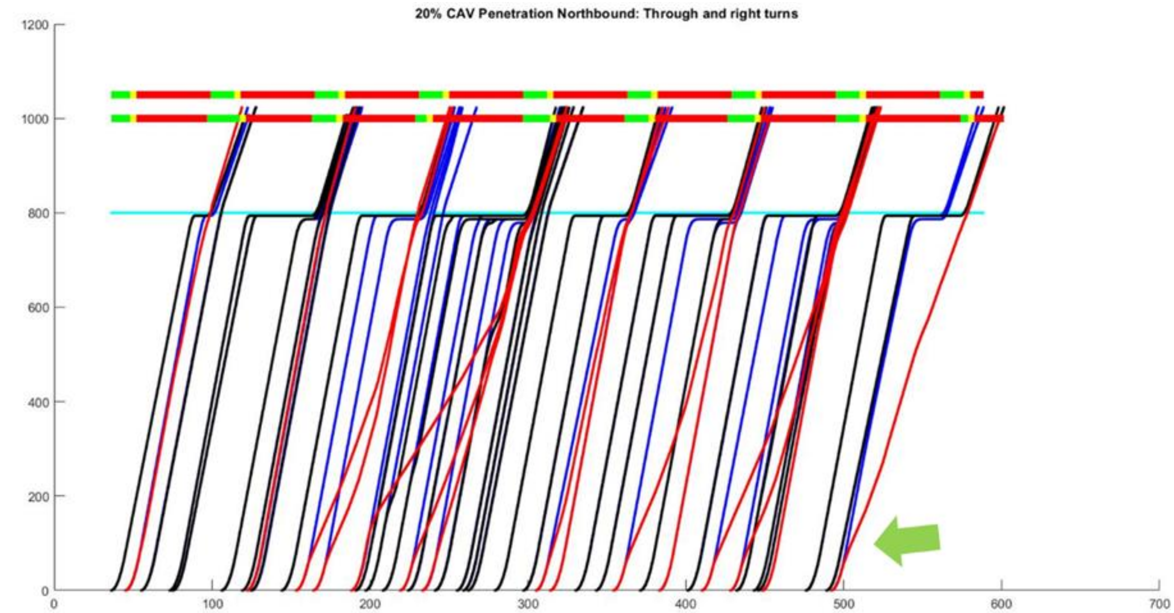
(a) Through and Right Turn



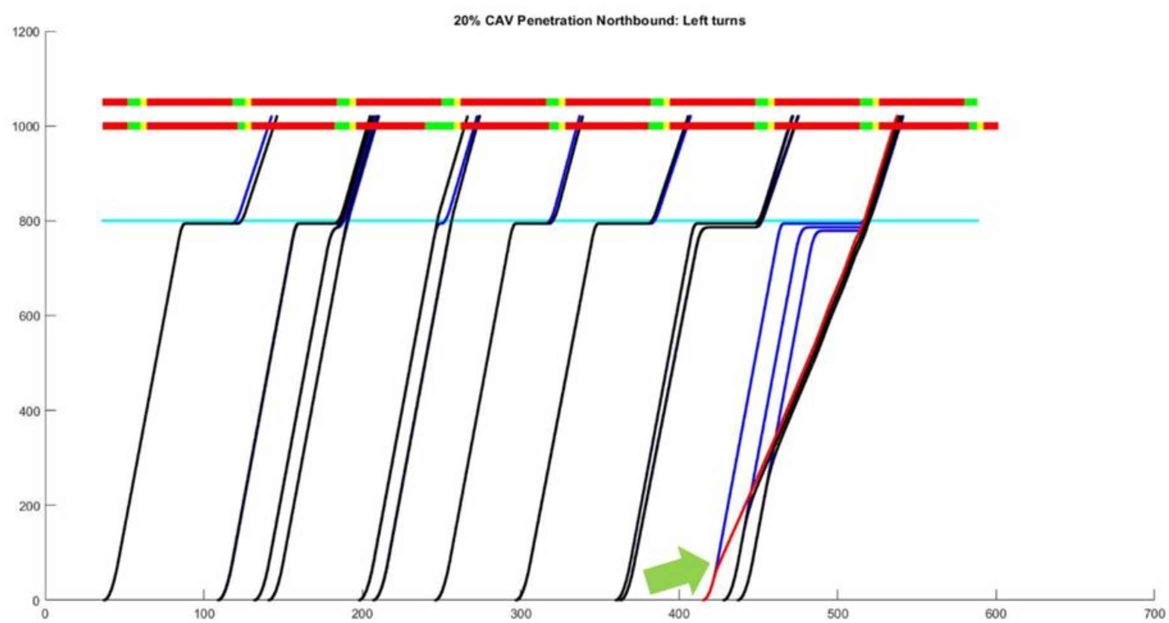
(b) Left Turn

Figure 15. Trajectory Plots for ECoTOp with 20% CAV penetration compared to Baseline in the Eastbound direction.

Figure 16 shows traffic trajectories for Northbound Through direction (a) and Northbound Left-turn (b) for traffic with that is 20% CAVs. The green arrows show examples of when a CAV changes its trajectory plan in order to pass through the intersection on a green light. The figure shows that the baseline vehicles stop and have to wait at almost each traffic signal cycle. For the ECoTOp vehicles, the CAVs have very a high non-stop ratio.



(a) Through and Right Turn



(b) Left Turn

Figure 16. Trajectory Plots for ECoTOp with 20% CAV penetration compared to Baseline in the Northbound direction.

5. Conclusions

This research proposes the Eco-friendly Cooperative Traffic Operation System framework, which specifically showcases an eco-driving strategy that will combine the efforts of a real-time phase and timing signal algorithm and real-time vehicle trajectory optimization. The network was built in the open-source traffic simulator SUMO, and simulations were run for different CAV percentage scenarios. The velocity trajectories from the SUMO simulation runs were saved and used in CMEM to estimate fuel consumption. SUMO provides an option to track vehicle waiting times and save to an output file similar to how the vehicle trajectories are saved. ECoTOp was able to reduce fuel consumption by up to 15.4% and reduced waiting times by up to 85.7% based on the simulation results. Under lower penetration rate, the fuel saving benefit is degraded, e.g., 11.8% reduction under 80% penetration, 84% under 60% penetration and 4.6% under 40% penetration. The simulation results also show that the ECoTOp outperforms the other scenarios including signal optimization only and EAD only cases.

Regarding future work, the performance of the system with mixed types of vehicles (including light-duty and heavy-duty trucks) will be tested and analyzed. In addition, this research optimizes the signal timing under adaptive signal framework, other approaches will higher flexibility on signal timing will be tested to investigate the co-optimization capability with vehicle dynamics. Furthermore, more experiments including micro- simulation and field experiments can be conducted to analyze the performance in more realistic situations.

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Data Summary

Products of Research

In this project, we collected vehicle speed trajectories for all CAVs and non-CAVs from all approaches in the SUMO-based traffic simulation, with varying penetration rate at 0% (baseline), 20%, 50%, 80%, and 100%. Those data are used to validate the proposed algorithms and estimate the performance on mobility improvement and energy savings.

Data Format and Content

The data were saved in txt files in the format of second-by-second trajectories. For each time stamp, the vehicle's dynamic state, e.g., location, speed and acceleration rate, the signal timing information, CAV status, turning status, etc.

Data Access and Sharing

The data are publicly available via the UC Riverside instance of Dryad: https://datadryad.org/stash, which is in compliance with the USDOT Public Access Plan. This dataset can be cited as:

> Hao, Peng; Oswald, David; Barth, Matthew; Wu, Guoyuan (2023), Vehicle trajectory data in Eco-friendly Cooperative Traffic Optimization (ECoTOp) system at signalized intersections, Dryad, Dataset, https://doi.org/10.6086/D1367Q

Reuse and Redistribution

The data are restricted to research use only. If the data are used, our work should be properly cited:

> Hao, Peng; Oswald, David; Barth, Matthew; Wu, Guoyuan (2023), Vehicle trajectory data in Eco-friendly Cooperative Traffic Optimization (EcoTOp) system at signalized intersections, Dryad, Dataset, https://doi.org/10.6086/D1367Q

Appendix

In Section 4. Numerical Results of this report, we show the trajectories of eastbound and northbound traffic. The westbound and southbound traffic are shown here in the appendix.

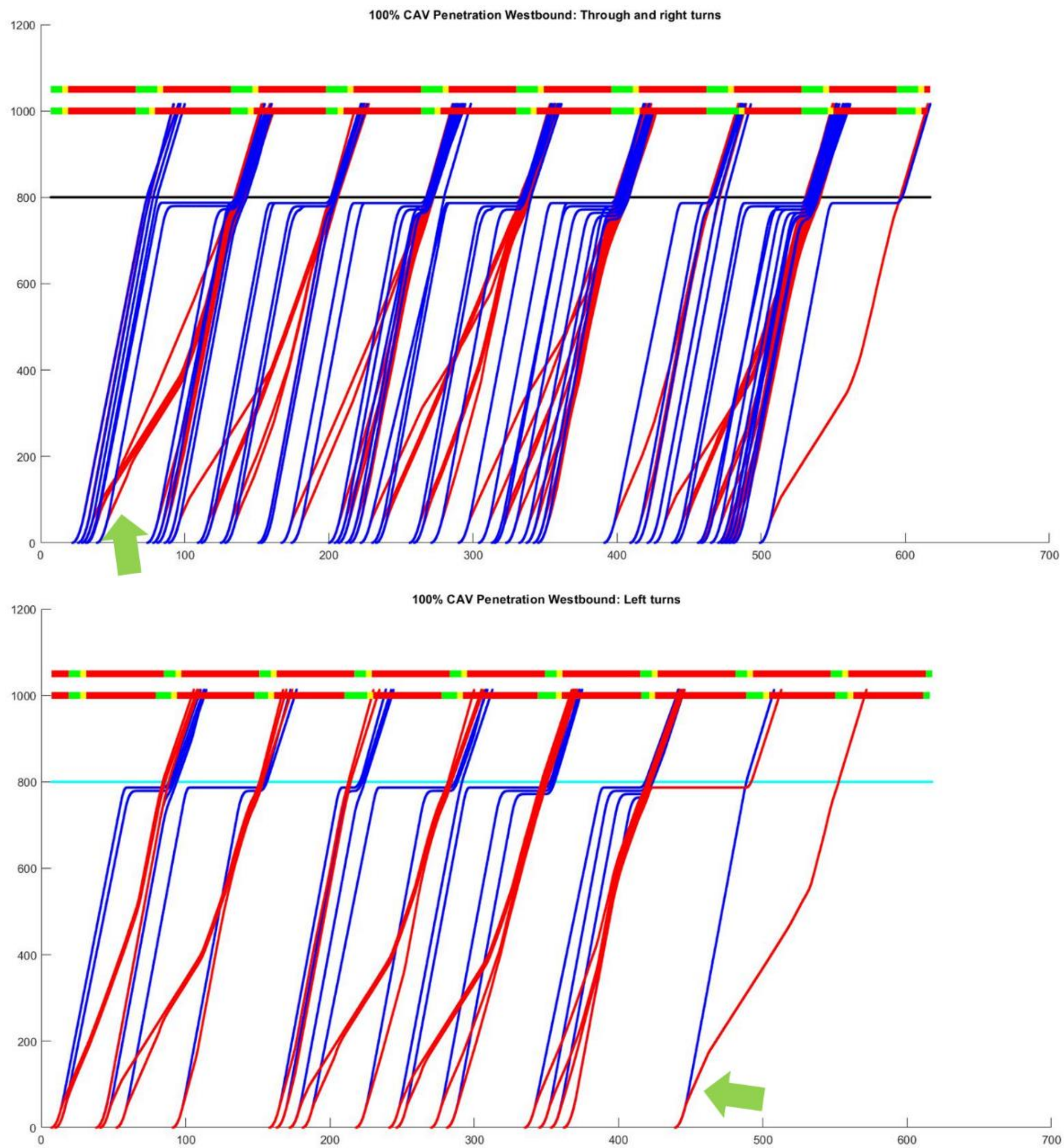

Figure 17. Trajectory Plots for ECoTOp with 100% CAV penetration compared to Baseline in the Westbound direction.

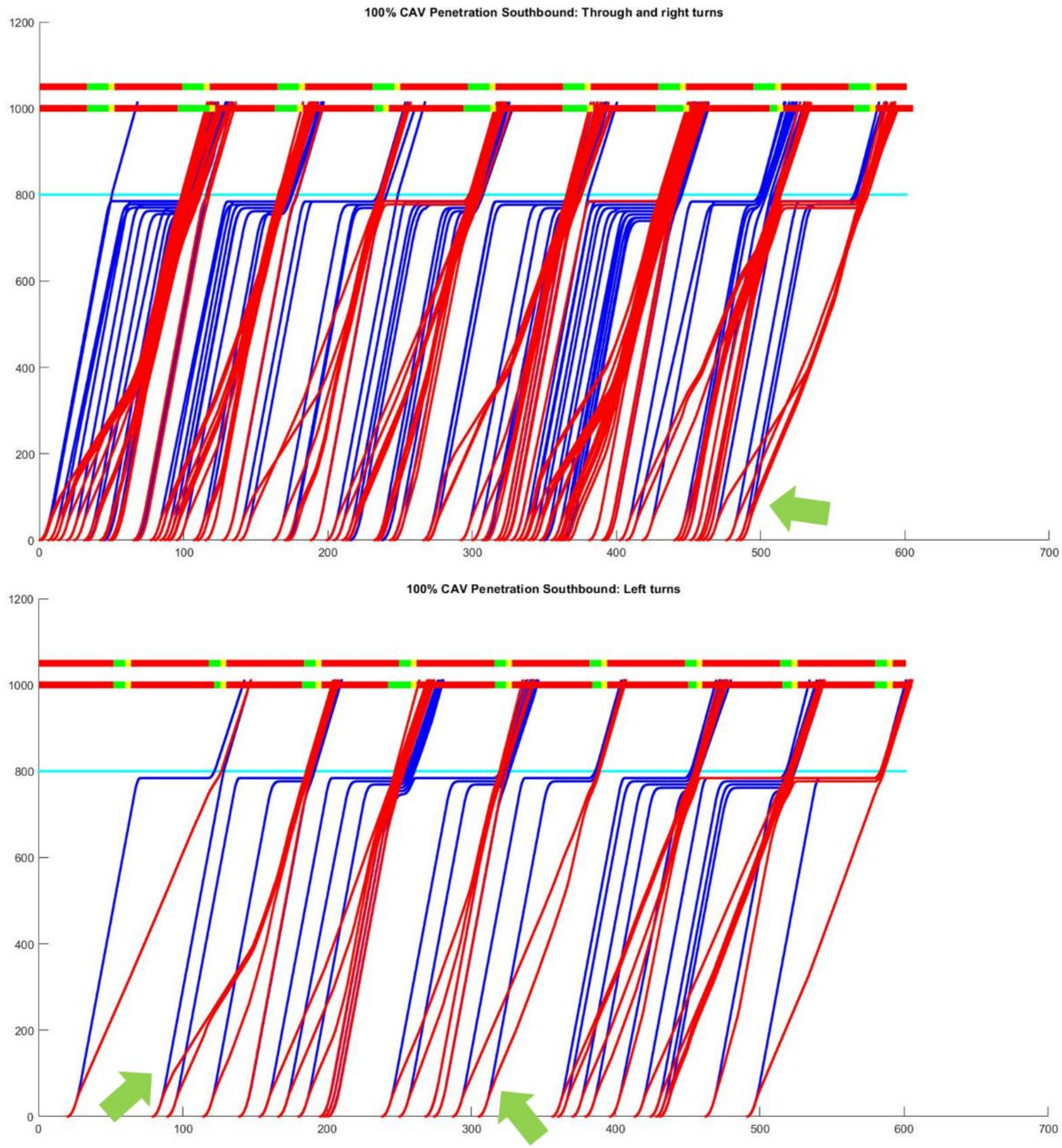

Figure 18. Trajectory Plots for ECoTOp with 100% CAV penetration compared to Baseline in the Southbound direction.

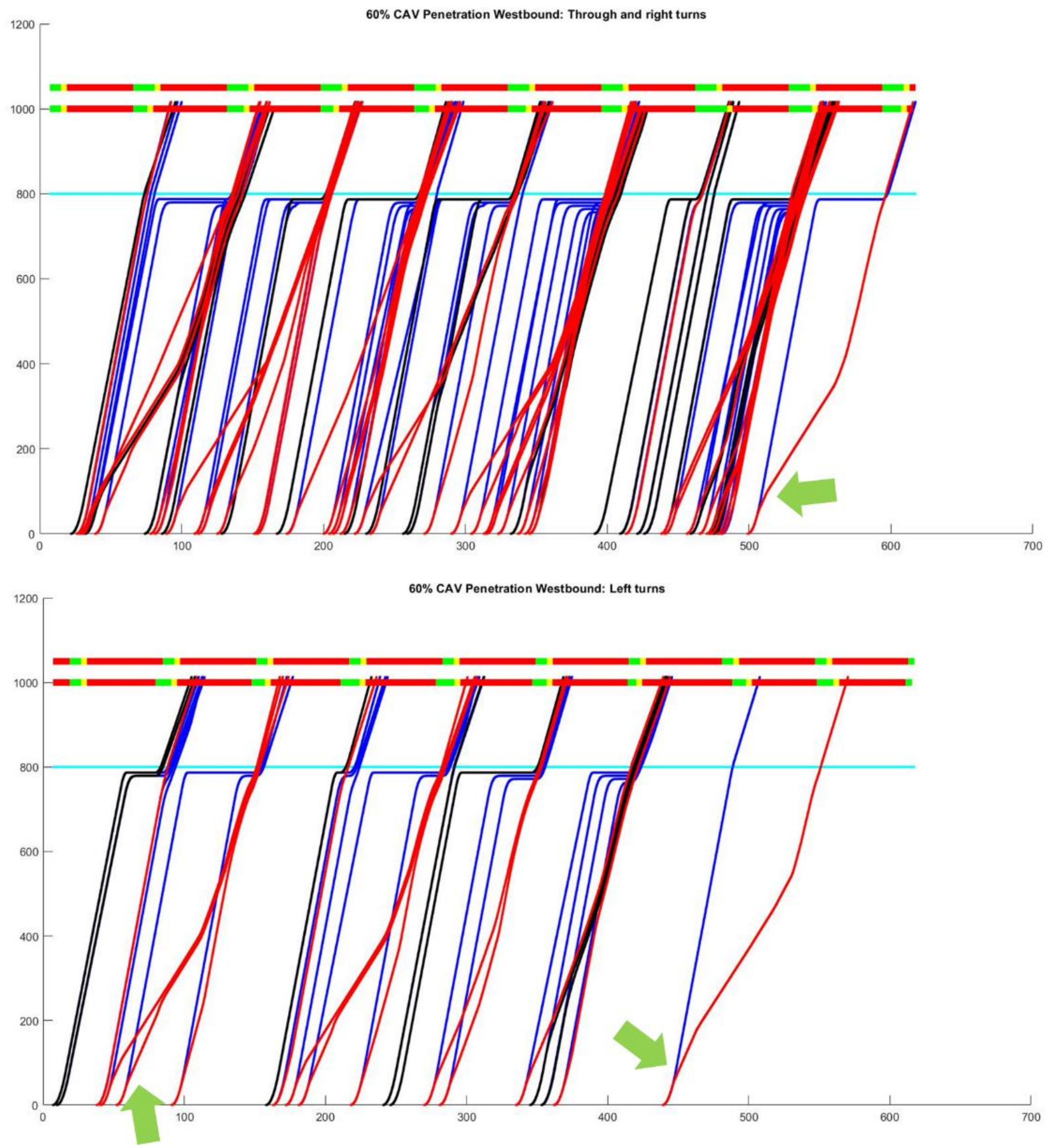

Figure 19. Trajectory Plots for ECoTOp with 60% CAV penetration compared to Baseline in the Westbound direction.

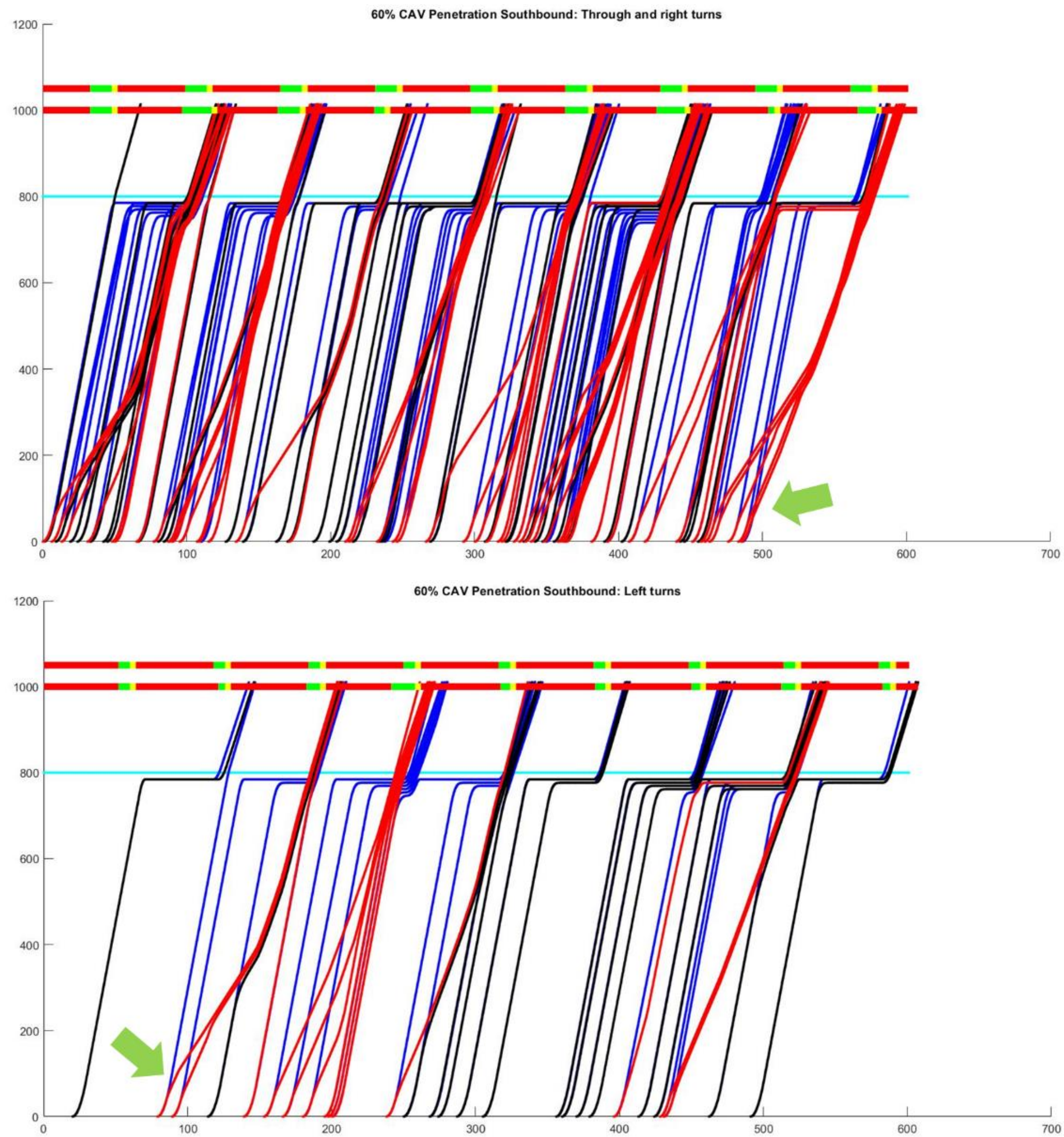

Figure 20. Trajectory Plots for ECoTOp with 60% CAV penetration compared to Baseline in the Southbound direction.

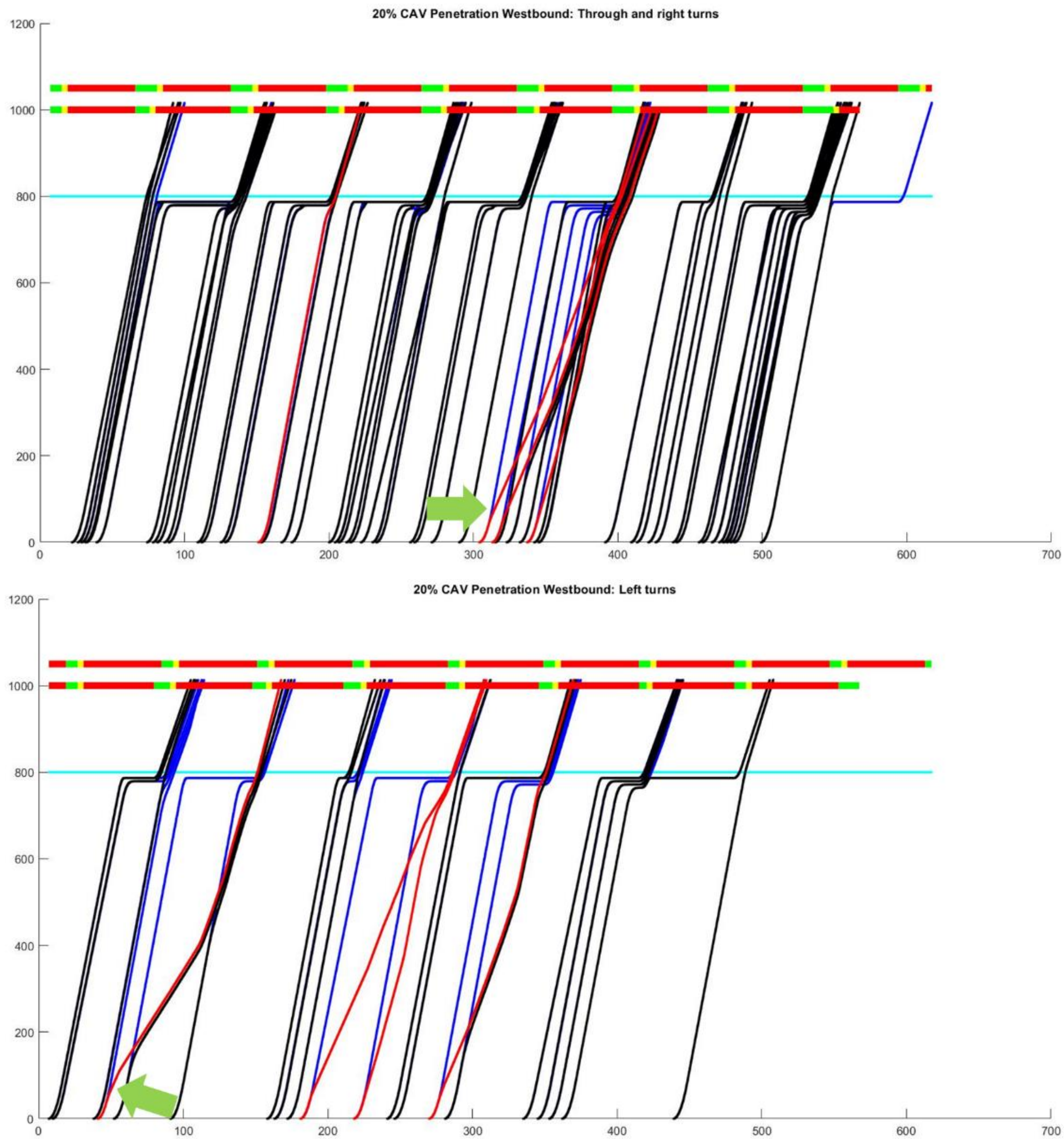

Figure 21 Trajectory Plots for ECoTOp with 20% CAV penetration compared to Baseline in the Westbound direction.

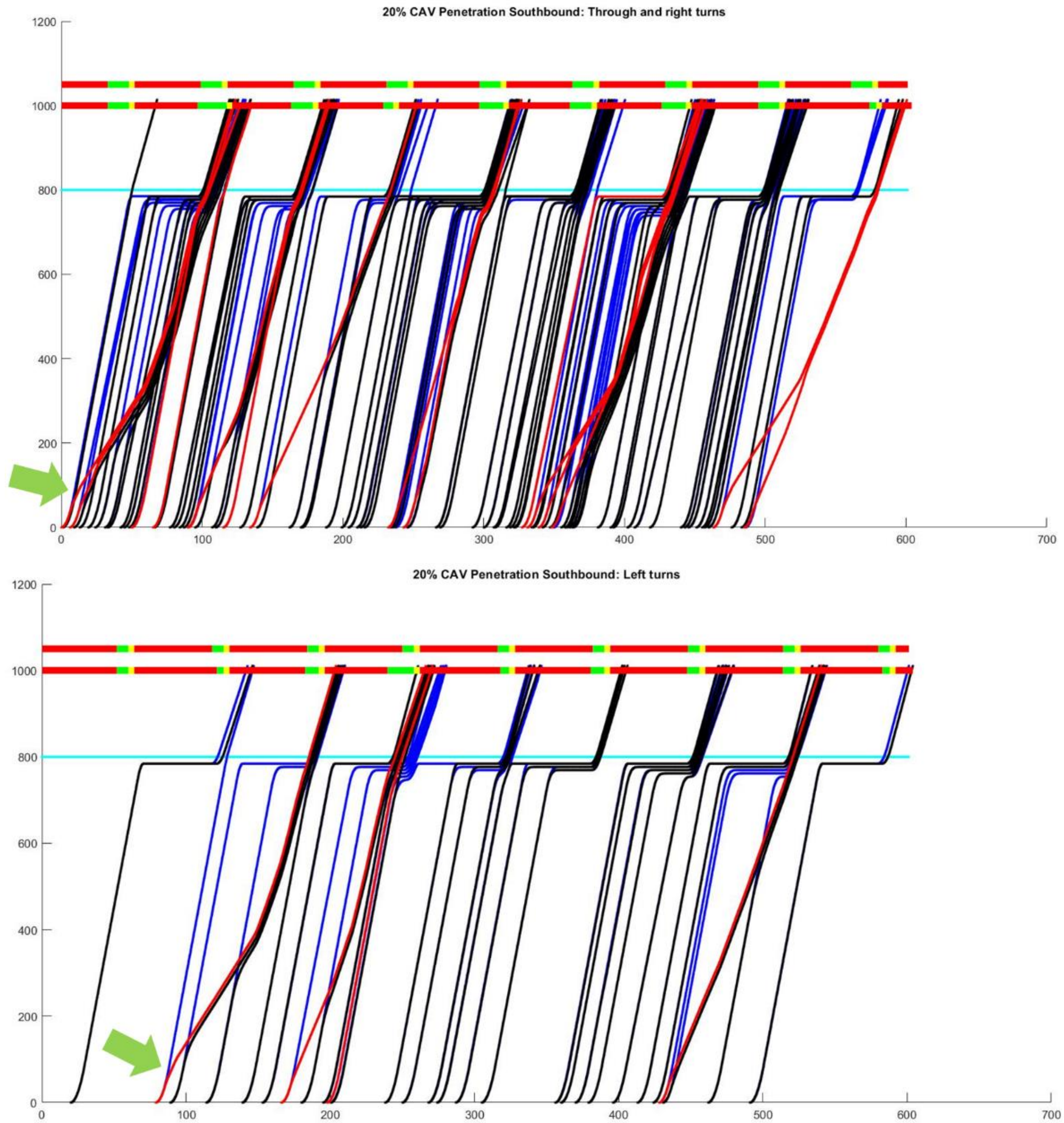

Figure 22. Trajectory Plots for ECoTOp with 20% CAV penetration compared to Baseline in the Southbound direction.