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Dynamic Cooperative Speed Optimization at Signalized Arterials with Various Platoons

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Abstract

Aggressive and inappropriate driving behaviors will lead to excessive fuel consumption. Both the Signal Phase and Timing (SPaT) and the status of preceding vehicles have significant impacts on driving behaviors. Drivers can obtain accurate SPaT information and the status of preceding vehicles via V2X communications. Many speed advisory strategies have been presented based on the consideration of this information. However, existing studies do not consider the cooperative optimization of multiple intersections and various platoons. Once connected vehicles travel through intersections with their own fuel-optimum trajectories, the following vehicles could be adversely affected by the preceding vehicles, leading to the following vehicles being stopped at the intersection. To address these problems, this paper presents an improved cooperative eco-driving model for when a vehicle passes two successive traffic signals during the green phase; a dynamic nonlinear programming algorithm is used to generate the optimal speed profile for various platoons considering the SPaT and the preceding vehicles' status. Numerous simulations on VISSIM for uninformed and connected vehicles haves been conducted to make comparison analysis. It is apparent that the proposed eco-driving model produces a significant fuel saving. In addition, cooperative optimization for the various platoons and separate optimization of multiple vehicles were performed to seek the most effective solution. The results indicated that systematic optimization (cooperative optimization of the all vehicles) is identified as the fuel-optimum approach in comparison to the separate optimization.

Over the last few decades, traffic congestion, energy consumption, and air pollution have become large-scale social problems because of the increase in car ownership. According to the report (*1*), energy consumption by the U.S. transportation sector was 11.307 trillion British thermal units up to May in 2017, more than 28% of the the country's total energy consumption.

Many factors may influence exhaust emissions and energy consumption, such as the size and age of the vehicle, type of the engine, quality of fuel, road conditions, driving behaviors, and so forth. Among these potential factors, driving behaviors, such as acceleration, deceleration, idling, cruising, and gliding, are quantifiable in that they require an adjustment of the gas or brake pedal, and are closely related to fuel consumption and exhaust emissions (*2–4*). Related research (*5–7*) has demonstrated that inexperienced operation or insufficient information often lead to hard acceleration or deceleration and unnecessary idling. Such aggressive and inappropriate driving behaviors lead to additional fuel consumption and exhaust emissions.

In urban traffic systems, blurred vision or have their attention distracted can prevent drivers from acquiring in time the accurate Signal Phase and Timing (SPaT) and the distance information of the current intersection. Drivers cannot obtain information on the next intersection because of restricted sight distance, which may lead to inappropriate driving behaviors, excessive exhaust emissions and fuel consumption.

Fortunately, with the development of the Internet of Vehicles, Vehicle to X (V2X) communications are now being widely used in analysis and in the construction of urban traffic infrastructure (*8*, *9*). It is entirely possible to receive the SPaT and distance information from

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hundreds of meters away from the traffic signals thanks to reliable communication technology. It is , therefore, possible to reduce extra fuel consumption and exhaust emissions by providing drivers with speed advice so that they can drive smoothly with fewer stops and delays.

Many approaches have been proposed to improve fuel efficiency and reduce emissions, including transmitting signal timing information to the upcoming vehicles through a variable message sign and adjusting the signal timing (*10–16*), thus reducing idling and minimizing acceleration and deceleration (*17–21*). Although acceleration, deceleration, and idling are taken into account as optimization objectives, the fuel savings are not directly estimated by the fuel consumption model.

With the presentation of the fuel consumption model, researchers have paid attention to building solutions based on an optimizing function of fuel consumption at isolated intersections (*22–25*). More recently, a few researchers have focused on dynamic speed advisory strategies on signalized arterial corridors (*26–31*). Most efforts have been devoted to providing advice on optimal speeds for drivers based on preceding queues and platoons (*32–34*). Jiang et al. (*32*) proposed an eco-driving system for an isolated signalized intersection in a mixed traffic environment of connected and conventional vehicles. Their control logic has been found to be robust and beneficial in relation to fuel consumption and throughput under different market penetration rates and traffic demands. Wan et al. (*33*) filled the gap left by Jiang et al. by looking at arterial corridors instead of isolated intersections. Furthermore, He et al. (*34*) took queue constraints into account and proposed a multi-stage optimal control model to provide optimal speed advice to drivers.

Although some researchers have considered the constraints from the preceding queues, the cooperative optimization between platoons or intersections has not been taken into account. To address these methodological gaps, this study proposes an improved cooperative eco-driving model by minimizing the fuel consumption. This is achieved by instructing the test vehicles to pass two adjacent intersections cooperatively. Many researchers (*30*, *31*, *33*, *34*) have studied optimal speed advice by considering an individual signalized intersection and then have applied this to arterial corridors, but when the test vehicles travel through the current intersection according to the optimal speed guidance and sometimes miss the crossing time of the latter intersection because of making no comprehensive consideration of the SPaT information of the latter intersection, this leads to additional fuel consumption and exhaust emissions and longer travel time. Many speed advisory strategies and eco-driving models have been presented using the SPaT information and the status of the preceding vehicles. However, the existing studies did not consider the cooperative optimization of multiple intersections and various platoons. Compared with other studies, the main contributions of this paper are:

- optimizing the speed trajectory cooperatively considering two successive signalized intersections, which avoids unnecessary fuel loss at the latter intersection because of the constraints on the optimization decision point;
- optimizing the speed trajectories cooperatively considering all vehicles in the network, which prevents the following vehicles from unnecessary idling; and
- considering the approaching platoon and the ahead platoon under different optimization modes to seek an optimal solution that can improve fuel efficiency.

The rest of this paper is organized as follows. The next section formulates the problem. The improved cooperative eco-driving model is then proposed. Simulations are then conducted for the connected vehicle and the uninformed vehicle, as well the various platoons. A summary concludes the paper.

Problem Statement

Cooperative Optimization for Consecutive Intersections

Existing research focuses on optimizing the speed profile for each intersection, and provides the drivers with speed advice on a corridor arterial merely through mathematical accumulation from several intersections. However, because of the position of the decision point (DP), as shown in Figure 1, when the connected vehicles arrive at the point and receive the speed advisory, they would fail to pass the intersection in time whether through acceleration or deceleration (the curve ③). Although the connected vehicles pass the first intersections with an optimal speed trajectory (the curve ②), the remaining time and the distance would make them unable to pass the second intersection, which consumes unnecessary fuel. As the curve ① in Figure 1 shows, if the optimization objective is the fuel consumption at the two intersections, the vehicles can pass the two intersections by taking full advantage of the time buffer as a result of cooperative optimization. Therefore, this paper continues our previous work to study the dynamic cooperative optimization for two consecutive intersections.

Cooperative Optimization Based on Various Platoons

The connected vehicles travel through the intersections with their own optimal trajectories, which would be identified as "selfless." If there were several vehicles behind

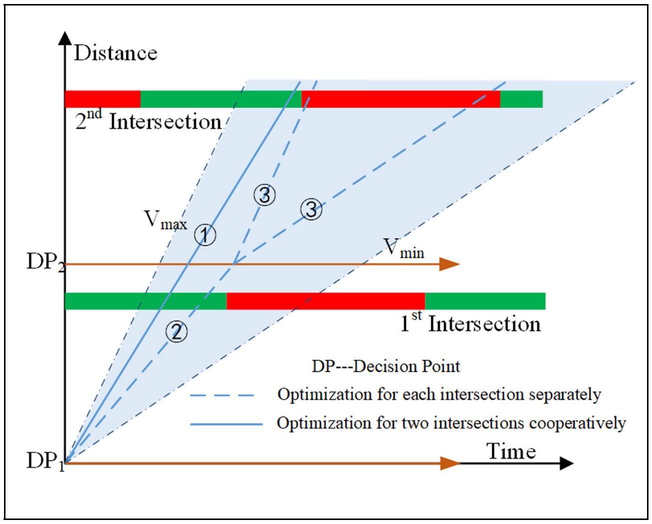

Figure 1. Cooperative optimization for two consecutive intersections.

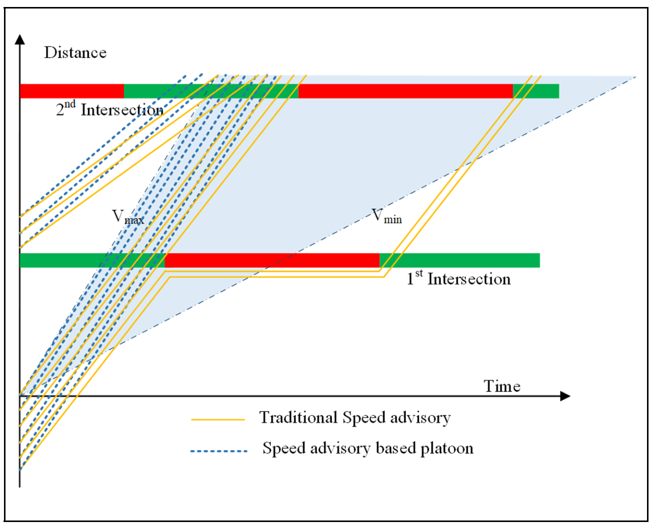

Figure 2. Cooperative optimization based on various platoons.

the test vehicles, the preceding vehicles should take the throughput of the following vehicles into account as much as possible, thus improving the road efficiency around the intersection and enhancing the fuel economy. In Figure 2, the blue dotted lines represent the optimal trajectories with platoons, while the yellow solid lines represent the trajectories that each vehicle follows on its own optimal speed profile. As we can see, if all vehicles travel with their own speed profiles, the following vehicles would be affected negatively, which can result in unnecessary stops. Therefore, cooperative optimization of various platoons around the intersection is significant and beneficial to fuel economy.

In our previous research (*35*), we presented a dynamic cooperative eco-driving model, which can provide speed

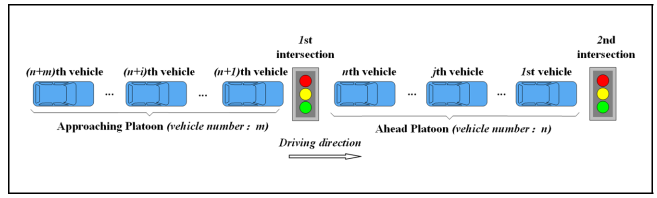

Figure 3. Concept of the proposed improved cooperative eco-driving model on an urban road.

advice to the connected vehicles to minimize little fuel consumption as much as possible. However, the model did not consider whether the following vehicles can pass the intersection. The test vehicles cross the signalized intersections selfishly with their own optimal fuel economy. Therefore, this paper proposes an improved cooperative eco-driving model considering the whole fuel economy of various platoons. In Figure 3, the vehicles between the two intersections are regarded as the ahead platoon; the vehicles before the first intersection are identified as the approaching platoon. This paper focuses on addressing the problem that yields optimal speed profiles of various platoons under different optimization modes and gains the optimal fuel economy. The proposed model relies significantly on V2X communications to obtain the SPaT information, position information sent by roadside infrastructure, position, and velocity sent by other connected vehicles. On-board equipment can process the information to output optimal speed trajectories, which can be applied to instruct the connected vehicles to pass the two signalized intersections in an eco-friendly behavior.

Improved Cooperative Eco-Driving Model

The improved cooperative eco-driving model is used to yield the fuel-optimum speed profiles for the vehicles of platoons approaching two successive signalized intersections. This model employs the Virginia Tech Comprehensive Power-Based Fuel Consumption Model (VT-CPFM) (*36*, *37*), which was presented by Rakha et al. to estimate fuel consumption for various pairs of velocity and acceleration.

The VT-CPFM model is formulated as follows:

$$FC(t) = \begin{cases} \alpha_0 + \alpha_1 P(t) + \alpha_2 P^2(t) & \forall P(t) \geq 0 \\ \alpha_0 & \forall P(t) < 0 \end{cases} \tag{1}$$

$$P(t) = \frac{R(t) + 1.04ma(t)}{3600\eta_d} \cdot v(t) \tag{2}$$

$$R(t) = \frac{\rho}{25.92} C_d C_h A_f v^2(t) + mg \frac{C_r}{1000}(c_1 v(t) + c_2) + mgG(t) \tag{3}$$

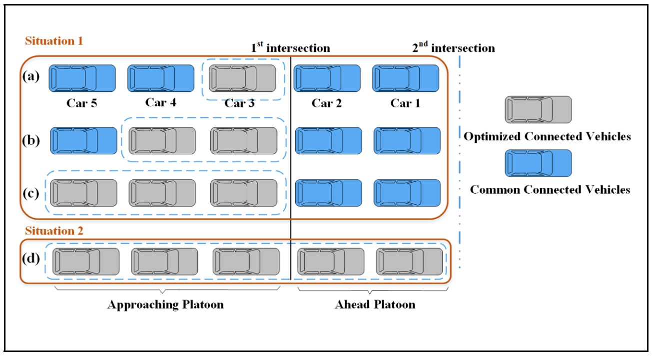

Figure 4. Optimization settings with various platoons.

where

$FC(t)$ is the fuel consumption rate,
$P(t)$ is the instantaneous power,
$R(t)$ is the total resistance force,
$a(t)$ is the instantaneous acceleration, and
$v(t)$ is the instantaneous velocity.

In this section, we design an improved cooperative eco-driving model considering the cooperative optimization of various platoons. As shown in Figure 4, we divide the optimization issue into two situations:

(1) The speed trajectories of the ahead platoon have already been optimized and the trajectories can be obtained by the approaching platoon. The optimization objective is the fuel consumption of the approaching platoon. The improved cooperative eco-driving model (CEM-1) is formulated as follows:

$$J = \min \sum_{i=1}^{n} \left(\int_{t_0}^{t_{si}} FC_i(t)dt \right) = \sum_{i=1}^{n} \left(\int_{t_0}^{t_{fi}} FC_i(t)dt + \int_{t_{fi}}^{t_{si}} FC_i(t)dt \right) \tag{4}$$

where i is the number of vehicles of the approaching platoon, t_{fi} and t_{si} are the time when the ith vehicle crosses the first and the second intersections, respectively. $FC_i(t)$ is the fuel consumption rate of the ith vehicle.

Subject to:

1. $t_{fi} \in [0, t_{r1}]$
2. $\int_{t_0}^{t_{fi}} v_i(t)dt = x_f + 6(i-1) \times \beta$
3. $t_{si} \in \begin{cases} [t_f, t_{g2} + T_G] \cup [t_{g2} + kT, t_{g2} + kT + T_G] & current\ \ \text{signal} = \text{red} \\ [t_f, t_{r2}] \cup [t_{r2} + kT + T_R, t_{r2} + (k+1)T] & current\ signal = green \end{cases}$
4. $\int_{t_{fi}}^{t_{si}} v_i(t)dt = x_s - x_f$
5. $a_{\min} \leqslant a_i(t) \leqslant a_{\max}$
6. $v_{\min} \leqslant v_i(t) \leqslant v_{\max}$
7. $x_{i+1}(t) + v_{i+1}(t) \cdot \alpha + \beta \leqslant x_i(t)$

where $v_i(t)$, $a_i(t)$, $x_i(t)$ are the velocity, acceleration and distance of the ith vehicle at time t, respectively. α is the dynamic gap between two vehicles with increased speed and β is the minimum static gap between two vehicles. In this paper, typical values of α and β are respectively 0.3 and 5.

(2) The speed trajectories of the ahead platoon combined with the approaching platoon are optimized together (i.e., systematic optimization). The improved cooperative eco-driving model (CEM-2) is formulated as follows:

$$J = \min \left(\sum_{j=1}^{n} \int_{0}^{t_{fj}} FC_j(t)dt + \sum_{i=1}^{m} \left(\int_{0}^{t_{fi}} FC_i(t)dt + \int_{t_{fi}}^{t_{si}} FC_i(t)dt \right) \right) \tag{5}$$

where i is the number of vehicles of the approaching platoon and j is the number of vehicles of the ahead platoon.

Subject to:

1 $t_{fj} \in \begin{cases} [t_{g2}, t_{g2} + T_G] \cup [t_{g2} + kT, t_{g2} + \ + kT + T_G] & current\ signal = \ red \\ [0, t_{r2}] \cup [t_{r2} + kT + T_R, t_{r2} + (k+1)T] & current\ \text{signal}\ = green \end{cases}$
2. $\int_0^{t_{fj}} v(t)dt = x_l + 6(j-1) \times \beta$
3. $t_{fi} \in [0, t_{r1}]$
4. $\int_{t_0}^{t_{fi}} v_i(t)dt = x_f + 6(i-1) \times \beta$
5. $t_{si} \in \begin{cases} [t_f, t_{g2} + T_G] \cup [t_{g2} + kT, t_{g2} + kT + T_G] & current\ \text{signal} = \text{red} \\ [t_f, t_{r2}] \cup [t_{r2} + kT + T_R, t_{r2} + (k+1)T] & current\ signal = green \end{cases}$
6. $\int_{t_{fi}}^{t_{si}} v_i(t)dt = x_s - x_f$
7. $a_{\min} \leqslant a_i(t) \leqslant a_{\max}$
8. $v_{\min} \leqslant v_i(t) \leqslant v_{\max}$
9. $x_{k+1}(t) + v_{k+1}(t) \cdot \alpha + \beta \leqslant x_k(t)$
$k = 1, 2, ...n, n+1, n+2, ...n+m$

where, x_l is the distance between the first vehicle of the ahead platoon and the second intersection. t_{fj} is the time when the jth vehicle of the ahead platoon travels across the second intersection. Table 1 lists the indices and parameters utilized hereafter.

The velocity, acceleration and distance expression are formulated as follows, which were proposed in our previous work.

$$v(t) = \begin{cases} v_f - (v_f - v_0) \cdot e^{-s_1 * t} & t \leqslant t_f \\ v_s + (v_f - v_s) \cdot e^{-s_2 * (t - t_f)} & t > t_f \end{cases} \tag{6}$$

$$a(t) = \begin{cases} (v_f - v_0) \cdot s_1 \cdot e^{-s_1 * t} & t \leqslant t_f \\ (v_f - v_s) \cdot (-s_2) \cdot e^{-s_2 * (t - t_f)} & t > t_f \end{cases} \tag{7}$$

$$x(t) = \begin{cases} v_f \cdot t + (v_f - v_0) \cdot \frac{1}{s_1} \cdot (1 - e^{-s_1 * t}) & t \leqslant t_f \\ x_f + v_s \cdot (t - t_f) - (v_f - v_s) \cdot \frac{1}{s_2} \cdot (1 - e^{-s_2 * (t - t_f)}) & t > t_f \end{cases} \tag{8}$$

Table 1. Indices and Parameters

s_1	Coefficients of the linearization solution to be optimized
s_2	Coefficients of the linearization solution to be optimized
T_R	All-red time of the signal cycle
T_G	Green time of the signal cycle
T	Time of the signal cycle
t_{r1}	Time to red of the 1st intersection
t_{g2}	Time to green of the 2nd intersection
t_{r2}	Time to red of the 2nd intersection
t_0	Time when the vehicle travels into communication range of DSRC
t_f	Time when the vehicle passes the 1st intersection
t_s	Time when the vehicle passes the 2nd intersection
x_f	Distance from origin to the 1st intersection
x_s	Distance from origin to the 2nd intersection
v_0	Velocity when the vehicle approaches communication range
v_f	Velocity when the vehicle passes the 1st intersection
v_s	Velocity when the vehicle passes the 2nd intersection
v_{max}	Speed limit
v_{min}	Desired minimal speed

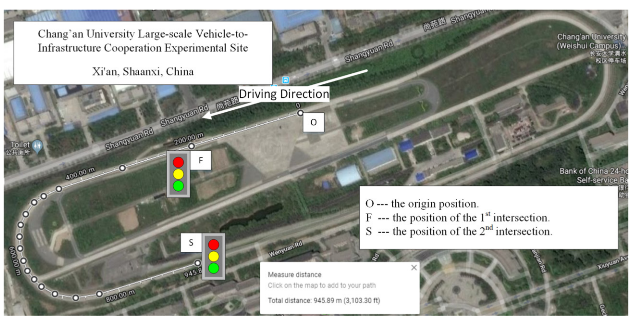

Figure 5. Simulation environment.

Numerical Examples

Simulation Settings

The Connected and Automated Vehicle (CAV) Test Field of Chang'an University in Weishui Campus of Chang'an University was chosen as the simulation environment. To simulate drivers who cannot obtain the SPaT and distance information accurately, two adjacent signalized intersections in the southwest and northwest were selected in our simulation environment. As shown in Figure 5, the position of the first intersection is marked as point F and the second intersection is marked as point S, which is also the end point, and point O is the start point. The distance between point F and S is 745 m. The distance between point O and F is 200 m, which is roughly equal to the communication range of DSRC. The traffic signal cycle is specified to 60 s, with 30 s on green and 30 s on red (the amber time is considered to be incorporated into red time). The phase difference between the adjacent intersections is 25 s. The connected vehicle and the uninformed vehicle are specified as a 2011 Honda Accord (*38*) to ensure the same simulation conditions, as Table 2 shows.

Table 2. Attributes in the Simulations

Related parameter	Value
Vehicle mass m (kg)	1,487
Vehicle frontal area $A_f(m^2)$	2.12
Vehicle drag coefficient C_d (unitless)	0.30
Altitude correction factor C_h (unitless)	0.95
Rolling resistance constant C_r (unitless)	1.25
Rolling resistance constant c_1 (h/km)	0.0438
Rolling resistance constant c_2(unitless)	6.10
Driveline efficiency η_d (unitless)	0.75
VT-CPFM parameter α_0 (unitless)	4.89E-04
VT-CPFM parameter α_1(unitless)	4.29E-05
VT-CPFM parameter α_2 (unitless)	1.00E-06

A Small Example

VISSIM, a micro traffic simulation software, can simulate the traffic scenes and evaluate the fuel consumption. In addition, the optimal speed trajectory can be used as the input of VISSIM to change driver behavior in real time through MATLAB plus a COM interface. The proposed eco-driving model is utilized to conduct simulations on VISSIM to produce real-time speed and change the driving behavior. Comparison analysis between the uninformed vehicle and the connected vehicle is conducted under two different desired speeds (40 and 50 km/h). The traffic signal will turn red in 27 and 23 s, respectively.

Figure 6*a* and *b* shows the trajectories of the uninformed vehicle (dotted lines) and the connected vehicle (solid lines) with two desired speeds. As indicated by the curves, many frequencies and magnitudes of the velocity and acceleration fluctuation of the uninformed vehicle have been caused, which lead to extra fuel consumption. The uninformed vehicle stopped at the second intersection because of the limited signal timing information received in advance, which consumes more fuel than that of the connected vehicle.

Table 3 indicates the fuel consumption and travel time of the uninformed vehicle and the connected vehicle. As shown in Figure 6, the uninformed vehicle stopped at the second intersection while the connected vehicle crossed two intersections by accelerating. The connected vehicle avoids unnecessary idling and saves a lot of fuel. The fuel saving is up to around 29%.

Simulations with Various Platoons

In this section, the ahead platoon and the approaching platoon are considered to gain fuel benefits under

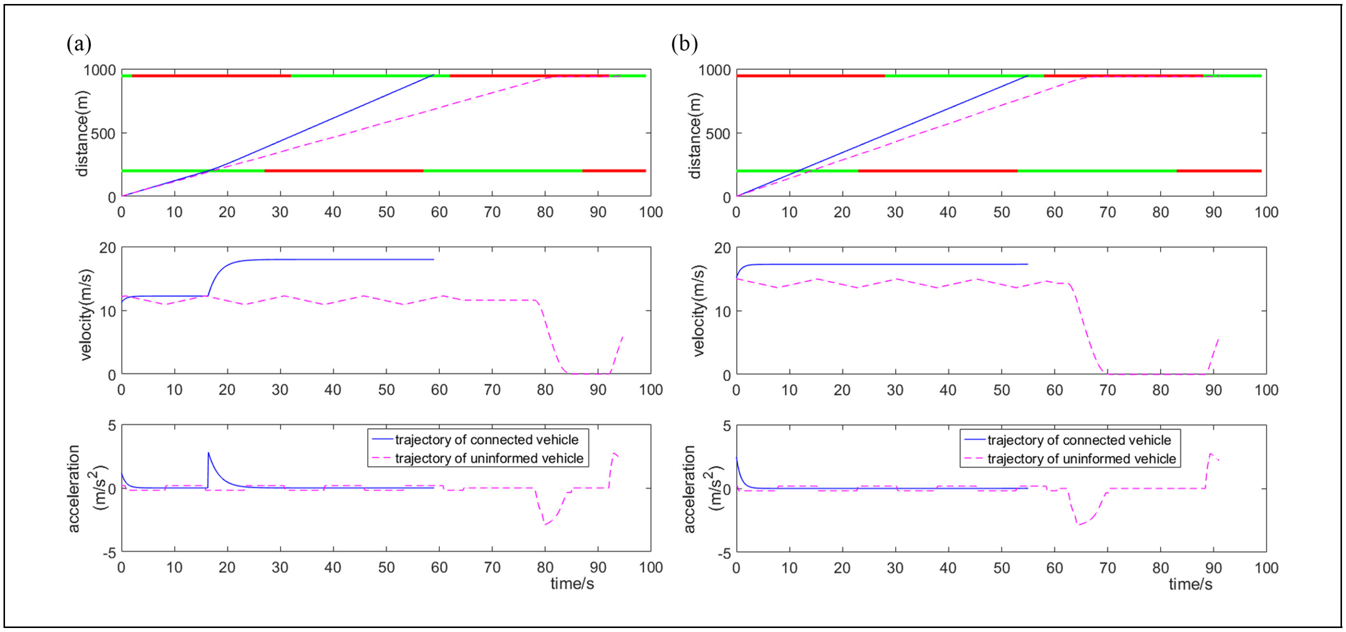

Figure 6. Trajectories of the uninformed vehicle and the connected vehicle: (*a*) desired speed = 40 km/h; and (*b*) desired speed = 50 km/h.

Table 3. Performance Comparison between the Uninformed Vehicle (UV) and the Connected Vehicle (CV)

	Travel time (s)		Fuel consumption (L)		Fuel economy (L/100 km)		Fuel saving (%)
	UV	CV	UV	CV	UV	CV	
40 km/h	95	59	0.0588	0.0534	6.222	5.651	9.18%
50 km/h	91	55	0.0580	0.0410	6.138	4.339	29.31%

different optimization modes (cooperative and separate optimization). Traffic scenes are shown in detail in Figure 3. For simplicity, we simulated the ahead platoon to include two vehicles and the approaching platoon to include three vehicles, as shown in Figure 4. The simulation settings and vehicle parameters are the same as those described in section 4.1.

As far as we can see (Figure 4), four scenarios are simulated and analyzed. The CEOM-1 proposed above is applied to the first three scenarios while the CEOM-2 is applied to the forth. The trajectories of the ahead platoon in the first three scenarios can be obtained by the approaching platoon. The gray vehicles are the optimization target that can produce a fuel-optimum trajectory. The blue vehicles in the approaching platoon use a typical car-following model (typically, IDM).

***Scenario 1*:** The connected vehicle to be optimized is approaching the intersection with two vehicles following (shown in Figure 4*a*). The dynamic constraints are from the traffic signal status and the ahead platoon. The optimized trajectories of the two platoons are shown in Figure 7. As we can see, the common connected vehicles in the approaching platoon are

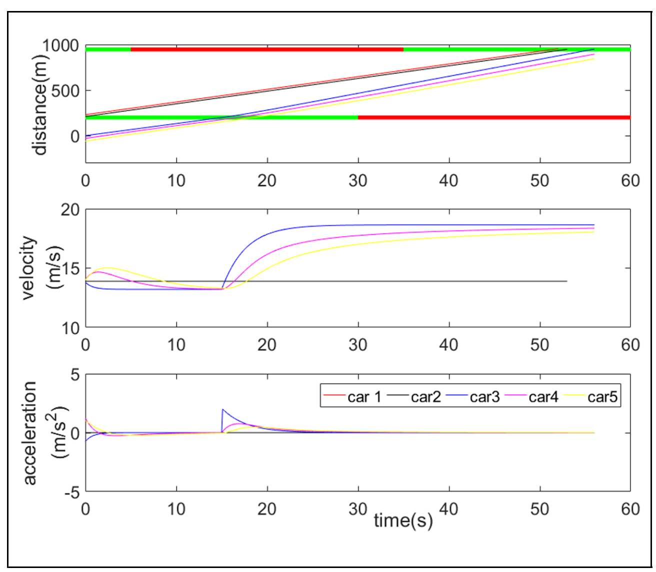

Figure 7. Trajectories of the platoons in Scenario 1.

following with IDM and then almost maintain a low velocity to pass the intersections.

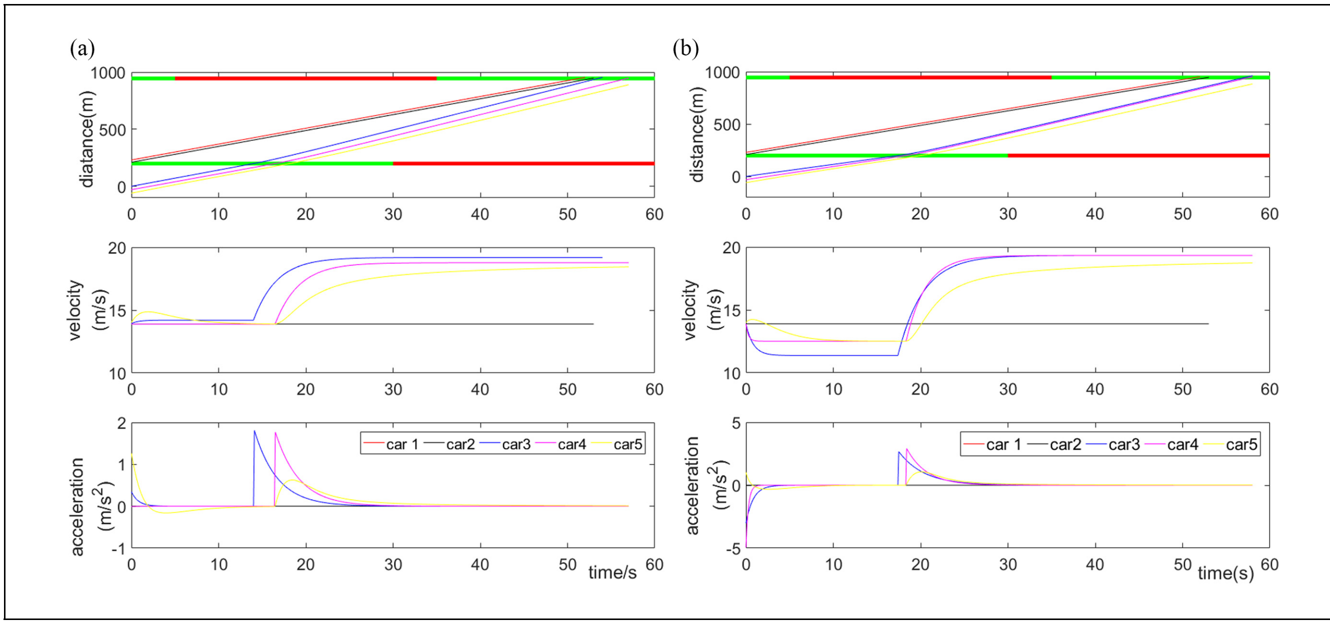

Figure 8. Trajectories of the platoons in Scenario 2: (*a*) cooperative optimization; and (*b*) separate optimization.

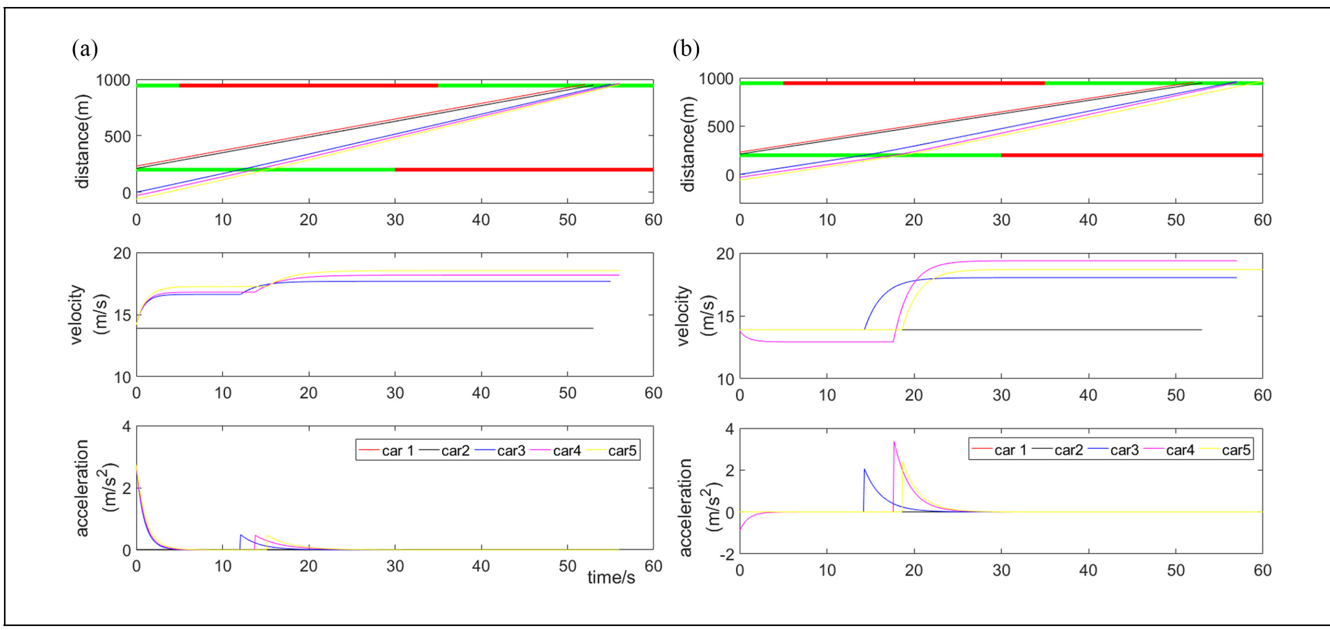

Figure 9. Trajectories of the platoons in Scenario 3: (*a*) cooperative optimization; and (*b*) separate optimization.

***Scenario 2*:** The two connected vehicles to be optimized are approaching the intersection with one vehicle following (shown in Figure 4*b*). The optimization process could be either optimizing the two vehicles together (cooperative optimization) or optimizing the two vehicles separately (separate optimization). The trajectories in the two optimization modes are shown in Figure 8*a* and *b*, respectively. It can be observed that the approaching platoon in the separate optimization is decelerating to cross the first intersection and then accelerating to pass the second, which yields more fuel consumption than that in the cooperative optimization. The distance between the first vehicle of the approaching platoon (car 3) and the last vehicle of the ahead platoon (car 2) in the cooperative optimization is tighter than in the separate optimization, which can improve road efficiency.

***Scenario 3*:** The three connected vehicles to be optimized are approaching the intersection (shown in Figure 4*c*). The optimization process could be either optimizing the three vehicles together (cooperative optimization) or optimizing the three vehicles

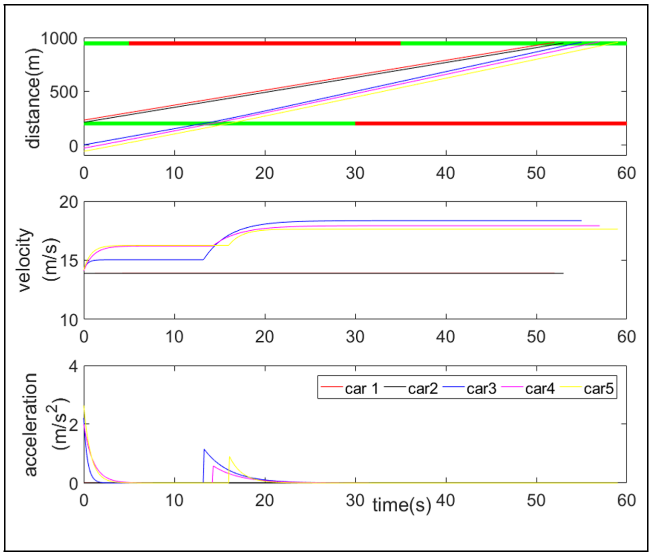

Figure 10. Trajectories of the platoons in Scenario 4.

separately (separate optimization). The trajectories in the two optimization modes are shown in Figure 9*a* and *b*, respectively. The approaching platoon in the separate optimization decelerates to pass the first intersection and then accelerates to cross the second intersection, which leads to larger fluctuations of speed and more fuel consumption than in the cooperative optimization.

Scenario 4: Both the approaching platoon and the ahead platoon are the connected vehicles to be optimized (shown in Figure 4*d*). All vehicles are considered as optimizing the fuel consumption systematically, which could cooperatively pass through the intersections (systematic optimization). The optimized trajectories are shown in Figure 10. It can be seen that the final velocities in the systematic optimization are lower than those in other optimization modes of other scenarios, which can produce less fuel consumption.

Figure 11 shows the total travel time and fuel consumption under the four scenarios mentioned above, respectively. The difference between the total travel times is tiny, but the travel time in systematic optimization is still less than that in other optimization modes. It can be observed that the fuel consumption in the cooperative optimization is generally less than in the separate optimization. It seems that systematic optimization could obtain the greatest benefit in fuel consumption among all the cooperative optimization.

Conclusion

This study proposed an improved dynamic eco-driving model to provide speed advice to vehicles that pass two successive signalized intersections on arterial corridors. The proposed dynamic optimization algorithm is adopted to optimize the trajectories of the various platoons via evaluating the fuel consumption on the trip. It improves efficiency and is able to: (1) provide speed trajectory with comprehensive consideration of the SPaT information of two successive intersections; (2) consider

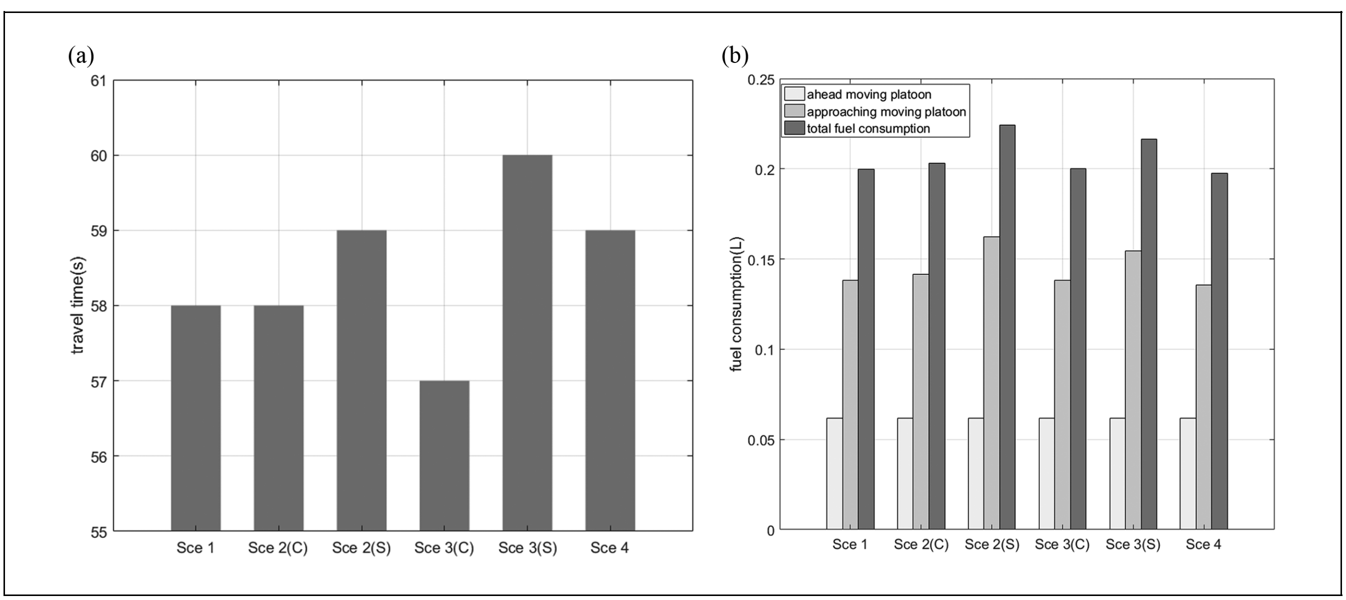

Figure 11. Comparison of fuel consumption and travel time under four scenarios: (*a*) travel time; and (*b*) fuel consumption (C represents cooperative optimization and S represents separate optimization).

the total fuel consumption of the ahead platoon and the approaching platoon; and (3) improve the fuel efficiency of all platoons with different optimization modes. In addition, numerous simulations on VISSIM for the connected vehicle and the uninformed vehicle were carried out to prove that the proposed dynamic optimization algorithm can provide a pretty effective solution to the issue. The results show that fuel savings reached up to 29%. Comparison analysis between different optimization modes is conducted and the simulation results show that the fuel consumption in the systematic optimization is the lowest compared with that in the other optimization modes.

On the other hand, the dynamic discharge of the front queues was not considered, the impacts from cut-in vehicles on other lanes and market penetration rate of the connected vehicles have not yet been discussed in this study. Moreover, the speed advisory decision system that embedded the proposed dynamic optimization algorithm has not been explored. The incomplete communication circumstance of the experimental site also put off our experiments. Once the communication environment and decision system are constructed, experiments will need to be carried out on how to instruct drivers to follow the speed advice.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: SY, XZ, QX, XW, QY; data collection: SY, QX, XW, KS; analysis and interpretation of results: SY, XW, XZ, QX, QY, KS; draft manuscript preparation: SY, XW, XZ, QY, QX. All authors reviewed the results and approved the final version of the manuscript.

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