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A Cyber-physical Optimal Coordination System for Connected and Automated Vehicles on the Multi-lane Freeways

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1 Introduction

Over the past few decades, the primary issues in road transportation systems around the world have been traffic congestion, fuel consumption, greenhouse gas (GHG) emissions, and accidents due to an increase in the number of vehicles and travel demand [1]. Furthermore, traditional human driving remains to be one of the major causes of traffic bottlenecks, since humans have difficulty accurately anticipating future road traffic conditions and frequently perform acceleration and braking, or an instant lane change. Schrank et al. [2] reported that traffic congestion caused American drivers to spend 8.8 billion extra hours on the road, consuming extra 3.3 billion gallons of fuel in 2017. Particularly, field studies show that stop-and-go vehicles produce 14% more emissions than vehicles traveling at a constant speed [3]. It is evident that effective measures should be taken to reduce the burden of uncontrolled traffic issues for better mobility, fuel economy, and the environment. Therefore, the concept of a coordinated traffic system is currently receiving great interest due to its potential to address a number of issues caused by human drivers, such as stop-and-go driving, travel delays, and traffic accidents [4, 5].

The recent developments in connected and automated vehicle (CAV) technologies enable real-time data access and sharing with other vehicles and infrastructure via vehicle-vehicle (V2V), infra-vehicle (I2V), and vehicle-infra (V2I) communications [6, 7]. When such necessary information is available, such as states (position, velocity, and acceleration) of other vehicles, destination, and speed limit, it is possible to precisely control the movement and trajectory of individual vehicles to enhance traffic flow efficiency, fuel economy, and driving safety under a connected vehicle environment (CVE) [8, 9]. The CVE offers both opportunities for effectively realizing better-coordinated traffic in a road network and difficulties in utilizing a large amount of data. Additionally, it is feasible to coordinate vehicles utilizing a cloud-based centralized or decentralized controller to enhance traffic flow performance, and safety [10, 11]. A traffic coordination system can improve traffic flow rate and capacity by making intelligent decisions using guidance information from the global controller. Moreover, the coordination can be repeated to ensure seamless operation even if the vehicle does not execute the command or if unexpected disruptions happen [12]. As a result, it can accurately modify the whole system, which would be very challenging for a human driver to achieve.

A number of studies have developed vehicle coordination systems for CAVs using centralized or decentralized controllers to achieve safe and efficient control of traffic. Some studies developed automated vehicle intersection control systems based on reservation algorithms [13–15], whereas some works utilized signal phase and timing (SPAT) information in advance via I2V communication to control the movement of automated vehicles [16–18]. Some works proposed optimization of traffic signal phases using the state information (e.g., location and speed) of autonomous vehicles [19–21], while some studies developed coordinated intersection control systems for autonomous vehicles under CVE without using traffic signals [22–24]. Some works reported coordinated merging control systems for a safe and smooth merging of automated vehicles using ramp metering [25–27], whereas some other works developed coordinated merging control schemes for efficient merging of CAVs into roundabouts [28–30]. These works [13–30] mainly focused on vehicle coordination systems for signalized intersections or merging roads.

On the other hand, some works proposed cooperative lane-changing methods for CAVs. For example, Hu et al. [34] and Awal et al. [35] proposed local lane change coordination of autonomous vehicles, which is limited to local modifications of the traffic condition. Atagoziyev et al. [36] developed a traffic coordination system for changing lanes of autonomous vehicles before reaching a critical position. In each scenario, only one vehicle intends to change lanes; the surrounding connective vehicles cooperate to adjust the formation until the central lane-change vehicle can do so safely; this single-vehicle lane change process continues sequentially if more than one vehicle intends to change lanes. Li et al. [37] proposed a two-stage multi-vehicle motion planning (MVMP) algorithm for cooperative lane changes of CAVs. After re-configuring a CAV platoon into a sufficiently sparse configuration, all lane changes are carried out simultaneously without attempts to avoid collisions. An and Jung [38] proposed a cooperative lane change protocol considering the impact of V2V communication delay. Although the aforementioned techniques [34–38] can enhance individual driving abilities, they are still inadequate to guarantee smooth lane changes for connected vehicles in congested situations.

In this paper, we develop a novel cyber-physical vehicle coordination system for efficient lane changing or merging of CAVs on multi-lane freeways. To reduce communication volume and computing burden, the vehicles are coordinated into small groups (or platoons) and their trajectories are successively optimized using a receding horizon control (RHC) approach. We assume that the information of CAVs is communicated to a cloud-based computing framework, where an optimization problem is solved to determine target trajectories (speeds and position) of individual vehicles with the goal of providing sufficient gaps during a lane change while minimizing the speed deviation and acceleration of the vehicles. Then the coordination information is provided to individual vehicles, and the local controller of each vehicle determines its control acceleration to follow the desired trajectories while ensuring driving safety. We have carefully chosen the size of vehicle groups and step and horizon sizes, which need less than one second to obtain the optimal solution, and periodically coordinate the vehicles every few seconds to enable the local controller to control the vehicle in smaller steps with that target smoothly. Therefore, our proposed traffic coordination system guarantees fast optimization and can be implemented in real-time. We evaluate the performance of the proposed system using microscopic traffic simulations in view of actual traffic behaviors on a real multi-lane road. It is found that our proposed system significantly improves fuel economy, average velocity, and travel time of vehicles for various traffic volumes compared to traditional human driving.

The paper is organized as follows. Section 2 describes the real traffic scenario and the fundamental idea of our proposed cloud-based vehicle coordination system. Section 3 formulates the optimization problem, including the vehicle driving system and the objective function. Section 4 presents the key simulation results. Finally, Section 5 provides the concluding remarks and future research directions.

2 Vehicle Coordination System

2.1 Real Scenario

In this paper, we consider a real-world traffic scenario on a real road stretch called *Persiaran Kewajipan* in Subang Jaya, Malaysia (as shown in Figure 1) to demonstrate the necessity and evaluate the effectiveness of the proposed cloud-based vehicle coordination system. The road segment is multi-lane, and traffic from two roads merges and diverts on both sides over a short distance, causing severe congestion daily. More than half of the vehicles typically perform multiple lane changes within common sections of about 300 meters before diverting onto two distinct routes and often struggle to find a safe gap to

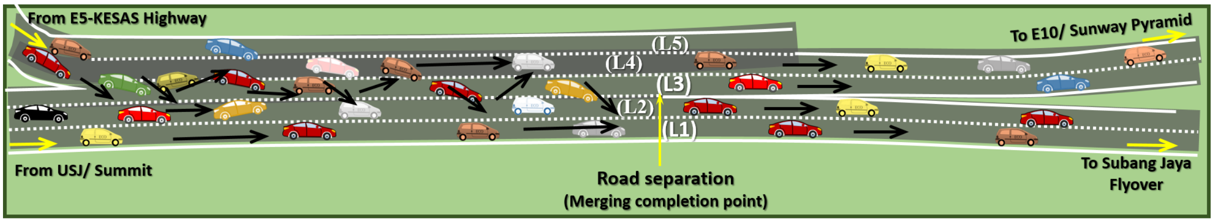


Figure 1: The study route in Subang Jaya, Malaysia, which shows an actual traffic scenario in which vehicles from two roads merge and divert in both ways over a short distance, causing massive congestion every day.

execute a lane change in such a congested situation. Traffic congestion worsens when a vehicle cannot change lanes efficiently, slows down, or stops other vehicles, causing disruptions in the surrounding traffic and endangering traffic safety. It is possible to prevent this sort of traffic congestion by efficiently coordinating all vehicles for timely arrival and lane changes.

2.2 Fundamental Idea

Figure 2 illustrates the fundamental idea of our proposed traffic coordination system in a cyber-physical framework. It is assumed that every vehicle on the study route is a next-generation CAV that is connected to a cloud or edge computing system, which can perform two-way communications and coordinate vehicles globally with negligible delay. The vehicles transmit their necessary information, such as the current state (position, velocity, and acceleration), the target destination, and other information to the cloud, and the coordination system computes the optimal trajectory of each vehicle. Since it is time-consuming to optimize a large number of vehicles in the cloud due to communication volume and computational burden, for online implementation, the vehicles are coordinated into small groups, and their trajectories are successively optimized. Specifically, vehicles

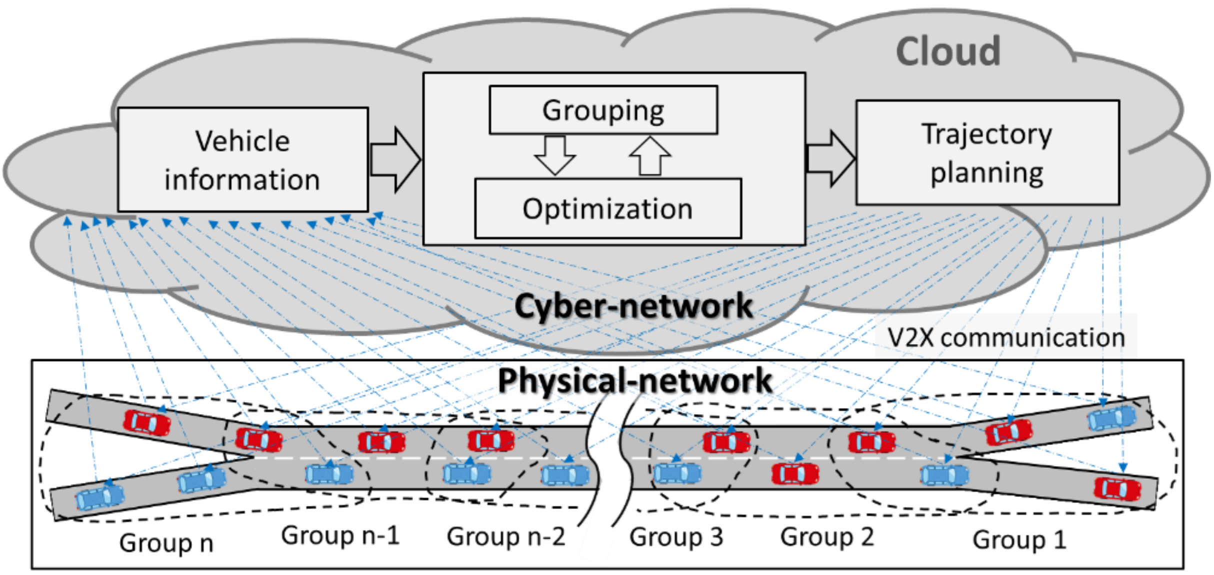
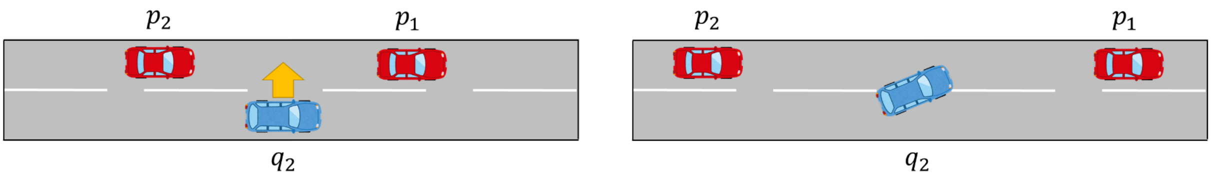


Figure 2: The fundamental idea of our proposed cyber-physical optimal traffic coordinating system. The vehicles are coordinated into groups, and their trajectories are successively optimized.

in each group are simultaneously optimized considering the safety constraint imposed by vehicles in the preceding group, and the optimization is repeated in a receding horizon approach. To maintain maximum traffic performance, the traffic coordination system optimizes vehicle speed and position based on the lane change or merging desires of all relevant vehicles. Based on the coordination information, individual vehicles decide their acceleration by ensuring smooth and safe lane changes or merging on the freeway.

3 Formulation of Optimization Problem

We consider a two-lane freeway where most vehicles require changing lanes in accordance with the real-world scenario. The coordination method divides all vehicles into groups based on their sequences on the road at regular intervals and successively optimizes each group. Since the optimization is the same for each group of vehicles, we demonstrate the coordination process for one of these groups. In Figure 3 (a), a scenario with three vehicles is depicted, with vehicle q_1 (in the right lane) needing coordination with vehicles p_1 and p_2 (in the left lane) for a smooth lane change. Vehicle q_1 requests a lane change but cannot change lanes due to the low safety gap between vehicles p_1 and q_1. An example of anticipated solutions is shown in Figure 3 (b). After receiving the request, vehicles p_1 and p_2 adjust their relative distance to allow vehicle q_1 to change lanes. However, depending on the relative positions and speeds of the vehicles, the expected solutions may differ. Considering traffic performance, a standard rule-based or hierarchical solution may not be effective. Therefore, optimal solutions are desired for all vehicles described below.



(a) (b)

Figure 3: (a) a typical scenario for lane change cooperation request, and (b) expected scenario after coordination.

3.1 Vehicle Driving System

During a trip, a vehicle may change lanes, merge onto a different road, or both, depending on the traffic flow in the lanes and the direction it travels. The state dynamics of any vehicle $n \in \mathcal{N} = \{p_1, p_2, \ldots, q_1, q_2, \ldots\}$ on either lane (left or right) in discrete time, with a time step t of the interval Δt, can be expressed as

$$s_n(t+1) = As_n(t) + Bu_n(t), \tag{1}$$

$$A = \begin{bmatrix} 1 & \Delta t & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \text{ and } B = \begin{bmatrix} \frac{1}{2}\Delta t^2 & 0 \\ \Delta t & 0 \\ 0 & 1 \end{bmatrix}, \tag{2}$$

$$\begin{aligned} s_n(t) &= [x_n(t), v_n(t), \zeta_n(t)]^{\mathrm{T}} \in \mathbb{R}^3, \\ u_n(t) &= [a_n(t), \lambda_n(t)]^{\mathrm{T}} \in \mathbb{R}^2, \\ \lambda_n(t) &\in \{-1, 0, 1\}, \end{aligned}$$

where $s_n(t)$ denotes the state of vehicle n in terms of position $x_n(t)$, velocity $v_n(t)$, and current lane $\zeta_n(t)$, respectively, and $u_n(t)$ is the control vector, including acceleration $a_n(t) \in \mathbb{R}$, and decision about lane change $\lambda_n(t)$, respectively. In this case, $\lambda_n(t) = -1$ or 1 represents a lane change to the left or right, while $\lambda_n(t) = 0$ indicates no lane change. Note that the decision to change lanes is constrained by factors related to driving conditions.

3.2 Human Driving Model

There are many car-following models in existence. The Gazis-Herman-Rothery (GHR) models are probably the most general car-following models and have been extensively studied. The main advantage of the GHR model is its simplicity. However, it was built upon several strong assumptions, leading to serious limitations as being frequently reported by researchers [31].

Desired measure models are based on the assumption that each driver has desired measures (for example, desired spacing, desired time headway, desired speed), and the driver seeks to minimize the difference between the actual state and the desired state. One of the most popular models using desired measures is the intelligent driver model (IDM) proposed by Treiber et al.. The main difficulty of models with desired measures is that most of the parameters are unobservable in nature, and this makes their estimation more challenging. [31]

Safety distance models differ from GHR models by hypothesizing that the driver reacts to the spacing relative to the preceding vehicle rather than to the relative speed. The Gipps model, one of those models, has been used in many simulation models, including AIMSUN. Despite their simplicity, these models show realistic driver behavior, have asymmetric accelerations and decelerations, and do not cause accidents. Unfortunately, they lose their realistic properties in the deterministic limit. In particular, they do not show traffic instabilities or hysteresis effects for fluctuation vanishing [32].

The psycho-physical models account for human perception in the definitions of the model regimes. For example, speed differences have to be of a certain magnitude to be perceived by the driver. The Wiedemann model, one of those models, has been used in the VISSIM traffic simulator. This model reproduces traffic as realistically as possible, but its formula is highly complex, and the computational cost is large [32].

The Cellular automata (CA) models can actually reproduce the macroscopic behavior of a complex system using minimal microscopic descriptions. Although the discreteness of the model does not correspond directly to any property of real traffic, this simple model shows a realistic and non-trivial behavior of the traffic flow [31].

3.2.1 Intelligent Driver Model

The intelligent driver model (IDM) is a continuous time-dependent vehicle follower model. It has the following advantages: (i) it behaves accident-free because of the dependence on the relative velocity, (ii) it allows for a fast numerical simulation, and (iii) an equivalent macroscopic version of the model is known [33], which is not the case for most other microscopic traffic models [32].

Figure 4 shows vehicle n and its preceding vehicle $n-1$, and the other vehicles. Instantaneous acceleration $a_n(t)$ of vehicle n is calculated using a dynamic microscopic car-following model f_{CF} called Intelligent Driver Model (IDM) [39] as

$$\begin{aligned}
a_n(t) &= f_{CF}(s_n(t), s_{n-1}(t)), \\
&= a\left[1 - \left(\frac{v_n(t)}{v_n^{\mathrm{d}}}\right)^4 - \left(\frac{d^*\left(v_n(t), \Delta v_n(t)\right)}{\Delta x_n(t)}\right)^2\right], \\
d^*\left(v_n(t), \Delta v_n(t)\right) &= R_0 + v_n(t)T + \frac{v_n(t)\Delta v_n(t)}{2\sqrt{a_{\max} a_{\min}}}, \\
\Delta x_n(t) &= x_{n-1}(t) - x_n(t) - l, \\
\Delta v_n(t) &= v_{n-1}(t) - v_n(t),
\end{aligned} \tag{3}$$

where the parameters v_n^{d}, R_0, T, l, $a_{\max}$, and $a_{\min}$ denote the desired speed, minimum gap between vehicles, safe headway time while following the preceding vehicle, length of the preceding vehicle, maximum acceleration, and comfortable deceleration, respectively, and $\Delta x_n(t)$ and $\Delta v_n(t)$ are the current gap to the preceding vehicle and the speed difference, respectively. In the framework, the control input at the t-th step is updated as

$$\forall t \in [t\Delta t, (t+1)\Delta t], \;\; a_n(t) \equiv a_n(t\Delta t).$$

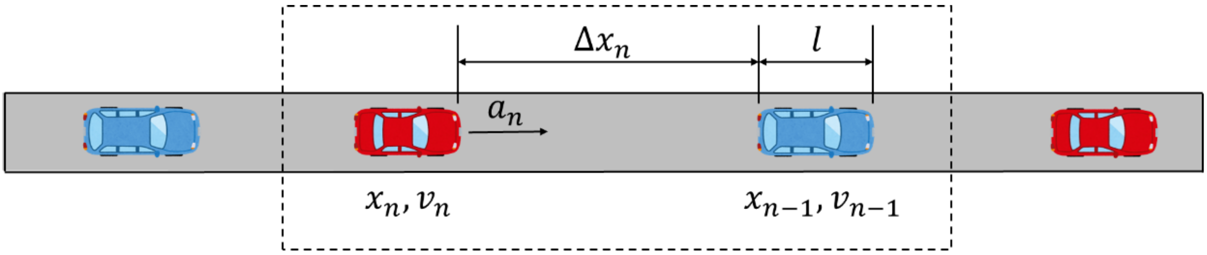


Figure 4: Motion control decision a_n of vehicle n depends only on the positions and speeds of vehicles n and $n-1$ on the same lane, and other vehicles have no immediate influences on vehicle n.

3.3 Lane Change Model

Figure 5 shows the traffic situation with vehicle n considering lane changes and its neighbors. The lane change decision of vehicle n depends on the states of some vehicles in the current and target lanes, which can be represented using a well-known lane change model f_{LC} called minimizing overall braking induced by Lane Change (MOBIL) [40] as

$$\begin{aligned}
\lambda_n(t) &= f_{LC}(s_n(t), s_{\mathrm{cp}}(t), s_{\mathrm{cf}}(t), s_{\mathrm{tp}}(t), s_{\mathrm{tf}}(t)), \\
&= \begin{cases} \tilde{\zeta}_n(t) - \zeta_n(t), & \text{if } \begin{cases} \tilde{a}_{\mathrm{tf}}(t) \geq -b_{\mathrm{safe}} \text{ and}, \\ \Delta a_n(t) + \rho \Delta a_{\mathrm{cf}}(t) \geq \tau, \end{cases} \\ 0, & \text{otherwise}, \end{cases}
\end{aligned} \tag{4}$$

$$\tilde{\zeta}_n(t) \in \{\zeta_n(t) + 1, \zeta_n(t) - 1\}.$$

where $s_{\mathrm{tp}}(t)$ and $s_{\mathrm{tf}}(t)$ respectively are the states of the relative preceding and following vehicles in the target lane, $\tilde{\zeta}_n(t)$ denotes a lane change from the current lane $\zeta_n(t)$ to the target lane, $\tilde{a}_{\mathrm{tf}}(t)$ represents an unsafe lane change of vehicle n that can cause aggressive braking of the relative following vehicle a_{tf} in the target lane, $-b_{\mathrm{safe}}$ is the safe braking

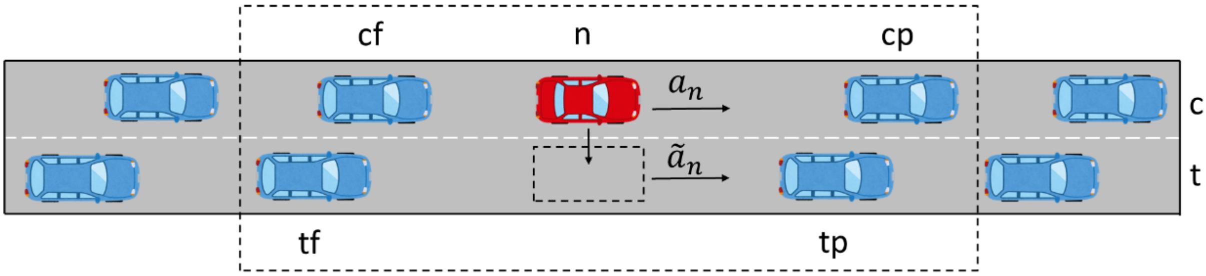


Figure 5: Neighbors of vehicle n considering lane change to the target lane (they are denoted cp, cf, tp, and tf, respectively) and other vehicles; accelerations after the possible change are denoted with a tilde

limit, $\Delta a_n(t)$ and $\Delta a_f(t)$ respectively denote an increase in acceleration of vehicle n and collective increase in acceleration of the following vehicles in the current and target lanes due to a lane change action, ρ is the politeness factor, and τ is the threshold.

The parameters $\Delta a_n(t)$ and $\Delta a_f(t)$ are calculated using (3) as

$$\begin{aligned}
\Delta a_n(t) &= \tilde{a}_n(t) - a_n(t), \\
\Delta a_f(t) &= (\tilde{a}_{\mathrm{cf}}(t) - a_{\mathrm{cf}}(t)) + (\tilde{a}_{\mathrm{tf}}(t) - a_{\mathrm{tf}}(t)),
\end{aligned}$$

$$\begin{aligned}
a_n(t) &= f_{CF}(s_n(t), s_{\mathrm{cp}}(t)), & \tilde{a}_n(t) &= f_{CF}(s_n(t), s_{\mathrm{tp}}(t)), \\
a_{\mathrm{cf}}(t) &= f_{CF}(s_{\mathrm{cf}}(t), s_n(t)), & \tilde{a}_{\mathrm{cf}}(t) &= f_{CF}(s_{\mathrm{cf}}(t), s_{\mathrm{cp}}(t)), \\
a_{\mathrm{tf}}(t) &= f_{CF}(s_{\mathrm{tf}}(t), s_{\mathrm{tp}}(t)), & \tilde{a}_{\mathrm{tf}}(t) &= f_{CF}(s_{\mathrm{tf}}(t), s_n(t)),
\end{aligned}$$

Based on these parameters, vehicle n decides whether to perform a safe lane change or stay at its current lane according to (4). If $\lambda_n(t) = 0$, vehicle n remains at the current lane $\zeta_n(t)$.

3.4 Objective Function

For fuel economy, safe and comfortable driving, sudden acceleration or braking is not beneficial [41]. The proposed cyber-physical traffic coordination system receives information on the state of vehicles within a group or platoon and computes the optimal trajectory for any vehicle n using a receding horizon control (RHC) approach. Specifically, we formulate an optimization problem that minimizes an objective function by providing a sufficient gap for a smooth and safe lane change or merging while maintaining the speed deviation and acceleration at the optimal level. Some constraints are defined in optimization considering driving comfort and regulations related to a road network, such as the speed limit. Moreover, to avoid collisions or aggressive braking, a safe distance between any preceding vehicle $n-1$ and its following vehicle n is necessary, which is dynamically given by the nonlinear constraint as $a_n(t) \le f_{CF}(s_n(t), s_{n-1}(t))$. This constraint, which blends the optimal action with the naturalistic car-following behavior, ensures a safe gap under any circumstances.

To implement the traffic coordination system, the optimization problem is solved by minimizing an objective function at each time t as

$$J(s_n(t), a_n(t)) = \sum_{t}^{H} \left\{ \sum_{n\in\mathcal{N}} \left(w_1(v_n(t) - v_n^{\mathrm{d}})^2 + w_2 a_n^2(t) \right) \right.$$
$$\left. + \sum_{p\in\mathcal{P}} \sum_{q\in\mathcal{Q}} w_3 \theta_{pq}(t) e^{-\alpha(x_p(t) - x_q(t))^2} \right\}, \tag{5}$$

subject to

$$\begin{aligned}
&v_{\min} \le v_{\mathrm{n}}(t) \le v_{\max}, \\
&a_{\min} \le a_n(t) \le a_{\max}, \\
&a_n(t) \le f_{CF}(s_n(t), s_{n-1}(t)), \\
&\theta_{pq}(t) = \begin{cases} 0, & \text{if} \quad \delta_p(t) + \delta_q(t) = 0, \\ 1, & \text{otherwise.} \end{cases}
\end{aligned}$$

where H is the time horizon, $\mathcal{N}$ is the set of vehicles in the partial optimization group, $\mathcal{P}$ and $\mathcal{Q}$ are the number of vehicles in the left and right lanes, $\theta_{pq} \in \{0, 1\}$ a binary variable to enable the third cost term in the objective function and depends on $\delta_p, \delta_q \in \{0, 1\}$ that denotes the need for vehicles to change lanes (i.e., 1 indicates a lane change is necessary and vice versa), α is a positive constant, x_p and x_q are the positions of vehicles in the left and right lanes, and w_1, w_2, and w_3 are the weighting factors corresponding to the velocity, acceleration, and safe lane change terms, respectively. The first term of the objective function implies a penalty when the current velocity $v_n(t)$ of vehicle n deviates from v_n^{d}, the second term is the cost of acceleration along the freeway, and the third term represents a penalty for an unsafe lane change at the target time t due to an insufficient gap.

Note that the weights w_1 and w_2 balance the squares of the speed deviation and acceleration costs into a single value in this composite single objective optimization. Usually, the square of speed deviation can be very large compared to the square of acceleration (with their typical ranges). Hence, to emphasize the influence of both in (5), w_1 needs to be smaller than w_2 (depending on the maximum values of each cost term). However, we further tuned w_1 and w_2 based on trials and performance observations, a common practice in similar single-objective optimization. On the other hand, w_3 is set at a high value to ensure that the safety cost is dominant when a lane change gap is necessary. The objective function J is minimized by selecting the proper speed for each vehicle n, subject to the aforementioned constraints. We assume that the states and destination (target lane) of all vehicles are available to the cloud-based computing framework, where the optimization problem is solved for successive groups of vehicles, and the optimized target speeds and positions are subsequently communicated to individual vehicles. After obtaining the coordination information, the lane change of each vehicle is implemented using (4). In such a manner, the controller drives the vehicles safely until the next coordination phase, and the optimization is repeated in the cloud for the new group of vehicles.

In this paper, the optimization aims to periodically coordinate vehicles to create sufficient gaps for lane-changing vehicles, which is possible with a larger step size since the actual vehicle control is performed with a short step size to ensure safety and smooth maneuvering. For any optimization scheme, the problem size increases with the number of vehicles involved and the horizon length, resulting in a costly optimal solution that is often impractical to apply in real-time. Here, we focus on the total computational costs with the necessary communication volume to keep it manageable for implementing the cyber-physical framework. We consider small vehicle groups to reduce the computational burden of coordinating them successively. However, with a long horizon, the interaction between the consecutive small groups becomes complicated due to many lane-change actions of vehicles on the divided road ahead with a short distance. With some sensitivity observation, we have manually tuned the vehicle group size, time step size, and horizon length and come to the settings considered in this paper. Note that the horizon length needs to be tuned similarly for different group sizes and road contexts.

4 Simulation Results

To demonstrate the effectiveness of the proposed traffic coordination system, we have developed a multi-lane simulation framework in MATLAB (which has been demonstrated to be mathematically reliable and utilized to model numerous real-world situations) based on the real study route and solved a nonlinear optimization problem (described in (5)) in discrete time. The arrival of vehicles in the simulator is decided randomly using a probability distribution to produce realistic traffic flows. In the simulation, all vehicles are considered to be the same size and length. The simulation parameters are chosen as Table 1. Note that ρ varies among drivers depending on the driving contexts and behavior. For realistic behavior in the discretionary lane change, the typical values of ρ can be between 0.2 to 0.5; however, in our context, it is a mandatory lane change, and thus, ρ is set to 0, i.e., lane change is executed only when the safety criteria are satisfied.

Table 1: Simulation parameters and their variables and values used in the experiment

Simulation parameters		**Variables**	**Values**
Desired speed of vehicle n	[m]	v_n^{d}	23
Minimum gap of vehicles	[m]	R_0	2
Safe headway time	[s]	T	1.5
Vehicle length	[m]	l	5
Speed of vehicle n	[m/s]	v_n	[0, 25]
Acceleration of vehicle n	[m/s^2]	a_n	[-2.5, 1.5]
Safe braking limit	[m/s^2]	b_{safe}	5
Politeness factor		ρ	0
Threshold		τ	0.25
Weight factor corresponding to velocity		w_1	0.1
Weight factor corresponding to acceleration		w_2	1
Weight factor corresponding to safe lane change terms		w_3	0.3
Positive constant		α	0.001
Set of vehicles in partial optimization group		N	4
Time horizon	[s]	H	5
Step size	[s]	Δt	0.5

The simulation framework is depicted in Figure 6, whereby roadways 1 and 2 share a portion between 0 and 500 m, where vehicles may change lanes depending on their destination. In traditional driving systems, vehicles that need to change lanes slow down and wait for the appropriate time to do so when approaching the merging junction. Consequently, the vehicles in the opposite lane may also slow down to make space for the awaiting vehicles to change lanes, which may reduce the overall traffic flow performance

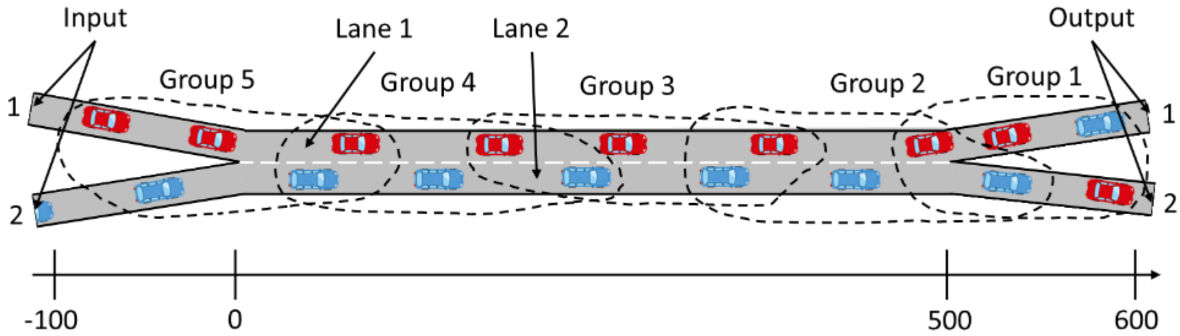
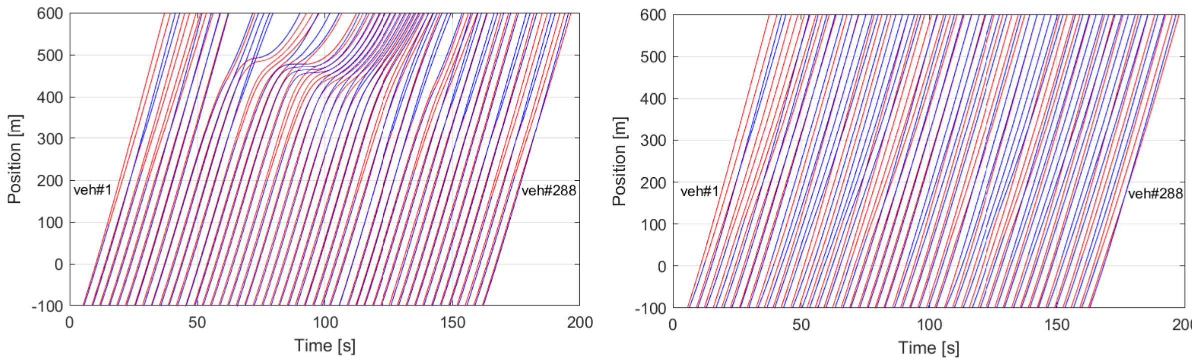


Figure 6: Multi-lane road network used for simulation and evaluation of the proposed traffic coordination system.

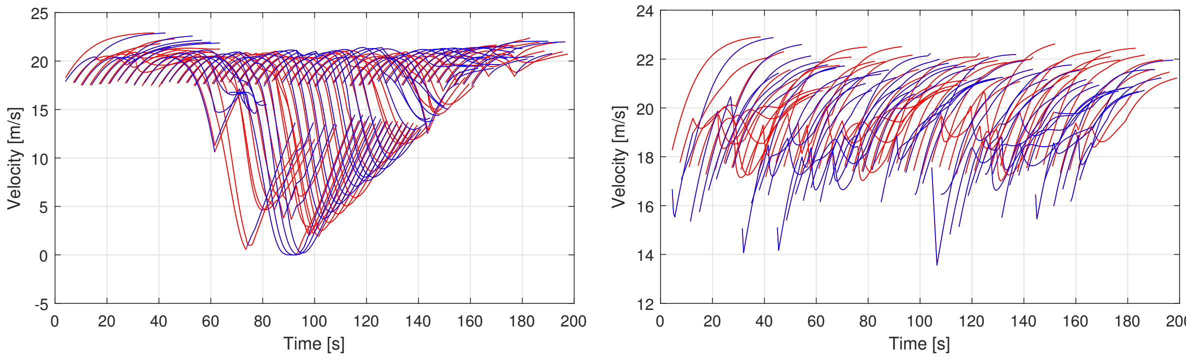
in the network. Moreover, finding safe gaps to perform lane changes in a congested situation is challenging. In the proposed traffic coordination system, vehicles between −100 and 600 m are divided into multiple groups and optimized every 5 s. Note that here we consider a suitable optimization horizon; since traffic flow experiences substantial variations, a long horizon would not be helpful.

Figure 7 shows the trajectory of each vehicle in dense traffic for both traditional and coordinated driving systems while traveling about 600 m on the study multi-lane freeway. In the traditional driving system (Figure 7(a)), some vehicles were unable to change lanes in time, slowing them down and blocking others, causing long queues and traffic congestion, whereas, in the proposed coordination system (Figure 7(b)), vehicles can smoothly change lanes without interrupting surrounding traffic. The velocity profiles of the vehicles for the traditional driving system and the proposed coordination system are shown in Figure 8(a) and 8(b), respectively. In the traditional driving system, some vehicles quickly slow down and/or come to a complete stop before lane changes. In the proposed coordination system, however, vehicles can smoothly change lanes by slowing down from the peak speed to a level of about 14 m/s. Figure 9 depicts the acceleration profiles of these vehicles. Compared to the traditional driving system, the proposed coordination system performs a significantly low deceleration of about -0.4 m/s^2 during lane changes. Aggressive braking in traditional driving reduces traffic performance and



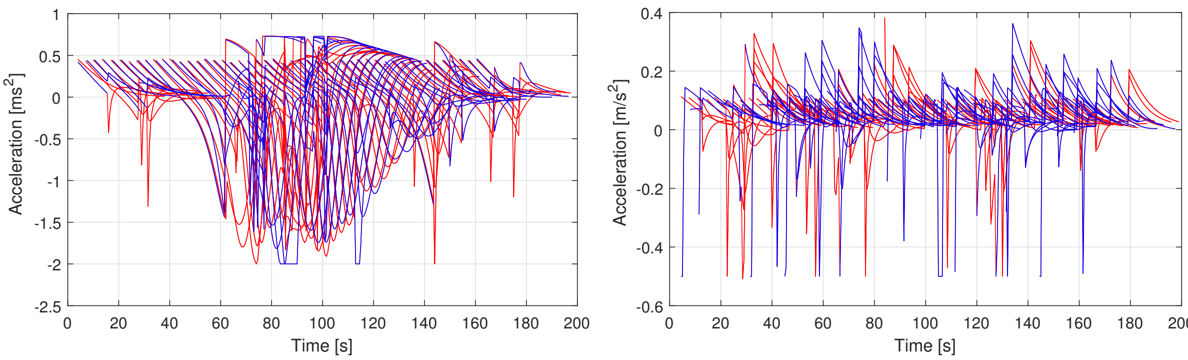
(a) (b)

Figure 7: Trajectories of the vehicles traveling about 600 m in 200 s on the study multi-lane freeway. The sub-figures show (a) the traditional driving system and (b) the proposed traffic coordination system.



(a) (b)

Figure 8: Velocity profiles of the vehicles showing speeding and slowing down characteristics for (a) the traditional driving system and (b) the proposed traffic coordination system.



(a) (b)

Figure 9: Acceleration profiles of the vehicles showing the level of aggressiveness for (a) the traditional driving system and (b) the proposed traffic coordination system.

driving safety. In contrast, smooth braking in coordinated driving promotes improved kinetic energy usage, which lowers vehicle fuel consumption.

Figure 10 compares the simulation results of the traditional driving system and the proposed traffic coordination system using four important performance measures of traffic flow, including average travel time, average idling time, average velocity, and average fuel consumption. The traveling time is the time it takes for a vehicle to drive the study road segment, and the idling time is the total time it takes for a vehicle to stop and wait at the merging junction during lane changing. The average speed is the total speed of all vehicles divided by the total number of vehicles in the simulation, while the average fuel consumption is the cumulative fuel consumption divided by the number of vehicles in the road segment. In the paper, the fuel consumption of vehicles is determined based on trajectory data (instantaneous speed and acceleration) of vehicles using the VT-Micro model [42]. The model was experimentally developed at Oak Ridge National Laboratory (ORNL) with nine regular-emitting light-duty vehicles. Using chassis dynamometer data collected at the ORNL, different polynomial combinations of acceleration and velocity were investigated using this model. The model is well-accepted and widely used in transportation studies to determine vehicle fuel consumption.

Figure 10(a) and (b) respectively show that the average travel time and the idling time of the proposed traffic coordination system are significantly reduced compared to the traditional driving system for different traffic demands. This is due to the fact that coordinated vehicles make early decisions and require minimal waiting time to execute lane changes. Furthermore, the proposed coordination system considerably increases the average speed compared to the traditional system (as shown in Figure 10(c)) because coordinated vehicles rarely need to slow down or stop before changing lanes or merging, resulting in smoother flow. Finally, Figure 10(d) illustrates the comparison of average fuel consumption for both systems. It is evident that the proposed traffic coordination system outperforms the traditional driving system for various traffic volumes. The percentage improvements in the average travel time, the average velocity, and the average fuel consumption by the proposed traffic coordination system are given in Table 2.

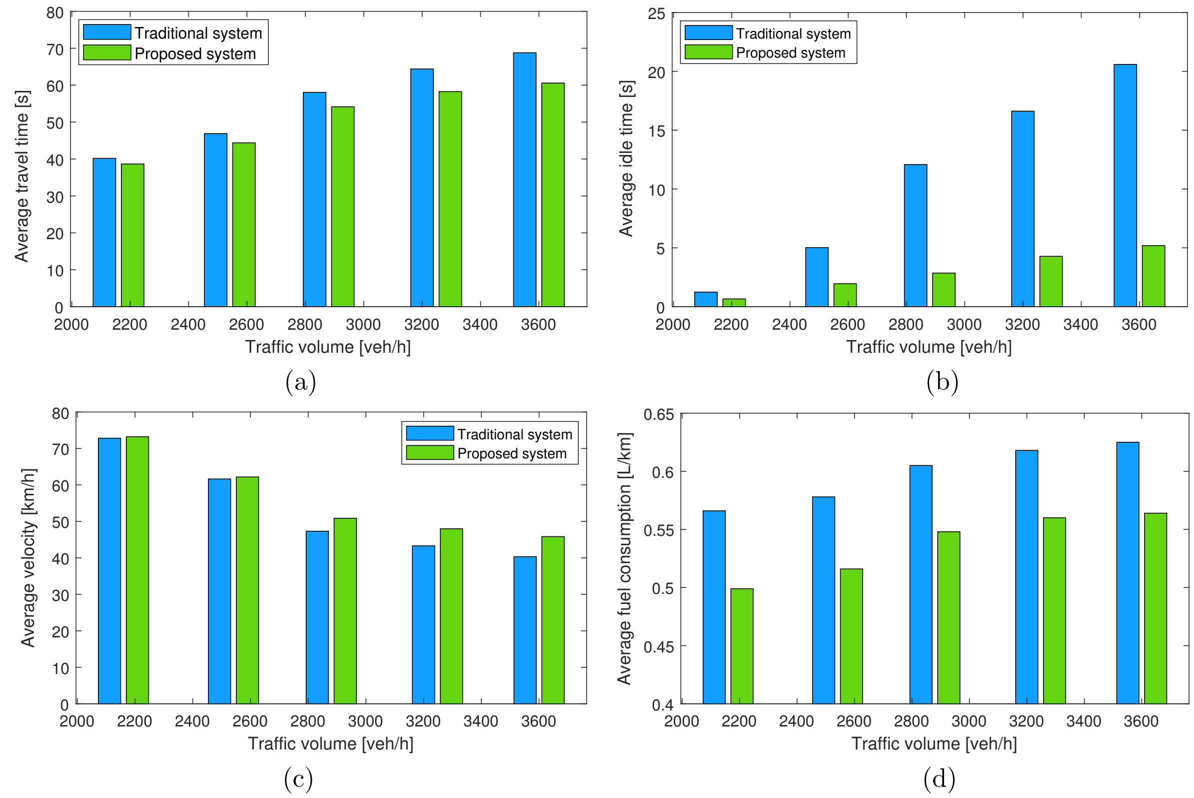


Figure 10: Performance comparison (a) average travel time, (b) average idling time, (c) average velocity, and (d) average fuel consumption of the traditional driving system and the proposed traffic coordination system for various traffic volumes on the study freeway.

Table 2: Performance comparison between the proposed traffic coordination system and the traditional driving system.

	Traditional System	**Coordination System**	**Improvement**
Average travel time [s]	55.68	51.20	8.05%
Average velocity [km/h]	53.08	56.02	5.53%
Average fuel consumption [L/km]	0.5984	0.5374	10.19%

5 Discussion

This model assumes a mixed environment of automated and human-driven vehicles on a two-lane road, where all vehicles are equipped with vehicle-to-Vehicle(V2V) communication. It is also assumed that the information is obtained from the cars and calculated in the cloud instantly, but as it is now, the calculation takes time, and at this point, we cannot predict the impact that calculation delays. As the first approach to a cyber-physical traffic control scheme, we consider only two-lane roads in this case, but it may be possible to optimize other-lane roads by repeating the optimization of two-lane roads.

6 Conclusions

In this paper, we have developed a novel cyber-physical framework for optimal coordination of CAVs on multi-lane freeways. Using a receding horizon control (RHC) approach, the vehicles are coordinated into successive groups for a smooth and safe lane change or merging. We assume that the information of all vehicles is available to a cloud-based computing framework, where an optimization problem is solved to calculate the target speeds and positions of individual vehicles in a group. Following that, the coordination information is provided to individual vehicles, and the local controller of each vehicle determines its control acceleration to follow the desired trajectories while ensuring driving safety. The proposed traffic coordination system is evaluated considering real-world traffic conditions on a real multi-lane road. The results show that the proposed framework significantly improves the fuel consumption, average velocity, and travel time of vehicles for different traffic demands. Our proposed method can be implemented online, as the computing burden is almost negligible.

In future work, we will investigate mixed traffic performances for various penetration rates of CAVs. The proposed framework can be further extended using distributed model predictive control (MPC) for individual vehicles.

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