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Improving Traffic Operations Using Real-time Optimal Lane Selection with Connected Vehicle Technology

Qiu Jin, Guoyuan Wu, *Member, IEEE,* Kanok Boriboonsomsin, and Matthew Barth, *Fellow, IEEE*

***Abstract*—To better regulate traffic flow and reduce the potential impacts due to uncoordinated lane changes, we proposed a real-time optimal lane selection (OLS) algorithm by using the information available from connected vehicle (CV) technology. Such information includes the location, speed, lane and desired driving speed of individual vehicle agents (VA) on a localized roadway. Microscopic traffic simulation studies show that the proposed algorithm can result in both mobility and environmental benefits for the entire traffic system. Specifically, the application of the OLS algorithm reduces the average travel time by up to 3.8% and the fuel consumption by around 2.2%. In addition, the reduction in emissions of criteria pollutants, such as CO, HC, NOx and PM2.5 ranges from 1% to 19%, depending on the congestion level of the roadway segment. Potential extensions of the proposed OLS algorithm are discussed at the end of this paper.**

***Keywords*—Lane selection, optimization, connected vehicles.**

I. Introduction

Limited roadway capacities along with ever-increasing travel demands continue to pose challenges to researchers and engineers on how to manage the traffic system more efficiently in terms of mitigating congestion. A significant amount of research effort focuses on improving traffic flows at congested roadway locations by coordinating traffic control devices, such as ramp meters (for freeways) and traffic signals (for arterials). These traffic management strategies, however, usually assume little knowledge and control on microscopic driving maneuvers, e.g., lane changes, which can affect the operational effectiveness of the roadway system. Previous studies also indicate that well-coordinated lane changes exhibit non-trivial potential to minimize shockwave impacts, increase roadway throughput, maintain desired speeds and ensure driving comfort [1].

As a key procedural element of lane change driving behavior, lane selection has been widely studied for years to achieve a better understanding of traffic systems in the real world. Typically, lane selection without external guidance can be classified as either discretionary or mandatory [2], where discretionary lane selection is performed to improve the current driving conditions, while mandatory lane selection is performed when the vehicle has to leave its current lane due to unavoidable constraints, such as lane drops or exiting the roadway. It turns out that discretionary lane selection (and the resultant lane changes) may be disruptive to traffic flow by creating moving bottlenecks under congested traffic conditions [3], thus impairing the operational performance of the entire traffic system. This results from both individual desires and the lack of system-wide traffic information for better decision making.

With the capabilities to share information through wireless communication among vehicles (vehicle-to-vehicle, V2V) as well as between vehicles and infrastructure (V2I/I2V), connected vehicle (CV) technology may provide a well-defined platform for developing cooperative lane selection/changing to improve traffic operation. Based on the CV technology, this paper presents a real-time lane selection algorithm, which can provide guidance on determining optimal target lanes for individual vehicles in order to better regulate traffic flow, thus achieving a system-wide optimal solution in terms of maintaining desired traffic speeds. It is noted that the proposed algorithm can be applied to both advanced driving assistance systems (ADAS) and automated vehicles.

The remainder of this paper is organized as follows: Section II introduces background information for the development and evaluation of the proposed lane selection algorithm, followed by a detailed description of the proposed lane selection algorithm in Section III. Section IV presents the algorithm evaluation using an extensive simulation study. Further discussions on the algorithm and evaluation results are presented in Section V. The last section concludes this paper along with suggestions on future work.

II. Background

A. Traffic Flow Impacts Due to Potential Vehicle Conflicts

Assume that a number of vehicles are traveling along a multi-lane highway segment and each of them has its own desired speed. Potential conflicts may occur if all vehicles want to maintain their own desired speeds which usually are not homogenous. Previous studies show that such potential vehicle conflicts could interrupt traffic flows and, even worse, lead to accidents [4]. To avoid these conflicts, vehicles may either change speeds or lanes. However, aggressive driving, such as hard braking and cutting-into small gaps, could have disproportionate impacts on the upstream traffic flow along the involved lanes, resulting in degradation of system performance in terms of safety, mobility, environmental sustainability and reliability. Figure 1 illustrates two example scenarios (slowing-down and

Qiu Jin, Ph. D Candidate, is with the Electrical Engineering Department and Center for Environmental Research and Technology (CE-CERT), University of California, Riverside, CA 92507 USA (email: qjin@ee.ucr.edu).

Guoyuan Wu, Ph. D, is with CE-CERT, University of California, Riverside, CA 92507 USA (email: gywu@cert.ucr.edu).

Kanok Boriboonsomsin, Ph. D, P.E., is with CE-CERT, University of California, Riverside, CA 92507 USA (email: kanok@cert.ucr.edu).

Matthew Barth, Ph. D, is with Electrical Engineering Department and CE-CERT, University of California, Riverside, CA 92507 USA (email: barth@ee.ucr.edu).

cutting-in) where potential conflicts of preceding vehicles may unfavorably influence the upstream vehicles E and F, respectively. Please note that the numbers indicate the desired speed of the individual vehicles.

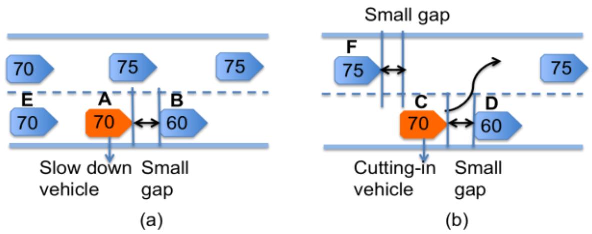

Figure 1. Conceptual example of (a) slowing down vehicle and (b) cutting-in vehicle due to potential vehicle conflicts

B. Lane Selection and Changing

Lane selection is a critical step in the decision-making process during lane changes [5]. The very early discussion on lane selection model can be found in Gipps [6], which has already been implemented in several micro-simulation modeling tools, e.g., CORSIM [7]. Since then, numerous studies [8, 9] on lane change (including lane selection) have attached importance to the modeling of driver behavior without external guidance from advanced driving assistance systems (ADAS). For example, the Freeway Lane Selection (FLS) algorithm introduced by the FHWA's Next Generation SIMulation (NGSIM) program [10] has incorporated the "target lane" concept, which facilitates the modeling of lane change behavior along freeway segments. To determine the best target lane, the FLS algorithm will assign an individual "score" to each lane based on a variety of parameters, such as the distance to the upcoming exit and average vehicle speed in each lane, and choose the lane with the highest score. Then, the vehicle will complete a lane change to the target lane if both the lead gap and the lag gap are acceptable. It is noted that, however, such an algorithm only assumes the availability of localized traffic conditions that can be perceived by the driver. As sensor technologies within ADAS advances, new features such as blind spot detection (BSD) have been commercialized to provide the driver guidance (not) to change lanes. However, the majority of this technology is purposefully developed for safety only [11]. Recently, the concept of predictive lane changing, particularly in the framework of automated driving, has been attracting increased attention [12]. Such strategies aim at optimizing the lane changing maneuvers of individual vehicles in terms of user-defined performance measures (e.g., travel time), without considering the impacts on other vehicles. With progress in vehicular communication technologies, Ralf and Paul [13] designed a cooperative driving system, which enabled the vehicle to automatically handle typical freeway lane-changing by taking into account the future intentions of surrounding vehicles in a more "win-win" manner. More recently, Kishore [14] proposed an intelligent lane-changing advisory system (iLCAS) based on vehicle-to-vehicle (V2V) and infrastructure-to-vehicle (I2V) communication. Such advisory systems can guide the driver to select better target lane under prevailing traffic conditions, in order to improve driving performance (e.g., reducing travel time) of the subject vehicle. Just like other existing ADAS, it might gain the benefit at the expense of other vehicles, thus only achieving sub-optimal, or even worse, degraded operational performance of the entire traffic system. In our proposed method described below, we aim to optimize lane changes from a systems perspective.

C. Simulation of Urban Mobility (SUMO)

To evaluate the performance of the proposed lane selection algorithm, we use SUMO (Simulation of Urban Mobility) [15], which was developed by the German Aerospace Center, in this study to build a variety of traffic scenarios. SUMO is a novel traffic simulation tool tightly integrated with simulated wireless communication capability. With SUMO, advanced traffic controls can be implemented in an Inter-Vehicular Communication (IVC) simulation framework composed of an event-based network simulator (e.g., OMNeT++[16], network simulator or NS-2[17]) and a microscopic traffic simulation model (e.g., SUMO) through a Traffic Control Interface (or TraCI). As common to most microscopic simulators, SUMO has implemented the fundamental core models, such as car-following model and lane-changing model [18]. To evaluate the impacts of the proposed lane selection algorithm on environmental sustainability (in terms of fuel consumption and criteria pollutant emissions) we used MOVES (Motor Vehicle Emission Simulator) developed by the US Environmental Protection Agency (EPA) [19], which is a state-of-the-art emission modeling tool based on analyses of millions of emission test results.

III. Real-time Optimal Lane Selection

As pointed out in the previous sections, well-coordinated lane changes can help maintain desired speeds, minimize shockwave impacts, and thus improve traffic system performance. However, if the real-time traffic information cannot be well shared, then the lane selection decision made by individual driver may not achieve the system-wide optimality, or may even deteriorate the system performance. Thanks to the connected vehicle (CV) technology, we are able to develop an improved lane selection algorithm as described in the following, to minimize potential vehicle conflicts of the entire traffic flow.

The basic idea of this algorithm is to determine the optimal target lane for each vehicle based on its current location, speed, lane index and desired speed, in order to avoid subsequent hard brakes or lane changes forced by slow vehicles or lane drops.

A. System Architecture

As shown in Figure 2, the proposed real-time optimal lane selection system consists of two components: a lane selection agent (LSA) and vehicle agents (VAs). The LSA, which may be a roadside unit, is capable of communicating with involved vehicles within a certain range (orange vehicles within the shadowed region in Figure 3) to access their real-time information, including the locations, speeds, lanes and desired driving speeds. The desired driving speed may be specified by the driver at the start of a trip, or inferred from the historical speed profile. Based on such information, the LSA can estimate the associated exiting speeds and provide drivers advice on target lanes.

The proposed lane selection optimization algorithm can be divided into three steps:

1) *Data collection:* In this stage, the lane selection agent collects real-time information of vehicles (orange vehicles in Fig. 3) within the infrastructure-to-vehicle (I2V) and vehicle-to-infrastructure (V2I) communication range. Before a vehicle leaves the communication range or its target lane has been optimized, the vehicle needs to update its states whenever they change.
2) *Optimal target lane determination:* An optimization for target lane selection is performed by using the information from Step 1). The problem formulation is detailed in the following section. It is noted that for real-time implementation, we apply the variable sliding window technique [20] to the optimization, which enables the optimization to be triggered once all the vehicles that have been optimized in the previous run leave the I2V communication range.
3) *Lane changing implementation:* After the target lane is selected, each vehicle (blue vehicles in Fig. 3) will perform its lane change accordingly.

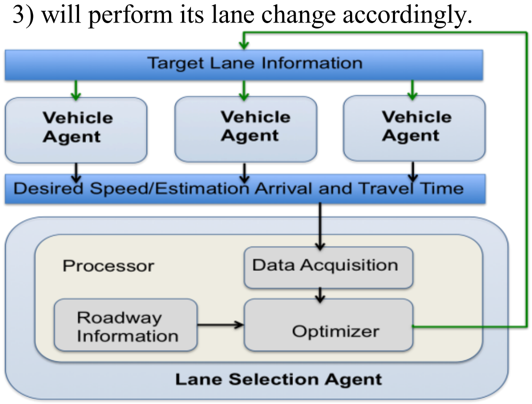

Figure 2. System architecture of the proposed lane selection algorithm

B. Problem Formulation for Target Lane Selection

As described earlier, our goal is to determine a target lane for each vehicle by using the Connected Vehicle technology, in order to achieve system-wide benefits for the entire traffic network. We model the optimal target lane selection as a multiple identical machines (the i-th machine represents the i-th lane) scheduling problem, where the objective is to minimize the overall number of conflicting jobs (i.e., VAs traveling through the segment).

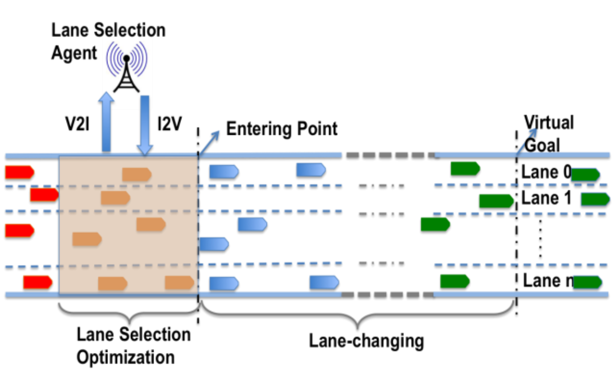

Figure 3. A highway segment with lane selection optimization

If we further define

$$y_{i,j,k} = \begin{cases} 1, & i-th\ VA\ is\ assigned\ to\ lane\ j\ in\ k-th\ place \\ 0, & otherwise \end{cases},$$

then the optimization problem can be formulated as follows:

$$\min \sum_{j\in L} \sum_{k\in K} sign\left(\max\left(0, \sum_{i\in I} t_i^{act,out} \cdot y_{i,j,k-1} - \sum_{i\in I} t_i^{act,out} \cdot y_{i,j,k}\right)\right) \quad (1)$$

s.t.

$$\sum_{j\in L} \sum_{k\in K} y_{i,j,k} = 1 \quad \forall i \in I \quad (2)$$

$$\sum_{i\in I} y_{i,j,k} \le 1 \quad \forall j \in L, k \in K \quad (3)$$

$$\sum_{i\in I} \sum_{k\in K} t_i^{in} \cdot y_{i,j,k} - \sum_{i\in I} \sum_{k\in K} t_i^{in} \cdot y_{i,j,k-1} \ge 0 \ \forall j \in L \quad (4)$$

$$t_i^{des,out} = d/v_i^{des} + t_i^{in} \quad \forall i \in I \quad (5)$$

$$\sum_{i\in I} \sum_{k\in K} t_i^{act,out} \cdot y_{i,j,k} \le \sum_{i\in I} \sum_{k\in K} t_i^{des,out} \cdot y_{i,j,k} \ \forall j \in L \quad (6)$$

$$\sum_{i\in I} \sum_{k\in K} t_i^{act,out} \cdot y_{i,j,k} = \sum_{i\in I} \sum_{k\in K} t_i^{act,out} \cdot y_{i,j,k-1} + \Delta T \quad \forall j \in L \quad (7)$$

$$\sum_{i\in I} t_i^{act,out} \cdot y_{i,j,1} = \sum_{i\in I} t_i^{des,out} \cdot y_{i,j,1} \quad \forall j \in L \quad (8)$$

where, I, L and K represent the set of VAs, lanes and placements, respectively. t_i^{in} and $t_i^{act.out}$ denote the entrance and exit times of the i-th VA. $t_i^{des.out}$ is the desired exit time of the i-th VA under the mean desired speed, v_i^{des}. d represents the length of the roadway segment, while ΔT represents the minimum time gap of two consecutive VAs.

In the above mathematical formulation, Eq. (1) will be minimized if the desired exit time of each VA is (at least ΔT) later than its preceding VA and the objective function is zero. However, due to the differences in entrance times and in desired speeds, there would be more or less potential conflicts which may render a non-zero value of the objective function. Eq. (2) through Eq. (8) govern the system dynamics and cast constraints on the placement of consecutive VAs. For example, Eq. (2) guarantees that each VA will only show up once on all placements across all lanes, while Eq. (7) ensures the consistency of placement, i.e., any vehicle cannot exit the roadway segment earlier than its predecessor along the same lane. It is noted that a CPLEX [21] Python API was coded in the study to conduct the real-time optimization.

IV. Simulation and Analysis

To evaluate the performance of the proposed real-time optimal lane selection algorithm under different congestion levels, we coded a three-lane highway segment with a communicable roadside lane selection agent and vehicle agents (using connected vehicle technology) in SUMO. The lane selection agent collected real-time information of vehicle agents on this highway segment that were within the V2I/I2V communication range, and determined an optimal target lane for each vehicle after which the vehicles performed lane changes accordingly. It should be noted that since the lane changing module of SUMO was used, it could not be guaranteed that all the vehicles had reached their target lanes upon the completion of the simulation. The simulation results in terms of average travel time, fuel consumption and emissions were compared with those for a standard three-lane highway segment without an implementation of the proposed lane selection algorithm.

A. Simulation Setup

The simulation network was set up in SUMO as follows:

- The highway segment is 2000 meters long;
- Speed limit for all lanes is 50 mph;
- Vehicular flow is homogeneous and all vehicles are light-duty vehicles;
- Vehicle length is 2.5 meters and the safety distance when stalled is 2.5 meters;
- Maximum acceleration and deceleration rates are 2.5 m/s^2 and -2.5 m/s^2, respectively;
- Vehicles are generated by a Poisson distribution;
- Simulation time step is 0.1 seconds and the total number of steps is 10,000;
- No on- and off- ramp is considered;
- Two scenarios were evaluated: 1) Optimal Lane Selection (OLS) based scenario; and 2) Non-Lane Selection (NLS) based scenario;
- For each of the OLS-based and NLS-based scenarios, we ran the simulation at five different congestion levels represented by volume to capacity ratio (V/C): 0.5, 0.6, 0.7, 0.8, and 0.95.
- For the OLS based scenario, The V2I/I2V communication range is 300 meters. The minimum update window between two optimizations is 10 seconds.
- For the NLS based scenario, no control strategy is applied to lane change maneuver. While for the OLS based scenario, vehicles change lane based their optimal target lane information.
- The desired speed of each vehicle, v_i^{des}, is sampled from a Gaussian distribution with the mean of roadway speed limit (i.e., 50 mph) and a predefined standard deviation, $\bar{\sigma}$ (we selected 2.5 mph in this study).
- If there is no interaction with other vehicles (i.e., not under the influence of the car-following logic), the actual speed of a vehicle at each time step follows a Gaussian distribution with the mean of its desired speed, v_i^{des}, and a standard deviation, σ_i (chosen as 0.4 mph).

B. Travel Time Comparison Results

For each congestion level in each scenario, we calculate the mean travel time of four simulation runs with different random seed numbers. The comparison results are summarized in Table 1. It can be observed that when the traffic volume is not so high, e.g., V/C = 0.5, there is trivial reduction in the mean travel time. This may be because the gaps between vehicles are large so unregulated lane changes have little impact on the traffic flow. As the congestion level increases, the benefits from the proposed optimal lane selection algorithm also increases. When V/C = 0.7, the mean travel time of the OLS based is about 4% lower than that of the NLS based. However, if the segment becomes heavily congested (say, V/C = 0.95), then the relative improvement in the mean travel time drops. A potential explanation is that there is less room for the VAs to conduct lane changes to their desired target lanes when the traffic volume is very high.

TABLE I. COMPARISON RESULTS ON MEAN TRAVEL TIMES (IN SECOND) BETWEEN TWO SCENARIOS: NLS BASED VS. OLS BASED

V/C	Scenarios		% Improvement
	NLS Based	OLS Based	
0.5	113.0	112.4	0.57
0.6	113.2	110.7	2.25
0.7	114.1	109.8	3.79
0.8	114.3	110.5	3.35
0.95	118.4	115.3	2.67

To verify whether the improvement is statistically significant, a two-sample t-test was performed on the case of V/C = 0.7. We conducted 20 runs with different seed numbers for each of the NLS based and OLS based scenarios and calculated the mean and standard deviation of the average travel time, respectively. It was found that if the proposed optimal lane selection algorithm is applied, then the average travel time is statistically smaller than the baseline (NLS based scenario) at the significance level of 5%, where p-value is 4.0e-05.

C. Energy Consumption and Emissions Analysis

Besides the travel time analysis, we also evaluated the benefits of the proposed lane selection algorithm in terms of reductions in energy consumption and emissions of criteria pollutants, such as CO, HC, NOx and PM2.5.

Figure 4 summarizes all these results for the different congestion levels. As shown in the figure, when traffic congestion is low, such as V/C = 0.5 and 0.6, the reductions in energy consumption and CO2 emissions are trivial while the reductions in other pollutant emissions are in the order of up to 4%. When V/C = 0.7, the maximum reductions in energy consumption and emissions are achieved. The energy consumption and CO2 emissions are reduced by around 2.2%, while other criteria pollutants emissions are reduced by more than 15%. However, as the traffic becomes more and more congested, those reductions become smaller potentially due to the limited room for better coordinated lane changes.

Similar to the travel time analysis, we also conducted a two-sample t-test on the energy consumption between the NLS based and the OLS based scenarios (V/C = 0.7), each of which were run with 20 different random seed numbers. The results show that the average energy consumption is significantly reduced (at 5% significance level) due to the implementation of the proposed lane selection algorithm. The p-value is 2.8e-04.

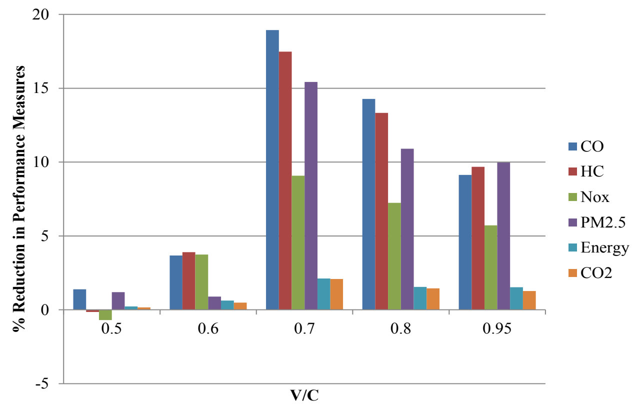

Figure 4. Improvement in energy consumption and emissions due to the proposed optimal lane selection algorithm

D. Statistics on Number of Lane Changes

The proposed algorithm aims to provide advice on the optimal (in terms of the system-wide benefits) target lanes for involved VAs, rather than forcing them to change to the desired target lane. Whether or not each VA can successfully change to its optimal target lane also depends on how the lane-changing module in SUMO works. To obtain further insight into the performance of the OLS algorithm and get better understanding on the simulation results, we compared the number of lane changes between the two scenarios. The results are presented in Table 2. It is noted that the number of lane changes is defined as the number of lane-changing maneuvers to the adjacent lane. For example, if a VA changes from lane 1 to lane 3 as guided by output of the OLS algorithm, then the number of lane changes is 2.

TABLE II. COMPARISON RESULTS ON NUMBER OF LANE CHANGES

V/C	Scenarios					
	NLS Based			OLS Based		
	Valid[a]	Total	vr[b] (%)	Valid[a]	Total	vr[b] (%)
0.5	82	182	45.05	179	324	55.25
0.6	92	225	40.89	200	372	53.76
0.7	108	244	44.26	206	383	53.79
0.8	110	269	40.89	181	357	50.70
0.95	124	294	42.18	178	343	51.90

[a] represents those lane changes completed at the desired target lanes
[b] valid lane change rate: # of valid lane change / # of total

It can be seen from Table 2 that as the volume to capacity ratio increases, the total number of lane changes without the application of optimal lane selection algorithm continues to grow, accompanied (almost linearly) by the number of valid lane changes. However, the total number of lane changes (and valid lane changes as well) under OLS based scenarios reaches the peak when V/C = 0.7. This may be reconciled by the increase in traffic demand and decrease in the available room for lane changes to the desired target lanes. In addition, the valid lane change rates in OLS-based scenarios are much higher than the NLS-based scenarios under different congestion levels.

V. DISCUSSION

In this study, we only explore the optimal lane selection algorithm that can minimize the number of potential vehicle conflicts. However, other objective functions could be used. For example, if the goal is to minimize the total travel time (i.e., overall job processing time), we can simply replace Eq. (1) with

$$\min \sum_{i\in I}\sum_{j\in L}\sum_{k\in K}\left(t_i^{act,out} - t_i^{in}\right)\cdot y_{i,j,k} \qquad (9),$$

without increasing the computational complexity compared to the original mathematical optimization problem.

On the other hand, we do not consider any constraints on the target lane of each vehicle agent. For instance, in some cases, certain type of VAs may have to choose a subset of lanes as their target lanes, due to the movement requirement at an intersection or leaving a freeway via the off-ramp. A simple way to include these cases is to modify Eq. (2) to

$$\sum_{j\in L_i}\sum_{k\in K} y_{i,j,k} = 1 \qquad \forall i \in I \ (10)$$

where L_i is the customized set for the i-th VA to accommodate its constraints on the target lanes.

In addition, the proposed mathematical optimization problem does not explicitly utilize the entrance lane index information, which may be useful to constrain the number of lane changes or even minimize the occurrence of lane-changing maneuvers. In such case, an external input variable related to the entrance lane has to be defined for each VA in the problem formulation.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we propose a real-time optimal lane selection algorithm in order to minimize the potential vehicle conflicts and to maintain the desired speed of each vehicle agent. All the required input information can be readily obtained through the connected vehicle technology. After formulating the problem into an integer programming problem, we solved the optimization by using CPLEX Python APIs, which works with the microscopic traffic simulation model in parallel. The simulation results indicate that the proposed algorithm cannot only shorten the system-wide travel times and lower energy consumption, but also significantly reduce the emissions of criteria pollutants.

In the future, more experiments of the proposed algorithm or its extension will be conducted for further validation. Another potential topic for future work would be to incorporate this algorithm into the modeling of lane changing behavior to achieve desired performance in a more cooperative way.

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