Optimal Control-Based Ramp Merging System for Connected and Automated Electric Vehicles

Zhouqiao Zhao, Student Member, IEEE, Guoyuan Wu, Senior Member, IEEE, Ziran Wang, Member, IEEE, and Matthew J. Barth, Fellow, IEEE

Abstract—Our current transportation system faces a variety of issues in terms of safety, mobility, and environmental sustainability. The emergence of innovative intelligent transportation system (ITS) technologies such as connected and automated vehicles (CAVs) and transportation electrification unfold unprecedented opportunities to address aforementioned issues. In this paper, we propose a hierarchical ramp merging system that not only allows microscopic cooperative maneuvers for connected and automated electric vehicles (CAEv) on the ramp to merge into mainline traffic flow, but also has controllability of ramp inflow rate, which enables macroscopic traffic flow control. A centralized optimal control-based approach is proposed to both smooth the merging flow and improve the system-wide mobility of the network. Linear quadratic trackers in both finite horizon and receding horizon forms are developed to solve the optimization problem in terms of path planning and sequence determination, and a microscopic electric vehicle (EV) energy consumption model is applied to estimate the energy consumption. Finally, traffic simulation is conducted through PTV VISSIM to evaluate the impact of the proposed system on a highway segment. The results confirm that under the regulated inflow rate, the proposed system can avoid potential traffic congestion and improve mobility up to 102% compared to the conventional ramp metering and the ramp without any control approach.

I. INTRODUCTION

A. Motivation

Connected and automated vehicle (CAV) technology has been widely developed during the past decade. With onboard sensors such as camera, radar, and Lidar, CAVs can sense the surrounding environment and be driven autonomously and safely by themselves without colliding into other objects on the road. In addition, CAVs are able to communicate with each other, equipping roadside infrastructure with vehicle-to-vehicle (V2V) communications and vehicle-to-infrastructure (V2I) communications, and sharing information of vehicle status, signal phase and timing (SPaT), and etc. This enables CAVs to make decisions in a collaborative manner.

As a common scenario, ramp merging attracts wide attention from many researchers due to the concerns of safety and mobility in the merging area, especially when the merging lane is relatively short and the merging vehicle cannot accelerate fast enough or reach a reasonable speed to merge into the main traffic flow. Also, since vehicles on the mainline often need to adjust their speeds upon observing the merging vehicles during a relatively short period of time, the speed fluctuations sometimes lead to traffic congestion along the upstream traffic, therefore potentially increasing the energy consumption of upstream vehicles. Moreover, uncontrolled inflow traffic from ramps to the highway may cause the oversaturation of the network and further aggravate the traffic congestion.

Ramp metering is a widely used ramp merging management method, which utilizes the traffic signals installed on highway on-ramps to regulate the inflow rate of traffic entering the mainline according to prevailing mainline traffic conditions. Ramp metering usually consists of two-phase signal light (red and green only) together with a signal controller. It is proved to be a cost-effective operational strategy to improve the safety, mobility and sustainability issue. The existing works have mainly fallen into three categories, namely rule-based approaches [1]–[6], control-based approaches [7]–[10], and learning-based approaches [11]–[15]. However, since it inevitably introduces stop-and-go driving maneuver to the ramp vehicles, it often costs extra travel time and energy consumption of vehicles. Also, the ramp metering system leaves ramp vehicles much smaller room to adjust their speeds to merge into the mainline stream (due to mandatory stops at the meter), which potentially increases the safety risk.

B. Literature Review

Besides the ramp metering, different kinds of technology have been proposed and developed to improve the ramp merging scenario by introducing the coordination of CAVs in terms of their motion control algorithms. Rios-Torres et al. [16], Scarinci et al. [17], and Zhao et al. [18] provided comprehensive reviews of the previous works regarding CAV-based cooperative ramp merging control. Milanes et al. developed a fuzzy-logic control method for vehicles to merge into the congested mainline, allowing flow speed changes of vehicles both on the ramp and on the mainline [19]. Marinescu et al. designed a slot-based approach for intelligent vehicles to merge from ramp to mainline, and the results showed a higher traffic throughput and lower delay, compared to the baseline human-driven scenario [20]. The virtual vehicle methodology was originated from Uno et al. [21], and it has been proposed and developed over the years by other researchers [22]–[24]. In their approaches, CAVs on the mainline are projected on the ramp as virtual vehicles, where their information (distance to the merging zone, speed, acceleration, etc.) can be estimated and transmitted through V2V communications and/or V2I communications. Linear feedback controllers were proposed for the ego vehicle in their studies to track the longitudinal movement of the virtual vehicle.

Other than the aforementioned approaches for ramp merging systems, optimal control has also been widely studied and implemented in this field of research. Rios-Torres et al. enabled online coordination of merging vehicles by proposing an optimization framework together with an analytical closed-form solution [25]. Awal et al.
developed a proactive optimal merging strategy to compute the optimal merging sequence of vehicles coming from mainline and ramp [26]. Once the merging sequences of vehicles were defined, Ravari et al. presented a methodology to optimize the time-to-conflict-zone for vehicles to reduce their travel time [27]. Cao et al. proposed a model predictive control (MPC)-based path generation algorithm, which can generate the merging path for vehicles with real-time optimization [28]. Numerical simulation was conducted based on traffic data recorded from a helicopter, and the results proved their proposed method can generate a cooperative merging path as long as the initial conditions of vehicles were reasonable.

C. Contribution of the Paper

Utilizing the CAV technique, many researchers have been trying to design a control system to cooperate vehicles’ maneuvers in the ramp merging area to improve traffic efficiency. However, none of the above approaches take energy consumption as major concern in the problem formulation. Also, although the previous research proposed many sophisticated control methods, they failed to consider the entrance sequence of both mainline and ramp vehicles into the merging zone – the first-come-first-serve strategy and simplified estimated time of arrival (ETA) scheme are commonly used [25]. More importantly, the cooperation of vehicles at merging area can only improve the local performance of the system. Unregulated inflow rate of the ramp vehicles can still lead to potential oversaturation the highway network, thus increasing the risk of upstream congestion and traffic accident around the merging area. In addition, very few studies have focused on the energy efficient merging, not to mention the application of electric vehicle or more specifically connected and automated electric vehicles (CAEVs). Lastly, previous research barely conducted traffic simulation. The seemingly sound results from snapshot of vehicles cannot represent long term impact on the traffic.

Our previous paper proposed a hierarchical system for corridor-wide ramp control [18]. At the corridor level of the system, a cooperative protocol is introduced to calculate system-wide optimal inflow rate for each on-ramp, given the estimate of macroscopic traffic condition. The lower level controller coordinates the maneuvers of CAEVs locally at the ramp area and regulates the inflow rate accordingly. In this paper, we focus on the development of ramp merging control subsystem (i.e., the lower level of the corridor-wide ramp control system) by assuming a suggested ramp inflow rate to be given (from the upper level of the hierarchical system) as the input. The proposed system first decides the set of vehicles to be controlled dynamically. Then the optimal merging sequence (involving both mainline and ramp vehicles) at the ramp level is identified, using a finite-horizon linear quadratic (LQ) tracker which predicts the optimal speed profiles in terms of energy consumption of the involved vehicles (both on-ramp and mainline) under specific conditions. With the identified optimal sequence, the vehicles are then controlled by a receding-horizon LQ tracker with the same parameters as the ones used in the prediction step. Finally, the next ramp leader vehicle (the first vehicle following the previous set of vehicles) is controlled to fit the suggested ramp inflow rate. It is important to note that the energy consumption was estimated through a microscopic electric vehicle energy consumption model developed in our previous study [29].

The structure of this paper is as follows. In Section II, we formulate the problem of highway ramp merging and discuss the hierarchical architecture of the developed system. Section III explains the details of the proposed methodology. The traffic simulation and associated results are presented in Section IV. Section V concludes the paper and discusses possible directions of future work.

II. PROBLEM FORMULATION AND SYSTEM ARCHITECTURE

A. Problem Formulation

Fig. 1 illustrates a typical highway-ramp merging area. However, different from the traditional ramp metering scenario which has a traffic light located at the end of the ramp, we consider the scenario with the following assumptions in this paper:

- All vehicles are CAEVs whose information (e.g., position, speed, and acceleration) are perfect and are shared via V2I or V2V communications. And their speeds can be fully controlled by the acceleration/deceleration signals sent from a centralized processor.
- There is no communication delay or package loss in either V2V or V2I communications.
- Once the affected mainline vehicles are selected by the merging algorithm, they will not change lanes to preserve the number of controlled vehicles, or overpass other mainline vehicles to disturb the entrance sequence into merging area.

With the appropriate control, it is expected that the involved CAEVs may avoid unnecessary stops (as mandatory by the ramp metering) before the completion of merging maneuvers, while the inflow rate on ramp or even
the time headway between on-ramp vehicles can be well regulated.

Since we only control the longitudinal dynamics of the vehicles, we set up a one-dimensional coordinate system and map the positions of vehicles on both mainline and ramp to the system.

The dynamics of \( n \) vehicles in the proposed ramp merging system can be given by:

\[
\dot{p}_i = v_i, \quad \dot{v}_i = u_i
\]

where \( i \in \{1, 2, \ldots, n\} \) is the vehicle index; \( p \) and \( v \) represent the position and speed of the vehicle, respectively; and \( u \) denotes the acceleration of the vehicle, which acts as the input of the proposed system. If we define the overall system state as

\[
\begin{pmatrix}
  p_1 \\
  p_2 \\
  \vdots \\
  p_n \\
  v_1 \\
  v_2 \\
  \vdots \\
  v_n
\end{pmatrix},
\]

and the observation as

\[
\begin{pmatrix}
  p_1 - p_2 \\
  p_2 - p_3 \\
  \vdots \\
  p_{n-1} - p_n \\
  v_1 \\
  v_2 \\
  \vdots \\
  v_n
\end{pmatrix},
\]

the system can be written as the following linear form:

\[
\begin{align*}
\dot{x} &= Ax + Bu \\
y &= Cx
\end{align*}
\]

where \( A \) is a \( 2n \times 2n \) system matrix of constant coefficients that describes the state transfer; \( B \) is a \( 2n \times n \) control matrix of the coefficients that weight the inputs; and \( C \) is a \( (2n - 1) \times 2n \) output matrix.

Then, we formulate the optimization problem in the following quadratic form. The cost function is defined as the sum of the deviations of the measurements and control effort.

\[
\begin{align*}
\min J &= \frac{1}{2} \sum_{k=0}^{N-1} (y_k - r_k)^T Q (y_k - r_k) + u_k^T R u_k \\
&\quad + \frac{1}{2} (y_N - r_N)^T Q (y_N - r_N) \\
s.\:t. \quad &x_{k+1} = Ax_k + Bu_k, \quad y_k = Cx_k \\
&Acc_{\min} \leq u_k \leq Acc_{\max} \\
&(p_{i,k} - (p_{i+1,k}) \geq Gap_{\min}
\end{align*}
\]

where \( r_i \) is the gap and speed reference to be tracked; \( Q \) and \( R \) matrices define the weights of the objective function to be tuned, respectively, for the system outputs and inputs. \([Acc_{\min}, Acc_{\max}]\) is a feasible input range that the vehicles can achieve. \( Gap_{\min} \) is the hard safety constraint to avoid collision. If vehicle \( i \) and vehicle \( i + 1 \) are on the same lane (i.e., either both on the ramp or both on the mainline), this constraint should be held strictly. If vehicle \( i \) and vehicle \( i + 1 \) are on different lanes (e.g., one on the mainline while the other on the ramp), this constraint need to be held when they arrive at (or very close to) the merging area.

**B. Control Zone and Buffer Zone**

To solve this problem, we first specify the roadway segment with two types of zones: control zone and buffer zone for the on-ramp and mainline, respectively, as shown in Fig. 1. In the control zones of both mainline and on-ramp, a centralized processor is employed to receive and process the incoming information from CAEVs and send the control signals back to CAEVs to achieve system-wide energy efficiency. Buffer zones (in orange) are located on the upstream portion of the control zones, and are designed to continuously monitor the incoming vehicles and collect information to support subsequent control decision. As vehicle streams keep flowing into the network, control decision cycles (in time) are segmented and the involved CAEVs (with the consideration of regulated inflow rate) of each cycle are determined once the first unregulated vehicle hits the downstream boundary of the on-ramp buffer zone. By controlling the speed of each involved CAEV, the inter-vehicle gaps and traveling speed can be well regulated to ensure the safety at the merging zone. It is noted that if the number of vehicles within the on-ramp buffer zone exceeds the inflow rate to be regulated during the current cycle, then the partial of stream will be controlled and deferred to enter the merging area in the next cycle.

Fig. 2 shows an example of the trajectories of vehicles in the system to illustrate how vehicles are controlled. The orange curves illustrate the vehicles' trajectories controlled by the optimal algorithm; The blue dash curves depict the predicted trajectories of the leading vehicles for the next control decision cycle without regulating the on-ramp inflow rates; The solid blue curves present the controlled trajectories of these leading vehicles with the compliance of the inflow rates; The yellow curves represent the trajectories of vehicles following the leading vehicles whose trajectories have been regulated for the sake of inflow rate (i.e., solid blue curves).
In this section, we will discuss the detailed methodology for each key step in the flow chart of the proposed ramp merging system (see Fig. 3), including ramp-level data collection, optimal sequence determination, and vehicle motion control.

A. Ramp-level Data Collection

The buffer zone is designed to differentiate the involved vehicles within each control decision cycle for online implementation. As aforementioned, the length of on-ramp buffer zone is predefined, while the length of the mainline buffer zone may change with the traffic condition, which is considered as

\[ L_{\text{main}} = \frac{q_{\text{main}}}{d_{\text{main}}} \]  

where \( q_{\text{main}} \) is the mainline traffic flow known from corridor traffic condition; \( q_{\text{suggested}} \) is the suggested on-ramp inflow rate assumed to be known; \( n \) is the number of on-ramp vehicles currently in the buffer zone; \( d_{\text{main}} \) is the mainline density. The vehicles in the buffer zones of both on-ramp and mainline would be controlled as a whole set till their travel through the merging area within the same control decision cycle. Until another vehicle reaches the downstream boundary of on-ramp buffer zone, a new control decision cycle is initiated and a new set of involved vehicles are determined. Depending on the prevailing traffic conditions, the number of involved vehicles in each set (during each control decision cycle) may vary and the control processes or multiple LQ tracker controllers for different vehicle sets may perform in parallel.

B. Optimal Sequence Determination

There are three sub-steps in the Optimal Sequence Determination process, including possible sequence generation, linear quadratic tracking, and energy consumption estimation. In this process, all the possible orders of the involved vehicles will first be generated. For each order, the optimal system inputs (acceleration of each involved vehicle) can be solved by a LQ tracker. Then based on the system dynamics, the speed profile can be calculated and the energy consumption can be estimated by a microscopic electric vehicle energy consumption model [29]. Each possible order is associated with one aggregated energy consumption value (for all the involved vehicles), and the sequence with the least aggregated energy consumption is picked as the optimal scenario. Vehicle-level will then use this order to control the vehicles motion.

1) Possible sequence generation: Given the assumption that all the involved vehicles within each control decision cycle would not change their lanes during the merging process, vehicles on the same lane can not overpass their preceding ones. Therefore, if there are \( M \) mainline vehicles and \( N \) on-ramp vehicles, the number of possible sequence after merging equals to \( P(M + N, N) \), where \( P(\cdot) \) is the permutation operation.
2) Linear quadratic tracking: Based on the initial states, the finite-horizon linear quadratic tracking algorithm is able to generate the optimal solution in the designated finite time. The weight $Q$ and $R$ matrices are fine tuned to keep the balance of tracking error and control input and also to hold the hard constraints. For better performance, the weighting factors for on-ramp vehicles and for those mainline vehicles are tuned independently. The solution is calculated iteratively as follows:

$$
\begin{align*}
\{S_N &= C^TQ_NC \\& V_N = C^TQ_Nr_N \\
S_i &= C^TQ + A^TS_{i+1} - S_{i+1}B(R + B^TS_{i+1}B)^{-1}B^TS_{i+1}A \\& V_i = (A^T - A^TS_{i+1}B(R + B^TS_{i+1}B)^{-1}B^T)V_{i+1} + C^TQr_i
\end{align*}
$$

The solution $\mu_i = -K_ix_i + K_i^TV_i$, where $K_i$ is the feedback gain and the $K_i^T$ is the feed-forward gain.

$$
\begin{align*}
\{K_1 &= (B^TS_{i+1}B + R)^{-1}B^TS_{i+1}A \\
K_i^T &= (B^TS_{i+1}B + R)^{-1}B^T
\end{align*}
$$

3) Energy consumption estimation: Based on the electric vehicle energy consumption estimation model, the energy consumption rate can be determined by the nonlinear function of current speed and acceleration: $P = f(v, a)$

$$
\begin{align*}
P &= f_0 + l_1v\cos(\alpha) + l_2v\sin(\alpha) + l_3v^3 + l_4va \\
&+ l_5v^2\cos(\alpha) + l_6v^2\sin(\alpha) + l_7v^4 + l_8v^2a
\end{align*}
$$

where $l_1$ is the model parameter calibrated by different driving conditions; $\alpha$ is the road grade (rad). In our simulation, we assume the road grade is zero.

C. Optimal Motion Control

This module uses the results from previous step to control the motion of the involved vehicles. The controller chosen in this study is a receding-horizon LQ tracker for potentially online implementation. At each rolling time window, the controller can update the initial states with the current state, and we only use the converged feedback gain and feed-forward gain to control the system. The Q and R parameters for this receding-horizon controller are selected to be the same as the ones used in the prediction step to get consistent results. When the constraints do not hold in certain time step, the optimal solution will be recalculated by enlarging the current time window until the constraints are satisfied.

As aforementioned, given the suggested ramp inflow rate, not all the vehicles within the on-ramp buffer zone should be controlled to enter the merging zone during the same time interval. Under the selected car-following model, if the leader arrives the trigger point earlier than this time, the ramp inflow rate would be higher than suggested. Therefore, we predict its ETA using the intelligent driver model (IDM) [30], given the predicted optimal trajectory from the optimal sequence determination module. The vehicle governed by the IDM presents a second order dynamic shown as follow:

$$
\begin{align*}
\dot{v} &= a(1 - \left(\frac{v}{v_0}\right)\delta - \left(\frac{s'(v-\Delta v)}{s}\right)^2) \\
s'(v - \Delta v) &= s_0 + VT + \frac{v\Delta v}{2ab}
\end{align*}
$$

where $v_0$ is desired velocity; $s_0$ is minimum spacing; $T$ is the desired time headway; a is the maximum vehicle acceleration; b is comfortable braking deceleration. The leader will be controlled by a linear feedback controller if ETA is smaller than the suggested time.

IV. SIMULATION STUDY AND RESULTS

In this section, we conduct a simulation study for the proposed ramp merging system with the microscopic traffic simulator PTV VISSIM [31] to validate the effectiveness of the system. Different from the numerical simulation that most of the previous research conducted, traffic simulation can offer more realistic real-time interaction between the equipped vehicles and other traffic in the network. This enables a better observation of the impact of the proposed system on the whole traffic over the time. Through the DriverModel API, the behavior of the CAEVs in the network can be controlled with the proposed algorithms. Uncontrolled vehicles in the network are modeled by the default vehicle model in VISSIM.

The simulation network is built based on the California State Route 91 (SR-91), with a focus on the Serfas Club Dr. on-ramp in Corona.

In our simulation, the conventional ramp metering system and the ramp without any control approach are introduced for comparison. Only longitudinal control is considered in the simulation, while the default lane change model is used for lateral control. Based on the observation, the merging area capacity is around 1800 passenger car unit/hour/ lane (pcu/hr/ln). According to this, the ramp inflow rate is dynamically adjusted to regulate the overall traffic flow not to exceed the capacity. For fair comparison, the baseline ramp metering rate is also set to match the inflow rate that is regulated by the proposed system. The desired speed for mainline/merging traffic is 73.8 mph. The initial speed of on-ramp vehicles while entering the control zone is 33.5 m/s.

We consider two scenarios based on different traffic conditions. Each scenario contains two phases, lasting 600s respectively. For mainline traffic, 1600 pcu/hr/ln is considered as heavy, and 1200 pcu/hr/ln is as moderate. For ramp traffic, 500 pcu/hr/ln is considered as heavy, and 300 pcu/hr/ln is as moderate. Table I shows the settings of simulation scenarios in this study.

| TABLE I. SCENARIO MATRIX |
|--------------------------|
| Phase 1: 0-600s | Phase 2: 600-1200s |
| Mainline Inflow | Ramp Inflow | Mainline Inflow | Ramp Inflow |
| Scenario 1 | 1600 | 300 | 1200 | 300 |
| Scenario 2 | 1600 | 300 | 1200 | 300 |

The simulation results measured by the mobility metric are shown in TABLE II and TABLE III. The mobility performance is measured by network efficiency, $Q = \frac{VMT}{VHT}$.
where VMT is the total vehicle-miles traveled in the network; and VHT is the total vehicle-hours traveled in the network accordingly.

In scenario 1, the heavy traffic of both mainline and ramp in phase 1 rapidly caused the congestion in the network for both ramp metering case and no control case. At each time when the ramp vehicle merged, a shockwave was generated and spread to the upstream, which eventually evolved to stop-and-go traffic along the mainline. In addition, the consistent shockwaves impeded the recovery of congestion, which led to low mobility of the network. As shown in Table II, the overall mobility of no control case has only 29.6 mph. Although ramp vehicles have relatively high mobility, their uncooperative behaviors severely influenced the mainline vehicles. Interestingly, even though the traffic experienced severe stop-and-go situations with very low average speed or network efficiency, the system energy consumption (in kWh per 100 mile) is decent. A hypothesis is that electric vehicles may operate efficiently in terms of energy consumption under relatively congested scenarios due to their regenerative braking feature [32]. On the other hand, in the ramp metering case, since the ramp inflow rate was regulated, less significant impact was involved on the mainline. The mainline mobility in this case was 57.9 mph, much better than the no control case. However, the ramp metering operation severely limited the mobility on ramp, and the extremely high frequency of stop-and-go maneuvers at very low speed also caused significant energy waste for electric vehicles. As to the case of the proposed optimal control, the cooperation led to the highest overall mobility (including both mainline and ramp), which is improved by 43.1% and 102.0%, respectively, compared to the ramp metering case and no control case. In terms of energy consumption, the proposed system outperformed both the ramp metering case and the no control case for ramp traffic with the smoothing effects, but the mainline traffic consumed more energy mainly due to the high speed (thus high load for EVs) to be maintained.

In scenario 2, since the heavy traffic of mainline and ramp were staggered, it was a generally moderate traffic condition compared to the scenario 1. Therefore, the mobility performance is better for all cases. The proposed optimal control system still achieved the best mobility, improving 45.3% compared to the ramp metering case and 95.6% compared to the no control case. In terms of energy consumption, high average speed resulted from the proposed system seems to be a penalty for electric vehicles. And the “sweet spot” in this study falls in the range between 27 mph and 34 mph.

V. CONCLUSION AND FUTURE WORK

In this paper we proposed a hierarchical ramp merging system for Connected and Automated Electric Vehicles (CAEVs). The system can not only cooperate the vehicles at ramp merging area to achieve a safer, smoother, and more efficient traffic flow, but also be able to regulate ramp vehicles’ inflow rate which has the potential to leverage the corridor-wise efficiency by integrating with effective perimeter control on multiple ramps. We developed a ramp-level data collection logic that can determine the right set of vehicles for online control and collect the associated information based on the prevailing traffic conditions. Unlike most existing studies using simple sequencing protocol (e.g., first-come-first-serve), we used a finite linear Quadratic (LQ) tracker to identify the optimal merging sequence in terms of energy consumption. An receding horizon LQ tracker with the same parameters was used for the optimal motion control. The simulation results verified the effectiveness of the proposed system.

An ongoing research direction is to develop the upper-level corridor-wise perimeter control algorithm which can provide the optimal ramp inflow rate (cooperatively) for each involved individual ramp along the corridor. In addition, more practical considerations on mixed traffic scenario would be one of our future steps.

ACKNOWLEDGMENT

This study is funded by the National Center for Sustainable Transportation (NCST). The contents of this paper reflect only the views of the authors, who are responsible for the facts and the accuracy of the data presented herein.

REFERENCES

[1] L. Jacobson, K. Henry, and O. Melbyar, “Real-time metering algorithm for centralized control,” Transp. Res. Rec., no. 1732, pp. 20–32, 1989.
[2] G. Paesani, J. Kerr, P. Perovich, and F. E. Khosravi, “SYSTEM WIDE ADAPTIVE RAMP METERING (SWARM),” Merging Transp. Commun. Revolutions. Abstr. ITS Am. Seventh Ann. Meet. Expo., 1997.
[3] Y. J. Stephanedes, “Implementation of on-line zone control strategies for optimal ramp metering in the Minneapolis ring road,” Road Traffic Monit. Control, vol. 26–28, pp. 181–184, 1994.
[4] C. Taylor and D. Meldrum, “Evaluation of a Fuzzy Logic Ramp Metering Algorithm: a Comparative Study Among Three Ramp Metering Algorithms,” 2000.
[5] J.-C. Liu et al., “An Advanced real-time ramp metering system (ARMS): the system concept,” Texas, 1994.
[6] O. J. Chen, A. F. Hotz, and M. E. Ben-Akiva, “Development and Evaluation of a Dynamic Ramp Metering Control Model,” IFAC Proc. Vol., vol. 62, no. 5, pp. 1089–1095, 2017.

TABLE II. SIMULATION RESULT FOR SCENARIO 1

| Mobility (mph) | Energy (kWh/100 mile) |
|---------------|----------------------|
| **Optimal Control** |                      |
| Overall       | 59.8                 | 48.84              |
| Mainline      | 62.1                 | 50.67              |
| Ramp          | 48.3                 | 37.26              |
| **Ramp Metering** |                     |
| Overall       | 41.8                 | 51.34              |
| Mainline      | 57.9                 | 47.15              |
| Ramp          | 13.6                 | 82.84              |
| **No Control** |                      |
| Overall       | 29.6                 | 44.13              |
| Mainline      | 27.6                 | 43.95              |
| Ramp          | 52.2                 | 45.43              |

TABLE III. SIMULATION RESULT FOR SCENARIO 2

| Mobility (mph) | Energy (kWh/100 mile) |
|---------------|----------------------|
| **Optimal Control** |                      |
| Overall       | 66.7                 | 51.53              |
| Mainline      | 69.0                 | 53.29              |
| Ramp          | 54.1                 | 39.58              |
| **Ramp Metering** |                     |
| Overall       | 43.9                 | 50.97              |
| Mainline      | 64.5                 | 46.93              |
| Ramp          | 14.5                 | 81.29              |
| **No Control** |                      |
| Overall       | 34.1                 | 42.87              |
| Mainline      | 32.7                 | 42.59              |
| Ramp          | 49.6                 | 44.95              |
on Intelligent Transportation Systems

Traffic merging using cooperative intelligent vehicles: A slot

Control Eng. Pract., vol. 14, pp. 757–767, 2006.

Development of the Next Generation Stratified Ramp Metering Algorithm Based on Freeway Design,” 2011.

Traffic merging using intelligent vehicles: A slot

Intelligent Transportation Systems

Cooperative Vehicle Merging at Highway On-Ramps,” IEEE Trans. Intell. Transp. Syst., vol. 18, no. 4, pp. 780–789, 2017.

Optimal traffic merging strategy for communication- and sensor-enabled vehicles,” in 16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013), 2013, pp. 1468–1474.

Merge Algorithms for Intelligent Vehicles,” in Next Generation Design and Verification Methodologies for Distributed Embedded Control Systems, 2007, pp. 51–65.

A hybrid approach to estimating electric vehicle energy consumption for e CODR applications,” in 2016 IEEE 19th International Conference on Intelligent Transportation Systems, 2016, pp. 719–724.

Enhanced intelligent driver model to access the impact of driving strategies on traffic capacity,” Philos. Trans. R. Soc. A Math. Phys. Eng. Sci., vol. 368, no. 1928, pp. 4585–4605, 2010.

Available: http://vision-traffic.ptvgroup.com/en-us/products/ptv-vissim

Modern Electric, Hybrid Electric, and Fuel Cell Vehicles: Fundamentals, Theory, and Design (2nd Edition)”. Taylor and Francis