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An Enhanced Predictive Cruise Control System Design with Data-driven Traffic Prediction

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Abstract

The predictive cruise control (PCC) is a promising method to optimize energy consumption of vehicles, especially the heavy-duty vehicles (HDV). Due to the limited sensing range and computational capabilities available on-board, the conventional PCC system can only obtain a sub-optimal speed trajectory based on a shorter prediction horizon. The recently emerging information and communication technologies such as vehicular communication, cloud computing, and Internet of Things provide huge potentials to improve the traditional PCC system. In this paper, we propose a general framework for the enhanced cloud-based PCC system which integrates a data-driven traffic predictive model and the instantaneous control algorithms. Specifically, we introduce a novel multi-view CNN deep learning algorithm to predict traffic situation based on the historical and real-time traffic data collected from fields, and the time-varying adaptive model predictive control (MPC) to calculate the instantaneous optimal speed profile with the aim of minimizing energy consumption. We verified our approach via simulations in which the impact of various traffic condition on the PCC-enabled HDV has been fully evaluated.

Index Terms

Predictive cruise control, cloud-based system, model predictive control, traffic prediction, deep learning algorithm

I. Introduction

With the dramatically increasing vehicles on the road, a high demand for energy savings and environmental concerns has become a major issue in transportation [1]. Substantial researches have focused on improving vehicle and traffic management technologies to reduce energy consumption, such as new powertrain systems, cooperative driving, and traffic signal optimization [2]–[6]. Specifically, the predictive cruise control (PCC) [7] has been regarded as a promising method for eco-driving which utilizes relevant traffic context information (e.g. Global Postioning Systems (GPS)) and adopts adaptive cruise control functions to optimize energy consumption of vehicles, especially HDVs.

Due to the limited sensing range and computational capabilities available on-board, the conventional PCC system can only obtain a sub-optimal speed trajectory based on a shorter prediction horizon. For a long-distance HDV journey, however, traffic contexts such as weather, road condition, and traffic condition (see Fig. 1) may dramatically change at different spatio-temporal points which would lead to the time-varying longitudinal vehicle model. Therefore, it is more challenging to achieve global energy optimization for HDVs in this situation.

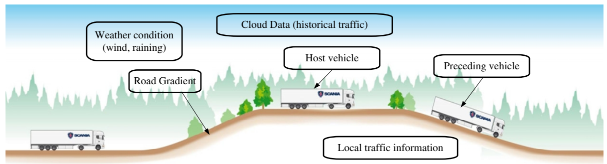

Fig. 1. Scenario of HDV eco-driving

The recently emerging information and communication technologies such as vehicular communication, cloud computing, and Internet of Things have enriched various real-time information available on traffic networks, and accordingly, provide huge potentials to improve the traditional PCC system. For example, vehicle-to-vehicle and traffic-light-signals-to-vehicle communications are introduced [8] to minimize fuel consumption of vehicles in urban area. With the help of V2X communication, the optimal vehicle trajectory planning [9] is designed for cooperative merging on highways. Moreover, the control system can be deployed from the physical machine to a cloud, i.e. control system as a service (CSaaS) [10]. [11] demonstrates the application of cloud computing for velocity profile optimization and verified a significant reduction in fuel consumption by adopting the new approach.

Nonetheless, there are still some challenges and potential issues to be addressed in the area of HDV eco-driving. First, most related work focuses on the instantaneous PCC system design and powertrain energy optimization by applying different approaches [12]–[16], for example the model predictive control for fuel economy and the hierarchical control strategy for cooperative eco-driving. These studies normally take local traffic information as the reference including the preceding road slope, the upcoming traffic signal, etc. However, in context of the Internet of Things and cloud computing, not only the real-time local information from surrounding vehicles, but also the globally/historically accessible information from the cloud could be adopted in HDV eco-driving. Consequently, a rethinking of general control framework for HDV eco-driving is required which can fully utilize both local and global information available information.

Second, the vehicle's perception capability can be significantly improved by taking advantage of big data and advanced machine learning [17], which, however, has been less considered in HDV eco-driving design. Moreover, it is still unclear how the the energy benefit can be brought by the data-driven traffic prediction.

Third, most research assumes a predefined or invariable traffic scenario, neglecting the impact of time-varying road traffic conditions on energy efficiency. Specifically, the interaction between the PCC-enabled HDV and surrounding common vehicles may significantly affect the energy efficiency, which has not been fully evaluated in the literature.

To address these issues, in this paper, we propose a general framework of the enhanced cloud-based PCC system for HDV's long-distance eco-driving. Specifically, we propose a data-driven predictive model to forecast the traffic situation based on historical and real-time traffic data, and adopt the time-varying model predictive control (MPC) algorithm to address the dynamics of vehicular longitudinal model and calculate the instantaneous optimal speed profile with the aim of minimizing energy consumption. To the best of our knowledge, this is the first attempt that PCC system combines with traffic prediction for the purpose of energy optimization. We verify our approach via simulations in which the impact of interaction between the PCC-enabled HDV and common vehicles has been fully evaluated in different traffic scenarios.

Our novel contributions in this paper are as follows:

- We first propose a general framework of the enhanced cloud-based PCC system which takes advantages of big data and cloud computing for HDV eco-driving. We then develop a joint design for HDV eco-driving, which combines a novel Multi-view CNN algorithm for traffic prediction, and a time-varying adaptive MPC algorithm for instantaneous energy optimization.
- We conduct extensive simulations to verify the efficiency of our approach. Specifically, the impact of interaction between the PCC-enabled HDV and surrounding common vehicles are comprehensively evaluated in different traffic scenarios.

The rest of this paper is organized as follows. We first summarize related work about vehicle eco-driving and to traffic prediction approaches in Section II. Then we present the control framework of the Cloud-based PCC system, and formulate and solve the instantaneous energy optimization in Section III. We then introduce the data-driven approach to traffic prediction model in Section IV. Finally, in Section V, we validate our approach and evaluate system performance through extensive simulation experiments, before concluding the paper in Section VI.

II. Related Work

A. Vehicle Eco-driving

Numerous methods have been proposed for vehicle eco-driving, in which the new engine/vehicle technologies, novel Information Communications Technology (ICT), and control optimization technologies have been widely applied [1]. In this paper, we only focus on the application of new ICT and control algorithms.

[18] considers the impact of road gradient information, and proposed a MPC algorithm to generate appropriate vehicle control inputs to avoid braking and high control inputs in the hilly roads driving scenario. In some situation, for example during downhill sections, the HDV sometimes has to brake to avoid speed limits breach which consequently wastes energy. The look-ahead control method is adopted in [19], where the information about the future disturbances is assumed to be accessible, and accordingly the optimization taking into account the future behavior of the system is formulated and solved by dynamic programming (DP). This advantage has been further applied in the cooperative vehicle platooning scenario which employs aerodynamic drag reduction of platoons [16], [20], [21]. Similarly, the system in [12] predicts the preceding vehicle's behaviour and considers the signal status of the upcoming intersections to compute the optimal vehicle control input. In [13], the driver behavior is considered and learned online which then is integrated into the scenario-based stochastic MPC algorithm for energy management of a hybrid electric vehicle. With the help of emerging vehicular communication technologies, a distributed optimal control scheme [22] is proposed to achieve cooperative highway driving at the level of individual vehicles, which demonstrates the improvement of fuel economy and traffic efficiency.

To address vehicle eco-driving for a long journey, a typical method is to optimize energy consumption with a two-stage hierarchy: one for long-term optimization before departure and the other for short-term adaptation while driving in real time [22], [23]. A traffic data-enabled predictive energy management strategy is proposed for a power-split plug-in hybrid electric vehicle in [24] which is composed of a two-tiered scheme. Specifically, the upper level uses real-time traffic flow velocity to compute a global state of charge trajectory, and the lower level applies a MPC algorithm which takes advantage of short-term velocity prediction. To reduce the computational costs and time for on-board controller of the HDV, [25]–[27] decouple the whole optimization into the velocity profile and shifting schedule calculation, in which an offline algorithm in the higher layer (can be deployed in cloud) is designed to optimize the vehicle velocity profile, while the on-line powertrain control is implemented in the lower layer based on the reference velocity profile. All these computation-intensive calculations can also be performed in the cloud [11] to generate the optimal speed profile which is provided as the reference for the driver via HMI.

In order to address the computational complexity of energy optimization, Pontryagin's maximum principle is adopted to solve the optimal control problem in [28] and [15]. [29] proposes an engine output energy optimization model with MPC for map-based anticipatory driving of heavy duty vehicles, which can be formulated into a Quadratic Programming (QP) optimization problem with a sparse matrix structure. Two real-time feedback controllers called the estimated minimum principle (EMP) and kinetic energy conversion (KEC) are designed [15] only based on the current road slope to realize eco-cruising control on varying slopes for the common vehicles. These designed controllers result in a very light computing load while maintaining fuel economy similar to the MPC method.

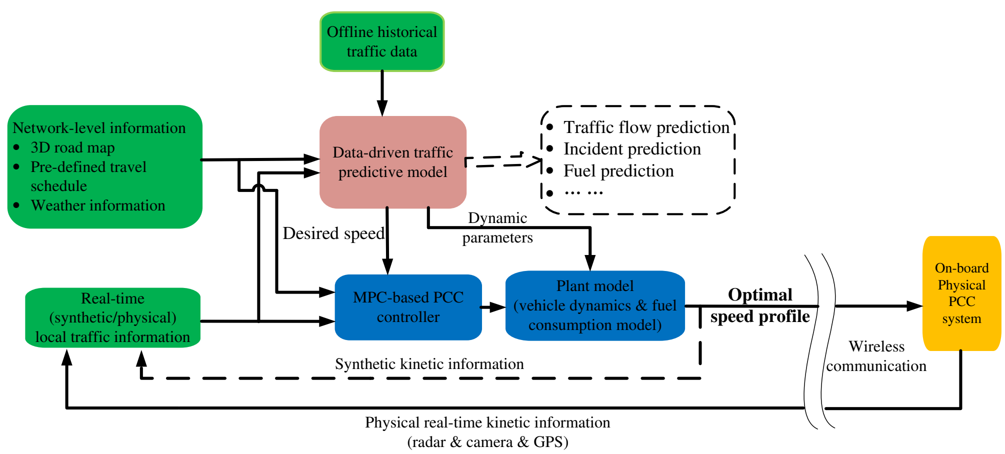

Fig. 2. General framework of enhanced cloud-based predictive cruise control system

B. Traffic Prediction

Accurate and timely traffic prediction plays a key role in HDV eco-driving, which generally can be classified into model-based and data-driven approaches [30].

The model-based approach uses a physical model describing traffic dynamics, namely, a traffic flow model normally characterized by empirical relation. Traffic states then can be predicted by applying the model and real-time data being as the input. Some typical models include Lighthill–Whitham–Richards (LWR) model [31], kinematic wave model [32], cellular automata model [33], and Boris Kerner's three-phase traffic theory [34]. To address modeling errors or uncertainties, The Kalman filter and its extensions are applied for online learning and calibration [35]–[37]

Model-based traffic prediction is computationally efficient for a large-scale road network with branches. However, most of these theoretical models are associated with ideal assumptions and limited data support [30]. In addition, careful selection and calibration of models are needed in different traffic scenarios.

With the increasing deployment of IoT devices and communication infrastructures in recently years, more and more traffic data become accessible and easily collected by the advanced ITS. Data-driven methods have drawn substantial attentions and become more popular for traffic prediction, such as classic statistical models and machine learning models [38]–[46].

In time-series analysis, autoregressive integrated moving average (ARIMA) has been widely applied into various traffic data analysis and modeling, for example seasonal ARIMA [38] and ARIMA with the Kalman filter [39]. However, these statistical models often lack adaptability in handling spatially and temporally varying sensor data as well as the stochastic characteristics of traffic flow.

The emerging deep learning methods have demonstrated their efficiency in complex traffic flow prediction [17]. The deep belief network (DBN) has been proved [40] to have the capability of capturing the stochastic features, and a stacked auto-encoder model (SAE) is used to learn generic traffic flow features in [41]. Long Short-Term Neural Network (LSTM) [42] is applied to capture nonlinear traffic dynamics with the short and long temporal dependency. To explore spatio-temporal features, a convolutional neural network (CNN)-based method is adopted in [43] that learns traffic as images using time and space dimension information. Compared with the benchmark models including typical neural networks, SAE, LSTM, etc., their CNN model achieves higher accuracy in traffic speed prediction. Recent work applies graph-based CNNs [44], [47] or the combination of LSTM and CNN [48] to further capture the spatio-temporal dependency of traffic flow.

To summarize, CNN-based models are regarded as powerful tools to capture the spatio-temporal dependencies of traffic flow. Therefore, in this paper, we applied the CNN-based model for traffic speed prediction in Section IV.

III. MPC-based Instantaneous Speed Control

In this section, we first present the control framework of enhanced PCC system. We then describe the longitudinal model of HDV with the dynamic environmental parameters, and formulate the optimal energy control problem in the space domain.

A. Framework of Enhanced PCC System

For the HDV eco-driving over a long-distance journey, we propose a control framework of the enhanced PCC system which combines the instantaneous MPC-based control algorithm with data-driven traffic prediction, as shown in Fig. 2. The real-time MPC-based control strategy is implemented to obtain the optimal speed profile which is transmitted to the physical HDV as a reference for the driver. Specifically, to tackle the challenge of time-varying road context and traffic condition, a data-driven traffic predictive model is designed in the enhanced PCC system, which provides precise predictions of traffic flow, incident, journey time, etc., on current and potential routes for real-time MPC controller as reference inputs.

The data-driven model periodically predicts the average traffic speed on a specific road segment at a certain time slot, which can be used as the desired speed for the instantaneous MPC controller. On the other hand, context prediction by the data-driven model can also provide more precise dynamic parameters (e.g. wind speed, rolling resistance, etc.) to update the time-varying longitudinal vehicle model.

The traffic information provided to the PCC system can be basically classified in term of the information coverage:

- Network-level information such as predefined traffic schedule, 3D road map, and weather condition.
- Real-time information such as vehicle kinetic information and local traffic condition.
- Offline historical traffic data to be used as the training data for traffic predictive model.

The workflow of the proposed ePCC system is described as follows. The instantaneous MPC-based PCC controller periodically calculates the HDV'S optimal speed profile only at the next location, normally a short distance ahead, by taking into account the real-time local traffic information and the target speed profile predicted from the traffic predictive model. The consequent results are sent to the HDV driver as a reference. In the following, we will focus on the instantaneous PCC control, in which MPC-based controller and the data-driven traffic predictive model will be specifically designed.

TABLE I
SYMBOLS AND NOTATIONS.

A_f	Vehicle Frontal Area
R_w	Tyre radius
J_w	Tyre Inertia
N_w	Number of wheels
M_v	Vehicle mass
M_e	Effective mass (including inertial effects)
η	Transmission efficiency
γ_g	Gear ratio
$C_r(t)$	Tyre rolling resistance coefficient
$\theta(t)$	Road grade
$C_d(t)$	Aerodynamic drag coefficient
$\rho(t)$	Air density
T_e	Engine torque
T_b	Brake torque
$v(t)$	Vehicle speed
F_{eng}	Tractive force
F_{brk}	Brake force
F_{rol}	Tire rolling resistance force
F_{aro}	Aerodynamic resistance force
F_{grd}	Road grade force

B. Vehicle Dynamics

The general longitudinal dynamics of HDV can be modelled by:

$$M_e \frac{dv}{dt} = F_{eng} - F_{brk} - F_{rol} - F_{aro} - F_{grd} \tag{1}$$

$$F_{rol} = M_v g C_r(t) \cos\theta(t) \tag{2}$$

$$F_{aro} = \frac{1}{2}\rho(t) A_f C_d(t) v(t)^2 \tag{3}$$

$$F_{grd} = M_v g \sin\theta(t) \tag{4}$$

$$F_{eng} = \frac{\eta \cdot \gamma_g(n)}{R_w} T_e \tag{5}$$

$$F_{brk} = \frac{T_b}{R_w} \tag{6}$$

$$M_e = M_v + N_w \frac{J_w}{R_w^2} \tag{7}$$

where all parameters are summarized in Table I. It shall be noted that γ_g is the discrete gear ratio with operational sets $\gamma_g(n) \in \{\gamma_{g1}, \gamma_{g2}, ...\}$. Additionally, the time-varying environmental parameters $\theta(t)$, $C_r(t)$, $C_d(t)$, and $\rho(t)$ are adopted in the longitudinal model, which can be influenced by road surface and weather conditions such as temperature, wind speed, humid level, etc.

Since all environmental parameters regarding traffic condition can be spatially changing, transforming the longitudinal model from the temporal domain to the spatial domain will facilitate the effective energy optimization [23]. Denoting the traveled distance by s and the trip time by t, then for a function $v(s(t))$:

$$\frac{dv}{dt} = \frac{dv}{ds}\frac{ds}{dt} = \frac{dv}{ds}v \tag{8}$$

We then define $E_k(s) = \frac{1}{2}M_e v(s)^2$ as the kinetic energy at space s, and combine with Eq. (1) $\sim$ Eq. (5), the longitudinal dynamics in the spatial domain can be modelled by:

$$\begin{aligned} \dot{E}_k(s) =& M_e v(s)\frac{dv}{ds} = \frac{\eta \cdot \gamma_g(n) T_e(s)}{R_w} - \frac{T_b}{R_w} - M_v g \sin\theta(s) \\ &- \frac{1}{2}\rho(s) A_f C_d(s) v(s)^2 - M_v g C_r(s)\cos\theta(s) \end{aligned} \tag{9}$$

Let the trip distance be discretized with the same distance step $S = n\Delta s$, $E_e(s) = \frac{\eta \cdot \gamma_g(n) T_e}{R_w}\Delta s$ be the engine output energy, and $E_b(s) = \frac{T_b}{R_w}\Delta s$ be the brake energy, the longitudinal dynamics of HDV then can be linearized by:

$$\begin{aligned} E_k(i+1) &= E_k(i) + \dot{E}_k(i)\cdot\Delta s \\ &= A(i)E_k(i) + B(i)U(i) - D(i) \end{aligned} \tag{10}$$

where

$$\begin{aligned} A(i) &= 1 - \frac{\rho(i) A_f C_d(i)\Delta s}{M_e}, \\ B(i) &= [1 \quad -1], \\ U(i) &= \begin{bmatrix} E_e(i) \\ E_b(i) \end{bmatrix}, \\ D(i) &= (M_v g C_r(i)\cos\theta(i) + M_v g \sin\theta(i))\cdot\Delta s \end{aligned}$$

The state variable E_k represents the HDV's longitudinal speed, whereas E_e and E_b can be seen as the control input variables of the system.

Note that, for a typical complicated powertrain system, thousands of parameters need to be identified to obtain a concise fuel consumption model.

C. Optimal Energy Control

The primary objective of the PCC system is to find the optimal velocity profile to minimize fuel consumption subject to the physical dynamics and safety constraints. The general form of the optimization can be presented as:

$$\begin{aligned} \min \quad & \text{fuel consumption} \\ \text{subject to} \quad & \text{vehicle dynamics} \\ & \text{physical constraints} \\ & \text{safety constraints} \end{aligned} \tag{11}$$

However, the typical fuel consumption model is continuous and nonlinear, non-quadratic, non-convex, and depending on the used interpolation of a non-smooth function of engine torque T_e and engine speed ω_e [1]. Specifically, the Euro VI powertrain system adopted in this paper consists of hundreds of components and, therefore, it is difficult to describe the fuel consumption model with explicit forms.

In view of the complexity of a fuel consumption model, we focus on the engine-energy optimization instead of a fuel consumption optimization. In addition, the HDV is expected to follow the target speed profile which is derived from the data-driven predictive model. To improve driver's comfort, less jerk is also taken into account in the optimization. Consequently, the standard quadratic cost function of energy optimization is defined by:

$$\begin{aligned} J(i) = {} & \lambda_e \sum_{j=i}^{i+n_p-1} E_e(j)^2 + \lambda_k \sum_{j=i}^{i+n_p-1} \Big(E_k(j) - \frac{1}{2} M_e v_d^2(j)\Big)^2 \\ & + \lambda_s \sum_{j=i}^{i+n_p-1} \Big(E_e(j) - E_e(j-1)\Big)^2 \end{aligned} \tag{12}$$

where the first, second, and third terms represent the engine energy consumption, the speed deviation from the target speed v_d at each location, and the engine energy increment, respectively. n_p is the MPC prediction horizon, i.e., the distance interval along which the cost function is integrated based on the prediction of the system dynamics. λ_e, λ_k, and λ_s are constant weights.

In the literature, there are two typical strategies for v_d to be determined at the next location:

- The constant speed policy (CSP) which requires the HDV trying to maintain the speed at the recommended value, e.g. the speed limit or the maximum allowable velocity of a road, and only considering the current road condition.
- The average traffic speed policy (ASP) in which the HDV follows the real-time average speed of its preceding vehicles which can in general reflect the traffic situation and considers the current road condition.

In this paper, we consider the latter strategy based on the fact that speed harmonization can significantly mitigate traffic perturbation and save energy consumption [49]. Furthermore, we propose the predicted traffic speed policy (PSP) which considers the influence of future traffic conditions as well as the road condition (e.g. road slope) within the MPC prediction horizon. The desired traffic speed profile v_d will be obtained by the data-driven traffic predictive model, as presented in Section IV.

To guarantee the vehicle running in the operating zone, physical constraints including kinetic energy, engine energy, and braking energy are added to the optimization:

$$\frac{1}{2}mv_{\text{min}} \leq E_k \leq \frac{1}{2}mv_{\text{max}} \tag{13}$$

$$0 \leq E_e \leq \frac{\eta \cdot \gamma_g(n) T_e^{\text{max}}}{R_w} \Delta s \tag{14}$$

$$-\frac{T_b^{\text{max}}}{R_w} \Delta s \leq E_b \leq 0 \tag{15}$$

$$\gamma_g \in \{\gamma_{g1}, \gamma_{g2}, ...\} \tag{16}$$

Based on the preceding vehicle's speed v_p and spacing headway ΔL, we can also obtain the safety constraints. Assume a constant acceleration of the preceding vehicle[1] which can be estimated by:

$$a_p(i-1) = \frac{(v_p(i) - v_p(i-1))}{\frac{\Delta s}{v(i-1)}} \tag{17}$$

then the estimated speed of preceding vehicle at the next location can be calculated by:

$$\hat{v}_p(i+1) \approx v_p(i) + a_p(i-1) \frac{\Delta s}{v(i)} \tag{18}$$

[1]Given the short length of distance step definition (5-50m in the simulation), the assumption is reasonable in practice.

Accordingly, the estimated spacing headway at the next location is calculated by:

$$\Delta\hat{L}(i+1) \approx \Delta L(i) + \Big(\frac{v_p(i)+\hat{v}_p(i+1)}{2}\frac{\Delta s}{v(i)} - \Delta s\Big) \tag{19}$$

For a constant time headway H_d and the length of vehicle l_0, the safety headway spacing should satisfy:

$$\Delta\hat{L}(i+1) \geq H_d v(i+1) + l_0 \tag{20}$$

Thus the expected $v(i+1)$ can be obtained by:

$$v(i+1) \leq \frac{\Delta\hat{L}(i+1) - l_0}{H_d} \tag{21}$$

Based on the inequality of Eq. (21), we can also estimated the minimum $v(i+1)$ to avoid collision in the extreme condition that the preceding vehicle decelerates at the maximum value of $a_p(i-1) = a^{max} < 0$.

Thus the MPC discretized optimization problem can be formulated by:

$$\begin{aligned} \min \quad & J(i) \quad \text{in} \quad Eq.\ (12) \\ \text{s.t.} \quad & \quad Eq.\ (10) \\ & \quad Eq.\ (13) - Eq.\ (16) \\ & \quad Eq.\ (21) \end{aligned}$$

One of the main issue in this optimization problem is the discrete gear ratio γ_g in the powertrain, which can be transformed to a typical switching nonlinear mixed-integer problem and is challenging to solve. To simplify the solution, we here adopt the similar method in [21] by introducing the following assumptions: 1) The gear ratio can be changed continuously on a unlimited span, and 2) The gear management system chooses the most efficient gear ratio. In this paper, to reduce the complexity, the gear selection is assumed to be constant for the drive mission.

The controller updates the prediction model at each control interval and also uses time-varying models across the prediction horizon, which gives the MPC controller the best knowledge of the plant behavior in the future. Meanwhile, given the fact that traffic speed may change dramatically under different traffic conditions, instead of fixed distance step setting, we apply an adaptive distance step setting method in this paper to avoid conservative or aggressive driving action. Specifically, the value of distance step is directly proportional to the ego-vehicle's speed, i.e., the distance step is set with a large value in case of higher vehicle speed. Moreover, due to safety issues and the limited prediction horizon of traffic speed in the congested traffic scenario, the HDV intends to follow the its surrounding traffic speed to avoid collision rather than to save energy consumption, and accordingly, the benefit brought by the traffic prediction is trivial. Therefore, we consider ASP in the condition that the average traffic speed is smaller than certain threshold (i.e. in the congested traffic scenario).

The pseudo-code for the time-varying adaptive MPC algorithm is shown as Algorithm 1.

Algorithm 1 Time-varying adaptive MPC algorithm

1: Initialize the longitudinal model, MPC parameters, and control input
2: Set $i := i + 1$
3: Update the ego-vehicle's kinetic information and context information
4: Update the distance-step value
5: Determine the desired speed policy
6: Obtain the target speed profile at the next location
7: Update the longitudinal model
8: Compute the optimal control input
9: Update the optimal speed profile
10: Go back to Step 2

IV. Data-driven Approach for Traffic Speed Prediction

In this section, we develop a data-driven traffic predictive model by applying the CNN-based deep learning method, and in particular predict the traffic speed which is adopted as the target speed v_d in energy optimization.

A. Spatio-temporal Traffic Information

Many factors may affect traffic speed, such as traffic flow, road occupation, driving behaviour, weather condition, and road surface. In particular, these factors are normally featured by both spatial and temporal dependencies of the traffic networks. To describe such spatio-temporal traffic information on each road segment, similar to the work in [43], we adopt a time-space matrix which serves as a time-space image input and can be processed by CNN neural network. Mathematically, traffic information X can be presented by the time-space matrix:

$$X = \begin{bmatrix} x(1,1) & x(1,2) & \dots & x(1,n) \\ x(2,1) & x(2,2) & \dots & x(2,n) \\ \vdots & \vdots & \vdots & \vdots \\ x(m,1) & x(m,2) & \dots & x(m,n) \end{bmatrix}$$

where m is the length of time intervals, n the length of road sections; the jth column vector is the traffic information of road segment j. Then entry (i,j) of the matrix represents the traffic information of road segment j at time i, which can capture the spatio-temporal dependency of nonlinear traffic flow. It is noteworthy that spatial relations of the traffic in a transportation network is transformed into linear representations and treated as a sequence of road segments represented by columns of the matrix, and this approach is only applicable for a simple long road composing of multiple segments such as highway scenarios in this paper.

B. *Multi-view CNN Structure*

CNN is adopted to take advantage of the 2D structure of an input image (or other 2D input such as a speech signal). A typical CNN is composed of one or more convolutional layers (often with a subsampling step) and then followed by one or more fully connected layers as in a standard multi-layer neural network. Specifically, to take into account multiple factors in the traffic speed prediction, we develop a new multi-view CNN in this paper: the data of each factor are described as the time-space matrix and trained individually using general CNN, the outputs of which are then fused into one vector and further learned using fully connected layers to integrate the relations between the factors and the traffic speed.

The structure of the proposed multi-view CNN is shown in Fig. 3. A CNN includes 3 convolutional layers where each convolutional layer is followed by a pooling layer. The convolutional ouputs are then flattened and fused into one vector, and further learned by using a fully-connected layer. The filter size and the pooling size are selected with the dimensions of 3×3 and 2×2, respectively, in order to better capture the correlations between each pair of adjacent loops as well as adjacent times. The number of filters for each convolutional layer is chosen as 256, 128, 64, respectively, based on experience and the consideration to balance efficiency and accuracy. The Relu function is adopted as the activation function to transform the output to a manageable

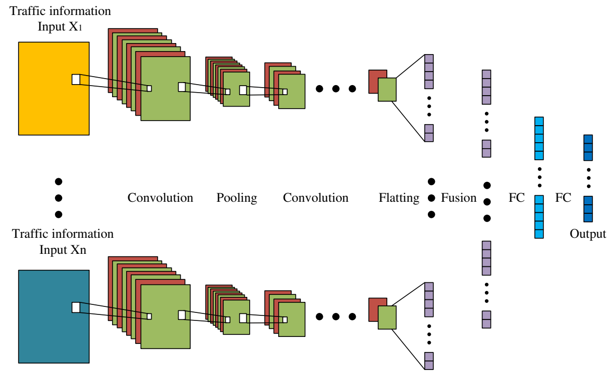

Fig. 3. Multi-view CNN for traffic speed prediction

and scaled data range. In addition, we adopt the Concatenate function to fuse the different traffic information into one vector.

The general loss function taking into account multiple sources of traffic information is designed as follows

$$L = \frac{1}{n}\sum_{j=1}^{k}\lambda_j\sum_{i=1}^{n}(\hat{Y}_{i,j} - Y_{i,j})^2 \tag{22}$$

where $\hat{Y}_{i,j}$ represents the predicted traffic information and $Y_{i,j}$ represents the ground truth traffic information, λ_j is nonnegative coefficient and $\sum_{j=1}^{k}\lambda_j = 1$. λ_j reflects the impact of traffic information X_j on traffic speed prediction. It should be noted that restricted by the original traffic data (from UK highway), in this paper, we only adopt traffic flow and average speed as the two types of input of the Multi-view CNN. In addition, the coefficient of traffic speed is overwhelming to that of traffic flow as it has the major and direct contribution to traffic speed prediction.

The Multi-view CNN is implemented in the time domain, i.e. the inputs and outputs are the time variables. Since the control strategy of PCC system is implemented in the space domain, a transformation is required for the traffic speed prediction from the time domain to the space domain. We denote by ΔT the detector sampling period which is assumed to be longer than the travel time of the HDV driving through the horizon distance $n_p \cdot \Delta s$. In fact, this assumption makes reasonable as the sampling period of loop detector in highways is 2-15 minutes, which is longer than the travel time for a HDV driving through 500-1000m even at heavy traffic conditions. In addition, we assume the spatially and temporally linear change of the average traffic speed within one distance step Δs and one time step ΔT. The assumptions indicate that only a two-steps traffic prediction is required for MPC controller over the prediction horizon. Then the predicted traffic speed at time t in location $k\Delta s$ ahead of the HDV is denoted as $\hat{v}(t, k)$, and can be calculated by:

$$\hat{v}(t, k) = \hat{v}(t, k-1) + \frac{\Delta s}{\hat{v}(t, k-1)\Delta T} \cdot (\hat{\bar{v}}(t+\Delta T, k) - \hat{\bar{v}}(t, k)) \tag{23}$$

where $\hat{\bar{v}}(t, k)$ is the average traffic speed at time t on the road segment that contains the targeted prediction location ahead of the HDV (which can be calculated by linearizing the average traffic speed between time step $[\frac{t}{\Delta T}]$ and $[\frac{t}{\Delta T}]+1$, and $\hat{\bar{v}}(t+\Delta T, k)$ is the corresponding traffic speed predicted by the proposed multi-view CNN.

V. Numerical Results

In this section, the proposed enhanced PCC system, including the data-driven traffic speed prediction and MPC-based controller, is extensively evaluated via numerical simulation.

A. Simulation Environment and Data Preparation

To verify the whole enhanced PCC system in a simulation environment, we adopt the traffic simulator SUMO [50] to generate traffic demands at different levels. The proposed traffic speed prediction is first developed and trained on Tensorflow platform [51], then exported as an external module for online prediction. The MPC-based controller is implemented in Matlab. All of the three modules can be connected via the Traffic Control Interface (TRACI), a TCP based client/server architecture, and run in parallel, wherein SUMO acts as the server and Matlab and the traffic speed predictive model serve as the clients. Intelligent Driving Model (IDM) is adopted in SUMO because of its widely-reported capability of realistically replicating driving behaviours compared to other models [52], [53]. In addition, the elevation information from the external resource (e.g. NASA SRTM) is added to the traffic networks.

In this paper, one segment of the UK M25 motorway integrated with the corresponding elevation information is chosen as the target route of HDV, as shown in Fig. 4. Historical loop data of the M25 motorway [54] are first used for performance evaluation of the proposed multi-view CNN-based speed prediction. To build up realistic traffic simulation scenarios for system evaluation, traffic demand will be generated based on the historical data to closely match the real-world in terms of both traffic volume and traffic speed, which can be implemented by the tool of DFROUTER in SUMO. The generated synthetic traffic flow data will be further used for the real-time application of traffic speed prediction in the enhanced PCC system.

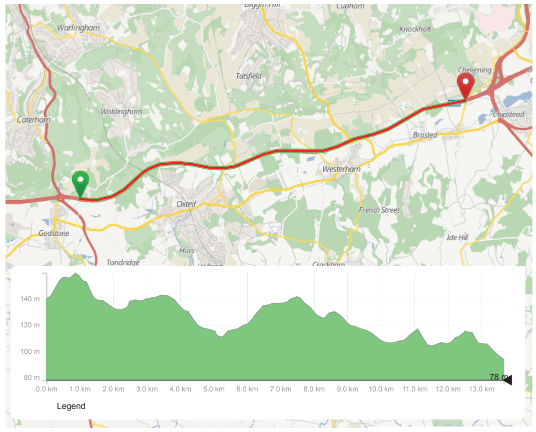

Fig. 4. The UK highway segment in simulation

B. Traffic Speed Prediction

The loop data were collected from April 1, 2015 to December 31, 2015 on M25 highway segment where total 30 detector points are approximately evenly distributed (about 450m intervals between sampling sites) for traffic prediction validation, in which the average traffic speed and traffic flow were recorded at the time interval of 15 minutes. Consequently, a two-view CNN is constructed with both traffic speed and traffic flow as the neural network inputs. To identify λ_j in the loss function Eq. (22), we adjust the coefficient λ of traffic flow from 0 to 0.9 with an interval of 0.1 and find the optimal value of 0.1, which can obtain a higher speed prediction accuracy. The result is also consistent with our previous justification on the coefficient selection.

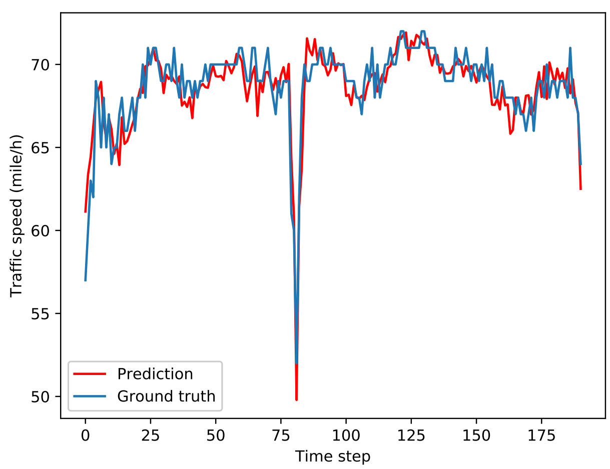

Fig. 5. Comparison of predicted traffic speed with ground truths at detector spot M4327B in 48 hours

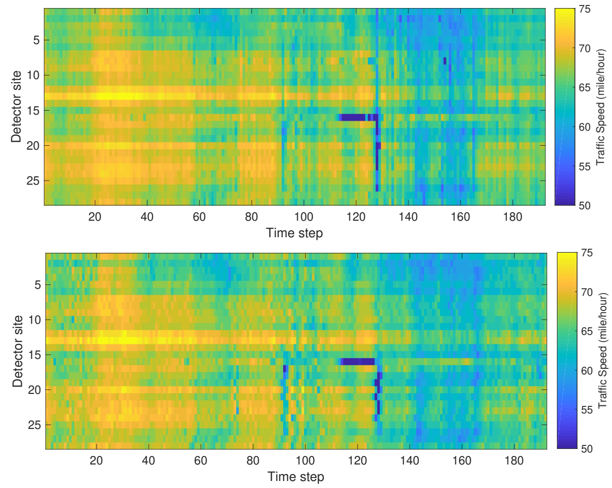

Fig. 6. Heat map comparison of predicted traffic speed (top figure) with ground truths (botom figure) over the selected corridor in 48 hours

Fig. 5 compares the predicted traffic speed with the ground truth at one detector spot in 48 hours and demonstrates a well-matched profile between them, which indicates the capability of the proposed multi-view CNN algorithm in characterizing the spatio-temporal traffic speed even in case of dramatic traffic speed drop. We then further compare the spatio-temporal predicted traffic speed of the whole corridor with the ground truth, as illustrated in the heat maps of Fig. 6. It is observed that the predicted traffic speed can capture the similar pattern with the ground truth in both free traffic and congested traffic scenarios.

TABLE II
PREDICTION PERFORMANCE (RMSE) COMPARISON

	Prediction step		
Network	1 step	2 step	3 steps
Multi-view CNN	2.80	3.29	3.71
CNN	2.88	3.53	4.16
LSTM	3.89	4.49	4.90

To validate the advantage of multi-view CNN algorithm, the prediction performance is compared between the proposed method and some baseline deep learning algorithms such as CNN and LSTM in terms of Root Mean Squared Error (RMSE). The results including three different prediction time steps, i.e., 15 mins, 30 mins, and 45 mins for each model are examined and summarized in Table II. It can be seen that the shorter the prediction time step is, the higher the accuracy becomes, which is consistent with most previous studies. In addition, the proposed multi-view CNN outperforms the baseline models in all three cases in terms of prediction accuracy. It is noteworthy that multi-view CNN does not always work better than CNN especially in free traffic condition. This is because the correlation between traffic speed and traffic flow is not significant in this case, which may introduce training noise in multi-view CNN.

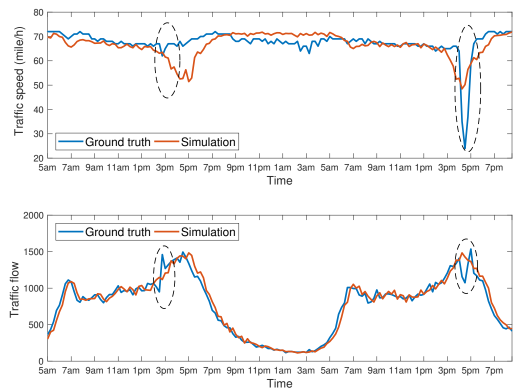

Fig. 7. Constructed simulation scenario based on collected loop data. Top figure: the traffic speed at the examined point C. Bottom figure: the traffic flow at the examined point C

Next, we verify if the traffic simulator SUMO can replicate the real traffic scenarios. Traffic demand is firstly generated by DFROUTER based on the historical loop data at the entrance point A in Fig. 4, and then is implemented in SUMO with IDM car-following model.An examined point C is randomly selected in the middle of the highway segment and its traffic information such as traffic flow and average speed will be collected which are to be compared with the real records. Vehicles recorded in real data sets are categorized into two types, passenger cars and freight cars, and the vehicle's parameters such as vehicle speed and acceleration are set with the default values. We then adjust the sensitive parameter time gap τ of IDM model to minimize the deviation between the real traffic data and simulation traffic data. The results in Fig. 7 clearly illustrate that the simulation profiles of traffic flow and traffic speed can reflect the real traffic situation in most cases especially in stable traffic situation. However, due to lacking high resolution of loop data on the detailed traffic description, as well as the general limitation of car-following model, the simulator can hardly capture the abnormal traffic phenomena, for example accidents or driving misbehavior, as indicated in the circled part of the figure. Therefore, to verify the MPC-based controller, we generate stable traffic scenarios (including free and heavy traffic) with realistic traffic demands based on the observed real-world loop detector data, and mimic the congested traffic scenario by creating fake accidents in SUMO, respectively. In addition, the sampling period of the loop detector is set with 2 minutes in SUMO which can capture timely traffic data for the instantaneous MPC application. Accordingly, the traffic prediction is conducted based on the synthetic simulation data.

C. MPC-based Controller with different desired speed policies

In this part, we evaluate the enhanced MPC-based PCC system in three typical traffic scenarios including free traffic, congested traffic with heavy traffic demand, and traffic accident scenario generated by SUMO. The main parameters of HDV and its MPC-based PCC system used in the experiments are summarized in Table III. Specifically, the distance step Δs is set in the range of 5-50m, depending on the HDV's speed (0-25m/s).

TABLE III
HDV AND MPC-BASED PCC SYSTEM PARAMETERS

Parameter	**Value**	**Parameter**	**Value**
Vehicle mass	40000 kg	Maximum acceleration	1 m/s^2
Vehicle length	10 m	Maximum deceleration	4 m/s^2
Tyre Inertia	15 kg.m^2	Maximum brake torque	10000 Nm
C_r	0.005	Maximum engine torque	2500 Nm
C_d	0.51	Maximum velocity	30 m/s
Time gap	6.5 s	Standstill distance	5 m
η	0.9	Air density	1.2
Δs	5-50 m	Initial velocity	23 m/s
λ_s	0.1	Road segment length	12 km
n_p	10		
Congested traffic speed	10 m/s		

We use Matlab to simulate the MPC controller which runs on the PC with MS WINDOWS 10 and an Intel (R) Xeon(R) E-2146G CPU @3.50GHz, and 32GB RAM (such resources can be easily obtained and deployed in current Clouds). Specifically, we adopt the Model Predictive Control Toolbox for the time-varying MPC programming. By running the MPC algorithm, we evaluate the mean elapsed time of one-step MPC calculation being approximately 0.009 seconds and the maximum being less than 0.013 seconds, which is far less than the typical MPC recall interval of about 2 seconds. Therefore, in terms of the computation capability, it is feasible to solve the real-time MPC optimization problem in the Cloud.

Furthermore, we compare the three typical desired speed policies implemented in the MPC algorithm and explore their impacts on the HDV's performance: CSP, ASP, and PSP. Note that the maximum speed of HDV is 25m/s, and CSP set the recommended speed with 25m/s which is actually the speed limitation of the HDV. Clearly, the CSP only adopts the constant desired speed without considering traffic condition, while the ASP adopts the average traffic speed which reflects the HDV's surrounding traffic situation at the current position. Both CSP and ASP can obtain the current road slope for the HDV MPC implementation, but lack the knowledge of the future road condition and traffic situation.

We first test the HDV's performance in the free traffic scenario where traffic flow from the real data set is set below 500 veh/lane/hour and the average traffic speed is close to the road speed limit (32 m/s in this paper). In this case, all three speed policies adopt the same target speed of 25 m/s, which means there is no difference between CSP and ASP.

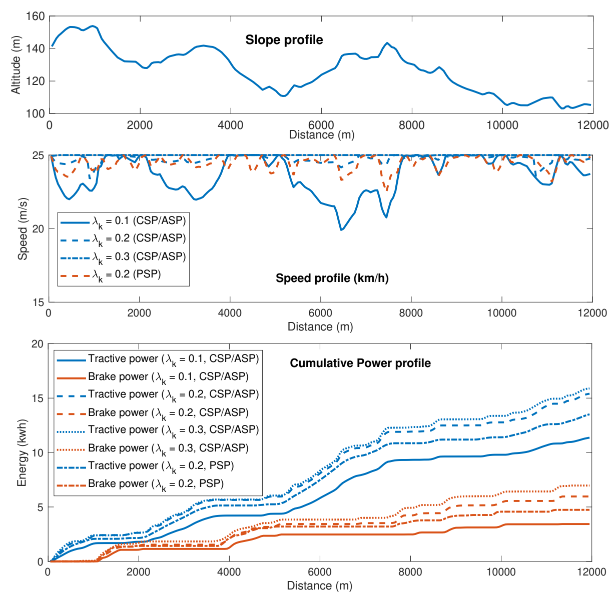

Fig. 8. HDV speed and energy profiles in free traffic scenarios

We fix the weight $\lambda_e = 1$ and set the weight speed deviation λ_k with different values to explore its impact on HDV's speed and energy consumption. The experiment results in Fig. 8 indicate that when λ_k increases from 0.1 to 0.3, the HDV's speed profile is closer to the target speed of 25 m/s (which means the travel time decreases accordingly), and meanwhile, the traction/brake energy increase as well. A further comparison can also find that, in case of $\lambda_k = 0.2$, PSP achieves a better performance than CSP/ASP in term of energy consumption. This observation also indicates that having knowledge of future road slope information can benefit the energy efficiency of HDV, which is consistent to some recent works [19]. In addition, as λ_k is more than 0.2, the performance difference in terms of speed deviation and energy consumption becomes less significant. Therefore, unless specified otherwise, we fix the weights with $\lambda_k = 0.2$ and $\lambda_e = 1$ in the following experiment verification.

We then test the HDV's performance in the heavy traffic scenario where traffic flow is set around 1500 veh/lane/hour based on the real data set and the average traffic speed changes around 20m/s.

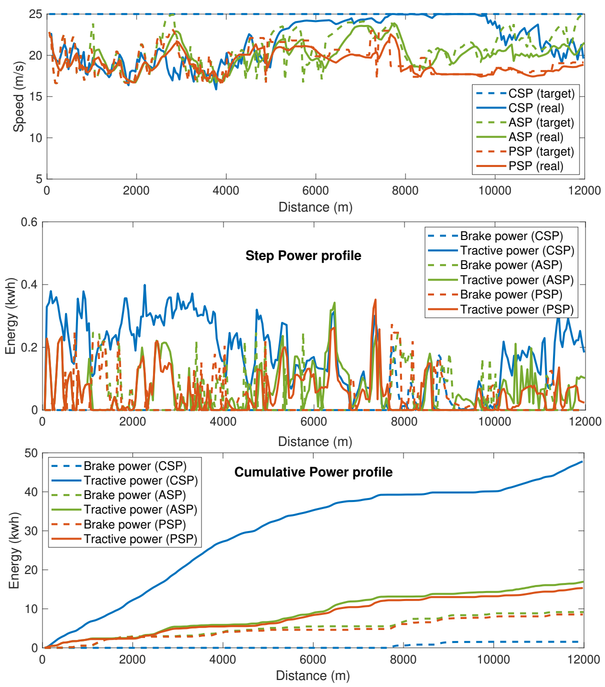

Fig. 9. HDV Performance comparison with different target speed strategies in heavy traffic scenarios

The HDV's speed and traction/brake energy profiles are displayed in Fig. 9. It can be easily observed that the HDV's speed with CSP is higher than the other two with ASP and PSP in most cases, and meanwhile consumes the highest traction energy among the three target speed policies. In addition, PSP obtains the minimum traction energy and relatively smaller brake energy compared to ASP. The further examination on system performance such as speed noise (standard deviation σ) and travel time is summarized in the top half of Table IV. By comparing the three speed policies, although CSP can save more travel time, it consumes the highest energy and brings significant speed perturbations. The comparison between PSP and ASP shows that the former consumes a bit longer travel time but much less energy consumption than the latter, which achieves a better performance in terms of energy consumption and speed perturbations. Therefore, a comprehensive consideration on the system performance indicates PSP is the best solution for the HDV in the heavy traffic scenario.

We then explore the system performance in the congested traffic scenario where traffic accidents are manually created at two different spots (4000m and 8000m) and only one lane is allowed to pass through. The corresponding heat map of the spatio-temporal traffic speed of the whole corridor is shown in Fig. 10, in which the sampling period of loop detector is set as 2 minutes.

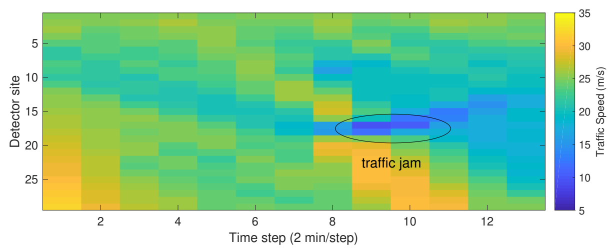

Fig. 10. Heat map of the congested traffic scenario generated by SUMO

TABLE IV

PERFORMANCE COMPARISON OF THREE SPEED STRATEGIES IN HEAVY AND CONGESTED TRAFFIC SCENARIOS

Speed policy	Speed noise (σ)	Travel time (second)	Traction (kwh)	Brake (kwh)
CSP	1.96	569	47.8	1.9
(I) ASP	1.62	615	16.9	9.2
PSP	1.30	622	15.2	8.5
CSP	5.04	696	59.4	0
(II) ASP	4.42	744	19.2	10.4
PSP	4.51	724	18.6	10.1

I: heavy traffic scenarios

II: congested traffic scenarios

The similar results can be obtained in Fig. 11 and the bottom half of Table IV. It can

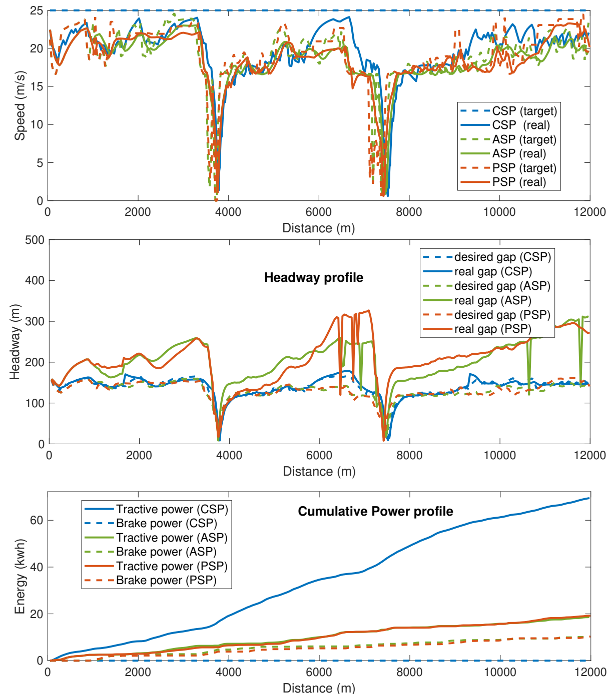

Fig. 11. HDV Performance comparison with different target speed strategies in congested traffic scenarios

be observed that among the three policies CSP can save the travel time but consumes much more energy. On the other hand, compared to ASP, PSP consumes slightly less traction energy in congested traffic. This result can be explained from two aspects: (1) due to the limited prediction horizon of traffic speed in the congested traffic scenario, the benefit brought by the traffic prediction in PSP is trivial in this situation, and (2) the sparse traffic prediction sites (approximately every 450m) cannot exactly capture the sharp decrease of traffic speed (as shown in the top of Fig. 11), which results in the unrealistic desired speed of PSP exceeding the actual road capacity in some road sites (e.g. road segment between 9000m and 12000m), and accordingly, may lead to small speed perturbations.

In addition, it is observed that from the headway profiles, the gap between the HDV and its preceding vehicle is always larger than the desired value for all three speed strategies, which indicates that the collision avoidance can be guaranteed with the safety constraint defined in Eq. (21).

By combining with Fig. 8, Fig. 9, and Fig. 11, another interesting finding is that the HDV's energy consumption significantly increases as the road traffic becomes congested. This is because frequent acceleration/deceleration actions are needed for the HDV to follow the reference speed

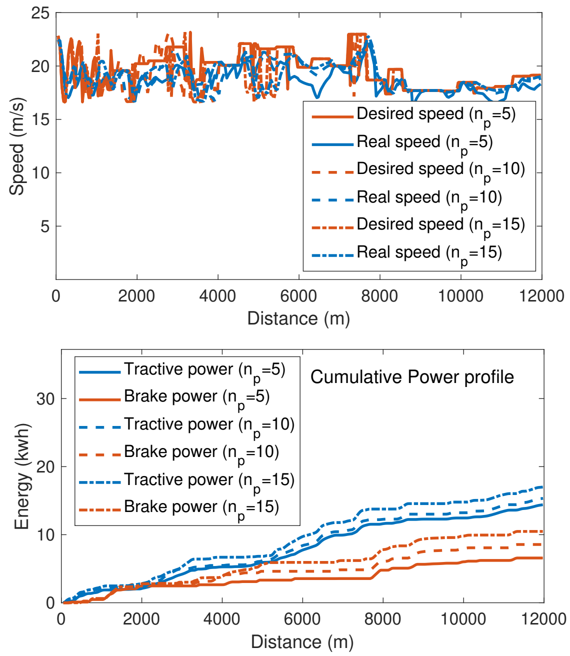

Fig. 12. The impact of prediction n_p on system performance

profile especially in congested traffic conditions. Nonetheless, both ASP and PSP outperfom CSP in terms of energy savings as the generated reference speed can reflect the real traffic condition, which may mitigate the unnecessary acceleration perturbations that would happen with CSP.

D. The impact of system parameters

Next, we estimate how the prediction horizon (n_p) and the desired speed (v_d) prediction length affect the MPC controller performance, respectively. The simulation runs in the heavy traffic scenario and the results are shown in Fig. V-C. In general, as n_p increases, the energy consumption increases accordingly. This is because the cost function (Eq. (12)) with the larger value of n_p forces the HDV to drive closer to the desired speed which leads to more energy consumption. On the other hand, however, the travel time will be slightly reduced accordingly.

We also evaluate the impact of speed prediction errors on the PCC system performance. In the MPC algorithm, the HDV adopts the predicted traffic speed as the reference signal which may bring some prediction errors. To explore the impact of such prediction imperfection, we assume a uniform distribution noise with zero mean added to the speed prediction in the range of $[-\rho_v, \rho_v], \rho_v > 0$. (It is noted that in case of adopting other model, e.g., standard derivation of a zero mean Gaussian noise, in the simulation, we can obtain similar results.) It is shown in

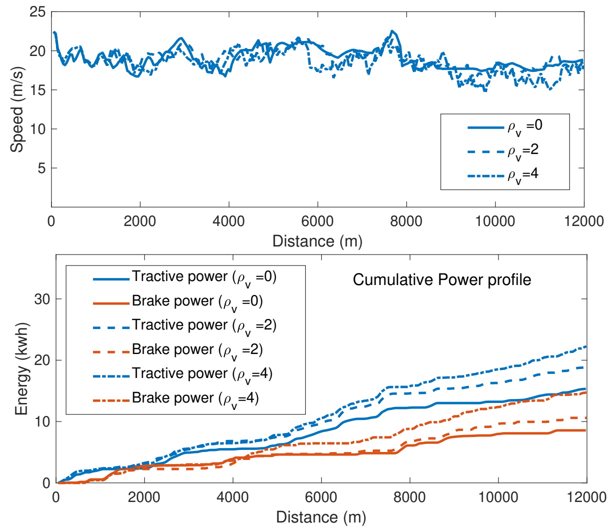

Fig. 13. The impact of prediction errors on system performance

Fig. 13 that the HDV's energy consumption (both traction and brake) increases with the larger prediction error in the heavy traffic scenario (such tendency can also be observed in free traffic and congested traffic conditions). This is because prediction errors may cause unnecessary speed perturbation and increase traction/brake energy accordingly.

E. Fuel consumption evaluation

Finally, we evaluate the performance of our method on HDV's fuel consumption, in both heavy traffic condition and congested traffic condition, respectively.

We use the GT-SUITE software, a professional vehicle modeling tool in which the details of the HDV are included e.g., internal combustion engine maps, transmission systems, to calculate the fuel consumption. The BSFC map of the engine is displayed in Fig. 14.

We only evaluate ASP and PSP as the two strategies perform similarly in terms of energy consumption. The simulation results are shown in Fig. 15. Clearly, PSP save more fuel consumption than ASP in heavy traffic condition. More specifically, in terms of fuel economy, Miles Per Gallon (mpg) of PSP is 7.01, higher than that of ASP with the value 6.28. Although both PSP and ASP have the equivalent fuel economy (4.96 mpg of PSP and 5.04 mpg of ASP, respectively) in congested traffic scenarios, travel time in PSP (724s) strategy is much less than that in ASP (744s). The results are consistent with the ones of energy consumption given in Section V-C.

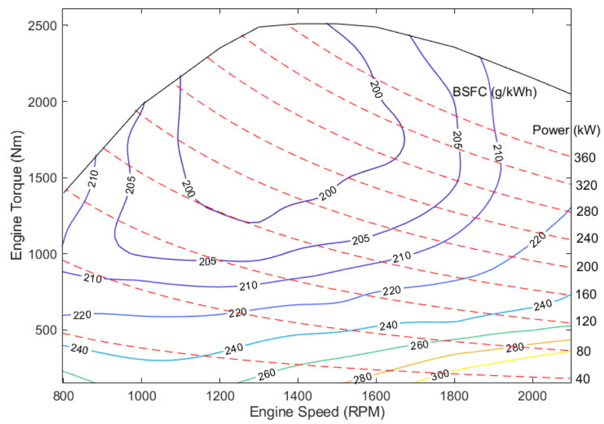

Fig. 14. BSFC Map of HDV

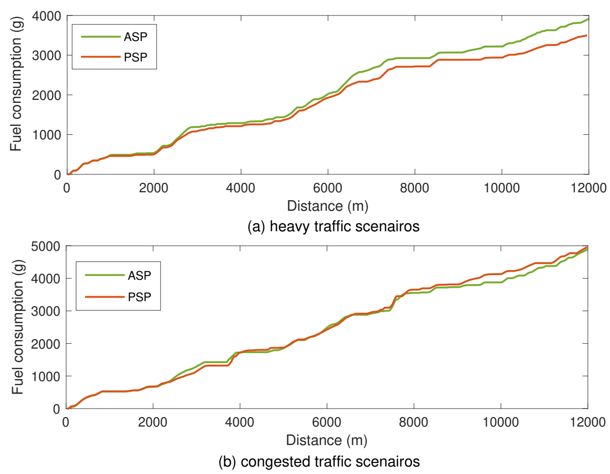

Fig. 15. Fuel consumption of HDV in both heavy and congested traffic scenarios

VI. Conclusion

This paper presented an enhanced predictive cruise control system for HDV by taking advantages of big data and model predictive control. A general framework of the enhanced cloud-based PCC system was proposed with the integration of the data-driven traffic predictive model. Specifically, to address the challenge of dynamic traffic conditions, a multi-view CNN algorithm was developed to predict traffic condition for the HDV. A time-varying adaptive MPC-based controller was designed to provide the optimal speed reference to the HDV. To the best of our knowledge, this is the first attempt that PCC system combines with deep-learning based traffic prediction for the purpose of energy optimization. Numerical simulation results have verified the efficiency of our approach. In particular, we explored the system performance in heavy/congested traffic scenarios where the interaction between HDV and common vehicles has been fully considered.

It should be noted that in this paper, we apply the loop detector data for traffic speed prediction, in which only the discrete information at the detector site is provided while the detailed information of the road segment could be missed. In the future, we will continue our work by adopting other types of traffic data, e.g. vehicle trajectories to further improve the PCC system performance. In addition, by taking advantages of both traffic flow model and data-driven method, our future work will extend the HDV eco-driving scheme to network-level traffic scenarios, in which the preceding vehicle's driving behavior will be considered to further improve traffic safety and energy efficiency. The performance comparison between PSP and popular approaches e.g. Connected cruise control [55] will be carried out to further evaluate our approach.

REFERENCES

[1] M. Zhou, H. Jin, and W. Wang, "A review of vehicle fuel consumption models to evaluate eco-driving and eco-routing," *Transportation Research Part D: Transport and Environment*, vol. 49, no. 5, pp. 203–218, 2016.

[2] A. Sciarretta and L. Guzzella, "Control of hybrid electric vehicles," *IEEE Control Systems Magazine*, vol. 27, no. 2, pp. 60–70, 2007.

[3] A. A. Alam, A. Gattami, and K. H. Johansson, "An experimental study on the fuel reduction potential of heavy duty vehicle platooning," *13th International IEEE Conference on Intelligent Transportation Systems*, pp. 306–311, sep 2010.

[4] M. Wang, W. Daamen, S. P. Hoogendoorn, and B. van Arem, "Rolling horizon control framework for driver assistance systems. Part II: Cooperative sensing and cooperative control," *Transportation Research Part C: Emerging Technologies*, vol. 40, pp. 290–311, 2014.

[5] C. Osorio and K. Nanduri, "Energy-Efficient Urban Traffic Management: A Microscopic Simulation-Based Approach," *Transportation Science*, vol. 49, no. 3, pp. 637–651, 2015.

[6] D. Jia, K. Lu, J. Wang, X. Zhang, and X. Shen, "A Survey on Platoon-Based Vehicular Cyber-Physical Systems," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 1, pp. 263–284, 2016.

[7] B. Asadi and A. Vahidi, "Predictive cruise control: Utilizing upcoming traffic signal information for improving fuel economy and reducing trip time," *Control Systems Technology, IEEE Transactions on*, vol. 19, no. 3, pp. 707–714, 2010.

[8] M. Alsabaan, K. Naik, and T. Khalifa, "Optimization of Fuel Cost and Emissions Using V2V Communications," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 3, pp. 1449–1461, 2013.

[9] I. A. Ntousakis, I. K. Nikolos, and M. Papageorgiou, "Optimal vehicle trajectory planning in the context of cooperative merging on highways," *Transportation Research Part C: Emerging Technologies*, vol. 71, pp. 464–488, 2016.

[10] J. Schlechtendahl, F. Kretschmer, Z. Sang, A. Lechler, and X. Xu, "Extended study of network capability for cloud based control systems," *Robotics and Computer-Integrated Manufacturing*, vol. 43, pp. 89–95, 2017.

[11] E. Ozatay, S. Onori, J. Wollaeger, U. Ozguner, G. Rizzoni, D. Filev, J. Michelini, and S. Di Cairano, “Cloud-based velocity profile optimization for everyday driving: A dynamic-programming-based solution,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 15, no. 6, pp. 2491–2505, 2014.

[12] M. A. S. Kamal, M. Mukai, J. Murata, and T. Kawabe, “Model predictive control of vehicles on urban roads for improved fuel economy,” *IEEE Transactions on Control Systems Technology*, vol. 21, no. 3, pp. 831–841, 2013.

[13] S. D. Cairano, D. Bernardini, A. Bemporad, and I. V. Kolmanovsky, “Stochastic MPC with learning for driver-predictive vehicle control and its application to HEV energy management,” *IEEE Transactions on Control Systems Technology*, vol. 22, no. 3, pp. 1018–1031, 2014.

[14] L. Guo, B. Gao, Y. Gao, H. Chen, and S. Member, “Optimal Energy Management for HEVs in Eco-Driving Applications Using Bi-Level MPC,” *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–10, 2016.

[15] S. Xu, S. E. Li, B. Cheng, and K. Li, “Instantaneous Feedback Control for a Fuel-Prioritized Vehicle Cruising System on Highways With a Varying Slope,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 5, pp. 1210–1220, 2017.

[16] N. Murgovski, B. Egardt, and M. Nilsson, “Cooperative energy management of automated vehicles,” *Control Engineering Practice*, vol. 57, pp. 84–98, 2016.

[17] Y. Wang, D. Zhang, Y. Liu, B. Dai, and L. H. Lee, “Enhancing transportation systems via deep learning: A survey,” *Transportation Research Part C: Emerging Technologies*, vol. 99, pp. 144–163, 2019.

[18] M. Kamal, M. Mukai, J. Murata, and T. Kawabe, “Ecological vehicle control on roads with up-down slopes,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 12, no. 3, pp. 783–794, 2011.

[19] E. Hellström, M. Ivarsson, J. Aslund, and L. Nielsen, “Look-ahead control for heavy trucks to minimize trip time and fuel consumption,” *Control Engineering Practice journal*, vol. 17, pp. 245–254, 2009.

[20] A. Alam, B. Besselink, V. Turri, J. Martensson, and K. H. Johansson, “Heavy-duty vehicle platooning for sustainable freight transportation: A cooperative method to enhance safety and efficiency,” *IEEE Control Systems Magazine*, vol. 35, no. 6, pp. 34–56, Dec 2015.

[21] V. Turri, B. Besselink, and K. H. Johansson, “Cooperative Look-Ahead Control for Fuel-Efficient and Safe Heavy-Duty Vehicle Platooning,” *IEEE Transactions on Control Systems Technology*, vol. 25, no. 1, pp. 12–28, 2017.

[22] P. Liu, U. Ozguner, and Y. Zhang, “Distributed MPC for cooperative highway driving and energy-economy validation via microscopic simulations,” *Transportation Research Part C: Emerging Technologies*, vol. 77, pp. 80–95, 2017.

[23] H. Lim, W. Su, and C. Mi, “Distance-based Ecological Driving Scheme using a Two-stage Hierarchy for Long-term Optimization and Short-term Adaptation,” *IEEE Transactions on Vehicular Technology*, vol. 66, no. 3, pp. 1940–1949, 2017.

[24] C. Sun, S. J. Moura, X. Hu, J. K. Hedrick, and F. Sun, “Dynamic traffic feedback data enabled energy management in plug-in hybrid electric vehicles,” *IEEE Transactions on Control Systems Technology*, vol. 23, no. 3, pp. 1075–1086, 2014.

[25] F. Donatantonio, A. D’Amato, I. Arsie, and C. Pianese, “A multi-layer control hierarchy for heavy duty vehicles with off-line dual stage dynamic programming optimization,” *Transportation Research Part C: Emerging Technologies*, vol. 92, no. July 2017, pp. 486–503, 2018.

[26] A. Weißmann, D. Görges, and X. Lin, “Energy-optimal adaptive cruise control combining model predictive control and dynamic programming,” *Control Engineering Practice*, vol. 72, no. December 2017, pp. 125–137, 2018.

[27] L. Guo, H. Chen, Q. Liu, and B. Gao, “A Computationally Efficient and Hierarchical Control Strategy for Velocity Optimization of On-Road Vehicles,” *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 49, no. 1, pp. 31–41, 2019.

[28] B. Saerens, H. A. Rakha, M. Diehl, and E. Van den Bulck, "A methodology for assessing eco-cruise control for passenger vehicles," *Transportation Research Part D: Transport and Environment*, vol. 19, pp. 20–27, 2013.

[29] M. Henzler, M. Buchholz, and K. Dietmayer, "Online velocity trajectory planning for manual energy efficient driving of heavy duty vehicles using model predictive control," *17th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, pp. 1814–1819, 2014.

[30] T. Seo, A. M. Bayen, T. Kusakabe, and Y. Asakura, "Traffic state estimation on highway: A comprehensive survey," *Annual reviews in control*, vol. 43, pp. 128–151, 2017.

[31] M. J. Lighthill and G. B. Whitham, "On kinematic waves ii. a theory of traffic flow on long crowded roads," *Proceedings of the Royal Society of London. Series A. Mathematical and Physical Sciences*, vol. 229, no. 1178, pp. 317–345, 1955.

[32] G. F. Newell, "A simplified theory of kinematic waves in highway traffic, part i: General theory," *Transportation Research Part B: Methodological*, vol. 27, no. 4, pp. 281–287, 1993.

[33] K. Nagel and M. Schreckenberg, "A cellular automaton model for freeway traffic," *Journal de physique I*, vol. 2, no. 12, pp. 2221–2229, 1992.

[34] B. S. Kerner, *The physics of traffic*. Springer, 2004.

[35] Y. Wang and M. Papageorgiou, "Real-time freeway traffic state estimation based on extended kalman filter: a general approach," *Transportation Research Part B: Methodological*, vol. 39, no. 2, pp. 141–167, 2005.

[36] Y. Wang, M. Papageorgiou, and A. Messmer, "Real-time freeway traffic state estimation based on extended kalman filter: Adaptive capabilities and real data testing," *Transportation Research Part A: Policy and Practice*, vol. 42, no. 10, pp. 1340–1358, 2008.

[37] C. P. Van Hinsbergen, T. Schreiter, F. S. Zuurbier, J. Van Lint, and H. J. Van Zuylen, "Localized extended kalman filter for scalable real-time traffic state estimation," *IEEE transactions on intelligent transportation systems*, vol. 13, no. 1, pp. 385–394, 2011.

[38] B. M. Williams and L. A. Hoel, "Modeling and Forecasting Vehicular Traffic Flow as a Seasonal ARIMA Process: Theoretical Basis and Empirical Results," *Journal of Transportation Engineering*, vol. 129, no. 6, pp. 664–672, 2003.

[39] M. Lippi, M. Bertini, and P. Frasconi, "Short-term traffic flow forecasting: An experimental comparison of time-series analysis and supervised learning," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 2, pp. 871–882, 2013.

[40] W. Huang, G. Song, H. Hong, and K. Xie, "Deep architecture for traffic flow prediction: Deep belief networks with multitask learning," *IEEE Transactions on Intelligent Transportation Systems*, vol. 15, no. 5, pp. 2191–2201, 2014.

[41] Y. Lv, Y. Duan, W. Kang, Z. Li, and F. Y. Wang, "Traffic Flow Prediction With Big Data: A Deep Learning Approach," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 2, pp. 865–873, 2014.

[42] X. Ma, Z. Tao, Y. Wang, H. Yu, and Y. Wang, "Long short-term memory neural network for traffic speed prediction using remote microwave sensor data," *Transportation Research Part C: Emerging Technologies*, vol. 54, pp. 187–197, 2015.

[43] X. Ma, Z. Dai, Z. He, J. Ma, Y. Wang, and Y. Wang, "Learning traffic as images: A deep convolutional neural network for large-scale transportation network speed prediction," *Sensors (Switzerland)*, vol. 17, no. 4, 2017.

[44] B. Yu, H. Yin, and Z. Zhu, "Spatio-temporal Graph Convolutional Neural Network: A Deep Learning Framework for Traffic Forecasting," 2017. [Online]. Available: http://arxiv.org/abs/1709.04875

[45] J. Zhang, Y. Zheng, and D. Qi, "Deep Spatio-Temporal Residual Networks for Citywide Crowd Flows Prediction," in *AAAI*, 2017, pp. 1655–1661.

[46] Z. Zheng and D. Su, "Short-term traffic volume forecasting: A k-nearest neighbor approach enhanced by constrained linearly sewing principle component algorithm," *Transportation Research Part C: Emerging Technologies*, vol. 43, pp. 143–157, 2014.

[47] M. Wang, B. Lai, X. Gong, X. Hua, and J. Huang, "Dynamic Spatio-temporal Graph-based CNNs for Traffic Prediction." 2018. [Online]. Available: http://arxiv.org/abs/1812.02019

[48] S. Mohanty and A. Pozdnukhov, "Graph CNN + LSTM Framework For Dynamic Macroscopic Traffic Congestion Prediction," in *14th international workshop on ming and learning with graphs*, 2018.

[49] A. A. Malikopoulos, S. Hong, B. B. Park, J. Lee, and S. Ryu, "Optimal Control for Speed Harmonization of Automated Vehicles," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 7, pp. 2405–2417, 2019.

[50] [Online]. Available: https://sumo.dlr.de/index.html

[51] [Online]. Available: https://www.tensorflow.org/

[52] M. Pourabdollah, E. Bjärkvik, F. Fürer, B. Lindenberg, and K. Burgdorf, "Calibration and evaluation of car following models using real-world driving data," in *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*, 2017, pp. 1–6.

[53] A. Sharma, Z. Zheng, and A. Bhaskar, "Is more always better? the impact of vehicular trajectory completeness on car-following model calibration and validation," *Transportation Research Part B: Methodological*, vol. 120, pp. 49 – 75, 2019.

[54] [Online]. Available: http://webtris.highwaysengland.co.uk/

[55] C. R. He, I. G. Jin, and G. Orosz, "Fuel efficient connected cruise control for heavy-duty trucks in real traffic," *IEEE Transactions on Control Systems Technology*, 2019.

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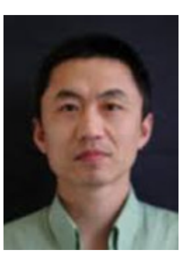

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