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Predictive Control of Connected Mixed Traffic under Random Communication Constraints

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Abstract—**Fully connected and automated vehicles have been envisioned to help improve the driving safety and efficiency of the transportation system. However, human-driven vehicles will still be present in the near future, which will lead to connected mixed traffic instead of fully connected and automated traffic. This is challenging because of the complexity of human-driving vehicles and the potential communication constraints in the connectivity. To address this issue, this paper models the connected mixed traffic and proposes model predictive control approaches with various prediction approaches including a new inverse model predictive control (IMPC) based approach to handle random communication delays and packet losses in connectivity. The human-in-the-loop experimental results for connected mixed traffic demonstrated the effectiveness and advantages of the proposed approaches, especially the predictive control with IMPC in handling communication constraints in mixed traffic.**

Index Terms— **connected mixed traffic, inverse model predictive control, communication constraints.**

I. Introduction

AUTOMATED driving technology is becoming increasingly prevalent in the automobile industry. It can reduce traffic congestions, mitigate traffic accidents, and improve energy efficiency [1]. To extract the maximum benefit from this technology, automated vehicles need to be connected to share information such as current vehicle states and future driving intentions with each other. Many researches have been devoted to the control of connected automated driving [2], especially the adoption of model predictive control (MPC) [3] [4] which can leverage predictive information to achieve a better control performance.

The communication constraints, especially random ones, among vehicles in connected automated driving impose new challenges on the safety and efficiency of the traffic [5] [6]. The string stability of a platoon can be seriously compromised by communication delays [7]. Some studies have attempted to investigate the effects of such constraints on connected vehicles [8] and tried to solve the problem by implementing different controller designs. H-infinity control [9] and other robust controllers are used to resist communication delays. For optimal controllers, potential delays can be directly incorporated in the prediction model [10], and the output of the controller can be compensated using available time stamps [11]. However, handling random communication constraints in connected mix traffic with advanced model predictive control strategies remains a challenge. An accurate and stable state predictor will be very helpful for the predictive controller when it is combined with the delay-handling methods.

An automated vehicle (AV) can generate predictions on its own motion easily since its control intentions are available. A human driven vehicle, meanwhile, does not directly provide driving intentions to the predictor due to the uncertainties in human driving behaviors. Instead, it can only share its current states with other agents such that the latter can leverage the available state information with predictive control. Incidents where automated driving controllers fail to predict or make wrong anticipations about the behaviors of human traffic participants have resulted in fatal results [12] [13]. This paper will focus on the problem of predicting human-driven vehicle's longitudinal states and its application among connected automated vehicles (CAVs).

To solve the problem, a prediction model for the human-driven vehicle needs to be built. Some researchers try to predict the vehicle speed solely based on general traffic conditions [14] [15]. Such methods neglect the human driver's behaviors thus can lead to very inaccurate predictions at times. Most researchers try to build a model for human drivers offline from the data collected during actual driving demonstrations. Analytical-equation-based car following models such as the Tampère (TMP) model [16], Optimal Velocity Model (OVM) [17], and Intelligent Driver Model (IDM) [18] have been developed. The limitations of these models come from their simple structure and their original purposes being generating smooth control outputs, which is not ideal when it comes to making predictions about individual human driving vehicles.

In recent years, many data-driven machine learning approaches have been proposed to model the behaviors of a human driver. Gaussian Mixture Models (GMM) [19], Hidden Markov Models (HMM) [20] and Particle Filter (PF) based methods [21] have been adopted to model and predict behaviors/states of human-driven vehicles. The most popular heuristic approaches are Artificial Neural Networks (ANN) based approaches [22] [23]. The biggest advantage of these approaches also becomes a challenge. Although they employ enough parameters to model individual driving habits, a large

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amount of carefully prepared data is necessary to train the parameters. More importantly, the scalability of such approaches is limited by the scenarios covered by the training data, and they consequently have difficulties to handle never-seen situations.

Therefore, this paper will leverage the existing achievements in connected vehicles and further extend them to the prediction and control of longitudinal motion of mixed traffic under communication constraints. The contributions of the paper can be summarized as follows:

1. Model the longitudinal motion of connected mixed traffic and propose model predictive control approaches based on various prediction approaches including a new inverse model predictive control (IMPC) based approach to handle random communication delays and packet losses in connected mixed traffic.
2. Evaluate and characterize the effects of various communication constraints on different predictive control approaches of connected mixed traffic via experiments and illustrate the advantages of the proposed approaches.

II. Predictive Control of Connected Mixed Traffic Under Communication Constraints

In a mixed traffic shown in Fig. 1, a human-driven vehicle (HDV) is following a lead automated vehicle (LAV), while a fleet of automated vehicles are following the HDV. The most important automated vehicle in the fleet is the one that is right behind the HDV. The control of this following automated vehicle (FAV) will affect not just this single vehicle, but the entire automated vehicle fleet. Thus, this paper will focus on the longitudinal predictive control of this FAV.

This section will provide the details about the predictive controller used by the FAV, how prediction information for HDV is utilized by the controller, and how to handle delays and packet losses in communication.

A. Motion Model of Automated Vehicle

The model used in the FAV's MPC is a linear time invariant (LTI) model with a first order lag with time constant τ [4]:

$$\begin{bmatrix} \dot{s_f} \\ \dot{v_f} \\ \dot{a_f} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & -\frac{1}{\tau} \end{bmatrix} \begin{bmatrix} s_f \\ v_f \\ a_f \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ -\frac{1}{\tau} \end{bmatrix} u_f \quad (1)$$

where s_f, v_f, a_f and u_f are the travelled distance, speed, acceleration and control input of the automated vehicle. The physical meaning of u_f is desired acceleration.

In the simulation, the plant model of FAV shares the same form with the prediction model (1). Using such an LTI model as plant model is acceptable in this paper since later all different predictors share predictions with this same plant model. Thus, the effects of inaccuracy in modelling vehicle dynamics can be ignored. The plant model of the automated vehicle differs from the prediction model by different time constants. Due to the differences in the dynamics of the powertrain and the brake systems, the time constant in the plant is different between braking and accelerating. The powertrain system is having a larger time constant $\tau_p = 0.45s$, and the braking system is having a smaller time constant $\tau_b = 0.1s$. The mean time constant $\tau_m = 0.275s$ is used for the prediction model in MPC. The switching between τ_p and τ_b is based on the drive force on the wheels F_w given in (2). The parameters for calculating F_w are listed in TABLE I.

$$\begin{gathered} F_w = m_{eff} u + \frac{1}{2} \rho_a A_f C_d {v_f}^2 + \mu m g \\ \tau = \begin{cases} \tau_p, F_w \geq 0 \\ \tau_b, F_w < 0 \end{cases} \end{gathered} \quad (2)$$

TABLE I
Plant Parameters

Parameter	Definition	Value
m_{eff}	Effective Mass	1706.9kg
m	Mass	1671kg
μ	Rolling Resistance Coefficient	0.01
g	Acceleration of Gravity	9.81m/s^2
ρ_a	Air Density	1.225kg/m^3
C_d	Aerodynamic drag coefficient	0.29
A_f	Vehicle Frontal Area	2.733m^2

B. MPC Control Formulation for Automated Vehicle

Due to the advantage of MPC, a variety of objectives can be designed for the FAV based on different requirements. In the paper, in order to make the performance comparison between different approaches clearer and more direct, without loss of generality, the objective is designed as maintaining a constant headway distance d_2, which is a common and also critical requirement in connected automated driving. The cost function can be then written as:

$$J_f = \sum_{\kappa=k}^{k+N} \left[w_d \left(d_f(\kappa) - d_f^{ref} \right)^2 + w_a a_f(\kappa)^2 + w_u u_f(\kappa)^2 \right] \quad (3)$$

where d_f is the spacing between the ego CAV and the

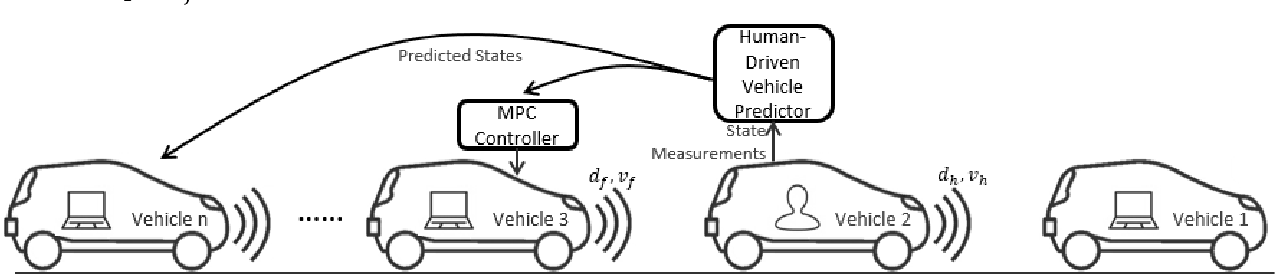

Fig. 1. Connected automated driving setup

preceding vehicle, d_f^{ref} is the reference of the spacing, N is the number of prediction steps, w_d, w_a and w_u are the corresponding weights.

This MPC configuration for the FAV remains unchanged when switching between different predictors. The performance indices for different predictors would be tracking error, vehicle acceleration and control input. The tracking error is a direct measurement of how close the controller is keeping the FAV to the control target, the vehicle acceleration can reflect how comfortable the ride in the FAV is, and the vehicle acceleration and control input together reflect how energy efficient the FAV is. While the first two statements obviously hold true, the relationships between vehicle acceleration, control input and energy efficiency need to be proven by some detailed modelling and experiments. A recent work [4] has demonstrated that if the vehicle acceleration and control input can be minimized using an MPC controller, then the same controller can reduce fuel consumption when applied to a very realistic simulation where the dynamic powertrain and transmission models are included. Thus, the values of the parameters above, including those in TABLE I and the time constants, are all determined based on [4]. In the next section where a three-vehicle connected driving simulation is conducted, if a state predictor can reduce the average control input and average vehicle acceleration at the same time, then it can also reduce the energy consumption.

The following constraints are introduced to ensure the feasibility and rationality of the MPC controller, where s_h and s_f are the displacements of the HDV and FAV respectively.

$$\begin{gathered}
-10m/s^2 \leq a_f \leq 5m/s^2 \\
0 \leq v_f \leq 40m/s \\
-10m/s^2 \leq u_f \leq 5m/s^2 \\
d_f = (s_h - s_f) \geq 0m
\end{gathered} \tag{4}$$

C. Prediction of Human-Driven Vehicles for MPC in Connected Mixed Traffic

In the MPC controller, the headway distance d_f at the beginning of every control step can be directly measured using the onboard radar of the FAV. The value of d_f in the rest of each prediction horizon of MPC can be calculated from the predicted HDV's speed v_h. The prediction information is generated by predictors running on the HDV. The HDV then broadcasts the information through vehicle-to-vehicle (V2V) communication network such that the FAV can acquire the necessary information. Constant speed (CS) predictor is used as the performance baseline in this paper. According to existing work [30], the Intelligent Driver Model and the Artificial Neural Network predictors are doing the best in predicting human-driven vehicle states. Thus, the performance comparison is conducted between the proposed IMPC predictor and the CS, the IDM and the ANN predictors.

1) Constant Speed Predictor

Constant speed predictor is assuming that the speed of HDV remains unchanged during a prediction. It uses a kinematic model to predict the motion of the human-driven vehicle:

$$\dot{\bar{s}}_h = \bar{v}_h \tag{5}$$

where $\bar{v}_h$ and $\bar{s}_h$ are the predicted speed and displacement of the HDV through the prediction.

Under the CS assumption, the FAV can measure the initial speed of the lead vehicle at the start of each prediction using the onboard radar directly. Therefore, when the CS predictor is used, the FAV does not need to connect to the HDV in the front to obtain driving information.

2) IDM-Based Predictor

Intelligent Driver Model is a widely used adaptive cruise control (ACC) model that can describe accelerations and decelerations in a satisfactory way. It is effective in simulating human driver behaviors in traffic [24]. The predicted acceleration of the HDV is given by:

$$\begin{gathered}
\bar{a}_h = a\left[1 - \left(\frac{\bar{v}_h}{v_0}\right)^4 - \left(\frac{d^*}{\bar{d}_h}\right)^2\right] \\
d^* = d_0 + \bar{v}_h T + \frac{\bar{v}_h \bar{v}_r}{2\sqrt{ab}}
\end{gathered} \tag{6}$$

$\bar{v}_r = \bar{v}_h - \bar{v}_l$ is the predicted relative speed between the LAV and the HDV. $\bar{v}_h$, $\bar{d}_h$ and $\bar{v}_r$ are the predicted outputs of the two-vehicle system. v_0 is desired velocity, d_0 is minimum desired spacing, T is desired time headway, a is maximum acceleration and b is comfort braking deceleration. These 5 parameters represent the preferences of a human driver and are trainable parameters of this model. The IDM model is paired with a kinematic model to predict the motion of HDV and LAV:

$$\begin{bmatrix} \dot{\bar{s}}_h \\ \dot{\bar{v}}_h \\ \dot{\bar{s}}_l \\ \dot{\bar{v}}_l \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \bar{s}_h \\ \bar{v}_h \\ \bar{s}_l \\ \bar{v}_l \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \bar{a}_h \tag{7}$$

where $\bar{v}_l$ and $\bar{s}_l$ are the predicted speed and travelled distance of the LAV. $\bar{v}_l$ is assumed to be constant during the prediction. The predicted acceleration calculated from (6) is fed to (7), then the states of the HDV at next prediction step can be obtained.

The IDM model is trained using real human driving data to obtain the optimal parameters for different drivers. The training algorithm utilizes pattern search algorithm in a higher-level optimization that minimizes the error between predicted speed and headway distance, and the real speed and headway distance in demonstration.

3) ANN-Based Predictor

The ANN predictor used in this paper is based on a feed-forward structure [22] with the hidden layer having 16 sigmoidal neurons and the output layer having linear neurons. The inputs to the network are the most basic system states v_l, v_h and the system output d_h. The training is done by fitting the output of the network to the human demonstrated accelerations a_h^{ref}. The training data set is the same one that is used by all other three predictors. The training algorithm we used is Levenberg-Marquardt method [26]. The ANN model is paired with the kinematic model given in (7) to predict the motion of HDV.

4) IMPC-Based Predictor

The IMPC predictor has been described in our previous work [25]. A brief description of this IMPC approach will be given in this section. The IMPC utilizes the cost function in MPC to represent a human driver's driving preferences. IMPC finds the best primitive costs to be included in the cost function and identifies the weights and references of those primitive costs to formulate the most suitable cost function dedicated to a human driver.

The HDV and LAV model used by IMPC is an LTI model given by (8). Constant speed assumption is used for the LAV.

$$\begin{bmatrix}\dot{s_h}\\ \dot{v_h}\\ \dot{a_h}\\ \dot{s_l}\\ \dot{v_l}\end{bmatrix}=\begin{bmatrix}0&1&0&0&0\\0&0&1&0&0\\0&0&0&0&0\\0&0&0&0&1\\0&0&0&0&0\end{bmatrix}\begin{bmatrix}s_h\\ v_h\\ a_h\\ s_l\\ v_l\end{bmatrix}+\begin{bmatrix}0\\0\\1\\0\\0\end{bmatrix}u_h \tag{8}$$

The MPC problem can be formulated by minimizing a proper cost function J_h over the prediction horizon:

$$J_h=\sum \Omega_h^T\Phi_h \tag{9}$$

where $\Phi_h=(\phi_1,\phi_2,\ldots)^T$ are a set of primitive costs for the HDV and each specifies the cost on a particular motion objective. As shown in (10), x_h and x_l are the states of the HDV and the LAV, r_j is the target value of the motion objective y_j, and $\Omega_h=(\omega_1,\omega_2,\ldots)^T$ are the associated weights.

$$\phi_j=g(x_h,x_l,r_j,u_h)=\sum_{\kappa=k}^{k+N}\left(y_j(\kappa)-r_j\right)^2 \tag{10}$$

When a human driver is conducting a driving task, he/she may focus on some of the motion targets while leaving the rest unattended. So, we propose to evaluate the primitive costs by using each of them independently as a stand-alone cost function, which can be written as:

$$J_{\phi_j}=\phi_j=\sum_{\kappa=k}^{k+N}\left(y_j(\kappa)-r_j\right)^2 \tag{11}$$

and then learning the reference r_j with a higher-level optimization:

$$\begin{gathered}r_j^*=arg\,min_{r_j}E\\ s.t.:\ r_j\in C_{r_j}\end{gathered} \tag{12}$$

E is the prediction error of the MPC over human driving demonstrations. When the higher-level optimization finishes, a minimum prediction error E_{ϕ_j} over demonstrations will be obtained for primitive cost ϕ_j. If the human driver is focusing on ϕ_j and trying to maintain y_j at a specific target value during driving, then the resultant E_{ϕ_j} should be small, which means ϕ_j can be a 'good' primitive cost in the final cost function. Otherwise, the resulted E_{ϕ_j} should be large, and ϕ_j might better be excluded from the cost function. All primitive costs can be ranked based on their E_{ϕ_j} values. We assume that $\Phi_h^*=(\phi_1^*,\phi_2^*\ldots,\phi_j^*)^T$ is the set of all available primitive costs that has been ranked from good to bad, with ϕ_1^* being the best and ϕ_j^* being the worst. Then we propose to formulate the cost function by combining the primitive costs from 'good' to 'bad', which can be described by (13).

$$\begin{gathered}J_1=\omega_1\phi_1^*,\\ J_2=\omega_1\phi_1^*,+\omega_2\phi_2^*,\\ \ldots\\ J_j=\omega_1\phi_1^*,+\omega_2\phi_2^*+\cdots+\omega_j\phi_j^*\end{gathered} \tag{13}$$

Since humans normally focus on more than one targets during driving, it is reasonable to start with a combination of the top two or three best primitive costs in the cost function first, then try adding the next best primitive cost to the cost function in the following attempts. Every cost function J_j learns its parameters using a higher-level optimization. Denote the set of references $r_1\ldots r_j$ by R_j, and the set of weights $\omega_1\ldots\omega_j$ by Ω_j, the optimization can be expressed as:

$$\begin{gathered}(\Omega_j^*,R_j^*)=arg\,min_{\Omega_h,R}\ E\\ s.t.:\ \Omega_j\in C_{\Omega_h},R_j\in C_R\end{gathered} \tag{14}$$

The total error E can be reduced by optimizing the weights Ω_j and references R_j in the cost function. Since only the relative values of weights are important, it is practical to fix one weight to 1 and optimize the remaining weights[27]. The object function of this higher-level optimization is yet another optimization problem, however, the Jacobian of E is not obtainable. Thus, the Pattern Search (PS) algorithm[29] is adopted in this paper.

Each cost function J_j will get a minimal evaluation error E_j from the higher-level optimization. Adding an effective primitive cost ϕ_j should improve the prediction accuracy and reduce the error E_j while adding an ineffective primitive cost will not bring any benefit but affect the optimization convergence, which will result in a larger prediction error. Thus, the adding of primitive costs will be repeated until the evaluated performance of the predictor starts to decrease, then the previous cost function can be selected to be the best cost function. It has shown that the proposed method to select the cost-function is effective, and the best cost function in this paper is chosen as (15), where $TTCi$ is time to collision inverse.

$$\begin{gathered}J_h=\sum_{\kappa=k}^{k+N}[w_a(a_h(\kappa)-a_h^{ref})^2+w_v(v_r(\kappa)-v_r^{ref})^2+\\ w_{TTCi}(TTCi_h(\kappa)-TCCi_h^{ref})^2+w_u(u_h(\kappa)-u_h^{ref})^2]\end{gathered} \tag{15}$$

When the IDM, ANN or IMPC-based speed predictor is used, the FAV can only obtain the prediction information via V2V communication from the HDV. Such communication is prone to delays and packet losses.

D. Handling of Delays and Packet Losses by Leveraging Prediction in Connected Mixed Traffic

In this paper, the performance of different predictors will be compared when delays and packet losses are present.

1) Injection of Delays and Packet Losses

Like mentioned in II.C, the prediction is made by the HDV and broadcasted to surrounding vehicles. The data collection and computing processes on the HDV are assumed to be ideal, which means that the prediction of the states of HDV is made based on the states of the LAV and HDV at the current time. The V2V communication between HDV and FAV however, is prone to delays and packet losses.

In this paper, delay and packet loss are injected as two separate disturbances. The delay can be caused by the misalignment between communication and control frequency, and the latency during communication, is assumed to be independent of packet loss.

2) Handling of Delays and Packet Losses

When communication delay and/or packet losses happens, the predictions received by the FAV are effectively made by the HDV a short while ago in the past:

$$X_P = [x_P(t - \Delta\tau), \dots, x_P(t + n_P \Delta t_P - \Delta\tau)] \quad (16)$$

In this paper, two different cases of dealing with such delayed information are compared. In the first case, no global timestamp information is assumed to be available to FAV. In other words, FAV will treat the prediction information available at every control loop as the latest information at time t. Such unawareness does not affect CS predictor since it is run locally. For IDM, ANN and IMPC-based predictors, the delayed prediction will be combined with on-board measurements $d_h(t)$, $a_f(t)$ and $v_f(t)$ in MPC. The mismatch of timestamps between predictions and measurements will generate unsatisfactory control input to the automated vehicle. Such a case represents the worst situation that can arise during connected automated driving.

In the second case, all vehicles are assumed to be sharing the same global time system, and the timestamps of the predictions are available to FAV. In other words, the combined delay time $\Delta\tau$ becomes available to the MPC controller. The whole predicted state trajectory can be shifted by $\Delta\tau$ into the future to match the timestamps of the current on-board measurements. The predicted states between $t + n_P \Delta t_P - \Delta\tau$ and $t + n_P \Delta t_P$ are assumed to be constant.

If a predictor is making accurate predictions of the human-driven vehicle's states, then the performance of the FAV controller should show a big improvement when delay handling situation is changed from the first case to the second case.

III. Experimental Results and Analysis

A. Experiment setup

In this section, a three-vehicle simulation that consists of two automated vehicles and one human driven vehicle is constructed. The system is shown in Fig. 1. The lead vehicle, vehicle 1, is the LAV that tracks given speed profiles. The vehicle in the middle, vehicle 2, is the HDV that can be controlled by a human driver in real-time on a driving simulator with motion feedback shown in Fig. 2.

The human driver drives the HDV to follow LAV. The HDV is built with complete longitudinal dynamics. The car in the back, vehicle 3, is the FAV that is controlled by an MPC. These three vehicles form a platoon. Each vehicle can measure its own speed and acceleration, while the HDV and FAV are additionally equipped with a radar to detect the headway distances and the speed of the vehicle in the front. Although the experiment in this paper only considers three vehicles, the size of the platoon is scalable. More automated vehicles, for instance vehicle n in Fig. 1 can join the platoon and follow vehicle 2 further behind as long as they are within the V2V communication range. In this paper, the MPC problem is solved using ACADO toolkit [28].

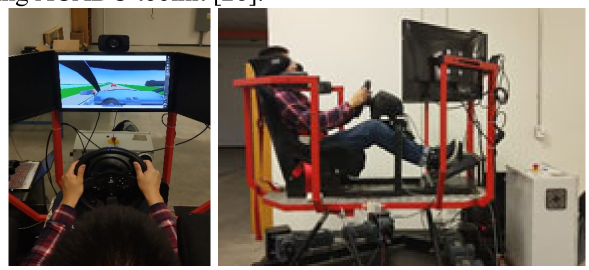

Fig. 2. Driving simulator used in this paper

In the experiment, the LAV is tracking three different driving cycles. The first one is the EPA Highway Fuel Economy Test Cycle (HWFET), which is a 12-minute-long mild highway cycle. The second is the Artemis Motorway 130 cycle which is an 18-minute-long aggressive motorway cycle with heavier braking and wider open throttle. The last one is the New York City Cycle (NYCC) with shortened stop time, which is an eight-minute-long urban driving cycle. The human driver was required to drive the HDV in his/her preferred way and maintain a comfortable distance from the lead vehicle. Four sets of data were collected, two of which were collected from the HWFET cycle, one from the Artemis cycle, and one from the NYCC cycle. The IMPC, ANN and IDM-based predictors are trained using the first set of HWFET cycle data. The other set of HWFET data and the Artemis and NYCC data is used to test the performance of the predictive controller with different predictors. In both learning and testing phases, the prediction horizon is chosen to be 10 seconds for all the predictors. The control frequency and the communication frequency are both set to 20Hz and d_f^{ref} is chosen to be 15 meters. The other parameters used in the tests are shown in TABLE II.

TABLE II
SIMULATION PARAMETERS

Parameter	Valus	Parameter	Value	Parameter	Value
Δt_p	0.5s	a_{min}	$-8m/s^2$	v_{min}	$0m/s$
t_P	10s	a_{max}	$4.5/s^2$	v_{max}	$40m/s$

B. Performance of Different MPCs under Combination of Random Delays and Packet Losses

In this section, four predictors' performance under a realistic combination of delay and packet loss is compared. Literature [8] suggests that the communication delay should be between one and two times of communication cycle time when there's no packet loss. In this paper, the communication frequency is 20Hz, thus the cycle time is 50ms. A random delay that is uniformly distributed between 50ms and 100ms is injected into the communication. Based on the measurements in [34], a high packet loss rate of 20% is selected to cover the nonideality in real V2V communication. The results are shown in TABLE III. In the table, green and blue-colored content represents the best and the second-best performer in each comparison.

TABLE III
MPC PERFORMANCE COMPARISON WITH DIFFERENT PREDICTORS, UNDER DELAY AND PACKET LOSS

Cycle		HWFET			Artemis (Unseen Cycle)			NYCC (Unseen Cycle)		
Error Type	Predictor	Mean Abs. Value	Max. Value	Min. Value	Mean Abs. Value	Max. Value	`Min. Value	Mean Abs. Value	Max. Value	Min. Value
Acceleration (m/s^2)	CS	0.3325	1.6430	-3.1692	0.5268	3.4344	-7.2628	0.5886	4.2969	-7.2768
	IDM	0.3356	1.7596	-3.4347	0.5300	3.5477	-8.0928	0.5977	4.2441	-7.2320
	IDM w.T.S.	0.3349	1.6856	-3.2615	0.5278	3.4893	-7.1537	0.5941	4.1666	-7.1106
	ANN	0.3371	1.8016	-3.5783	0.5414	4.2512	-8.7517	0.6484	4.1219	-8.6492
	ANN w. T.S.	0.3394	1.8482	-3.6275	0.5484	4.2870	-8.5804	0.6628	4.0981	-8.9689
	IMPC	0.3306	1.7106	-3.5891	0.5192	3.0352	-8.1423	0.5843	3.8202	-8.1328
	IMPC w. T.S.	0.3288	1.5964	-3.2538	0.5148	2.9258	-7.5707	0.5748	3.5314	-7.5347
Control Input (m/s^2)	CS	0.3435	2.3479	-3.6377	0.5515	5.0000	-8.3082	0.6353	5.0000	-8.1180
	IDM	0.3416	2.4307	-5.1604	0.5436	5.0000	-10.0000	0.6267	5.0000	-8.3189
	IDM w.T.S.	0.3410	2.2928	-3.5065	0.5426	5.0000	-7.5911	0.6267	5.0000	-7.5245
	ANN	0.3432	2.3576	-4.1043	0.5586	5.0000	-9.5075	0.7212	5.0000	-9.5424
	ANN w. T.S.	0.3625	3.1931	-3.8531	0.5991	5.0000	-9.9338	0.8094	5.0000	-9.2429
	IMPC	0.3360	2.3498	-4.1054	0.5324	4.2687	-9.6111	0.6117	5.0000	-10.0000
	IMPC w. T.S.	0.3363	2.0029	-3.3152	0.5312	3.9999	-8.0647	0.6046	4.7592	-7.8806
Tracking Error (m)	CS	0.1015	0.3922	-1.2072	0.2124	0.5770	-3.7301	0.5844	0.8275	-4.0949
	IDM	0.0921	0.3822	-1.0314	0.1868	0.5783	-3.5721	0.4956	0.7638	-3.4427
	IDM w.T.S.	0.0883	0.4643	-0.9781	0.1790	0.5964	-3.3770	0.4761	0.7543	-3.2387
	ANN	0.1168	1.7640	-0.8797	0.2728	2.0591	-3.2475	1.1257	2.3921	-2.9065
	ANN w. T.S.	0.1395	2.4237	-0.8410	0.3348	2.8168	-3.1769	1.3027	2.8690	-2.8202
	IMPC	0.0757	0.3143	-0.6864	0.1426	0.4423	-2.3926	0.4110	0.5984	-2.4620
	IMPC w. T.S.	0.0579	0.2460	-0.5394	0.1120	0.3423	-2.1126	0.3465	0.4764	-2.0944

Since CS predictor does not require V2V communication, it is not affected by the communication uncertainties. With the delays and packet losses injected, the MPC controllers with IDM and ANN predictors are causing larger average absolute acceleration than the one with CS predictor. However, even without timestamps for delay correction, the IMPC predictor still manages to achieve the smallest average control error, lowest average absolute acceleration, and control cost among all four predictors and under all the three driving cycles. The IDM predictor's performance in control error and control cost is between the CS and the IMPC predictors. We noticed that the IDM and the CS predictors sometimes outperformed the IMPC predictor when it came to minimum acceleration. However, we also noticed that at the same time, the minimum tracking error of IMPC was much better than that of the CS and the IDM. These two observations combined indicate that the CS and IDM were not able to make accurate predictions so that the FAV could decelerate enough when the HDV suddenly slowed down. The ANN predictor is having the worst performance in every aspect in these four predictors due to scalability issue caused by the limited training data. Thus, the IMPC predictor is the best predictor for riding comfort and fuel-efficiency.

When the timestamps for the shared information are available, the performance of the IMPC predictor is improved noticeably while that of the IDM predictor is only improved slightly. The IDM predictor is still falling behind the CS predictor in many aspects. The ANN predictor is the only predictor that gets worse performance when delay compensation is available. The phenomena reflect that the IMPC is having the most accurate prediction over the horizon, while the ANN requires far more training data to make accurate and stable predictions.

Overall, the results prove that with our new IMPC based predictor, the predictive controller of connected automated vehicles can perform better under communication constraints. Moreover, with the communication delay and packet loss correction method, the performance of the predictive controller can be further improved.

IV. CONCLUSION

In this paper, model predictive control based on various prediction approaches for connected mixed traffic is proposed and compared. The new IMPC-based prediction approach is the most effective in modelling and predicting the longitudinal behaviors of human-driven vehicles in connected mixed traffic environments. Its predictions can be utilized by the model predictive controllors of connected automated vehicles for improved control accuracy, riding comfort and energy efficiency. The proposed approach can handle communication uncertainties better than other approaches. Comparisons are done between the IMPC-based prediction and IDM and CS based predictions and controls under random communication constraints. The results illustrate the effectiveness and advantages of the proposed approaches in handling delays and packet losses. It obviously outperforms other approaches when communication delay and packet losses are present, which is reflected in the lowest control error, average vehicle acceleration and average control input. With correction using the timestamps, the IMPC-based approach can almost recover its performance with communication constraints to ideal situation.

As for future work, we plan to apply the current IMPC to a larger platoon of vehicles to study its effect on the large mixed traffic flow. We are also planning to use more complex cost function designs to reveal the different driving preferences between different drivers more evidently. Extending the proposed framework to the prediction and control of other behaviors/states of connected mixed vehicles such as lane switching in addition to the studied longitudinal driving will also be further work to explore.

REFERENCES

[1] R. Bishop, "Intelligent vehicle applications worldwide." IEEE Intelligent Systems and Their Applications 15.1 (2000): 78-81.

[2] Kesting, Arne, et al. "Adaptive cruise control design for active congestion avoidance." Transportation research. Part C, Emerging technologies 16.6 (2008): 668-683.

[3] Kamal, Md Abdus Samad, et al. "Efficient control of vehicles in congested traffic using model predictive control." 2012 IEEE International Conference on Control Applications. IEEE, 2012.

[4] Dollar, Robert Austin, and Ardalan Vahidi. "Efficient and Collision-Free Anticipative Cruise Control in Randomly Mixed Strings." IEEE Transactions on Intelligent Vehicles 3.4 (2018): 439-452.

[5] Jin, I. Ge, and Gábor Orosz. "Dynamics of connected vehicle systems with delayed acceleration feedback." Transportation Research Part C: Emerging Technologies 46 (2014): 46-64.

[6] Li, Shengbo Eben, et al. "Dynamical modeling and distributed control of connected and automated vehicles: Challenges and opportunities." IEEE Intelligent Transportation Systems Magazine 9.3 (2017): 46-58.

[7] Liu, Xiangheng, et al. "Effects of communication delay on string stability in vehicle platoons." ITSC 2001. 2001 IEEE Intelligent Transportation Systems. Proceedings (Cat. No. 01TH8585). IEEE, 2001.

[8] Orosz, Gábor. "Connected cruise control: modelling, delay effects, and nonlinear behaviour." Vehicle System Dynamics54.8 (2016): 1147-1176.

[9] Gao, Feng, et al. "Robust control of heterogeneous vehicular platoon with uncertain dynamics and communication delay." IET Intelligent Transport Systems 10.7 (2016): 503-513.

[10] Jin, I. Ge, and Gábor Orosz. "Optimal control of connected vehicle systems with communication delay and driver reaction time." IEEE Transactions on Intelligent Transportation Systems 18.8 (2016): 2056-2070.

[11] Srinivasagupta, Deepak, Heinz Schättler, and Babu Joseph. "Time-stamped model predictive control: an algorithm for control of processes with random delays." Computers & Chemical Engineering 28.8 (2004): 1337-1346.

[12] Associated Press, “Google self-driving car caught on video colliding with bus," The Guardian, Mar. 9, 2016. [Online]. Available: https://www. theguardian.com/technology/2016/mar/09/google-self-driving-%carcrash-video-accident-bus

[13] E. C. Baig, “Uber halts self-driving car tests after Arizona crash,” USA Today, Mar. 26, 2017. [Online]. Available: https://www.theguardian. com/technology/2016/mar/09/google-self-driving-%car-crash-video-accident-bus

[14] Park, Jungme, et al. "Real time vehicle speed prediction using a neural network traffic model." The 2011 International Joint Conference on Neural Networks. IEEE, 2011.

[15] Jiang, Bingnan, and Yunsi Fei. "Traffic and vehicle speed prediction with neural network and hidden markov model in vehicular networks." 2015 IEEE Intelligent Vehicles Symposium (IV). IEEE, 2015.

[16] Tampère, Chris MJ. Human-kinetic multiclass traffic flow theory and modelling. With application to Advanced Driver Assistance Systems in congestion. Diss. 2004.

[17] Bando, Masako, et al. "Dynamical model of traffic congestion and numerical simulation." Physical review E 51.2 (1995): 1035.

[18] Kesting, Arne, and Martin Treiber. "Calibrating car-following models by using trajectory data: Methodological study." Transportation Research Record: Journal of the Transportation Research Board 2088 (2008): 148-156.

[19] Lefevre, Stéphanie, et al. "Lane keeping assistance with learning-based driver model and model predictive control." 12th International Symposium on Advanced Vehicle Control. 2014.

[20] Qu, Ting, et al. "Modeling driver's car-following behavior based on hidden Markov model and model predictive control: A cyber-physical system approach." 2017 11th Asian Control Conference (ASCC). IEEE, 2017.

[21] Hermes, Christoph, et al. "Long-term vehicle motion prediction." 2009 IEEE intelligent vehicles symposium. IEEE, 2009.

[22] Khodayari, Alireza, et al. "A modified car-following model based on a neural network model of the human driver effects." IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans 42.6 (2012): 1440-1449.

[23] Gindele, Tobias, Sebastian Brechtel, and Rüdiger Dillmann. "A probabilistic model for estimating driver behaviors and vehicle trajectories in traffic environments." Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference on. IEEE, 2010.

[24] Kesting, Arne, Martin Treiber, and Dirk Helbing. "Enhanced intelligent driver model to access the impact of driving strategies on traffic capacity." Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 368.1928 (2010): 4585-4605.

[25] Guo, Longxiang and Yunyi Jia,. " Modeling, Learning and Prediction of Longitudinal Behaviors of Human-Driven Vehicles by Incorporating Internal Human Decision-Making Process using Inverse Model Predictive Control." International Conference on Intelligent Robots and Systems. Accpted.

[26] Lv, Chen, et al. "Levenberg–Marquardt Backpropagation Training of Multilayer Neural Networks for State Estimation of a Safety-Critical Cyber-Physical System." IEEE Transactions on Industrial Informatics 14.8 (2018): 3436-3446.

[27] Mombaur, Katja, Anh Truong, and Jean-Paul Laumond. "From human to humanoid locomotion—an inverse optimal control approach." Autonomous robots 28.3 (2010): 369-38.

[28] Houska, Boris, Hans Joachim Ferreau, and Moritz Diehl. "ACADO toolkit—An open-source framework for automatic control and dynamic optimization." Optimal Control Applications and Methods 32.3 (2011): 298-312.

[29] Lewis, Robert Michael, and Virginia Torczon. "Pattern search algorithms for bound constrained minimization." SIAM Journal on Optimization 9.4 (1999): 1082-1099.

[30] Lefèvre, Stéphanie, et al. "Comparison of parametric and non-parametric approaches for vehicle speed prediction." 2014 American Control Conference. IEEE, 2014.

[31] Reichardt, Dirk, et al. "CarTALK 2000: Safe and comfortable driving based upon inter-vehicle-communication." Intelligent Vehicle Symposium, 2002. IEEE. Vol. 2. IEEE, 2002.

[32] Tokuda, Kiyohito, Masami Akiyama, and Haruki Fujii. "DOLPHIN for inter-vehicle communications system." Proceedings of the IEEE Intelligent Vehicles Symposium 2000 (Cat. No. 00TH8511). IEEE, 2000.

[33] Durresi, Mimoza, Arjan Durresi, and Leonard Barolli. "Emergency broadcast protocol for inter-vehicle communications." 11th International Conference on Parallel and Distributed Systems (ICPADS'05). Vol. 2. IEEE, 2005.

[34] Wang, Yizhi, et al. "Reliability evaluation of IEEE 802.11 p-based vehicle-to-vehicle communication in an urban expressway." Tsinghua Science and Technology 20.4 (2015): 417-428.