

# Optimizing Vehicle Trajectories at a Signalized Intersection in Mixed Traffic

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**Abstract**—With the advancement of connected and automated vehicles (CAVs), achieving accurate vehicle trajectory prediction and optimal control has become a critical challenge for improving the efficiency and safety of mixed traffic flow. However, due to the complex dynamic interactions between CAVs and human-driven vehicles (HVs) and the nonlinear nature of signal coordination, existing studies lack comprehensive consideration of CAV position adjustments within the platoon and their guidance effects on trailing HVs. We propose a data-driven method for CAV state prediction and trajectory optimization. Employing an application-specific improved Informer model, our method accurately predicts CAV arrival states at a signalized intersection in mixed traffic. Additionally, Bayesian optimization is utilized to achieve automated and rapid tuning of CAV model predictive control parameters through learning human driving characteristics. Experimental results demonstrate that our proposed method significantly enhances overall traffic efficiency and optimization when CAVs operate within mixed traffic, showing strong feasibility and adaptability.

## I. INTRODUCTION

The rapid development of Connected and Automated Vehicles (CAVs) is profoundly transforming modern transportation systems [1]. In recent years, high-level autonomous vehicles, such as Tesla's Full Self-Driving system [2] and Waymo's autonomous taxis [3], have entered mass production. The widespread adoption of CAVs promises to enhance road safety, optimize traffic flow, and alleviate urban congestion, marking a pivotal trend in future transportation development [4].

However, the large-scale application of CAVs faces significant challenges. On one hand, public concerns about the reliability and safety of autonomous systems in complex traffic environments persist, necessitating improvements in acceptance and trust. On the other hand, incomplete legal frameworks and policy uncertainties restrict their promotion. Consequently, the widespread adoption of CAVs is set to be a gradual process, during which CAVs will coexist with Human-driven Vehicles (HVs) in Mixed Traffic (MT) for an extended period [5].

In such an environment, CAVs can interact in real-time with traffic infrastructure, accessing Signal Phase and Timing

(SPaT) information to optimize vehicle trajectories and achieve dynamic traffic management and control [6]. A critical challenge lies in realizing efficient collaboration between CAVs and traffic infrastructure, such as traffic signals, while considering the influence of HVs. As traffic participant diversity increases, novel collaborative methods are urgently needed to optimize traffic flow, improve road safety, and enhance operational efficiency. Existing studies primarily focus on trajectory optimization in purely autonomous environments, where CAV states are predictable and stable. However, existing studies on the collaboration between CAVs, HVs, and traffic signals in mixed traffic neglect the uncertainty and variability of human-driven vehicles [7]. Moreover, current studies on CAVs in MT predominantly rely on simulations with limited field experiments [8].

To address these gaps, this work focuses on an essential problem in MT: achieving collaborative trajectory optimization of CAV and traffic signals through accurate state prediction, enabling CAV to guide following HVs and ensuring the platoon passes signalized intersections with optimal efficiency. To this end, we collect extensive car-following scenario data and adopt a data-driven approach to predict the arrival time of CAV in MT. Additionally, we optimize CAV trajectory planning and control parameters based on human driver data and validate the proposed method through field experiments. Experimental results demonstrate that the proposed method effectively predicts the state of the MT system under limited information, smoothing the speed profiles of both CAV and following HVs, thereby achieving platoon trajectory optimization. The proposed method is highly flexible and accommodates varying orders of CAV within the platoon. The contributions of this article are summarized as follows.

- 1) An improved Informer model is employed to predict the arrival state of CAV at signalized intersection in MT.
- 2) Bayesian optimization is utilized to train CAV to learn the features of HVs in MT, thus optimizing CAV controllers, enhancing control comfort, and improving their ability to guide following HVs, ultimately improving traffic efficiency.
- 3) Extensive real-vehicle data collection and experiments validate the feasibility of the proposed methods, proving their ability to enhance overall platoon performance.

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## II. RELATED WORK

### A. State Prediction in Intelligent Transportation Systems

Accurately predicting the arrival state of CAVs is fundamental to intelligent transportation systems, especially under signalized intersections. Existing research mainly includes model-based and machine learning approaches.

Model-based methods rely on historical vehicle and traffic data (e.g., GPS, network flow, AVI), using statistical or probabilistic models for forecasting. Prior studies have explored various directions: Uchida [9] estimated travel time and reliability based on user equilibrium considering risk preferences; Ma et al. [10] proposed a generalized Markov chain to model dynamic transitions between link times; Chiabaut et al. [11] applied Gaussian mixtures with k-means clustering to identify traffic patterns; Kumar et al. [12] employed Kalman filtering for robust bus time prediction; and Zhang et al. [13] integrated signal priority and adaptive control to estimate queue and distance to the stop line. While grounded in theory, these methods assume stable traffic and often struggle with long-term uncertainty. To address complexity, machine learning methods utilize large-scale heterogeneous data. Shallow methods [14] like SVMs and K-NN depend on manual feature engineering and suit simpler tasks. In contrast, deep learning methods such as CNNs, LSTMs, and GRUs [15]–[18] automatically extract high-level spatial-temporal features. For example, Sun et al. [15] embedded driving styles into LSTM for ride-hailing prediction; Li X. [16] et al. modeled interactions among dwell time, behavior, and traffic; and N. Li et al. [17] used GRU-FC networks for port truck arrival forecasting.

Despite progress, few works target CAV prediction in MT, where collaboration with HVs and signal control is essential. Future CAV states influence not only individual planning but also system-wide safety and efficiency.

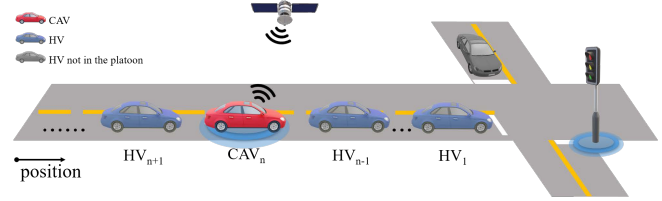
### B. CAV Model Predictive Control Optimization Methods

CAV planning and control are naturally formulated as a finite-horizon optimization problem. Model Predictive Control (MPC [19]) enables real-time trajectory planning by considering multi-objective constraints. However, in mixed traffic, increased uncertainty and nonparametric variations expand the solution space and challenge MPC stability.

Recent works explore data-driven strategies to optimize MPC. Piga et al. [20] introduced Identification for Control into Bayesian MPC for learning optimal strategies. Hewing et al. [21] used offline sampling to build probabilistic reachable sets. Zanon et al. [22] embedded MPC as a safety filter in RL; Akhil et al. [23] simplified deterministic policy gradients to enhance MPC-RL integration. H. Li et al. [24] designed a distributed MPC framework considering surrounding vehicle behaviors.

Despite these advances, key challenges remain: data dependency, limited interpretability, and over-reliance on simulation. To address these gaps, this paper constructs a scenario-specific dataset, incorporates physical constraints, and conducts validation using real vehicles.

## III. PROBLEM STATEMENT



**Fig. 1.** Vehicles pass through signalized intersection.

### A. Scenario Description

As shown in Fig. 1, this paper considers a scenario in mixed traffic flow where a vehicle platoon passes through a signalized intersection. The CAV is positioned at the  $n$ -th spot in the platoon, with  $n-1$  HVs ahead and trailing HVs behind. The following assumptions are made:

**Assumption 1:** The CAV can obtain real-time SPaT information and position among the platoon through V2I communication but cannot control the traffic signal. The CAV also utilizes GPS for self-localization.

**Assumption 2:** The CAV can only access the state of the immediately preceding HV using onboard sensors such as millimeter-wave radar.

**Assumption 3:** Every vehicle in the mixed traffic flow must not exceed the road segment's speed limit  $v_{lim}$ .

**Assumption 4:** After passing the intersection, the HVs ahead of the CAV gradually accelerate to the road speed limit.

**Assumption 5:** The CAV possesses fully autonomous longitudinal driving capabilities.

**Assumption 6:** For simplicity, the yellow light period of the traffic signal is merged into the green light period.

### B. Optimal Traffic Efficiency Problem

The primary objective of our study is to achieve maximum traffic efficiency by deriving the optimal speed planning for the CAV. This ensures that, under the guidance of the CAV, the vehicle platoon, including the following HVs, passes through the signalized intersection at maximum speed while ensuring a safe inter-vehicle distance and ensuring comfort.

To optimize the CAV's speed trajectory, the desired arrival time  $t_{s,n}$  and speed  $v_{s,n}$  at the intersection must be determined. Given that the CAV's position  $n$  within the platoon is variable and the traffic signal cycle is uncontrolled, three potential scenarios are derived:

- 1) During the current green light cycle, the CAV can pass through the intersection alongside the HVs ahead;
- 2) The HVs ahead of the CAV either pass through or fail to pass before the light turns red, while the CAV fails to pass during this green light cycle. In this case, the CAV aims to pass during the next green light cycle at as high a speed as possible without stopping while maintaining a safe distance;
- 3) The HVs ahead of the CAV either pass through or fail to pass before the light turns red, and the CAV must stop and wait under constraints such as safe distance and acceleration limits.

Considering the efficiency of the HVs following the CAV, the control strategy for the CAV should consider human driving features while maintaining optimal efficiency. Additionally, human drivers exhibit significant nonlinear and black-box behaviors near traffic signals, heavily influenced by SPaT information, making explicit modelling difficult. Thus, the optimization and control of the CAV inherently involve learning and predicting HVs' behaviors in scenarios where vehicles pass through intersection.

#### IV. ARRIVAL STATE PREDICTION FOR CAV USING IMPROVED INFORMER MODEL

Since predicting the CAV's arrival state at a signalized intersection is a long-sequence prediction problem, we introduce an improved **Informer** model to balance accuracy and computational complexity for training and prediction. This section illustrates our dataset construction and presents our model in detail.

##### A. Dataset Construction

To the best of our knowledge, there is no publicly available dataset related to this research. To fill this gap, this paper conducts extensive field experiments. As shown in Fig. 2, a straight road segment of approximately 350 meters with a speed limit of 40 km/h ( $\approx 11.1\text{m/s}$ ) and equipped with a connected signalized intersection is selected. A 6-vehicle platoon is formed for dataset collection. To improve the accuracy of the dataset, each vehicle is equipped with a high-precision GPS positioning system. The red and green light phases of the signal cycle are both set to 15 seconds.



Fig. 2. Field for dataset construction and experiment.

During each round of data collection, the platoon starts from the initial point  $p_0$  ( $p_0 = 0$ ), travels toward the traffic signal position  $p_s$  ( $p_s = 250$ ), and continues to the endpoint  $p_e$  ( $p_e = 350$ ). To ensure the diversity of the data, each round begins under different signal states  $s$  (Green or Red) and countdown values  $T_s$ . Besides, the vehicles and their positions within the platoon are randomly assigned to different drivers, and the entire process is repeated for 10 rounds.

In each round, the time step  $\tau$  is set to 0.1s. At  $k$ -th time step  $t^k$ , the speed  $v_j(t^k)$ , acceleration  $a_j(t^k)$ , and jerk  $u_j(t^k)$  ( $j \in \{1,2,3,4,5,6\}$ ) of each vehicle (which are operated by skilled human drivers) are recorded and calculated. The  $n$ -th ( $n \in \{2,3,4,5,6\}$ ) vehicle is manually designated as the CAV. For the CAV, the following data are recorded and calculated at  $t^k$ :

- 1) CAV real-time parameters: position  $p_n(t^k)$ , speed  $v_n(t^k)$ , distance to the preceding HV  $d_n(t^k) = p_n(t^k) - p_{n-1}(t^k)$ , speed of the preceding HV  $v_{n-1}(t^k)$ ,

distance to the traffic signal  $d_n(t^k)$ ;

- 2) Traffic signal information: signal state  $s(t^k)$ , signal countdown  $T_s(t^k)$ ;
- 3) Arrival state of CAV: time of arrival at the traffic signal  $t_{s,n}$  speed passing the traffic signal  $v_{s,n}$ .

##### B. Improved Informer Prediction Model

The **Transformer** [25] and its variants have demonstrated excellent performance in long-sequence prediction tasks. **Informer** [26] is an efficient model designed for long-sequence time-series forecasting tasks. The core advantage of Informer lies in its sparse self-attention mechanism [27] that reduces computational complexity from  $O(L^2)$  to  $O(L\log L)$  while maintaining accuracy. Based on the Transformer architecture, Informer incorporates several key improvements: **ProbSparse Self-Attention** computes only the most relevant attention scores, replacing less important ones (Lazy Queries) with averaged outputs, significantly reducing computation and memory usage. **Self-Attention Distilling** uses convolution and pooling to down sample long input sequences, capturing dominant attention features with reduced complexity. **Generative Decoder** predicts the entire output sequence in a single step, avoiding cumulative errors from step-wise decoding and accelerating inference. **Multi-scale Temporal Encoding** incorporates not only positional encodings but also time-related features (e.g., daily, weekly cycles) to better capture temporal patterns.

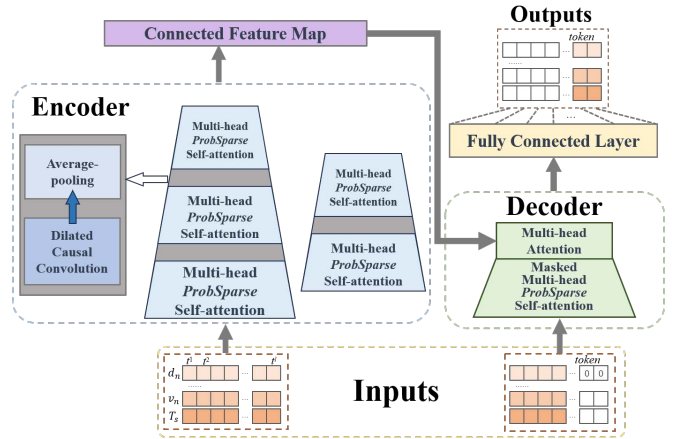


Fig. 3. Structure of the improved Informer model.

Considering the trade-off between computational complexity and efficiency, this study employs the Informer model as the base prediction model. In this paper, targeted improvements have been made to the Informer model, focusing on refined feature extraction and adaptation to the prediction task, as detailed below (as shown in Fig.3).

**Inputs & Outputs:** Balancing accessibility and accuracy, the features below are selected for input at  $t^k$  to predict the CAV arrival time:

$$I(t^k) = \{n, d_n(t^k), v_n(t^k), v_{n-1}(t^k), s(t^k), T_s(t^k)\}, \quad k \in \{1, 2, \dots, m\} \quad (1)$$

where  $n$  and  $s(t^k)$  are discrete variables, with  $s(t^k) \in \{0,1\}$ , where 0 represents a red light, and 1 represents a green light.

Among these variables, the speed of CAV  $v_n$  and the speed of the preceding HV  $v_{n-1}$  exhibit a strong correlation, directly determining the motion state and future acceleration or deceleration behavior of the CAV. Additionally, the distance of the CAV to the traffic signal  $d_n$ , the signal state  $s$ , and the signal countdown  $T_s$  are critical factors in assessing whether the vehicle can pass through the current signal phase. Moreover, the signal state and the distance of the vehicle platoon to the signal (which can be reflected by  $d_n$ ) also influence the operations of HVs drivers in mixed traffic. For instance, due to the inevitable subjective factors of human drivers,  $T_s$  and the distance to the signal directly affect the real-time acceleration or deceleration behavior and driving style (e.g., smooth or aggressive) of human drivers when the signal is visually perceptible. Importantly, these variables can be obtained through onboard sensors of the CAV in practical applications without requiring additional prior information about the HVs, thereby significantly enhancing the applicability of our prediction model.

To obtain the CAV arrival state  $O = \{t_{s,n}, v_{s,n}\}$ , the sequence length  $l$  for prediction is calculated as follows.

The theoretical minimum arrival time  $t_{\min}$  for the CAV, assuming no preceding HVs, is determined using the current state  $I(t^m)$  at  $t^m$ . The CAV accelerates from  $v_n(t^m)$  to the road speed limit  $v_{\lim}$  with the maximum acceleration  $a_{\max}$ , and travels to the traffic signal position. Thus,  $t_{\min}$  consists of three segments: the current moment  $t^m$ , the time required for the acceleration process, and the time for constant speed travel, which can be calculated as:

$$t_{\min} = t^m + \frac{v_{\lim} - v_n(t^m)}{a_{\max}} + \frac{L_s - \left(\frac{v_{\lim}^2 - v_n(t^m)^2}{a_{\max}}\right)}{v_{\lim}} \quad (2)$$

where  $L_s$  is the distance from the road segment's starting point to the intersection, and the corresponding time step index is  $k_{\min} = \lfloor t_{\min}/\tau \rfloor$ . The lower bound for the sequence prediction length is thus defined as  $l > k_{\min} - m$ . The model predicts the output sequence:

$$\hat{Y}^i = I(t^k) = \{n, d_n(t^k), v_n(t^k), v_{n-1}(t^k), s(t^k), T_s(t^k)\} \\ k \in \{m+1, \dots, k_{\min}, k_{\min}+1, \dots\}, \\ i \in \{1, \dots, k_{\min} - m, k_{\min} - m + 1, \dots\} \quad (3)$$

Using a sliding window, the predicted arrival time  $\hat{t}_{s,n}$  is identified as the nearest time step satisfying  $|d_n(\hat{t}_{s,n})| < \varepsilon$ ,  $\varepsilon \rightarrow 0$ . The predicted CAV state is then  $\hat{O} = \{\hat{t}_{s,n}, \hat{v}_n(\hat{t}_{s,n})\}$ .

**Network Structure Improvements:** To enhance prediction causality, the self-attention distillation layer of Informer is modified by replacing traditional convolution with dilated causal convolution [28], represented as:

$$DC(\cdot) = \sum_{q=0}^4 c_q * I_q(t^{k-d}) \quad (4)$$

where  $I_q(t^{k-d})$  represents the  $q$ -th input feature offset at  $t^{k-d}$ ,  $d$  is the dilation factor, and  $c_q$  is the convolution kernel weight. This choice is motivated by the need to capture long-range dependencies in time series data without increasing the number of parameters. Dilated causal convolution introduces "holes"

between the kernel points, effectively expanding the receptive field while maintaining computational efficiency.

Additionally, the traditional Max-Pooling operation is replaced with Average-Pooling. This change is driven by the desire to enhance feature retention and reduce overfitting. While Max-Pooling is effective in retaining dominant features and being robust to noise, it can lead to significant information loss by discarding non-maximal values. In contrast, Average-Pooling considers all values within the pooling window, preserving more spatial information and being more robust to outliers [29]. This approach helps in maintaining the overall feature distribution, which is crucial for accurate time series prediction.

The activation function in the Informer model is modified to use Parametric Rectified Linear Unit (PreLU) [30] instead of the traditional Exponential Linear Unit (ELU) [31]. PreLU dynamically learns the negative slope parameter, allowing for better adaptation to diverse data distributions. This flexibility is particularly beneficial in time series prediction, where data can exhibit varying patterns and distributions. By optimizing the nonlinear mappings, PreLU provides a more robust and adaptive activation mechanism compared to ELU, which has a fixed negative slope.

**Loss Function:** In the training process, according to the characteristics of the predicted variables, we hope to improve the model's reasoning ability of sequences near  $d_n = 0$ , the following weighted mean squared error (MSE) loss function is used for backpropagation (BP):

$$\text{Weighted MSE} = \frac{1}{l} \sum_{i=1}^l \omega_i (Y^i - \hat{Y}^i)^2, \\ \omega_i = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{d_n^i}{2\sigma^2}\right) \quad (5)$$

where  $Y^i$  is the true value used for verification and  $\hat{Y}^i$  is the predicted value during training. We use the weight factor  $\omega_i$  described by Gaussian distribution to reflect the importance of the prediction accuracy of CAV state at signal light, so that the model can adapt to different scenarios by adjusting the variance.

During training, the first 70% of each sequence is used for training, while the remaining 30% is used for validation.

## V. DATA-DRIVEN MODEL PREDICTIVE CONTROL FOR CAV

Considering the strong nonlinearity of the dynamics in the interaction between CAVs and HVs in MT, this paper incorporates human driving characteristics into the CAV's model predictive control. By transforming the adjustment of MPC parameters into an optimization problem, data-driven prior information helps expedite the determination of the CAV's control strategy. This approach facilitates smoother driving trajectories, reduces the frequency of abrupt braking or acceleration by following HVs, and thus minimizes driving stress and collision risks. Smoother speed variations also mitigate the accumulation of "shockwave" effects in traffic flow, preventing congestion or queuing and ultimately improving overall road traffic efficiency.

### A. Model Predictive Control of CAV

Model predictive control is a method for controlling systems by solving optimization problems. Its core objective is to predict future states and optimize current control inputs, enabling the CAV to follow a desired trajectory over a future time horizon [32]. In this paper, MPC is applied to optimize the trajectory of the CAV as it approaches a signalized intersection, with the expected terminal state defined as  $O = \{t_{s,n}, v_{s,n}\}$ .

For the CAV positioned as the  $n$ -th vehicle in the platoon, its state vector at time  $t$  is defined as:

$$X_n(t) = [p_n(t), v_n(t), a_n(t)]^T \quad (6)$$

The state dynamics of the CAV is expressed as:

$$\dot{X}_n(t) = [v_n(t), a_n(t), u_n(t)]^T \quad (7)$$

where  $a_n(t)$  is the control input, representing the acceleration of the CAV, and  $u_n(t)$  represents the jerk (rate of change of acceleration) of the CAV.

To ensure the CAV reaches the traffic signal position  $p_s$ , the total control cost  $\mathcal{T}$  is defined as:

$$\mathcal{T} = \mathcal{S}(X_n(t_{s,n})) + \int_0^{t_{s,n}} \mathcal{R}(X_n(t)) dt \quad (8)$$

where terminal cost  $\mathcal{S}$  describes the deviation of the CAV's position, speed, and acceleration upon reaching the signal:

$$\mathcal{S} = r_1(p_n(t_{s,n}) - L_s)^2 + r_2(v_n(t_{s,n}) - v_{s,n})^2 + r_3 a_n(t_{s,n})^2 \quad (9)$$

Running cost  $\mathcal{R}$  represents the ongoing control costs and is defined as:

$$\begin{aligned} \mathcal{R}(X_n(t)) = & r_4 + r_5 Q(v_n(t), a_n(t)) \\ & + r_6 M v_n(t) a_n(t)^2 H(a_n(t)) + r_7 u_n(t)^2 \end{aligned} \quad (10)$$

where  $M$  is the mass of the CAV,  $Q$  is nonlinear function associated with speed and acceleration:

$$\begin{aligned} Q(v_n(t), a_n(t)) = & r_8 v_n(t) + r_9 v_n(t)^2 + r_{10} v_n(t)^3 \\ & + M v_n(t) a_n(t) \end{aligned} \quad (11)$$

and  $H$  is the function preventing acceleration being negative:

$$H(a_n(t)) = \begin{cases} 1 & a_n(t) > 0 \\ 0 & a_n(t) \leq 0 \end{cases} \quad (12)$$

To ensure that the optimization results are consistent with physical and safety constraints, the limits are imposed:  $v_n \in [v_{\min}, v_{\lim}]$ ,  $a_n \in [a_{\min}, a_{\max}]$ ,  $u_n \in [u_{\min}, u_{\max}]$ .

Additionally, the acceleration must satisfy the safety constraints of the vehicle platoon:  $a_n(t) \leq a_n^{\text{ACC}}(t)$ ,  $a_n^{\text{ACC}}(t)$  is the target acceleration of the CAV based on a linear car-following model:

$$\begin{aligned} a_n^{\text{ACC}}(t) = & r_{11}(p_{n-1}(t) - p_n(t) - v_n(t)\tau) \\ & + r_{12}(v_{n-1}(t) - v_n(t)). \end{aligned} \quad (13)$$

### B. Bayesian Optimization for MPC Parameter Tuning

Manually adjusting the numerous parameters of MPC is inefficient and subject to uncontrollable interference factors. To rapidly determine reasonable parameter ranges and identify potential optimal parameter sets, this paper employs Bayesian optimization [20]. Using the real HV dataset collected in 4.1, we focus on optimizing the seven MPC parameters  $r_1$  to  $r_7$ .

For each complete HV trajectory (from the starting point to the signalized intersection) in the real dataset, we extract the following data for the  $n$ -th HV (corresponding to the CAV's position in the platoon): average speed  $\bar{v}_n^{\text{HV}}$ , average acceleration  $\bar{a}_n^{\text{HV}}$  and average jerk  $\bar{u}_n^{\text{HV}}$ . These form the HV feature vector:  $\boldsymbol{\phi}_{\text{HV}} = [\bar{v}_n^{\text{HV}}, \bar{a}_n^{\text{HV}}, \bar{u}_n^{\text{HV}}]^T$ . We also record the HV's arrival state  $\{t_{s,n}^{\text{HV}}, v_{s,n}^{\text{HV}}\}$  at the SPaT information. Using HV's state as control target of CAV, the CAV's MPC is performed for a given parameter vector  $\mathbf{r} = [r_1, \dots, r_7]^T$ . The resulting CAV trajectory data is used to extract the feature vector:  $\boldsymbol{\phi}_{\text{CAV}}(\mathbf{r}) = [\bar{v}_n^{\text{CAV}}(\mathbf{r}), \bar{a}_n^{\text{CAV}}(\mathbf{r}), \bar{u}_n^{\text{CAV}}(\mathbf{r})]^T$ .

The objective of BO is to minimize the Euclidean norm between the HV and CAV feature vectors:

$$J(\mathbf{r}) = \arg \min \|\boldsymbol{\phi}_{\text{CAV}}(\mathbf{r}) - \boldsymbol{\phi}_{\text{HV}}\| \quad (14)$$

where  $\|\cdot\|$  denotes the Euclidean norm. To approximate  $J$ , Gaussian Process Regression (GPR) is used:

$$J(\mathbf{r}_{1:M}) \sim \mathcal{GP}(\mu_0(\mathbf{r}_{1:M}), K(\mathbf{r}_{1:M}, \mathbf{r}'_{1:M})) \quad (15)$$

where  $\mu_0$  is the prior mean of  $J$ ,  $K$  is covariance function,  $M$  is number of observed data points. In GPR, the posterior distribution of the estimate for  $\mathbf{r}'$  obtained through observed data can be expressed as [33]:

$$J(\mathbf{r}') \sim \mathcal{GP}(\mu(\mathbf{r}'), \sigma^2(\mathbf{r}')) \quad (16a)$$

$$\begin{aligned} \mu(\mathbf{r}') = & K(\mathbf{r}', \mathbf{r}_{1:M}) K(\mathbf{r}_{1:M}, \mathbf{r}_{1:M})^{-1} \\ & \cdot (J(\mathbf{r}_{1:M}) - \mu_0(\mathbf{r}_{1:M})) + \mu_0(\mathbf{r}') \end{aligned} \quad (16b)$$

$$\begin{aligned} \sigma^2(\mathbf{r}') = & K(\mathbf{r}', \mathbf{r}') \\ & - K(\mathbf{r}', \mathbf{r}_{1:M}) K(\mathbf{r}_{1:M}, \mathbf{r}_{1:M})^{-1} K(\mathbf{r}_{1:M}, \mathbf{r}') \end{aligned} \quad (16c)$$

For smoothness and adaptability, the Matérn kernel is chosen as the covariance function in the GPR model:

$$K(\mathbf{r}, \mathbf{r}') = \frac{1}{\Gamma(\xi) 2^{\xi-1}} \left( \frac{\sqrt{2\xi} |\mathbf{r} - \mathbf{r}'|}{\ell} \right)^\xi K_\xi \left( \frac{\sqrt{2\xi} |\mathbf{r} - \mathbf{r}'|}{\ell} \right) \quad (17)$$

where  $\xi$  is the smoothness parameter, which can balance the smoothness and flexibility of the model.  $\ell$  is the length scale, which controls the range of influence of parameter changes on the similarity of target values.  $\Gamma(\xi)$  is the Gamma function, and  $K_\xi(\cdot)$  is the modified Bessel function. The Matérn kernel performs exceptionally well in handling non-linear and non-smooth target functions. It also demonstrates excellent stability in the presence of noisy data and high uncertainty.

The iterative optimization process begins with the expert-derived initial parameter set  $\mathbf{r}_0$ . Based on the GPR model, the Expected Improvement (EI) [34] as acquisition function is used to select the next optimal parameter set:

$$\begin{aligned} \mathbf{r}' = & \arg \min_{\mathbf{r}} \alpha_{\text{EI}}(\mathbf{r}), \alpha_{\text{EI}}(\mathbf{r}) \\ = & \mathbb{E}[\max(\mathbf{0}, J_{\min} - J(\mathbf{r}))] \end{aligned} \quad (18)$$

where  $J_{\min}$  is the current optimal target value, and the above acquisition function can be evaluated analytically as:

$$\alpha_{\text{EI}}(\mathbf{r}) = (J_{\min} - \mu(\mathbf{r})) \Phi(Z) + \sigma(\mathbf{r}) \phi(Z) \quad (19)$$

where  $Z = (J_{\min} - \mu(\mathbf{r})) / \sigma(\mathbf{r})$ ,  $\Phi(\cdot)$  and  $\phi(\cdot)$  are cumulative distribution function and probability density function, respectively. EI effectively balances exploration and exploitation. When the standard deviation is large, EI tends to

explore regions with higher uncertainty. When the mean is low and the standard deviation is small, EI is more inclined to exploit known good regions. Because EI accounts for the uncertainty in predictions, it can avoid getting trapped in local optima. Even if the predicted mean in certain regions is low, EI may still choose to explore these areas if the standard deviation is high, thereby discovering the global optimum.

Each iteration is conducted offline through simulation, generating a new set of controller parameters  $\mathbf{r}'$ , which is then used to collect new control data and update the GPR model. This process repeats until convergence.

## VI. EXPERIMENTAL SETTINGS AND RESULTS ANALYSIS

### A. Experimental Setup & Parameter Optimization

CAV's MPC parameter optimization is conducted in MATLAB 2022 using a time step consistent with the dataset to ensure temporal alignment between model calibration and control execution. To validate the controller beyond ideal numerical simulation, a real-time virtual scenario is constructed in Unity 2020.3 as a digital twin interaction environment. Control commands computed in MATLAB are transmitted to Unity via UDP at each control cycle, where vehicle motion is executed under dynamic constraints. The traffic signal logic is independently implemented in Unity to emulate real-time SPaT broadcasting, allowing the CAV to obtain signal phase information through a communication process rather than direct variable access. The updated vehicle states and signal information are then fed back to MATLAB, forming a distributed real-time closed-loop architecture. This co-simulation framework enables verification of controller performance under realistic execution and information-interaction conditions prior to field deployment.



Fig. 4. MPC parameters optimization in Unity & MATLAB.

The CAV (red vehicle in Fig. 4) operates on a 400-meter straight road with a signal light at the endpoint. For simplification, only one additional vehicle is included as the HV (blue vehicle in Fig. 5) preceding the CAV.

We select 10 sets of HV arrival states at the signal light  $\{t_{s,n}^{HV}, v_{s,n}^{HV}\}$  as the control targets for the CAV. Each set's corresponding real  $(n-1)$ -th HV data is used in the simulation as the CAV's preceding vehicle to calculate the car-following constraint information (using the IDM). The same initial values are used for data-driven MPC parameter iterative optimization in all cases. After completing MPC parameter optimization, the optimized parameters are applied to vehicle trajectory optimization in field experiments.



Fig. 5. Top view of the selected road in the test field.

TABLE I. HVs' INFORMATION IN FIELD EXPERIMENTS

No.	Model	Transmission	Maker	Amount
1	YUAN	Auto	BYD	1
2	F3	Auto	BYD	1
3	Focus	Auto	Ford	1
4	CX5	Auto	Mazda	1
5	M3	Manual	JAC	1

The field experiments are conducted at the same location as the dataset collection: the autonomous driving test field in Xi'an, China (as shown in Fig. 5). The test road segment is equipped with DSRC, providing real-time SPaT information for the CAV. During the experiments, the CAV employs millimeter-wave radar to acquire the relative distance and speed between the nearest preceding HV.

A total of six vehicles are used in the field experiments, with 5 HVs listed in Table 1. The CAV is a modified BYD gasoline vehicle (SURUI), equipped with a CAN-based drive-by-wire system and an onboard ECU capable of controlling throttle, brake, and gear. All vehicles are equipped with high-precision GPS receiver for experimental data recording. Based on the throttle and braking capabilities of vehicles, we set  $a_{\min} = -4 \text{ m/s}^2$  and  $a_{\max} = 3.5 \text{ m/s}^2$ .

### B. Arrival Time Prediction Results

Fig. 6 shows the arrival time prediction results for the CAV at different positions ( $n = 2, 3, 4$ ) during the field experiments. The black curves represent the prediction error of the Informer-based method, while the red dashed line serves as a zero-error reference. Throughout the approach to the intersection, the CAV's arrival state is continuously predicted in real time and compared against the actual arrival time.

Regardless of the CAV's position in the platoon, the prediction method delivers relatively stable and accurate estimates of arrival time:

**At  $n=2$ ,** where the CAV is right next to the first HV and experiences fewer speed fluctuations, the prediction error typically remains within  $\pm 0.5$  seconds. This highlights our model's capacity for quick, precise adaptation under simpler driving conditions.

**At  $n=3$ ,** despite increased influences from both preceding and following vehicles as well as changes in signal phases, the overall prediction error stays around  $\pm 1$  second.

**At  $n=4$ ,** although the vehicle is subject to more complex interactions and varying speeds, the error remains within approximately  $\pm 1.5$  seconds, indicating robust performance even in more challenging car-following scenarios.

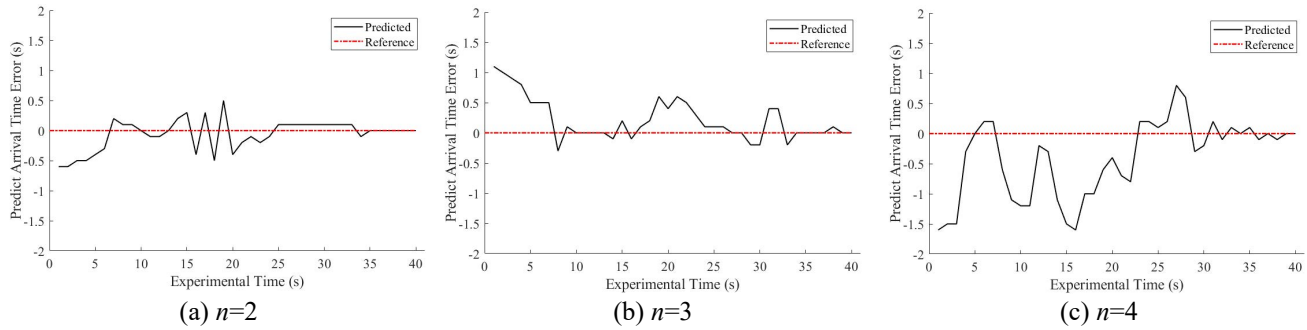


Fig. 6. Arrival time prediction results.

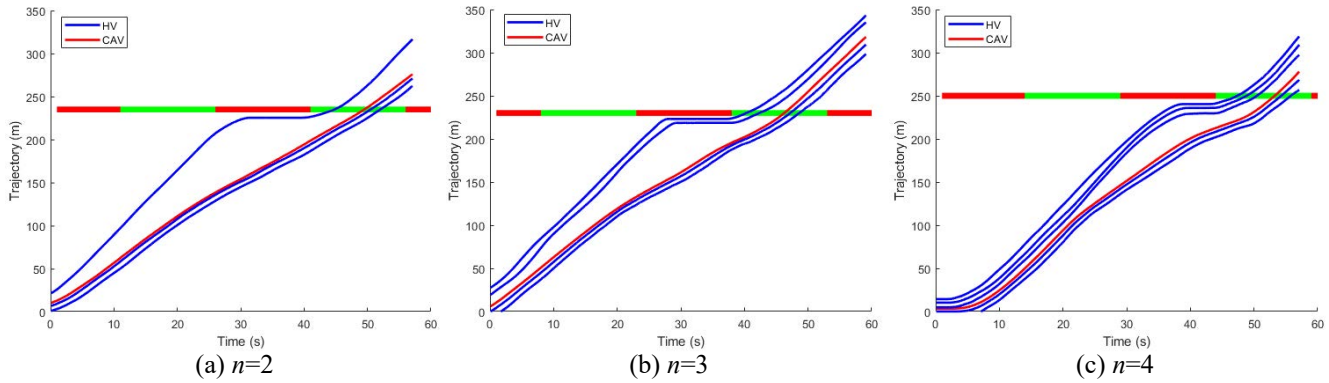


Fig. 8. Platoon trajectories optimization results.

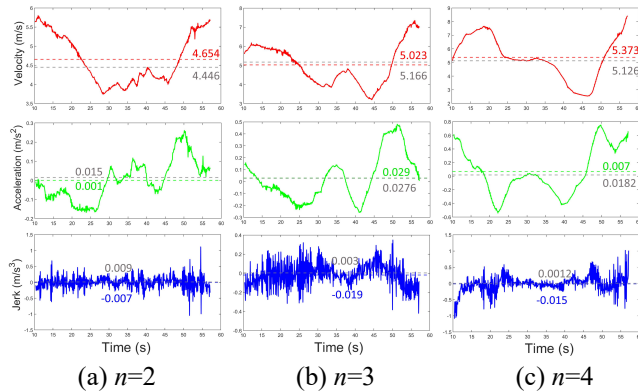


Fig. 7. CAV's MPC optimization results.

The fact that the prediction accuracy remains relatively stable across different platoon positions demonstrates the method's adaptability to multiple dynamic factors such as speed variations, acceleration, and traffic signals in a mixed traffic flow environment. This consistent accuracy can provide valuable input for subsequent trajectory planning and control, enabling more flexible signal timing strategies and coordinated platoon control. Specifically, the improved arrival time prediction reduces uncertainty in terminal state constraints within the MPC optimization horizon, thereby improving trajectory feasibility and reducing unnecessary braking events. Such reliable arrival time predictions hold potential for improving overall traffic efficiency and reducing congestion in real deployments.

### C. Optimization Results of MPC and Trajectory

Here, we show the effect of CAV control enhanced by Bayesian optimization, with CAV positions  $n = 2, 3, 4$ , respectively. In Fig. 7, red, green and blue curves are used to describe the speed, acceleration and jerk of CAV passing through the signalized intersection respectively. The dashed lines in corresponding colors are the mean value of CAV features, and the dashed gray lines are the target HVs' features used for MPC learning (as introduced in Section V.B). Our BO method, driven by human driver's data set, effectively realizes MPC parameter optimization, thereby improving the CAV control effect in mixed traffic flow. In terms of speed, there is no stopping phenomenon, in terms of acceleration and jerk, there is less rapid acceleration and deceleration, and small fluctuations within the comfortable range. Compared with the baseline MPC without Bayesian parameter tuning, the optimized controller increases average passing speed by 9.6%, reduces acceleration variance by 23%, and decreases jerk RMS by 18%, indicating significant improvements in both efficiency and comfort. Thus, the optimized CAV controller enables smooth guidance of the rear HV.

The trajectory optimization results are presented in Fig. 8. The red lines represent the trajectories of the CAV, while the blue lines represent trajectories of the HVs, with the red and green segments indicating the signal light states. When the leading HVs come to a complete stop at the signalized intersection, the optimized CAV control through our method can guide the following platoon of HVs to pass the intersection smoothly during the green light phase, achieving both high traffic efficiency and driving comfort.

## VII. CONCLUSION

In this work, we propose a data-driven framework for CAV trajectory optimization in mixed traffic aimed at improving both CAV performance and platoon-level efficiency. Extensive field data are utilized to characterize vehicle behavior near signalized intersections. An enhanced Informer model enables accurate long-horizon prediction of CAV arrival states under HV interactions, while Bayesian optimization learns HV driving features to identify near-optimal MPC parameters for deployment. Field experiments validate that the proposed framework achieves accurate arrival prediction, smoother trajectories for both CAVs and trailing HVs, and significant improvements in traffic efficiency.

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